A STUDY OF CONTENT BASED IMAGE RETRIEVAL SYSTEM

THESIS

SUBMITTED TO
BABASAHEB BHIMRAO AMBEDKAR UNIVERSITY
LUCKNOW

BABASAHEB BHIMRAO AMBEDKAR UNIVERSITY
LUCKNOW
प्रज्ञा शील करुणा
ESTABLISHED 1996

FOR THE DEGREE OF

Doctor of Philosophy

IN
COMPUTER SCIENCE

SUMITTED BY

Bably Dolly

ENROLLMENT NO.-1415/16

UNDER THE SUPERVISION OF

DR. DEEPA RAJ

ASSOCIATE PROFESSOR

DEPARTMENT OF COMPUTER SCIENCE
SCHOOL FOR INFORMATION SCIENCE & TECHNOLOGY
BABASAHEB BHIMRAO AMBEDKAR UNIVERSITY
(A CENTRAL UNIVERSITY; NAAC- 'A' GRADE)
VIDYA VIHAR, RAEBARELI ROAD, LUCKNOW-226 025 (U.P.), INDIA

2021

CANDIDATE'S DECLARATION

I, **Bably Dolly**, solemnly declare that the research work embodied in this thesis entitled **"A STUDY OF CONTENT BASED IMAGE RETRIEVAL SYSTEM"** carried out by me under the guidance and supervision of **Dr. Deepa Raj, Associate Professor, Department of Computer Science, Babasaheb Bhimrao Ambedkar University, (A Central University), Lucknow, India** is an original work and does not contain part of any work submitted for the award of any degree either in this university or any other university around the globe. It is further undertaken that the thesis is essentially free from all kinds of plagiarism.

Date: **(Bably Dolly)**

Place: Lucknow

Research Scholar
Department of Computer Science
Babasaheb Bhimrao Ambedkar
University, Lucknow

CERTIFICATE

This is certify that the thesis titled **"A STUDY OF CONTENT BASED IMAGE RETRIEVAL SYSTEM"** submitted by **Ms. Bably Dolly** is an original research work and has not been previously submitted in part or full of any other degree or diploma to this or any other university.

The thesis submitted to Babasaheb Bhimrao Ambedkar University, (A Central University), Lucknow, satisfy all the requirements as stipulated in the *Doctor of Philosophy (Ph.D.) regulations-1999 as amended in 2013* and it is fit for submission and evaluation for the award of the degree of Doctor of Philosophy of the University.

Date: **Supervisor**

Head of the Department

ACKNOWLEDGEMENTS

Being a Doctor of Philosophy is a rewarding journey that would not be possible without the assistance of many people, especially as this journey nears its conclusion. In honor of these wonderful people who have encouraged and inspired me during the highs and lows of this beautiful journey, I'd want to take this moment to thank them.

Firstly, I would like to express my sincere gratitude to my supervisor **Dr. Deepa Raj, Associate Professor, Department of Computer Science, Babasaheb Bhimrao Ambedkar University(A Central University), Lucknow,** for the continuous support of my Ph.D. study and related research, for her patience, motivation, and immense knowledge. Her guidance helped me in all the time of research and writing of this thesis. Her invaluable insight into technical and professional matters has helped me immensely throughout my research work.

My sincere thanks to **Prof. Sanjay K. Dwivedi, Dean, School of Information Science & Technology, and Head, Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Lucknow.** His Valuable suggestions made the contribution of the thesis more valuable.

I am also thankful to **Prof. Vipin Saxena, Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Lucknow,** for his valuable suggestions.

I am also thankful to **Prof. R. A. Khan, Head, Department of Information Technology, Babasaheb Bhimrao Ambedkar University(A Central University), Lucknow,** to encourage, support and motivation throughout the research work.

I would like to thank **Prof. Shishir Kumar, Professor, Dr. Babita Pandey, Associate Professor, Dr. Manoj Kumar, Assistant Professor, Dr. Narendra Kumar, Assistant Professor, and Dr. Shalini Chandra, Assistant Professor, Department of Computer Science, Babasaheb Bhimrao Ambedkar University(A Central University), Lucknow,** for their insightful comments and encouragement.

I would like to extend my sincere thanks to **Dr. Raj Shree, Associate Professor, Dr. Alka, Assistant Professor, Department of Information Technology, Babasaheb Bhimrao Ambedkar University, Lucknow**, for motivating me to complete my Ph.D. research work.

My sincere thanks go to **Prof. Sanjay Singh, Vice Chancellor, Babasaheb Bhimrao Ambedkar University, Lucknow,** for his excellent inspirational environment for research and for providing all research facilities in this university. A special thanks to University Grant Commission, India, for providing financial assistance to the Central University for doing research work.

I extend thanks to all my friends, especially friend cum colleague **Dr. Nikhat Parveen, Associate Professor, K.L. University, Vaddeswaram,** for helping whenever needed.

I would like to thank **non-teaching staff members of the Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Lucknow**, for their effort to take care of the maintenance of lab resources and work systematically.

I'm extremely grateful to my loving family for providing me unfailing and continuous support and encouragement throughout my study and through the process of research and writing this thesis. The real source of my inner strength and confidence comes from **my parents**. I'm extremely grateful to my brothers **Mr. S.K. Gupta, Mr. Ravi Gupta, Rakesh Gupta,** and **sisters Mrs. Shashi Gupta, Dr. Anju Gupta** for continuous support and help throughout the research duration. This accomplishment would not have been possible without them.

BABLY DOLLY

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF PUBLICATIONS

1. **Bably Dolly**, D. Raj, (Jul 2018) "*Various Methods of Enhancement in Colored Images: A Review*", published in '**International Journal of Computer Sciences and Engineering'**, Volume-6, Issue-7-**(UGC Indexed)**
2. **Bably Dolly**, D. Raj,(December 2019)"*Color Based Image Retrieval by Combining Various Features*", published in '**International Journal of Engineering and Advanced Technology'**, ISSN: 2249-8958 (Online), Volume-9, Issue-2, ,Page No. 454-460-**Scopus(UGC Indexed)**
3. **Bably Dolly**, Deepa Raj,(2020) "*Image Retrieval Based on Color Feature Similarity*", published in **Journal of Physics Conference Series** 1478:012014, **IOP publication-Scopus(UGC Indexed)**
4. Bably Dolly, Deepa Raj(2021), "*Image Processing Using Quantum Computing: Trends and Challenges*", published in "**Limitations and Future Applications of Quantum Cryptography**", DOI: 10.4018/978-1-7998-6677-0 ISBN13: 9781799866770-**Scopus**
5. **Bably Dolly**, Deepa. Raj(2021), "*Texture Based Image Retrieval using GLCM and LBP*" , published in **Advances in Intelligent Systems and Computing(AISC) Series, Springer**
6. **Bably Dolly**, Deepa Raj(2021), "*Image Retrieval Based on Texture using Local Binary Pattern and Local Phase Quantiszation*" published in **Algorithms for Intelligent Systems, Springer**
7. **Bably Dolly**, Deepa Raj "Image retrieval Based on Hybrid Texture Feature Extraction Techniques"-communicated in **IETE Technical Review**
8. **Bably Dolly**, Deepa Raj, "*Feature Extraction for Image Retrieval Based on hybrid features of Colour, Texture and Shape*- communicated in**International Journal of Grid and Distributed Computing**
9. **Bably Dolly**, DeepaRaj, "*Image Retrieval Classification using Machine Learning Approach*"-communicated **International Journal of Image, Graphics and Signal Processing (IJIGSP)**

SUMMARY

Image retrieval is widely required instead of text retrieval in the current scenario. The CBIR (Content-Based Image Retrieval) System becomes more valuable in this scenario to excess the most similar images from the large set of images. In CBIR, image retrieval is based on the similarity measures between the query image and the targeted dataset with concerns to color, shape, and texture descriptors which are taken as low-level feature descriptors. With the advancement of the CBIR system, its advantages in different areas of research are in need like in satellite image detection, army security, image security, medical stream, etc. In this regards many works have been carried out by taking the low-level features. As a result of the widespread use of the internet and online technologies, a large variety of data collections containing a wide variety of images are available. Book categories, educational content, newspaper ads, newspaper articles, and other media are all being digitised and will be made available to users as they see fit. Different ways have been used to extract images from databases, depending on the user's requirements. The computer vision's application from the perspective of image problems is the content-based image retrieval system. Based on the extraction of local features including colors, forms, and textures, our research aims to find the most comparable images to the given Query image. It takes a lot of time, effort, and money to manually annotate images. We present a method for image retrieval systems based on a variety of techniques. the proposed work can be used to search for a specific image that is content-based (i.e. it's based on colors, shapes, or textures).Our objectives are Extracting the color feature, shape feature and texture feature of the image in data base and same for the query image and retrieving the most similar image related to the query image from the data base. Machine learning approach is also used for fast retrieving of similar images after doing classification using training set to train the model by using classifier algorithm and retrieving the similar images related to the query image.

CHAPTER I

INTRODUCTION

This chapter describe the fundamental aspects of Text based image retrieval system as well as content based image retrieval system. Starting with the content based image retrieval system and describe all the local level features like color, texture and shape. Focus on previously various ways which have been created to obtain images from different set of databases. Various methods have been created to retrieve images based on their utility. The content-based image retrieval system utilises computer vision to solve an image issue. There are use of diverse multimedia data, such as music, video, and , has increased in recent years, particularly in the last couple of years, as a result of the widespread use of smartphones, internet surfing, and the digitization of a wide range of applications, among other factors. The retrieval of such multi-media material is one of the most difficult challenges facing researchers in the contemporary environment. Different ways are used to meet all of the requirements from time to time.Extracting the color feature, shape feature and texture feature of animage Some of the application areas of CBIR system also defined. Machine learning approach is also used for fast retrieving of similar images after doing classification using training set to train the model by using classifier algorithm and retrieving the similar images related to the query image. This chapters described the different color features, texture features, shape features with machine learning approaches.

CHAPTER II
LITERATURE SURVEY

This chapter is summaries previously published techniques for content-based image retrieval in medical applications, highlighting areas that could be improved. Researchers have worked tirelessly over the last decade to advance automated content-based image retrieval methods to assist medical practitioners in diagnosing, monitoring drug application results, and conducting medical research. However, a content-based image retrieval system that is efficient, user-friendly, fast, and commercially viable is still a long way off.A content-based image retrieval system combines several processes, such as image processing, machine learning, information retrieval, and computer vision. Based on a review of the literature, a few of the features are summarized in this.

CHAPTER III

IMAGE RETRIEVAL BASED ON COLOR FEATURE SIMILARITY

This chapter introduces the concept of a color based image retrieval system with different approach. This chapter focuses on extracting images from a large image database using color features of an image, and give a novel approach for retrieving images from large image database. Color is the most important, dependable, and extensively used of the visual elements. The RGB color combination is considered in this chapter for image retrievalUsing color projections, we were able to find images in a vast collection by applying segmentation and quantification to several color models and comparing the results. This method has been tested on a variety of image sets and its retrieval rate has been examined in a variety of models.

CHAPTER IV

COMPARATIVE ANALYSIS OF FEATURE EXTRACTION APPROACHES BASED ON TEXTURE DESCRIPTORS

In this chapter, we examine and compare the efficiency of image retrieval using different texture feature extraction techniques, such as Gray Level Co-occurrence Matrixes (GLCM), Local Binary Pattern (LBP), and Local Phase Quantisation (LPQ), by analysing and comparing different research papers based on texture feature extraction. The comparison of the GLCM, LBP, and LPQ methodologies is the focus of this research. A wide range of applications, from remote sensing to biological imaging, require some raw data image to extract relevant features that characterise the image's features. When searching for images that are similar to a query image, content-based image retrieval (CBIR) plays an important role. However, there is still a lot of work that needs to be done in these areas. In this research, we analysed and compared the efficiency of image retrieval with reference to their texture feature vectors dataset of images with the use of different texture feature extraction techniques, including GLCM, LBP, and LPQ. A comparative study of GLCM, LBP, and LPQ procedures is the subject of this research project.

CHAPTER V

IMAGE RETRIEVAL BASED ON HYBRID INVARIANT FEATURE EXTRACTION TECHNIQUES

In this research work, a texture-based feature extraction framework is proposed and compared with the existing techniques available. The images of the Brondetz database are used in this research, and belong to the same category, but have varied wall tile textures in the TIFF format and are of the same size. The proposed work shows a texture-based retrieval framework for retrieving similar images. To build this framework, used database colors and then returned the relative texture characteristics retrieved from each image to the database. Using a distance metric, the same procedure is used to extract texture features from of the query image. The similarity between the query image and the returnedimages has been calculated.

CHAPTER VI

FEATURE EXTRACTION FOR IMAGE RETRIEVAL BASED ON HYBRID FEATURES OF COLOR, TEXTURE AND SHAPE

In this chapter an experimental analysis is carried out to improve the optimal method of feature extraction. These results showed that the color (L*a*b, RGB), hybrid texture (GLCM, LBP, LPQ), and shape (zero-crossing rate) features for efficient and effective retrieval. This efficient image retrieval model study may be utilised in a different area of the present scenario. In the current scenario, many databases of images and video for any area have grown rapidly. Retrieving the query-based image is in demand for a quick response. In this chapter, a hybrid feature based content retrieval system proposed using color descriptors, shape descriptors, and texture descriptors. The proposed system was evaluated on COREL database. The color descriptors such as color histogram, color moments, color map, in the LBP model, LBP and LPQ, and GLCM for the texture feature, color feature, and shape features and shape descriptors as HOG features.

CHAPTER VII

CONTENT BASED IMAGE RETRIEVAL USING MACHINE LEARNING

This chapter proposes a new methodology for image retrieval using the local descriptors of an image in combination with one another. HSV histogram, Color moments, Colormap, are used to form the feature descriptor. In this work, it is found that a combination of all these features produces promising results that supersede previous research. To make a fast image retrieval process Machine Learning approaches have been utilized and also illustrate a comparative accuracy of different used machine learning approach. In this regard a supervised learning algorithm, Quadratic SVM is used for the classification of the images in the database, and then a similar image is retrieved by using distance metric in only the same class images. CBIR is better suited to massive volumes of visual input. Color-based features have been extracted in this work.The proposed system was evaluated on COREL and CIFAR databases. The proposed work outperformed other state-of-the-art methods in terms of retrieval performance. For validation, a database of roughly 500images was divided into three categories. to compare based on retrieval of similar imagesand accuracy through machine learning techniques. The proposed approach results in image categorization accuracy.

CHAPTER VIII

CONCLUSIONS AND FUTURE ENHANCEMENTS

This research work provides the overall idea of content based image retrieval (CBIR) system. CBIR is very much required in today's scenario. We have developed a novel approach to retrieve most similar images from large datasets based on local features of an image with respect to improved efficiency. Most of the time, there is a maximum chance of not to retrieved most similar images from a large dataset as per queried images. For this, we have some new approaches to extract features based on color, shape, and texture to overcome such issues.We looked into the low-level components of CBIR color features extraction and texture features extraction. This

chapter concludes all the research work discussed in the chapters and the potential scope of the thesis. The work produced a CBIR system combining color, texture, and shape features. Inputting an image quickly and accurately retrieves similar images. The system will be strengthened by fusing low-level features with the spatial position in the future. The CBIR system also includes image feature matching and semantic-based image retrieval.Machine learning algorithms have shown promising results in several fields for CBIR and image representation. Recent CBIR research has shifted to deep neural networks, Managing a big image collection for supervised deep network training is complex and time-consuming. Thus, evaluating a deep network's performance on a large unlabeled dataset in unsupervised learning mode is a potential future study direction.

CHAPTER I

INTRODUCTION

1.1 BACKGROUND

Nowadays as the internet and web technology are growing days by days, there are numerous databases with huge image categories. Books, learning content, newspapers, and advertisements have been digitised and made available online for users. Various ways have been created to obtain images from databases. Various methods have been created to retrieve images based on their utility. The content-based image retrieval system utilises computer vision to solve an image issue. There are use of diverse multimedia data, such as music, video, and images, has increased in recent years, particularly in the last couple of years, as a result of the widespread use of smartphones, internet surfing, and the digitization of a wide range of applications, among other factors. The retrieval of such multi-media material is one of the most difficult challenges facing researchers in the contemporary environment. Different ways are used to meet all of the requirements from time to time.

1.2 IMAGE RETRIEVAL SYSTEM

An image retrieval system is a computer system that retrieves, browses, and searches images from a large digital image database [1]. The most common image retrieval approaches use some method of adding metadata to the images, such as captioning, keywords, or descriptions, to perform annotation word retrieval. Manual image annotation is time-consuming, labor-intensive, and costly. There are two types of image retrieval techniques: The first is text-based image retrieval (TBIR), and the second is content-based image retrieval (CBIR).

1.3 APPROACHES TO IMAGE RETRIEVAL

1.3.1 Image Retrieval Using Text (TBIR)

In the beginning, Text-Based Image Retrieval (TBIR) was developed for retrieval reasons. TBIR is currently used in the majority of web image retrieval systems. A keyword-centered search is used in the text-based approach. This method retrieves images from an image database by using the text associated with the image[30]. Text-based techniques are used as a starting point for image search in the beginning stages. These strategies are based on keyword research. These keywords behave in the same way as the images' contents, such as the file name, alternative tags, the caption of the image, and so forth. Two major techniques to text-based image retrieval are natural language processing (NLP) and the idea of "bags of words." These are the two basic approaches to text-based image retrieval [25]. The most prominent image search engines are Lycos multimedia search and Google image search, both of which are mostly utilised for keyword-based procedures. The inability of modern search engines to provide a flawless text query generator is a fundamental restriction of their operation. The text engine is responsible for processing this text-based inquiry. This engine divides the text into tokens and then reassembles them. These tokens are compared to the tokens for the image that have been recorded in the database. Text matching is the most efficient way to information retrieval when compared to all other alternatives. As a result, there is a semantic gap between the token supplied by the user and the tokens of the database images that have been stored. In the majority of cases, the TBIR results are not entirely satisfactory. The user must enter the text he desires from the multimedia database, and the database will return relevant results for the user's request. If the user knows exactly what he wants from the system, this strategy will work well; but, if the user is not efficient in creating textual inquiries, this approach may fail. Annotation is a further issue with the TBIR. All of the photographs, videos, and other media must be accompanied by some form of text annotation. When the similarity computation is performed, this text is transferred to the user's intended outcome. If the database is huge, this annotation will take time and effort, and it will necessitate the use of an efficient database annotator. If the annotation of the image does not correspond to the user's requirements, It will result in data that is completely irrelevant. In addition, annotation is a time-consuming procedure, and it is not possible to accurately annotate all of the images at the same time. The comprehensive image description, on the other hand, is not always possible to communicate in text, increasing the semantic gap between the user and the retrieval system, as shown in Figure 1.1.

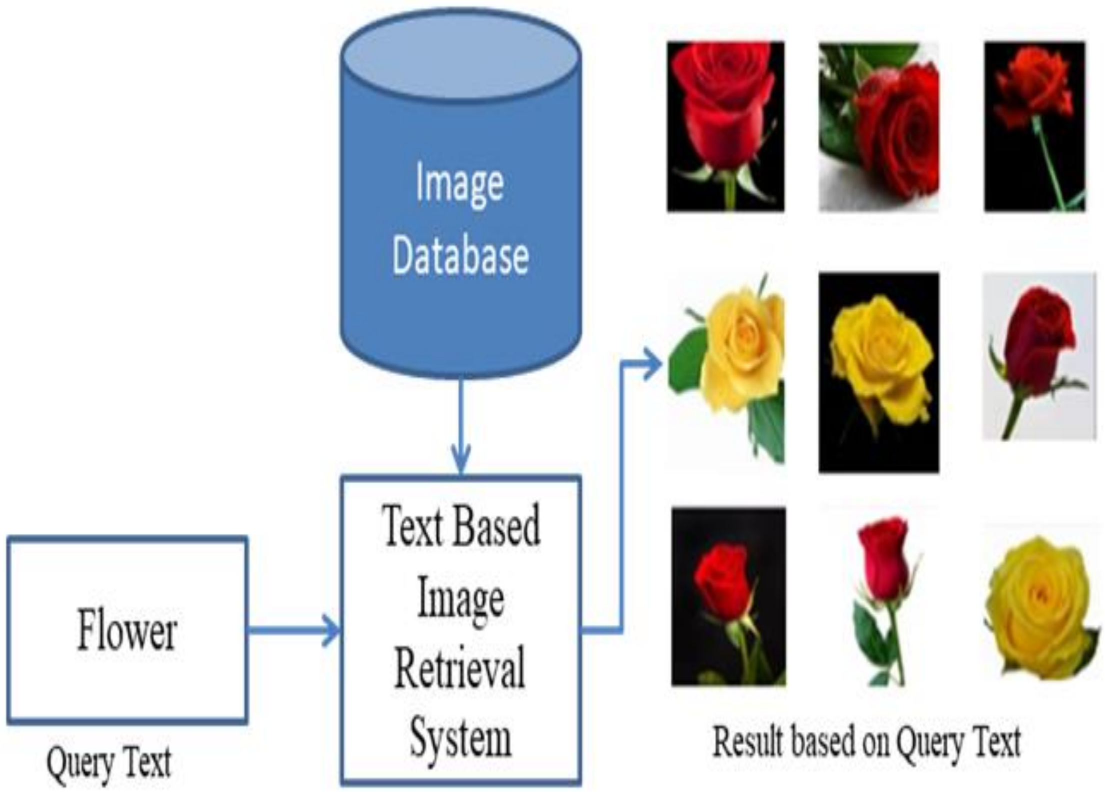

Figure1.1 Block Diagram of Text Based Image Retrieval System

The disadvantage of TBIR is that manual annotation is impossible and expensive for a large database. This limitation of text-based image retrieval paves the way for content-based image retrieval (CBIR). Visual contents such as color, texture, and shape are important in image search in this approach.

1.3.2 Image-Retrieval-Based-On-Content (CBIR)

An alternate technique to overcoming the shortcomings of text-based image retrieval (TBIR) is content-based image retrieval (CBIR), which does not require the use of annotation. The Center for Biomedical Image Retrieval (CBIR) was established in 1994 and can be considered the beginning of the research and development period in image retrieval by content. Instead of sending the text for the question, this solution provides the retrieval system with a complete query image. By comparing the visual contents of the query image with those of the stored database images, the retrieval system is able to conduct the return. Color, texture, and shape, as well as some hybrid features resulting from the low-level traits, may be included in these visual components.

Content-based image retrieval (CBIR) retrieves images based on automatically derived color, texture, and shape features. The CBIR system is made up of a basic set of components that interact to retrieve database images based on a given query. In a traditional content-based image retrieval system, multidimensional feature vectors extract and state the visual contents of the images in the database [123]. The feature vectors of the images in the database are used to create a feature database. To retrieve images, users submit query images or sketched figures to the retrieval system. The query image is then converted into feature vectors by the system. The similarities and differences between the query example's feature vectors and the database images are calculated, and retrieval is performed using an indexing scheme as shown inFigure 1.2.

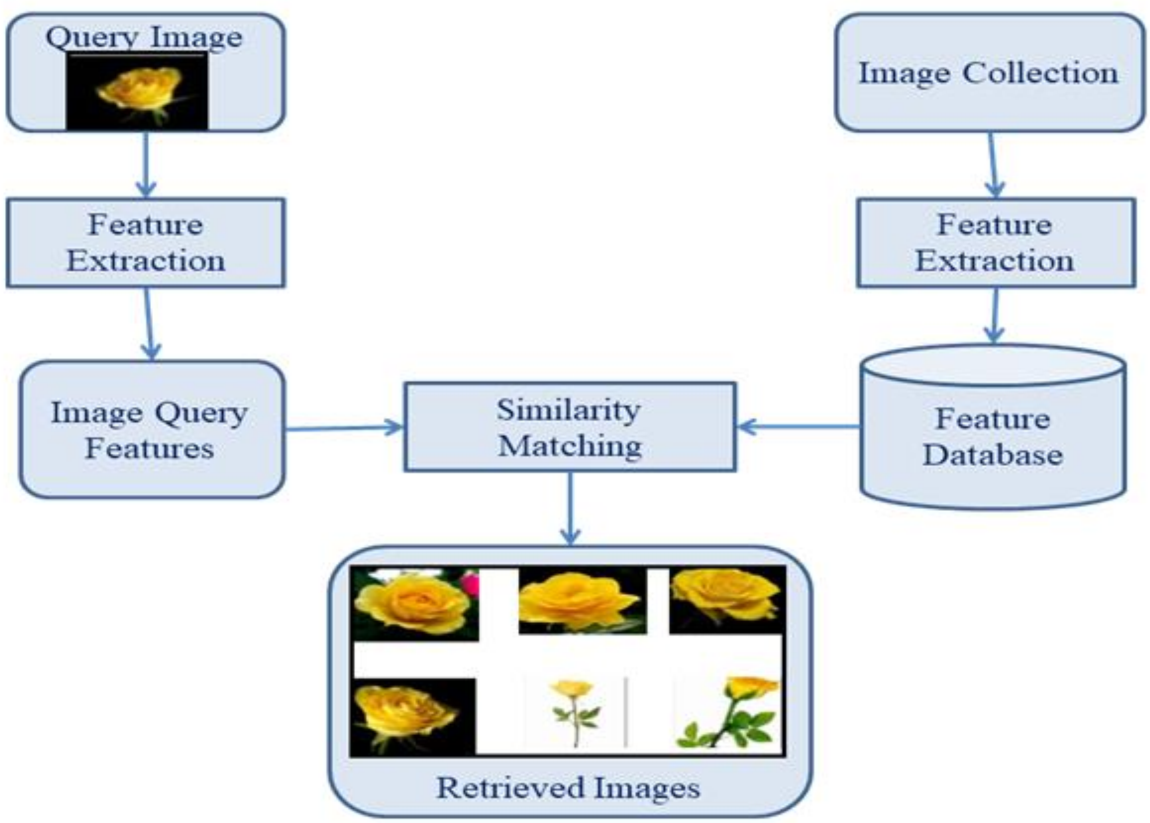

Figure 1.2: General Block Diagram of Content Based Image Retrieval System

In some CBIR systems, an optional module related to relevance feedback is used, in which the user gradually improves the search results by marking images in the results as "relevant," "not relevant," or "neutral" to the search query. The search is restarted with the new information. As a result, the user can evaluate those relevant images based on the query results. The data can be reused by the system to improve the results.

Our research is based on the automatic retrieval of the most similar images to the Query image using local feature extraction such as colors, shapes, texture, and so on. Few systems use the lower-level feature in an image retrieval system for searching, browsing, and retrieving images from a large database of images; manually image annotation is time-consuming, difficult, and expensive. To address this, we present an approach for image retrieval systems that employs various methods for searching any query image that is Content-based in terms of colors, shapes, and textures; analyzed for actual image presence in the database.

1.4 FEATURE EXTRACTION

The feature extraction and representation procedure lies at the heart of CBIR systems. Image attributes such as color, texture, shape, and edge information are extracted using image processing methods and are referred to as features. The research focuses on three general feature representations that have been extensively researched in the literature.

1.4.1 Color Feature

Color is an important feature that aids in image recognition for humans. As a result, it is widely employed in CBIR and extensively researched in the literature. Color is a dominating descriptor used to quickly identify an object and is one of the most widely employed visual features for content-based image retrieval. To extract color information from an image's content, we must first choose an effective color descriptor and a suitable color space. The color space makes it easier to specify colors. In a coordinate system, the color is represented as a single point. For diverse uses, color spaces such as RGB, HSV, CIE L*a*b, and CIE L*u*v have been developed. Despite the fact that there is no consensus on which color space is optimal for CBIR, we need a color scheme to assure perceptual consistency. After choosing a color space, we must construct an effective color descriptor to characterise the color of global or regional areas. Color histograms[106], color moments[141] , color edge [57], color texture[62], and color correlograms[1] are some of the color descriptors that have evolved from diverse representation systems. The Color Space Descriptor lets you choose the color space to describe with. The Color Quantization Descriptor specifies how a color space is partitioned into discrete bins. The Dominant Color Descriptor allows you to specify a small number of dominant color values as well as statistical features such as distribution and variation. Its goal is to give a simple, effective, and intuitive depiction of colors in a region or image. A color histogram defined in the Hue-Saturation-Value (HSV) color space with fixed color space quantization yields the Scalable Color Descriptor. Based on color histograms, the Color Structure Descriptor seeks to identify localised color distributions using a limited structuring window. The Color Layout Descriptor describes the spatial arrangement of dominant colors on a grid overlay on a region or image. The Discrete Cosine Transform coefficients are used to represent the data (DCT).

1.4.2 Texture feature

A set of metrics calculated in image processing to measure the perceived texture of an image is known as an image texture. Texture descriptions are based on texture analysis techniques and image attributes retrieved. A repetitive pattern of pixels over a spatial area can be thought of as texture. Texture properties are visual patterns in an image that have properties of homogeneity that aren't caused by the existence of only one color or intensity. Directionality and regularity are two texture features that are sensed by the human eye.

In image processing and computer vision, image textures are extremely useful. They include texture classification (the recognition of image regions), texture boundary recognition, texture segmentation, texture synthesis, and texture image production from known texture models. Texture does not have a standard mathematical definition. As a result, several various ways of producing texture features have been presented over time. Unfortunately, no single technique works well with all textures. Texture feature description is often done using statistical, model-based, and transform-based methods.

The roughness of the surface is represented by texture. This feature describes the image's structure in terms of behaviour. This property can be computed in both the spatial and spectral domains. features in the image Low-level characteristics (Texture, Color and Shape) Characteristics of the middle level (Region, Blob, Edge etc.) Features at a high level (Object, Semantic, Derived features etc.) Researchers have given numerous strategies in the spectrum domain. Wavelet and its derivatives are commonly utilised in the spectral domain to extract texture information. One of the most significant advantages of extracting texture features in the spectral domain is that the retrieved texture features are less susceptible to noise. Local binary patterns and its modifications are commonly used by academics in the spatial realm. In the spatial domain, the binary pattern is calculated by calculating the relationship between nearby pixels and the center pixel. Because they rely on center pixels, these approaches are more susceptible to noise. Various advanced approaches are used to extract texture features. In general, three approaches are utilised to extract texture features: structural, stochastic, and statistical approaches. The orientation of the primitives within an image, and locally in an image region, with respect to each other, is frequently captured using the structural texture measure technique[64][152]. For structural texture investigation, mathematical morphology[23][151] is a better tool**.** The percentage of granularity and repeated patterns of surfaces present in the image is measured by texture features. Water, brick walls, grassland, and the sky, for example, have different textures in terms of granularity and roughness of the surface. Statistical approaches to texture analysis[70][79] calculate the features at each point of the image based on the spatial distribution of pixel values. By determining a set of statistics, this study determines the texture's behaviour[70][79]. The Markov random field[90], Tamura feature [127], Fourier power spectra, multi-resolution filtering techniques like Gabor[101][89] and wavelet transform[32][87], and Wold decomposition[82][52]are examples of statistical methods. These approaches describe how the image's statistical intensity distribution is measured. There are three types of statistics: first-order, second-order, and higher-order statistics. The derivative of a first order statistic is computed without taking into account the spatial relationship between two or more pixels, whereas second and third order statistics produce the derivative by computing the spatial relationship between surrounding pixels. The most extensively utilised statistical texture analysis of the image is the grey level co-occurrence matrix (GLCM) and LBP and its derivatives.

There are supervised and unsupervised approaches for statistical texture analysis, each with its own set of advantages and disadvantages. The Texture Spectrum Operator (TSO) has the advantage in the unsupervised approach that texture characteristics of the images are characterised by the associated texture spectrum rather than a set of texture measures. The Local Binary Pattern (LBP) operator, on the other hand, is appealing. Despite the implementation challenge in the form of delta value definition, a user can establish a threshold value that is reliant on gray scale values. The most widely used statistical approach is the Gray-level Co-occurrence Matrix (GLCM). It's a two-dimensional matrix of joint probabilities between pixels separated by a distance, d, in a specific direction, r. It is frequently used in texture description and is based on the occurrence of a particular gray-level configuration on a regular basis. In fine textures, this arrangement changes quickly with distance, but in coarse textures, it changes slowly. Haralick identifies 14 statistical characteristics. For texture classification, the GLCM uses energy, contrast, entropy, autocorrelation, maximum probability, and inverse difference moment. The gray-level co-occurrence matrix technique for representing texture characteristics has been proven to be beneficial in the classification and retrieval of rock textures as well as the detection of fabric flaws.

The GLCM approach is good for unsupervised texture classification; however it has limitations when it comes to categorizing huge primitives. Finally, the Entropy-Based Local Descriptor (EBLD) technique has the drawback of considering data in probabilistic terms, which leads to uncertainty and instability. Fractal and stochastic models are used in model-based texture analysis[21][27][35][107]. However, stochastic models have a large computational complexity and do not provide orientation selectivity. For local image structures, these models are ineffective.

1.4.3 Shape Feature

One of the most common features in CBIR approaches is the form. The outline or contour of an object denotes the precise surface configuration of the object. Shape identification is a systematic way for humans to comprehend their surroundings. It's essential in CBIR since it refers to the image's region of interest.

The image's shape is equally crucial in terms of its visual content. Shape feature extraction is done based on the image's region or object, and several approaches based on region-based shape features have been proposed so far. The approaches used to characterize shape feature representations. They are "region-based" and "boundary-based". The initial step in the shape feature extraction procedure is image segmentation. The features of the shape feature are the only thing that distinguishes segmented image regions. It is a significant feature of image regions that have been segmented, and its well-organized and powerful representation aids image retrieval. Shape feature extraction methods require strong segmentation methods to divide the image into meaningful parts or objects, but color and texture features do not need to be divided for feature extraction. However, good image segmentation for natural images is challenging to perform. Different ways for estimating shape features include shape transform domains, polygonal approximation, scale-space approaches, moments, and spatial interrelation features. Shape feature descriptors are divided into two categories: boundary-based and region-based descriptors. External descriptors are also known as boundary descriptors, while internal descriptors are also known as region descriptors. The shape of the items was initially identified using global descriptors.

For image retrieval, CBIR systems created in the early 1990s utilized only one feature. Although single-feature CBIR systems are faster than multi-feature systems, they do not provide superior retrieval accuracy. Because the image is made up of multiple zones, each of which has its visual qualities. Using a combination of these factors to improve image retrieval accuracy is possible. Some approaches combine any two features, while others combine two features at one level and then add more features at the following level. This research project intends to improve the methodologies and methods for obtaining images by combining features rather than employing a single feature to achieve better outcomes. Most early research on the CBIR method used only one feature from various features such as color, texture, and form. However, because each image has various visual features and texture properties, it isn't easy to achieve adequate retrieval results with a single feature. When compared to a single feature such as color, shape, or texture, combining many features boosts the efficiency of the retrieval process.

1.5 MACHINE LEARNING

Machine learning is the study of underlying computer algorithms that learn and evolve on their own as a result of their exposure to and accumulation of data over time. Author Arthur Samuel, a former IBM employee and pioneer in the fields of computer games and artificial intelligence, coined the phrase "machine learning" in 1959. During this time period, the term "self-teaching computers" was also used to describe these machines. For most of the 1960s, Nilsson's book on Learning Machines, which was primarily concerned with machine learning for pattern classification, was a landmark in the field of machine learning research. Pattern recognition remained popular well into the 1970s, according to Duda and Hart, who published their findings in 1973. In 1981, a paper was made on teaching approaches for teaching a neural network to recognise 40 characters from a computer terminal, which was published in the Journal of Neuroscience (26 letters, 10 digits, and 4 special symbols).

Machine learning in the present era is intended to do two things. One way is to perform categorization using models that have already been developed. The other objective is to utilise these models to make predictions about what will happen in the future. A hypothetical system for categorising data might be trained using computer vision on moles, along with supervised learning to detect cancerous moles, in order to improve its classification accuracy. Instead, a machine-learning stock trading system may provide the trader with forecasts about the stock's future performance, according to the system.

In the field of artificial intelligence, it is considered to be a sort of machine learning. When given a sample of data, known as "training data," machine learning algorithms build a model that may be used to generate predictions or judgments without being explicitly programmed. Machine learning techniques are used in a wide range of applications, including healthcare, online filtering, natural language processing, and computer vision, among many others. It is difficult or impossible to develop standard algorithms that can do the needed tasks.

However, not all machine learning falls within the category of statistical learning. A subset of machine learning that is closely associated with computational statistics is concerned with making predictions with the aid of computers. The study of machine learning benefits from the science of mathematical optimization because it provides methods, theory, and application domains that are useful to machine learning researchers and practitioners. Data mining is a closely related field of study that focuses on unsupervised learning for the purpose of exploratory data analysis. [5] The incorporation of data and neural networks in some machine learning implementations is intended to mimic the functioning of the biological brain. When machine learning is applied to solve business problems, it is referred to as predictive analytics (or predictive modelling).

Learning algorithms are predicated on the notion that methods, algorithms, and conclusions that have proven successful in the past will most likely continue to be successful in the future. There can be no doubt about such deductions; for example, "since the sun has risen every day for the last 10,000 months, it will most likely rise again tomorrow morning." "X percent of families have species with color variants that are found in different geographical locations. As a result, there is a Y percent chance that previously undiscovered black swans exist "as an illustration.

Machine learning algorithms have the ability to fulfil tasks even if they were not explicitly designed to do so. It entails computers learning to perform specific tasks by analysing data. It is feasible to develop algorithms that instruct the machine on how and when to perform all steps necessary to solve the problem at hand for fundamental jobs that are given to computers; no learning on the part of the computer is required. When faced with more complex jobs, it might be challenging for people to manually construct the algorithms that are required. In practise, supporting the computer in constructing its algorithm rather than having human programmers explain each and every step required can be more fruitful in terms of productivity.

Machine learning is a discipline that uses a number of techniques to teach computers how to do jobs for which there is no completely satisfactory solution currently available. An approach that can be used when there are many viable responses is to classify a few of the correct answers as valid. As a result, the computer can use this information as training data to develop the algorithm (s) that it employs to identify the correct responses.

In terms of typical classification, machine learning can be divided into three categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is used to do predictive modelling tasks, such as predicting the link between data properties and one or more target variables or labels, among other things. Unsupervised learning aims to model the hidden structure inside data without the need of label information, whereas supervised learning makes use of labelled data to accomplish this. Finally, reinforcement learning is concerned with the development of incentive systems that are capable of representing complex decision techniques and learning sequences of actions. The topic of supervised learning is covered in this chapter.

In supervised training, the classifier is given a set of training data as well as class labels. This previous knowledge is used by the classifier. With supervised learning, there are a variety of ways for designing a classifier. Some of the most popular techniques are discussed.

1.5.1 k-Nearest Neighbor (k-NN)

The k-Nearest-neighbor classification is simple to understand and implement, with high classification accuracy. The majority vote of the k-nearest classes determines this classification. The distance between the points in the training data set is dictated by the feature vectors, which are represented as points in feature space. The classifier then uses only the k-nearest neighbour classes to forecast the best-fit class for a point using a majority vote.

1.5.2 Decision Tree

A decision tree works by partitioning input space. It's a tree structure with internal nodes and leaf nodes that represent tests and classes, respectively. The root node is the beginning point for a new test point's classification. The root's various links present various outcomes, after which the next stage is to make decisions on succeeding nodes, and so on until leaf nodes are reached. ID3 and Classification and Regression Tree are two common tree-building techniques (CART).

1.5.3 Support- Vector -Machines (SVM)

SVMs (Support-Vector-Machines) are machine-learning algorithms that perform better in most fields. SVM was proposed by Vapnik[123] and is gaining popularity in the field of machine learning due to its many appealing features and ability to demonstrate practical performance. The use of a classifier in a CBIR system minimizes the need for a similarity measure. By applying features to the training set, images with similar attributes are sorted into one group. Support vector machines, Bayesian classifiers, neural network classifiers, and random forests are the most common classifiers used throughout CBIR applications. SVM is a representational classifier, which means it is used to address machine learning problems. To reduce the upper bound of the generalisation error, the SVM machine learning technique optimises the space (margin) among hyperplane and data. Directed Acyclic Graph, Binary Tree, One-Against-One, and One-Against-All classifiers are some of the techniques to tackle multi-class classification issues with SVM. Multi-Class SVM is used to create one SVM per class, which aids in distinguishing one class from others. The greatest output within all SVMs is used to classify an unknown pattern. The best hyper-plane leaves the most margins from both classes; hence the goal is to find the hyper-plane that leaves the most (supreme) margin towards a sample object. In other words, the larger the margin, the less likely any feature vector will be misclassified. In image classification, nonlinear transformation is used to convert input vectors into a high-dimensional feature space. A kernel function is used to construct an ideal hyper-plane.(Agrawal et al., 2011) [3]Offered a unique approach for color image content classification using SVM (SVM). In SVM, multi-class classification is done using a one-against-all or one-against-one technique.

A popular kernel-based learning technique, Support vector machines (SVMs) were developed by Vapnik and his team in the late 1970s. By solving a convex quadratic optimization issue, SVMs can avoid the local extremum conundrum that other machine learning algorithms suffer from. A non-parametric supervised approach, SVM ignores the data distribution. In contrast to other statistical techniques such as maximum likelihood, SVMs do not require prior knowledge of data distribution. In its simplest form, SVM is a binary linear classifier that finds a single class border. Assumption of linear separability of multi-dimensional data shown in Figure 1.3.

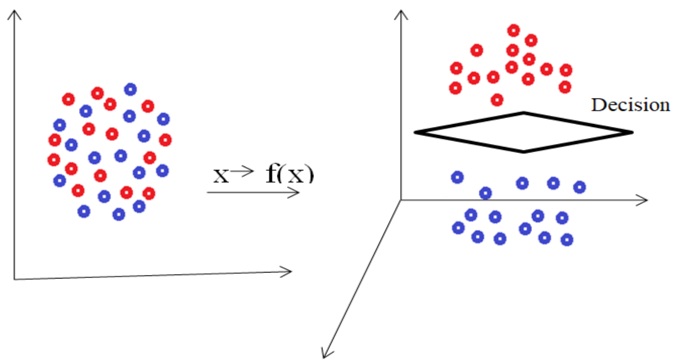

Figure 1.3: A Support Vector Machine Example for Non-Linearly Separable Data with Kernel Trick

To categorise a dataset, SVMs use training data to determine an ideal hyperplane (a line in the simplest case). Support vectors are used in SVMs to maximize separation or margin[134] Classification of these samples directly affects the optimal decision boundary location [8]. Mathematically and geometrically, the optimal hyperplane can be defined. Misclassification errors are minimised by a decision boundary [8]. Based on the maximum margin of separation, the ideal hyperplane is chosen[49]. The learning process is the iterative process of building a classifier with an optimal decision boundary. In practice, classifications of data samples often overlap (see Figure 1.4).

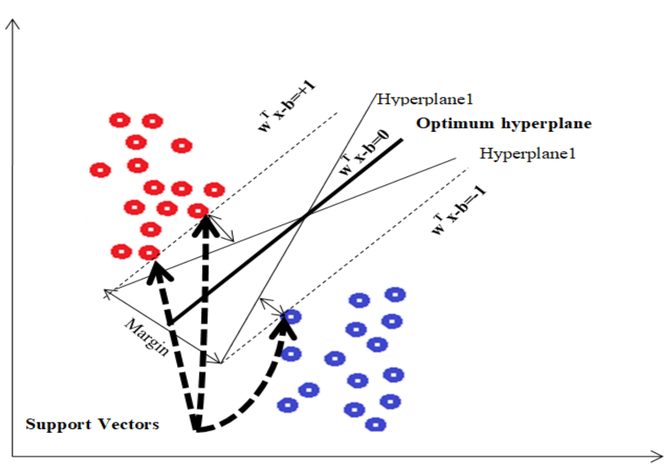

Figure 1.4: A Support Vector Machine example for linearly separable data

To identify such data accurately, linear SVM needs to be modified. These methods were developed by Cortes and Vapnik[26]. The soft margin strategy can deal with non-linearly separable data by adding slack variables (i.e. By mapping feature space into higher dimensions (Euclidean or Hilbert space), the kernel approach can improve class separation[71]. A dataset is transformed into a higher dimensional feature space where the training samples are linearly separable using the kernel approach. It's important to choose a kernel function that produces dot products in higher dimensional feature space. This space is infinitely dimensional and allows linear discrimination. Sigmoid, Radial basis function, Polynomial, and Linear[24] are all kernel models that generate SVMs that satisfy Mercer's requirement. The polynomial and radial basis function (RBF) kernels are commonly employed for remote sensing image analysis. These are picked by establishing the kernel model (Gaussian, polynomial, etc.) and then setting the parameters. Selected kernel functions must perform well on a subset of the training sample or validation set (classifier performance). A major flaw in kernel-based algorithms like SVM is their sensitivity to overfitting. Automatic kernel selection[77][71][6], and multiple kernel learning[125] were offered as creative solutions to this issue. An optimization challenge [72][149][124][114][61] includes determining the best kernel. Optimising SVM parameters takes a lot of time and resources A genetic optimization algorithm (GA)[58][59][96] or a particle swarm optimization (PSO) technique[17] are needed to find the SVM parameters. They both use evolutionary algorithms to maximise C and gamma. PSO offers some advantages over GA and other related evolutionary algorithms[17]. This is because SVMs are binary, which makes them difficult to utilise in multi-class applications. An SVM binary classifier can be used to classify a multi-class problem[95]. An optimization procedure is required to expand the binary SVM to multiclass classification. As an example, setting the kernel parameters C (controls the amount of penalty during SVM optimization) and RBF kernel spread only requires one optimization, against five for one-against-all and 10 for one-against-one approaches, and a total of five class classifications. Unlike the typical one-against-all technique, one-shot multi-class classification guarantees a complete confusion matrix[92]. A limited number of support vectors allows SVM to swiftly classify high-dimensional large data into subgroups. However, massive data classification is always computationally costly. The

SVM is used in many areas, including hybrid SVMs such as the Granular Support Vector Machine (GSVM). In contrast to the standard SVM, the GSVM achieves good generalisation performance while utilising granular computing and statistical learning theory. These approaches are often more accurate than SVMs in remote [17][59][96]. For example, in remote sensing image analysis, where dimensionality might be high[95][92], SVM is an efficient classifier. A fraction of training data is also required to assign new members. Due to this, SVM is one of the memory-efficient algorithms [135]. With fresh kernels instead of linear boundaries, SVMs are more flexible and perform better. Unbelievably intricate mathematics behind the SVM limits effective cross-disciplinary applications[13].

1.5.4 Neural network (NN)

Artificial networks are made up of a vast number of interconnected neurons that work in parallel to complete learning tasks, and their success is determined by their ability to learn. The Multi-Layer Perceptron (MLP) is a popular supervised learning network model that comprises of an input layer, one or more hidden layers, and an output layer, with linkages between layers established (manufactured) by connecting nodes from one layer to neurons in the next layer. During the training phase, the scalar weight of each connection is modified. The output nodes provide the outputs. Each connection has a scalar weight that can be adjusted during the training phase based on output node outcomes. At the input layer, a feature vector x is given as input, with the output representing a discriminator between its class and other classes. During the training process, training examples are fed, and the computed outputs are compared to the goal output. If there are any errors, they are measured and propagated back across the network, and the weights are modified.

1.6 APPLICATIONS OF CBIR SYSTEM

The CBIR has a number of uses in numerous fields, including the following:

Medical diagnosis: As medical diagnostic procedures such as computerised tomography and radiology become more widely used, the amount of images created has skyrocketed, making medical images increasingly important. The CBIR approaches are used to improve diagnosis by comparing the current situation to similar cases in the past [37].**Melanoma is** one of the most deadly cancers, so research into its detection has been intensive. Barata et al., (2014)[10] described two methods for detecting melanomas in dermoscopy images. Local features and a bag-of-features classifier were used to classify skin lesions in the first and second systems.

Criminal prevention: Law enforcement agencies keep records of visual evidence, such as fingerprints and photographs. Since the 1980s, basic approaches for automatically matching fingerprints have been employed, and systems based on this technology are used by police agencies all over the world.Gavrielides et al.,(2006) [56]offers an image fingerprinting method. CBIR aids in the search of the entire database for the most closely matching records. Another extensively utilised use is face recognition. Yuan et al., (2016) [143]discussed that a fingerprint authentication system verifies users' identities using their fingerprints. But this system has security and privacy issues. For example, some fake fingerprints can fool the fingerprint authentication system and access real users' data. **Military:** CBIR is commonly utilised in the defence industry to identify hostile aircraft using radar screens, analyse satellite images, and provide cruise missile directing systems. Several crime-prevention tactics are also applicable to the military.Zheng et al., (2018) [148]given a novel transductive transfer subspace learning method for challenging cross-domain facial expression recognition. Improve Security over accidental cases by using Crowd detection over festivals and control security failure by the military. Indian National Border Security by Intrusion Detection can also be done.

Copyright protection and trademark image registration are two more major areas where CBIR can be used. To avoid confusion, the new logo is compared to existing logos.

Journalism and advertising: Newspapers save archives of still images to illustrate advertising material or articles. These archives are often rather large. Similarly, radio companies deal with millions of hours of archive video footage, which tagging makes retrieval impossible. Handling such a large collection of photographs necessitates the use of automatic measures. To handle a huge set of images, such as still photographs in newspapers and video footage in a broadcasting business, automated measurements are required.

Researchers attempting to trace historical influences and art lovers searching for paintings/sculptures that suit their interest use the capability to identify objects with aspects of visual similarity to identify cultural heritage.

CBIR is now a source of entertainment and information because it can effectively locate images and text on the Internet. Text-based search engines have exploded in popularity as the World Wide Web (WWW) has grown. The difficulty in finding images on the Internet (R. Jain, 2006)[80] highlights the need for powerful image search tools. On the other hand, it should be ensured that easy access to pornographic images is not possible. Imageretrieval also carried out in quantum image processing.[41] In recent years, many schemes for content-based image searching on the Web have been demonstrated.

1.7 WORK MOTIVATING FACTORS:

The enormous increase in Internet resulted in a wide range collection of digital images. This is the result of web applications that allow users to upload images and create digital albums. Images are used to transfer information in all spheres around the world. This raised concerns about the images' security and policy implications, as the massive data can be interpreted or manipulated in a variety of ways. Image retrieval was introduced as a safeguard, with the primary goal of streamlining the usage policies of these images.

1.8 PRESENT RESEARCH CONTRIBUTION

Extracting the color feature, shape feature and texture feature of the image in data base and same for the query image and retrieving the most similar image related to the query image from the data base. Machine learning approach is also used for fast retrieving of similar images after doing classification using training set to train the model by using classifier algorithm and retrieving the similar images related to the query image. Thesis consists of the following:

1.8.1. Chapter 2: Literature Survey

This chapter provides a review of the most recent CBIR techniques. In this chapter, we began to look at color, texture, and shape features separately. Aside from that, several research papers on texture-based image retrieval, color-based image retrieval, shape-based image retrieval, and machine learning approaches to image classification have been reviewed.

1.8.2. Chapter 3: Feature Extraction Based on Color Descriptor

It retrieves images according on their content, such as color, texture, and shape. While semantic features cannot perfectly predict visual features, they can be easily incorporated into mathematical models. In this work, we focused on extracting images from a vast image collection using color projection by segmenting and quantifying different color models. This approach is tested on several image sets and its retrieval rate in other models. MATLAB is used for the experiments. This evaluation uses the Corel image library and atlas websites. This experiment uses 4000 images sorted into groups of 20 to 130 images each.

1.8.3 Chapter 4: Comparative Analysis of Feature Extraction Approaches Based on Texture Descriptors

From remote sensing to biomedical imaging, texture analysis requires raw data images to extract significant features that describe an image's qualities. In this way, content-based image retrieval (CBIR) helps identify images that are comparable to a query image. While some work has been done in these lines, more remains to be done. Continuing, We tried to compare the efficiency of image retrieval using different texture feature extraction techniques, namely GLCM, LBP, and LPQ. This study compares the GLCM, LBP, and LPQ methodologies.

1.8.4 Chapter 5:Content Based Image Retrieval Based on Texture Descriptors

This research compares and contrasts existing texture-based feature extraction methods. Images from the Brodetz database, different textures of wall tiles in TIFF format having similar size. Retrieving query image using texture features was proposed. Propose approach takes test images from the database, extracts texture features from each image, and stores them back in the database. The same method is used to extract texture features from the query image using distance metric, and similarity is used to retrieve related images.

1.8.5 Chapter 6: Content Based Image Retrieval Using Hybrid Feature Extraction Based on Color, Texture and Shape

We present a system for color, shape, and texture based image retrieval. An experiment is run to improve the optimal feature extraction approach. Currently, an enormous range of image and video databases for any place has evolved. Quickly retrieving the query-based image is required. This study used content-based image retrieval with hybrid feature descriptors: color, shape, and texture descriptors. LBP model, LBP and LPQ and GLCM for texture feature descriptors and shape descriptors taken from HOG features.

1.8.7 Chapter 7:Image Retrieval Using Machine Learning

This chapter presents a new approach for retrieving images using local descriptors. It is composed of HSV histogram, Color moments and Color auto correlogram. Combining all of these aspects yields promising findings that outperform earlier research. Machine Learning is used to retrieve images quickly. Here, the database images are classified using supervised learning technique Quadratic SVM, and then a similar image is found using distance metrics in only the same class images. The suggested method is evaluated using an online dataset of flower and fruit images. This research project aims to improve the process of searching and retrieving query relevant images from a multimodal medical image collection.

1.8.7 Chapter 8: Conclusions and Future Enhancements

This chapter wraps up the thesis's successfully completed work and discusses the scope of future improvisation in the field.

CHAPTER II

LITERATURE SURVEY

The purpose of this chapter is to summaries previously published techniques for content-based image retrieval in medical applications, highlighting areas that could be improved. Researchers have worked tirelessly over the last decade to advance automated content-based image retrieval methods to assist medical practitioners in diagnosing, monitoring drug application results, and conducting medical research. However, a content-based image retrieval system that is efficient, user-friendly, fast, and commercially viable is still a long way off. It would conduct a scan of the internet's web servers and return the desired result. When a query for image retrieval is submitted, the query image features are extracted and compared to the extracted features of the database images. In response to the query, images with identical features are returned in ascending order of similarity. At the feature extraction stage, the image's lowest-level pixel values are used to extract and combine higher-level features such as grey levels, texture, and shape. A content-based image retrieval system combines several processes, such as image processing, machine learning, information retrieval, and computer vision. Based on a review of the literature, a few of the most salient features are summarized here.

2.1 CONTENT BASED IMAGE RETRIEVAL

As per Chadha et al., (2012)[18], compared the feature extraction strategies average RGB, Color moments, co-occurrence, local color histogram, global color Histogram, and geometric moment. And examined the most efficient combination of approaches and optimized for each kind of image query. Chadha et al., (2012)[18]also proposed improving image retrieval performance by modifying queries by image cropping that allows the user to enhance and personalize image retrieval results by identifying a location of interest.

For forest species recognition, Cavalin et al., (2013)[16] investigate the usage of several feature vectors. As a result, offering a system for extracting multiple feature vectors using image segmentation and various feature sets. Using proposed framework, it may improve the system's recognition rates from around 55.7 percent (with a single feature vector) to around 93.2 percent.

Mukhopadhyay et al., (2013)[99] discussed that there is no single optimum image representation that can differentiate classes in feature space. Thus, standard distance-based content-based image retrieval (CBIR) is inefficient in the texture feature space. Methods that classify and retrieve images from a classifier classify the query image. They were very dependent on the classifier's performance. And said that these methods work well for correctly classified images but fail for incorrectly classified images. It causes substantial performance variations. It tackles the shortcomings of traditional distance-based and conventional classifier-based retrieval systems and presents "Class Membership-based Retrieval" as an alternative. Author Mukhopadhyay et al., (2013) proposed a technique that used a neural network to generate the query image's class label and fuzzy class membership. The second step employs a combination of basic and weighted (class membership-based) distance metrics to overcome the limitations of typical classifier-based retrieval strategies. The proposed method also allows for an incremental decrease of the search space, enhancing retrieval speed at the expense of accuracy. Based on three texture data sets, the method's performance was tested. On comparing the suggested technique to other promising texture retrieval schemes, the experimental findings are encouraging.

According to Tian, (2013)[128], the problem of extracting ideal features that fully capture the fundamental content of images remains difficult in computer vision. However, little research has been done on this issue in recent decades. They used classic models and literature examples to examine the usefulness of combining global and local features in automatic image annotation and content-based image retrieval.

As per FelciRajam&Valli, (2013)[48], Content-Based Image Retrieval (CBIR) is significant research was in image processing. Lately, the goal of CBIR research has been to bridge the semantic gap between low-level characteristics and high-level image semantics. This survey includes low-level feature extraction, image similarity measurement, semantic gap reduction, and invariant image retrieval.

Piras&Giacinto, (2017)[109] expanded and discussed the main information fusion ingredients that a CBIR system should have to meet the users' demanding needs. Due to the low cost of powerful cameras on smartphones and storage space. The rising popularity of social networking sites like Facebook, Twitter, Instagram, and instant messaging apps like WhatsApp and WeChat proves this phenomenon. They allow users to shwas a pictorial representation of their current context in real-time. The media quickly exploited this phenomenon, who used the same channel to publish reports or gather additional information from the user community. While images were managed in real-time by their metadata (timestamp, geolocation, tags, etc.), retrieving them from an archive may be difficult due to their rich semantic content. After more than two decades of CBIR research, the massive increase in the number and variety of images available in digital format is challenging the research community. Any approach addressing these issues must rely on various image representations that can be combined to adapt to the subjectivity of image semantics.

Smeulders et al., (2000)[119] compared the similarity of images and items in photographs to the sorts and means of input that a system's user can give by interaction. We briefly examine databases, system architecture, and evaluation. This section concludes with our views on the field's driving force, the field's legacy, the influence of computer vision, the function of similarity and interaction, the requirement for databases, the challenge of evaluation. Image processing is done under color, texture, and local geometry by following accumulative and global characteristics, conspicuous points, object- and shape features.

Datta et al., (2005)[31] discussed adapting existing image retrieval algorithms to construct practical systems that can handle real-world data. The recent decade has seen a surge in content-based image retrieval research and led to many innovative approaches and systems and a growing interest in related topics. The author also reviews 120 references over the last decade relating to image retrieval and automated image annotation. Finally, we examine the volume and effect of field articles by venues/journals and sub-topics. Similarly, digital imaging has widened its horizons, requiring more image data to be organized.

Liu et al., (2007)[84] focused on closing the "semantic gap" between visual features and human semantics. They took a survey that includes recent major publications covering low-level image feature extraction, similarity measurement, and deriving high-level semantic features.

2.2 IMAGE SEGMENTATION

Image segmentation is the process of dividing an image into regions. Many tasks require the regions to represent relevant sections in the image, such as agriculture, cities, and woods. Also, in photographs of 3D industrial products, the regions could be border pixels arranged into structures like lines and circular arcs. Regions were sometimes defined as collections of pixels with a border and a specific form (circle, ellipse, polygon). However, if the interesting parts do not encompass the entire image, we can still consider segmentation into the foreground and background. 10.1 Football image (left) and region segmentation (right). Each zone is made up of similar-colored pixels. It serves two purposes. The first step is to segment the image for further analysis. It is possible to regulate the environment so that the segmentation procedure reliably extracts only the sections that require additional analysis. For example, in the color chapter, a human face was segmented from a color video clip. The segmentation works well as long as the person's clothing or the room's background doesn't match a human face. The segmentation problem can be difficult in sophisticated circumstances, such as recovering a whole road network from a greyscale aerial image.

2.3 COLOR BASED IMAGE RETRIEVAL

Chakravarti&Meng, (2009)[19] described and tested a basic color histogram-based image search and retrieval system. The study found the strategy effective in utilizing the RankPower measurement. The testing revealed the model's flaws and strengths, determining that it needed to be enhanced and changed for practical application.

Schettini et al., (2002)[115] scrutinized image preprocessing, color information representation characteristics, and approaches to determine feature similarity between two images. Color is a common feature in content-based image retrieval systems. That said, its utility in image indexing is currently untested. Their study presented a complete review of color image indexing and retrieval strategies. Specifically,

Dou et al., (2005)[46] proposed the standard frame of histogram-based image retrieval is proposed. Eight image retrieval methods were developed based on two-color spaces and four histogram distance techniques, with two objective criteria for assessing their performance. The authors showed that HSV color space outperforms RGB color space. For histogram distance, EMD outperforms other distances, although it requires more processing. Compared to EMD, histogram intersection distance is less computationally intensive.

Gavrielides et al., (2006)[56] offered an image fingerprinting method that extracts unique and robust image descriptors (in analogy to human fingerprints). And compared several quantization approaches, histograms produced using color-only or spatial-color information, and similarity measures for color-based descriptors. The system was tested on an extensive database of 919 original images, each with 30 transformed images, totaling 27570 images. The transformed images have been created using various changes like scaling, rotation, cropping, smoothing, additive noise, compression, and illumination contrast. Color and especially spatial chromatic descriptors perform well in this system for image fingerprinting. Content-based image retrieval systems typically take an image or image description as input and get images from a database comparable in color, texture, shape, or layout. A system that looks for not similar images but identical replicas of the same image that has been transformed received less attention than CBIR methods.

Susstrunk, (2007)[126] discussed various color spaces, color encodings, and color image encodings. (Bansal et al., 2012)[9]demonstrated the effort academics put into developing image retrieval systems based on color and discussed the strategies, their merits and cons, and their use in relevant disciplines. In the last decades, digital images have been widely employed for information sharing, interpretation, and meaningful expression. This widespread use improved the usability of digital communication and created undesired issues with digital photographs. Due to their widespread usage, it might not be easy to filter images based on their visual content. Content-Based Image Retrieval (CBIR) was recently presented as a new approach to efficiently find specific images in vast collections of digital photographs to tackle these issues. Due to extensive CBIR research, many CBIR systems have been expected, built, and implemented in recent years. Depending on the image content, different CBIR techniques use other image search implementations, resulting in varying performance and accuracy—some of these works immensely well for content-based image retrieval. The techniques were also grouped by standard methodology.

Niu et al., (2018)[102] proposed to use an image registration algorithm to build a matching image between the reference and target/result images to compensate for the scene difference. The matching image has the same scene as the target image and the same color feature as the reference image, which is used as our color correction reference image. The weighting map for assessment uses a confidence map of the matching image and a saliency map of the target/result image to improve the consistency of the objective and subjective assessment results. It's color correction assessment metric outperforms 19 other correlations, accuracy, and monotonicity metrics with subjective user scores.

FathyAtlam et al., (2013)[47] discussed and compared color-based feature extraction approaches by comparing the query image to images in the WANG database using Euclidean distance and correlation coefficients. Then, each technique's accuracy, error rate, and time were compared. Color Histogram, HSV Color Histogram, and Equalization Color Histogram have been taken.

Raghuwanshi&Tyagi, (2017)[111] proposed an object-based image retrieval method for retrieving images from a location-independent region (ROI). Instead of extracting the query image's features, their method extracts the features of the objects of interest. The image was morphologically processed for this. Background subtraction reduces the effect of background intensities, followed by segmentation and extraction of regions. The image was divided into texture and non-texture regions for the reduction of the number of image comparisons. It would reduce retrieval time by categorizing ROI. During feature extraction, a flag was set to indicate the image's texture or non-textured (natural) category. An image's feature vector was stored with the image's objects. For texture regions, tetrolet transform retrieves texture features, while non-texture regions used moment invariants and edge features.

HamzahAbed& Salman Jasim Al-Farttoosi, (2015)[63]proposed a novel CBIR system based on the color image's prime Histogram and described a Matlab project that tests three simple color histogram-based image search and retrieval algorithms. It was found the technique to be the most effective of the three.

As per Srivastava et al., (2015)[122], Content-Based Image Retrieval has been a research topic for over a decade. Color, texture, and shape were the three primitive visual features used in content-based image retrieval. While semantic features couldn’t wholly determine visual features, they were easier to incorporate into mathematical formulations. So good visual feature extraction is essential for compact image representation.Colors is the most vital, reliable, and widely used visual feature. They reviewed various color extraction methods such as global color histogram, histogram intersection, image bitmap, local color histogram, color correlogram, etc. They described the various methods of color feature extraction and compared them for various applications.

As mentioned by Rama Varioret al., (2016)[113], matching people across multiple camera views, is difficult due to variations in lighting. The subject's color appears to change depending on the lighting. Previous works either use color as is or design color spaces around a specific cue. A method for learning color patterns from pixels sampled across two camera views was proposed here. The idea was that even though different lighting conditions affect pixel values of the same color, the final representation should be stable and invariant to these variations, i.e., encoded with the same values. To generate color features, they learned a linear transformation and a dictionary to encode pixel values and examine popular color constancy algorithms for reidentification. They compared their approach to all photometric invariant color spaces and showed superior performance. Using VIPeR, Person Re-ID 2011, and CAVIAR4REID data sets, authors got promising results.

Agrawal et al., (2011)[3] offered a unique approach for color image content classification using SVM (SVM). Color image classification was done using histograms of color components. Color image histograms have the advantage of being insensitive to tiny changes in camera viewpoint (translation and rotation). For validation, a database of roughly 500 images was divided into four groups to compare histogram features for RGB, CMYK, Lab, YUV, YCbCr, HSV, HVC, and YIQ color spaces. And their proposed method's results in color image categorization accuracy, which was encouraging.

2.4 TEXURE BASED IMAGE RETRIEVAL

Ojala et al., (2002)[104] have presented **an** effective multi-resolution approach, in which gray-scale and rotation invariant texture classification was done based on local binary patterns and nonparametric sample and prototype distribution discrimination. Local binary patterns called "uniform" is essential aspects of local image texture, and their occurrence histogram is a very significant texture feature. In addition, authors provided a strategy for merging various operators for multi-resolution analysis. Ojala et al., (2002)proposed a method that particularly resistant to gray-scale fluctuations since the operator is monotonically invariant. The operator can be achieved with a few operations in a small neighborhood and a lookup database. Excellent experimental results in real rotation invariance issues, where the classifier was trained at one rotation angle and tested with samples from other rotation angles, show that basic rotation invariant local binary patterns can be discriminated well. These operators characterize the spatial structure of local image texture and can be combined with rotation invariant variance measurements to increase performance. These orthogonal joint distributions were powerful tools for rotation invariant texture analysis.

D. Zhang et al., (2000)[146] presented an image retrieval method based on the Gabor filter. Texture features were found by calculating the mean and variation of the Gabor filtered image. Rotation normalization is realized by a circular shift of the feature elements so that all images have the same dominant direction. The indexing of image and retrieval of the image was carried via texture based images and natural images. Gabor wavelet proves to be a very useful texture analysis and is widely adopted in the literature.

Jain &Farrokhnia, (1991)[67] provided a texture segmentation technique based on multichannel filtering theory for early visual information processing. A systematic filter selection approach is proposed based on reconstructing the input image from the filtered images. A nonlinear transformation is applied to each filtered image, computing "energy" in a window around each pixel. The feature images were then combined using a square-error clustering technique. The authors offer a straightforward method to include spatial information in clustering when estimating texture categories' "real" numbers.

Raghuwanshi&Tyagi, (2016)[110] expressed that retrieving images from large databases has always been a difficult problem in image retrieval and described how rough a surface was. Due to the size of multimedia databases, image retrieval has been a hot topic in image processing for two decades. Getting texture images is easy. Using benchmark databases, the authors reviewed texture image retrieval methods and compared the retrieval accuracy and computation time of various texture image retrieval methods. Image retrieval methods include feature extraction and distance measures. Raghuwanshi&Tyagisurveyed various texture feature extraction methods using wavelet transforms.

Kiss et al., (1995)[75]discussed that texture analysis is crucial in image processing and is frequently used in industrial quality control and biomedical imaging industries. Feature extraction is critical for every texture classification/segmentation job. Statistical approaches, transform-based methods, and pixel-based structural descriptions have been discussed in their study. Proposed pixel-based structural characteristics that seek to bridge the statistical and structural feature extraction methods.

Do &Vetterli, (2002)[38] describe a statistical approach to texture retrieval by merging two related tasks, feature extraction, and similarity measurement. They showed that determining the Kullback-Leibler distance (KLD) between estimated models for the SM step is asymptotically optimal in terms of retrieval error probability. With the generalized Gaussian density (GGD) and a closed-form for the KLD between GGDs, the statistical scheme leads to a new wavelet-based texture retrieval approach. And suggested a method that captures texture information with better accuracy and flexibility than previous methods, use energy distribution in the frequency domain to identify textures. The author tries to give a new method that dramatically improves retrieval rates (from 65% to 77%) while maintaining computing complexity.

Yue et al., (2011)[144] proposed a method for quickly extracting color and texture information from images (CBIR). First, HSV color space is rationalized. Color histogram and texture features were retrieved using a co-occurrence matrix. Then the global, local, and textural features were compared and assessed for CBIR. Based on these studies, a CBIR system incorporating color and texture fused features is built and showed a better visual feeling than single feature retrieval in relevant retrieval trials.

W. Zhang et al., (2018)[147] proposed an NDV for texture representation. Unlike local-binary-pattern-based descriptors, the proposed NDV can cover a large local region. The bag-of-words model is also used to combine local descriptors into a global feature representation. The proposed NDV also has two strategies for achieving rotation invariance. These include AniTex, VehApp, KTH-TIPS2a, OpenSurface, and Kylberg. The proposed descriptor outclasses other classification methods.

As per Ji et al., (2018)[69] , LBP is a simple yet efficient coding model for texture feature extraction. Ji et al., (2018) proposed a training-based feature model mapping method and then developed a texture classification frame using multi-resolution feature fusion of four gLBP descriptors to improve texture classification. Four descriptors encode a pixel by central gradient, radial-gradient, magnitude gradient, and tangent gradient to generate initial gLBP patterns. The maximal relative variation rate (mr2) of rotation-invariant patterns was used to build the feature mapping models of gLBP descriptors. Initial patterns could be mapped into low-dimensional patterns. A combination of gLBP descriptors with different sampling parameters produces multi-resolution texture features. Textures were classified using feature histograms and a trained new neighbor classifier. The proposed method is reliable and efficient in texture classification, as shown by simulation on five public texture databases. Their proposed method outperformed nine other similar approaches, including two state-of-the-art techniques, regarding classification accuracy and noise robustness. It was more accurate and robust to SaltPepper and Gaussian noise added to texture images.

Rajadell et al., (2009)[112] described, some easily-computed textural features could be apply to three different image data types- photomicrographs of five different sandstone types, 120,000 panchromatic aerial photographs of eight land-use categories, and Earth Resources Technology Satellite (ERTS) multispecial imagery.

Lin et al., (2009)[112] proposed three image retrieval features and presented a feature selection strategy to select optimal characteristics to increase detection rate while simplifying image retrieval computation. The first and second image features were color co-occurrence matrix (CCM) and the difference between pixels of scan pattern (DBPSP). The final image feature is a color histogram for K-mean (CHKM). The CCM is a standard pattern co-occurrence matrix that determines the probability of the same pixel color occurring between consecutive pixels in an image. DBPSP calculates the difference between pixels and turns it into the probability of occurrence on the full image. The CHKM feature replaces each pixel color in aimage with a common color palette most similar to the pixel color. Various visual qualities and contents represent distinct features.

Some images were more color and texture sensitive, while others were more color and spatial sense. That is why their study combines CCM, DBPSP, and CHKM. Sequential forward selection is used to improve the image detection rate and simplify image retrieval computation. And authorsinvestigation also uses the CTCHIRS image retrieval system to do analysis and comparisons. With varying qualities, three image databases were used to choose features. Original features have been optimized to improve the detection rate.

Malik F, Baharudin B (2013)[86] discussed effective content-based image retrieval (CBIR), low-level features like- color, texture, and form extraction was required, and quick query image matching with indexed images. Images in pixel and compressed domains were extracted. Currently, most images were compressed in JPEG utilizing discrete cosine processing (DCT). Malik &Baharudin, investigated efficient feature extraction and image matching in the compressed domain. Using the significant energy of the DC and the first three AC coefficients of the blocks, we extract quantized histogram statistical texture features. Various distance metrics was used to quantify similarities utilizing texture data for effective image matching. The effective CBIR was analyzed using various distance measurements and quantization bins. Tested on the Corel image database, our technique offers robust image retrieval for multiple distance metrics and histogram quantization in a compressed domain.

Zujovic J, Pappas TN, Neuhoff DL (2013)[150] advised new texture similarity measures that take into account human vision and texture variability. The measurements rely solely on local image information, allowing significant point-to-point differences between textures that were otherwise identical. Studies inspire the suggested metrics in texture analysis-synthesis and structural similarity. They used a steerable filter decomposition and a small collection of global or sliding window subband statistics. Zujovic et al.,assessed metric performance in 'known-item search,' retrieving 'identical' textures to the query texture. An extensive database might be compared to human performance without cumbersome subjective testing. Zujovic et al., suggested metrics beat PSNR, SSIM, its derivatives, and state-of-the-art texture classification metrics using standard statistical techniques.

Melanoma is one of the most deadly cancers, so research into its detection has been intensive.[10]described two methods for detecting melanomas in dermoscopy images. Local features and a bag-of-features classifier were used to classify skin lesions in the first and second systems, to determine the best classification system for skin lesions. The other goal was to compare the discriminative power of color and texture features in lesion classification. Color features outperform texture features when used alone, and both methods achieve perfect results, with global methods having Sensitivity = 96% and Specificity = 80% and local methods having Sensitivity = 100% and Specificity = 75%. The results were based on 176 dermoscopy images from Matosinhos Hospital Pedro Hispano.

As per Jeena Jacob et al., (2014)[68], currently, image retrieval focuses on local texture patterns. LTP represents the image by directional information and shows promising results. An enhancement of LTrP called Local Oppugnant Color Texture Pattern (LOCTP) allows discrimination of information derived from spatial inter-chromatic texture patterns of different spectral channels within a region. It establishes the intensity and direction of the relationship between the referenced pixels and their adjacent neighbors. The LOCTP strives to use a harmonious link between color and texture, which aids in human perception. (Jeena Jacob et al., 2014), proposed a method that was tested using the standard image databases Brodatz texture database (DB1) and Corel database (DB2). The evaluation was also done in YCbCr, HSV, Lab, and RGB color models. A feature-level fusion framework also combines the CPAM and LOCTP for better results in natural images. The experimental results show significant improvements in average precision, recall, and retrieval rate compared to previous works.

Dang,Choi et al.(2017)[29]proposed Color Local Texture Features (CLTF) to maximize the complementary effect taken using color and texture information for face recognition. Previous studies have shown that CLTF extracted from ZRG and RQCr color spaces outperform FR approaches using only color or texture information. Nevertheless, it has been established that different color spaces have different discriminating powers for visual classification. So, authors compared CLTF extracted from various color spaces on four data sets: Color FERET, AR, SCFace, and Postech01. The results showed that their performance varies across databases. It necessitates developing a framework for selecting components from existing color spaces to improve CLTF's discriminating power.

Srivastava et al., (2017)[118] For the retrieval of relevant images from a dataset, CBIR is an active research field. Color, texture, shape, and combinations were used to achieve this. Compared to existing methods, Srivastava et al., (2017) proposed combining texture and color features in a pipelined manner. It has two phases. Phase one compared the query image to the dataset and ranked them according to similarity. The top 25% of the output images were used in the second phase, where the query image was compared again using the color feature to rank the images. The proposed method was 1.5 times faster than other state-of-the-art approaches while maintaining precision.

As per Singh et al., (2017)[118], the Grey Level Co-Occurrence matrix is an old texture analysis technique. The distance and direction of the Grey Level Co-Occurrence matrix are vital. The authors examined various distance and directional angle combinations used in GLCM calculation to recognize patterned images based on textural features. The patterns considered were horizontal, vertical, right diagonal, left diagonal, checkered, and irregular. Their proposed method achieved 96, 98, 96, 90, 96, and 94 percent accuracy for horizontal, vertical, right diagonal, left diagonal, checkered, and irregular patterns. Thus, GLCM achieves a pattern recognition accuracy of 95%.

Chandana et al., (2017)[20] focused on texture features for a content-based image retrieval system and discussed the gray-level co-occurrence matrix (GLCM) technique for image retrieval. Technology has increased the collection of digital media, which included both still images and videos. Extensive collections of digital images on storage devices slow down a system's response time, reducing performance. Various search skills were required to find items in extensive collections. Images were manually annotated with a set of keywords. Their method retrieved images of interest, but it was time-consuming. It was make it challenging to create a suitable classification and annotate images with the exact keywords. For all of these reasons, content-based image retrieval

(CBIR) is used to extract images. . It considers color histogram, texture, and edge density.

Yadav et al., (2015) [136]proposed using multi-resolution local binary pattern (MRLBP) variants to extract texture features from hardwood species. Initially, Daubechies wavelet (db2) decomposition filter was used to decompose each image up to 7 levels. Six texture feature extraction techniques (local binary pattern and its variants) were used to extract important features from these images. The images of hardwood species were classified using three classifiers: LDA, RBF, and SVM. Then, the classification results from conventional and MRLBP variants based on texture feature extraction were compared using different classifiers. With a linear SVM classifier, texture features extracted using discrete wavelet transform based uniform completed local binary pattern (DWTCLBPu2) produced the best classification accuracy of 97.40 1.06 percent. This accuracy was achieved using the full feature (1416) dataset at the 3rd level of image decomposition. The LDA classifier achieved the best classification accuracy of 97.87 0.82 percent for DWTCLBPu2 at the 3rd level of image decomposition. It also outperforms MRLBP techniques with reduced dimension features for randomly dividing databases into fixed training and testing ratios.

Dong et al., (2015) [44]discussed that wavelet subband statistical modeling has been used for image recognition and retrieval. But traditional wavelets can't handle images with distributed discontinuities like edges. Shearlets was a new wavelet extension designed for image characterization. Author proposed novel texture classification and retrieval methods based on linear regression. Because subband coefficients were complex numbers, we used two energy features to represent each shearletsubband for texture classification. The regression residuals were used to define the distance from a test texture to a texture class. Texture retrieval uses statistics in contourlet domains and a pseudo-feedback mechanism based on linear regression modeling of shearletsubbanddependences. The proposed classification and retrieval methods outperform the current state-of-the-art on five large texture datasets.

Verma et al., (2015) [132]considered a real-world image retrieval and searches problem. Managing images from a large storage medium are not easy nowadays. Research on texture features has resulted in numerous descriptors based on uniform, rotation invariant, and edge properties. However, most of them use histogram to represent the local pattern as a feature vector. The authors proposed a new image retrieval technique called LECoP, which used the HSV color space. This method uses HSV color space to utilize image color, intensity, and brightness. A grey level co-occurrence matrix was used to obtain the co-occurrence of LEP map pixels. It converted the local directional information into a feature vector using the grey level co-occurrence matrix. The method was tested on five databases: Corel, MIT VisTex, STex, Corel-1k, Corel-5k, and Corel-10k. Their algorithm's precision and recall were compared to previously proposed methods in their work.

Yuan et al., (2016) [143]discussed that a fingerprint authentication system verifies users' identities using their fingerprints. But this system has security and privacy issues. For example, some fake fingerprints can fool the fingerprint authentication system and access real users' data. Thus, an aliveness detection algorithm is required to prevent illegal users from accessing private data. The authors proposed a new software-based liveness detection method based on multi-scale local phase quantity (LPQ) and PCA. A fingerprint's feature vectors were built using multi-scale LPQ. PCA reduces the dimensionality of feature vectors and gains more compelling features. Finally, a support vector machine classifier was used to gain a training model and detect a fingerprint's liveness. The results shown thatdipicted their method might accurately recognize users' fingerprints and detect their liveness. The multi-resolution analysis was helpful for texture feature extraction during fingerprint liveness detection, as their study showed.

Pham et al., (2016) [108]developed a novel algorithm for textural feature description in VHR satellite imagery. It used a PW approach to the feature covariance matrix. The main goal of their work is to build a nondense covariance matrix of oriented gradients (COG) using image-extracted characteristic points (keypoints). The proposed descriptor, PW-COG, should work well with VHR images. One advantage is that a COG-based descriptor can encode the image's radiometric and geometric information and their joint distribution and correlation, essential for texture characterization and discrimination. Second, using a keypoint-based approach, the proposed method can handle large VHR image data without requiring the stationarity hypothesis. Texture-based image classification was used for testing the proposed descriptor's effectiveness. The proposed algorithm outperformed reference methods in texture discrimination and algorithm complexity on the Brodatz texture database and VHR satellite images.

2.5 SHAPE-BASED IMAGE RETRIEVAL SYSTEM

Wang &Yagi, (2008) [133]created an adaptive mean-shift tracker by selecting reliable features from color and shape-texture signals. The tracker was more resilient because the target model was updated based on the initial and current models' closeness. Wang &Yagi, suggesteda technique that outperformed previous trackers on demanding image sequences.

Shrinivasacharya&Sudhamani, (2013) [117]have suggested method leverages edge information and median filtering to extract features from an image. The retrieved image characteristics were clustered using SOM. The original image was smoothed using median filtering. The image might be decomposed bi-directionally to retrieve edge information. Then, the smooth image's edge position values were replaced with the BEMD's edge image values and extracted only 64 bin grey features. These collected features were fed into the SOM neural network for grouping into nine categories. Finally, the neural network used the query image's attributes to determine its cluster. In that case, the surrounding clustered features as compared to the query image features. The experiment used a ground truth database of 1000 images from several categories. The experimental findings were compared to the Median filter histogram. The retrieval system's performance is good due to the employment of median, edge, and SOM approaches. It improves precision by 2.37 percent and recalls 2.82 percent over the old system.

B. Zhang et al., (2014)[145] proposed a method that used three features extracted. These features were extracted from tongue images to detect nonproliferative diabetic retinopathy (NPDR) based on the early stage of DR. Color, texture, and geometry. In the 21st century, diabetes mellitus and its complications, such as diabetic retinopathy, will be major health issues. The tongue images were first captured noninvasively with image correction. The tongue color gamut was established with 12 colors. The nine tongue texture features were defined by the texture values of eight blocks strategically placed on the tongue surface, plus the mean of all eight blocks. Finally, 13 geometry features extracted from tongue images were based on measurements, distances, and ratios. Using features from each of the three groups, the proposed method can separate Healthy/DM tongues and NPDR/DM-sans NPDR tongues with average accuracies of 80.52 and 80.33 percent, and used a database of 130 healthy and 296 diabetic samples, 29 of which were NPDR.

Srivastava et al., (2018)[121] proposed combining SURF and Texture with a discussion about SIFT (Scale-Invariant Feature Transform), SURF, and local features. Only images from the training set might be classified accurately by SURF. Their method's accuracy improves to 94% even when using non-training images. Image classification is vital in applications such as video surveillance and image and video retrieval. It was the task of correctly assigning an image to a class.

Garcia F, Cervantes J, et al., (2016)[55]presented an artificial vision approach for fruit recognition in supermarkets. The fruit visual features extracted were shape, texture, and color chromaticity. A few studies on fruit recognition have extracted colors in RGB (Red, Green, Blue) space. Color chromaticity was required to describe the color of the fruits. As a result, Garcia et al., proposeda approach using the HSV space to extract and process chromaticity data without the undesirable intensity effects of the RGB space. However, before defining the color, it must be first selected the chromaticity that provide helpful information about the fruits. Garcia et al., approach outperforms the color characterization of related work on 20 common fruit classes.

Dhanashree M, Kalel S, et al., (2016)[36] Color, shape, and texture were considered content in a content-based image retrieval system. Color, shape, and texture were used because they were easier to assimilate into mathematical calculations. Color, shape, and texture were the most commonly used image retrieval content. The goal of content-based image retrieval is to retrieve images from large databases. Measure the similarity of a query image to a database image and retrieve similar images as a query image extraction feature.

Mistry Y, Ingole DT, Ingole MD (2018)[97]proposed a hybrid feature-based efficient CBIR system using distance measures. Color auto-correlograms, color moments, HSV histograms, and frequency domain features like SWT moments and Gabor wavelet transforms were used. To improve precision, binarized statistical image features and color and edge directivity descriptor features were used. Retrieval uses various distance metrics. The experiments use the WANG database, which contains 1000 images from ten classes. The proposed approach outperforms other existing systems in terms of precision for image retrieval with hybrid features and distance metrics.

Lee et al., (2015) [78]proposed a new system and method for identifying flowers in natural settings. The optimal method of feature extraction for color, texture, and shape was improved experimentally. The most useful features for flower images were color (HS, CbCrCg, and RGB), texture (grey level co-occurrence matrix), and shape (zero-crossing rate). Their study developed mobile flower image recognition technology.

2.6 MACHINE LEARNING APPROACH

Tolambiya A, Venkatraman S, Kalra PK (2010) [129]compared relevance vector machines (RVMs) for content-based image classification to support vector machines (SVMs). The RVM used many wavelet kernels. In addition, it offered a new wavelet-based feature extraction method that extracted fewer features than previous methods. The results told that RVM outperforms SVM, in the trade-off between reduced accuracy, increased solution sparsity, and free parameter adjustment ease.

Byun H, Lee SW (2002) [15]introduced SVMs and discussed their many applications, and gave a complete survey on SVM pattern recognition applications. SVMs have a strong generalization performance on various real-life data, and the method is logically justified.

Zheng W, Zong Y, Zhou X, Xin M (2018)[148] given a novel transductive transfer subspace learning method for challenging cross-domain facial expression recognition. Due to the different marginal distributions between training and testing facial feature vectors,their method used a transductive transfer regularised least-squares regression (TTRLSR) model to jointly learn a discriminative subspace and predict the class labels of unlabelled facial images. Trained an SVM classifier on the auxiliary facial image set to classify other facial images in the target domain. Color scale-invariant feature transform (CSIFT) features associated with 49 landmark facial points were extracted to describe each color facial image. Finally, extensive tests on BU-3DFE and Multi-PIE multiview color facial expression databases were performed to assess the proposed method's cross-database and cross-view performance. The experiments also compared state-of-the-art domain adaptation methods. The experimental results presented that the proposed method outperforms existing methods in terms of recognition performance.

As per (Z. Zhang et al., 2018) discussion, the spiking neuron network is the third generation of neural networks. This type of network is used for supervised or unsupervised feature extraction, image classification, texture segmentation, and image recognition. For texture feature extraction and image structure characterization, the grey-level co-occurrence matrix algorithm is widely used. Identical-sized,-shaped,-colored, and textured buttons cannot be identified using conventional methods. They proposed an improved GLCM algorithm that was used to extract, classify, and recognize button image features. The proposed method can segment button images with texture features.

To improve the efficiency of Content-Based Image Retrieval, (Tzelepi&Tefas, 2018) proposed a model retraining method and used a deep CNN model to extract feature representations from convolutional layer activations using max-pooling and then adaptedand retrained the network to produce more efficient compact image descriptors that improve retrieval performance and memory requirements. It was suggested three basic model retraining strategies. That was, Fully unsupervised retraining if no other information than the dataset itself was available, Relevance Information Retraining if the training dataset's labels were available, and Relevance Feedback Retraining if user feedback was available. The proposed method outperforms other CNN-based retrieval techniques and conventional hand-crafted feature-based approaches in all three datasets tested.

2.7 SUMMARY

Feature extraction from database and query images, similarity index matching, ranking, and retrieval are all part of a content-based image retrieval system. Color, shape, and texture are used in content-based retrieval. Color space represented color images. The sum of red, green, and blue intensities represented the grey levels. Red, Green, and Blue histograms represent the color distribution in an image. The histograms of the query and database images are compared for similarity or differences. An image's shape is also vital. Edges and contours are extracted using Canny edge detector, Sobel operator, and Robert's Cross operator. In shape-based retrieval, the user can provide a similar image as the query image or a similar image sketch. Texture is a visual pattern that is not caused by a single color or intensity. Multi-resolution techniques such as Gabor and wavelet transforms were used to extract texture features. And furthermore, many techniques are also there. The system receives the query image of the desired texture. The system finds images with similar texture to the query image. Several researchers have used features to retrieve images.

CHAPTER III

IMAGE RETRIEVAL BASED ON COLOR FEATURE SIMILARITY

Colors were the most vital, reliable, and widely used visual feature. Many image processing applications benefit from image retrieval techniques. Content-based image retrieval systems compare the query image to the searched image to assess distinct image datasets. Color, texture, and shape are three common image retrieval approaches. These algorithms are used to find an image in a dataset of images. These haven't been affected by the various image resolutions, sizes, or color distributions. As a result, it appears that these methodologies do not apply to the image retrieval system. Different techniques, such as color, size, and texture, are used by many other image retrieval systems. Many user interactive systems operated with fundamental principles in the early days, however these systems did not meet the user's requirements. The CBIR system had piqued a lot of people's interest. A lot of work has been done in the content-based image retrieval system in recent years. When it comes to content-based image retrieval, there are three basic visual qualities to consider: color, texture, and shape.

3.1 RELATED WORK

As per Srivastava et al., (2015)[122], Content-Based Image Retrieval has been a research topic for over a decade. Color, texture, and shape were the three primitive visual features used in content-based image retrieval. While semantic features cannot wholly determine visual features, they were easier to incorporate into mathematical formulations. So good visual feature extraction is essential for compact image representation. Colors were the most vital, reliable, and widely used visual feature. They reviewed various color extraction methods such as Global Color Histogram, Histogram Intersection, Image Bitmap, Local Color Histogram, Color Correlogram, etc. They described the various methods of color feature extraction and compared them for various applications. Raghuwanshi&Tyagi, (2017)[111]proposed an object-based image retrieval method for retrieving images from a location-independent region (ROI).which extracts the features of the objects of interest instead of Query image features. HamzahAbed& Salman Jasim Al-Farttoosi, (2015)[63] Proposed a novel CBIR system based on the color image's prime Histogram by working on three simple color histogram-based image search and retrieval algorithms. Chakravarti&Meng, (2009)[19] described and tested a basic color histogram-based image search and retrieval system. Schettini et al., (2002)[115] scrutinized image preprocessing, color information representation characteristics, and approaches to determine feature similarity between two images. Color is a common feature in content-based image retrieval systems. That said, its utility in image indexing is currently untested. This study presents a complete review of color image indexing and retrieval strategies. Dou et al., (2005)[46] proposed the standard frame of histogram-based image retrieval, and developed eight image retrieval methods based on two-color spaces and four histogram distance techniques, with two objective criteria for assessing their performance. Dou et al.,described that HSV color space outperforms RGB color space. Gavrielides et al., (2006)[56] offers an image fingerprinting method that extracts unique and robust image descriptors (in analogy to human fingerprints), and compared several quantization approaches, histograms produced using color-only or spatial-color information, and similarity measures for color-based descriptors; tested on an extensive database of 919 original images, each with 30 transformed images, totaling 27570 images. Susstrunk, 2007)[126] discussed various color spaces, color encodings, and color image encodings. Bansal et al., (2012) [9]demonstrated the effort academics put into developing image retrieval systems based on color and discussed the strategies, their merits and cons, and their use in relevant disciplines. Niu et al., (2018)[102] proposed to use an image registration algorithm to build a matching image between the reference and target/result images to compensate for the scene difference. The matching image has the same scene as the target image and the same color feature as the reference image, which is used as our color correction reference image. The weighting map for assessment uses a confidence map of the matching image and a saliency map of the target/result image to improve the consistency of the objective and subjective assessment results. FathyAtlam et al., (2013) [47]discussed and compared color-based feature extraction approaches by comparing the query image to images in the WANG database using Euclidean distance and correlation coefficients. For color histogram, HSV color histogram, and equalization color histogram. As mentioned by Rama Varior et al., (2016)[113], matching people across multiple camera views, is difficult due to variations in lighting. The subject's color appears to change depending on the lighting. To generate color features, they learned a linear transformation and a dictionary to encode pixel values and examine popular color constancy algorithms for reidentification, and compared their approach to all photometric invariant color spaces and showed superior performance. Agrawal et al., (2011)[3] offered a unique approach for color image content classification using SVM (SVM). Color image classification is done using histograms of color components. Color image histograms have the advantage of being insensitive to tiny changes in camera viewpoint (translation and rotation).

3.2 BACKGROUND

This chapter introduces the concept of a color based image retrieval system with different approach. This chapter focuses on extracting images from a large image database using color features of an image, and give a novel approach for retrieving images from large image database. Color is the most important, dependable, and extensively used of the visual elements. The RGB color combination is considered in this chapter for image retrieval. The focus of this chapter is on approaches to retrieve most similar images for CBIR. First, RGB was quantified in L*a*b and combined with a novel method for determining the most similar images from a set of image data. The proposed method demonstrates an effective image retrieval system, resulting in a method that is good to previous strategies. The proposed system was evaluated on COREL and CIFAR databases. The proposed work outperformed other state-of-the-art methods in terms of retrieval performance. For validation, a database of roughly 500 images was divided into three groups to compare histogram features for RGB, Lab, YCbCr, and HSV color spaces. The proposed approach results in color image categorization accuracy.

3.3 COLOR IMAGE

A color image is a collection of primary colors (Red, Green and Blue). Different matrices are constructed for each color band R, G, and B. The number of colors in an RGB image are reduced by converting it to an indexed image[131][74]. The following approaches for estimating the colors in the original image are used in this process:

ColorHistogram : The Red, Green, and Blue color channels are changed back to 24-bit color channels by creating the remaining color channels as black to view the image in other color channels. As a result, each color channel has its own histogram, and the color image can be divided into several color channels independently, as shown in Figure 3.1. Figure 3.2 also shows color histograms of the same image in red, green, and blue (A).[39]

Figure 3.1 Original RGB Image and Red, Green and Blue Color Component Images

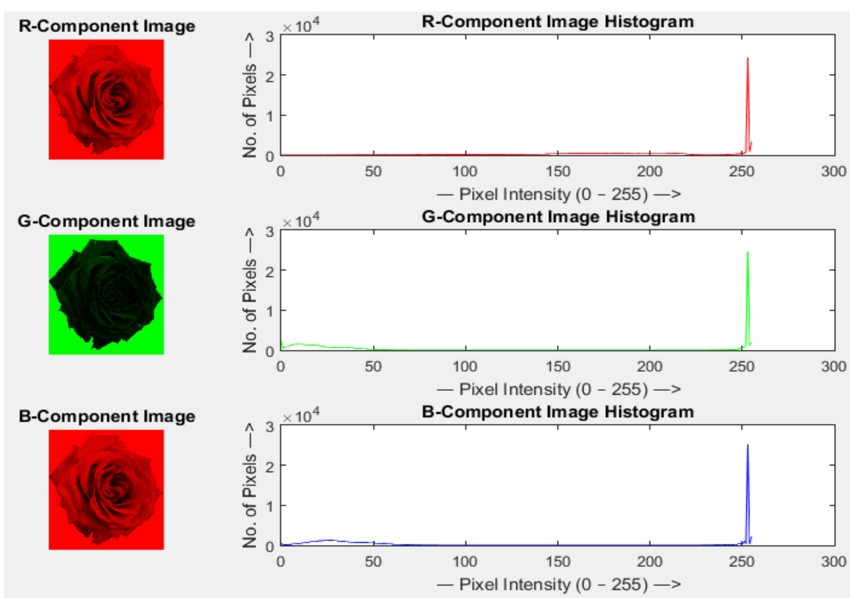

Figure 3.2: Red, Green and Blue Color Component Image Histograms

Quantization:Quantization is a technique for reducing the number of colors in an image.. The RGB color cube is a popular image quantization method. The RGB color cube is a three-dimensional (3D) array of all the colors that are used to display for a specific data type, such as uint8, uint16, or double RGB images.

3.4 EXTRACTION OF AN IMAGE'S COLOR FEATURE

There are several characteristics associated with colorful images:

3.4.1 Histogram of color:

The probability mass function of the image intensities is referred to as an image histogram. This is extensive for color images, limiting the combined likelihood of the intensities of the three distinct color channels.[40] More precisely, a color histogram is defined as follows:

$$H_{c1,c2,c3}(x,y,z) = P.Prob(c1 = x, c2 = y, c3 = z) \quad \textbf{(3.1)}$$

Where c1, c2, and c3 are the three channels of the color model image (RGB, HSV, L*a*b, and YCbCr), respectively, and P denotes the number of pixels in the supplied image.

3.4.1.1 Histogram of colors Euclidean distance:

For image retrieval, three distance formulae are available: Euclidean histogram distance, histogram intersection distance, and histogram quadratic (cross) distance. The histogram Euclidean Distance has been used as the unit of analysis in this study. Take a look at the H' and H "as two color histograms, one for the Query image and one for the searched image. The Euclidean separation between H' and H "may be calculated as follows:

$$D(H',H'') = \sqrt{\sum_{c1} \quad \sum_{c2} \quad \sum_{c3}(H'(x,y,z) - H''(x,y,z))} \quad \textbf{(3.2)}$$

Where D is the Euclidean distance between two color histograms H' and H" computed, the highest histogram value of an image's separate channels was used in the initial calculation.

3.4.2 Moments of Color

The second characteristic has been dubbed "color moments." Each channel's mean and standard deviation have been computed as follows:

3.4.2.1 Mean: The first color moment can be interpreted as the image's average color, and that can be calculated using the formula below.

$$\mathrm{Mean}(\mathrm{E_r}) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{Ii, j} \quad \textbf{(3.3)}$$

Where n stands for the number of pixels in an image and "$P_{i,j}$" denotes the value of the image's j^{th} pixel in the i^{th}color channel.

3.4.2.2 Standard Deviation: The second color moment is the standard deviation, which is calculated by taking the square root of the color distribution's variance.

$$\text{Standard Deviation}(\delta) = \sqrt{\frac{1}{\mathrm{n}} \sum_{k=0}^{n} (Ii, j - \mathrm{E_r}, i)^k} \quad \textbf{(3.4)}$$

where "E_r" represents the mean value, or first color moment, for the image's i-thcolor channel.

3.4.2.3 Color Moments Euclidean distance:

The Euclidean distance between the mean and standard deviation may be calculated as follows:

$$D_M = \sqrt{(\mathrm{M}' - \mathrm{M}'')^2} \quad \textbf{(3.5)}$$

$$D_{std} = \sqrt{(\delta' - \delta'')^2} \quad \textbf{(3.6)}$$

Where M’ and M’’ are two points between the Euclidean space for one feature and **δ**’ and **δ**” are two points between the Euclidean space for another feature.

3.4.3 Colormap:

Colormap returns a three-column matrix containing RGB triplets. Each row of the matrix provides a single RGB triplet corresponding to one of the colormap's colors. The values are contained within the range. The colormaps can be any length, but they should have three columns. A single color represents each row in the matrix through the RGB triplet. Numerous elements provide the intensities of the red, green, and blue RGB triplets color components, which is a three-element row vector. The intensities must fall within a certain range. A 0 number indicates no color, whereas a 1 indicates maximum intensity.

3.4.3.1 Colormap Euclidean distance: The Euclidian distance between colormaps can be calculated as follows:

$$\mathrm{D_{map}} = \sqrt{\sum_{n=1}^{3}(c'_n - c''_n)^{2}} \qquad \textbf{(3.7)}$$

Where Dmap denotes the Euclidian distance for Colormap and c'_n and c''_n denotes the two points for Dmap and n is number of channels, e.g., n=1,2,3 for three channels.

3.5 PROPOSED COLOR FEATURE BASED CBIR SYSTEM:

This chapter explained proposed approach to retrieve most similar images from large image dataset based on color features in comparison to previously defined approach by using different color spaces. The proposed method reduces the problem description by combining color-based elements, illustrated by Figure 3.3.

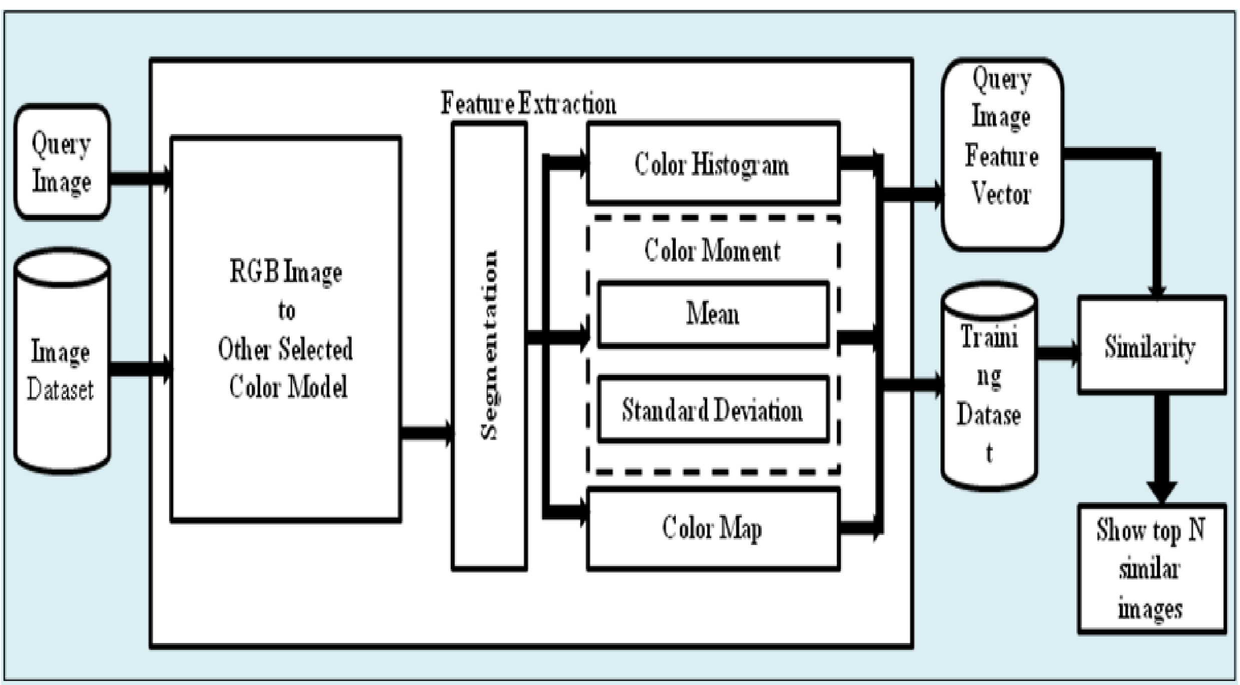

Figure 3.3: Framework of CBIR System

The proposed method is implemented and focused on the visual contents of an image, particularly color application on the dataset of three categories. It chooses image databases with similar feature values using this method. For problem-solving, the suggested system extracted R, G, and B values for each visual feature independently. Color histograms and color projections were included in the proposed method. For effective retrieval, mathematical strategies such as mean, median, and standard deviation are offered, as well as a platform for retrieving images from the database utilising the user query method.

Let us take a query image or input image. Make a two dataset first is test image dataset and other is training dataset. The some sort of original image dataset have been shown in Figure 3.5. A query image taken from test image, if the image is in RGB image, convert it to other color space of choice. Then applied the color segmentation on converted query image as shown in Figure 3.4. Then there would be segmentation for colors[assemble four features]. After that, a segmented image's histogram is created. For the first feature, calculate the highest histogram value for each channel of the color image individually. Following that, look at the color moment's mean and standard deviation as the second and third features, respectively. As the fourth feature, take the color map value of each channel of such a segmented color image individually. Repeat all these steps for each image in the dataset of images, storing the image's feature vector. Calculate the query image's feature vector. Euclidean distance has calculated the score for each feature in the dataset associated with the query image. Sort the score to find the top N most similar images. These all the steps have been demonstrated using Figure 3.3.

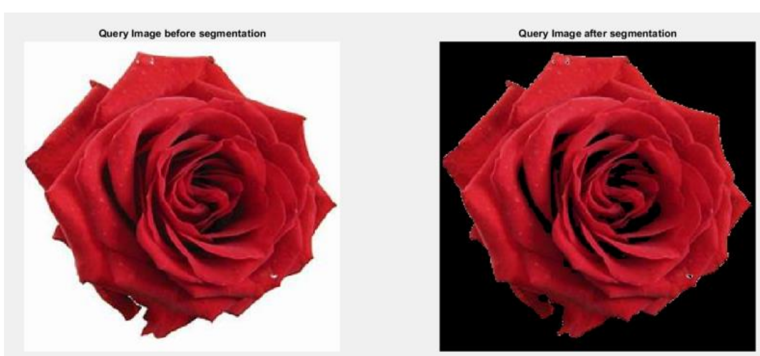

Figure 3.4: Query image (a) Before Segmentation (b) After Segmentation

Figure 3.4 depicts the input image; Figure 3. 5 shows a segmented image. Whereas Figure 3.6 illustrates the dataset of the image collection.

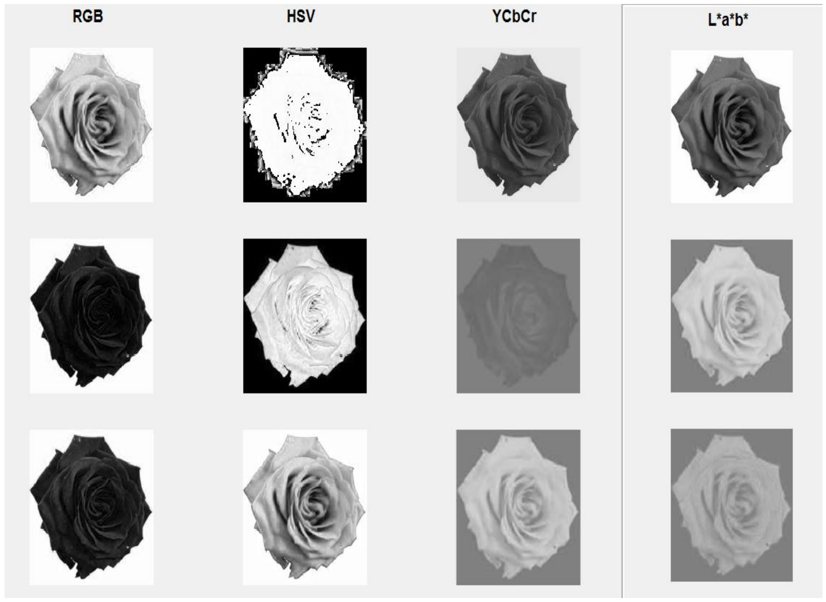

Figure 3.5: Different Color Models for Input Image

Figure 3.6 : Image Dataset

3.6 STATISTICAL ANALYSIS OF COLOR FEATURES:

The color features such as the color histogram and color moment and color map of images are returned using a statistical approach. Different color models such as RGB, YCbCr, and HSV were used in this chapter for feature collections, which are as follows:

The RGB model's first feature is the highest value of R, G, and B in the RGB Histogram.

Feature 1: Image histogram Max value

Feature 2: RGB Color Map Value

Feature 3: Image intensity mean

Feature 4: RGB image standard deviation

The same procedure was followed for the next three models: YCbCr, HSV, and L*a*b. Table 3.1 illustrates the features of the query image in each model.

The following formula is used to calculate the score for image retrieval based on the query image:

$$\text{Euclidian distance (D)} = \sqrt{\sum_1^n (Fn - Fq_n)^2} \quad \textbf{(3.8)}$$

Where n refers to the number of F features in dataset image I and qn refers to the number of features in a query image.

The Euclidian distance (D) is computed after taking four features as described above: Feature1 is F1 for D(H',H''), Feature2 is F2 for DM, Feature3 is F3 for Dstd, and Feature4 is F4 for Damp. The Euclidian distance(D) for these four images may be computed as follows: F1..n for four features of dataset images and Fq1..n for four features of query image in this study article.

$$D = \sqrt{(F1 - Fq_1)^2 + (F2 - Fq_2)^2 + (F3 - Fq_3)^2 + (F4 - Fq_4)^2} \quad \textbf{(3.9)}$$

D is a scorecard for each image in the collection in this case.

Where:

F1 is the image histogram's Rmax, Gmax, and Bmax.

F2 is the RGB color map value.

F3 denotes the image's average.

F4 denotes the image's standard deviation.

Same has been taken for Query image as Fq1, Fq2, Fq3, Fq4 respectively.

Based on the proposed system, some similar images were retrieved as per the specified query image, and the best measurement calculations were conducted for all images to determine their performance. The following formula clearly demonstrates the system's precision. If the total N number of images has been obtained for Query image Q in this study, Precision and Recall may be calculated as follows:

$$P(Q,N) = \frac{\text{Number of relevant images retrieved}}{\text{N}} \quad \textbf{(3.10)}$$

$$R(Q,N) = \frac{\text{Number of relevant images retrieved}}{\text{Nrd}} \quad \textbf{(3.11)}$$

3.7 EXPERIMENTAL RESULT:

Table 3.2 shows the highest value of the color histogram of each channel in the various color models for each image in the database. In Table 3.3 for the query image, the score of the dataset images is sorted in ascending order using the RGB color model. Table 3.4 shows the image's YCbCr model score in comparison to the query image. Table 3.5 shows the image's L*a*b model score in comparison to the query image. Table 3.6 shows the image's HSV model score in comparison to the query image. We discovered that YCbCr and RGB do not retrieve similar images from the top 1 to 14 in the tables. The top 14 images of the same color are returned by L*a*b, while the top 14 images of the same color are returned by HSV.

Following Table 3.1 shows the four features retrieved from query image using different color models such as L*a*b, RGB, HSV, and YCbCr. The next step is to do the same process for images of the training dataset, shown in Table 3.2.

TABLE 3.1: RETRIEVED FEATURES FROM THE QUERY IMAGE

Sn.	QueryImage	Color Models	F1			F2			F3	F4
			Histogram's Max value			Color Map			Mean	Std. Deviation
			channel1	channel2	channel3	channel1	channel2	channel3		
1	RedImg2	L*a*b	44005.0	48590.0	48800.0	0.153	0.012	0.012	0.061	0.161
2	RedImg 2	RGB	40620.0	46276.0	47635.0	0.157	0.004	0.004	14.522	40.081
3	RedImg 2	HSV	46211.0	50367.0	50427.0	0.157	0.008	0.008	15.001	42.961
4	RedImg 2	YCbCr	39666.0	45014.0	45549.0	0.192	0.016	0.016	19.497	46.781

Following Table 3.2 shows the retrieved features for each image of the training dataset, using different color models such as L*a*b, RGB, HSV, and YCbCr.

TABLE 3.2: MAXIMUM VALUE OF COLOR HISTOGRAM OF EACH CHANNEL SEPARATELY

Sn.	Image	Color Models Histogram Values											
		L*a*b			HSV			YCbCr			RGB		
		max(L)	max(a)	max(b)	max(H)	max(S)	max(V)	max(Y)	max(Cb)	max(Cr)	max(R)	max(G)	max(B)
1	Red01	57423.0	60483.0	60839.0	51721.0	57722.0	57702.0	51550.0	57215.0	57591.0	51721.0	57722.0	57702.0
2	Red0 10	57423.0	58462.0	57576.0	53124.0	54637.0	53421.0	55057.0	56500.0	55456.0	53124.0	54637.0	53421.0
3	Red0 11	57423.0	51170.0	45199.0	41417.0	50370.0	42600.0	40447.0	49478.0	41929.0	41417.0	50370.0	42600.0
4	Red0 12	57423.0	60270.0	59046.0	54544.0	57739.0	56541.0	54594.0	58530.0	57041.0	54544.0	57739.0	56541.0
5	Red0 13	57423.0	57435.0	54933.0	54815.0	57456.0	55227.0	53351.0	56794.0	54192.0	54815.0	57456.0	55227.0
6	Red0 14	57423.0	55319.0	53130.0	53528.0	56176.0	54326.0	51313.0	54547.0	52343.0	53528.0	56176.0	54326.0
7	Red0 15	57423.0	42907.0	42702.0	44221.0	44928.0	44655.0	40400.0	41226.0	41055.0	44221.0	44928.0	44655.0
8	Red0 2	57423.0	48590.0	48800.0	46211.0	50367.0	50427.0	39666.0	45014.0	45549.0	46211.0	50367.0	50427.0
9	Red0 3	57423.0	52808.0	47499.0	42741.0	49851.0	42766.0	43996.0	50656.0	44044.0	42741.0	49851.0	42766.0
10	Red0 4	57423.0	56663.0	56204.0	54460.0	55644.0	54692.0	54154.0	55157.0	54510.0	54460.0	55644.0	54692.0
11	Red0 5	57423.0	50975.0	42149.0	41452.0	51349.0	42755.0	39925.0	50764.0	41780.0	41452.0	51349.0	42755.0
12	Red0 7	57423.0	60828.0	59754.0	59125.0	60314.0	59229.0	59092.0	60344.0	59262.0	59125.0	60314.0	59229.0
13	Red08	57423.0	62681.0	62045.0	58074.0	60470.0	59423.0	59227.0	61105.0	60298.0	58074.0	60470.0	59423.0
14	Red0 9	57423.0	53170.0	50212.0	44398.0	50864.0	47734.0	44258.0	51153.0	47990.0	44398.0	50864.0	47734.0
15	Yel01	57423.0	65536.0	65536.0	65536.0	65536.0	65536.0	49891.0	49891.0	53604.0	65536.0	65536.0	65536.0
16	Yel010	57423.0	65344.0	65500.0	65534.0	65536.0	65536.0	40085.0	40087.0	46795.0	65534.0	65536.0	65536.0

17	Yel011	57423.0	62917.0	62087.0	60884.0	61806.0	60885.0	37277.0	38259.0	38773.0	60884.0	61806.0	60885.0
18	Yel02	57423.0	65503.0	65513.0	65536.0	65536.0	65536.0	38848.0	38848.0	43132.0	65536.0	65536.0	65536.0
19	Yel03	57423.0	65536.0	65536.0	65536.0	65536.0	65536.0	46244.0	46244.0	49625.0	65536.0	65536.0	65536.0
20	Yel04	57423.0	65527.0	65535.0	62592.0	62592.0	62592.0	49018.0	49018.0	49439.0	62592.0	62592.0	62592.0
21	Yel05	57423.0	65390.0	65432.0	65536.0	65536.0	65536.0	56854.0	56854.0	58322.0	65536.0	65536.0	65536.0
22	Yel07	57423.0	65194.0	65200.0	65536.0	65536.0	65536.0	49653.0	49653.0	50735.0	65536.0	65536.0	65536.0
23	Yel08	57423.0	65536.0	65536.0	65536.0	65536.0	65536.0	62237.0	62237.0	62266.0	65536.0	65536.0	65536.0
24	Yel09	57423.0	65536.0	65536.0	65284.0	65278.0	65303.0	60204.0	60204.0	61245.0	65284.0	65278.0	65303.0

Based on the features vector of the query image, the similarity index is created in the form of a score. The score is created in between the Query image and selected image of the training dataset. Following Tables 3.3 shows the score generated concerning the Query image. Scores are based on the Euclidian distance between a Query image and the RGB color model training dataset.

TABLE 3.3 : SCORE IN RGB COLOR MODEL

Images	RGB Feature Extracted				Score
	F1	F2	F3	F4	
Red2	0.00	0.00	0.00	0.00	0.00
Red 11	6362.00	0.07	6.26	12.02	6380.00
Red 3	6474.00	0.03	3.56	9.65	6487.00
Yel5	7136.00	0.15	13.42	38.52	7188.00
Red 5	8683.00	0.02	1.26	2.90	8687.00
Red 9	10929.00	0.02	3.02	3.14	10936.00
Yel3	13377.00	0.16	13.62	38.40	13429.00
Red 15	13543.00	0.07	5.56	10.60	13559.00
Yel2	15596.00	0.16	13.56	37.36	15647.00
Red 14	16202.00	0.08	6.87	14.14	16223.00
Red 12	16503.00	0.07	6.17	5.84	16515.00
Red 10	18022.00	0.04	2.87	3.82	18029.00
Red 1	18278.00	0.02	2.23	4.43	18285.00
Yel11	18601.00	0.12	9.68	13.77	18624.00
Red 13	18661.00	0.09	7.95	15.79	18685.00
Yel7	19633.00	0.15	13.27	38.26	19684.00
Red4	21893.00	0.07	5.93	3.81	21903.00
Red7	27834.00	0.11	9.89	14.99	27859.00
Yel9	35664.00	0.16	14.48	39.40	35718.00
Yel10	36114.00	0.16	14.51	39.34	36168.00

Yel4	36223.00	0.16	14.52	40.05	36278.00
Yel1	36224.00	0.16	14.52	40.08	36279.00
Yel8	36224.00	0.16	14.52	40.08	36279.00
Red8	38600.00	0.07	1.15	8.62	38610.00

Following Tables 3.3 shows the score generated concerning the Query image. Scores are based on the Euclidian distance between a Query image and the YCbCrcolor model training dataset

TABLE 3.4 : SCORE IN YCbCr COLOR MODEL

Sn.	images	YCbCr Feature Extracted				Score
		F1	F2	F3	F4	
1	Red02	0000.0	0.0000	0.0000	0.0000	0000.0
2	Yel010	5099.0	0.2200	24.2900	26.6600	5151.0
3	Red011	5800.0	0.0400	2.1400	6.0200	5808.0
4	Red015	5923.0	0.0300	4.1400	2.5800	5930.0
5	Yel02	6673.0	0.3000	35.2000	42.4500	6751.0
6	Red05	6880.0	0.0500	5.3700	8.1600	6894.0
7	Red03	7270.0	0.0200	2.5200	7.4000	7279.0
8	Yel03	7836.0	0.1700	16.8800	26.8700	7880.0
9	Red09	8046.0	0.0300	3.1900	2.5900	8051.0
10	Yel011	9862.0	0.2500	31.6600	35.2700	9929.0
11	Yel04	10891.0	0.1700	19.8300	31.5600	10943.0
12	Yel07	12172.0	0.1300	10.2100	20.1000	12202.0
13	Yel01	13900.0	0.1800	19.8500	37.5300	13958.0
14	Red014	16513.0	0.1100	10.1700	17.3800	16541.0
15	Red04	19826.0	0.0700	6.6800	3.7200	19837.0
16	Red013	20019.0	0.1200	11.3900	19.3100	20050.0
17	Red01	20859.0	0.0600	7.0900	2.6600	20869.0
18	Red010	21609.0	0.0800	6.9200	2.0200	21618.0
19	Red012	23186.0	0.1200	12.2100	15.5400	23214.0

20	Yel05	24470.0	0.1100	3.4000	4.0600	24477.0
21	Red07	28292.0	0.1400	13.0500	16.9600	28322.0
22	Red08	29310.0	0.1400	13.8600	17.0000	29341.0
23	Yel09	29982.0	0.1200	7.8500	1.0700	29991.0
24	Yel08	32948.0	0.1500	10.7800	5.0900	32964.0

The exact process is also carried out for the L*a*b color model, generating the score between a query image and images of the training dataset as shown in Table 3.5.

TABLE 3.5: SCORE IN L*a*b COLOR MODEL

Sn.	images	L*a*b Features Extracted				Score
		F1	F2	F3	F4	
1	Red02	0.0	0.0000	0.0000	0.0000	0.0
2	Red011	4431.0	0.0400	0.0100	0.0300	4431.0
3	Red03	5610.0	0.0200	0.0100	0.0300	5610.0
4	Red09	5843.0	0.0200	0.0100	0.0100	5843.0
5	Red05	7881.0	0.0900	0.0400	0.0500	7881.0
6	Red015	8549.0	0.0500	0.0300	0.0300	8549.0
7	Red014	11510.0	0.0700	0.0300	0.0500	11510.0
8	Red013	14898.0	0.0800	0.0300	0.0600	14898.0
9	Red04	16168.0	0.0600	0.0200	0.0100	16168.0
10	Red010	18682.0	0.0600	0.0200	0.0100	18682.0
11	Red012	20276.0	0.1000	0.0400	0.0700	20276.0
12	Red01	21597.0	0.0900	0.0400	0.0500	21597.0
13	Red07	22662.0	0.1000	0.0400	0.0500	22663.0
14	Red08	26065.0	0.1200	0.0500	0.0800	26065.0
15	Yel011	26556.0	0.1200	0.0500	0.0700	26556.0
16	Yel07	31522.0	0.1500	0.0600	0.1300	31522.0
17	Yel010	31857.0	0.1500	0.0600	0.1400	31857.0

18	Yel05	31878.0	0.1500	0.0600	0.1400	31878.0
19	Yel02	32055.0	0.1500	0.0600	0.1500	32056.0
20	Yel04	32095.0	0.1500	0.0600	0.1600	32096.0
21	Yel01	32107.0	0.1500	0.0600	0.1600	32107.0
22	Yel03	32107.0	0.1500	0.0600	0.1600	32107.0
23	Yel08	32107.0	0.1500	0.0600	0.1600	32107.0
24	Yel09	32107.0	0.1500	0.0600	0.1600	32107.0

Again, the same process for score generation between Query image and images of the training dataset is shown in Table 3.6 for the HSV color model.

TABLE 3.6: SCORE IN HSV COLOR MODEL

Sn.	Images	HSV Feature Extracted				Score
		F1	F2	F3	F4	
1	Red02	0.0	0.000	0.000	0.000	0.0
2	Red09	3284.0	0.010	1.920	1.420	3288.0
3	Red015	8177.0	0.040	5.660	4.610	8187.0
4	Red03	8426.0	0.080	9.230	14.940	8450.0
5	Red010	8659.0	0.010	0.350	7.840	8668.0
6	Red05	9081.0	0.080	9.150	11.590	9102.0
7	Red011	9178.0	0.070	5.960	9.480	9194.0
8	Red014	10123.0	0.080	7.220	16.200	10147.0
9	Red04	10681.0	0.040	2.460	0.950	10684.0
10	Red01	11721.0	0.020	2.630	1.900	11726.0
11	Red013	12138.0	0.090	7.530	16.480	12162.0
12	Red012	12695.0	0.060	6.030	5.990	12707.0
13	Red08	17992.0	0.080	7.810	7.100	18007.0
14	Red07	18525.0	0.100	8.860	14.100	18548.0
15	Yel011	21343.0	0.110	8.560	11.040	21363.0

16	Yel04	23786.0	0.150	12.190	27.960	23826.0
17	Yel09	28415.0	0.160	14.850	39.820	28470.0
18	Yel010	28840.0	0.160	15.000	42.710	28898.0
19	Yel01	28842.0	0.160	15.000	42.960	28900.0
20	Yel02	28842.0	0.160	15.000	42.960	28900.0
21	Yel03	28842.0	0.160	15.000	42.960	28900.0
22	Yel05	28842.0	0.160	15.000	42.960	28900.0
23	Yel07	28842.0	0.160	15.000	42.960	28900.0
24	Yel08	28842.0	0.160	15.000	42.960	28900.0

For the best outcome, examine the retrieval rates of HSV and L*a*b in Tables 3.7 and Table 3.8. To compare with the proposed technique, three types of databases of particular color images were chosen: apple dataset, bus dataset, and flower dataset. For each pre-categorized database, famous precision and recall metrics were determined. Precision and recall are both effective assessment tools. During the majority of each trial, image retrieval was done for each query image. In Table 3.7 and Table 3.8, all red images in separate datasets are renamed as 'r,' green as 'g,' and yellow as 'y.' Table 3.7 used the HSV model to extract all top comparable red images from the apple dataset, as well as all top red images from the bus dataset with reference to the query image and all top red images from the flower dataset. The L*a*b color model produces the same results for the apple, bus, and lower datasets.

TABLE 3.7: HSV COLOR IMAGE SCORE FOR THREE DIFFERENT CATEGORIZED DATASET

HSV Color Image Score for Three Different Dataset					
apple	**score**	**bus**	**score**	**flower**	**score**
Red0ed01	0.0	Red02	0.0	Red02	0.0
Red013	1293.0	Red012	1267.0	Red09	3288.0
Red015	2564.0	Red05	1992.0	Red015	8187.0
Red012	4132.0	Red07	3483.0	Red03	8450.0
Red09	4233.0	Red017	3773.0	Red010	8668.0

Red08	5707.0	Red03	5053.0	Red05	9102.0
Red07	6416.0	Red06	5582.0	Red011	9194.0
Red014	9033.0	Red04	5755.0	Red014	10147.0
Red011	9054.0	Red014	6124.0	Red04	10684.0
Red06	15667.0	Red08	8052.0	Red01	11726.0
Red02	16902.0	Red015	8083.0	Red013	12162.0
Red03	16902.0	Red016	8087.0	Red012	12707.0
Red04	17839.0	Red010	13043.0	Red08	18007.0
Red010	18558.0	Red011	14442.0	Red07	18548.0
Red05	19621.0	Red09	14816.0	Yell11	21363.0
Green016	24171.0	Red01	21162.0	Yell4	23826.0
Green017	28078.0	Yell4	24172.0	Yell9	28470.0
Green018	28078.0	Yell3	24889.0	Yell10	28898.0
Green019	28078.0	Yell6	25090.0	Yell1	28900.0
Green020	28078.0	Yell7	25190.0	Yell2	28900.0
Green021	28078.0	Yell9	25199.0	Yell3	28900.0
Green022	28078.0	Yell2	25220.0	Yell5	28900.0
Yell23	28078.0	Yell5	25221.0	Yell7	28900.0
Yell24	28078.0	Yell1	25223.0	Yell8	28900.0
Yell25	28078.0	Yell8	25223.0	Red06	31884.0

TABLE 3.8: L*a*bCOLOR IMAGE SCORE FOR THREE DIFFERENT CATEGORIZED DATASET

L*a*bColor Image Score for Different Category of Dataset					
Apple	**Score**	**Bus**	**Score**	**Flower**	**Score**
Red01	0.0	Red02	0.0	Red02	0.00
Red02	2844.0	Red05	707.0	Red011	4431.00
Red06	3977.0	Red014	1046.0	Red03	5610.00
Red05	4622.0	Red08	1061.0	Red09	5843.00
Red011	7070.0	Red015	3130.0	Red05	7881.00

Red08	1163.0	Red012	5946.0	Red015	8549.00
Red013	1331.0	Red010	6936.0	Red014	11510.00
Red015	1359.0	.Red04.	7831.0	Red013	14898.00
Red012	1699.0	Red07	9647.0	Red04	16168.00
Red09	1882.0	Red03	10375.0	Red010	18682.00
Red02	2138.0	Red017	10828.0	Red012	20276.00
Red03	2131.0	Red01	12287.0	Red01	21597.00
Red07	2266.0	Red06	13385.0	Red07	22663.00
Red04	2389.0	Red016	15754.0	Red08	26065.00
Red014	4418.0	Red011	19363.0	Yell011	26556.00
Yell024	4903.0	Red09	21251.0	Red06	30840.00
Green016	4917.0	Yell06	34238.0	Yell07	31522.00
Green017	4919.0	Yell03	34290.0	Yell010	31857.00
Green018	4919.0	Yell09	34458.0	Yell05	31878.00
Green019	4919.0	Yell04	34597.0	Yell02	32056.00
Green020	4919.0	Yell02	34721.0	Yell04	32096.00
Green021	4919.0	Yell01	34785.0	Yell01	32107.00
Green022	4919.0	Yell07	34817.0	Yell03	32107.00
Yell023	4919.0	Yell05	34822.0	Yell08	32107.00
Yell025	4919.0	Yell08	34822.0	Yell09	32107.00

3.7.1 The Image Retrieval Efficiency:

Three types of databases containing specific color images were used to test the suggested approach and were compared to the proposed method. For pre-categorized databases, notable precision and recall measures have been determined as shown in Table 3.9. Precision and recall are both effective evaluation tools. For the most part, each experiment involved image retrieval for each query image.

As shown in Table 3.9, the suggested approach is used in a variety of dataset types. The first dataset is just for the gathering of red, green, and yellow-colored images of apples.

The second piece of data is a collection of red and yellow buses. The final piece of data is a collection of red and yellow flowers

TABLE 3.9 IMAGE RETRIEVAL RESULTS CONCERNING PRECISION AND RECALL

Proposed Techniques using given HSV in Different Image Categories	Apple Database	Bus Database	Flowers Database
Query Image(n1)	R1	R2	R2
Recall	1.0000	1.0000	0.9300
Precision	0.6000	0.6400	0.5600
F-Score	0.75	0.78	0.69

Following Figure 3.7 depicts the comprehensive analysis of three categorised dataset namely Apple, Bus, Flowers based on precision and recall.

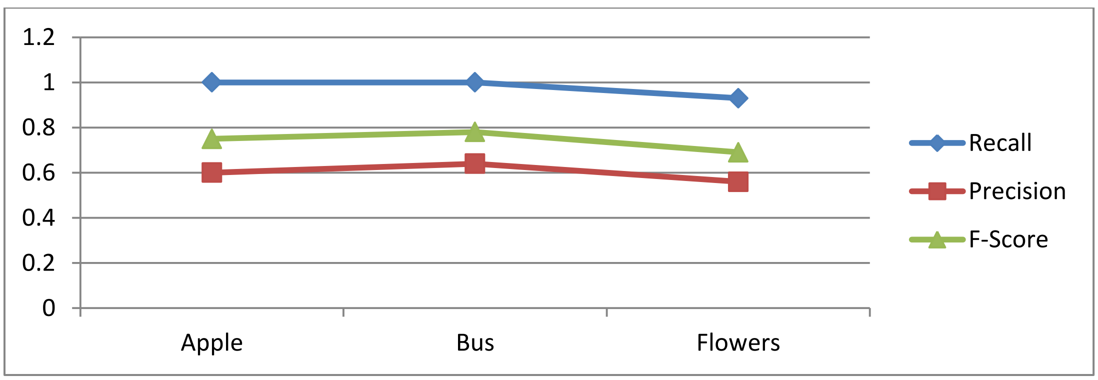

Figure 3.7: Graph Representation of Precision, Recall and F-score for Categorised Dataset

3.7.2 Comprehensive Analysis of Color Models in the Proposed Work:

In the proposed work, a comparative study utilising several color models is conducted as Table 3.10

TABLE 3.10: A COMPREHENSIVE STUDY UTILISING SEVERAL COLOR MODELS

Proposed Techniques using given	RGB	YCbCr	L*a*b	HSV

ColorModel				
Input Images	Red2	Red2	Red2	Red2
Precision	0.4166	0.2916	0.5833	0.5833
Recall	0.7142	0.5000	1.0000	1.0000

Based on the foregoing comparison research of several color models using the CBIR system's recommended procedures, it's evident from Table3.10 that both L*a*b and HSV produce superior results because their accuracy is equal. Out of some relevant images, both provide the top 14 images linked to the query. In this article, it can be concluded that, in terms of color characteristics, both HSV and L*a*b, as opposed to RGB and YCbCr, are performing admirably. Because HSV and L*a*b both have the same color feature accuracy as shown in Figure 3.8. This study work presents a category that includes all three datasets as shown in Figure 3.9. The Table 3.11 shows score for mix of all dataset in a single dataset for a more accurate outcome.

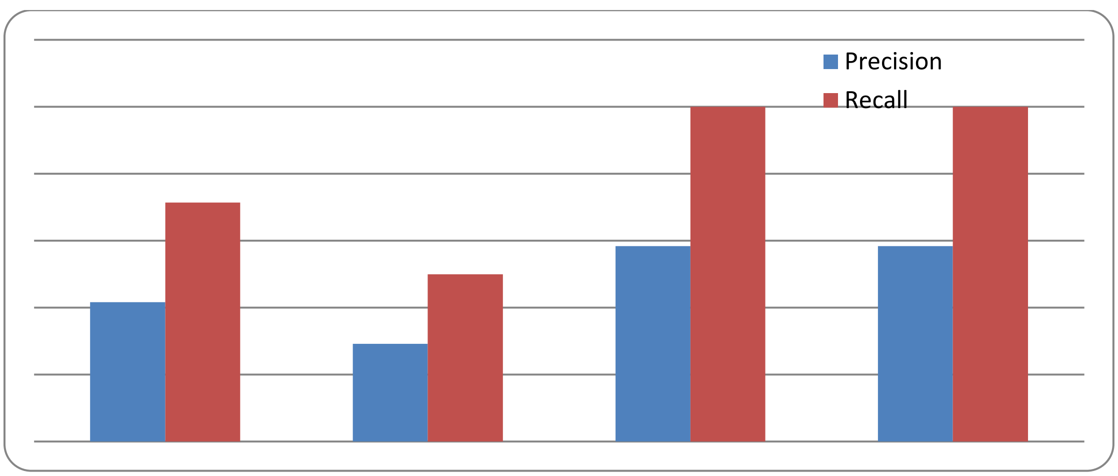

Figure 3.8: Graph Representation of Precision, Recall for Different Color Models

Figure 3.9: Mixed Dataset of Dataset for Apple, Bus and Flower

TABLE 3.11: COMPARATIVE ANALYSIS OF PROPOSED WORK USING HSV AND L*A*B COLOR MODELS

Sn.	HSV		L*a*b		Sn.	HSV		L*a*b	
	image	score	image	score		image	score	image	score
1	RedRo2	0	RedRo2	0	38	RedRo8	18007	RedBus9	18688
2	RedRo9	3288	RedBus15	3753	39	RedBus11	18227	RedRo12	20276
3	RedApp13	3329	RedApp12	3828	40	RedBus9	18546	RedApp6	21566
4	RedApp1	3478	RedApp9	4116	41	RedRo7	18548	RedRo1	21597
5	RedBus5	3728	RedBus8	4199	42	RedApp4	18754	RedApp5	22271
6	RedApp15	3890	RedRo11	4431	43	RedApp5	19308	RedRo7	22663
7	RedBus12	4068	RedBus2	4749	44	RedApp10	19478	RedRo8	26065
8	RedBus14	4222	RedBus12	4801	45	YellRo11	21363	YellRo11	26556
9	RedBus2	4854	RedBus5	5255	46	YellRo4	23826	RedApp14	27142
10	RedBus15	5726	RedApp2	5302	47	RedBus1	24862	YellRo7	31522
11	RedApp12	5849	RedApp3	5302	48	GrApp16	25016	YellBus6	31523
12	RedApp9	5936	RedApp15	5305	49	YellBus4	27856	YellBus3	31579
13	RedApp8	6093	RedBus14	5404	50	YellRo9	28470	YellBus9	31743
14	RedApp7	7472	RedApp13	5429	51	YellBus3	28568	YellRo10	31857
15	RedBus7	7635	RedBus10	5508	52	YellBus6	28767	YellRo5	31878
16	RedBus17	7799	RedBus4	5560	53	YellBus7	28866	YellBus4	31884
17	RedRo15	8187	RedRo3	5610	54	YellBus9	28875	YellApp24	31941
18	RedRo3	8450	RedRo9	5843	55	YellBus2	28896	YellBus2	32006
19	RedRo10	8668	RedApp7	6160	56	YellBus5	28898	YellRo2	32056
20	RedApp11	9065	RedApp8	6819	57	YellRo10	28898	YellBus1	32070
21	RedApp14	9085	RedApp4	7566	58	GrApp17	28900	GrApp16	32090
22	RedRo5	9102	RedBus7	7610	59	GrApp18	28900	YellRo4	32096
23	RedBus3	9165	RedRo5	7881	60	GrApp19	28900	YellBus7	32102
24	RedRo11	9194	RedBus3	8326	61	GrApp20	28900	GrApp17	32107
25	RedBus4	9481	RedRo15	8549	62	GrApp21	28900	GrApp18	32107
26	RedBus6	9695	RedBus17	8560	63	GrApp22	28900	GrApp19	32107
27	RedRo14	10147	RedBus1	10058	64	YellApp23	28900	GrApp20	32107
28	RedRo4	10684	RedApp11	10892	65	YellApp24	28900	GrApp21	32107
29	RedRo1	11726	RedBus6	11111	66	YellApp25	28900	GrApp22	32107

30	RedBus8	12008	RedRo14	11510	67	YellBus1	28900	YellApp23	32107
31	RedBus16	12054	RedBus16	13368	68	YellBus8	28900	YellApp25	32107
32	RedRo13	12162	RedRo13	14898	69	YellRo1	28900	YellBus5	32107
33	RedRo12	12707	RedApp10	14973	70	YellRo2	28900	YellBus8	32107
34	RedApp6	15377	RedRo4	16168	71	YellRo3	28900	YellRo1	32107
35	RedBus10	16865	RedBus11	16835	72	YellRo5	28900	YellRo3	32107
36	RedApp2	17774	RedApp1	17737	73	YellRo7	28900	YellRo8	32107
37	RedApp3	17774	RedRo10	18682	74	YellRo8	28900	YellRo9	32107

3.6CONCLUSION

Content-Based Image Retrieval systems are designed to cope with a variety of image datasets and do not address issues such as vast specialised image collections or effective image retrieval by image content. The research work concentrated on large set of images with different categories. This chapter analyzed that the retrieval rate of HSV model and L*a*b model for color based image retrieval are approximately same using the proposed approach. While of RGB and YCbCrcolor model. We focused our investigation on a vast number of images from various categories. This work will aid in the development of a number of image retrieval applications. Using the proposed method, we can identify appropriate methods and apply good approaches in a huge set of images by taking into account the dataset.

CHAPTER IV

COMPARATIVE ANALYSIS OF TEXTURE BASED APPROACH

Texture analysis is a vast discipline with many applications, ranging from remote sensing to biomedical imaging, and so on. Each of these areas requires some raw data image to extract some significant features that characterise an image's properties. In this way, content-based image retrieval (CBIR) is critical for determining image similarity to query images. There has been a lot of progress in such areas, and there's still much more to be achieved. This chapter examines and compares the efficiency of image retrieval using different texture feature extraction techniques, particularly Gray Level Co-occurrence Matrixes **(**GLCM), Local Binary Pattern (LBP) and Local Phase Quantisation (LPQ), by analysing and comparing different research papers based on texture feature extraction, particularlyGray Level Co-occurrence Matrixes, Local Binary Pattern, and Local Phase Quantisation. The GLCM, LBP and LPQ methods are the subject of this study, as well as their comparison.

4.1 RELATED WORK

(Ojala et al., 2002) have presented **an** effective multi-resolution approach, in which gray-scale and rotation invariant texture classification was done based on local binary patterns and nonparametric sample and prototype distribution discrimination. Local binary patterns called "uniform" are essential aspects of local image texture, and their occurrence histogram is a very significant texture feature. In addition, the authors provided a strategy for merging various operators for multi-resolution analysis. (Ojala et al., 2002) proposed a method that is particularly resistant to gray-scale fluctuations since the operator is monotonically invariant. (D. Zhang et al., 2000) presented an image retrieval method based on the Gabor filter. Texture features were found by calculating the mean and variation of the Gabor filtered image. Rotation normalisation is realised by a circular shift of the feature elements so that all images have the same dominant direction. The indexing of images and retrieval of the images were carried out via texture based images and natural images. The Gabor wavelet has proven to be very useful in texture analysis and is widely adopted in the literature. (Jain &Farrokhnia, 1991) provided a texture segmentation technique based on multichannel filtering theory for early visual information processing. A systematic filter selection approach is proposed based on reconstructing the input image from the filtered images. (Raghuwanshi&Tyagi, 2016) expressed that retrieving images from large databases has always been a difficult problem in image retrieval and described how rough the surface was. And surveyed various texture feature extraction methods using wavelet transforms. (Kiss et al. (1995) discussed that texture analysis is crucial in image processing and is frequently used in industrial quality control and biomedical imaging industries; and proposed pixel-based structural characteristics that seek to bridge the statistical and structural feature extraction methods. (Do &Vetterli, 2002) describe a statistical approach to texture retrieval by merging two related tasks, feature extraction, and similarity measurement. They showed that determining the Kullback-Leibler distance (KLD) between estimated models for the SM step is asymptotically optimal in terms of retrieval error probability. With the generalised Gaussian density (GGD) and a closed-form for the KLD between GGDs, the statistical scheme leads to a new wavelet-based texture retrieval approach. (Yue et al., 2011) proposed a method for quickly extracting color and texture information from images (CBIR). (W. Zhang et al., 2018) proposed an NDV for texture representation. Unlike local-binary-pattern-based descriptors, the proposed NDV can cover a large local region. The proposed NDV also has two strategies for achieving rotation invariance. As per (Ji et al., 2018) , LBP is a simple yet efficient coding model for texture feature extraction. (Ji et al., 2018) proposed a training-based feature model mapping method and then developed a texture classification frame using multi-resolution feature fusion of four gLBP descriptors to improve texture classification. The proposed method is reliable and efficient in texture classification, as shown by simulation on five public texture databases. As (Rajadell et al., 2009) described, some easily-computed textural features could be applied to three different image data types- photomicrographs of five different sandstone types, 120,000 panchromatic aerial photographs of eight land-use categories, and Earth Resources

Technology Satellite (ERTS) multi special imagery. (Lin et al., 2009) proposed three image retrieval features and presented a feature selection strategy to select optimal characteristics to increase detection rate while simplifying image retrieval computation. (Malik &Baharudin, 2013) discussed effective content-based image retrieval (CBIR), low-level features like-color, texture, and form extraction that were required, and quick query image matching with indexed images. (Zujovic et al., 2013) advised new texture similarity measures that take into account human vision and texture variability. **Melanoma is** one of the most deadly cancers, so research into its detection has been intensive. (Barata et al., 2014) described two methods for detecting melanomas in dermoscopy images. Local features and a bag-of-features classifier were used to classify skin lesions in the first and second systems. To determine the best classification system for skin lesions. The other goal was to compare the discriminative power of color and texture features in lesion classification. As per (Jeena Jacob et al., 2014), they proposed a method that was tested using the standard image databases, Brodatz texture database (DB1) and Corel database (DB2). (Dang, 2017)Choi et al. proposed Color Local Texture Features (CLTF) to maximise the complementary effect taken using color and texture information for face recognition. (Srivastava et al., 2017) proposed combining texture and color features in a pipelined manner. It has two phases. Phase one compared the query image to the dataset and ranked them according to similarity.

4.2 BACKGROUND

One of the most important things that have been used is texture in image retrieval approach. In earlier studies, several approaches that were defined for a specific application were offered. In any event, there is no general approach or established methodology that can be applied to a huge number of images.

4.2.1 Gray Level Co-occurrence Matrixes (GLCM):

The Gray Level Co-occurrence Matrix is one of the quantifiable techniques for removing highlights that is reliant on the analysing texture. GLCM is a grid that defines two measurements between pixels for joint probability with a certain spacing. Many scientists have used this approach in a variety of applications, including clinical imaging, satellite images, and so on, to perform various research in contrast ways. The GLCM algorithm is used to determine the image's particular dependant grey level. The image utilises m as the number of Gray levels, and the matrix size is M x M. Co-occurrence matrices can be arranged in four different ways (0^0 ,45^0, 90^0 and 135^0). The GLCM matrix that results is an averaging of all the orientations. Perfection, normalcy, coarseness, and invariance are all qualities that result from this. This method, illustrated in figure 1 in 00, may be used to produce a GLCM matrix. For each orientation, the same approach is used. It is also referred to as SGLDM (Special Gray Dependence Matrix) when using the Second-order statistic technique, where the research is carried out for particular remarkable relations for sets of pixels.[42]

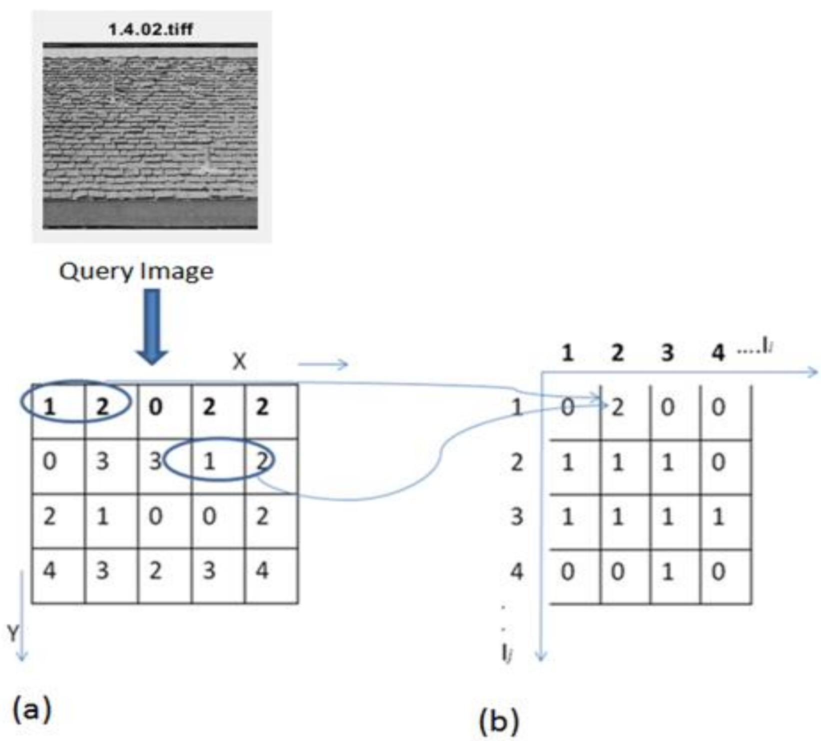

Figure 4.1: GLCM Matrix of an Image

There are 14 highlights to be characterised by the Haralick in GLCM for the arrangement dependent on texture features. A significant number of researchers [9] utilised the four to five highlights in their research since they are so closely connected. It outperforms the LBP due of its excellent time management and multifunctional character. GLCM, on the other hand, isn't much better for a number of datasets. The GLCM second-order statistic describes the connection between a reference pixel P (i, j) and its adjacent pixel at various angles and distances.

$$Contrast(F1) = \sum_{i,j=0}^{N-1} P_{ij}(i-i)^2 \tag{4.1}$$

$$Correlation(F2) = \sum_{i,j=0}^{N-1} P_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{4.2}$$

$$Energy(F3) = \sum_{i,j=0}^{N-1} (P_{ij})^2 \tag{4.3}$$

$$Homogeneity(F4) = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-i)^2} \tag{4.4}$$

$$Entropy(F5) = \sum_{i,j=0}^{N-1} \ln(P_{ij})P_{ij} \tag{4.5}$$

Where:

P_{ij} = Normalized symmetrical GLCM element i,j

N = Amount of grayscale information in the image, as determined by the value entered under Quantization:

μ = The GLCM mean(It estimates the intensity of all pixels in the relationships that have contributed to the GLCM.) determined as follows:

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij}$$

These are all the five characteristics of the GLCM matrix. The range of Gray levels in the input image is represented by n in the formula above. The following formula is used to compute GLCM's Euclidean distance:

$$\text{Euclidean Distance} = \sqrt{(F_{q1}-F_1)^2+(F_{q2}-F_2)^2+(F_{q3}-F_3)^2+(F_{q4}-F_4)^2+(F_{q5}-F_5)^2} \qquad \textbf{(4.6)}$$

Where, F and F_q are the two points for Euclidean space. F1, F2,F3, F4, and F5 are features for GLCM, F_{q1}, F_{q2} , F_{q3}, F_{q4} and F_{q5} are the features of Query image for GLCM.

4.2.2 Local Binary Patterns (LBP):

Local Binary Patterns (LBP) were initially proposed as a texture analysis approach by Ojala et al. [10], and the LBP is connected with both the study of local structures and the analysis of occurrences. It uses a binary pattern to represent each pixel in the image. LBP is based on the difference in grey level values between each central pixel 'g' and its neighbours in a circular region with a defined radius 'r' as shown in Figure 4.2.

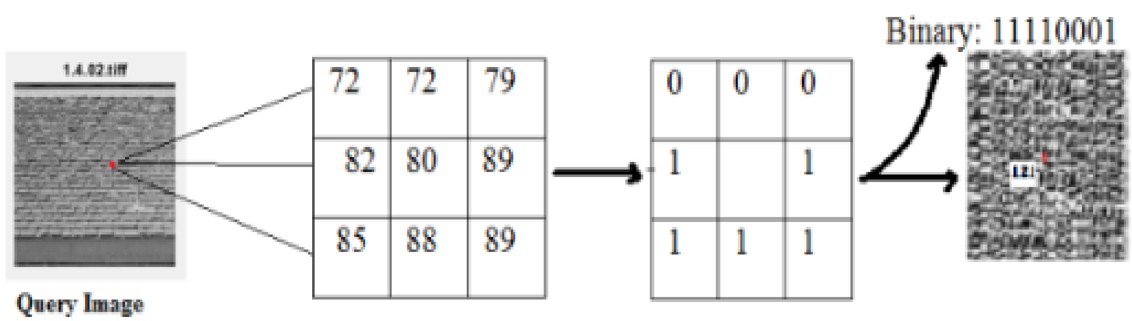

Figure 4.2: Steps in LBP Process

As a consequence, the LBP result may be represented as follows:

$$\text{LBP}_{\text{p,r}}(x_c, y_c) = \sum_{k=0}^{7} \partial(g_n - g_c)2^n \qquad (4.7)$$

Where the value of a center pixel is represented by gc at (xc,yc), the values of eight surrounding pixels are represented by r, and the number of pixels in the whole neighbourhood is represented by p, and the function is represented as:

$$\partial(\mathrm{x}) = \begin{cases} 1 & \text{if } \mathrm{x} > 0, \\ 0 & \text{otherwise} \end{cases} \tag{4.8}$$

The LBP labels-based histogram can be used as a texture description. A distribution of patterns related LBP may be used to represent the texture of an image; the representation can also be done using the LBP histogram vector H:

$$\mathrm{H} = \sum_{x=0}^{U} \quad \sum_{y=0}^{V} \partial(\mathrm{LBP}_{\mathrm{p,r}}(x \quad , y \quad) - \mathrm{k} \quad) \tag{4.9}$$

Where H is the LBP histogram vector, 0 k d = 2n is the number of patterns through LBP, and U and V are the image dimensions, and H is the LBP histogram vector.

The advantages of utilising LBP are that they combine structural and statistical approaches to increase texture analysis performance. It is simple to implement and reduces the computational cost.[43]

4.2.3 Linear Phase Quantization (LPQ)

Ojansivu and Heikkila used the LPQ for texture analysis [16]. Local Phase Quantization, which uses the Fourier Transform to examine lattice data, is an usually regular and productive surface descriptor. After haze processing, the LBP uses the Fourier Phase Spectrum's Blur Invariance characteristic to produce the watched image from the first query image (unique image). LPQ extracted data from neighbouring stages by using the 2-D transient Fourier change reported around a rectangle neighbourhood at every region of every pixel in Figure 2's image. In terms of 2-D frequencies, only four complex coefficients are evaluated in Local Phase Quantization. Refer to [15] for further mathematical information. Before the feature extraction stage, we resize the images to 256256 pixels.

$$F(u,x) = \sum_{y \in N_x} \int (\mathrm{x}-\mathrm{y}) \mathrm{e}^{-\mathrm{j}2\pi \mathrm{uTy}} \tag{4.10}$$

F (u, x) represents local Fourier coefficients computed across 'u' points, while x represents one-dimensional convolution for the rows and columns.

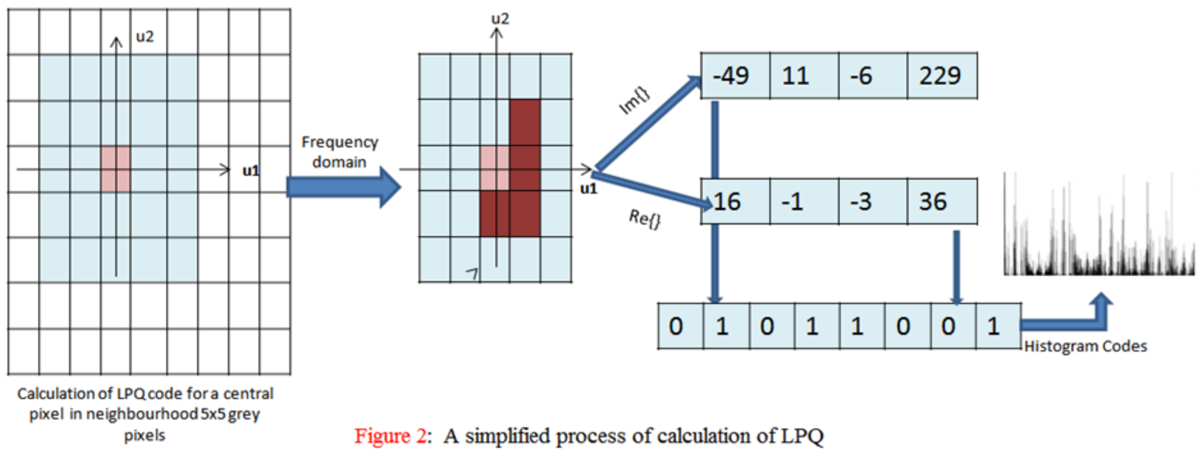

Figure 4.3: A Simplified Process of Calculation of LPQ

4.3 STATISTICAL ANALYSIS

The GLCM, LBP and LPQ algorithms are evaluated using three statistical parameters: P for Precision, R for Recall and Fs for F-score measurements. The F-score rating, which is a single number, indicates how successful image retrieval is overall. The GLCM method is used to extract five features (F1, F2, F3, F4, and F5) for dataset images in order to test the texturing algorithm's effectiveness. According to the abovementioned formula no. (1,2,3,4,and 5), these are contrast, correlation, energy, homogeneity, and entropy[42][43].

Score is estimated by the Euclidian distance formula:

$$\text{Euclidian Distance}=\sqrt{\sum_1^n (F_q - F_n)^2}) \qquad (4.11)$$

Where, n indicates the number of retrieved features from each image collection for each feature extraction. Fq and Fn are the features of the Query image (Qimage) and the features of each chosen image in the dataset, respectively. The Euclidian distance is used as a score for each image in relation to the query image.

Precision (P): Precision is a metric that compares the returned relevant images to those of the requested images out of all recovered images.

$$P = n/Tn. \qquad (4.12)$$

Recall (R): The estimate of the necessary retrieved image to the whole dataset images is known as recall (R).

R=n/Tr (4.13)

F-Score: The F-Score(Fs) is a single score that indicates the overall efficacy of image retrieval. The F-score is calculated using the following formula:

Fs = (2 * P * R) / (P + R) (4.14)

Where n, Tn, and Tr represent the number of relevant images retrieved, the total number of retrieved images, and the total number of relevant images, respectively.

4.4 COMPARATIVE ANALYSIS OF GLCM AND LBP

In this chapter the sets of images are gathered from the internet for comparative study and analysis. There are grey images in the database with different textures of wall tiles in the same category. They're TIFF files with a 256pixel resolution. Again for retrieval of simila r images and the comparative examination, there are primarily two phases. Scanning all o f the images from the entire dataset in Figure 4 for feature extraction vectors and using re processing methods such as a 2D median filter to minimise noise is the first step.The resu lting characteristics are saved in a software archive. The step two is to use the above appr oaches to collect the features from the query image. The final stages are to collect related and most similar images from the feature dataset that use the GLCM and LBP as needed f or evaluating the effectiveness of various techniques Figure 4.4 shows a block structure of the comparing of GLCM and LBP based image retrieval.To begin, MATLAB was use d to extract feature vectors from the input and dataset images using GLCM and LBP. Sep arately, the score was assessed using Euclidean distance, the input image was translated t o dataset_images_based on the produced score, and the topmost N similar images were s hown. Both GLCM and LBP were subjected to this procedure. Based on the top N image s recovered using GLCM and LBP individually, the statistical metrics Precision, Recall, a nd F-Score were used to compare GLCM and LBP[42].

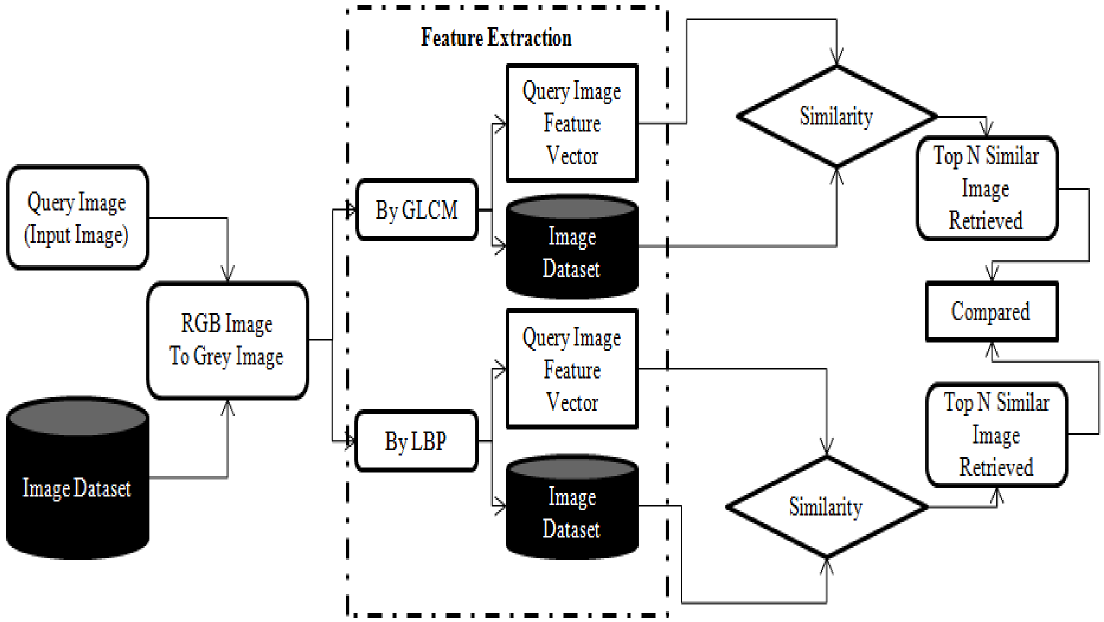

Figure 4.4: A Block Diagram Comparing GLCM and LBP Based Image Retrieval Methods

4.5 EXPERIMENTAL RESULTS

In this chapter, some images from the Brodetz database that are freely available on the internet have been shown, all in the same category although with different textures of wall tiles in the TIFF format with a size of 256 pixels, in the same category but also with various textures of wall tiles in the TIFF format with a size of 256 pixels.

Table 4.1 shows the results of extracting the features of GLCM, Fn=[F1, F2, F3, F4,..., Fn], using formula no. (1,2,3,4 and 5) for image dataset (Figure 4.5).

TABLE 4.1:GLCM-BASED FEATURES

S.n	Dataset Image	F1	F2	F3	F4	F5
1	1.1.01	3.68	0.34	0.03	0.53	0.09
2	1.1.12	1.08	0.49	0.16	0.75	0.64
3	1.2.01	7.00	0.33	0.02	0.47	0.00
4	1.2.06	7.77	0.26	0.02	0.45	0.00
5	1.2.07	7.31	0.31	0.02	0.47	0.00

6	1.2.11	6.12	0.45	0.02	0.51	0.00
7	1.2.12	4.94	0.53	0.03	0.56	0.00
8	1.2.13	4.27	0.59	0.03	0.57	0.00
9	1.3.12	0.61	0.66	0.19	0.79	0.88
10	1.4.01	0.70	0.67	0.14	0.77	0.96
11	1.4.02	1.17	0.76	0.11	0.78	0.68
12	1.4.03	0.59	0.82	0.26	0.85	0.79
13	1.4.04	0.25	0.86	0.24	0.88	0.99
14	1.5.01	0.27	0.45	0.53	0.90	0.96
15	te1	7.16	0.32	0.02	0.48	0.00
16	te2	7.22	0.31	0.02	0.47	0.00
17	te3	6.88	0.35	0.02	0.48	0.00
18	te3b	6.85	0.35	0.02	0.48	0.00

Table 4.2 shows the results of extracting the features of LBP, Fn=[F1, F2, F3, F4,..., Fn], using formula no. (7) for image dataset (Figure 4.5).

TABLE 4.2: LBP-BASED FEATURES

S.n	Dataset Image	F1	F2	F3	F4	F5
1	1.1.01	0.17	0.26	0.24	0.39	0.52
2	1.1.12	0.28	0.30	0.20	0.29	0.33
3	1.2.01	0.17	0.27	0.23	0.39	0.50
4	1.2.06	0.23	0.29	0.20	0.33	0.45
5	1.2.07	0.19	0.25	0.24	0.42	0.41
6	1.2.11	0.20	0.26	0.24	0.37	0.39
7	1.2.12	0.27	0.30	0.19	0.28	0.32
8	1.2.13	0.18	0.24	0.17	0.30	0.57
9	1.3.12	0.28	0.27	0.22	0.28	0.34
10	1.4.01	0.28	0.26	0.16	0.25	0.39
11	1.4.02	0.29	0.25	0.14	0.29	0.41

12	1.4.03	0.33	0.28	0.14	0.18	0.25
13	1.4.04	0.33	0.27	0.15	0.17	0.19
14	1.5.01	0.30	0.26	0.15	0.26	0.32
15	te1	0.19	0.27	0.20	0.35	0.49
16	te2	0.19	0.28	0.19	0.34	0.48
17	te3	0.19	0.27	0.20	0.36	0.49
18	te3b	0.19	0.27	0.20	0.36	0.49

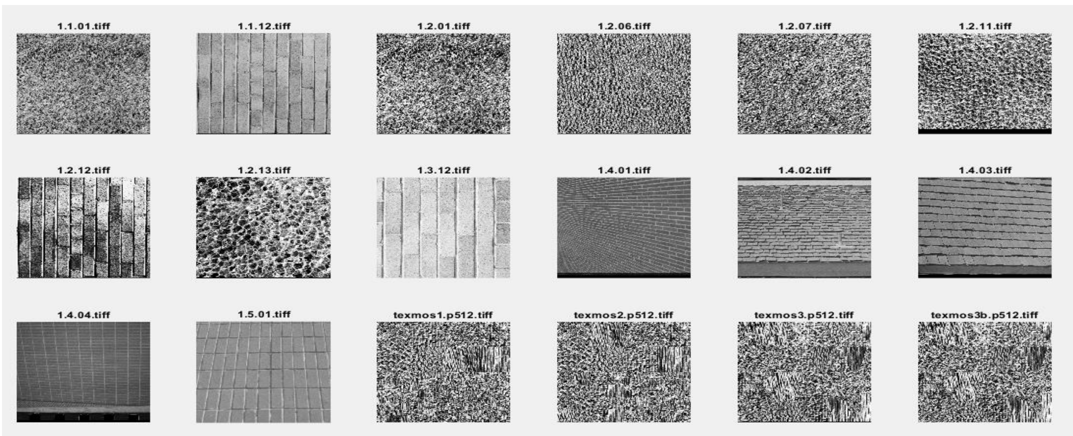

Figure 4.5: Original Image Dataset

4.5.1 Comparative Analysis between GLCM, LBP and LPQ

The processes for retrieving similar images and conducting a comparison research are shown in this chapter as below:

In the first stage, all of the images from of the collection of images (source dataset-Figure 3) are gathered in a continuous succession for feature extraction. The features extracted are stored in the form as feature vectors and gathered inside the database indicated in Table 1 to build a feature database.

The query image is used as an input image to retrieve the most similar image from the component information base using GLCM, LBP and LPQ as needed to compare the efficacy of various techniques. By analysing the similarities using the Euclidian distance, a technique for building the feature vector and comparing the feature vectors of a dataset is available.

Table 4.3 depicts the GLCM, LBP and LPQ scores. As can be seen in Table 4.3, the score for each image in the dataset has also been produced. The efficiency of image retrieval is mostly determined by the scorecard created for the collection of images. The retrieval of a comparable image from of the dataset is founded on a scorecard generated for each image with in dataset using GLCM and LBP and LPQ[42][43].

TABLE 4.3: EUCLIDIAN DISTANCE (SCORE) FOR GLCM, LBP, AND LPQ

Sn	Image of Dataset	Score		
		GLCM	LBP	LPQ
1	1.1.01.tiff	2.63	0.01	3557.40
2	1.1.12.tiff'	0.30	0.00	3447.18
3	1.2.01.tif'f	5.90	0.01	3611.97
4	1.2.06.tiff'	6.67	0.00	3585.05
5	1.2.07.tiff'	6.21	0.01	3400.84
6	1.2.11.tiff'	5.02	0.01	6926.24
7	1.2.12.tiff'	3.85	0.00	3478.25
8	1.2.13.tiff'	3.19	0.01	3506.73
9	1.3.12.tiff'	0.61	0.00	3445.05
10	1.4.01.tiff'	0.56	0.00	5288.88
11	1.4.02.tiff'	0.00	0.00	0.00
12	1.4.03.tiff'	0.61	0.01	5342.54
13	1.4.04.tiff'	0.99	0.01	5476.19
14	1.5.01.tiff'	1.08	0.00	3500.17
15	texmos1.tiff'	6.05	0.01	3471.33
16	texmos2.tiff'	6.12	0.01	3522.69
17	texmos3.tiff'	5.77	0.01	3451.17
18	texmos3b.tiff'	5.75	0.01	3475.72

Each image in the collection was given a score based on the estimated Euclidian distance, as shown in Table 4.3. The scorecard created for the collection of images was used to analyse and evaluate the image retrieval's efficacy. The image retrieval from the database is relied on the scorecards generated by GLCM, LBP and LPQ for every image in the collection. The query image 1.4.02.tiff was used to extract the most comparable images from the original dataset . The most nearly comparable images are retrieved and presented as per the query image utilising GLCM, LBP and LPQ, as these are texture-based feature extraction algorithms, based on such a score card generated based upon Euclidian distance using formula as shown in Figure 4.6, Figure 4.7 and Figure 4.8 respectively. Figure 4.6shows a comparable returned image based on the scores of images with in dataset based upon that query images for GLCM. Figure 4.7 depicts comparable images from the dataset that can be used for LBP. Figure 4.8 depicts comparable images from the dataset that can be used for LPQ.

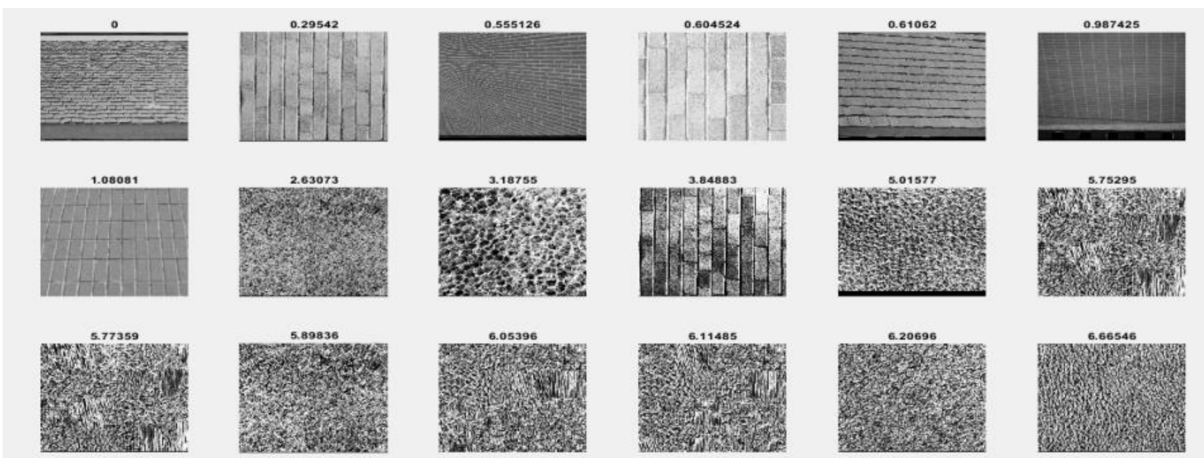

Figure 4.6: GLCM Images Retrieved from the Database

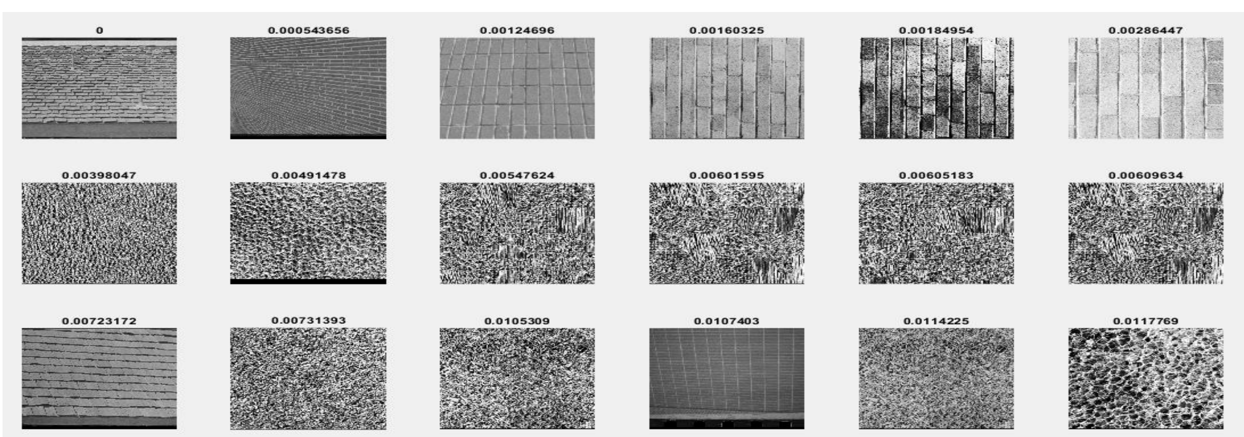

Figure 4.7: LBP Images Retrieved from the Database

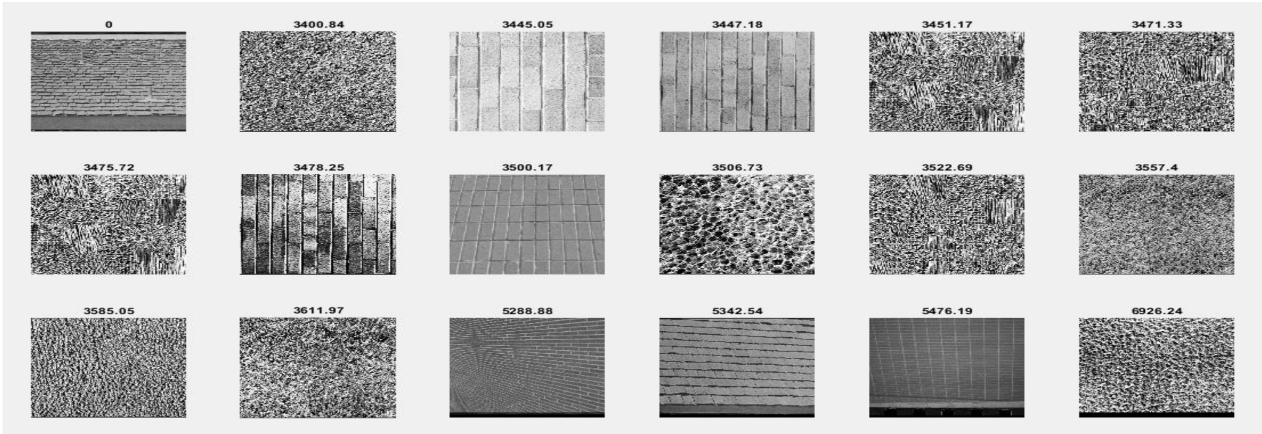

Figure 4.8: LPQImages Retrieved from the Database

Table 4.4 calculates and displays precision, recall, and F-Score using formula number 13, 14, 15 respectively based on the GLCM and LBP scorecards. Figure 4.9 depicts a line graph of GLCM, LBP and LPQ, with red, green and blue lines including nodes for Precision, Recall, and F-Score for the both GLCM and LBP. According to the graph, GLCM has a greater value than both LBP and LPQ in terms of statistical characteristics. This demonstrates the better outcomes of the image retrieval technique for GLCM, LBP and LPQ.

TABLE 4.4: PRECISION, RECALL, AND F-SCORE FOR EXISTING TECHNIQUES AND PROPOSED APPROACH

Feature Extraction Technique	GLCM	LBP	LPQ
Precision	0.3890	0.3330	0.1660
Recall	1.0000	0.8570	0.4280
F-score	0.5601	0.4796	0.2392

Figure 4. 9 compare the results of image retrieval with terms of precision, recall, and f-score in a bar graph. On the bar graph chart, the efficacy of the GLCM approach has the highest values in comparison to both LBP and LPQ.

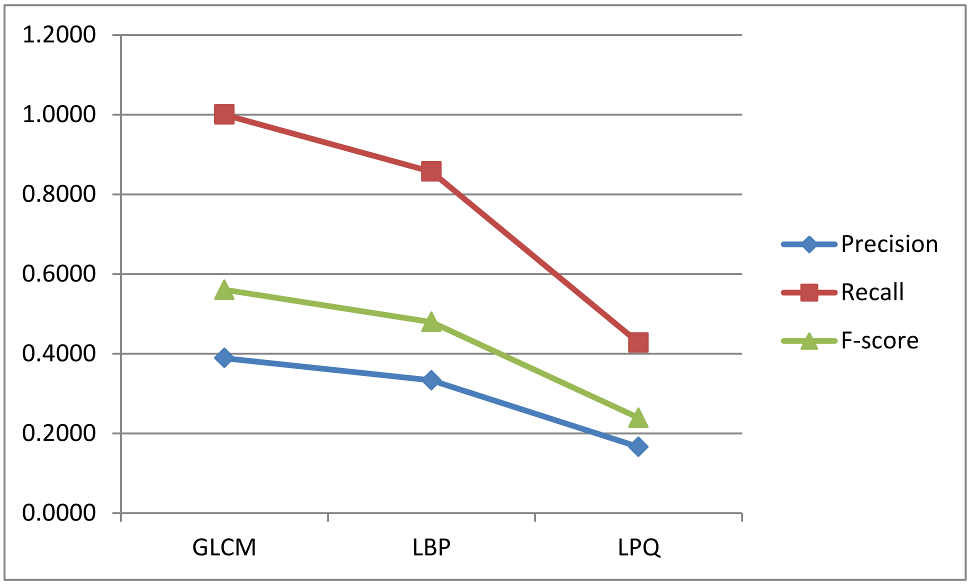

Figure 4.9: Precision and Recall

Based Graphical Representation of GLCM, LBP, and LPQ

4.6 CONCLUSION

Table 4.9 shows the performance of the GLCM, LBP and LPQ for image similarity from a collection of images in the same category over the input image. It is evident that the GLCM perform better than LBP, and LBP has the best accuracy, recall, and F-score, implying that the LBP will function better than the LPQ techniques for a short dataset. For comparative study and analysis of three alternative methods: GLCM, LBP and LPQ for similar image retrieval systems, a plot (Figure 4.9) is generated based on Table 4.9. As demonstrated in a query image for the resultant analysis.

CHAPTER V

IMAGE RETRIEVAL BASED ON HYBRID INVARIANT FEATURE EXTRACTION TECHNIQUES

Using content-based image retrieval (CBIR), researchers have been able to successfully extract content from a wide range of databases during the past few years Generally speaking, multimedia devices create gigabytes of image-based content on a regular basis and make that data available in multimedia databases. It's critical to gather the colors you need from all of these different repositories. Several papers on texture-based image retrieval are reviewed using CBIR approaches in this study. When using CBIR texture approaches, the results of several algorithmic models, including Gray Level Co-occurrence Matrixes, Local Binary Patterns, and Local Phase Quantization, are examined for various images. This study proposes and compares a texture-based feature extraction approach with the already available methods.

5.1 RELATED WORK

Ojala et al., (2002)[104] have presentedaneffective multi-resolution approach, in which gray-scale and rotation invariant texture classification was done based on local binary patterns and nonparametric sample and prototype distribution discrimination. Local binary patterns called "uniform" are essential aspects of local image texture, and their occurrence histogram is a very significant texture feature. In addition, the authors provided a strategy for merging various operators for multi-resolution analysis. Ojala et al., (2002)[104] proposed a method that is particularly resistant to gray-scale fluctuations since the operator is monotonically invariant. D. Zhang et al., (2000)[147] presented an image retrieval method based on the Gabor filter. Texture features were found by calculating the mean and variation of the Gabor filtered image. Rotation normalisation is realised by a circular shift of the feature elements so that all images have the same dominant direction. The indexing of images and retrieval of the images were carried out via texture based images and natural images. The Gabor wavelet has proven to be very useful in texture analysis and is widely adopted in the literature. Jain &Farrokhnia, (1991)[67] provided a texture segmentation technique based on multichannel filtering theory for early visual information processing. A systematic filter selection approach is proposed based on reconstructing the input image from the filtered images. Raghuwanshi&Tyagi, (2016)[111] expressed that retrieving images from large databases has always been a difficult problem in image retrieval and described how rough the surface was. And surveyed various texture feature extraction methods using wavelet transforms. (Kiss et al. (1995)[75] discussed that texture analysis is crucial in image processing and is frequently used in industrial quality control and biomedical imaging industries; and proposed pixel-based structural characteristics that seek to bridge the statistical and structural feature extraction methods. Do &Vetterli, (2002)[38] describe a statistical approach to texture retrieval by merging two related tasks, feature extraction, and similarity measurement. They showed that determining the Kullback-Leibler distance (KLD) between estimated models for the SM step is asymptotically optimal in terms of retrieval error probability. With the generalised Gaussian density (GGD) and a closed-form for the KLD between GGDs, the statistical scheme leads to a new wavelet-based texture retrieval approach. Yue et al., (2011)[22] proposed a method for quickly extracting color and texture information from images (CBIR). W. Zhang et al., (2018)[147] proposed an NDV for texture representation. Unlike local-binary-pattern-based descriptors, the proposed NDV can cover a large local region. The proposed NDV also has two strategies for achieving rotation invariance. As per Ji et al., (2018) [77], LBP is a simple yet efficient coding model for texture feature extraction. Ji et al., (2018)[69] proposed a training-based feature model mapping method and then developed a texture classification frame using multi-resolution feature fusion of four gLBP descriptors to improve texture classification. The proposed method is reliable and efficient in texture classification, as shown by simulation on five public texture databases. As Rajadell et al., (2009) [112]described, some easily-computed textural features could be applied to three different image data types- photomicrographs of five different sandstone types, 120,000 panchromatic aerial photographs of eight land-use categories, and Earth Resources Technology Satellite (ERTS) multi special imagery. Lin et al., (2009) [112]proposed three image retrieval features and presented a feature selection strategy to select optimal characteristics to increase detection rate while simplifying image retrieval computation. Malik &Baharudin, (2013)[86] discussed effective content-based image retrieval (CBIR), low-level features like- color, texture, and form extraction that were required, and quick query image matching with indexed images. Zujovic et al., (2013)[150] advised new texture similarity measures that take into account human vision and texture variability. Melanoma is one of the most deadly cancers, so research into its detection has been intensive. Barata et al., (2014)[10] described two methods for detecting melanomas in dermoscopy images. Local features and a bag-of-features classifier were used to classify skin lesions in the first and second systems. To determine the best classification system for skin lesions. The other goal was to compare the discriminative power of color and texture features in lesion classification. As per Jeena Jacob et al., (2014)[68], they proposed a method that was tested using the standard image databases, Brodatz texture database (DB1) and Corel database (DB2). Dang, (2017)[29] proposed Color Local Texture Features (CLTF) to maximise the complementary effect taken using color and texture information for face recognition. Srivastava et al., (2017)[120] proposed combining texture and color features in a pipelined manner. It has two phases. Phase one compared the query image to the dataset and ranked them according to similarity.

5.2 BACKGROUND

One of the most important tasks in content-based image retrieval (CBIR) system is feature extraction using texture extraction algorithms. From the searched dataset of images, the CBIR technique is used to find the most similar images to the input image (Query image). As a result, retrieving similar images to the query image from a wide number of databases is an important research field in computer vision in the CBIR system. One of the most important characteristics that were used to organise the images was texture. Although different strategies relevant to a given application have been offered in prior articles, there is no broad strategy or traditional methodology that is useful for a big group of images.

5.2.1 Gray Level Co-occurrence Matrix (GLCM):

Highlights can be removed using the Gray-Level Co-Occurrence Matrix (GLCM), one of the quantifiable ways. Two measurements are made between sets of pixels for joint probability using GLCM, which is a grid characterising these two measurements. GLCM is used to figure out how much a grey level's color depends on its hue. If you utiliseaMxM matrix, M refers to how many different shades of grey were employed to create the image. The co-occurrence matrix is made up of four distinct axes of symmetry (0^0, 45^0, 90^0, and 135^0). The GLCM matrix that's generated is a sum of all the different orientations. This results in a wide range of qualities, including perfection, normality, coarseness and invariant.

5.2.2 Local Binary Patterns (LBP)

Local Binary Patterns (LBPs) were first proposed by Ojala et al. [104] as a texture analysis tool; the LBP is related with the investigation of local structures and occurrences. It uses a binary pattern to represent each pixel in the image. LBP is based on the difference between the grey level value of the central pixel 'g' and the neighbours situated inside its circular area defined by the radius 'r.' As a texture description, the LBP labels-based histogram might be used. The texture of aimage can be described as a dispersion of LBP patterns. The advantages of LBP are that they combine structural and statistical methodologies, especially for the purpose of improving the performance of texture analysis. It is simple to implement and reduces the computational cost.

5.2.3 Linear Phase Quantization

Local Phase Quantization is the most often used texture descriptor since it makes use of the Fourier Transform to evaluate matrix data. A 2-D short-term Fourier transform estimated around a rectangle neighbourhood at each pixel of the image is used by LPQ to extract local phase information. In terms of 2-D frequencies, Local Phase Quantization takes four complex coefficients into account.

5.3 PROPOSED WORK

The images of the Brodatz database which available online, are used in this research; they are shown in figure 5.2 and belong to the same category, but have varied wall tile textures in the TIFF format and are of the same size. Figure 5.1 shows a texture-based retrieval model for query images. To build this framework, used database colors and then returned the relative texture characteristics retrieved from each image to the database. Using a distance metric, the same procedure is used to extract texture features from of the query image. The similarity between the query image and the returned images has been calculated .

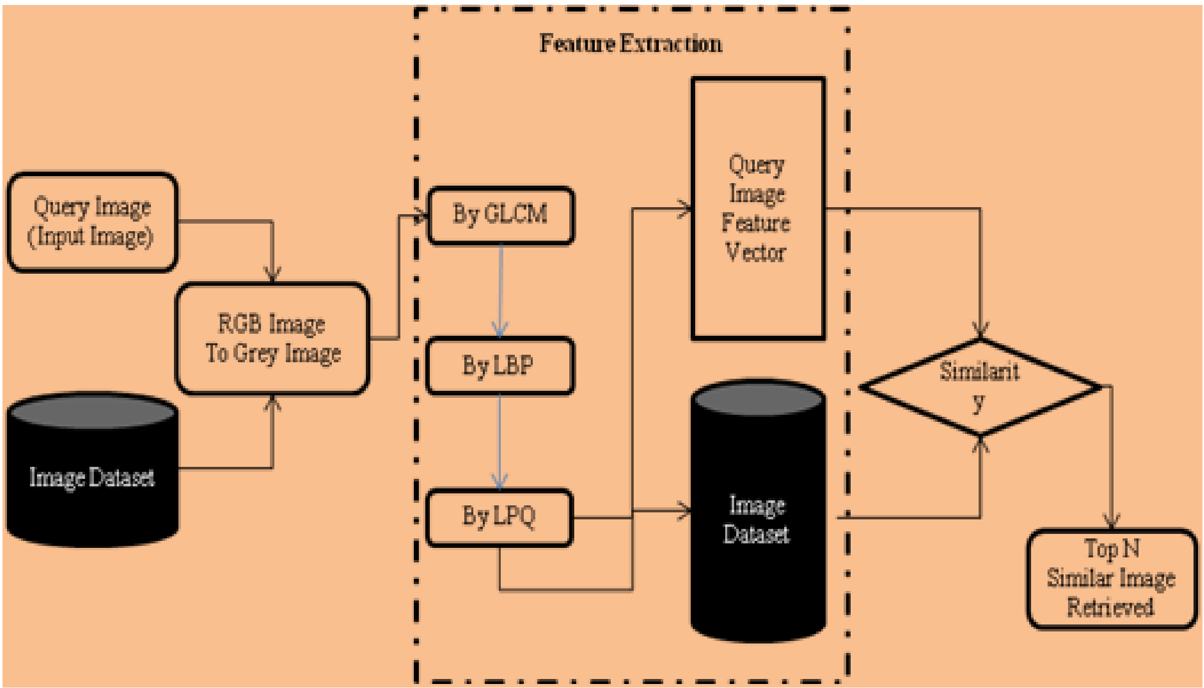

Figure 5.1: Proposed Framework for Image Retrieval

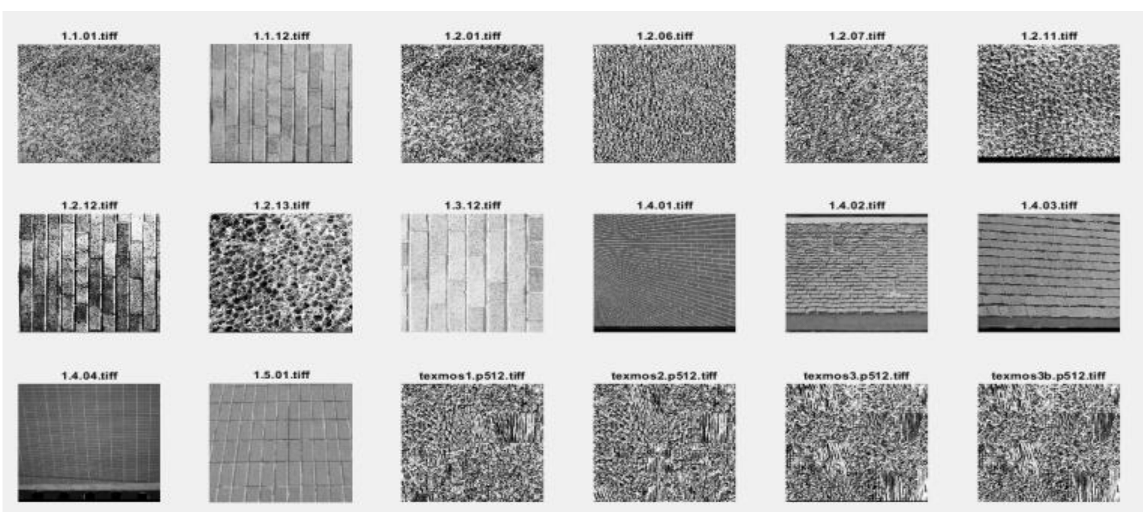

Figure 5.2: Original Dataset

The following are the steps involved in implementing the suggested framework:

1. Construct the original dataset for feature extraction as just a set of files in the first step.
2. Use an input images.
3. Verify that the image is colored.
4. Convert the colored image to a grayscale image.
5. Make a matrix of the image you want to use and turn it to GLCM format.
6. The GLCM matrix is transferred to a LBP matrix, which retrieves LBP features.
7. For the LPQ matrix, more LBP features are employed, and then LPQ features were taken.
8. For each image in the dataset, repeat steps 2–8 and save the output features with in database for future reference.
9. To compute the similarity, the Euclidian distance can be calculated employing extracted feature vectors with each Query image and each selected image in the dataset.
10. To compute the similarity, the Euclidian distance can be calculated employing extracted feature vectors with each Query image and each selected image in the dataset.
11. Build a Scorecard for each image that will be compared.
12. Use the scorecard to sort the images.
13. Using a scorecard based on Euclidian distance, the most nearly similar colors are found for the input image (query image).
14. Relying here on query (input) image, display the top N images.

5.4STATISTICAL ANALYSIS

Euclidian Distance: A formula is used to calculate the Euclidian distance between query images and all test images in the database.

Euclidian Distance =$\sqrt{\sum_{1}^{n}(F_q - F_n)^2}$ (5.1)

Where denotes the number of features extracted from every image in the image dataset for each LPQ feature extraction, and Fq and Fn represent the features of the query image as well as each target image with in dataset, respectively.

Precision, recall, and the F-score with all methods is measured and taken for analysis to evaluate overall performance of the methods stated below, where precision, recall, and the F-score are described below:

Precision (P): Precision is a metric that compares the number of relevant colors returned to the total number of images returned.

$$P = n/ Tn \tag{5.2}$$

Recall (R): Recall is a metric that compares the number of relevant colors retrieved to the total number of images in the database.

$$R=n/Tr \tag{5.3}$$

F-Score (Fs): Pt is a single score that indicates how effective image retrieval is on the entire. The following formula is used to determine the F-score:

$$Fs = (P + R) / (2 * P * R) \tag{5.4}$$

Where n, Tn, Tr denote the number of relevant colors recovered, the total number of retrieved images, as well as the total number of relevant images, respectively.

5.5EXPERIMENTAL ANALYSIS AND RESULTS

5.5.1 Extraction of Features using Existing Techniques

Against determine the efficiency of the proposed work, it must be compared to existing texture-based algorithms. The proposed strategy, which incorporates a technique called as GLCM+LBP+LPQ, is compared using LBP, LPQ, GLCM+ LBP, and GLCM+LPQ. If an image is now a binary image, it is only scaled by two levels in GLCM. Furthermore, if such image is an intensity image, it's also scaled in eight levels. For each pixel pair, there must be 8x8=64 expected arranged combinations based on this reference. The GLCM comatrix is made up of 16, 8x8 matrices pieces. Table1 shows one block about an 8x8 matrix as an example.

TABLE 5.1: GLCM MATRIX

2021	36	0	0	0	0	0	0
36	3962	971	156	38	0	0	0
0	892	5883	1121	515	63	0	0
0	191	1044	11724	1302	478	3	0
0	66	465	1291	6490	2511	7	0
0	2	107	432	2443	17909	35	0
0	0	0	0	2	43	3041	0
0	0	0	0	0	0	0	0

The LBP features are determined using the GLCM matrix shown in Table 5.1 as an input matrix. The features of LBP are represented as a vector including several LBP-related features. Table 5.2 shows the LBP features for one query image, where f1 to f10 denotes the number of features. All of the LBP features of the dataset images are calculated as described previously, and the results are given in Table 5.3.

TABLE 5.2: LBP FEATURES OF QUERY IMAGE

Extracted Features for Query Image									
f1	**f2**	**f3**	**f4**	**f5**	**f6**	**f7**	**f8**	**f9**	**f10**
0.000	0.000	0000	0.050	0.000	0.330	0.000	0.030	0.930	0.00

TABLE5.3: LBP FEATURES OF DATASET IMAGES

Sn.	Images of	Extracted Features

	Dataset	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10
1	1.1.01.tiff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
2	1.1.12.tiff	0.0000	0.0000	0.0000	0.0200	0.0000	0.0800	0.0000	0.0900	0.9900	0.0000
3	1.2.01.tiff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
4	1.2.06.tiff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
5	1.2.07.tiff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
6	1.2.11.tiff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
7	1.2.12.tiff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
8	1.2.13.tiff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
9	1.3.12.tiff	0.0000	0.0000	0.0000	0.2000	0.1200	0.5100	0.0000	0.0000	0.8300	0.0000
10	1.4.01.tiff	0.0000	0.0000	0.0000	0.1700	0.0000	0.3300	0.0000	0.1300	0.9200	0.0000
11	1.4.02.tiff	0.0000	0.0000	0.0000	0.0500	0.0000	0.3400	0.0000	0.0400	0.9400	0.0000
12	1.4.03.tiff	0.0000	0.0000	0.0000	0.0700	0.0000	0.2800	0.0000	0.0400	0.9600	0.0000
13	1.4.04.tiff	0.0000	0.0000	0.0000	0.1800	0.0000	0.2200	0.0000	0.0700	0.9600	0.0000
14	1.5.01.tiff	0.0000	0.0000	0.0400	0.4800	0.0000	0.4300	0.0000	0.1700	0.7400	0.0000
15	texmos1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
16	texmos2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
17	texmos3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
18	texmos3b	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000

These LBP characteristics are now transmitted into the LPQ for the purpose of determining LPQ descriptors, as seen in Table 5.4 for such Query image and for dataset images as in Table 5.5.

TABLE5.4: LPQ FEATURES OF QUERY IMAGE

Extracted Features for Query Image									
f1	**f2**	**f3**	**f4**	**f5**	**f6**	**f7**	**f8**	**f9**	**f10**
0.00	0.00	38.0	119.0	38.0	213.0	132.0	38.0	213.0	132.0

Then, for each image in the dataset, LPQ features are retrieved, as shown in Table 5.5. Table 5.4 shows the LPQ features for one query image, where f1 to f10 denotes the number of features as well.

TABLE 5.5: LPQ FEATURES OF DATASET IMAGES

Sn.	Dataset Image	Extracted Features									
		f1	f2	f3	f4	f5	f6	f7	f8	f9	f10
1	1.1.01.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
2	1.1.12.tiff	0.0	0.0	38.0	85.0	38.0	85.0	38.0	38.0	213.0	132.0
3	1.2.01.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
4	1.2.06.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
5	1.2.07.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
6	1.2.11.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
7	1.2.12.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
8	1.2.13.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
9	1.3.12.tiff	0.0	0.0	38.0	119.0	38.0	213.0	132.0	38.0	85.0	132.0
10	1.4.01.tiff	0.0	0.0	38.0	119.0	38.0	213.0	132.0	38.0	213.0	132.0
11	1.4.02.tiff	0.0	0.0	38.0	119.0	38.0	213.0	132.0	38.0	213.0	132.0
12	1.4.03.tiff	0.0	0.0	38.0	119.0	38.0	213.0	132.0	38.0	213.0	132.0
13	1.4.04.tiff	0.0	0.0	38.0	119.0	38.0	213.0	132.0	38.0	213.0	132.0
14	1.5.01.tiff	0.0	38.0	38.0	213.0	132.0	85.0	132.0	38.0	213.0	132.0
15	texmos1.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
16	texmos2.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
17	texmos3.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0
18	texmos3b.tiff	0.0	0.0	0.0	0.0	0.0	0.0	0.0	38.0	85.0	132.0

5.5.2 Evaluation and Analysis of Proposed Approach:

Table 5.5 shows the features of the each image that use LPQ after having passed LBP and GLCM practiced to the original images, according to the proposed work. For evaluation, the Euclidian Distance of the each mentioned method (LBP, LPQ, GLCM to LBP, GLCM to LPQ) is calculated. Table 5.6 shows the Euclidian distance in the form of scores of the proposed technique to that of existing methods.

TABLE 5.6: FOR EXISTING TECHNIQUES AND THE PROPOSED APPROACH, THE EUCLIDIAN DISTANCE (SCORE) IS CALCULATED.

Sn.	Image of Dataset	Scores				
		LBP	LPQ	GLCM + LBP	GLCM +LPQ	Proposed Approach
1	1.1.01.tiff	0.010	3557.400	0.010	0.190	0.570
2	1.1.12.tiff	0.000	3447.180	0.000	0.160	0.140
3	1.2.01.tiff	0.010	3611.970	0.010	0.320	0.570
4	1.2.06.tiff	0.000	3585.050	0.010	0.240	0.570
5	1.2.07.tiff	0.010	3400.840	0.010	0.320	0.570
6	1.2.11.tiff	0.010	6926.240	0.010	0.320	0.570
7	1.2.12.tiff	0.000	3478.250	0.010	0.190	0.570
8	1.2.13.tiff	0.010	3506.730	0.010	0.250	0.570
9	1.3.12.tiff	0.000	3445.050	0.000	0.220	0.140
10	1.4.01.tiff	0.000	5288.880	0.010	0.310	0.000
11	1.4.02.tiff	0.000	0.000	0.000	0.000	0.000
12	1.4.03.tiff	0.010	5342.540	0.000	0.270	0.000
13	1.4.04.tiff	0.010	5476.190	0.020	0.460	0.000
14	1.5.01.tiff	0.000	3500.170	0.040	0.160	0.200
15	texmos1	0.010	3471.330	0.010	0.320	0.570
16	texmos2	0.010	3522.690	0.010	0.260	0.570
17	texmos3	0.010	3451.170	0.010	0.330	0.570
18	texmos3b	0.010	3475.720	0.010	0.330	0.570

The top most similar images employing LBP, LPQ, GLCM+LBP, GLCM+LPQ, as well as the proposed method are shown in Figure 5.3, Figure 5.4, Figure 5.5, Figure 5.6, and Figure 5.7, respectively.

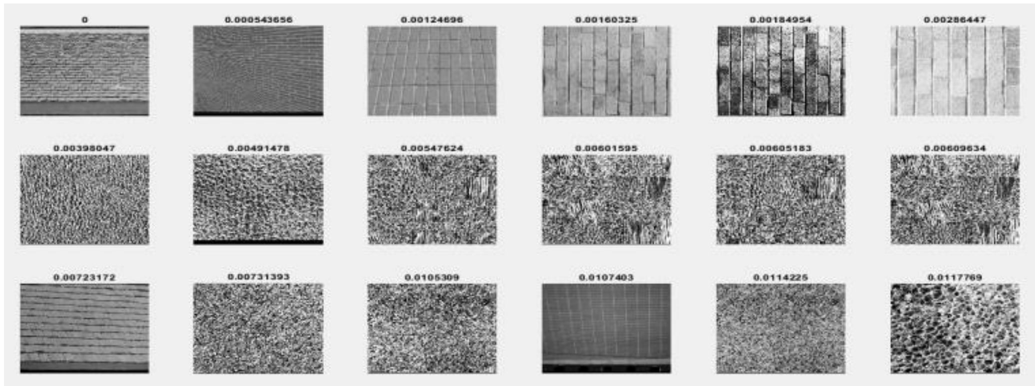

Figure 5.3: Retrieved Similar Images using LBP

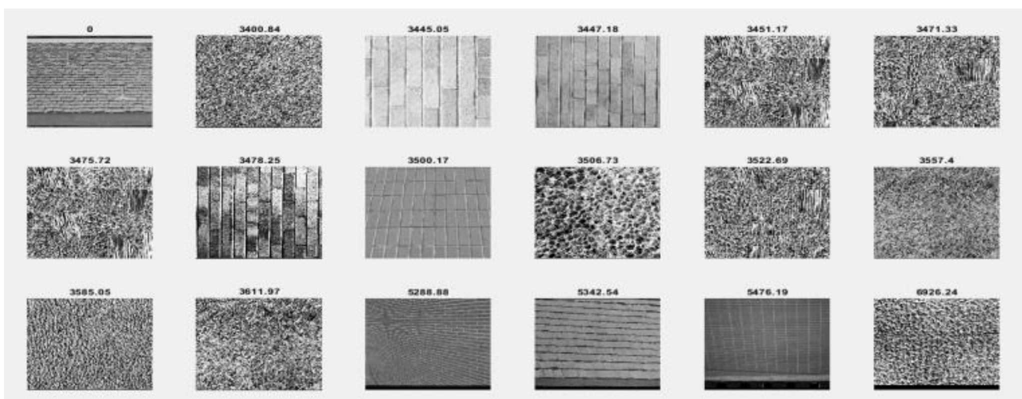

Figure 5.4:Retrieved Similar Images Using LPQ

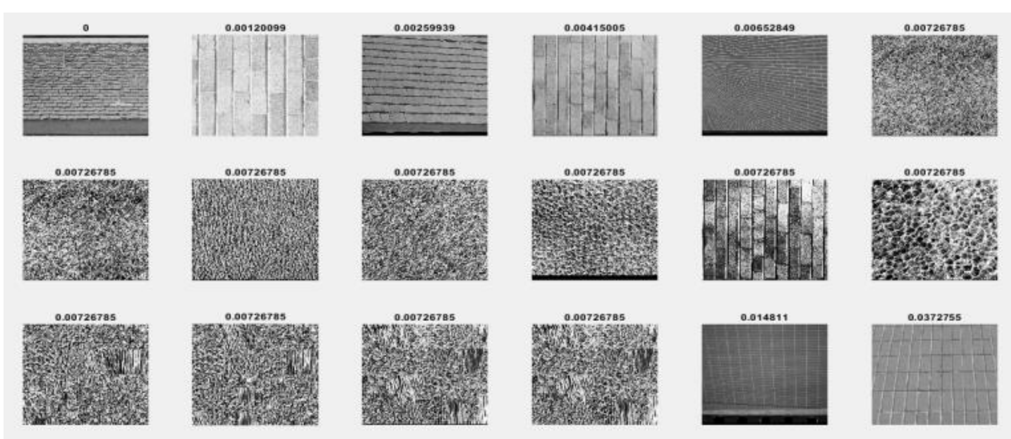

Figure 5.5:GLCM and LBP Result

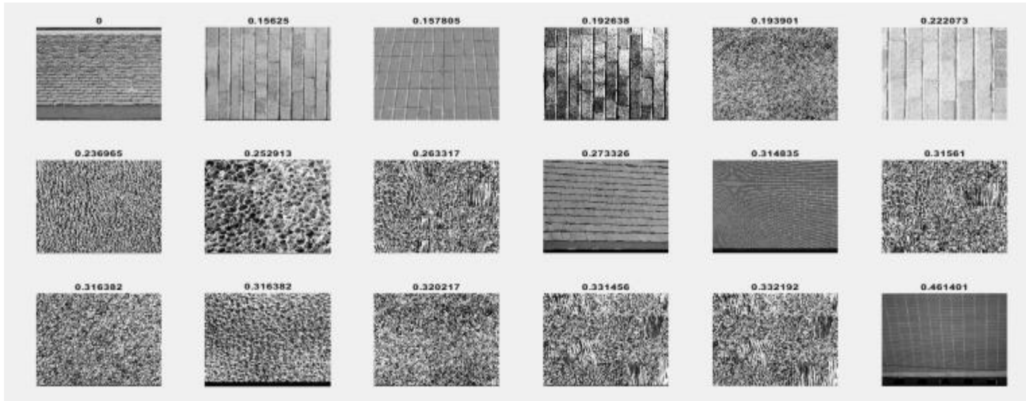

Figure 5.6: GLCM and LPQ Result

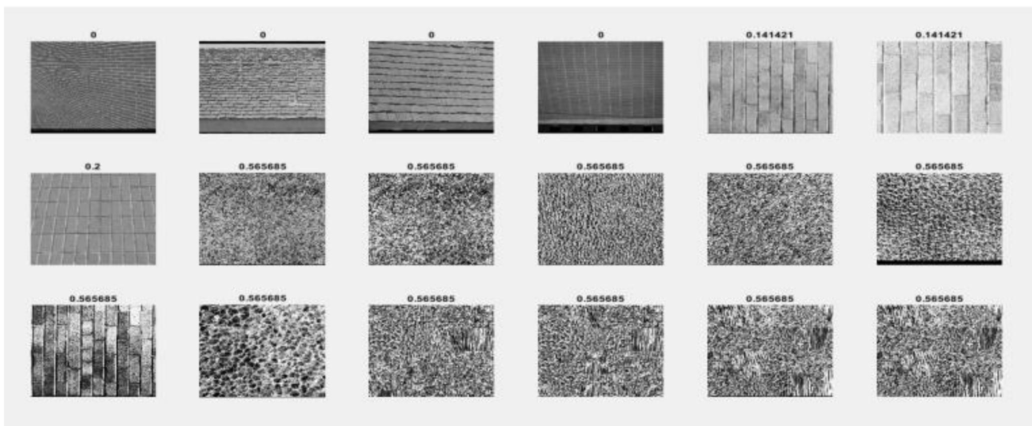

Figure 5.7: Result Using Proposed Approach

Table 5.7 displays the calculated precision, recall, and F-score for all existing methods and the proposed approach.

TABLE 5.7: PRECISION, RECALL, AND F-SCORE FOR EXISTING AND PROPOSED TECHNIQUES

Feature extraction technique	LBP	LPQ	GLCM+ LBP	GLCM +LPQ	Proposed approach
Precision	0.390	0.170	0.280	0.220	0.390
Recall	0.860	0.430	0.710	0.570	1.000
F-score	0.540	0.240	0.400	0.320	0.560

Figure 2.8 depicts image retrieval performance in terms of precision, recall, and f-score using a bar graph. Using a bar graph chart, the proposed method does have highest value compared to all existing methods, as shown in Table 5.7.

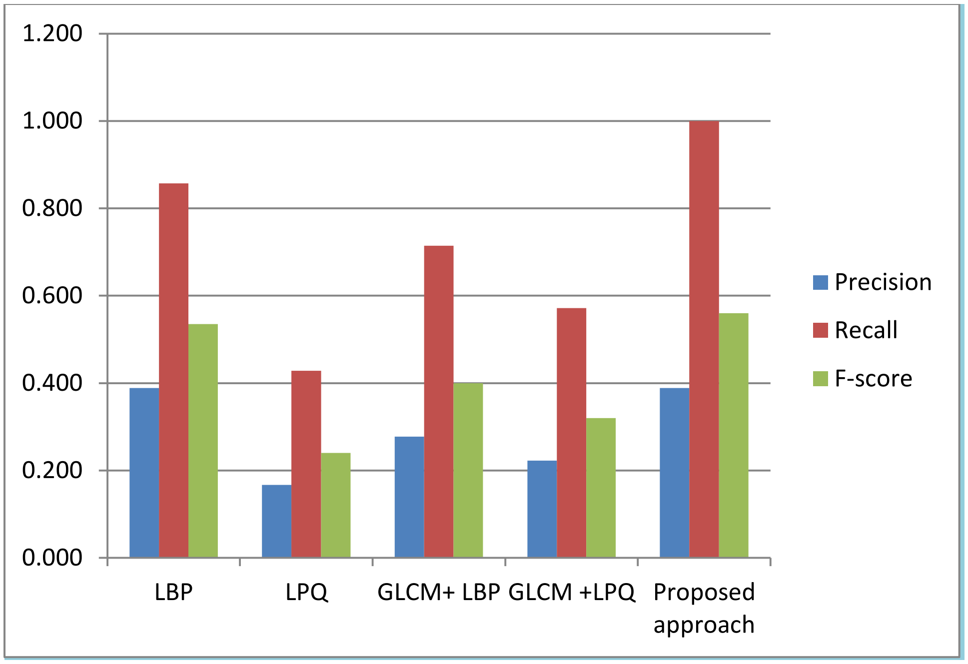

Figure 5.8:Precision, Recall, and F-score of Multiple Existing Methods Versus the Proposed Method

5.6 CONCLUSION

The F-score values, as well as the execution time as well as precision, were used to arrive at the aforesaid result. Because it employs a feature vector of LBP sent through LPQ to just get the final output as just a feature vector for calculating the score, it takes considerably less time to retrieve the most comparable images than other approaches. The suggested work outperforms LBP, and LPQ, GLCM+LBP, GLCM+LPQ, and proposed work in terms of precision, recall, and F-score when applied to the query image seeking image similarity from a set of images belonging to the same category.

CHAPTER VI

FEATURE EXTRACTION FOR IMAGE RETRIEVAL BASED ON HYBRID FEATURES OF COLOR, TEXTURE AND SHAPE

Nowadays, large collections of images are gathered in the internet cloud, which is widely used in daily life. With the rapid advancement and development of technology, backing up and transforming a large set of images is possible. Image retrieval is widely required instead of text retrieval in the current scenario. The CBIR (Content-Based Image Retrieval) System becomes more valuable in this scenario to excess the most similar images from the large set of images. In CBIR, image retrieval is based on the similarity measures between the query image and the targeted dataset, with concerns about color, shape, and texture descriptors taken as low-level feature descriptors. In this regard, many researchers have been working to make this more effective.

6.1 RELATED WORK

Wang & Yagi, (2008)[133] created an adaptive mean-shift tracker by selecting reliable features from color and shape-texture signals. The tracker was more resilient because the target model was updated based on the initial and current models' closeness. Wang & Yagi, suggested a technique that outperformed previous trackers on demanding image sequences. Shrinivasacharya & Sudhamani, (2013)[117] have suggested a method that leverages edge information and median filtering to extract features from an image. B. Zhang et al., (2014) [145]proposed a method that used three features extracted. These features were extracted from tongue images to detect nonproliferative diabetic retinopathy (NPDR) based on the early stage of DR.Color, texture, and geometry. Srivastava et al., (2018)[121] proposed combining SURF and Texture with a discussion about SIFT (Scale-Invariant Feature Transform), SURF, and local features. Garcia et al., (2016) [55]presented an artificial vision approach for fruit recognition in supermarkets. The fruit visual features extracted were shape, texture, and color chromaticity.

Dhanashree et al., (2016)[36] Color, shape, and texture were considered content in a content-based image retrieval system. Mistry et al., (2018) [97]proposed a hybrid feature-based, efficient CBIR system using distance measures.The proposed approach outperforms other existing systems in terms of precision. Retrieved image with hybrid features and distance metrics. Lee et al., (2015)[78] proposed a new system and method for identifying flowers in natural settings. The optimal method of feature extraction for color, texture, and shape was improved experimentally. The most useful features for flower images were color (HS, CbCrCg, and RGB), texture (grey level co-occurrence matrix), and shape (zero-crossing rate). Their study developed mobile flower image recognition technology.

Chiou-Shann Fuh, Shun-Wen Cho and K. Essig [53] give the CBIR system a combination of color segmentation, relationship tress, and tree matching method to accurately represent the required objects in images. J. Guo and H. Prasetyo [84] try to represent a method for giving a simple and effective type descriptor to index images in CBIR by exploring the merits of low-complexity ordered –dither block truncating coding to generate content descriptors for an image. With the advancement of the CBIR system, its advantages in different areas of research are needed, like satellite image detection, army security, image security, medical stream, etc. In this regard, much work has been carried out by taking the low-level features. The author[145]] has taken color, texture, and geometry for diabetes detection using tongue images for disease detection; the author proposes a non-invasive technique to detect Diabetes Mellitus and Non-proliferative Diabetic Retinopathy.

In this chapter, we go through many approaches based on texture for feature extraction. Color-based features are important features that play an important role in image processing. The author[102] views image quality assessment for color correction and proposes an image registration algorithm. The author[22] develops a novel approach in the same manner as CFSCF about solar cells. In this overall process, there were three sections: optimal color space model selection, its extraction and fusion of features, and classification based on GMM.

One of these is Gabor [97], co-occurrence matrix-based approaches[33], random features[83], ranket transform based approach[50], human perception-based features[100], texon dictionary-based[130], etc. The disadvantage of these approaches is that they have increasing computational costs to extract the features because they have spectral and statistical features, which ensure improved texture representation and modelingability. Hence the new concept as local feature extraction techniques have been given and employed in feature extraction and analysis based on texture. One of the techniques of local teacher extraction is local binary pattern (LBP), given by Ojala et al. [103], which gives one of the most eminent features descriptors and has taken more interest over the past few years. Texture-based feature extraction is based on features extracted through the various methods associated with it. The author[108] proposes a COG-based descriptor that tries to capture both radiometric and local geometric information from the image and encode their joint distribution and correlation, relevant to texture features. The author[69] gives the concepts for designing a median sampling regulation, a group of gradient LBP (gLBP) descriptors, a training-based feature model mapping method, and a texture classification frame using the multi-resolution feature-based fusion of four gLBP descriptors. Author[140] proposes descriptors to be utilised to get an image yraid by using dual tree complex wavelet transform and generating LBP (Local Binary Pattern) in the DTCWT domain, as local texture features to achieve better efficiency than other methods. Author [147] proposes work based on LBP as NDV (Normalised Difference Vector), which tries to take full advantage of local differences to cover the entire large local region, with the ability to expand in size. Author[139] proposed an unsupervised MS-FACE method for simultaneous inspection of various texture surface defects while requiring only a small number of defect or defect-free texture samples for training. Due to many problems with segmentation, there is a maximum possibility of getting data of low quality and limited data. By employing statistical information about the objects' shape to be segmented, segmentation can be improved and give significant results.

In image processing, shape matching has reached a high peak in various areas like image retrieval[2][137], target recognition[93], and biometric recognition. Matching based on shape measures similarity between the shapes of the query image and the searched image using similarity features calculated according to the concern criteria. Since shape deformation, its scaling and transformation need efficient retrieval accuracy, stable feature descriptors[76] are now a key part of shape-based matching.

Based on shape matching approaches, many researchers have done a lot of work in this state of the art. Algorithms based on global features generally focus on the spatial distribution of the pixels of an image or features points to make feature descriptors and get the similarity of features between images based on shape similarities, like as Fourier transform [50], curvature scale space [98], shape context [12][81], feature invariants [66][73], etc. As the global features are to have the significance of being insensate concerning noise, as per performance based on matching on deformation and occlusion, it is not good as local details are missing.

The algorithm based on local features generally takes attention to a shape based on the local region and makes feature descriptors through the local region features, likewise SIFT (scale-invariant feature transform)[85], integral invariants[88], multi-scale concave-convex representation[2], multi-scale concave-convex representation[28], HOG (histograms of oriented gradient)[28] etc. Nowadays, combining a different number of approaches has become a new trend in research[65][138][142][4][5][45]. While retaining the local details, the feature descriptors could get the global information into shape. By utilising the hybrid features, the shape-based similarity can take the best place in this regard concerning improved robustness in the nose etc.

In today's scenario, histograms of oriented gradients are most commonly used to extract features based on geometric shape detection [34], object detection[54], biometrics e.g. signature recognition[7], mobile object detection[105], bird detection[94] etc.

6.2 BACKGROUND

In this chapter an experimental analysis is carried out to improve the optimal method of feature extraction. These results showed that the color (L*a*b, RGB), hybrid texture (GLCM, LBP, LPQ), and shape (zero-crossing rate) features for efficient and effective retrieval. This efficient image retrieval model study may be utilised in a different area of the present scenario. In the current scenario, many databases of images and video for any area have grown rapidly. Retrieving the query-based image is in demand for a quick response. In this chapter, a hybrid feature based content retrieval system proposed using color descriptors, shape descriptors, and texture descriptors. The proposed system was evaluated on COREL database. The color descriptors such as color histogram, color moments, color map, in the LBP model, LBP and LPQ, and GLCM for the texture feature, color feature, and shape features.

6.2.1 Color Features

This chapter introduces the concept of a color based image retrieval system with different approach. This chapter focuses on extracting images from a large image database using color features of an image, and give a novel approach for retrieving images from large image database. Color is the most important, dependable, and extensively used of the visual elements. The RGB color combination is considered in this chapter for image retrieval. The focus of this chapter is on approaches to retrieve most similar images for CBIR. First, RGB was quantified in L*a*b and combined with a novel method for determining the most similar images from a set of image data. The proposed method demonstrates an effective image retrieval system, resulting in a method that is good to previous strategies. The proposed system was evaluated on COREL database. The proposed work outperformed other state-of-the-art methods in terms of retrieval performance. For validation, a database of roughly 500 images was divided into four groups to compare histogram features for RGB, Lab, YCbCr, and HSV color spaces. The proposed approach results in color image categorization accuracy.

Following are features associated with colorful images:

6.2.1.1 Histogram of Color:

The probability mass function of the image intensities is referred to as an image histogram. This is extensive for color images, limiting the combined likelihood of the intensities of the three distinct color channels. More precisely, a color histogram is defined as follows:

$$\mathrm{H}_{c1,c2,c3}(\mathrm{x},\mathrm{y},\mathrm{z}) = \mathrm{P}.\,\mathrm{Prob}(\mathrm{c}1 = \mathrm{x}, \mathrm{c}2 = \mathrm{y}, \mathrm{c}3 = \mathrm{z}) \qquad \textbf{(6.1)}$$

Where c1, c2, and c3 are the three channels of the color model image (RGB, HSV, L*a*b, and YCbCr), respectively, and P denotes the number of pixels in the supplied image.

Histogram of Color Euclidean distance:

For image retrieval, three distance formulae are available: Euclidean histogram distance, histogram intersection distance, and histogram quadratic (cross) distance. The histogram Euclidean Distance has been used as the unit of analysis in this study. Take a look at the H' and H "as two color histograms, one for the Query image and one for the searched image. The Euclidean separation between H' and H "may be calculated as follows:

$$D(H', H'') = \sqrt{\sum_{c1} \quad \sum_{c2} \quad \sum_{c3}(H'(x,y,z) - H''(x,y,z))} \qquad \textbf{(6.2)}$$

Where D is the Euclidean distance between two color histograms H' and H" computed, the highest histogram value of an image's separate channels was used in the initial calculation.

6.2.1.2 Moments of Color

The second characteristic has been dubbed "color moments." Each channel's mean and standard deviation have been computed as follows:

(a) Mean: The first color moment can be interpreted as the image's average color, and that can be calculated using the formula below.

$$\mathrm{Mean}(\mathrm{E_r}) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{Ii,j} \qquad \textbf{(6.3)}$$

Where n stands for the number of pixels in an image and "$P_{i,j}$" denotes the value of the image's j^{th} pixel in the i^{th}color channel.

(b) Standard Deviation: The second color moment is the standard deviation, which is calculated by taking the square root of the color distribution's variance.

$$\text{Standard Deviation}(\delta) = \sqrt{\frac{1}{\mathrm{n}} \sum_{k=0}^{n} (Ii, j - \mathrm{E_r}, i)^k} \quad \textbf{(6.4)}$$

where "E_r" represents the mean value, or first color moment, for the image's i-thcolor channel.

Color Moments Euclidean distance:

The Euclidean distance between the mean and standard deviation may be calculated as follows:

$$D_M = \sqrt{(\mathrm{M}' - \mathrm{M}'')^2} \quad \textbf{(6.5)}$$

$$D_{std} = \sqrt{(\delta' - \delta'')^2} \quad \textbf{(6.6)}$$

Where M’ and M’’ are two points between the Euclidean space for one feature and **δ**’ and **δ**” are two points between the Euclidean space for onother feature.

6.2.1.3 Colormap:

Colormap returns a three-column matrix containing RGB triplets. Each row of the matrix provides a single RGB triplet corresponding to one of the colormap's colors. The values are contained within the range. The colormaps can be any length, but they should have three columns. A single color represents each row in the matrix through the RGB triplet. Numerous elements provide the intensities of the red, green, and blue RGB triplets color components, which is a three-element row vector. The intensities must fall within a certain range. A 0 number indicates no color, whereas a 1 indicates maximum intensity.

Colormap Euclidean distance: The Euclidian distance between colormaps can be calculated as follows:

$$\mathrm{D_{map}} = \sqrt{\sum_{n=1}^{3} (c'_n - c''_n)^{\,2}} \quad \textbf{(6.7)}$$

Where Dmap denotes the Euclidian distance for Colormap and c'_n and c''_n denotes the two points for Dmap and n is number of channels, e.g., n=1,2,3 for three channels.

6.2.2 Texture Feature Extraction:

One of the most important things that have been used is texture in image retrieval approach. In earlier studies, several approaches that were defined for a specific application were offered. In any event, there is no general approach or established methodology that can be applied to a huge number of images.

6.2.2.1 Gray Level Co-occurrence Matrixes (GLCM):

The Gray Level Co-occurrence Matrix is one of the quantifiable techniques for removing highlights that is reliant on the analysing texture. GLCM is a grid that defines two measurements between pixels for joint probability with a certain spacing. Many scientists have used this approach in a variety of applications, including clinical imaging, satellite images, and so on, to perform various research in contrast ways. The GLCM algorithm is used to determine the image's particular dependant grey level. The image utilises m as the number of Gray levels, and the matrix size is M x M. Co-occurrence matrices can be arranged in four different ways (0^0 ,45^0, 90^0 and 135^0). The GLCM matrix that results is an averaging of all the orientations. Perfection, normalcy, coarseness, and invariance are all qualities that result from this. For each orientation, the same approach is used. It is also referred to as SGLDM (Special Gray Dependence Matrix) when using the Second-order statistic technique, where the research is carried out for particular remarkable relations for sets of pixels. There are 14 highlights to be characterised by the Haralick in GLCM for the arrangement dependent on texture features. A significant number of researchers utilised the four to five highlights in their research since they are so closely connected. It outperforms the LBP due of its excellent time management and multifunctional character. GLCM, on the other hand, isn't much better for a number of datasets. The GLCM second-order statistic describes the connection between a reference pixel P (i, j) and its adjacent pixel at various angles and distances.

$$Contrast(F1) = \sum_{i,j=0}^{N-1} P_{ij}(i-i)^2 \quad \textbf{(6.8)}$$

$$Correlation(F2) = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad \textbf{(6.9)}$$

$$Energy(F3) = \sum_{i,j=0}^{N-1} (P_{ij})^2 \quad \textbf{(6.10)}$$

$$Homogeneity(F4) = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-i)^2} \quad \textbf{(6.11)}$$

$$Entropy(F5) = \sum_{i,j=0}^{N-1} \ln(P_{ij})P_{ij} \quad \textbf{(6.12)}$$

Where:

P_{ij} = Normalized symmetrical GLCM element i,j

N = Amount of grayscale information in the image, as determined by the value entered under Quantization:

μ = The GLCM mean(It estimates the intensity of all pixels in the relationships that have contributed to the GLCM.) determined as follows:

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij}$$

These are all the five characteristics of the GLCM matrix. The range of Gray levels in the input image is represented by n in the formula above. The following formula is used to compute GLCM's Euclidean distance(D):

$$D = \sqrt{(F_{q1}-F_1)^2 + (F_{q2}-F_2)^2 + (F_{q3}-F_3)^2 + (F_{q4}-F_4)^2 + (F_{q5}-F_5)^2} \quad \textbf{(6.13)}$$

Where, F and F_q are the two points for Euclidean space. F1, F2,F3, F4, and F5 are features for GLCM, F_{q1}, F_{q2} , F_{q3}, F_{q4} and F_{q5} are the features of Query image for GLCM.

6.2.2.2 Local Binary Patterns (LBP):

Local Binary Patterns (LBP) were initially proposed as a texture analysis approach by Ojala et al. [10], and the LBP is connected with both the study of local structures and the analysis of occurrences. It uses a binary pattern to represent each pixel in the image. LBP is based on the difference in grey level values between each central pixel 'g' and its neighbours in a circular region with a defined radius 'r' .

As a consequence, the LBP result may be represented as follows:

$$\mathrm{LBP}_{\mathrm{p,r}}(x_c, y_c) \quad = \sum_{k=0}^{7} \partial(g_n - g_c)2^n \qquad \textbf{(6.14)}$$

Where the value of a center pixel is represented by gc at (xc,yc), the values of eight surrounding pixels are represented by r, and the number of pixels in the whole neighbourhood is represented by p, and the function is represented as:

$$\partial(\mathrm{x}) = \begin{cases} 1 & \text{if x} > 0, \\ 0 & \text{otherwise} \end{cases} \qquad \textbf{(6.15)}$$

The LBP labels-based histogram can be used as a texture description. A distribution of patterns related LBP may be used to represent the texture of an image; the representation can also be done using the LBP histogram vector H:

$$\mathrm{H} = \sum_{x=0}^{U} \quad \sum_{y=0}^{V} \partial(\mathrm{LBP}_{\mathrm{p,r}}(x \quad , y \quad) - \mathrm{k} \quad)$$

(6.16)

Where H is the LBP histogram vector, 0 k d = 2n is the number of patterns through LBP, and U and V are the image dimensions, and H is the LBP histogram vector.

The advantages of utilising LBP are that they combine structural and statistical approaches to increase texture analysis performance. It is simple to implement and reduces the computational cost.

6.2.2.3 Linear Phase Quantization

Ojansivu and Heikkila used the LPQ for texture analysis [16]. Local Phase Quantization, which uses the Fourier Transform to examine lattice data, is an usually regular and productive surface descriptor. After haze processing, the LBP uses the Fourier Phase Spectrum's Blur Invariance characteristic to produce the watched image from the first query image (unique image). LPQ extracted data from neighbouring stages by using the 2-D transient Fourier change reported around a rectangle neighbourhood at every region of every pixel. In terms of 2-D frequencies, only four complex coefficients are evaluated in Local Phase Quantization. Refer to [15] for further mathematical information. Before the feature extraction stage, we resize the images to 256256 pixels.

$$F(u,x) = \sum_{y \in N_x} \int (\mathrm{x} - \mathrm{y}) \mathrm{e}^{-\mathrm{j}2\pi \mathrm{uTy}} \quad \textbf{(6.17)}$$

F (u, x) represents local Fourier coefficients computed across 'u' points, while x represents one-dimensional convolution for the rows and columns

6.2.3 Extraction of Shape Features

In this chapter, for the best result, the HOG is used for feature extraction, which is fused with the other proposed techniques based on the Color and Texture approach, which can be seen in the proposed model in the figure 6.1.

6.3PROPOSEDMETHODOLOGY

The proposed work is based on the image retrieval process based on local features, which includes color, texture, and shape, as shown in the Figure 6.1. Images are taken from the dataset. If the dataset is in the RGB color model, change it to the L*a*b color model for better results. After performing segmentation on the selected image, the next step is to extract features by collecting the features in terms of the histogram, color moment (mean and standard deviation), and color map. The texture feature extraction block extracts features through the fusion of the GLCM, LBP, and LPQ approaches, and feature vectors are generated. In the shape feature extraction block, the features are extracted using the Histogram of Gradients and a shape feature vector is generated.

The proposed approach shows the desired work to be done in four block sections. In the first block, the color feature vector was created in the color feature extraction block. In the second block, texture feature extraction has been done, and a texture feature vector has been created. In the third block section, shape-based feature extraction has been done, and its shape feature vector has been created for the query image and each image in the dataset. The next block of action calculates color distance matrices, texture distance matrices, and shape distance matrices between the query image and each image in the dataset. Then generate the scorecard for similarity measures based on Euclidean distance and show the best N similar images.

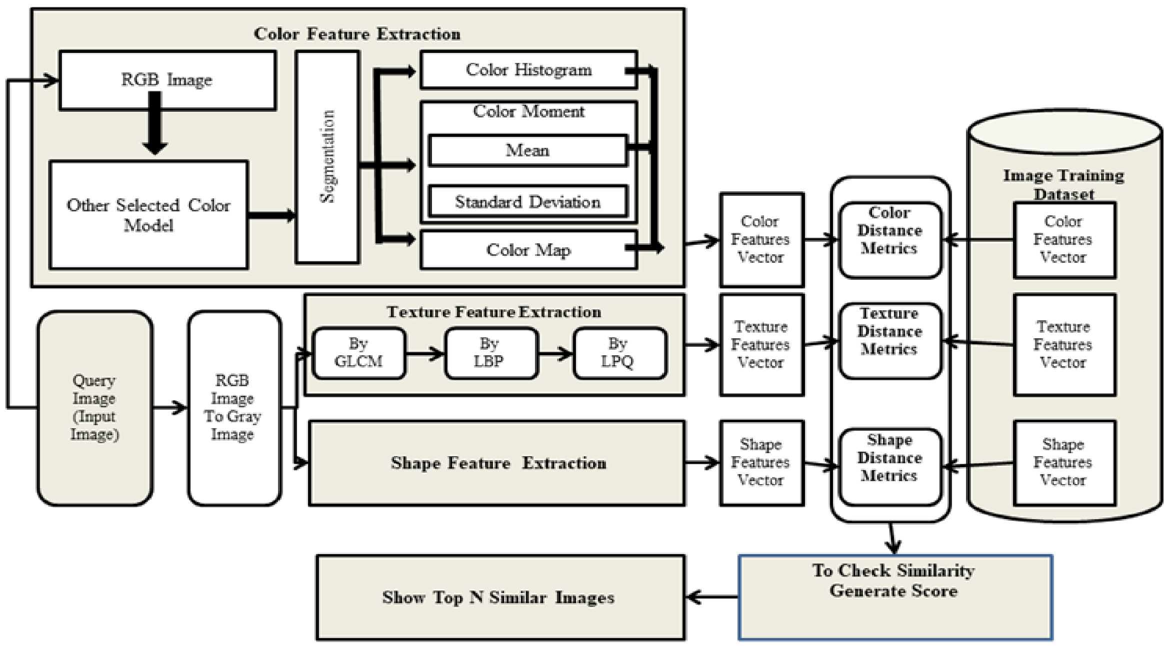

Figure 6.1: Proposed Model for Image Retrieval Based on Hybrid Features

The following are the steps involved in the proposed approach:

1. Input the query image
2. Extract the features based on color:
    a. Convert an RGB image to a color model of your choice.
    b. Do segmentation for a particular area.
    c. Color features such as the color histogram, color moment, and color map can be extracted

3. Generate the color feature vector of a given image.
4. Extract Features based on Texture:
   a. Convert a color image to a greyscale image. Create a GLCM Matrix using the GLCM Technique.
   b. GLCM matrix for LBP to extract LBP features
   c. Extract LPQ features using LBP features.
   d. Generate the Texture Feature Vector.
5. Extract Shape Features based on HOG descriptors:
   a. Convert original image to grey image
   b. Convert grey image to binary image
   c. Visualise the cell size and select the image of cell size [4 4]
   d. Generate the Shape Feature Vector.
6. Repeat the steps from step 2 to step 5 for each image in the training dataset.
7. Calculate the color distance metrics using the query image's color feature vectors concerning the training dataset images.
8. Calculate the texture distance metrics using the query image's color feature vectors concerning the training dataset images.
9. Calculate the shape distance metrics using the query image's color feature vectors concerning the training dataset images.
10. Generate a scorecard for each image in the training dataset concerning the query image for the most similar image.
11. Show the top N images for similarity checking.

6.4 STATISTICAL ANALYSIS

Euclidian Distance: A formula is used to calculate the Euclidian distance between query images and all test images in the database.

Euclidian Distance $=\sqrt{\sum_{1}^{n}(F_q - F_n)^2}$ **(6.18)**

Where n denotes the number of features extracted from every image in the image dataset for each LPQ feature extraction, and Fq and Fn represent the features of the query image as well as each target image with in dataset, respectively.

Precision, recall, and the F-score with all methods is measured and taken for analysis to evaluate overall performance of the methods stated below, where precision, recall, and the F-score are described below:

Precision (P): Precision is a metric that compares the number of relevant colors returned to the total number of images returned.

$$P = n/ Tn \quad \textbf{(6.19)}$$

Recall (R): Recall is a metric that compares the number of relevant colors retrieved to the total number of images in the database.

$$R=n/Tr \quad \textbf{(6.20)}$$

F-Score (Fs): Pt is a single score that indicates how effective image retrieval is on the entire. The following formula is used to determine the F-score:

$$Fs = (P + R) / (2 * P * R) \quad \textbf{(6.21)}$$

Where n, Tn, Tr denote the number of relevant colors recovered, the total number of retrieved images, as well as the total number of relevant images, respectively.

6.5 EXPERIMENT ANALYSIS AND RESULTS

Data Description: In this work, datasets from various leaf categories were taken and re-sampled in 256X256 size. All files are in JPEG format, as shown in Figure 6. 2.

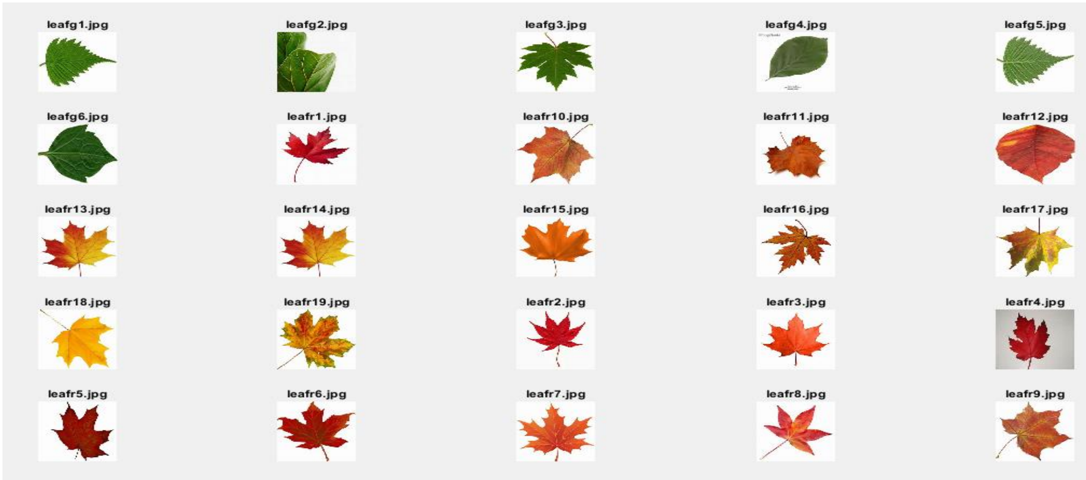

Figure 6.2: Original Dataset

6.5.1 Using Color Feature Extraction:

This chapter explained proposed approach to retrieve most similar images from large image dataset based on color features in comparison to previously defined approach by using different color spaces. The proposed method reduces the problem description by combining color-based elements. The proposed method is implemented and focused on the visual contents of an image, particularly color application on the dataset of three categories. It chooses image databases with similar feature values using this method. For problem-solving, the suggested system extracted R, G, and B values for each visual feature independently. Color histograms and color projections were included in the proposed method. For effective retrieval, mathematical strategies such as mean, median, and standard deviation are offered, as well as a platform for retrieving images from the database utilising the user query method.

Let us take a query image or input image. Make a two dataset first is test image dataset and other is training dataset. The some sort of original image dataset have been shown in Figure 6.1. A query image taken from test image, if the image is in RGB image, convert it to other color space of choice. Then applied the color segmentation on converted query image. Then there would be segmentation for colors[assemble four features]. After that, a segmented image's histogram is created. For the first feature, calculate the highest histogram value for each channel of the color image individually. Following that, look at the color moment's mean and standard deviation as the second and third features, respectively. As the fourth feature, take the color map value of each channel of such a segmented color image individually. Repeat all these steps for each image in the dataset of images, storing the image's feature vector. Calculate the query image's feature vector. Euclidean distance has calculated the score for each feature in the dataset associated with the query image. Sort the score to find the top N most similar images. These all the steps have been demonstrated in color feature extraction block as shown in Figure 6.1. The resultant retrieved top N images as per query image is shown below Figure 6.3.

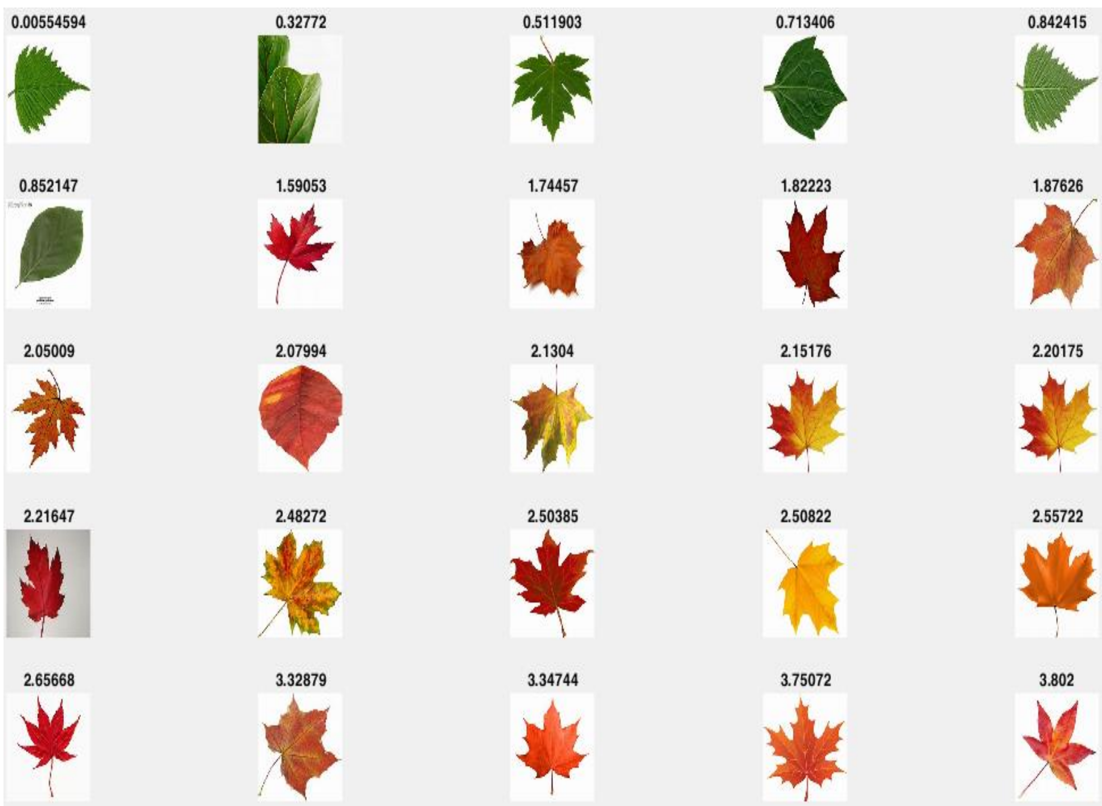

Figure 6.3: Color Based Result

6.5.2 Using texture feature extraction:

Using a distance metric, the same procedure is used to extract texture features from of the query image. The similarity between the query image and the returned images has been calculated.Construct the original dataset for feature extraction as just a set of files in the first step. Let us take the same input image. Verify that the image is colored. Convert the colored image to a grayscale image. Make a matrix of the image you want to use and turn it to GLCM format.The GLCM matrix is transferred to a LBP matrix, which retrieves LBP features. For the LPQ matrix, more LBP features are employed, and then LPQ features were taken.For each image in the dataset, repeat steps 2–8 and save the output features with in database for future reference.To compute the similarity, the Euclidian distance can be calculated employing extracted feature vectors with each Query image and each selected image in the dataset.To compute the similarity, the Euclidian distance can be calculated employing extracted feature vectors with each Query image and each selected image in the dataset.Build a Scorecard for each image that will be compared.Use the scorecard to sort the images.Using a scorecard based on Euclidian distance, the most nearly similar colors are found for the input image (query image).Relying here on query (input) image, display the top N images as shown in Figure 6.4 based on scores generated by using Euclidean distance for texture feature extraction block designed in proposed work shown in Table 6.1.

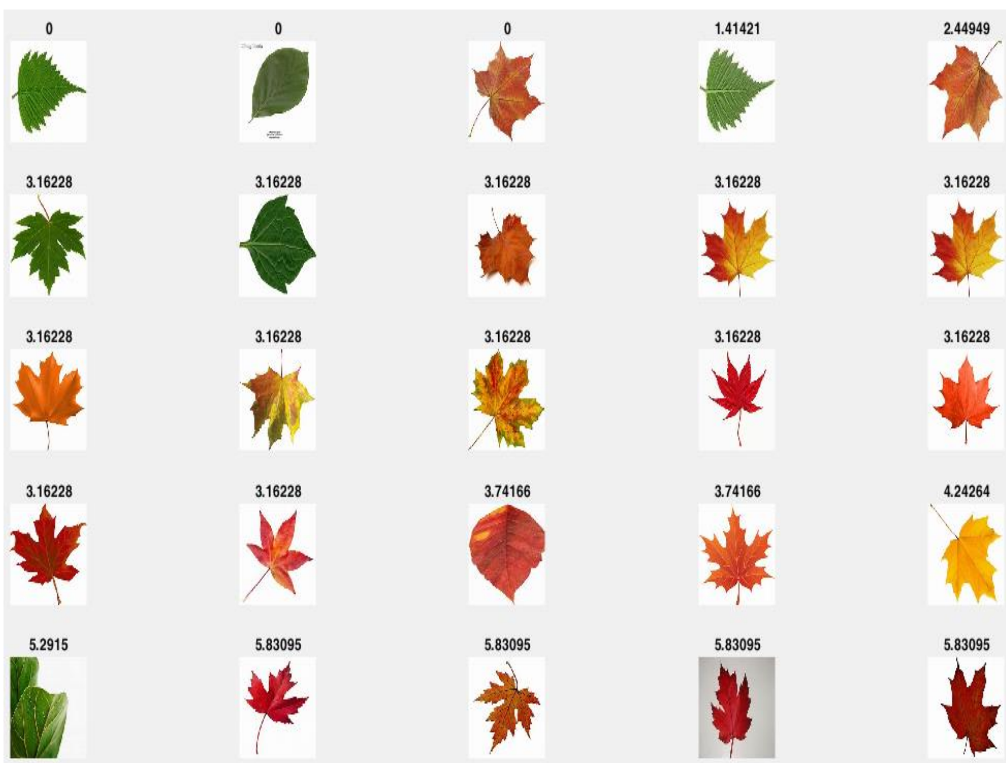

Figure 6.4: Texture Based Result

6.5.2 Using HOG Based Feature Extraction:

Images are taken online. Available images are used for training. The training images each contain a number of different categories of leaves, which shows how leaves usually are shown together. Using these images is convenient, and it enables the creation of a variety of training samples. Although this is not the most representative data set, there is enough data to train and show the approach's feasibility. In this chapter, the training set consists of number of images where some of images are shown in Figure 6.2. A pre-processing step is applied to remove noise artefacts introduced while collecting the image samples. This provides better feature vectors for training the classifier.

Figures 6.5 (A) OriginalImage and (B) Binary Image

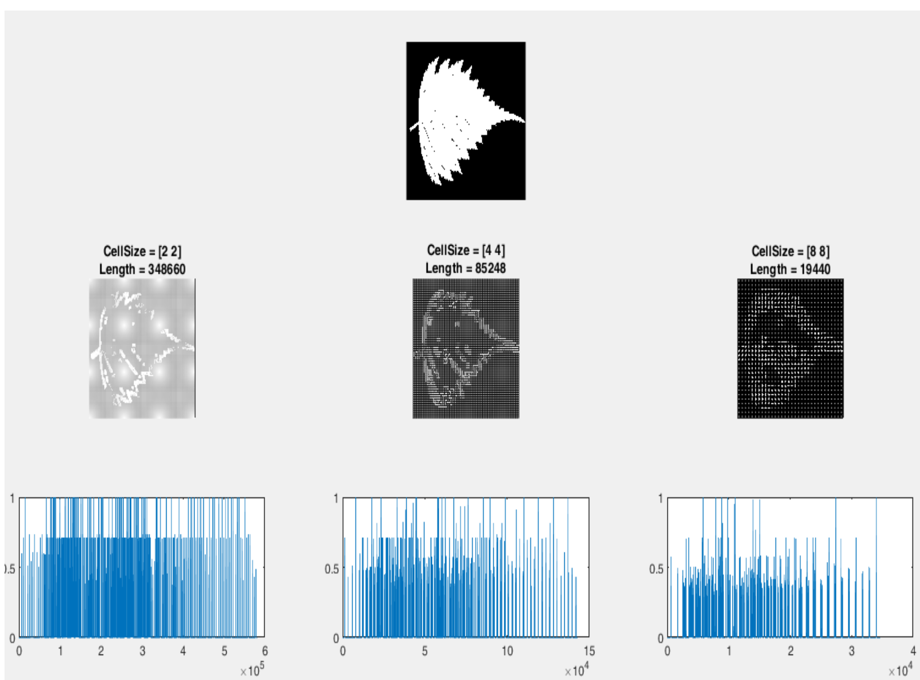

Figure 6.6 Visualisation of Image in [8 8], [4 4] and [2 2] Cell Sizes

The visualization shows Figure 6.6 that a cell size of [8 8] does not encode much shape information. In contrast, a cell size of [2 2] encodes a lot of shape information but significantly increases the HOG feature vector's dimensionality. A good compromise is 4-by-4 cell size. This size setting encodes enough spatial information to visually identify a digit shape while limiting the number of dimensions in the HOG feature vector, which helps speed up training. In practice, the HOG parameters should be varied with repeated classifier training and testing to identify the optimal parameter settings. Start by extracting HOG features from the training set. These features will be used to train. Following Figure 6.7. shows the retrieval of the top N images.Top similar images retrieved as per query image, based on scores for HOG features generated by using Euclidean distance for HOG based features vectors shown in Table 6.1.

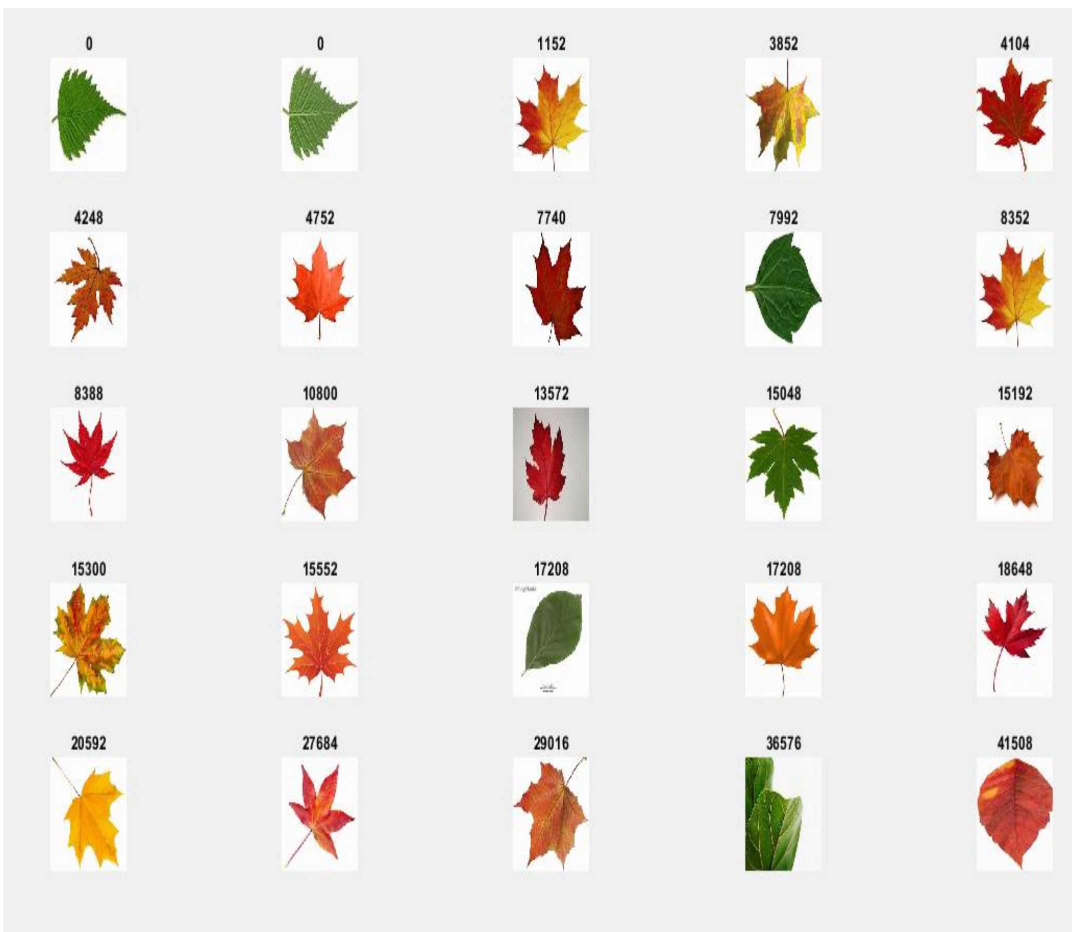

Figure 6.7: Result Based on HOG Features

6.5.3 Using Proposed Feature Extraction:

This chapter proposes an approach to retrieve similar images from datasets. This approach used hybrid features of color, texture and shape. The Color based features like color histogram, color moment, and colormap have been taken as feature vectures. In the same way, the features vector based on texture features using GLCM, LBP and LPQ have been taken. And the additional Histogram of Gradient features taken in combination with the color and texture features. The scores are then generated based on the calculated Euclidean distance for the proposed approach as mentioned in Table 6.1. The top N images retrieved from the dataset for similar images are shown in Figure 6.8.

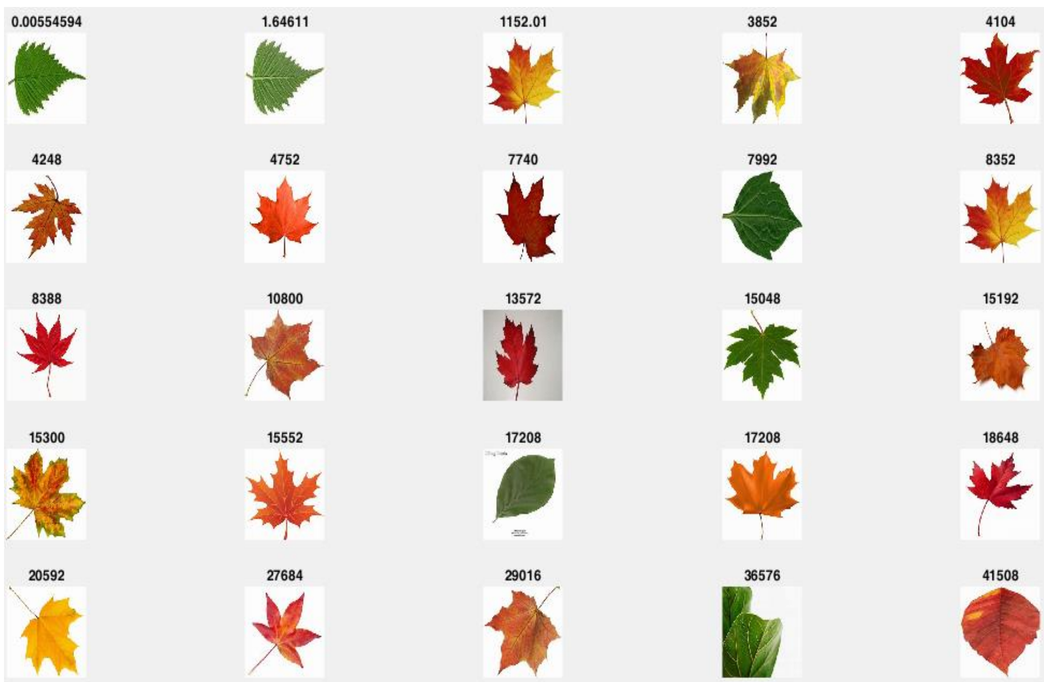

Figure 6.8: Result Based On Proposed Work

6.6 RESULT ANALYSIS

Based on the experimental analysis using the proposed approach for an image retrieval system. The scores generated for color-based features, texture-based features, shape-based features, and the proposed approach are shown in Table 6.1.The scores are generated based on the calculation of Euclidean distance using formula (6.18) for concern in Euclidian space.

TABLE 6.1 COMPARATIVE RESULT ANALYSIS WITH PROPOSED WORK

SCORE			
COLOR	TEXTURE	HOG	PROPOSED WORK
0.0055	0.0000	0000	1.1200
0.3277	5.2915	36576	36576.00
0.5119	3.1623	15048	15048.00
0.8521	0.0000	17208	17208.00
0.8424	1.4142	00000	002.39
0.7134	3.1623	7992	7992.00
1.5905	5.8310	18648	18648.00
1.8763	2.4495	29016	29016.00
1.7446	3.1623	15192	15192.00
2.0799	3.7417	41508	41508.00
2.1518	3.1623	8352	8352.00
2.2018	3.1623	1152	1152.01
2.5572	3.1623	17208	17208.00
2.0501	5.8310	4248	4248.01
2.1304	3.1623	3852	3852.00
2.5082	4.2426	20592	20592.00
2.4827	3.1623	15300	15300.00
2.6567	3.1623	8388	8388.00
3.3474	3.1623	4752	4752.00
2.2165	5.8310	13572	13572.00
1.8222	5.8310	7740	7740.00
2.5039	3.1623	4104	4104.00
3.7507	3.7417	15552	15552.00
3.8020	3.1623	27684	27684.00
3.3288	0.0000	10800	10800.00

On the basis of scores, the top images are retrieved. Firstly, have a look at color based image retrieval. Based on the scores generated, it can be seen in the figure that all the top similar images are shown at the top as per the query image. The query image is taken as a green leaf, and it produces all the green leaves based on the query image being a green leaf. Its accuracy is 97% in retrieving similar images, but it will provide only the same image, which can be of similar color not similar in shape or texture. As a result, another approach is used with texture and color based features for image retrieval purposes. Because the texture cannot be determined, a similar shape as shown in Figure 6.6 is used. Only shape-based images are also retrieved. In continuation with color and texture, other features are extracted based on the HOG features for shape. Hence, This chapter provides the accurate result regarding the color, shape and texture as shown in Figure 6.8. The following Table 6.2 shows the precision and recall for color, shape, texture, and hybrid based approaches, which show the effectiveness of the approach used.

TABLE 6.2: COMPARATIVE ANALYSIS OF DIFFERENT WORK WITH PROPOSED WORK

	Color Based	Texture Based	Shape Based	Hybrid approach
Precision	0.6	0.4	0.2	0.2
Recall	0.9	0.7	1.0	1.0

The graphical representation is shown in in the following Figure 6.9.

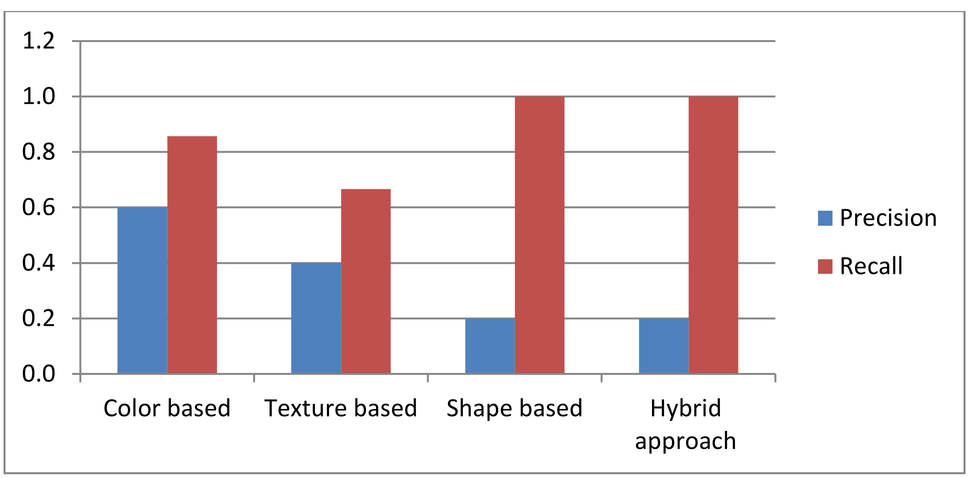

Figure 6.9: Graphical Representation of Precision and Recall for Proposed Work

6.7 CONCLUSION

Based on the experimental analysis using the proposed approach for an image retrieval system, the scores generated for colorbased features, texture-based features, shape-based features, and the proposed approach show that 98% accuracy in comparison with other approaches based on shape only, texture only, and color only.

CHAPTER VII

IMAGE RETRIEVAL USING MACHINE LEARNING

Color, form, and texture are only a few of the visual components that make up an image. When it comes to distinguishing images, these elements serve as the key distinguishing factor. A content-based image retrieval system extracts these key features from aimage and compares them to the features of the image provided by the user to determine whether the extracted features are similar. As a consequence, a collection of images that are comparable to the query image is generated. It is proposed in this study that a novel image retrieval methodology be developed that makes use of the local descriptors of an image in conjunction with one another. The HSV histogram, Color moments, and Color auto correlogram are utilised to create the feature descriptor, which is then used to describe the feature. Researchers discovered that combining all of these characteristics yielded promising findings that outperformed earlier research. The classification of the images is accomplished through the use of a supervised learning method, the Quadratic SVM. The suggested method is evaluated using a collection of flower and fruit photographs that may be found on the internet.

7.1 RELATED WORK

SVMs (Support-Vector-Machines) are machine-learning algorithms that perform better in most fields. SVM was proposed by Vapnik[26] and is gaining popularity in the field of machine learning due to its many appealing features and ability to demonstrate practical performance. The use of a classifier in a CBIR system minimizes the need for a similarity measure. By applying features to the training set, images with similar attributes are sorted into one group. Support vector machines, Bayesian classifiers, neural network classifiers, and random forests are the most common classifiers used throughout CBIR applications. SVM is a representational classifier, which means it is used to address machine learning problems. To reduce the upper bound of the generalisation error, the SVM machine learning technique optimises the space (margin) among hyperplane and data. Directed Acyclic Graph, Binary Tree, One-Against-One, and One-Against-All classifiers are some of the techniques to tackle multi-class classification issues with SVM. Multi-Class SVM is used to create one SVM per class, which aids in distinguishing one class from others. The greatest output within all SVMs is used to classify an unknown pattern. The best hyper-plane leaves the most margins from both classes; hence the goal is to find the hyper-plane that leaves the most (supreme) margin towards a sample object. In other words, the larger the margin, the less likely any feature vector will be misclassified. In image classification, nonlinear transformation is used to convert input vectors into a high-dimensional feature space. A kernel function is used to construct an ideal hyper-plane. Agrawal et al., [3] offered a unique approach for color image content classification using SVM (SVM). In SVM, multi-class classification is done using a one-against-all or one-against-one technique.

Polynomial, and Linear[24] are all kernel models that generate SVMs that satisfy Mercer's requirement. The polynomial and radial basis function (RBF) kernels are commonly employed for remote sensing image analysis. These are picked by establishing the kernel model (Gaussian, polynomial, etc.) and then setting the parameters. Selected kernel functions must perform well on a subset of the training sample or validation set (classifier performance). A major flaw in kernel-based algorithms like SVM is their sensitivity to overfitting. Automatic kernel selection[77][71][6], and multiple kernel learning[125] were offered as creative solutions to this issue. An optimization challenge[72][149][124][114][61] includes determining the best kernel. Optimising SVM parameters takes a lot of time and resources A genetic optimization algorithm (GA)[58][59][96] or a particle swarm optimization (PSO) technique[17] are needed to find the SVM parameters. They both use evolutionary algorithms to maximise C and gamma. PSO offers some advantages over GA and other related evolutionary algorithms[17]. This is because SVMs are binary, which makes them difficult to utilise in multi-class applications. An SVM binary classifier can be used to classify a multi-class problem[95]. An optimization procedure is required to expand the binary SVM to multiclass classification. As an example, setting the kernel parameters C (controls the amount of penalty during SVM optimization) and RBF kernel spread only requires one optimization, against five for one-against-all and 10 for one-against-one approaches, and a total of five class classifications. Unlike the typical one-against-all technique, one-shot multi-class classification guarantees a complete confusion matrix [92]. A limited number of support vectors allow SVM to swiftly classify high-dimensional large data into subgroups. However, massive data classification is always computationally costly. The SVM is used in many areas, including hybrid SVMs such as the Granular Support Vector Machine (GSVM). In contrast to the standard SVM, the GSVM achieves good generalisation performance while utilising granular computing and statistical learning theory. These approaches are often more accurate than SVMs in remote sensing[59][96][17]. For example, in remote sensing image analysis, where dimensionality might be high[95][92], SVM is an efficient classifier. A fraction of training data is also required to assign new members. Due to this, SVM is one of the memory-efficient algorithms[135]. With fresh kernels instead of linear boundaries, SVMs are more flexible and perform better. Unbelievably intricate mathematics behind the SVM limits effective cross-disciplinary applications[13].

7.2 BACKGROND

Manually scanning thousands and thousands of photographs in a flood of visual data is a massive task. The essential attributes of every image in a dataset are extracted by the content-based image retrieval system and compared to those of the image provided by the user. Following the query matching, the system ranks all images into descending order of similarity to the given input query, according to the general flow. The result is a list of all the photographs with the highest ranking. Shape, Color, and Texture are the three essential components of every image. A CBIR extracts and runs similarity algorithms on these extracted features, either singly or in combination. While CBIR relies solely on the contents of the image, image retrieval utilising image information is also possible. Each image has textual data connected with it, and typical retrieval methods such as keyword retrieval can be used. While an annotation technique is time-consuming and labor-intensive, there is another drawback to this system: the absence of consistency. In other words, no two people see an image in much the same way. Multiple users may give multiple annotations that are unlikely to match and there is no classic way to see an image. This will also result in a big volume of unnecessary trash data. As a result, CBIR is better suited to massive volumes of visual input. Color-based features have been extracted in this work.The proposed system was evaluated on COREL and CIFAR databases. The proposed work outperformed other state-of-the-art methods in terms of retrieval performance. For validation, a database of roughly 500images was divided into three categories to compare histogram features for RGB, Lab, YCbCr, and HSV color spaces and accuracy through machine learning techniques. The proposed approach results in color image categorization accuracy.

7.2.1 MACHINE LEARNING

Machine learning is the study of underlying computer algorithms that learn and evolve on their own as a result of their exposure to and accumulation of data over time. Author Arthur Samuel, a former IBM employee and pioneer in the fields of computer games and artificial intelligence, coined the phrase "machine learning" in 1959. During this time period, the term "self-teaching computers" was also used to describe these machines. For most of the 1960s, Nilsson's book on Learning Machines, which was primarily concerned with machine learning for pattern classification, was a landmark in the field of machine learning research.

The other objective is to utilise these models to make predictions about what will happen in the future. A hypothetical system for categorising data might be trained using computer vision on moles, along with supervised learning to detect cancerous moles, in order to improve its classification accuracy. Instead, a machine-learning stock trading system may provide the trader with forecasts about the stock's future performance, according to the system.

In the field of artificial intelligence, it is considered to be a sort of machine learning. When given a sample of data, known as "training data," machine learning algorithms build a model that may be used to generate predictions or judgments without being explicitly programmed. Machine learning techniques are used in a wide range of applications, including healthcare, online filtering, natural language processing, and computer vision, among many others. It is difficult or impossible to develop standard algorithms that can do the needed tasks.

In terms of typical classification, machine learning can be divided into three categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is used to do predictive modelling tasks, such as predicting the link between data properties and one or more target variables or labels, among other things. Unsupervised learning aims to model the hidden structure inside data without the need of label information, whereas supervised learning makes use of labelled data to accomplish this. Finally, reinforcement learning is concerned with the development of incentive systems that are capable of representing complex decision techniques and learning sequences of actions. The topic of supervised learning is covered in this chapter.

7.2.1.1 Supervised Learning

In supervised training, the classifier is given a set of training data as well as class labels. This previous knowledge is used by the classifier. With supervised learning, there are a variety of ways for designing a classifier. Some of the most popular techniques are discussed.

Nearest Neighbor (1.4.2.1) (k-NN)

The k-Nearest-neighbor classification is simple to understand and implement, with high classification accuracy. The majority vote of the k-nearest classes determines this classification. The distance between the points in the training data set is dictated by the feature vectors, which are represented as points in feature space. The classifier then uses only the k-nearest neighbour classes to forecast the best-fit class for a point using a majority vote.

7.2.1.1.2 Decision Tree

A decision tree works by partitioning input space. It's a tree structure with internal nodes and leaf nodes that represent tests and classes, respectively. The root node is the beginning point for a new test point's classification. The root's various links present various outcomes, after which the next stage is to make decisions on succeeding nodes, and so on until leaf nodes are reached. ID3 and Classification and Regression Tree are two common tree-building techniques (CART).

7.2.1.1.3Support- Vector -Machines (SVM)

To improve the accuracy for extraction and output efficacy. To increase output results and reduce error margins, a proposed strategy combines the best of several strategies. To improve the findings of a robust dataset, the images are categorisedutilising Supervised Vector Machines (SVM) technique. For image recognition, audio recognition, and face detection, SVM has to be the most efficient supervised learning method. It is the most reliable, accurate, and efficient method for binary classification.

A popular kernel-based learning technique, Support vector machines (SVMs) were developed by Vapnik and his team in the late 1970s. By solving a convex quadratic optimization issue, SVMs can avoid the local extremum conundrum that other machine learning algorithms suffer from. A non-parametric supervised approach, SVM ignores the data distribution. In contrast to other statistical techniques such as maximum likelihood, SVMs do not requireprior knowledge of data distribution. In its simplest form, SVM is a binary linear classifier that finds a single class border. Assumption of linear separability of multi-dimensional data (see Figure 7.1).

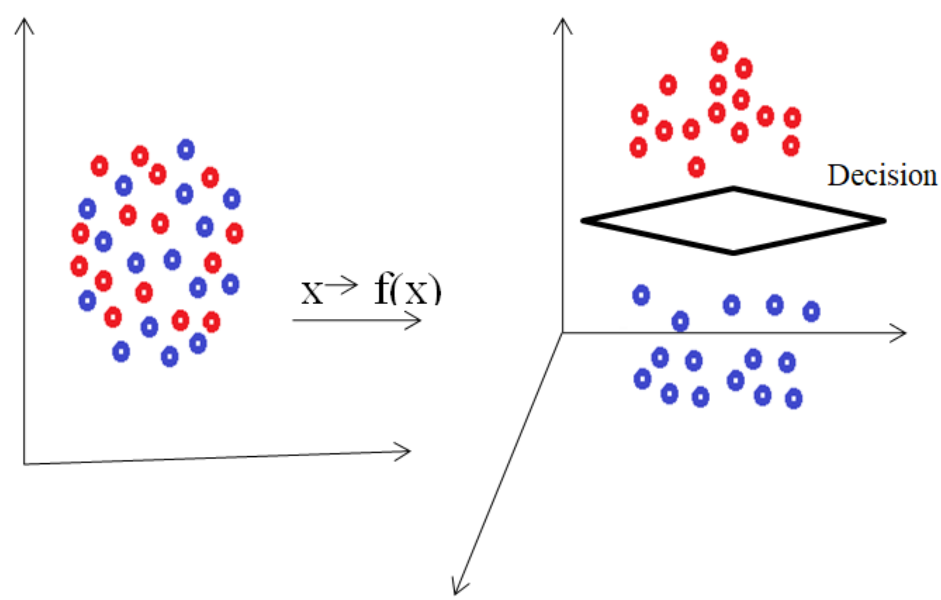

Figure 7.1: A Support Vector Machine Example for Non-Linearly Separable data with Kernel Trick

To categorise a dataset, SVMs use training data to determine an ideal hyperplane (a line in the simplest case). Support vectors are used in SVMs to maximise separation or margin [134][51][11][77]. Classification of these samples directly affects the optimal decision boundary location[14][91]. Mathematically and geometrically, the optimal hyperplane can be defined. Misclassification errors are minimised by a decision boundary[60]. Based on the maximum margin of separation, the ideal hyperplane is chosen [91][49]. The learning process is the iterative process of building a classifier with an optimal decision boundary. In practise, classifications of data samples often overlap as illustrated in see Figure 7.2.

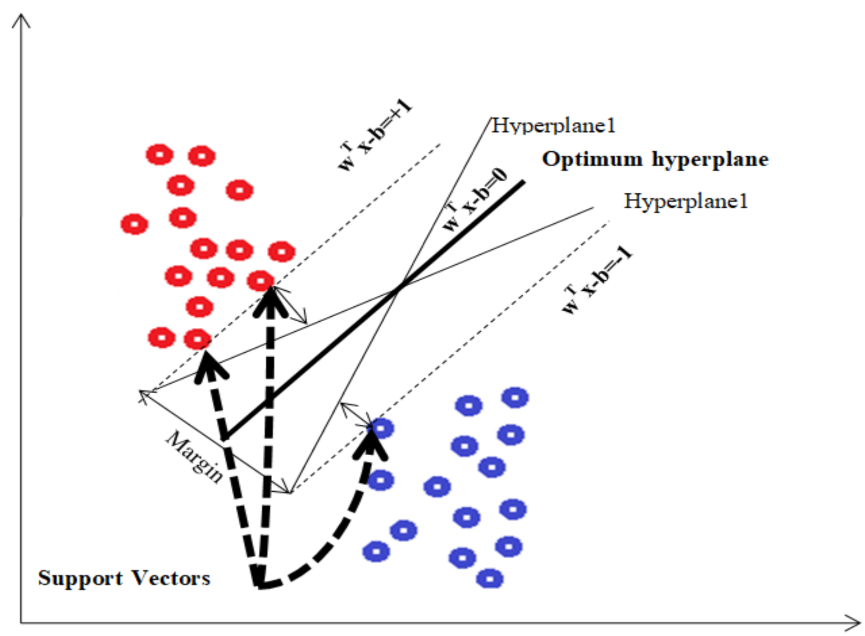

Figure 7.2: A Support Vector Machine Example for Linearly Separable Data

To identify such data accurately, linear SVM needs to be modified. These methods were developed by Cortes and Vapnik[123]. The soft margin strategy can deal with non-linearly separable data by adding slack variables (i.e. By mapping feature space into higher dimensions (Euclidean or Hilbert space), the kernel approach can improve class separation[26][71]. A dataset is transformed into a higher dimensional feature space where the training samples are linearly separable using the kernel approach. It's important to choose a kernel function that produces dot products in higher dimensional feature space. This space is infinitely dimensional and allows linear discrimination. Sigmoid, Radial basis function.[116]

7.3 PROPOSED METHODOLOGY

The suggested work's main purpose is to obtain similar images from a database in response to a particular query image being given. This method makes use of image's low-level features. The main goal of this chapter is to develop an image retrieval system that is both efficient and simple. For such an objective, comparative research of image retrieval employing various features is carried out. Initially, images are obtained independently based on color attributes. All color-based features are also merged, and the results are compared. The Support Vector Machine (SVM) method is employed for classification in this approach. The dataset utilized here is the Flower and Fruits dataset, randomly accessed from the COREL dataset and comprised more than 500 images divided into three classes: red, green, and yellow colors of flowers and fruits and bus, some short of images as shown in Figure 7.2. The images are 256x256 pixels in size. Figure 7.1 is an illustration of the proposed CBIR approach.

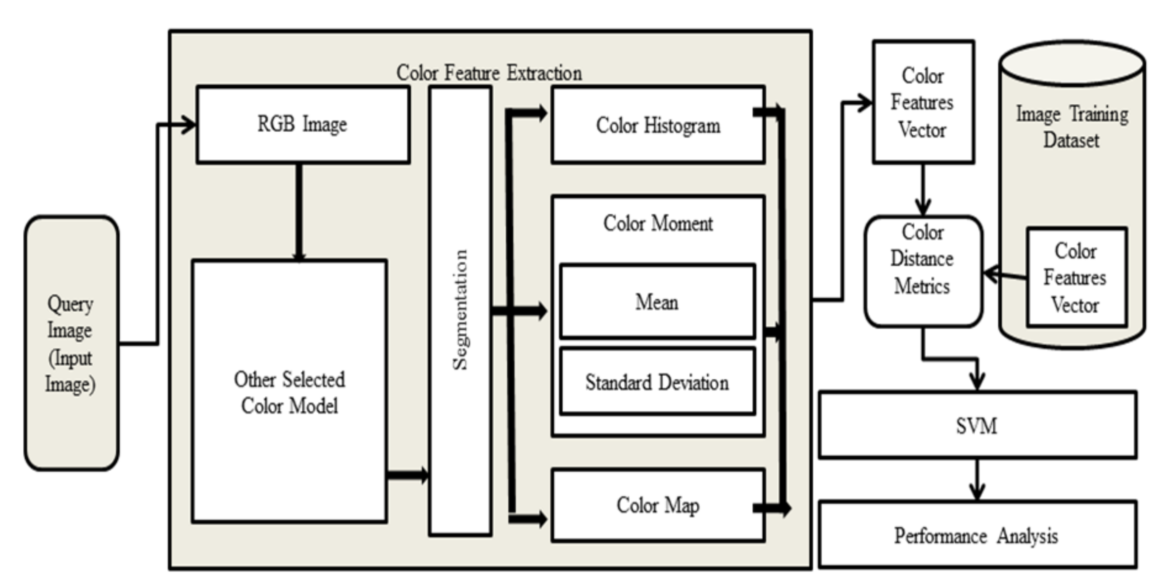

Figure 7.3: Proposed Approach for Image Retrieval and Classification

Figure7.4: Some Set of Original Images

7.4 EXPERIMENTAL ANALYSIS AND RESULT

The experimental study is covered in this chapter utilizing a variety of machine learning algorithms, including SVM, KNN, and Decision Tree. Following Table 7.1 is the different color based features collected based on color based approach for similar image retrieval.

TABLE 7.1: IMAGE DATASET CATEGORIES BASED ON COLOR FEATURES

Img	F1	F2	F3	F4	Category
img1	34818.33	50.81	75.10	0.20	Green
img2	27557.67	72.14	77.43	0.28	Green
img3	34908.33	52.07	69.99	0.20	Green
img4	25522.67	82.50	82.60	0.32	Green
img5	43605.67	42.89	68.99	0.17	Green
img6	41908.00	42.21	65.35	0.16	Green
img7	60876.00	17.09	62.65	0.07	Green
img8	55736.33	9.01	36.81	0.03	Red
img9	50373.67	11.32	33.24	0.04	Red
img10	48552.33	13.39	35.63	0.05	Red
img11	31450.67	34.68	54.26	0.13	Red
img12	44013.00	24.32	52.89	0.09	Red
img13	44666.67	24.57	54.92	0.09	Red
img14	62136.67	1.53	9.43	0.00	Red
img15	58798.67	7.37	35.90	0.03	Red
img16	7835.67	36.02	42.91	0.14	Red
img17	36634.00	35.20	61.19	0.14	Red
img18	41245.00	24.96	54.63	0.10	Red
img19	31472.00	74.19	88.31	0.29	Red
img20	30036.67	87.11	96.91	0.34	Red
img21	36431.00	66.40	90.30	0.26	Red
img22	29393.00	52.04	62.48	0.20	Red
img23	36141.33	50.65	74.55	0.20	Red
img24	39101.67	34.81	64.49	0.13	Red
img25	45309.33	31.38	61.32	0.12	Red
img26	43735.67	29.06	57.60	0.11	Red
img27	43779.67	33.90	73.85	0.13	Red
img28	41202.33	23.81	49.59	0.09	Red
img29	48650.67	23.26	50.27	0.09	Red
img30	48650.67	23.26	50.27	0.09	Red
img31	47151.33	28.68	57.88	0.11	Red
img32	27320.00	42.17	59.79	0.16	Red
img33	26037.33	54.27	62.56	0.21	Red
img34	47133.33	21.31	47.62	0.08	Red
img35	41080.33	29.89	56.02	0.12	Red
img36	44211.00	27.12	49.12	0.10	Red
img37	40848.67	66.19	98.54	0.26	Yellow
img38	39464.33	56.05	89.47	0.22	Yellow
img39	46910.67	37.04	74.04	0.14	Yellow
img40	36060.33	58.48	82.19	0.23	Yellow
img41	35078.67	55.40	77.36	0.22	Yellow

7.4.1 Comparative Analysis of SVM WithKNN and Decision Tree

The accuracy of various classification methods, such as SVM, KNN, and Decision Tree, is shown in the Table 7.2 below. It is possible to assess the suggested system's accuracy by utilizing following formula.

$$\boldsymbol{Accuracy} = \{(\boldsymbol{N} - \boldsymbol{X})/\boldsymbol{N}\} * \mathbf{100} \tag{7.1}$$

Here, N represents the True positive value, while X represents the True negative value.

TABLE 7.2: COMPARISON BETWEEN SVM, KNN, AND DECISION TREE

	Method	**Accuracy**
SVM	Linear SVM	92.50
	Quadratic SVM	97.50
	Cubic SVM	97.50
	Fine Gausian SVM	80.00
	Medium Gaussian SVM	90.00
	CoarseGaussian SVM	72.50
KNN	Fine KNN	95.00
	Medium KNN	72.50
	Coarse KNN	72.50
	Cosine KNN	75.00
	Cubic KNN	72.50
	Weighted KNN	95.00
Tree	FineTree	95.00
	Medium Tree	95.00
	Coarse Tree	95.00

Based on the results given above, a graphical representation of the accuracy using KNN method is presented below.

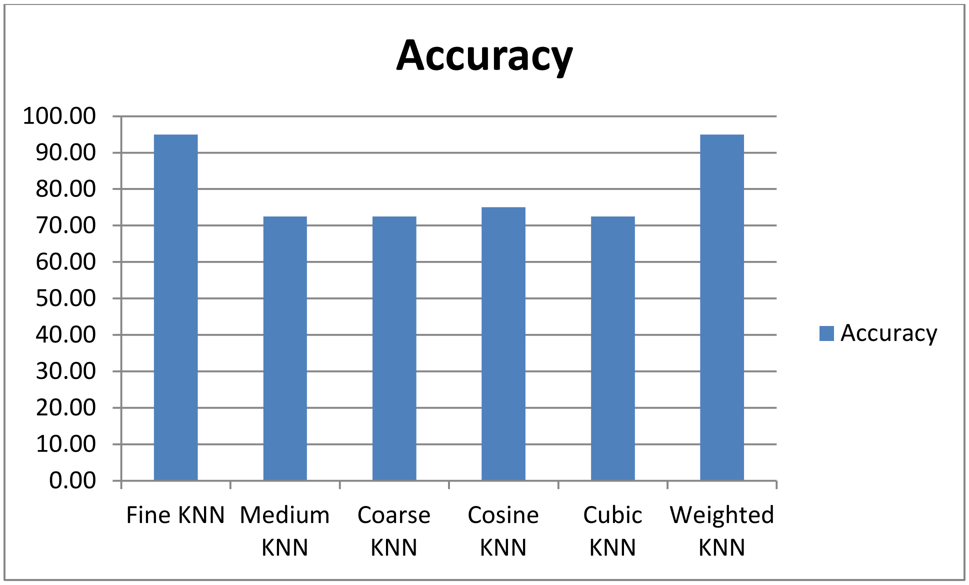

Figure 7.5: Representation of Accuracy Using the KNNApproach

Based on the results given above, a graphical representation of the accuracy using Decision Tree method is presented below.

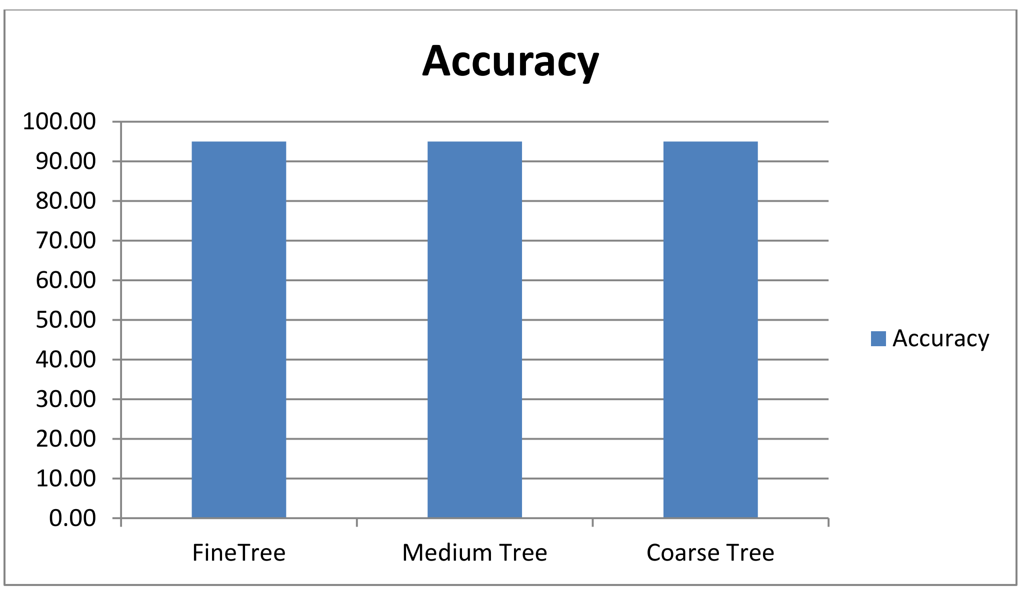

Figure7.6 : Representation of Accuracy Using the Decision Tree Approach

Based on the results given above, a graphical representation of the comparative accuracy using various methods is presented below.

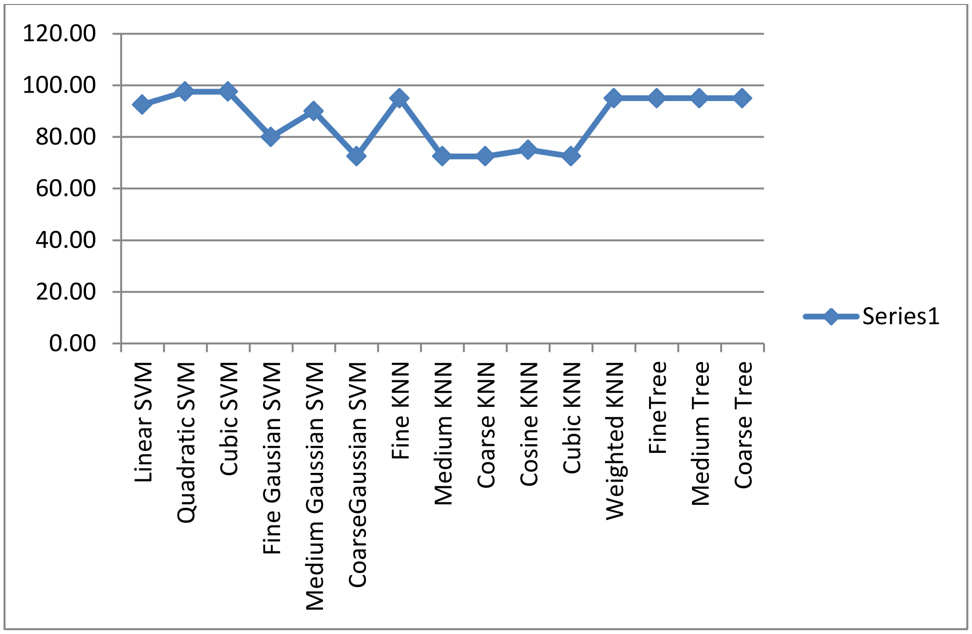

Figure 7.7: Representation of Comparative Accuracy Using SVM, KNN, and Decision Tree

We used a different approach of the SVM, and compared the results. The quadratic strategy is detailed in more following section. Based on the results given above, a graphical representation of the accuracy using SVM method is presented below.

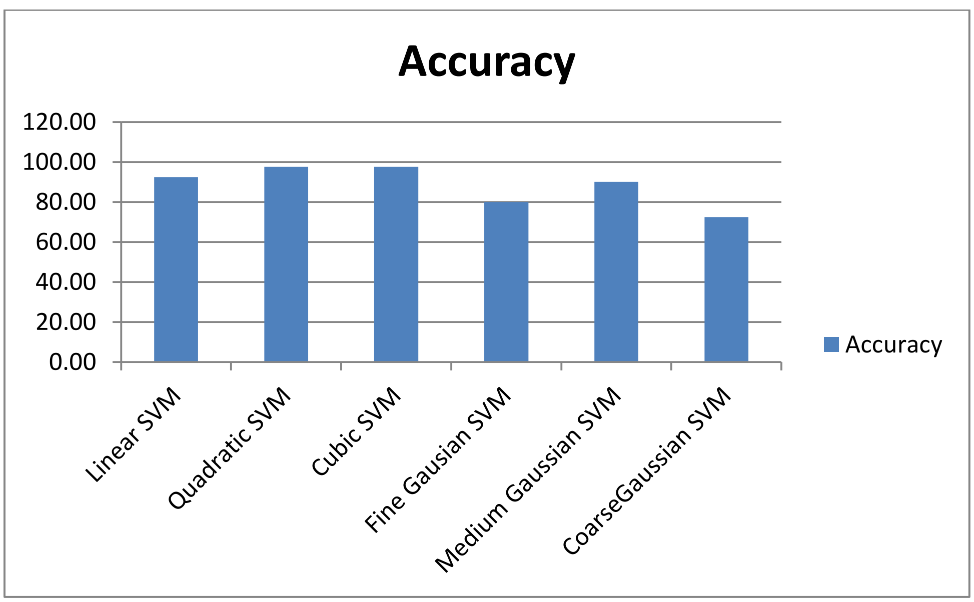

Figure 7.8:Representation of Accuracy Using the SVM Approach

7.4.2 QuadraticSupport Vector Machines (SVM)Classification

These feature vectors are used to categorise the database once they have been extracted from the image dataset using color-based feature extraction. During the feature extraction phase, the Quadratic SVM classification algorithm is employed, which is then followed by the feature extraction process. In the database, the SVM is used to classify each and every image. There are two types of classification or regression algorithms that use this algorithm: supervised and unsupervised learning. The "one-versus-one" strategy is utilised, in which n! classifiers must be trained for a k-way problem in order to be successful. An (nk)! k! binary pair of classes is differentiated at a time by this algorithm. An input query image is used to generate a voting system that is applied to every n! with the highest number of "+1" predictions for the query image. (nk)!k! classifiers are a subset of (nk)!k! classifiers. The class is represented by the projected output of the classifier. The color-based Quadratic SVM classifier outperforms all others. The diagram below depicts the confusion matrix for the Color features-based Quadratic SVM classifier. The image below is a jumbled up kaleidoscope of floral and fruity images.

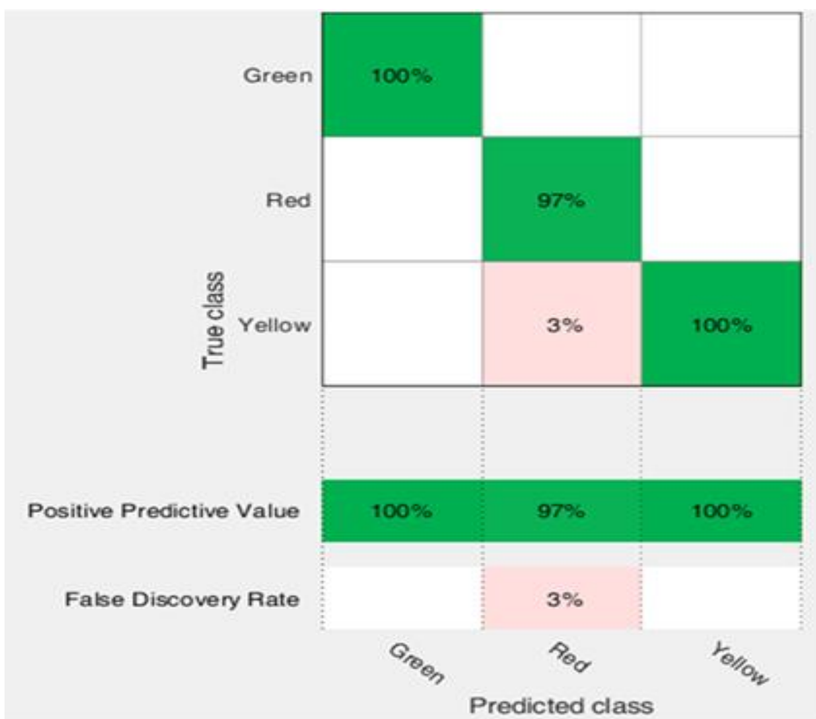

Figure 7.9: Confusion Matrix Using Quadratic SVM

Figure indicates that the classification of flower and fruit images using MATLAB's quadratic SVM classifier is based on color features. Figure 7.9 depicts the confusion matrix created from the flower and fruit image and bus data set. The for Green and Yellow categories dataset are given 100% positive response while for images based on red color gives 97% positive results. The accuracy is best given by Quadratic SVM rather than others as per Figure 7.10.

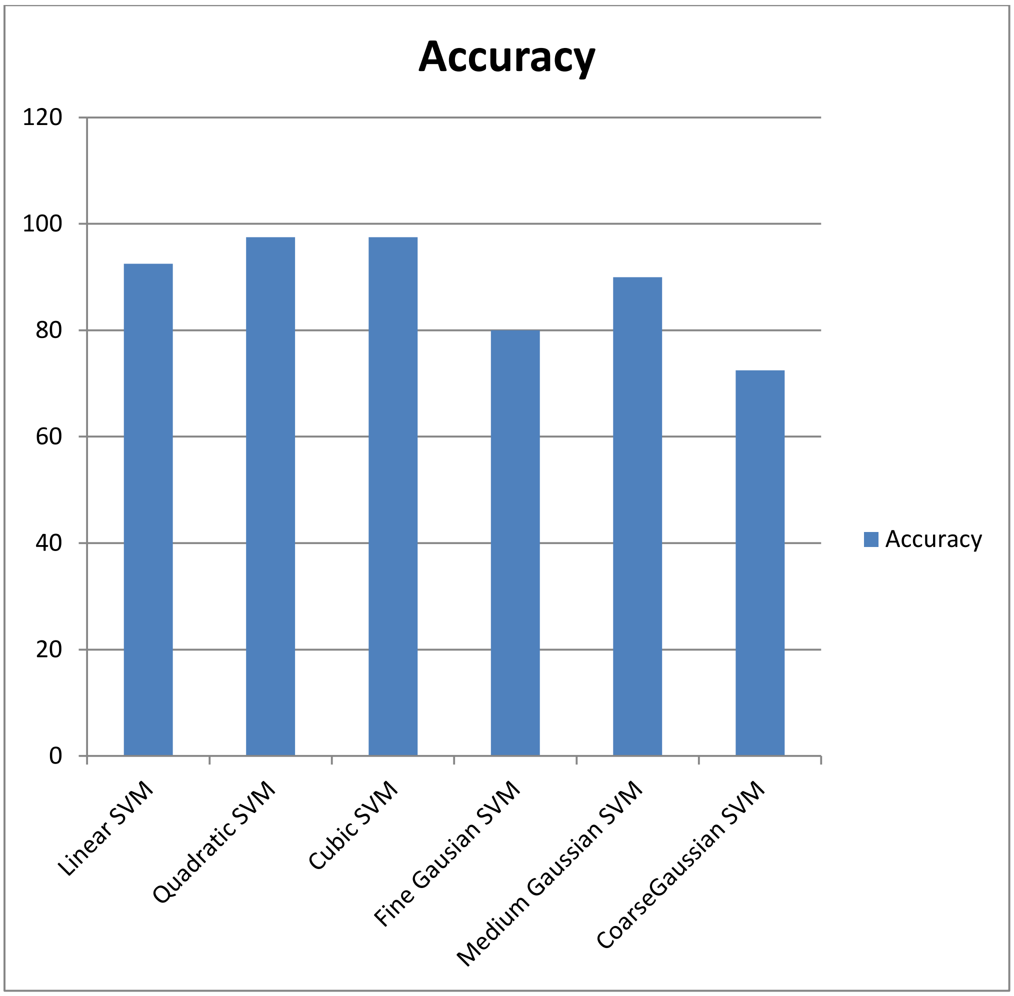

Figure 7.10: Performance Analysis of Accuracy

The predictor data on which the SVM classifier is trained is defined as a matrix of numeric values as shown in Figures 7.11 and Figure 7.12. There are three classes in the data: red, green, and yellow, with one of them being linearly separable from the others. Predictor data and an index are used to train an SVM classifier.

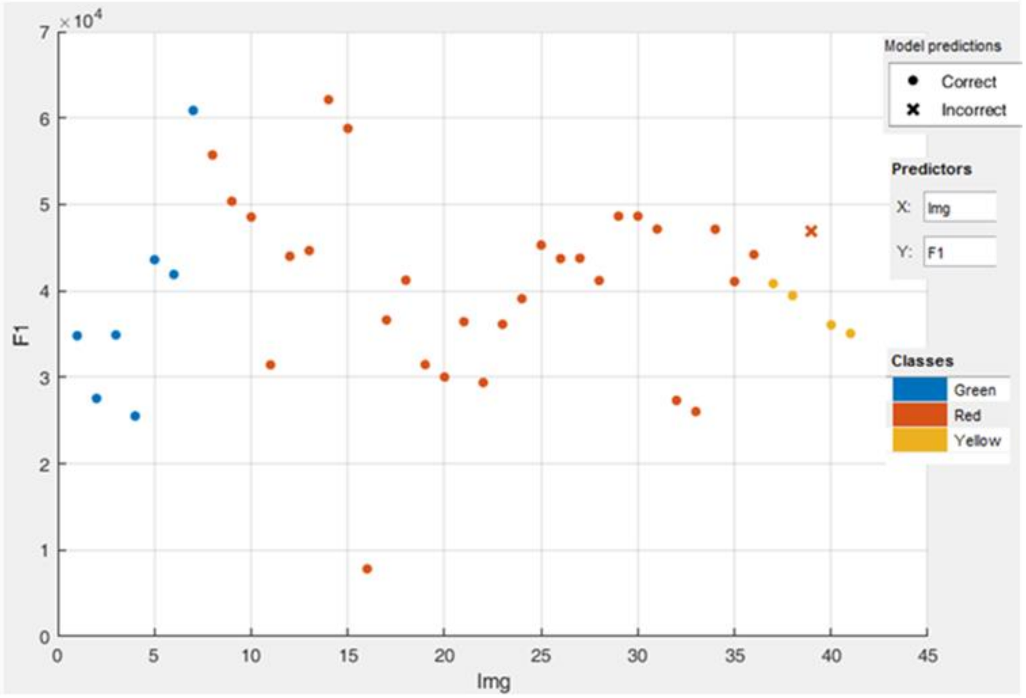

Figure 7.11: Predicators: Quadratic SVM

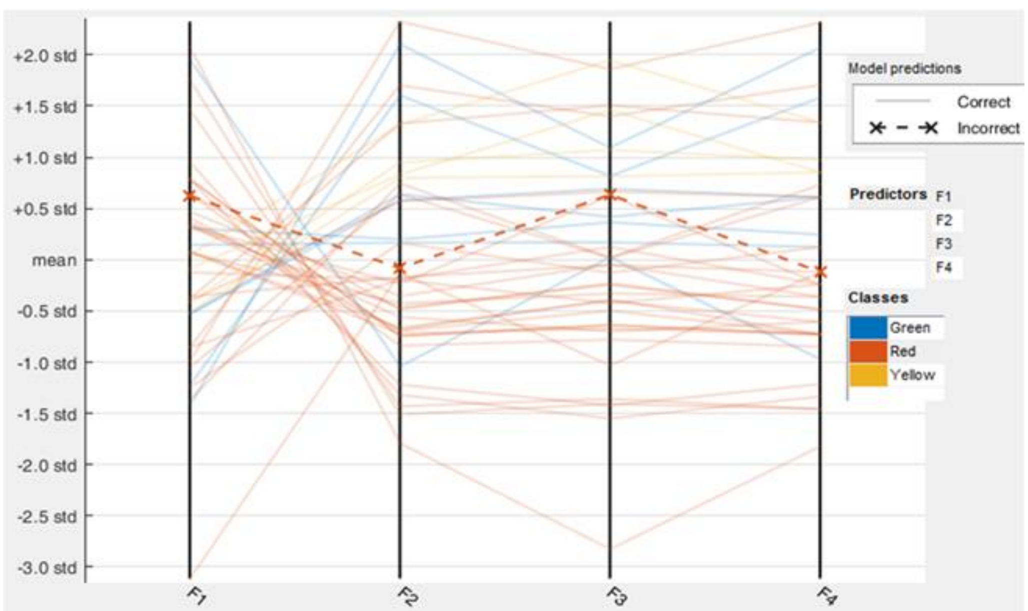

Figure 7.12: Parallel Coordinate Plot

To demonstrate the effectiveness of the proposed strategy, numerous tests were carried out. Once a query image is received, the system looks for the top N matching images in the database and returns them. And over 90% of the images are used to train the system, while 10% of the images are utilised to test the system's performance. For each image in the search results, there are a slew of related ones. Numerous metrics can be used to assess performance.Color-based features produce the best results, as evidenced by the outcomes of the tests we ran. In order to arrive at this result, precision and recall were used.

7.5 CONCLUSION

Using a combination of strategies, we hope to retrieve images from a database with high reliability and precision. We offer a new approach for retrieving similar images using CBIR, which is more integrated. A new methodology based on color-based features and quadratic SVM was developed in this chapter for use in various applications. The color features of the input image are extracted in order to improve categorization. There's no doubt about the value of the color features-based Quadratic SVM technique provided in this work. With an average classification accuracy of 97.5%, the network was successfully trained using color-based flower and fruit images in MATLAB program using Quadratic SVM, classifier.

CHAPTER VIII

CONCLUSION AND FUTURE ENHANCEMENTS

In this current scenario, image retrieval is widely required instead of text retrieval. The Content-Based Image Retrieval System becomes more valuable in this scenario to find the most similar images from a large set of images. Image retrieval in CBIR is based on similarity measures between the query image and the targeted dataset, focusing on color, shape, and texture descriptors as low-level feature descriptors. With the advancement of the CBIR system, its advantages in different areas of research are needed, like in satellite image detection, army security, image security, medical research, etc.

From the present research work, the following essential point is concluded:
Computer systems that obtain, browse, and search for images from a large digital database are image retrieval systems. The most typical image retrieval methods involve adding metadata to the images, such as captions, keywords, or descriptions, to get annotated words from an image. There are many drawbacks to manually annotating images. An alternative to text-based image retrieval is content-based image retrieval, which does not necessitate any annotation. CBIR uses color, texture, and shape features that are automatically deduced to obtain similar images. To obtain database images, the CBIR system consists of a simple collection of components that work together. We can automatically extract the most similar images to the query image using local feature extraction techniques such as color, shape, texture, and more. There are few systems that search, browse, and retrieve images from a large database of images using the lower-level features in an image retrieval system since manually annotating images is time-consuming and expensive.

In the first system, Content-Based Image Retrieval systems are designed to cope with various image datasets. They do not address issues such as vast specialized image collections or effective image retrieval by image content. The research work concentrated on a large set of images with different categories. It is analyzed that the retrieval rate of HSV model and L*a*b model for color-based image retrieval are approximately the same using the proposed approach. While of RGB and YCbCr color model. We focused our investigation on a vast number of images from various categories. This work will aid in the development of several image retrieval applications. Using the proposed method, we can identify appropriate methods and apply promising approaches in a massive set of images by considering the dataset.

In the second approach, a comparative analysis is done based on the experiment with the online available Brodatz dataset. With the GLCM, LBP, and LPQ for image similarity from a collection of images in the same category as the input image, it is evident that the GLCM performs better than LBP, and LBP has the best accuracy, recall, and F-score. The experimental analysis in the previous chapters shows that the LBP will function better than the LPQ techniques for a short dataset.

In the next approach, the given work outperforms LBP, LPQ, GLCM+LBP, GLCM+LPQ, and proposed work in terms of precision, recall, and F-score when applied to the query image seeking image similarity from a set of images belonging to the same category. Concerning the effectiveness of the proposed method-based texture features, it is considerably more effective to retrieve the most similar images than other approaches.

In the next system, based on the experimental analysis using the proposed approach for an image retrieval system, the scores generated for color-based features, texture-based features, shape-based features, and the proposed approach show that 98% accuracy in comparison with other approaches based on shape only, texture only, and color only.

The next system is to retrieve images from a database with high reliability and precision using a combination of strategies. We offer a new approach for retrieving similar images using CBIR that is more integrated. In this research work, a new methodology based on image retrieval using a machine learning approach was developed. The features of the input image are extracted to improve categorization. With an average classification accuracy of 97.5%, the network was successfully trained using COREL dataset images in the MATLAB program using different machine learning techniques.

FUTURE ENHANCEMENTS

Following are the future task related to improvements in CBIR system:

i. In the research work, we looked into the low-level components of CBIR color features extraction and texture features extraction. The work produced a CBIR system combining color, texture, and shape features. Inputting an image quickly and accurately retrieves similar images. The system will be strengthened by fusing low-level features with the spatial position in the future. The CBIR system also includes image feature matching and semantic-based image retrieval.

ii. Because image databases are diverse and have non-homogeneous features, they cannot be described by a single feature. Using low-level features infusion can improve CBIR and image representation performance. The semantic gap can be decreased by combining local features representing the image as patches, and the performance can be improved. One of the next study directions in this area is to combine local and global features.

iii. Traditional machine learning algorithms have shown promising results in several fields for CBIR and image representation. Recent CBIR research has switched to using deep neural networks, which have surpassed handcrafted features on numerous datasets when fine-tuned. Large image datasets and powerful computers are essential for deep networks. Managing a big image collection for supervised deep network training is complex and time-consuming. Thus, evaluating a deep network's performance on a large unlabelled dataset in unsupervised learning mode is a potential future study direction.

iv. The system can be expanded to support mobile-based image retrieval, allowing users to retrieve remote server images in a wireless network environment.

As a result, there is room for future research in this area, leading to better solutions.

LIST OF REFERENCES

1. Abrishami Moghaddam H, Taghizadeh Khajoie T, Rouhi AH (2003) A New Algorithm for Image Indexing and Retrieval Using Wavelet Correlogram. In: IEEE International Conference on Image Processing
2. Adamek T, O'Connor NE (2004) A Multiscale Representation Method for Nonrigid Shapes with a Single Closed Contour. IEEE Trans Circuits Syst Video Technol 14. doi: 10.1109/TCSVT.2004.826776
3. Agrawal S, Verma NK, Tamrakar P, Sircar P (2011) Content Based Color Image Classification Using SVM. Proc - 2011 8th Int Conf Inf Technol New Gener ITNG 2011 1090–1094. doi: 10.1109/ITNG.2011.202
4. Alajlan N, Kamel MS, Freeman G (2006) Multi-object Image Retrieval Based on Shape and Topology. Signal Process Image Commun 21. doi: 10.1016/j.image.2006.09.002
5. Alajlan N, El Rube I, Kamel MS, Freeman G (2007) Shape Retrieval Using Triangle-Area Representation and Dynamic Space Warping. Pattern Recognit 40. doi: 10.1016/j.patcog.2006.12.005
6. Ali S, Smith-Miles KA (2006) A Meta-Learning Approach to Automatic Kernel Selection for Support Vector Machines. Neurocomputing 70. doi: 10.1016/j.neucom.2006.03.004
7. Aravinda C V., Meng L, Uday Kumar Reddy KR, Prabhu A (2019) Signature Recognition and Verification Using Multiple Classifiers Combination of Hu's and HOG Features. In: International Conference on Advanced Mechatronic Systems, ICAMechS
8. Ashby FG, Gott RE (1988) Decision Rules in the Perception and Categorization of Multidimensional Stimuli. J Exp Psychol Learn Mem Cogn 14. doi: 10.1037/0278-7393.14.1.33
9. Bansal M, Kaur G, Kaur M (2012) Content-Based Image Retrieval Based on Color. 8491:295–297
10. Barata C, Ruela M, Francisco M, Mendonca T, Marques JS (2014) Two Systems for the Detection of Melanomas in Dermoscopy Images using Texture and Color

Features. IEEE Syst J 8:965–979. doi: 10.1109/JSYST.2013.2271540

11. Bazi Y, Melgani F (2006) Toward an Optimal SVM Classification System for Hyperspectral Remote Sensing Images. IEEE Trans Geosci Remote Sens 44. doi: 10.1109/TGRS.2006.880628
12. Belongie S, Malik J, Puzicha J (2002) Shape Matching and Object Recognition using Shape Contexts. IEEE Trans Pattern Anal Mach Intell 24. doi: 10.1109/34.993558
13. Bruzzone L, Chi M, Marconcini M (2006) A Novel Transductive SVM for Semisupervised Classification of Remote-Sensing Images. IEEE Trans Geosci Remote Sens 44. doi: 10.1109/TGRS.2006.877950
14. Bruzzone L, Persello C (2009) A Novel Context-Sensitive Semisupervised SVM Classifier Robust to Mislabeled Raining Samples. IEEE Trans Geosci Remote Sens 47. doi: 10.1109/TGRS.2008.2011983
15. Byun H, Lee SW (2002) Applications of Support Vector Machines for Pattern Recognition: A Survey. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 2388:213–236. doi: 10.1007/3-540-45665-1_17
16. Cavalin PR, Martins J, Kapp MN, Oliveira LES (2013) A Multiple Feature Vector Framework for Forest Species Recognition. Proc ACM Symp Appl Comput 16–20. doi: 10.1145/2480362.2480368
17. Ch S, Anand N, Panigrahi BK, Mathur S (2013) Streamflow Forecasting by SVM with Quantum Behaved Particle Swarm Optimization. Neurocomputing 101. doi: 10.1016/j.neucom.2012.07.017
18. Chadha A, Mallik S, Johar R (2012) Comparative Study and Optimization of Feature-Extraction Techniques for Content based Image Retrieval. Int J Comput Appl 52:35–42. doi: 10.5120/8320-1959
19. Chakravarti R, Meng X (2009) A Study of Color Histogram based Image Retrieval. ITNG 2009 - 6th Int Conf Inf Technol New Gener 1323–1328. doi: 10.1109/ITNG.2009.126
20. Chandana P, Srinivas Rao P, Satyanarayana CH, Srinivas Y, Gauthami Latha A (2017) An Efficient Content-Based Image Retrieval (CBIR) using GLCM for Feature Extraction. Adv Intell Syst Comput 555:21–30. doi: 10.1007/978-981-10-

3779-5_4

21. Chellappa R, Chatterjee S (1985) Classification of Textures Using Gaussian Markov Random Fields. IEEE Trans Acoust 33. doi: 10.1109/TASSP.1985.1164641
22. Chen H, Cui Y, Li S, Liu J, Liu K (2018) An Improved GMM-Based Algorithm with Optimal Multi-Color Subspaces for Color Difference Classification of Solar Cells. IEEE Trans Semicond Manuf 31:503–513. doi: 10.1109/TSM.2018.2867254
23. Chen Y (1994) Gray-scale Morphological Granulometric Texture Classification. Opt Eng 33. doi: 10.1117/12.173552
24. Cherkassky V, Ma Y (2004) Practical Selection of SVM Parameters and Noise Estimation for SVM Regression. Neural Networks 17. doi: 10.1016/S0893-6080(03)00169-2
25. Christianus Van Gemert J (2003) Retrieving Images as Text Combining Images and Text for Information Retrieval
26. Cortes C, Vapnik V (1995) Support-Vector Networks. Mach Learn 20. doi: 10.1023/A:1022627411411
27. Cross GR, Jain AK (1983) Markov Random Field Texture Models. IEEE Trans Pattern Anal Mach Intell PAMI-5. doi: 10.1109/TPAMI.1983.4767341
28. Dalal N, Triggs B (2005) Histograms of Oriented Gradients for Human Detection. In: Proceedings - 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2005
29. Dang TD (2017) The effect of Color Space on Discriminating Power of Color Local Texture Feature for Color Face Recognition. Proc - 2017 Int Conf Syst Sci Eng ICSSE 2017 249–252. doi: 10.1109/ICSSE.2017.8030875
30. Datta R, Joshi D, Li J, Wang JZ (2008) Image Retrieval: Ideas, Influences, and Trends of the New Age. ACM Comput Surv 40. doi: 10.1145/1348246.1348248
31. Datta R, Li J, Wang JZ (2005) Content Based Image Retrieval - Approaches and Trends of the New Age. MIR 2005 - Proc 7th ACM SIGMM Int Work Multimed Inf Retrieval, Co-located with ACM Multimed 2005 253–262
32. Daubechies I (1990) The Wavelet Transform, Time-Frequency Localization and Signal Analysis. IEEE Trans Inf Theory 36. doi: 10.1109/18.57199

33. Davis LS (1981) Polarograms: A New Tool for Image Texture Analysis. Pattern Recognit 13. doi: 10.1016/0031-3203(81)90098-4
34. Dehghani A, Moloney D, Griffin I (2016) Object Recognition Speed Improvement using BITMAP-HoG. In: Proceedings - International Conference on Image Processing, ICIP
35. Derin H, Elliott H (1987) Modeling and Segmentation of Noisy and Textured Images Using Gibbs Random Fields. IEEE Trans Pattern Anal Mach Intell PAMI-9. doi: 10.1109/TPAMI.1987.4767871
36. Dhanashree M, Kalel S, Pooja M, Pisal M, Ramdas M, Bagawade P, Scholar BE (2016) Color, Shape and Texture Feature Extraction for Content Based Image Retrieval System: A Study. Int J Adv Res Comput Commun Eng 5:303–306. doi: 10.17148/IJARCCE.2016.5477
37. Dhara AK, Mukhopadhyay S, Dutta A, Garg M, Khandelwal N (2017) ContentBased Image Retrieval System for Pulmonary Nodules: Assisting Radiologists in Self-Learning and Diagnosis of Lung Cancer. J Digit Imaging 30. doi: 10.1007/s10278-016-9904-y
38. Do MN, Vetterli M (2002) Wavelet-based Texture Retrieval using Generalized Gaussian density and Kullback-Leibler Distance. IEEE Trans Image Process 11:146–158. doi: 10.1109/83.982822
39. Dolly B, Raj D (2019) Color Based Image Retrieval by Combining Various Features. Int J Eng Adv Technol 9:454–460. doi: 10.35940/ijeat.b3163.129219
40. Dolly B, Raj D (2020) Image Retrieval Based on Color Feature Similarity. J Phys Conf Ser 1478. doi: 10.1088/1742-6596/1478/1/012014
41. Dolly B, Raj D (2021) Image Processing Using Quantum Computing. pp 186–201
42. Dolly B, Raj D (2021) Texture Based Image Retrieval Using GLCM and LBP. In: Advances in Intelligent Systems and Computing
43. Dolly B, Raj D (2021) Image Retrieval Based on Texture Using Local Binary Pattern and Local Phase Quantization
44. Dong Y, Tao D, Li X, Ma J, Pu J (2015) Texture Classification and Retrieval using Shearlets and Linear Regression. IEEE Trans Cybern 45:358–369. doi: 10.1109/TCYB.2014.2326059

45. Donoser M, Riemenschneider H, Bischof H (2010) Efficient Partial Shape Matching of Outer Contours. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)
46. Dou JJ, Wen J, Liu CQ (2005) Histogram-Based Color Image Retrieval. Hongwai yu Jiguang Gongcheng/Infrared Laser Eng 34:84–88
47. FathyAtlam H, Attiya G, El-Fishawy N (2013) Comparative Study on CBIR based on Color Feature. Int J Comput Appl 78:9–15. doi: 10.5120/13605-1387
48. Felci Rajam I, Valli S (2013) A Survey on Content Based Image Retrieval. Life Sci J 10:2475–2487
49. Fernández-Delgado M, Cernadas E, Barro S, Amorim D (2014) Do We need Hundreds of Classifiers to Solve Real World Classification Problems? J Mach Learn Res 15. doi: 10.1117/1.JRS.11.015020
50. Fernández A (2009) Robust Color Texture Features based on Ranklets and Discrete Fourier Transform. J Electron Imaging 18. doi: 10.1117/1.3273946
51. Foody GM, Mathur A (2004) A Relative Evaluation of Multiclass Image Classification by Support Vector Machines. IEEE Trans Geosci Remote Sens 42. doi: 10.1109/TGRS.2004.827257
52. Francos JM (1993) 7 Orthogonal Decompositions of 2D Random Fields and Their Applications for 2d Spectral Estimation. Handb. Stat. 10
53. Fuh CS, Cho SW, Essig K (2000) Hierarchical Color Image Region Segmentation for Content-Based Image Retrieval System. IEEE Trans Image Process 9. doi: 10.1109/83.817608
54. Gan L, Liu P, Wang L (2016) Rotation Sliding Window of the HOG Feature in Remote Sensing Images for Ship Detection. In: Proceedings - 2015 8th International Symposium on Computational Intelligence and Design, ISCID 2015
55. Garcia F, Cervantes J, Lopez A, Alvarado M (2016) Fruit Classification by Extracting Color Chromaticity, Shape and Texture Features: Towards an Application for Supermarkets. IEEE Lat Am Trans 14:3434–3443. doi: 10.1109/TLA.2016.7587652
56. Gavrielides MA, Šikudová E, Pitas I (2006) ColorBased Descriptors for Image

Fingerprinting. IEEE Trans Multimed 8:740–748. doi: 10.1109/TMM.2006.876290

57. Gevers T, Stokman H (2003) Classifying Color Edges in Video into Shadow-Geometry, Highlight, or Material Transitions. IEEE Trans Multimed 5. doi: 10.1109/TMM.2003.811620
58. Ghoggali N, Melgani F (2008) Genetic SVM Approach to Semisupervised Multitemporal Classification. IEEE Geosci Remote Sens Lett 5. doi: 10.1109/LGRS.2008.915600
59. Ghoggali N, Melgani F, Bazi Y (2009) A Multiobjective Genetic SVM Approach for Classification Problems with Limited Training Samples. In: IEEE Transactions on Geoscience and Remote Sensing
60. Giacco F, Thiel C, Pugliese L, Scarpetta S, Marinaro M (2010) Uncertainty Analysis for the Classification of Multispectral Satellite Images using SVMs and SOMs. IEEE Trans Geosci Remote Sens 48. doi: 10.1109/TGRS.2010.2047863
61. Gu Y, Feng K (2013) Optimized Laplacian SVM with Distance metric Learning for Hyperspectral Image Classification. IEEE J Sel Top Appl Earth Obs Remote Sens 6. doi: 10.1109/JSTARS.2013.2243112
62. Guan H, Wada S (2002) Flexible Color Texture Retrieval Method using Multi-Resolution Mosaic for Image Classification. In: International Conference on Signal Processing Proceedings, ICSP
63. HamzahAbed M, Salman Jasim Al-Farttoosi D (2015) Content based Image Retrieval based on Histogram. Int J Comput Appl 110:42–47. doi: 10.5120/19300-0748
64. Haralick RM (1979) Statistical and Structural Approaches to Texture. Proc IEEE 67. doi: 10.1109/PROC.1979.11328
65. Hel-Or Y, Hel-Or H, David E (2014) Matching by Tone Mapping: Photometric Invariant Template Matching. IEEE Trans Pattern Anal Mach Intell 36. doi: 10.1109/TPAMI.2013.138
66. Hu MK (1962) Visual Pattern Recognition by Moment Invariants. IRE Trans Inf Theory 8. doi: 10.1109/TIT.1962.1057692
67. Jain AK, Farrokhnia F (1991) Unsupervised Texture Segmentation using Gabor

Filters. Pattern Recognit 24:1167–1186. doi: 10.1016/0031-3203(91)90143-S

68. Jeena Jacob I, Srinivasagan KG, Jayapriya K (2014) Local Oppugnant Color Texture Pattern for Image Retrieval System. Pattern Recognit Lett 42:72–78. doi: 10.1016/j.patrec.2014.01.017
69. Ji L, Ren Y, Liu G, Pu X (2018) Training-Based Gradient LBP Feature Models for Multiresolution Texture Classification. IEEE Trans Cybern 48:2683–2696. doi: 10.1109/TCYB.2017.2748500
70. Julesz B (1975) Experiments in the Visual Perception of Texture. Sci Am 232. doi: 10.1038/scientificamerican0475-34
71. Kavzoglu T, Colkesen I (2009) A Kernel Functions Analysis for support VectorMachines for Land Cover Classification. Int J Appl Earth Obs Geoinf 11. doi: 10.1016/j.jag.2009.06.002
72. Khemchandani R, Jayadeva, Chandra S (2009) Optimal Kernel Selection in twin Support Vector Machines. Optim Lett 3. doi: 10.1007/s11590-008-0092-7
73. Khotanzad A, Hong YH (1990) Invariant Image Recognition by Zernike Moments. IEEE Trans Pattern Anal Mach Intell 12. doi: 10.1109/34.55109
74. Kim N, Kehtarnavaz N (2005) DWT-Based Scene-Adaptive Color Quantization. Real-Time Imaging 11. doi: 10.1016/j.rti.2005.06.003
75. Kiss CI, Nemeth G, Chetverikov D, Boroczky L (1995) On Feature Extraction for Texture Analysis. Period Polytech Electr Eng 39:115–130
76. Kun Z, Xiao M, Xinguo L (2019) Shape Matching Based on Multi-Scale Invariant Features. IEEE Access 7:115637–115649. doi: 10.1109/ACCESS.2019.2935879
77. Kuo BC, Ho HH, Li CH, Hung CC, Taur JS (2014) A kernel-based feature Selection Method for SVM with RBF Kernel for hyperspectral Image Classification. IEEE J Sel Top Appl Earth Obs Remote Sens 7. doi: 10.1109/JSTARS.2013.2262926
78. Lee HH, Kim JH, Hong KS (2015) Mobile-based Flower Species Recognition in the natural Environment. Electron Lett 51:826–828. doi: 10.1049/el.2015.0589
79. Lerski RA, Straughan K, Schad LR, Boyce D, Blüml S, Zuna I (1993) VIII. MR image Texture Analysis-an Approach To Tissue Characterization. Magn Reson Imaging 11. doi: 10.1016/0730-725X(93)90205-R

80. Lew MS, Sebe N, Djeraba C, Jain R (2006) Content-Based Multimedia Information Retrieval: State Of The Art And Challenges. ACM Trans Multimed Comput Commun Appl 2. doi: 10.1145/1126004.1126005

81. Ling H, Jacobs DW (2007) Shape Classification using the Inner-Distance. IEEE Trans Pattern Anal Mach Intell 29. doi: 10.1109/TPAMI.2007.41

82. Liu F, Picard RW (1996) Periodicity, Directionality, and Randomness: Wold Features for image Modeling and Retrieval. IEEE Trans Pattern Anal Mach Intell 18. doi: 10.1109/34.506794

83. Liu L, Fieguth P (2012) Texture Classification from random Features. IEEE Trans Pattern Anal Mach Intell 34:574–586. doi: 10.1109/TPAMI.2011.145

84. Liu Y, Zhang D, Lu G, Ma WY (2007) A Survey of Content-Based Image Retrieval with High-Level Semantics. Pattern Recognit 40:262–282. doi: 10.1016/j.patcog.2006.04.045

85. Lowe DG (1999) Object Recognition from Local Scale-Invariant Features. In: Proceedings of the IEEE International Conference on Computer Vision

86. Malik F, Baharudin B (2013) Analysis of Distance Metrics in Content-Based Image Retrieval using Statistical Quantized Histogram Texture Features in the DCT Domain. J King Saud Univ - Comput Inf Sci 25:207–218. doi: 10.1016/j.jksuci.2012.11.004

87. Mallat SG (1989) A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. IEEE Trans Pattern Anal Mach Intell 11. doi: 10.1109/34.192463

88. Manay S, Cremers D, Hong BW, Yezzi AJ, Soatto S (2006) Integral Invariants for Shape Matching. IEEE Trans Pattern Anal Mach Intell 28. doi: 10.1109/TPAMI.2006.208

89. Manjunath BS (1996) Texture Features for Browsing and Retrieval of Image Data. IEEE Trans Pattern Anal Mach Intell 18. doi: 10.1109/34.531803

90. Mao J, Jain AK (1992) Texture Classification and Segmentation using Multiresolution Simultaneous Autoregressive Models. Pattern Recognit 25. doi: 10.1016/0031-3203(92)90099-5

91. Mather P, Tso B (2016) Classification Methods for Remotely Sensed Data, Second

Edition

92. Mathur A, Foody GM (2008) Multiclass and Binary SVM Classification: Implications for Training and Classification Users. IEEE Geosci Remote Sens Lett 5. doi: 10.1109/LGRS.2008.915597
93. Mattoccia S, Tombari F, Di Stefano L (2011) Efficient Template Matching for Multi-Channel Images. Pattern Recognit Lett 32. doi: 10.1016/j.patrec.2010.12.004
94. Mihreteab K, Iwahashi M, Yamamoto M (2012) Crow Birds Detection using HOG and CS-LBP. In: ISPACS 2012 - IEEE International Symposium on Intelligent Signal Processing and Communications Systems
95. Milgram J, Cheriet M, Sabourin R (2006) "One Against One" or "One Against All": Which One is Better for Handwriting Recognition with SVMs? Tenth Int Work Front Handwrit Recognit
96. Ming D, Zhou T, Wang M, Tan T (2016) Land Cover Classification using Random Forest with Genetic Algorithm-Based Parameter Optimization. J Appl Remote Sens 10:035021. doi: 10.1117/1.jrs.10.035021
97. Mistry Y, Ingole DT, Ingole MD (2018) Content Based Image Retrieval Using Hybrid Features and Various Distance Metric. J Electr Syst Inf Technol 5:874–888. doi: 10.1016/j.jesit.2016.12.009
98. Mokhtarian F, Abbasi S, Kittler J (1998) Efficient and Robust Retrieval by Shape Content through Curvature Scale Space
99. Mukhopadhyay S, Dash JK, Das Gupta R (2013) Content-based Texture Image Retrieval using fuzzy Class Membership. Pattern Recognit Lett 34:646–654. doi: 10.1016/j.patrec.2013.01.001
100. Nanni L, Lumini A, Brahnam S (2010) Local Binary Patterns Variants as Texture Descriptors for Medical Image Analysis. Artif Intell Med 49. doi: 10.1016/j.artmed.2010.02.006
101. Nava R, Escalante-Ramírez B, Cristóbal G (2012) Texture Image Retrieval Based on log-Gabor Features. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 7441 LNCS:414–421. doi: 10.1007/978-3-642-33275-3_51

102. Niu Y, Zhang H, Guo W, Ji R (2018) Image Quality Assessment for Color Correction Based on Color Contrast Similarity and Color Value Difference. IEEE Trans Circuits Syst Video Technol 28:849–862. doi: 10.1109/TCSVT.2016.2634590

103. Ojala T, Pietikäinen M, Harwood D (1996) A Comparative Study of Texture Measures with Classification Based on Featured Distributions. Pattern Recognit 29:51–59. doi: 10.1016/0031-3203(95)00067-4

104. Ojala T, Pietikäinen M, Mäenpää T (2002) Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns. IEEE Trans Pattern Anal Mach Intell 24:971–987. doi: 10.1109/TPAMI.2002.1017623

105. Omid-Zohoor A, Young C, Ta D, Murmann B (2018) Toward Always-On Mobile Object Detection: Energy Versus Performance Tradeoffs for Embedded HOG Feature Extraction. IEEE Trans Circuits Syst Video Technol 28. doi: 10.1109/TCSVT.2017.2653187

106. Ouyang A, Tan YP (2002) A Novel Multi-Scale Spatial-Color Descriptor for Content-Based Image Retrieval. In: Proceedings of the 7th International Conference on Control, Automation, Robotics and Vision, ICARCV 2002

107. Pentland AP (1984) Fractal-Based Description of Natural Scenes. IEEE Trans Pattern Anal Mach Intell PAMI-6. doi: 10.1109/TPAMI.1984.4767591

108. Pham MT, Mercier G, Michel J (2016) PW-COG: An Effective Texture Descriptor for VHR Satellite Imagery Using a Pointwise Approach on Covariance Matrix of Oriented Gradients. IEEE Trans Geosci Remote Sens 54:3345–3359. doi: 10.1109/TGRS.2016.2516042

109. Piras L, Giacinto G (2017) Information Fusion in Content Based Image Retrieval: A Comprehensive Overview. Inf Fusion 37. doi: 10.1016/j.inffus.2017.01.003

110. Raghuwanshi G, Tyagi V (2016) A Survey on Texture Image Retrieval. Adv Intell Syst Comput 381:427–435. doi: 10.1007/978-81-322-2526-3_44

111. Raghuwanshi G, Tyagi V (2017) A Novel Technique for Location Independent Object based Image Retrieval. Multimed Tools Appl 76:13741–13759. doi: 10.1007/s11042-016-3747-x

112. Rajadell O, García-Sevilla P, Pla F (2009) Textural Features for Hyperspectral

Pixel Classification BT - Image and Signal Processing. Image Signal Process. 5524:208–216

113. Rama Varior R, Wang G, Lu J, Liu T (2016) Learning Invariant Color Features for Person Reidentification. IEEE Trans Image Process 25:3395–3410. doi: 10.1109/TIP.2016.2531280
114. Samadzadegan F, Hasani H, Schenk T (2012) Simultaneous Feature Selection and SVM Parameter Determination in Classification of Hyperspectral Imagery using Ant Colony Optimization. Can J Remote Sens 38. doi: 10.5589/m12-022
115. Schettini R, Ciocca G, Zuffi S (2002) A Survey of Methods for Colour Image Indexing and Retrieval in Image Databases. Colour Image Sci Exploit Digit Media 54:183–212
116. Sheykhmousa M, Mahdianpari M, Ghanbari H, Mohammadimanesh F, Ghamisi P, Homayouni S (2020) Support Vector Machine Versus Random Forest for Remote Sensing Image Classification: A Meta-Analysis and Systematic Review. IEEE J Sel Top Appl Earth Obs Remote Sens 13:6308–6325. doi: 10.1109/JSTARS.2020.3026724
117. Shrinivasacharya P, Sudhamani M V. (2013) Content Based Image Retrieval using Self Organizing Map. Lect Notes Electr Eng 221 LNEE:535–546. doi: 10.1007/978-81-322-0997-3_48
118. Singh S, Srivastava D, Agarwal S (2017) GLCM and its Application in Pattern Recognition. 5th Int Symp Comput Bus Intell ISCBI 2017 20–25. doi: 10.1109/ISCBI.2017.8053537
119. Smeulders AWM, Worring M, Santini S, Gupta A, Jain R (2000) Content-based Image Retrieval at the End OF the Early Years. IEEE Trans Pattern Anal Mach Intell 22:1349–1380. doi: 10.1109/34.895972
120. Srivastava D, Goel S, Agarwal S (2017) Pipelined Technique for Image Retrieval using Texture and Color. 2017 4th Int Conf Power, Control Embed Syst ICPCES 2017 2017-Janua:1–6. doi: 10.1109/NAFOSTED.2017.8117611
121. Srivastava D, Rajitha B, Agarwal S (2018) An Efficient Image Classification using Bag-of-Words based on SURF and Texture Features. 2017 14th IEEE India Counc Int Conf INDICON 2017. doi: 10.1109/INDICON.2017.8488010

122. Srivastava D, Wadhvani R, Gyanchandani M (2015) A Review: Color Feature Extraction Methods for Content Based Image Retrieval. Int J Comput Eng Manag 18:9–13

123. Srivastava DK, Bhambhu L (2010) Data classification using Support Vector Machine. J Theor Appl Inf Technol 12

124. Su L (2009) Optimizing Support Vector Machine Learning for Semi-Arid Vegetation Mapping by using Clustering Analysis. ISPRS J Photogramm Remote Sens 64. doi: 10.1016/j.isprsjprs.2009.02.002

125. Sun Z, Wang C, Wang H, Li J (2013) Learn multiple-kernel SVMs for Domain Adaptation in Hyperspectral Data. IEEE Geosci Remote Sens Lett 10. doi: 10.1109/LGRS.2012.2236818

126. SUSSTRUNK S (2007) Color Spaces, Color Encodings, and Color Image Encodings. Focal Encycl Photogr 394–398. doi: 10.1016/b978-0-240-80740-9.50064-7

127. Tao H, Lu X (2018) Smoky Vehicle Detection based on Multi-Scale Block Tamura Features. Signal, Image Video Process 12. doi: 10.1007/s11760-018-1254-4

128. Tian DP (2013) A Review on Image Feature Extraction and Representation techniques. Int J Multimed Ubiquitous Eng 8:385–395

129. Tolambiya A, Venkatraman S, Kalra PK (2010) Content-Based Image Classification with Wavelet Relevance Vector Machines. Soft Comput 14:129–136. doi: 10.1007/s00500-009-0439-8

130. Varma M, Zisserman A (2009) A Statistical Approach to Material Classification using Image Patch Exemplars. IEEE Trans Pattern Anal Mach Intell 31. doi: 10.1109/TPAMI.2008.182

131. Venkata Ramana Chary R (2012) Feature Extraction Methods For Color Image Similarity. Adv Comput An Int J 3. doi: 10.5121/acij.2012.3215

132. Verma M, Raman B, Murala S (2015) Local Extrema Co-Occurrence Pattern for Color and Texture Image Retrieval. Neurocomputing 165:255–269. doi: 10.1016/j.neucom.2015.03.015

133. Wang J, Yagi Y (2008) Integrating Color And Shape-Texture Features for

Adaptive Real-Time Object Tracking. IEEE Trans Image Process 17:235–240. doi: 10.1109/TIP.2007.914150

134. Williams CKI (2003) Learning With Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. J Am Stat Assoc 98. doi: 10.1198/jasa.2003.s269
135. Wu Y, Yang X, Plaza A, Qiao F, Gao L, Zhang B, Cui Y (2016) Approximate Computing of Remotely Sensed Data: SVM Hyperspectral Image Classification as a Case Study. IEEE J Sel Top Appl Earth Obs Remote Sens 9. doi: 10.1109/JSTARS.2016.2539282
136. Yadav AR, Anand RS, Dewal ML, Gupta S (2015) Multiresolution Local Binary Pattern Variants Based Texture Feature Extraction Techniques for Efficient Classification of Microscopic Images of Hardwood Species. Appl Soft Comput J 32:101–112. doi: 10.1016/j.asoc.2015.03.039
137. Yang C, Wei H, Yu Q (2018) A novel method for 2D Nonrigid Partial Shape Matching. Neurocomputing 275. doi: 10.1016/j.neucom.2017.09.067
138. Yang C, Yu Q (2019) Multiscale Fourier Descriptor based on triangular Features For shape retrieval. Signal Process Image Commun 71. doi: 10.1016/j.image.2018.11.004
139. Yang H, Chen Y, Song K, Yin Z (2019) Multiscale Feature-Clustering-Based Fully Convolutional Autoencoder for Fast Accurate Visual Inspection of Texture Surface Defects. IEEE Trans Autom Sci Eng 16:1–18. doi: 10.1109/TASE.2018.2886031
140. Yang P, Zhang F, Yang G (2018) Fusing DTCWT and LBP Based Features for Rotation, Illumination and Scale Invariant Texture Classification. IEEE Access 6:13336–13349. doi: 10.1109/ACCESS.2018.2797072
141. Yu H, Li M, Zhang HJ, Feng J (2002) Color Texture Moments for Content-Based Image Retrieval. In: IEEE International Conference on Image Processing
142. Yu Q, Wei H, Yang C (2017) Local Part Chamfer Matching for Shape-Based Object Detection. Pattern Recognit 65:82–96. doi: 10.1016/J.PATCOG.2016.11.020
143. Yuan C, Sun X, Lv R (2016) Fingerprint Liveness Detection Based on Multi-Scale

LPQ and PCA. China Commun 13:60–65. doi: 10.1109/CC.2016.7559076

144. Yue J, Li Z, Liu L, Fu Z (2011) Content-Based Image Retrieval using Color and Texture Fused Features. Math Comput Model 54. doi: 10.1016/j.mcm.2010.11.044
145. Zhang B, Vijaya Kumar BVK, Zhang D (2014) Detecting Diabetes Mellitus and Nonproliferative Diabetic Retinopathy using tongue Color, Texture, and Geometry Features. IEEE Trans Biomed Eng 61:491–501. doi: 10.1109/TBME.2013.2282625
146. Zhang D, Wong A, Indrawan M, Lu G (2000) Content-Based Image Retrieval Using Gabor Texture Features. IEEE Trans PAMI 3656 LNCS:13–15
147. Zhang W, Zhang W, Liu K, Gu J (2018) A Feature Descriptor Based on Local Normalized Difference for Real-World Texture Classification. IEEE Trans Multimed 20:880–888. doi: 10.1109/TMM.2017.2760102
148. Zheng W, Zong Y, Zhou X, Xin M (2018) Cross-Domain Color Facial Expression Recognition Using Transductive Transfer Subspace Learning. IEEE Trans Affect Comput 9:21–37. doi: 10.1109/TAFFC.2016.2563432
149. Zhu X, Li N, Pan Y (2019) Optimization Performance Comparison of Three Different Group Intelligence Algorithms on a SVM for Hyperspectral Imagery Classification. Remote Sens 11. doi: 10.3390/RS11060734
150. Zujovic J, Pappas TN, Neuhoff DL (2013) Structural Texture Similarity Metrics for Image Analysis and Retrieval. IEEE Trans Image Process 22:2545–2558. doi: 10.1109/TIP.2013.2251645
151. (1982) Image Analysis and Mathematical Morphology. Comput Graph Image Process 20. doi: 10.1016/0146-664x(82)90078-8
152. (1985) Vision in Man and Machine. Comput Vision, Graph Image Process 31. doi: 10.1016/s0734-189x(85)80079-7