Image Classification Using Wavelet and LBP based features for Image Retrieval Applications

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Abstract--*This paper involves image retrieval technique based on GLCM features. The aim of CBIR is to get accurate results with lower computational time. The content-based image retrieval has been employed in several application areas such as biomedicine, military, commerce, education, and web image classification and searching. Content-based Image Retrieval (CBIR) technology overcomes the defects of traditional text-based image retrieval technology, being appreciated for accuracy and efficiency. Intensity -Histogram is a simple method used to compare images with corresponding intensity values. The accuracy and efficiency is less if single feature (colour, texture, shape, etc.) is considered for extraction, to achieve the effective retrieval. To provide better accuracy, different features like colour, texture and shape are combined. SVM classifier is preferred for classification as it is producing accurate results. The features for classification are extracted using wavelet and LBP based feature extraction. Comparing state-of-art methods, the proposed method is at good accuracy and efficiency.*

Key words:Content based image retrieval, GLCM, Histogram, SVM classifier, Classification

I.INTRODUCTION

With the launch of more than ten Very High Resolution (VHR) optical satellites in the past 15 years (QuickBird, GeoEYE, WorldView, Pleiades, ...), satellite image data ´ of metric and sub-metric resolution became increasingly available. The level of details provided in such data enables to distinguish geometric structures only observable through their spectral properties at coarser resolutions. These geometric structures can be associated with a regular spatial organisation specific to particular types of land covers. In agricultural landscapes, this is the case of cereal crops, orchards and vineyards which typically display a periodic row structure visible in VHR image data. Because of forest management practices, young tree stands in cultivated forests may also feature specific spatial patterns. Similarly, in urban areas, the juxtaposition of buildings can generate a specific framework. These specific spatial patterns can hence be exploited to detect such land covers and improve the classification of VHR optical image data.

Many studies addressed this challenge by considering patterns observed in the landscape as textures. The main objective of texture-based analysis is to explore the local spatial dependencies observed between neighbouring pixels in the image. This analysis generally leads to the extraction of a small sized set of features that can be further used in a classifier. Various approaches were proposed in the literature to represent textures for the classification of VHR image data. Among these approaches, the Gray Level Co-occurrence Matrix (GLCM) initially proposed in [1] is still very popular within the remote sensing community. In many publications, texture descriptors derived from GLCMs were successfully used for various remote sensing applications, e.g. the classification of urban areas [2], [3], the mapping of forest species [4], [5], the estimation of forest structure variables in mono-specific forests [6], [7], [8] and the classification of agricultural land covers [9], [10]. Rather than directly characterizing the texture in the image domain as it is the case with GLCM, other authors suggested to proceed with the texture analysis in a transformed domain of the original data by applying filter banks. For example, texture features extracted by applying scale and orientation selective Gabor filters were proposed in [11] to map hedgerows in rural landscapes. An unsupervised segmentation algorithm based on Gabor filters was also introduced in [12] for the detection of vineyards. In the same way as Gabor filters, wavelet filters also offer a multi-scale and multi-orientation framework for the texture analysis. Features such as energy and entropy [13] or GLCM descriptors [14] can be extracted from each wavelet sub-band to characterize the texture in this transformed domain. In another common approach, probabilistic models are used in the image domain to describe local spatial dependencies and further characterize the textural information. Markov Random Fields, known for their use in the regularization of labelled image, can be modelled with these probabilistic distributions for the classification of VHR remote sensing data [15], [16]. Finally, rather than relying on pre-defined texture features, the increasingly popular deep-learning algorithms efficiently detect patterns in images through unsupervised or semi-supervised feature learning in a deep neural network architecture with many applications in remote sensing data [17], [18].

Disadvantages of Existing system are Not accurate, highly complex, Image Classification Efficiency is very less, Time consuming method, High processing time, Existing Approaches cannot classify the optical images, not accurate, highly complex, Image Classification Efficiency is very less, Time consuming method, High processing time and Existing Approaches cannot classify the optical images.

II.PROPOSED SYSTEM:

The main contribution of this paper is to demonstrate that such texture analysis approaches are also suitable for the supervised classification of textured soil occupations in VHR optical remote sensing data. Moreover, we propose a complete strategy to apply such models in the context of the classification of VHR optical satellite data. This strategy consists in two steps. First, a content-based image retrieval system is used to identify the best probabilistic models to be considered in the context of application. Once identified, the best models are used in a region-wise supervised classification procedure applied on a pre-partitioned image. From a more practical point of view, the main objective of this paper is also to highlight the universality of the proposed strategy which can easily be adapted to various thematic applications with a limited parameter to be set. In this project we proposed a novel supervised learning algorithm for high resolution optical image classification using the robust Discrete Wavelet Transform (DWT) Framework and LBP.

The schematic block overview of the proposed Optical image classification algorithm is shown in figure (1).The proposed system first creates a database of several significant features derived from the different standard high-resolution optical satellite images. While Creating the data base each data base image is preprocessed first and then processed with the robust Discrete Wavelet Transform.

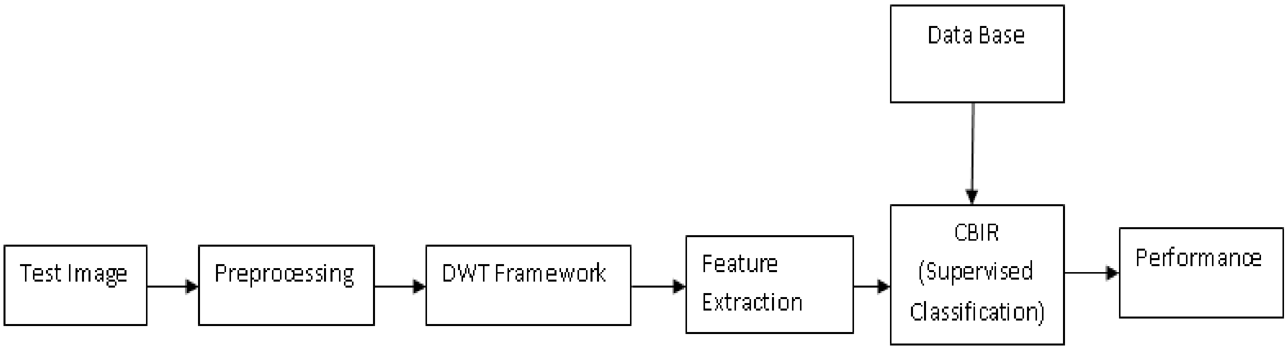

Figure (1): Block diagram of the proposed system

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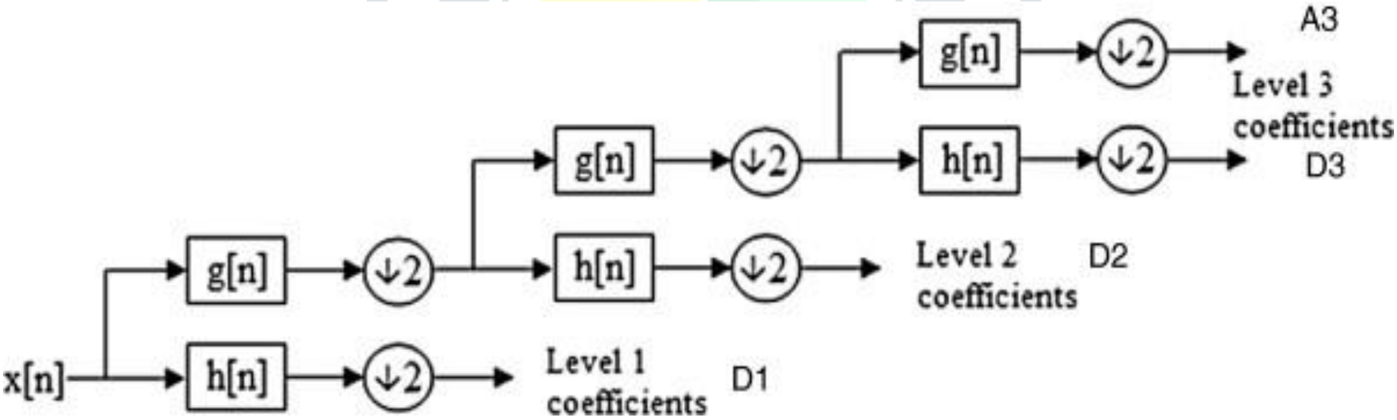
A. Discrete wavelet transforms Frame Work with LBP:



Figure(2): Discrete Wavelet Transform

B. Feature Extraction

Color:

Extracting RGB components from image Decompose each RGB components using Symletand Coiflet Wavelet Transforms at 1st level to get approx. coefficients and vertical, horizontal, diagonal detailed coefficients. Combine and covert the horizontal and vertical coefficients of RGB into HSV plane. Color quantization method is used in color histogram.In Discrete wavelet transforms shown in figure(2),copula-based model is used to extract the colorfeatures.

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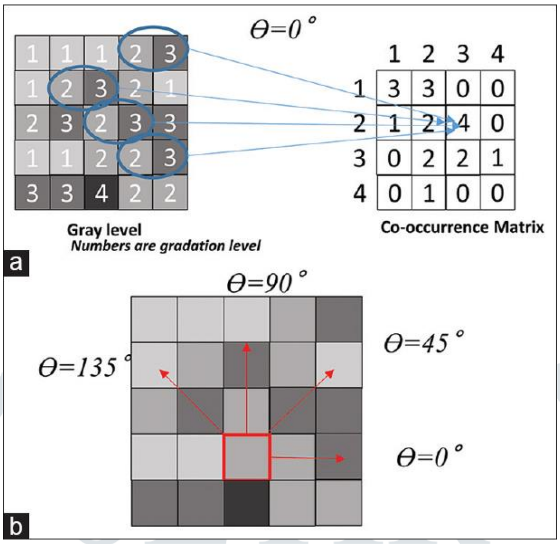
Texture:

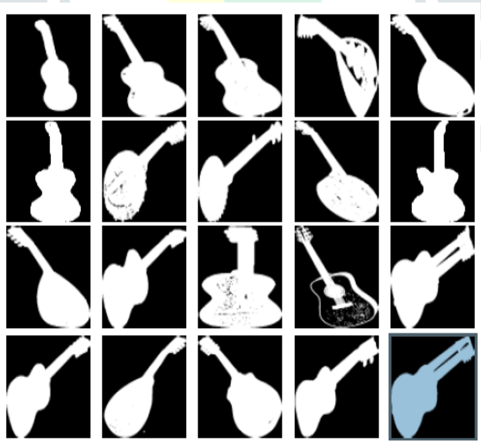
The GLCM is a well-established statistical device for extracting second order texture information from images. A GLCM is a matrix where the number of rows and columns is equal to the number of distinct gray levels or pixel values in the image of that surface. GLCM is a matrix that describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation. Given an image, each with an intensity, the GLCM is a tabulation of how often different combinations of gray levels co-occur values obtained are shown in Figure(3).



Figure(3): GLCM Matrix

Shape:

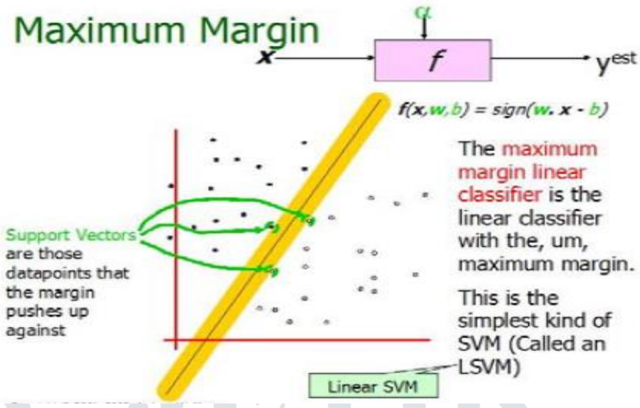
In this methodit measures the geometric attributes of an object which is present in an image and classifies that image for matching purpose. The techniques used for shape representation are Fourier descriptors, Wavelet descriptors. In this technique two categories of methods are used for extracting shape features such as Region based and Boundary based methods. Boundary based methods use only the contour of the objects' shape, while the region based as shown in figure(4) methods use the internal details in addition to the contour.



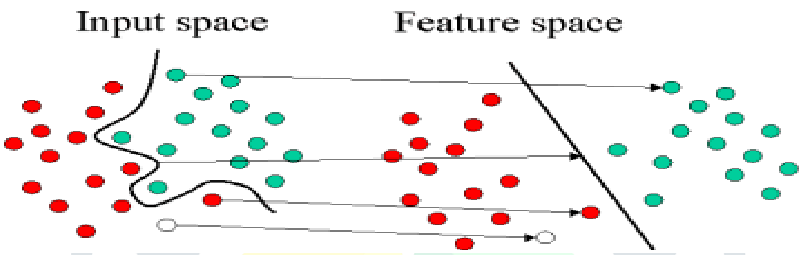
Figure(4): Examples of Region based classification

CBIR Classification

In CBIR framework we will use the classification engines such as ML classifier and SVM classifiers. In ML classifier a log-likelihood criterion is computed between the multivariate models estimated spatial dependency within each region. The proposed system uses the SVM classifier kernel-based transformation is first applied on the data to project them in a new space where a hyperplane between classes can be defined.In SVM classification there are two kinds of methods such as Linear SVM classification and Non-Linear classification. In the Linear classification the hyper plane classifies the pixels of an image linearly means the hyper plane is linear and straight. The pixels which are very close to that hyper plan are known as “Support Vectors”. The Linear SVM classification method is shown in Figure (5). In Non-Linear SVM classification the hyper plane classifies the pixels of an image non-linearly means the hyper plane is curvy. According to the image complexity hyper plane automatically bends for getting more accurate classification. The Non-Linear SVM classification is shown in figure (6).



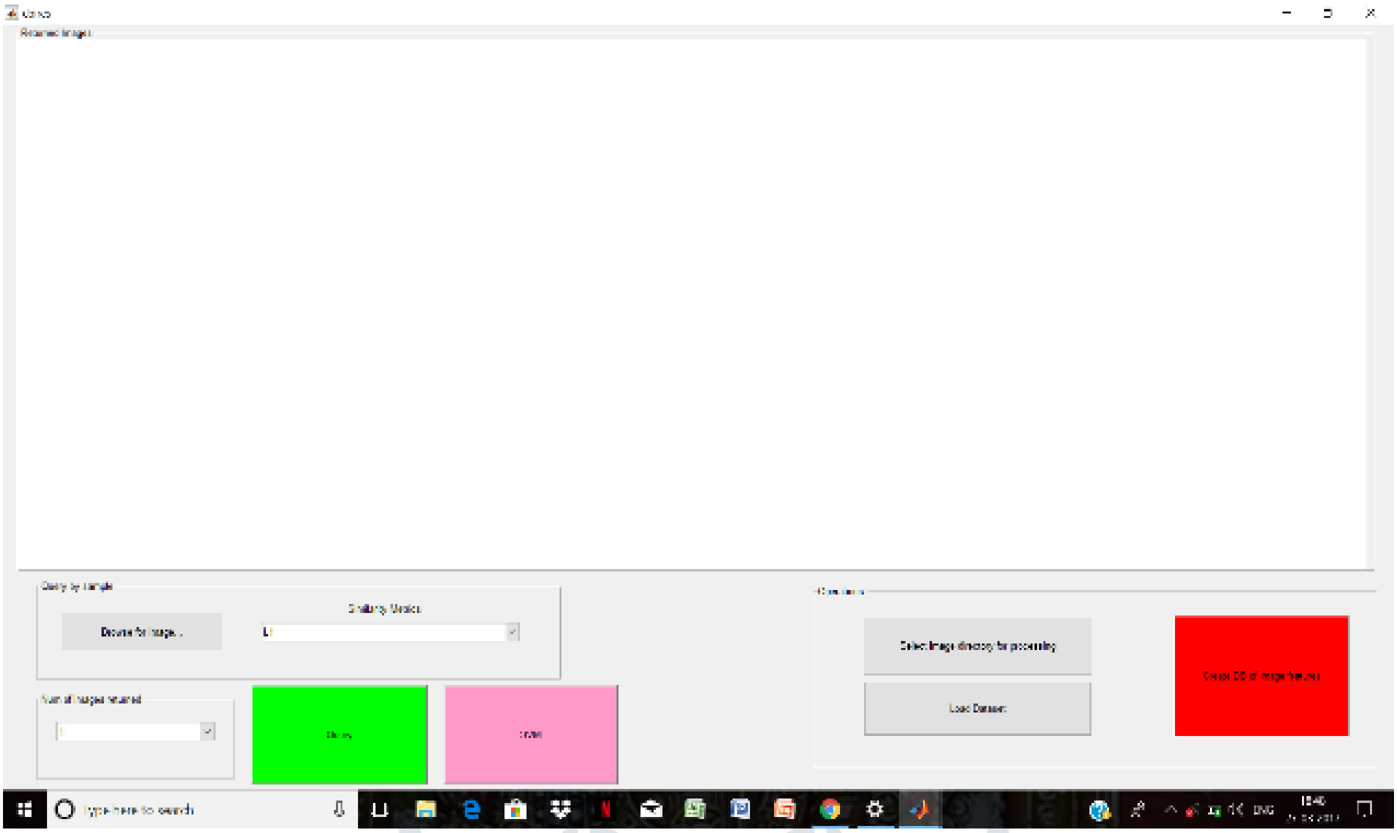
Figure(5): Linear SVM classification



Figure(6): Non-Linear SVM classification

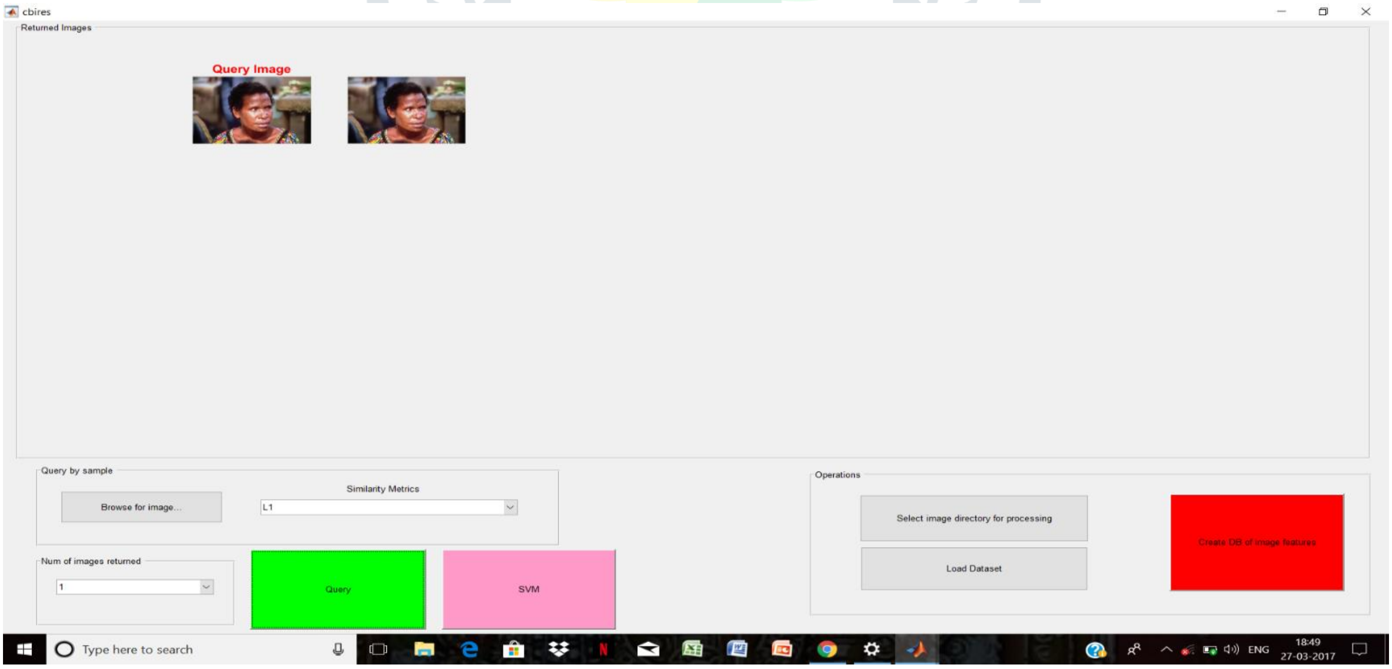
The advantages of proposed system areHighly accurate, less complex, Image Classification Efficiency is very high, computationally redundant free, Low processing time, Proposed approach can classify the optical images effectively, Low Operational and maintenance cost.

III. RESULTS:



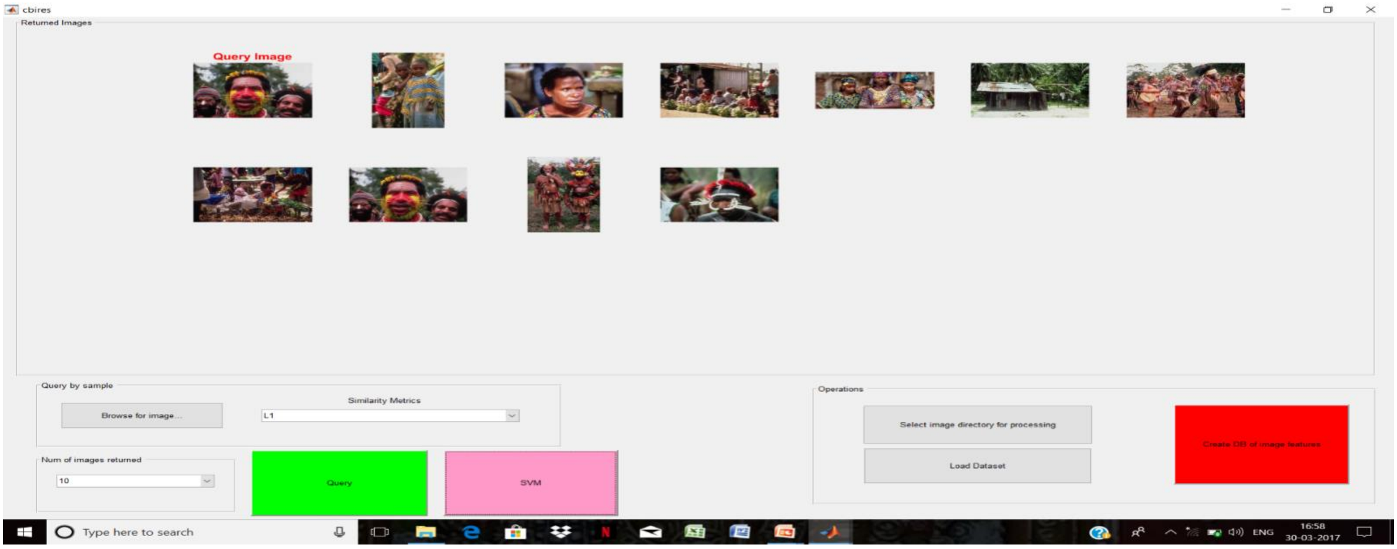
Figure(7): GUI Interface

The above figure(7) is the Graphical User Interface which is used in our Project. The GUI consists of options Load Database, Browse Query Image, Extract Features, SVM classifier, Query button and SVM button. The dataset has to be loaded first and then query image has to be browse from the computer. Now the query button has to be pressed for extracting the features from the image. Finally, SVM button is pressed for the classification of the image and shows the similar images in the GUI interface as shown in the figure(9).



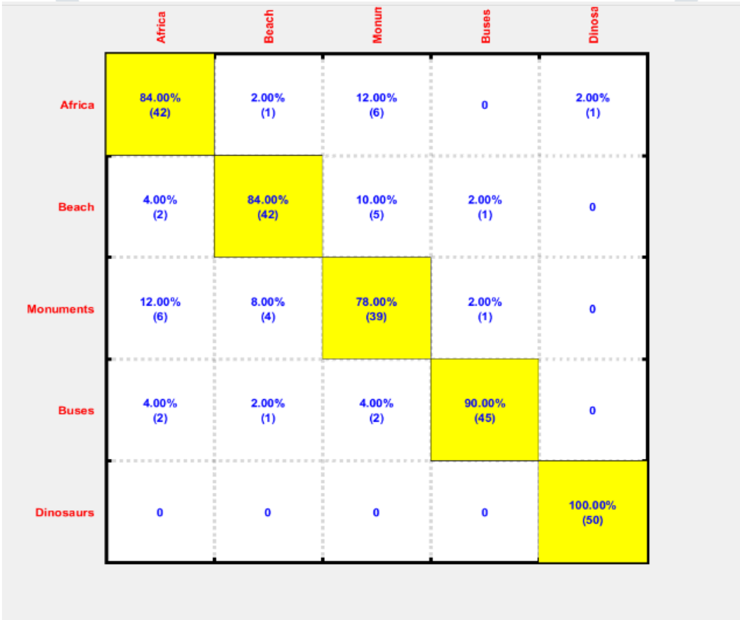
Figure(8): Inserting Query Image

The above figure(8) shows about the query image which we have to be selected. The query image will bebrowsed from the computer which can be treated as the test image which will be given to the dataset by pressing query button as shown in figure(8). Now the given query image is then displayed in the GUI interface.



Figure(9): Getting Similar images in Database

The above figure(9) shows the output of the project. In this user enters any class of image which are already loaded in the database. In the output we get the similar images which are related to that class. All the similar images are then displayed in the GUI interface.



Figure(10): Confusion Matrix

The above figure (10) is the confusion matrix in which we can obtain the matching score of the image with the similar images in the database. When we give an image, which is related to the Africa class, the confusion matrix displays the matching score of the that image to that class and also displays the matching score of that image with the other classes such as beach, monuments, buses and dinosaurs. All the diagonal elements in the confusion matrix represents the matching score of an image with their related classes and other elements of the confusion matrix represents the matching score of the image with other classes in the dataset.

IV. CONCLUSION

The proposed approach is perfectly suitable for the supervised classification of images in such VHR optical data. Moreover, the proposed system is a complete strategy to apply wavelet-based multivariate models in a supervised classification procedure of textures in VHR data. The features are extracted from the learning database by using multivariate models to represent the distribution of observed local spatial dependencies in wavelet sub-bands in a multi-scale and multi-orientation framework. A CBIR analysis carried on the learning database is first conducted to identify the most efficient models to retrieve features in the context of images. A classifier based on a similarity measure or a likelihood criterion is next used to produce classification results with the most performant models.

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