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A FINAL YEAR PROJECT REPORT ON

"CONTENT BASED IMAGE RETRIEVAL USING MACHINE LEARNING"

Submitted in partial fulfillment of the requirement for the award of the Degree of

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CERTIFICATE

This is to certify that the final project report entitled **"CONTENT BASED IMAGE RETRIEVAL USING MACHINE LEARNING"** is a bonafide work carried out by **POORNA CHANDRA D** (4VV18IS068), **POORNESH H** (4VV18IS069), **SHOBITHA B** (4VV18IS101), **SPOORTHY N** (4VV18IS105), student of 8th Semester Information Science and Engineering, **Vidyavardhaka College of Engineering, Mysuru** in partial fulfillment for the award of the degree of **Bachelor of Engineering** in **Information Science & Engineering** of the **Visvesvaraya Technological University, Belagavi**, during the academic year **2021-2022**. It is certified that all the suggestions and corrections indicated for the internal assessment have been incorporated in the report deposited in the department library. The report has been approved as it satisfies the requirements in respect of Project work prescribed for the said degree.

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ABSTRACT

In various application domains such as entertainment, biomedicine, commerce, education, and crime prevention, the volume of digital data archives is growing rapidly. The very large repository of digital information raises challenging problems in retrieval and various other information manipulation tasks. Content-based image retrieval (CBIR) is aimed at efficient retrieval of relevant images from large image databases based on automatically derived imagery features. The Content Based Image Retrieval aims to find the similar images from a large-scale dataset against a query image. Generally, the similarity between the representative features of the query image and dataset images is used to rank the images for reclamation. Also, the cornucopia of online networks for product and distribution, as well as the number of images accessible to consumers, continues to expand. Thus, in numerous areas, endless as well as wide digital image processing takes place. Thus, the quick access to these large image databases as well as the extraction of identical images from this large set of images from a given image (Query) pose significant challenges as well as involves effective ways. A CBIR system's effectiveness depends basically on the computation of point representation as well as similarity. For this purpose, we present a introductory but important Machine learning algorithm like Convolutional Neural Networks (CNN) or DCNN which has further delicacy and we can train further and further images, which has comparatively bigger database. CBIR systems allow another image dataset to detect affiliated images to such a query image. The search per picture function of Google search has to be the most popular CBIR method.

Key Words: CBIR, Content-based Image Retrieval, CNN, Convolutional Neural Networks, DCNN, Image processing, Query image.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

In the recent past the advancement in computer and multimedia technologies has led to the product of digital images and cheap large image depositories. The size of image collections has increased fleetly due to this, including digital libraries, medical images etc. To attack this rapid-fire growth, it's needed to develop image reclamation systems which operates on a large scale. The primary end is to make a robust system that creates, manages and query image databases in an accurate manner. CBIR is the following advancement to the stride of keyword-grounded systems in which images are mended grounded on the data of their contents. The reclamation prosecution of a CBIR frame for the utmost part relies upon the two variables; 1) feature representation 2) similarity estimation. The fundamental substance of CBIR is the point birth process. CNNs made out of a class of learnable models which can make use in operations like Image Retrieval, Image Bracket, Image Annotation, Image Recognition and so forth. With the provocation of the extraordinary success of deep learning algorithms to the invention in this paper, they've used for the reclamation the images. CBIR is substantially used for looking through grounded on the content as opposed to the image reflections. It incorporates the system of representing and sorting out images grounded on the word query image.

Content based image retrieval (CBIR) is a computer vision fashion that gives a way for searching applicable images in large databases. This hunt is grounded on the image features like color, texture and shape or any other features being deduced from the image itself. The performance of a CBIR system substantially depends on the named features. The images are first represented in terms of features in a high dimensional point space. Also, the similarity among images stored in the database and that of a query image is measured in the point space by using a distance metric e.g., Euclidean distance. Hence, for CBIR systems, representation of image data in terms of features and opting a similarity reassimilated, are the most critical factors. In CBIR, certain image features incorporate shading, face, and shape that can be resolved from the images. CBIR can be acted in two different ways. for illustration the primary fashion is ordering and second are looking. Exercising the strategy ordering, the birth of the features from the image and can be used to store this feature in point database as point vectors. In the alternate strategy for illustration in looking, the birth of the point vectors from the information images and these separated features are taken for correlation with point vectors accessible in the database. And this outgrowth is used for recovering most matched images from the database to the query image. Unnaturally, there are two kinds of images recovery live, (1) exact image retrieval and (2) applicable image retrieval. For exact image reclamation, the coordinating of 100% with the query is done and in applicable image reclamation, the reclamation relies upon the contents or features of image. In this we probe, Machine learning algorithm like Convolutional Neural Networks (CNN) or DCNN which has further delicacy and we can train further and further images, which has comparatively bigger database.

1.2 PROBLEM STATEMENT

Image search engines become indispensable tools for users who look for images from a largescale image collection and World-Wide Web. Its key technique is content-based image retrieval (CBIR) having the ability of searching images via automatically derived image features, such as color, texture or shape. The major difficulty of CBIR lies in the big gap between low-level image features and high-level image semantics.

The problem involves entering an image as a query into a software application that is designed to employ CBIR techniques in extracting visual properties and matching them.

This is done to retrieve images in the database that are visually similar to the query image.

1.3 OBJECTIVES

The objective of CBIR is to excerpt visual content of an image inevitably, like color, shape or texture:

- To design and evaluate a model to build multimodal information spaces for content-based image retrieval.
- To define strategies to extract and represent visual and geometric contents separately using kernel functions.
- To propose a method for combining visual and geometric kernels to represent image contents together with geometric features information space.

- To design a ranking algorithm to search for images using different query paradigms in the multimodal information space induced by kernels.
- To evaluate the performance of the system using standard information retrieval measures.

1.4 RELATED WORK IN IMAGE RETRIEVAL AND CATEGORIZATION

Content-based image retrieval (CBIR) and image categorization are two closely related and rapidly expanding research areas. CBIR aims at developing techniques that support effective searching and browsing of large image digital libraries based on automatically derived image features. Image categorization refers to classifying images into a collection of predefined categories. We review the related work in CBIR and image categorization.

1.5 RELATED WORK IN MACHINE LEARNING

The field of machine learning is concerned with constructing computer programs that automatically improve with experience. Machine learning draws on concepts and results from many fields, including artificial intelligence, statistics, control theory, cognitive science, and information theory. In this, we summarize, Feature vectors, Accuracy, CNN.

1.6 INTRODUCTION TO CNN

CNN represents a massive breakthrough in image recognition. They're most usually used to parse visual imagery and frequently work behind image classification scenes. A CNN learned features with input data and uses 2D convolutional layers. It means that this type of network is exemplary for processing 2D images. Corresponding to other image classification algorithms, CNN uses barely any pre-processing. It means that they can learn the filters that have to be hand-made in different algorithms. CNN's have an input layer, and an output layer, and hidden layers. The hidden layers habitually consist of convolutional layers.

A CNN works by eliciting features from images, hence eliminating the need for old-fashioned feature extraction. The features are not trained; they're learned while the network trains on a set of images. It makes deep learning models extremely specific to computer vision tasks.

CNN's learn feature detection over tens or hundreds of hidden layers. Each layer raises the complexity of the learned features.

Convolutional Neural Networks, commonly called CNN, is a deep neural network class most commonly used in analyzing visual imagery. CNNs are regularized versions of multilayer perceptron. The "fully- connectedness" of these networks makes them prone to over-fitting data.

Over-Fitting data - Overfitting refers to a model that models the training data too well. Overfitting happens when a model learns the feature and noise in the training data to the degree that it negatively reshapes the model's performance on new data. It means that the noise or random vacillations in the training data are picked up and learned as the model's concepts. The problem is that these concepts do not apply to new data and negatively impact the model's capacity to generalize.

CNN is made up of neurons with learnable biases and weights. Each neuron receives multiple inputs and then takes a weighted sum over them, where it passes it through an activation function and responds with an output.

CNN is a complex feed-forward neural network. CNNs used for image classification and recognition because of its high precision. CNNs are used in many domains, including image and pattern recognition, speech recognition, natural language processing, and video analysis. There are many reasons why CNNs are becoming essential. In traditional models for pattern recognition, feature extractors are hand-designed. In recent days CNN is hugely popular because of its architecture. The best thing is there is no need for feature extraction. The system learns to do feature extraction. The core concept of CNN is that it uses convolution of images and filters to generate invariant features passed on to the next layer. The following layer features are convoluted with different filters to generate more invariant and abstract features. The process continues till one gets the final feature/output, which is invariant to occlusions.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cover the entire visual area.

A ConvNet is able to successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better.

1.7 BULIDING BLOCKS OF CNN

1.7.1 Stride

Stride is a component of convolutional neural networks, or neural networks tuned for the compression of images and video data. Stride is a parameter of the neural network's filter that modifies the amount of movement over the image or video. For example, if a neural network's stride is set to 1, the filter will move one pixel, or unit, at a time. The size of the filter affects the encoded output volume, so stride is often set to a whole integer, rather than a fraction or decimal.

If stride = 1, the filter will move one pixel. If stride = 2, the filter will move two pixel.

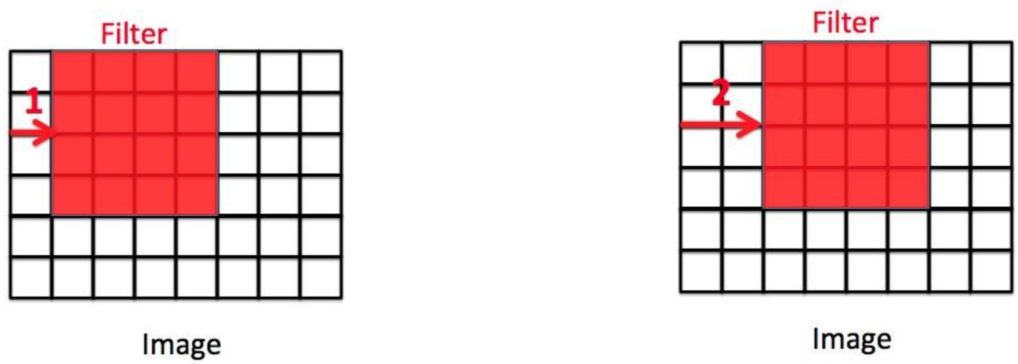

Figure 1.7.1 Stride

1.7.2 Padding

Padding is a term relevant to convolutional neural networks as it refers to the number of pixels added to an image when it is being processed by the kernel of a CNN. For example, if the padding in a CNN is set to zero, then every pixel value that is added will be of value zero. If, however, the zero padding is set to one, there will be a one-pixel border added to the image with a pixel value of zero.

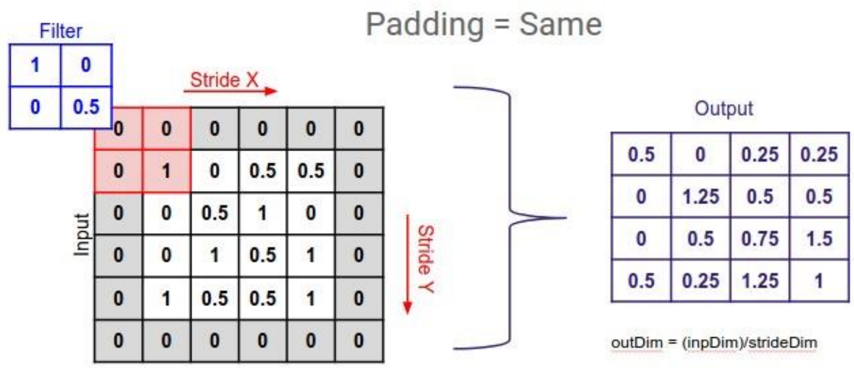

Figure 1.7.2 Padding

1.7.3 Pooling

The pooling operation involves sliding a two-dimensional filter over each channel of feature map and summarizing the features lying within the region covered by the filter.

1.7.4 Max Pooling

Max pooling is a pooling operation that selects the maximum element from the region of the feature map covered by the filter. Thus, the output after max-pooling layer would be a feature map containing the most prominent features of the previous feature map.

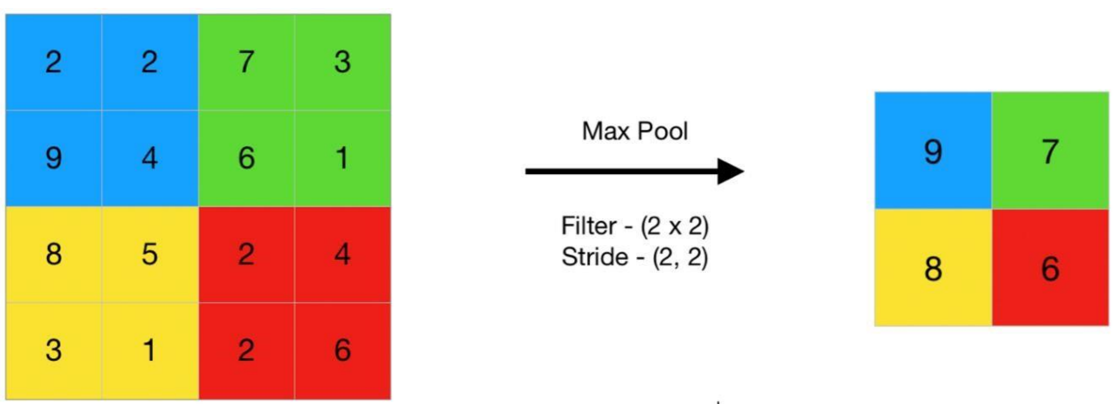

Figure 1.7.4 Max pooling

1.7.5 Average Pooling

Average pooling computes the average of the elements present in the region of feature map covered by the filter. Thus, while max pooling gives the most prominent feature in a particular patch of the feature map, average pooling gives the average of features present in a patch.

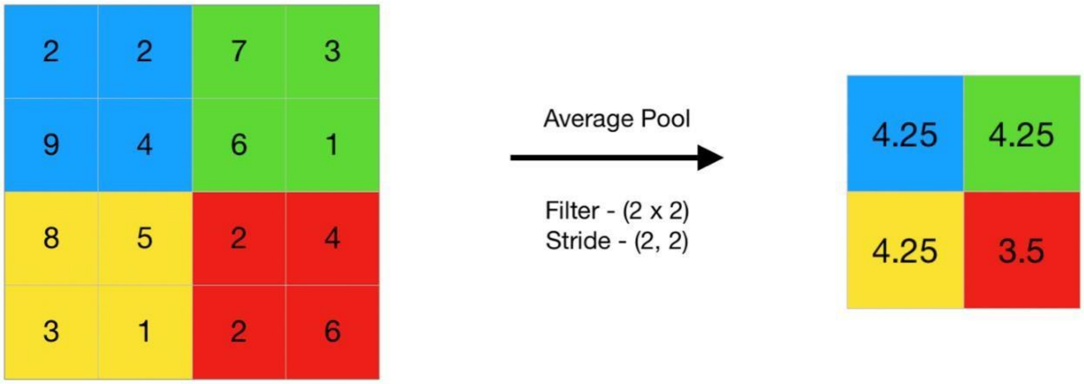

Figure 1.7.5 Average pooling

1.7.6 Image Resizing

Image resizing refers to the scaling of images. It helps in reducing the number of pixels from an image and that has several advantages e.g. It can reduce the time of training of a neural network as more is the number of pixels in an image more is the number of input nodes that in turn increases the complexity of the model.

1.7.7 Flatten layer

Flattening is used to convert all the resultant 2-Dimensional arrays from pooled feature maps into a single long continuous linear vector. The flattened matrix is fed as input to the fully connected layer to classify the image.

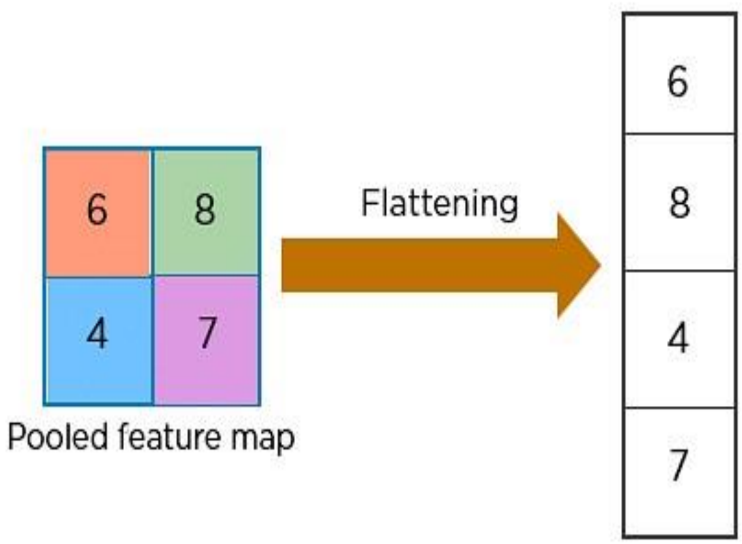

Figure 1.7.7 Flattening

1.7.8 Fully Connected Layer

Fully Connected Layer is simply, feed forward neural networks. Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer.

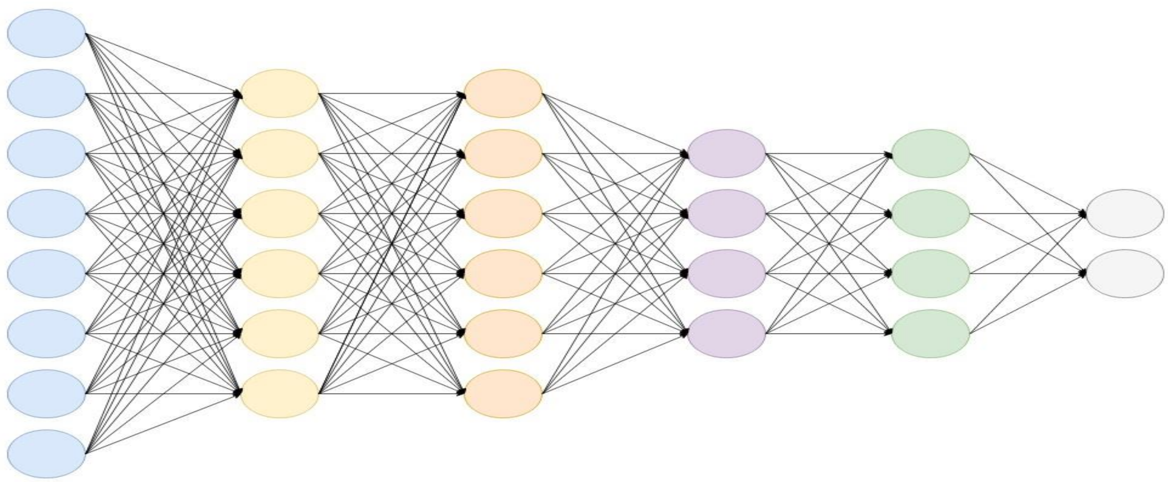

Figure 1.7.8 Fully Connected Network

CHAPTER 2

LITERATURE SURVEY

The reviews based on the methodology used by various authors in their research works for Content Based Image Retrieval (CBIR), following are:

2.1 Content based Image Retrieval using Deep Learning Technique with Distance Measures

The exploration work carried out in [1], Sirisha Kopparthi, Dr. N. K. Kameswara Rao, used Convolution neural networks (CNN) with deep learning performed an excellent performance in numerous operations of image processing. The use of CNN based techniques to extract image features from the final layer and the use of a single CNN structure may be used for identifying matching images. Learning feature extraction and effective similarity comparison comprises the Content-Based Image Retrieval (CBIR). In CBIR feature extraction, as well as similarity measures, play a vital role. The experiments are carried out in two datasets such as UC Merced Land Use Dataset By using a pre-trained model that is trained on millions of images and is fine-tuned for the reclamation task. Pre-trained CNN models are used for generating feature descriptors of images for the retrieval process. This method deals with the attribute extraction from the two fully connected layers, which is present in the VGG-16 and VGG19 network by using transfer learning and retrieval of feature vectors using various similarity measures. The proposed architecture demonstrates an outstanding performance in extracting the features as well as learning features without a prior knowledge about the images. By using various performance metrics.

2.2 Image Retrieval based on the Combination of Color Histogram and Color Moment

The research work carried out in [2], S. Mangijao Singh, K. Hemachandran, used a novel technique for Content based image retrieval (CBIR) that employs color histogram and color moment of images is proposed. The color histogram has the advantages of rotation and translation invariance and it has the disadvantages of lack of spatial information. In this paper, to improve the retrieval accuracy, a content-based image retrieval method is proposed in which color histogram and color moment feature vectors are combined. For color moment, to improve the discriminating power of color indexing techniques, a minimal amount of spatial information is encoded in the color index by dividing the image horizontally into three equal nonoverlapping regions. The three moments (mean, variance and skewness) are extracted from each region (in this case three regions), for all the color channels. Thus, for a HSV color space, 27 floating point numbers are used for indexing. The HSV (16, 4, 4) quantization scheme has been adopted for color histogram and an image is represented by a vector of 256-dimension. Weights are assigned to each feature respectively and calculate the similarity with combined features of color histogram and color moment using Histogram intersection distance and Euclidean distance as similarity measures.

2.3 Content-Based Image Retrieval Using Deep Learning

The exploration work carried out in [3], Anshuman Vikram Singh, used deep learning approaches especially Convolutional Neural Networks (CNN) in working computer vision operations which has inspired author to work on this thesis so as to break the problem of CBIR using a dataset of annotated images. He worked with only 3000 images from 41 orders and 8 classes. In future to make the system more generalized and effective the dataset can be increased and further number of classes similar as man, person, aeroplane etc can be added. The neural network was trained on the dataset for each marker. It can be observed that the confirmation error rate and testing error rate for each marker was relatively low. The stylish test and confirmation error rates are achieved on replication 3, 6 or 9. Training runs for 500 duplications just to validate that there's no change in the error rate after every 100 duplications and once it reaches 500 with a constant rate it stops and returns the stylish error rates. The images in our dataset contain reflections of different regions in the form of XML lines. The Extensible Markup Language (XML) reflections give the annotated image description of each image in the dataset. A semantic gap exists between low- position image pixels captured by machines and the high- position semantics perceived by humans. The thesis shows that deep learning will produce better results for annotated images and which will affect in more accurate image reclamation.

2.4 Fast content-based image retrieval using Convolutional Neural Network and hash function

The exploration work carried out in [4], Domonkos Varga and Tamas Sziranyi, habituated success ways of deep learning similar as Convolution Neural Network (CNN), it has motivated them to explore its operation in their own environment. Due to the explosive increase of online images, content- based image retrieval has gained a lot of attention. The main donation of their work is a new end-to- end supervised learning frame that learns probability- grounded semantic- position similarity and point- position similarity contemporaneously. The main advantage of new mincing scheme that it's suitable to reduce the computational cost of reclamation significantly at the state-of-the- art effectiveness position. They report on comprehensive trials using publicly available datasets similar as Oxford, Leaves and ImageNet 2012 retrieval datasets.

2.5 Medical Image Retrieval using Deep Convolutional Neural Network

The exploration work carried out in [5], Adnan Qayyum, Syed Muhammad Anwar, Muhammad Awais, Muhammad Majid, used a frame of deep learning for CBMIR system by using deep Convolutional Neural Network (CNN) that's trained for bracket of medical images. A major challenge in CBMIR systems is the semantic gap that exists between the low position visual information captured by imaging bias and high position semantic information perceived by mortal. The efficacity of similar systems is more pivotal in terms of point representations that can characterize the high- position information fully. The learned features and the bracket results are used to recoup medical images. For reclamation, stylish results are achieved when class grounded prognostications are used. An average bracket delicacy of 99.77 and a mean average perfection of 0.69 is achieved for reclamation task. The proposed system is best suited to recoup multimodal medical images for different body organs.

2.6 Content based image retrieval using deep learning process

The exploration work carried out in [6], R. Rani Saritha, Varghese Paul, P. Ganesh Kumar, used the deep belief network (DBN) system of deep learning which is used to prize the features and bracket and is an arising exploration area, because of the generation of large volume of data. A multi-feature image reclamation system is introduced by combining the features of color histogram, edge, edge directions, edge histogram and texture features, etc. In this model, the content grounded image will be uprooted from a collection of intended image groups. After performing some pre-processing way like selection junking, its below features are uprooted and are stored as small hand lines. CBIR uses image content features to search and recoup digital images from a large database. A variety of visual point birth ways have been employed to apply the searching purpose. Due to the calculation time demand, some good algorithms aren't been used. The reclamation performance of a content- grounded image reclamation system crucially depends on the point representation and similarity measures. The ultimate end of the proposed system is to give an effective algorithm. The proposed system is tested through simulation in comparison and the results show a huge positive divagation towards its performance.

2.7 Content-based Image Retrieval from Videos using CBIR and ABIR algorithm

The exploration work carried out in [7], Vrushali A. Wankhede, used Annotation-based image retrieval (ABIR) and Content based image retrieval (CBIR). Videotape reclamation can be used for videotape hunt and browsing which are useful in web operations. Selection of uprooted features play an important part in content-based videotape reclamation. There are two types of point birth, low position point birth and high position point birth. Low position point birth grounded on color, shape, texture, spatial relationship. The main thing of this paper is that, stoner can give the two different types of input in the form of image query and the textbook query. The ABIR is more practical in some other sphere. In that, they will get the set of frames or set of images from the below step, also give the labelling of one image from every videotape. The information store in the XML train information contains their path, images assign with the word or textbook. Reflection means what's in the image, what's it about, what does it bring? Give the detail description to that image. Prepare annotated data. Take any one word or textbook as an input from the annotated data. Find the keyword from pre-processed data if they match take that image as an affair image. Display the result means retrieves the image by using the textbook query hunt. With the help of labelling, they got the image from the particular path. The main thing of this paper is to apply the multi query image retrieval.

2.8 Context-aware Recommendation System using Content Based Image Retrieval with Dynamic Context Considered

The exploration work carried out in [8], Yuta Miyazawa, Yukiko Yamamoto, Takashi Kawabe, proposed paper conceptually proposes a environment-apprehensive recommendation system that gives optimal information for druggies grounded on 1) a content- based image retrieval (CBIR) medium to search the similar images aiming to prize the detailed information to the textbook-indescribable images 2) the contextual information of similar analogous images searched from the Web, and 3) stoner’s dynamic environment or situation considering time-variant factors as well as space factors. It's anticipated to increase the perfection or optimality of recommendation by matching and fusing the environment of analogous images attained by CBIR with textual and star information about stoner’s situation or dynamic environment. is described just at a abstract position; thus, as a coming step for the exploration, the prototype system will be developed grounded on more detailed perpetration design. Also, the utility and effectiveness of the proposed idea and its perpetration will be validated through the evaluation trial using the prototype system.

2.9 Content-based image retrieval: A review of recent trends

The exploration work carried out in [9], Ibtihaal M. Hameed, Sadiq H. Abdulhussain & Basheera M. Mahmmod, says that there are adding exploration in this field, this paper checks, analyses and compares the current state-of-the- art methodologies over the last six times in the CBIR field. This paper also provides an overview of CBIR frame, recent low- position point birth styles, machine literacy algorithms, similarity measures, and a performance evaluation to inspire farther exploration sweats. To negotiate an effective CBIR frame, the frame's factors must be chosen in a balanced way; this study helps in probing these factors. To add up, an algorithm that elevates the semantic gap is largely demanded. The design of the algorithm should consider the following first, the algorithm needs to consider the point birth as well as similarity measure as they impact the performance of the CBIR. Second, further features can be uprooted to enhance the delicacy of the CBIR and maintain the computational cost as it's considered important factor in the real- time operations. Third, incorporating original and global features will lead to a balanced design because original features are more robust against scale, restatement and gyration changes than global features; and global features are briskly in point birth and similarity measures. Fourth, machine literacy algorithms can be used in different stages of CBIR to increase system delicacy but need further attention to be paid to their calculation cost. Eventually, there's a dicker between system's delicacy and computational cost.

2.10 A Decade Survey of Content Based Image Retrieval using Deep Learning

The exploration work carried out in [10], Shiv Ram Dubey, this check also presents a performance analysis for the state-of-the-art deep literacy grounded image reclamation approaches. The Mean Average Precision (chart) reported for the different image reclamation approaches is epitomized. ThemAP@5000 (i.e., 5000 recaptured images) using colorful being deep learning approaches is epitomized over CIFAR-10, NUS-WIDE and MS COCO datasets. The results over CIFAR-10, ImageNet and MNIST datasets using different state-of-the- art deep literacy grounded image reclamation styles are collected in terms of themAP@1000. ThemAP@54000 using many styles is reported over the CIFAR-10 dataset. The standard chart is also depicted by considering all the recaptured images for CIFAR-10 dataset using some of the available literature. In general, information reclamation algorithms in recent times attained the benefits of using different machine learning algorithms similar as deep literacy, SVM, and k- means. Thus, they're prognosticated to admit further attention in the forthcoming times.

CHAPTER 3

SYSTEM DESIGN AND SPECIFICATION

3.1 EXISTING SYSTEM

In earlier days, image retrieval from large image database can be done by:

a) Automatic image Annotation and Retrieval using Cross Media relevance models.

b) Concept Based Query Expansion.

c) Query System Bridging - The semantic gap for large image databases.

d) Detecting image purpose in World Wide Web documents.

3.2 PROPOSED SYSTEM

Relevance feedback is an interactive process that starts with normal CBIR. The user input a query, and then the system extracts the image features and measures the distance with images in the database. We have used machine learning so that we can select more accurate image. Here, large image database can be added for training set. We have used feature vectors in every layer i.e., 15 to 16 layers can be added and more. 2000 and more million images can be shown. An initial retrieval list is generated. Digital images database opens the way for Content-based searching. Content Based Image Retrieval occupies a well ranked position among the research areas as it provides the practical solution for narrowing the semantic gap between the image retrieval process and human perception.

3.3 HARDWARE REQUIREMENTS

• Processor: Pentium IV 2.4 GHz.

• Hard Disk: 250 GB.

• Monitor: 15 VGA Color.

- RAM: 1 GB
- Mouse: Optical
- Keyboard: Multimedia

3.4 SOFTWARE REQUIREMENTS

- Operating system: Windows XP Professional / Windows7 or More
- Coding Language: Java
- IDE: MATLAB 2019

CHAPTER 4

DESIGN

4.1 CONTENT-BASED IMAGE RETRIEVAL: OVERVIEW

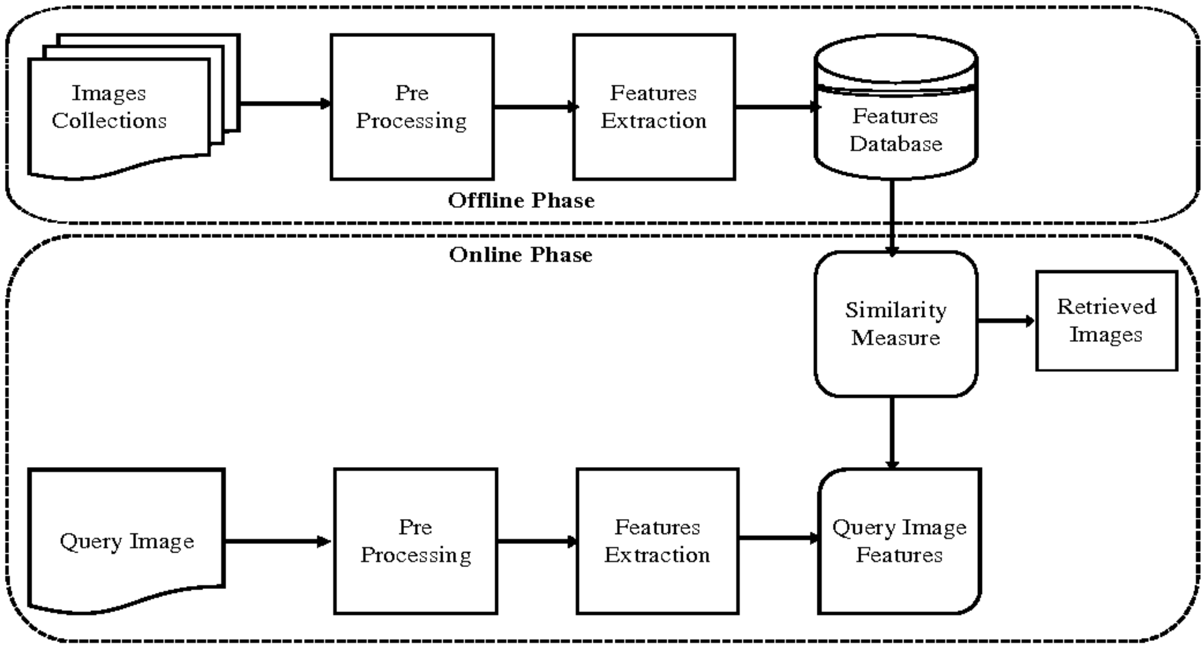

Figure 4.1 Shows a generic description of a standard image retrieval system.

Any CBIR system involves at least four main steps:

- Feature extraction and indexing of image database according to the chosen visual features, which form the perceptual feature space, e.g., color, shape, texture or any combination of the above.

- Feature extraction of query image (s)

- Matching the query image to the most similar images in the database according to some image similarity measure. This forms the search part of the CBIR - User interface and feedback which governs the display of the outcomes, their ranking, the type of the user interaction with possibility of refining the search through some automatic or manual preference (weighting) scheme, etc.

Query Techniques: Query via illustration is a query manner that includes providing the CBIR procedure with an example image that it'll then base its search upon.

Semantic Retrieval: The perfect CBIR process from a person perspective would contain what's known as semantic retrieval, the place the user makes a request like “to find pictures of Abraham Lincoln”. This sort of open-ended assignment is very complex for desktops to perform pictures of excellent Danes seem very distinctive and Lincoln may not always be dealing with the digital camera or in the identical pose.

Content Compare Content Comparison using distance measure: The most common process for evaluating two images in CBIR is utilizing an image distance measure. An image distance measure compares the similarity of two images in various dimensions corresponding to colors.

Common features for image retrieval: A function is outlined as capturing a particular visual property of an image. Regularly, image features can be both world or regional. The global aspects describe the visible content material of the complete image, whereas local features describe the areas or objects (i.e., A small group of pixels) of the image content. The potential of global extraction is its high speed for both extracting features and computing similarity. However, global features are often too rigid to represent an image. Specifically, they can be oversensitive to location and hence fail to identify important visual characteristics. Local feature approaches give a somewhat preferred recovery adequacy over worldwide elements. They speak to images with different focuses in a component space as opposed to single point worldwide element representations. While local methodologies give more robust data, they are more costly computationally because of the high dimensionality of their component spaces and more often than not require closest neighbors guess to perform focuses coordinating.

A few important features that can be utilized as a part of IR will be clarified in the following subsection

Color Features: The color has broadly been utilized as a part of IR systems, as a result of its simple and quick calculation. Color is additionally a natural element and assumes an essential part in image matching. Most IR systems use color space, histogram, moments, color coherence vector, and prevailing color descriptor represent color The color histogram is a standout amongst the most regularly used color highlight representation in IR. The first thought to utilize histogram for retrieval comes from Swain and Ballard, who understood the ability to distinguish an item utilizing color is much bigger than that of a gray scale. Despite the fact that the worldwide color feature is easy to compute and can give sensible discriminating power in IR. It tends to give an excess of false positives when the image accumulation is huge. Numerous research results recommended that utilizing color design is a superior answer for IR. To extend the worldwide color feature to a local one, a characteristic methodology is to isolate the whole image into sub- blocks and extract color features from each of the sub- blocks. The advantage of this methodology is its precision while the disadvantage is the general troublesome issue of reliable image segmentation.

Local Image Features: Local features are small square, sub-images extricated from the first image. They can be considered to have two different sorts:

- The patches: They separated from the images at salient points and dimensionality diminished utilizing Principal Component Analysis (PCA) transformation.
- SIFT descriptors They removed at Harris interest focuses. To utilize local features for IR, three different techniques are accessible.
- Direct transfer: The local features extricated from every database image and from the query image. At that point, the closest neighbors for each of the local features of the query searched and the database images containing the greater part of these neighbors returned.
- Local feature image distortion model (LFIDM): The local features from the query image contrasted with the local features of every image of the database and the separations between them summed up. The images with the most reduced aggregate separations are returned.
- Histograms of local features: A moderately large number of local points from the database is clustered after which each and every database image represented by using a histogram of indices of those clusters. These histograms are then when compared using the Jeffrey divergence.

CHAPTER 5

METHODOLOGY

5.1 DATASETS DESCRIPTION

The data used in this research are images of horse database. The horse database is a subset of the animal database. It consists of 1000 natural images in JPEG format in different sizes shown in below figure.

Figure 5.1 Sample of Dataset

5.1.1 Image File Formats

Image file formats provide a standardized way to store the information describing an image in a computer file. A variety of image file formats are available at present, Like JPEG, GIF, BMP, TIFF.

* JPEG: Is short for Joint Photographic Experts Group. It has '.jpg', '.jpeg' as the allowed extensions. It is the most common format for storing and transmitting photographic images on the World Wide Web and is a commonly used method of compression for photographic image.

5.1.2 Images Types

The image types include: binary, gray scale, color image, multispectral. In this research we used gray scale.

* Color Images: can be modeled as three-band monochrome image data where each band of data corresponds to a different color. The actual information stored in the digital image data is the gray-level information in each spectral band. Typical color image is represented as red, green, and blue (RGB). corresponding color image would have 24 bit/pixel (8 bit for each of three color).

*Gray-scale images: Gray-scale image are referred to as monochrome (one color) images. They contain gray-level information, no color information. The number of bits used for each pixel determines the number of different gray levels available. The typical gray-scale image contains 8 bit/pixel data, which allows us to have 256 different gray levels.

5.2 COLOR MODEL

Color helps in recognition of images by human brain and is the main feature for recognition of visual features in image retrieval. Color depends on reflection and processing of that information occurs in the brain. Color features are relatively easy to extract and match, and have been found to be effective for indexing and searching of colour images in image databases. One of the main aspects of color feature extraction is the choice of a color space. A color space is a multidimensional space in which the different dimensions represent the different components of color. An example of a color space is RGB.

The RGB color model is an additive color model in which the red, green, and blue primary colors of light are added together in various ways to reproduce a broad array of colors.

The main purpose of the RGB color model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography.

RGB is a device-dependent color model: different devices detect or reproduce a given RGB value differently, since the color elements (such as phosphors or dyes) and their response to the individual red, green, and blue levels vary from manufacturer to manufacturer, or even in the same device over time. Thus, an RGB value does not define the same color across devices without some kind of color management.

Color spaces such as HSV, CIE 1976 (LAB), and CIE 1976 (LUV) are generated by non-linear transformation of the RGB space. The CIE 1931 color spaces are the first defined quantitative links between distributions of wavelengths in the electromagnetic visible spectrum, and physiologically perceived colors in human color vision. The mathematical relationships that define these color spaces are essential tools for color management, important when dealing with color inks, illuminated displays, and recording devices such as digital cameras. The system was designed in 1931 by the "Commission Internationale de l'éclairage", known in English as the International Commission on Illumination.

The HSV color space is widely used in the field of color vision. The chromatic components hue, saturation and value correspond closely with the categories of human color perception. The HSV values of a pixel can be transformed from its RGB representation according to the following formula:

$$H = \cos^{-1} \frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}$$

$$S = 1 - \frac{3[\min(R,G,B)]}{R+G+B}$$

$$V = \left(\frac{R+G+B}{3}\right)$$

5.3 COLOR QUANTIZATION

In computer graphics, color quantization or color image quantization is quantization applied to color spaces; it is a process that reduces the number of distinct colors used in an image, usually with the intention that the new image should be as visually similar as possible to the original image. Computer algorithms to perform color quantization on bitmaps have been studied since the 1970s. Color quantization is critical for displaying images with many colors on devices that can only display a limited number of colors, usually due to memory limitations, and enables efficient compression of certain types of images.

Most standard techniques treat color quantization as a problem of clustering points in three-dimensional space, where the points represent colors found in the original image and the three axes represent the three-color channels. Almost any three-dimensional clustering algorithm can be applied to color quantization, and vice versa. After the clusters are located, typically the points in each cluster are averaged to obtain the representative color that all colors in that cluster are mapped to.

The three-color channels are usually red, green, and blue, but another popular choice is the Lab color space, in which Euclidean distance is more consistent with perceptual difference.
The most popular algorithm by far for color quantization, invented by Paul Heckbert in 1979, is the median cut algorithm.

CHAPTER 6

SYSTEM MODEL

6.1 FRAMEWORK DESCRIPTION PROPOSED CBIR SYSTEM

In this section, the methods used for developing CBIR method includes the integration of different components given in Figure.7.1.

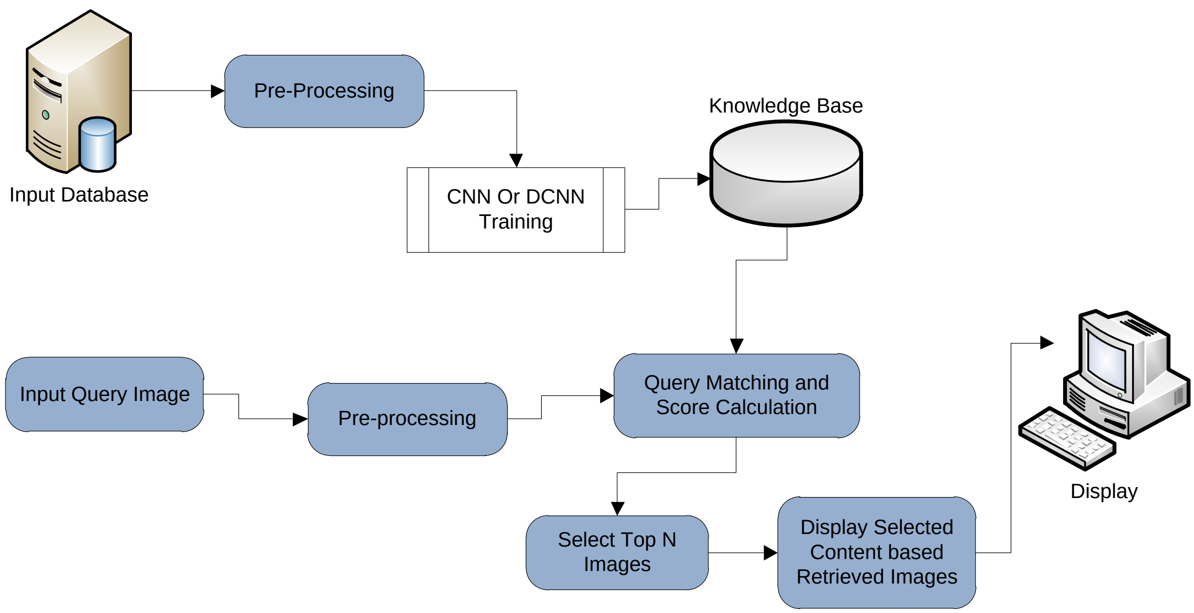

Figure 6.1 Proposed System.

6.1.1 Offline Feature Extraction

In the first stage is collecting images and then extract the information from these images by one of the ways mentioned in chapter (2), and the information is stored in the database in the form of feature vectors. The sample images are input in the second stage, then the images feature will extract and go to the third stage where initialize weight are obtained by calculating the similarity between the query image and images stored in the database using predefined distance measure, the results are then ranked and the weight feature vector saved. Finally, we assign weights to each feature respectively. This process generates and stores a new feature vector.

6.1.2 Apply Algorithm for Feature Extraction

Image feature selection plays an important role because it can represent content of the image efficiency and higher accuracy. There are many methods to extract these features, in this study uses three feature extraction methods i.e., color histogram, color moment, Gabor filter feature extraction.

6.1.2.1 Histogram Feature Extraction

In this study used the histogram approach because its extracts both local and global features of color, fast computation and simple.
Proposed algorithm to find the histogram of an image is following:

Step 1: Read the image.

Step 2: Convert the images from RGB color space into HSV color space.

Step 3: Split image into h, s and v planes.

Step 4: Compute histogram.

Step 5: Store the value in a database.

6.1.2.2 Color Moment Feature Extraction

In this study used the moment approach because its compact feature of color and sensitive to spatial information.
Proposed algorithm to find the moment of an image is following:

Step 1: Read the image.

Step 2: Split image into R, G and B planes.

Step 3: Compute mean value for each channel.

Step 4: Compute standard Deviation for each channel.

Step 5: Construct feature vector and store in a database.

6.1.2.3 Gabor filters feature extraction

There are different approaches of texture feature extraction, in this study used

Gabor filters because it detects different frequency and orientation.

Our proposed algorithm to find the Gabor filters of image is following:

Step 1: Read the image.

Step 2: Convert the RGB images into gray level.

Step 3: Construct bank of 24 Gabor filters using the Gabor function with 4 scales and 6 orientations.

Step 4: Apply Gabor filters on the gray level of the image by convolution.

Step 5: Get the energy distribution of each of the 24 filters responses.

Step 6: Compute the mean 11 and the standard deviation o of each energy distribution.

Step 7: Construct feature vector and store in a database.

6.1.3 Online Image Retrieval

This phase describes the retrieval process. The retrieval process is initiated when a user queries the system using an example image. The query image is converted into the representation of feature vector using the same feature extraction that was used for building the feature database. The similarity measure is a calculate the distance between the feature vectors of query image and new feature vectors database. Finally, the ranks the search results and then returns the images that are most similar to query examples.

6.1.4 Input Query

- This module receives inputs from the Feature extraction Module.
- Extracted features from the Feature extraction Module are clustered and stored by this module.
- Features are divided in to several clusters based on their similarity.
- Only the features extracted by the image set are stored.
- This module is very important, because otherwise need to extract features of the image set in each time when the application reopens.

- As this module stores features in a file, features are stored permanently until user extract features of another image set.
- This module is used to give the image as a query input.
- The feature extraction will be done on this image.
- Results produce by this module is used to query matching and score calculation.

6.1.5 Query Matching and Score Calculation

- First this module calculates the nearest cluster for the queried image based on the features of it.
- Then this module retrieves the stored features of each image in that selected cluster and calculates the similarity value for each image with the extracted features of the querying image.
- This outputs a value for each image in the selected cluster with relevance to the similarity with the query image.
- Then these calculated similarity values are sorted.
- Finally send the resulted image set with their similarity value to the Display module.
- This module retrieves the stored features of each image in that knowledge base and calculates the similarity value for each image with the extracted features of the querying image.
- This outputs a value for each image with relevance to the similarity with the query image.
- Then these calculated similarity values are sorted. Finally sends the resulted image set with their similarity value to the Display module.

6.1.6 Display Model

This module retrieves the resulted image set and the similarity values from the Score Calculation Module and consists of three main functionalities as described below.

- Index the image set user input, according the number of clusters given.
- User has the ability to see the member images each cluster have after indexing.
- Search images from the image set that is similar to the image user is querying.

6.2 CONTENT BASED IMAGE RETRIEVAL SYSTEM

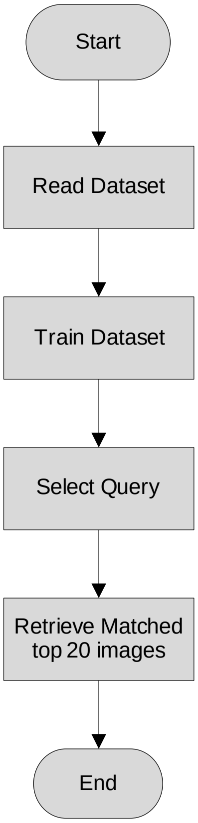

Figure 6.2 Flow diagram of CBIR

a) Read Dataset:

The images in the training dataset are read. In Machine Learning we have to try to generate certain patter of images. So, to what kind of datasets we give names, to understand this, read operation is carried out.

b) Train Dataset:

First, we read the file structure, then we extract features of images in the dataset and create knowledge base. This Knowledge base contains all feature extracted images of the dataset uploaded.

c) Select Query:

An image from the testing set is selected and added for retrieval of similar and selected images.

d) <u>Retrieve Matched top 20 images:</u>

The images that are more accurate or similar to the query image are retrieved. The count of how many images is to be retrieved can be given. Here, we have given the count to be 20. The image displayed here is received from knowledge base.

6.3 TRAINING DATASET

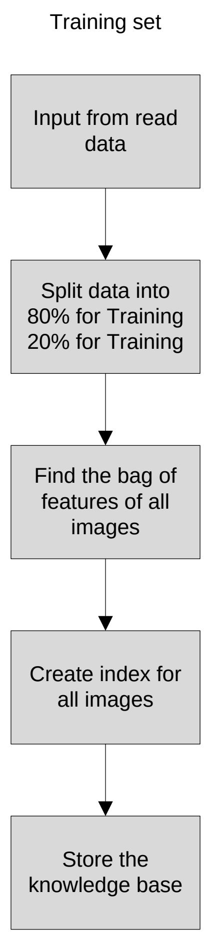

Figure 6.3 Flow Diagram of Training Set

a) <u>Input from read data:</u>

Image datasets used in this system are read into fine structure for feature extraction.

b) <u>Split Data:</u>

The data that is read is then split into training set and testing test for query and retrieval process. Among which, training set 80% of the data and testing set contains 20% of the data.

c) Bag of Features:

Bag of features is created containing entire dataset. In this feature point locations are selected using grid method. Then, SURF features are selected from the selected feature point locations. The images are categorized based on the classes that belongs to. The grid step is [8 8] and the block width is [32 64 96 128].

d) Create Index for All Images:

Since the images are stored in files, certain index values are assigned to all the images present in the bag of features. This is done after feature extraction.

e) Store Knowledge Base:

The images of the specify indexes are stored in the knowledge base for easy retrieval for the query images.

CHAPTER 7

APPLICATIONS

A wide range of possible applications for CBIR technology has been identified. Potentially fruitful areas include:

- Crime prevention
- The military
- Intellectual property Architectural and engineering design
- Fashion and interior design
- Journalism and advertising
- Medical diagnosis
- Geographical information and remote sensing systems
- Cultural heritage
- Education and training
- Home entertainment
- Web searching.

Closer examination of many of these areas reveals that, while research groups are developing prototype systems, and practitioners are experimenting with the technology, few examples of fully operational.

CBIR systems can yet be found. A search of public-domain sources, including the trade and scientific literature and the Web, suggests that the current state of play in each of these areas at the end of 1998 is as follows:

7.1 CRIME PREVENTION

Law enforcement agencies typically maintain large archives of visual evidence, including past suspects' facial photographs (generally known as mugshots), fingerprints, tyre treads and shoeprints. Whenever a serious crime is committed, they can compare evidence from the scene of the crime for its similarity to records in their archives. Strictly speaking, this is an example of identity rather than similarity matching, though since all such images vary naturally over time, the distinction is of little practical significance. Of more relevance is the distinction between systems designed for verifying the identity of a known individual (requiring matching against only a single stored record), and those capable of searching an entire database to find the closest matching records

7.2 THE MILITARY

Military applications of imaging technology are probably the best-developed, though least publicized. Recognition of enemy aircraft from radar screens, identification of targets from satellite photographs, and provision of guidance systems for cruise missiles are known examples – though these almost certainly represent only the tip of the iceberg. Many of the surveillance techniques used in crime prevention could also be relevant to the military field.

7.3 INTELLECTUAL PROPERTY

Trademark image registration, where a new candidate mark is compared with existing marks to ensure that there is no risk of confusion, has long been recognized as a prime application area for CBIR. Copyright protection is also a potentially important application area. Enforcing image copyright when electronic versions of the images can easily be transmitted over the Internet in a variety of formats is an increasingly difficult task. There is a growing need for copyright owners to be able to seek out and identify unauthorized copies of images, particularly if they have been altered in some way.

7.4 ARCHITECTURAL AND ENGINEERING DESIGN

Architectural and engineering design share a number of common features – the use of stylized 2- and 3-D models to represent design objects, the need to visualize designs for the benefit of non-technical clients, and the need to work within externally-imposed constraints, often financial. Such constraints mean that the designer needs to be aware of previous designs, particularly if these can be adapted to the problem at hand. Hence the ability to search design archives for previous examples which are in some way similar, or meet specified suitability criteria, can be valuable.

7.5 FASHION AND INTERIOR DESIGN

Similarities can also be observed in the design process in other fields, including fashion and interior design. Here again, the designer has to work within externally-imposed constraints, such as choice of materials. The ability to search a collection of fabrics to find a particular combination of color or texture is increasingly being recognized as a useful aid to the design process. So far, little systematic development activity has been reported in this area. Attempts have been made to use general-purpose CBIR packages for specific tasks such as color matching of items from electronic versions of mail-order catalogues, and identifying textile samples bearing a desired pattern, but no commercial use appears to be made of this at present.

7.6 JOURNALISM AND ADVERTISING

Both newspapers and stock shot agencies maintain archives of still photographs to illustrate articles or advertising copy. These archives can often be extremely large (running into millions of images), and dauntingly expensive to maintain if detailed keyword indexing is provided. Broadcasting corporations are faced with an even bigger problem, having to deal with millions of hours of archive video footage, which are almost impossible to annotate without some degree of automatic assistance. This application area is probably one of the prime users of CBIR technology at present – though not in the form originally envisaged. In the early years of CBIR development, hopes were high that the technology would provide efficient and effective retrieval of still images from photo libraries, eliminating or at least substantially reducing the need for manual keyword indexing. Disillusionment set in as the realization spread that the CBIR techniques under development were of little use for retrieval by semantic content. Stock shot agencies now seem likely to base their retrieval systems on manual key wording for many years to come, though a few are experimenting with the use of CBIR software as adjuncts to keyword indexing.

CHAPTER 8

EXPERIMENT RESULTS AND DISCUSSION

In this chapter, we present the evaluation of our proposed system that was introduced in the previous chapter. We compare our system results with other CBIR systems that use three feature or same image database.

8.1 IMPLEMENTATION ENVIRONMENT

The proposed CBIR is implemented using MATLAB (R2019a) version 8.1.0.604 with image processing toolbox on Intel Core 2.60 GHz processor with 8 GB of RAM and also using horse database, which consist of 10 classes and each class containing 100 images mentioned in Chapter 6.

8.2 PERFORMANCE EVALUATION METRICS FOR CBIR SYSTEM

For experimental results it is significant a suitable metric for performance evaluation. We have used average precision and it is defined as follows:

Number of relevant images retrieved Precision =

—Total Number of images retrieved

8.3 EXPERIMENTAL RESULTS

In this section, we present the experimental result of our work. For each experiment, we select some query images randomly from different classes.

Each query returns the top 10 images from the database. In particular, a retrieved image is considered a match if and only if it is in the same class as the query image. Present the six experimental results from our work.

8.3.1 Options Menu

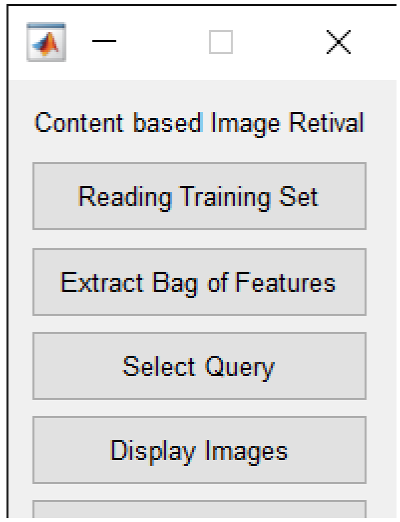

Figure 8.3.1 Option Menu Screenshot

8.3.2 Reading Training Image Dataset

answer = 900

Reading Training Image Dataset ... Done

8.3.3 Extract Bag of Features

Creating Bag-Of-Features.

----

* Image category 1: beaches
* Image category 2: bus
* Image category 3: dinosaurs
* Image category 4: elephants
* Image category 5: flowers
* Image category 6: foods
* Image category 7: horses
* Image category 8: monuments
* Image category 9: mountains_and_snow
* Image category 10: peolpe_in_Africa
* Selecting feature point locations using the Grid method.

* Extracting SURF features from the selected feature point locations.

*The Grid Step is [8 8] and the Block Width is [32 64 96 128].

* Extracting features from 720 images...done. Extracted 4423680 features.

* Keeping 80 percent of the strongest features from each category.

* Using K-Means clustering to create a 500-word visual vocabulary.

* Number of features: 3538940

* Number of clusters (K): 500

* Initializing cluster centers...100.00%.

* Clustering...completed 36/100 iterations (~23.65 seconds/iteration) ...converged in 36 iterations.

* Finished creating Bag-Of-Features

Creating an inverted image index using Bag-Of-Features.

Encoding images using Bag-Of-Features.

----

* Image category 1: beaches

* Image category 2: bus

* Image category 3: dinosaurs

* Image category 4: elephants

* Image category 5: flowers

* Image category 6: foods

* Image category 7: horses

* Image category 8: monuments

* Image category 9: mountains_and_snow

* Image category 10: peolpe_in_Africa

* Encoding 900 images...done.

Finished creating the image index.

Extract Bag of Features ... Done

8.3.4 Selecting the query image

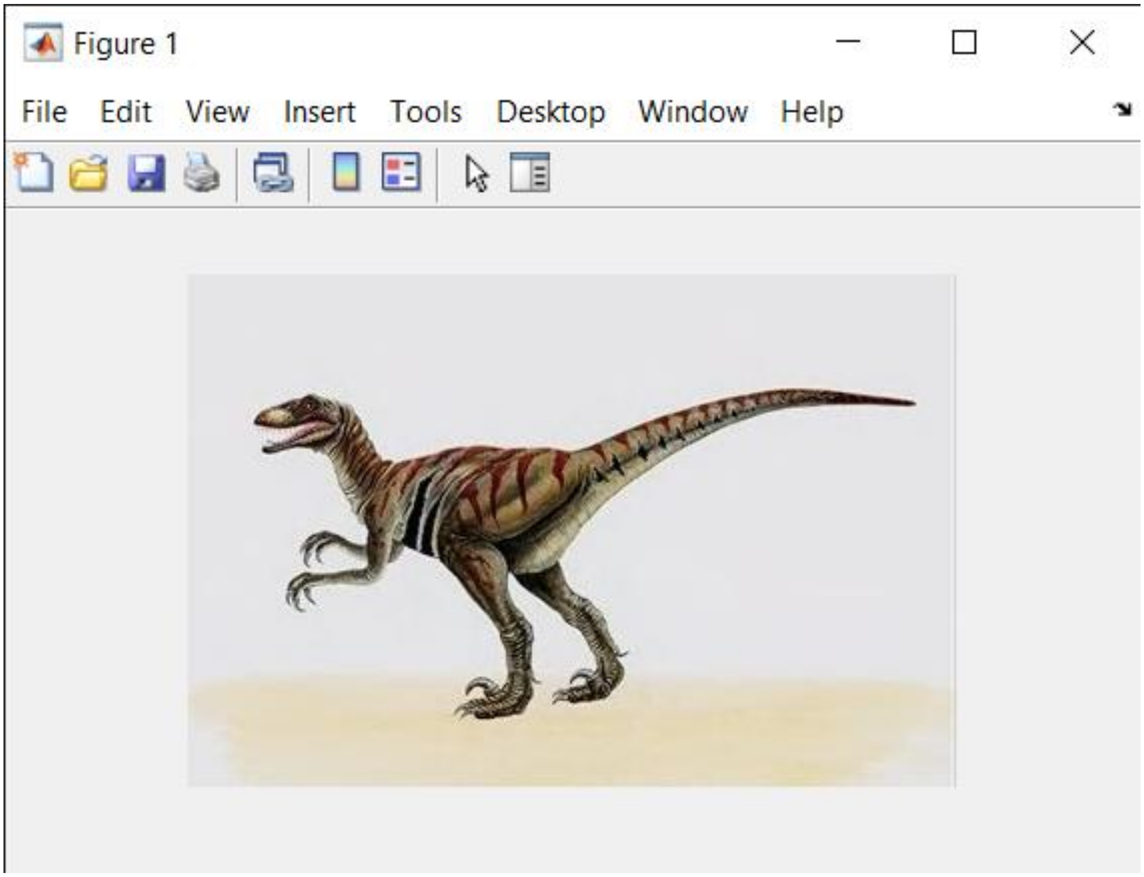

Figure 8.3.4 Screenshot of Selecting the query image

8.3.5 Experiment (1): Dinosaur Class

Selected the query image from the dinosaur class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.5.

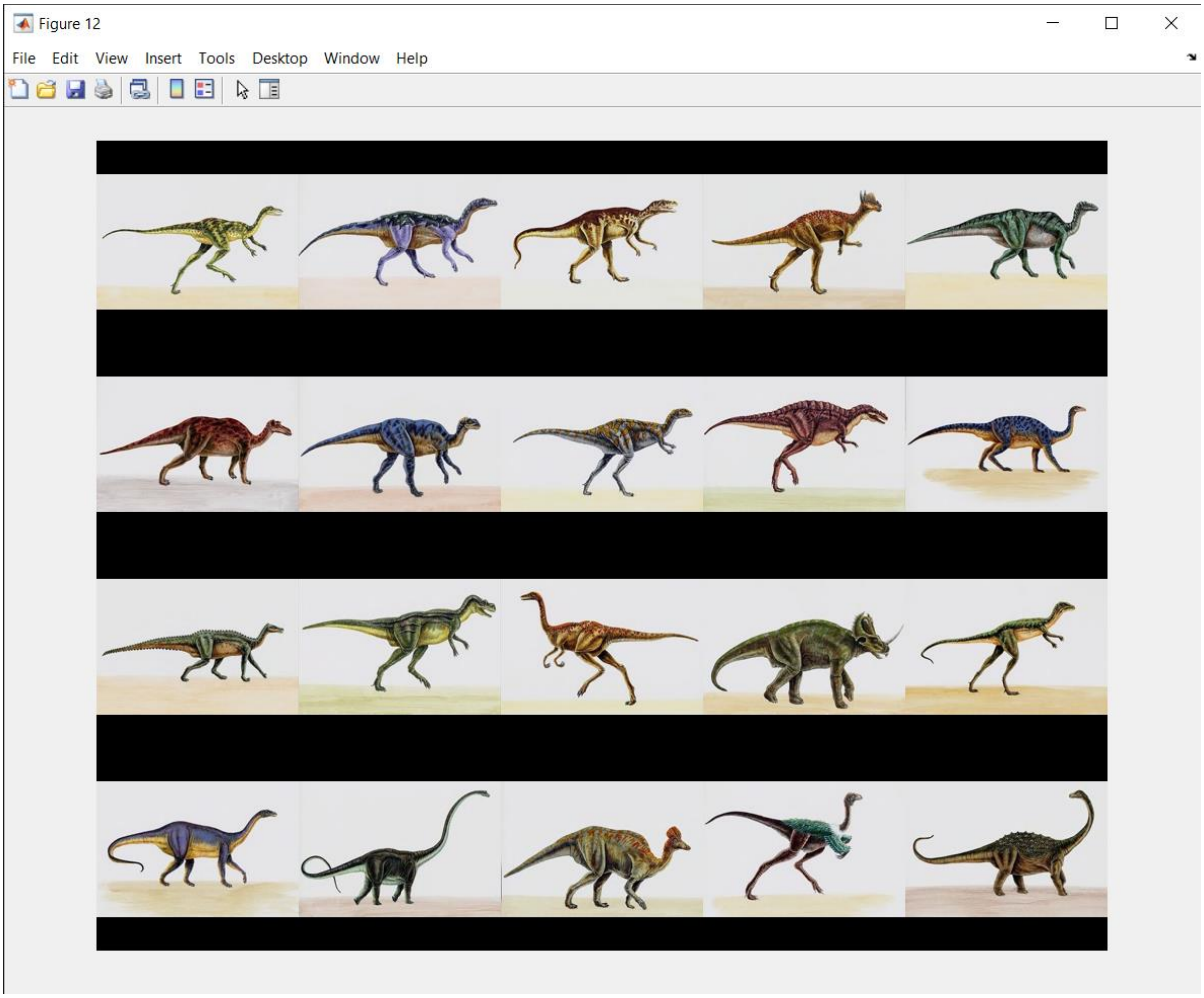

Figure 8.3.5 Dinosaur Query Result

Accuracy 100%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 100% accurate images.

8.3.6 Experiment (2): Flower Class

Selected the query image from the flower class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.6.

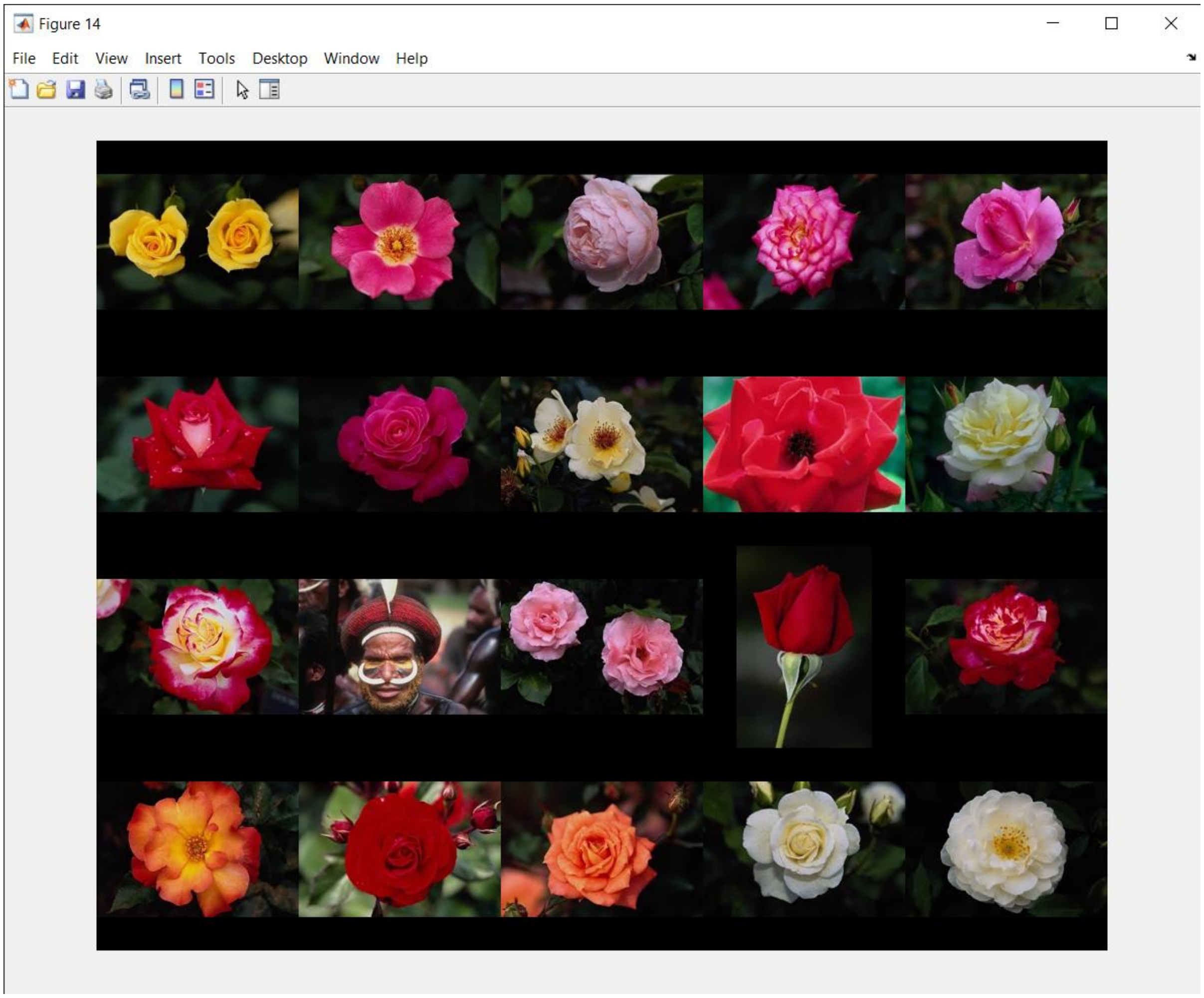

Figure 8.3.6 Flower Query Result

Accuracy 95%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 95% accurate images.

8.3.7 Experiment (3): African People Class

Selected the query image from the African people class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.7.

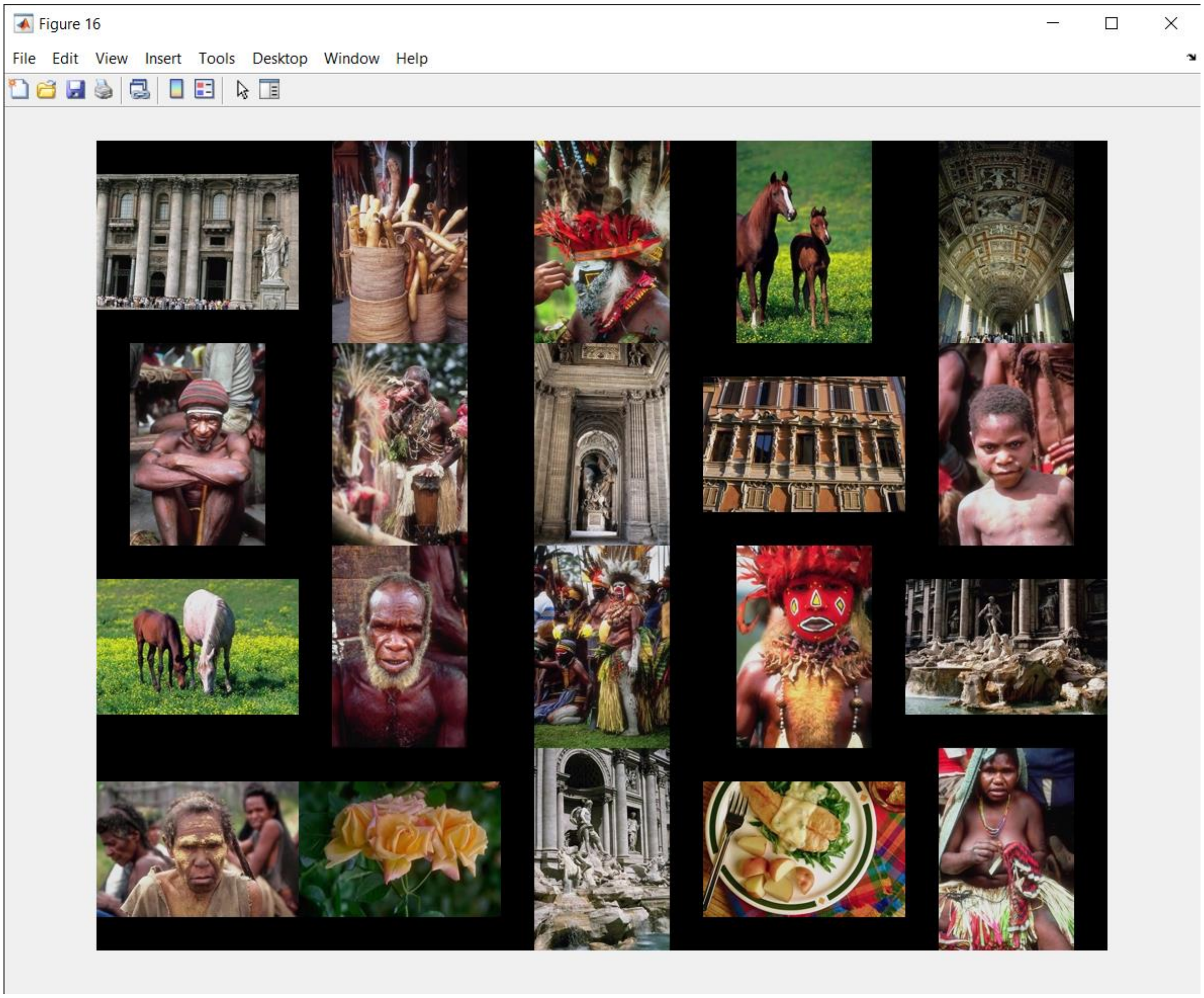

Figure 8.3.7 African People Query Result

Accuracy 50%

The result by the system is partially relevant to query image. The retrieved image does not belong to the same class. So, the system retrieves all images of the class because top 20 images are relevant. Hence, we obtain 50% accurate images.

8.3.8 Experiment (4): Beach Class

Selected the query image from the Beach class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.8.

Figure 8.3.8 Beach Class Query Result

Accuracy 97%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 97% accurate images.

8.3.9 Experiment (5): Bus Class

Selected the query image from the Bus class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.9.

Figure 8.3.9 Bus Class Query Result

Accuracy 100%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 100% accurate images.

8.3.10 Experiment (6): Elephant Class

Selected the query image from the Elephant class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.10.

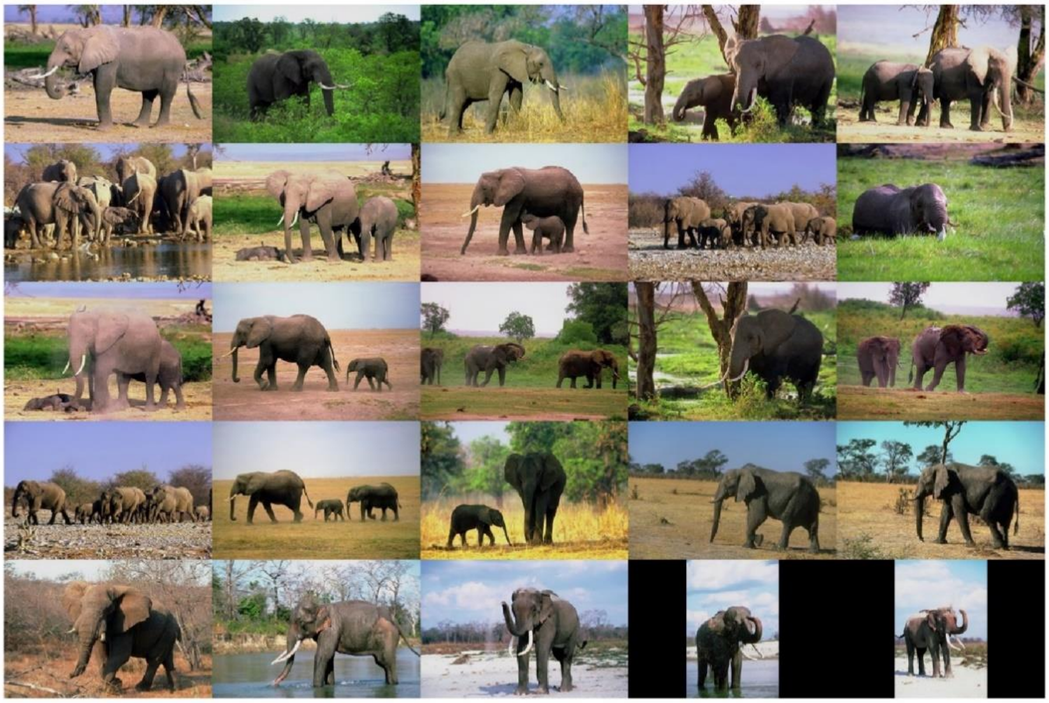

Figure 8.3.10 Elephant Class Query Result

Accuracy 100%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 100% accurate images.

8.3.11 Experiment (7): Food Class

Selected the query image from the Food class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.11.

Figure 8.3.11 Food Class Query Result

Accuracy 100%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 100% accurate images.

8.3.12 Experiment (8): Mountain Class

Selected the query image from the Mountain class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.12.

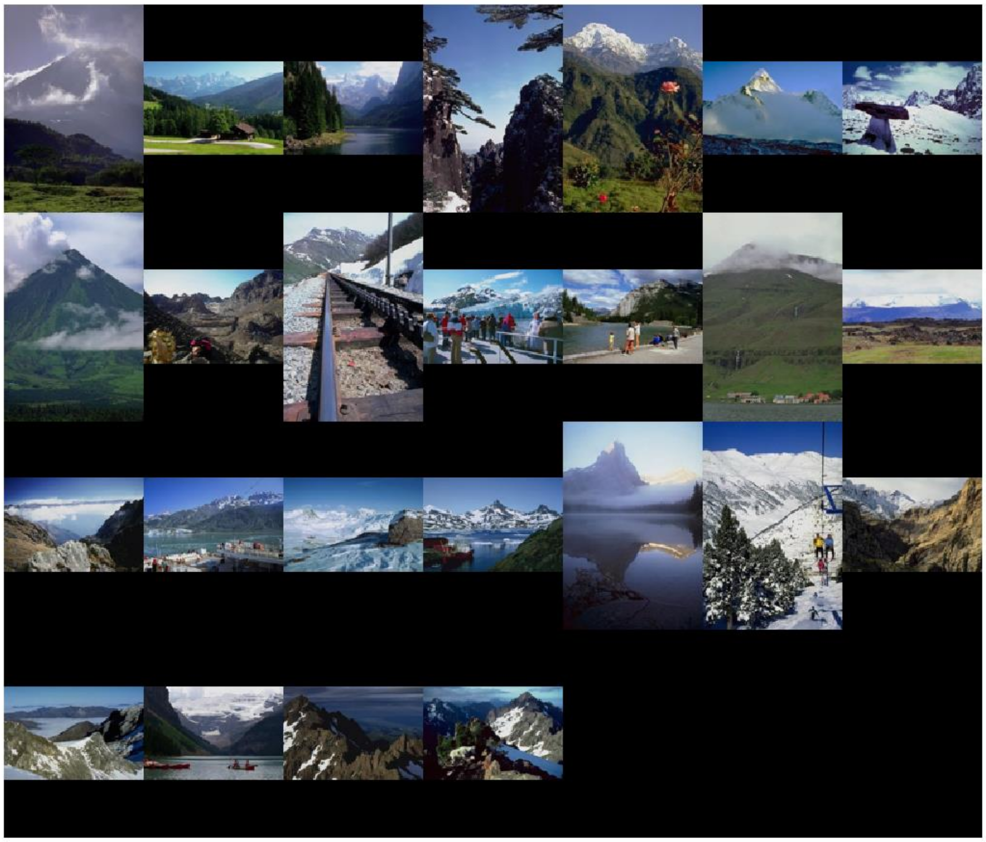

Figure 8.3.12 Mountain Class Query Result

Accuracy 90%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 90% accurate images.

8.3.13 Experiment (9): Monuments Class

Selected the query image from the Monuments class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.13.

Figure 8.3.13 Monuments Class Query Result

Accuracy 98%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 98% accurate images.

8.3.14 Experiment (10): Horses Class

Selected the query image from the Horses class randomly and retrieve the most top 20 images that are similar to the query image. Output is shown in Figure 8.3.14.

Figure 8.3.14 Horses Class Query Result

Accuracy 100%

The result by the system is relevant to query image. The retrieved image belongs to the same class so we obtain 100% accurate images.

CHAPTER 9

CONCLUSION AND RECOMMENDATIONS

In this Chapter we present the conclusions from this thesis and some recommendation for future works.

9.1 CONCLUSION

In recent years, the quantity of the digital image collection is growing rapidly due to the development of the internet and the availability of image capturing procedures and devices. The problem appears when retrieving these images from storage media. Thus, image retrieval systems become efficient tools for managing large image databases. A content-based image retrieval system allows the user to present a query image in order to retrieve images stored in the database according to their similarity to the query image. In this research, we have proposed a method for retrieval using the color, texture and shape feature of an image. For texture features, we use Gabor Filter which is a powerful texture extraction technique in describing the content of image. To find the similarity between the images the Euclidean distance is used. The images are ranked according to the similarity value by using the sorting algorithm. To evaluated the performance of system, we used precision in retrieving the images. The efficiency of the system is improved through extraction of the feature color, texture, and shape and integrating them in one feature vector then calculate the similarity between the images.

The experimental results showed that the proposed system has increased the average precision - retrieval accuracy - to 86%. This is better than the 56% result reported by other systems which combine these three features without weight assignment.

This system is a solution for the issues faced with the text-based image retrieval systems. It does not need to tag images or interpret terms to search images as this system uses the concept. When the user enters an image, this system finds the best matching similar images for the image queried. This system is implemented for the images with objects. This provides solutions for the following issues arouses with object comparison in images.

- Size of the object inside the image.
- Orientation of the object in the image.
- Background of the object.

- Image consists with several objects.

This system does not train images but consider the features of the images. So, this system fulfills its main requirement which is implementing an image search system using the concept Content Based Image Retrieval.

9.2 RECOMMENDATIONS

Although the research used different feature extraction techniques and assignment of the weights for the different features to give good results, but still the results are not highly satisfied to reduce semantic gap. There are a number of issues that can be improved in future:

- The system architecture and modules used in this research. Can be further optimized
- A generalized CBIR system which increase the system searching ability and provide more accurate results by combine different feature extraction technique and use other distance measure can be build and tested.
- Reduce the semantic gab between the local features and the high-level user semantic to achieve higher accuracy.

Improve the retrieval results by introducing feedback and user’s choice in the system.

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