Published by :
http://www.ijert.org
International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 06, June-2019

Content Based Image Retrieval for the Medical Domain

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***Abstract*— The exponential increment and pervasive openness of visual information on the Web has given rise to extensive research activity in the retrieval of images. Conventional strategies that utilize text for image retrieval may endure irregularity between the words specified and visual content. Content-based image retrieval systems utilize the outline of the content present in the image to spot and retrieve related images and this has been the reason of interest for many researchers in the last two decades. A CBIR system is able to query an image over a database of images and return a set of results that most closely matches the queried image. CBIR systems are especially valuable in the medical domain because it retrieves images from a large dataset based on similarities which helps in speedy and efficient diagnosis of patients. There is continuous analysis happening within the space of CBIR systems particularly for medical images, and different algorithms are being developed to create frameworks that can be widely utilized. The aim of this paper is to is to develop a content-based image retrieval (CBIR) system architecture to support querying of very large image databases with user-specified distance measures that can be used for a wide variety of datasets in the medical domain.**

Keywords*— *Content-based image retrieval; euclidean distance; manhattan distance; similarity measure; indexing; feature vector;

I. INTRODUCTION

The utilization of large image databases for a number of applications has now become feasible due to the development of faster and more powerful processors along with access to cheaper memories and storage on the cloud. The rapid increase in the size of these multimedia records as of late can also largely be attributed to the World Wide Web picking up prominence in recent years, enabling ubiquitous accessibility and availability of visual information. The need for large databases containing records of medical images, criminals, works of art, satellite images etc. has been recognized in various professional domains including but not limited to architecture, design, medicine, history, fashion, national and international security etc. Finding and retrieving the desired records from these large collections is a feature required by journalists, design engineers, art historians, police, doctors and more. Developing a tool to achieve this has led to research into the domain of image retrieval methodologies which deals with the retrieval of visual data. Content-based image retrieval (CBIR) enables efficient and viable access and retrieval of visual information. A CBIR system is able to query an image over a database of images and return a set of results that most closely matches the queried image.

A. Implementation Methodology

Content based image retrieval matches features extracted from the query image with the features extracted from the images present in the database using various distance metrics for similarity estimation. While the requirements can vary a great deal from user to user, image features can broadly be divided into three levels of abstraction: the lowest level of abstraction consists of primitive features such as shape and color, the next level consists of logical features such as objects present in the image and the third level consists of abstract features like the importance and interpretation of a scene portrayed. CBIR frameworks presently operate viably only when primitive features are considered. The images stored in the database of a content based image retrieval framework are indexed based on their visual content using the specific chosen features such as color (color intensity distribution of the image, RGB content of the image, HSV values of the image etc.), texture (presence of homogenous patterns in the image, or the spatial arrangement of color and intensities in various regions of the image), shape (boundaries of various objects present in the image along with their interiors), other visual features or a union of these features.

B. Significance of CBIR in Medical Imaging

In the last few years, numerous CBIR techniques have been developed, each using different methods for extraction of features for image retrieval. Some years back, the medical information systems only provided literary details about patients undergoing treatment. This data was later stored in sizeable databases and the records of patients could be accessed using text searching queries. Nowadays, easy access to medical imaging equipment such as MRI, CT, PET Scanners, etc. and the sheer volume of medical information that is generated has made the development of efficient databases to store this data an imminent need. Conventional searches utilizing keywords did not effectively accomplish the tasks that needed to be performed by medical personnel.

Content based image retrieval (CBIR) frameworks are particularly important in the medical domain as it returns similar images from an extensive dataset which helps in speedy and efficient diagnosis of patients. Due to the development of remote diagnosis and treatment facilities in the medical domain, it is also necessary to share these medical images amongst various hospitals and research centers which can help a doctor evaluate the medical condition of a patient by searching for similar medical images and clinical data to refer to. Content-Based Medical Image Retrieval (CBMIR) is used to identify and retrieve similar medical images in the database thereby helping the radiologist recall and examine previous relevant cases during diagnosis.

The effectiveness of CBMIR depends mainly on the visible features chosen to represent the images. The commonly used features are: texture, color, boundaries etc. Texture plays a very important role in the processing of medical images. These patterns of texture provide information regarding the collection of repetitive grouping of pixels and provides data in with respect to its external environment. The objects in a medical image can be distinguished only by their texture sequence. [19]

Another important feature that is considered is the boundary of the object. It is a line that sets an object apart from its surroundings. It is used to identify the shape of the object in the image. Medical images don't have distinct boundaries. This leads to a few problems while scanning the medical images, such as less illumination, noise and poor contrast. Hence, it is difficult to identify tissue patterns, distinguish between benign and malignant tissue, arrangement of organs etc. [19]

Due to the importance of storage and retrieval of medical images in today's world, the Digital Imaging and Communications in Medicine (DICOM) standard was created by the American College of Radiology (ACR) and National Electrical Manufacturers Association (NEMA). This standard aims to integrate various medical imaging devices from different manufacturers and precisely handle, store and transmit medical images. Additionally, DICOM data objects consists of a number of attributes describing the images including patient information such as name, ID etc. along with pixel information. DICOM is a wide spread standard, providing compatibility between numerous medical imaging and information systems and will soon be employed throughout the medical industry. Some medical professions where this standard is utilized are radiology, surgery, endoscopy, mammography, orthopedics, pediatrics, cardiology and other related domains.

Moreover, Picture Archiving and Communication Systems (PACS) store and transfer medical images in DICOM format to provide economical and convenient image storage, retrieval, distribution and presentation facilities. PACS modules use DICOM to form secured networks of machines from different modalities. PACS archives store textual information about the image such as patient information, image description, diagnostic reports etc. in the DICOM header which is used to access and retrieve the required images.

C. Main Features Employed in CBIR

1) Color

CBIR frameworks most frequently utilize color to describe the visual features of the image. The image is first represented using a color space. The most commonly used color space is RGB (Red Green Blue). Next, one histogram representing each primary color is created in the RGB space. The histogram depicts the distribution of colors and the number of bins in the histogram determines the color quantization in the image. The query image and database image are compared using a distance metric which ascertains the similarity between the two histograms. However, the restriction to color distribution across the entire image without taking into consideration spatial constraints is not enough to accurately distinguish between images.

2) Texture

Texture refers to homogenous visual patterns that provides information about the spatial distribution of colors in the image. Two classes of texture representation are: structural methods and statistical methods. Structural methods include morphological operators and adjacency graphs, describe texture through the identification of structural primitives and their arrangement in the image, for example, the presence of objects that are adjacent, perpendicular or parallel to one another. On the other hand, statistical methods identify texture through quantitative distributions of image intensity and include techniques such as Gabor, wavelet transforms, co-occurrence matrices, Fourier power spectra, Tamura feature etc. The method chosen to represent texture dictates how the images are compared using texture features.

3) Shape

Shape extraction involves a number of features characterizing the shape of the object that are independent of size or orientation, such as edges and contours, to be calculated for each object identified within the images stored in the database. Here, a k-dimensional metric (where k represents the number of feature characteristics) is utilized to determine the similarity between two images. The set of matching features are then computed for the query image and images in the database having similar to those of the query image are retrieved. Shape features can be divided into two categories: global features that describe the image as a whole, such as aspect ratio, circularity, invariant moments etc. and local features that describe each object, such as consecutive boundary segment sets.

D. Query-Image Matching

By matching the distances between two points or a series of two points, i.e. distance of one image compared to the distance of the second image, if the distance of object X and object Y are equal, and if repetitions of the distance measurement and comparison of the series of measurements show that the distances are the same then the program will conclude that a match has been found.

Alternatively, if shape and scale comparison measures are used, the function that creates the first image needs to be approximated and then this estimation is repeated for the second image. Once the scale and shape of the two images are determined, then they may be compared for matching. This process is more complicated than comparing distance. Difficulties may arise when certain points in the image are accessible, making it impossible to estimate shape with good accuracy.

Content-based retrieval systems process a query and retrieve the closest available prototypes present in the database. The judgment of how alike the query and database image is contingent on the distance measure or measures chosen. Similarity measures are divided into 4 major categories: color, texture, shape and object and relationship similarity.

E. Evaluation Strategies

Two main evaluation metrics are used to measure the performance of image retrieval systems: Precision and Recall. Precision (also known as specificity) refers to the fraction of relevant images retrieved and recall (also known as sensitivity) refers to the fraction of all the relevant images present in the database that was actually retrieved by the system. These metrics require the meaning of relevance to be properly defined in order to accurately evaluate the performance of the system, which may be subjective. The results are represented as a precision-recall curve which summarizes the trade-offs between the true positive rate (precision) and value of positive prediction (recall). Since information retrieval systems deal with a large number of queries, average precision over a range of different queries is used to evaluate the system.

F. Major Challenges

1) Semantic Gap: The user might interpret the results of the system's feature-based classification differently. Images that are classified similar according to a feature based metric by the system might be found dissimilar by the user and inversely, the user may find images classified as distinct by the system to be quite similar.
2) Word-Picture Association: A system that retrieves images relevant to a text query generates an expansive set of open questions on the best way to accurately extricate the semantic sense of the request, how to allocate word based descriptions to images in the database, how to discover equal articulations to image annotations etc.
3) High Dimensionality: High dimensionality due to the large images that need to be stored in CBIR systems is a huge challenge. Dimensionality reduction needs to be employed in order to boost the efficiency and potency of the system.
4) Coherent Databases: Development of coherent databases that can be used across all CBIR systems is a difficult task due to the wide range of images that need to be stored.
5) Combining various features: Aggregating various features improves the performance of the CBIR system but determining the correct weights to assign to each feature is no easy task and the effectiveness of using weighted sums to aggregate various features is questioned.
6) Personalization of the system based on the user: In order to address the issue of subjectivity of image interpretation, future CBIR systems should analyse the user's search history and develop a user profile which can be used to retrieve images that will match the expectations of the user.

We experiment by combining color and texture features to build a CBIR system in this paper. The remainder of the paper is organized as follows: Section 2 highlights some of the existing works in CBIR. Section 3 describes our proposed CBIR system and the procedure followed. The paper is concluded in Section 5.

II. EXISTING WORK

Research into the design and development of CBIR systems is popular due to its importance in the healthcare industry.

V. V. Satyanarayana Tallapragada et al. (2016) [4] have highlighted the importance of segmentation of images and propose a method to segment the medical image using a semi decision algorithm that separates only the tumour from the CT image and extracting it using morphological image processing techniques. Avi Kak et al. (2002) [5] focused on providing solutions for problems related to the automated retrieval of high-resolution CT images of the liver and lung from large medical image databases. They improved diagnostic accuracy by utilizing a hierarchical retrieval mechanism and extracting features using domain related knowledge gained from certain low-level features. They also shed some light on interactive contour extraction methods. G. Schaefer et al. (2004) [6] developed a CBIR system to retrieve medical infrared images whose features are similar to the query image built on the notion that thermal images are characterized by a set of seven moment invariants and the images can be reconstructed using a combination of these moments. Luiz A. P. Neves et al. (2013) [7] extended the existing Shared Biological Image Manager (SBIM) system for the fulfilment of the increasingly complex requirements for sharing, storing and processing of data in medical centres and hospitals. This was accomplished using data mining concepts and image retrieval techniques using the Support Vector Machine (SVM) framework. Mrs.L.Malliga et al.(2014) [8] have come up with a fuzzy database management system (FDBMS) that stores and retrieves the medical image by performing various flexible queries. The two processes involved comprise of an image retrieval process that retrieves the medical images from the database and the second one segments the image using segmentation algorithms like region-based, data clustering, or edge-based segmentation. Harshita Sharma et al. (2012) [9] used unique techniques like higher order graph-based approach, tree search, text descriptions of images and matching for establishing similarity between histological images during content-based image retrieval. Chunyan Zhang et al. (2017) [10] have recognized the problems that arise when medical images are uploaded onto third party platforms, namely issues with privacy and authenticity. Their CBIR system encrypts the medical image using DWT and DCT before being uploaded to the server. The similarity of two encrypted medical images are represented by the Normalized Correlation Coefficient (NC) and is used to determine the corresponding image and return it. The experimental results have shown that their proposed method is robust and is effective against conventional and geometric attacks. B. Jyothi et al. (2016) [11] focused on texture components that are integrated with user feedback to improve the retrieval accuracy of the BIR system. Some complex techniques such as intensity, gradient and edge mapping techniques were used to achieve their goal. If the user is dissatisfied with the images retrieved, the system provides an interface where the

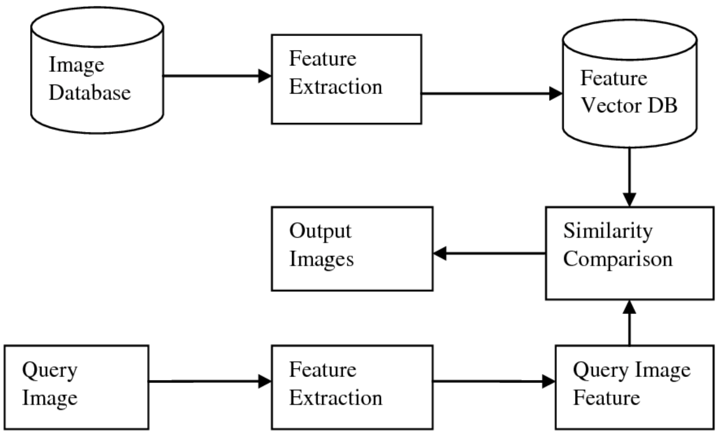
International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 06, June-2019

user can select the most relevant image for searching again. The system analyses the relevance feedback from the user and returns better results. Roshi Choudhary et al. (2014) [12] have described an integrated CBIR method to extract both texture and color features. A technique called color moment (CM) extracts the color features from colored images and local binary pattern (LBP) extracts the texture features from grayscale images. A feature vector is then formed by combining the color and texture features of the image.The Euclidean distance between the feature vectors of the database images and query image are computed and images in the database corresponding to the query that fall below the Euclidean Distance threshold value are returned. Yu-Chen Wang et al. (2015) [13] They have proposed a method called biased discriminant analysis which is a subspace learning algorithm, with feature line embedding for enhancing performance in relevance feedback schemes by identifying the correlation between feature lines and samples. Relevance feedback is used for dimensionality reduction and feature line embedding is utilized to reduce the gap between abstract high-level semantic features and low-level features. Zhi-Chun Huang et al. (2010) [14] have attempted to simplify the complexity involved in computation and improve the retrieval accuracy of relevant images by combining colour and texture features and allowing the user to specify the weights that must be assigned to these features while measuring the similarity between images. They have used HSV (Hue,Saturation,Value) colour space for colour features. Gabor texture descriptors were used for the texture feature.

III. METHODOLOGY AND EXPERIMENTAL PROCEDURE

Many studies have been conducted in recent years on proximity distance measures that effectively measure the similarity between images to improve visual similarity while retrieving the images in CBIR systems as well as on different feature extraction techniques that can comprehensively describe the image. But there are limitations in the existing methods in terms of precision level of the retrieved images. To overcome these limitations, this paper aims at developing an improved technique for visual similarity search in content-based image retrieval that combines two color features and one texture feature. To evaluate the effectiveness of the proposed technique, it will be applied on image data sets consisting of colored images of scans of the retina as well as greyscale images of chest X-rays. This technique would help retrieve visually similar images with high average precision. The overall outcome of this paper would be to prove that the suggested technique transcends the existing techniques in terms of retrieving relevant images from the database.

A. High Level Design



a.

Fig. 1. High level design

B. Low level design

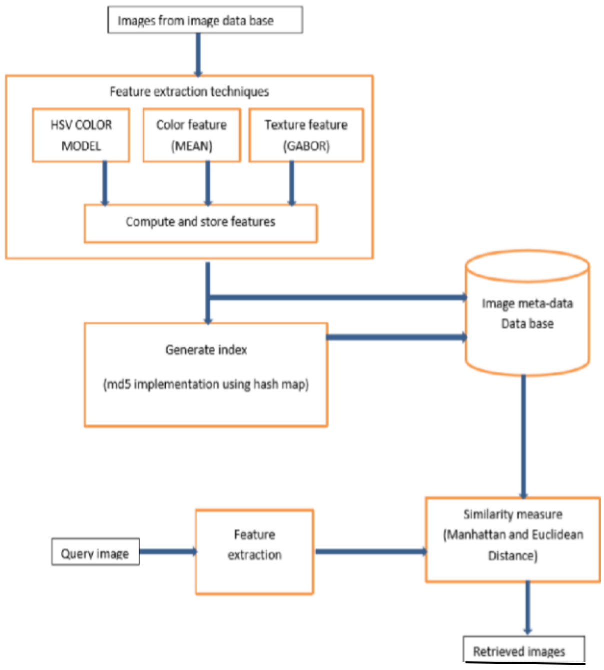


Fig. 2. Low level design

C. Implementation Details

1) Color Histogram

Color features are used in image retrieval systems to describe the image. Color is represented as a histogram which denotes the pixe distribution every color intensity within the image. Each color is quantized into distinct levels in order to define the histogram.

2) Normalized HSV Domain

The histogram is normalized so that images of various sizes can be retrieved. HSV is a color space that is based on how the human eye perceives color. The HSV color space

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 06, June-2019

represents color as three components, Hue (H), Saturation (S) and Value (V). Image processing systems generally represent color using the RGB color model because these colors can be displayed technically with ease. Color conversion is required in order to bridge the 2 models so the color can be processed and displayed accurately.

The color is converted from RGB to HSV in the following steps:
Step 1: Red, Green and Blue values are obtained by normalizing each pixel.
Step 2: The Red(R), Green(G) and Blue(B) values are divided by 255 in order to change the range from 0..255 to 0..1.

R'' = R/255
G'' = G/255
B'' = B/255
Cmax = max(R''', G'', B'')
Cmin = min(R'', G'', B'')
Δ = Cmax – Cmin

Formulas:

Value calculation:

$$V = Cmax \tag{1}$$

Saturation calculation:

$$S = \begin{cases} 0 & , C_{max} = 0 \\ \frac{\Delta}{C_{max}} & , C_{max} \neq 0 \end{cases} \tag{2}$$

Hue calculation:

$$H = \begin{cases} 0^\circ & \Delta = 0 \\ 60^\circ \times \left(\frac{G'-B'}{\Delta} mod 6\right) & , C_{max} = R' \\ 60^\circ \times \left(\frac{B'-R'}{\Delta} + 2\right) & , C_{max} = G' \\ 60^\circ \times \left(\frac{R'-G'}{\Delta} + 4\right) & , C_{max} = B' \end{cases} \tag{3}$$

3) Mean Feature

1. Read query image from user.
2. Extract the RGB components from the query image.
3. Calculate their means individually (mean of all the red components of all the pixels of the query image).
4. The RGB component of each pixel is compared with the results obtained in step 3 for each component.
5. If the comparison performed in step 4 results true, then RGB component of each pixel is assigned to RH, GH and BH respectively otherwise, to RL, BL and GL respectively (stored as array).
6. Calculate the mean of RH, RL, GH, GL, BH, BL and store it into a 256 bit color feature vector in database.

4) Gabor Feature

Gabor filters are employed in order to extract and analyze the texture features from the image. It is a linear filter which analyzes the frequency content in specific directions in a localized region around the point or region of analysis in the image. Gabor filters analyze images in a manner that is similar to the perception of texture by the human eye.

5) Distance Metrics

- Euclidean distance

$$D(q,s) = \{\sum_{i=0}^{L-1} (q_i - s_i)^2\}^{1/2} \tag{4}$$

- Manhattan distance

$$D(q, s) = \sum L-1|qi- si| \tag{5}$$

where q_i is the query image feature vector, s_i is the feature vector of the images present in the database and L is the dimension of the image feature.

D. Algorithm

1. For each image present in the database Do,
2. Read the image and resize it into 256x256.
3. Compute MD5 hash of that image and store it as a key in hashtable1 which is the image meta-database.
4. Extract the Red, Green and Blue elements from an image and store it in object of class Image (contain all properties of the corresponding image as attributes).
5. Convert the R, G, B components to HSV color domain and store it in same image object.
6. Extract and store mean color feature of the image in mean feature vector in same image object
7. Extract texture feature of the image using gabor filter and store texture feature vector in same image object
8. Combine both the feature vectors using vector concatenation and store it in same image object
9. Store the image object as value to the key in image meta-database.
10. End For
11. Repeat Steps 2 to 8 for the query image.
12. For each image in the database Do
13. Compute the distances using the user-selected similarity measure (Euclidean or Manhattan) between the feature vector of the
query image and the corresponding feature vector of the current image in the database and form the hashtable2 (which contains the same md5 digest of the image as the key and distance as the value).
14. End For
15. Sort the hash table2 and retrieve the top 5 images that most closely match the query image.
16. Using the key present in hash table2, we can fetch the image record from hash table1 (image meta-database) and find out the path to the image stored in the Image object and display it to the user.

IV. RESULTS

Fig 3. and 4. is the result of selecting COLOR FEATURES + EUCLIDEAN DISTANCE METRIC and the database used is retina database and lungs x-ray database respectively.

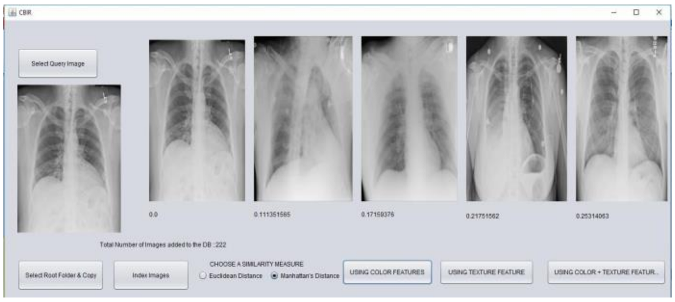


Fig. 3. Result of x-ray

Fig. 4. Result of retina

Fig 5. and 6. is the result of selecting TEXTURE FEATURE + EUCLIDEAN DISTANCE METRIC and the database used is retina database and lungs x-ray database respectively.

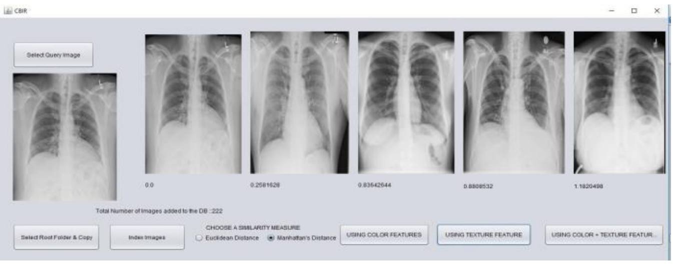


Fig. 5. Result of x-ray

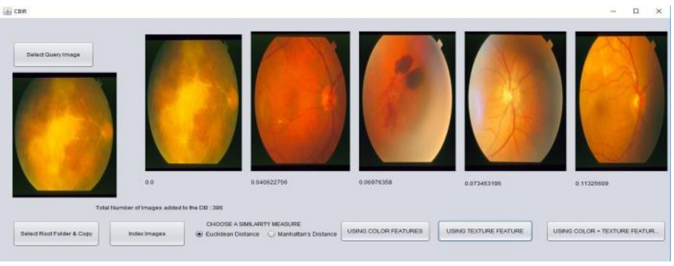


Fig. 6. Result of retina

Fig 7. and 8. is the result of selecting ALL FEATURES + EUCLIDEAN DISTANCE METRIC and the database used is retina database and lungs x-ray database respectively.

Fig. 7. Result of retina

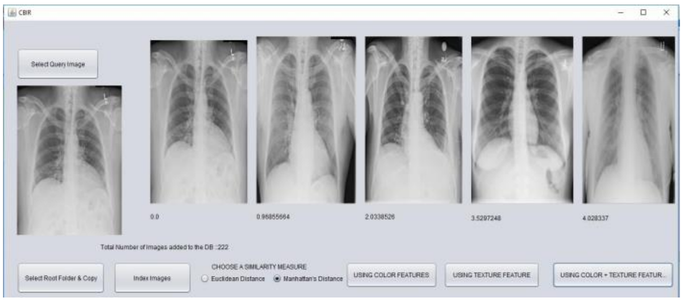


Fig. 8. Result of x-ray

III. CONCLUSION

A method for content-based image retrieval using two color features and one texture feature is proposed in this paper. Texture and color features are extracted from these images separately. HSV domain and Mean algorithm serve as color features and Gabor filter responses are used as texture features. Euclidean distance and Manhattan distance are utilized to determine image similarity. A combination of these color and texture features retrieves better sets of similar images to the query image compared to only color or only texture features. The images retrieved have similarity measure values between 0.0 and 1.0.The system is designed to retrieve top 5 images that are similar to the query image under all conditions (based on the similarity measure chosen) , with the aim that user can get the most similar images from his dataset always. The incorporation of key selection and hashing mechanisms has improved the retrieval efficiency of our system considerably. We also incorporated two different distance measures with which the user can conduct searches.The experiments were performed using test databases of real medical image data from the Drive and Stare Retina database as well as National Institutes of Health Chest X-Ray Database and by the outcomes observed for these datasets, we conclude that the combination of HSV, Mean and Gabor Filter shows the best results as we obtained images that most closely match the query image for the same set of queries by using the combination of features as compared to only color or only texture features. This demonstrates the efficacy of this method in comparison with the existing methods in the literature.

ACKNOWLEDGMENT

The authors would like to acknowledge the Drive database [31], the STARE project [32,33] along with National Institutes of Health Chest X-Ray Dataset [34] for facilitating this research activity.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 06, June-2019

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