



## MEDICAL IMAGE RETRIEVAL USING FUSION MODEL FOR HETEROGENEOUS MULTI FEATURES

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**ABSTRACT-**Image Retrieval has become a major research area due to the increasing rate of images on internet as well as in many other fields like medical, military, multimedia etc. Image retrieval is the process of browsing, searching, retrieving the images from large database. Histology is the basic tool which provides information on structure & composition of tissues. Present days images of tissues are digitized to support clinical findings. These collections are very much large in size and consist of latent source of information. Histological image retrieval is useful tool for data analysis, teaching, training, and decision making in diagnosis. Template matching is used to get the closest image as output in accordance with the query image. The results shows Euclidean algorithm best suited for histology based retrieval.

**Keywords-**

Histology, Gabour, Tamura, Euclidean, Support Vector Machine.

### 1.INTRODUCTION

Medical image retrieval is the process of browsing, searching, retrieving the medical images from large medical image database. Tissues are important parts in human body. Cells are combined to form tissues and tissues combine to form organs, except bones and teeth all other organs are made up of tissues[1]. If any organ of the human body is infected, a tissue from that part will be fetched and given

as input then the images closer to the input query image based on textures will be obtained as output from the stored image database. This will help to determine the disease the person has[2][3]. In proposed method, three algorithm are compared to get the highly efficient algorithm for retrieving tissue images, The Three algorithm used in this project are Correlation, SVM, Euclidean Distance method. Correlation is the mutual relationship or connection between two or more images[5][6]. PSO method is proposed by the adaptive weight of SVM to improve retrieval performance. SVM is used for learning the high level concepts from the low level image features and concepts. SVM can give output in two extraction feature classification only[7][8]. Euclidean method has high performance rate and accuracy level. Euclidean method will give output in all extraction feature classifications.[9][10].

### A.Content Based Image Retrieval

Content-based image retrieval is an information retrieval from searching the digital images in large database. The search will analyze the actual contents of image.



## B. Tissue Recognition

Tissue image is given as an input. Image segmentation is the process of segmentation of images. The K means is a simple algorithm of segmenting and classifying images into k different clusters based on feature, attribute or intensity value. Feature extraction is the process of extracting features or parameters based on which comparison has to be done between the input image and the stored image database. Here, textures like Gabor and Tamura textures will to be extracted from the input image. Template matching is to compare the input image with the stored image database. it is done by using the algorithms like Correlation, SVM and Euclidean.

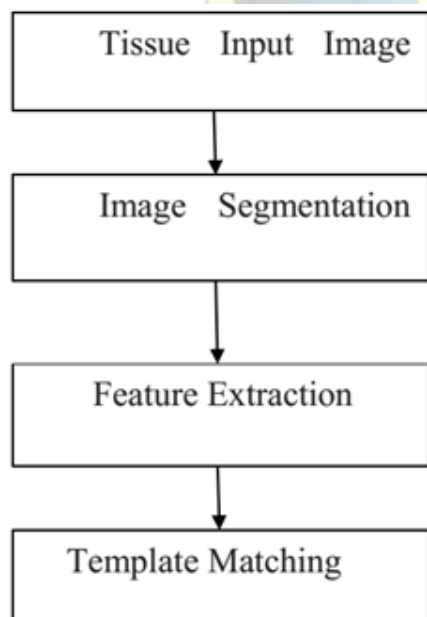


Fig.1. Flow Diagram

## II. IMAGE SEGMENTATION:

### A.K-mean Clustering Algorithm for Segmentation

The K-means is a simple algorithm of segmenting or classifying the images into k different clusters depending about the feature, attribute and intensity values. It is efficient and does not require many parameters for segmentation. Unlike local thresholding, which can group two main classes but in K-mean Algorithm group into k different classes. This method of distance calculation compatible with K-means Algorithm includes Manhattan and Euclidean distance etc.

## III. FEATURE EXTRACTION:

### A. Gabor Textures:

Gabor filters are used to extract the textures with different size and orientations.

### B. Gray Level Co-Occurrence Matrices:

**Co-Occurance:** Along with Gabor-based textural features, the spatial dependency among pixels by using the Gray-Level Co-occurrence Matrices is defined. GLCM is a matrix which shows the frequency of adjacent pixels with gray scale values  $i$  and  $j$ . GLCM represents the frequency of all pairs of adjacent pixel values with in the whole image.

**Contour:** In order to extract contour features, threshold the image for identifying the foreground pixels set the threshold to 0.95 times the largest pixel value in the image.



Then, the outermost pixel relative to the centre of mass of the foreground in angular increments of 1 degree, and stored the distance between centre mass and the radically-spaced outermost pixels in a 360-dimensional feature vector was identified. Finally, principal component analysis (PCA) is employed to identify the directions of maximum variance in the 360-dimensional contour vector, by keeping the top three principal components as contour features. It shows the resulting average contour superimposed over the contour plus three and minus three deviations away from the average along each of the three principal components.

### C. Tamura Textures

**Coarseness** relates to distances of notable spatial variations of grey levels elements to form the texture. The proposed computational procedure to find differences of the average signals from the non-overlapping windows of different size.

**Contrast** measures how grey levels vary in the image and what extent their distribution is biased to black or white.

The **line likeness** feature  $F_{lin}$  is defined as an average coincidence of the edge directions they co-occurred in pairs of pixels separated by a distance “ $d$ ” along the edge direction in each and every pixel value. The edge strength is likely be larger than a threshold by eliminating weaker edges. Coincidence is measured using the cosine of angles, thus the co-occurrences in the same

direction are measured by plus one and those in the perpendicular directions by minus one.

The **regularity** feature is defined as the standard deviation of the corresponding feature in each sub image of the texture is partitioned into many. The **roughness** feature is the sum of coarseness and contrast measures:  $F_{rgh} = F_{crs} + F_{con}$

Normally top three Tamura's features are used in CBIR. These features are used to capture the high-level perceptual attribute values of a texture well which are useful for image browsing. These are not effective method to find finer texture discrimination.

### IV. TEMPLATE MATCHING

Last step of a tissue recognition system is template matching which is used to compare two tissue templates. Its purpose is to measure the similar tissues. There are many different methods for template matching. They are Euclidean distance measure, weighted Euclidean distance and Hamming distance.

**Euclidean:** The distance between two samples or two variables is fundamental in multivariate analysis. Squared length of a vector is the sum of squares of its all the coordinates. The distances between two vectors in multidimensional space are their coordinates. This multidimensional distance is called the **Euclidean distance**, and is the natural generalization of our three-dimensional notion of physical distance to more dimensions. When variables indifferent measurement scales, standardization is mostly needed to balance the contributions of the variables in the computation of distance. Standardized





Euclidean distance is the Euclidean distance calculated by using standardized variables. Standardization is the evaluation of distances by equivalently thought of as weighting the variables. Euclidean distances by weight is called **weighted Euclidean distance**. A particular weighted Euclidean distance applicable to count data is the square distance, which is calculated between the relative counts for every sample, by the inverse of the variable's overall mean count. Christo Ananth et al. [4] proposed a system which uses intermediate features of maximum overlap wavelet transform (IMOWT) as a pre-processing step. The coefficients derived from IMOWT are subjected to 2D histogram Grouping. This method is simple, fast and unsupervised. 2D histograms are used to obtain Grouping of color image. This Grouping output gives three segmentation maps which are fused together to get the final segmented output. This method produces good segmentation results when compared to the direct application of 2D Histogram Grouping. IMOWT is the efficient transform in which a set of wavelet features of the same size of various levels of resolutions and different local window sizes for different levels are used. IMOWT is efficient because of its time effectiveness, flexibility and translation invariance which are useful for good segmentation results.

## V. SIMULATION RESULTS:

MATLAB simulation has been done using the algorithms like Euclidean, Correlation, and SVM. They are compared based on the parameters like DCT, GT, SIFT and TT and values are noted with the help of a comparison table and graph. It is found that Euclidean method stands higher than all the parameters. It will show good results in all

extraction feature classifications where as correlation and SVM can afford only two classifications at a time.

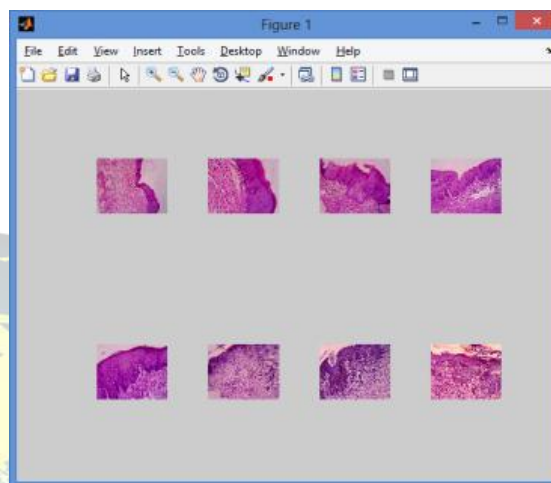


Fig .2. Database Images

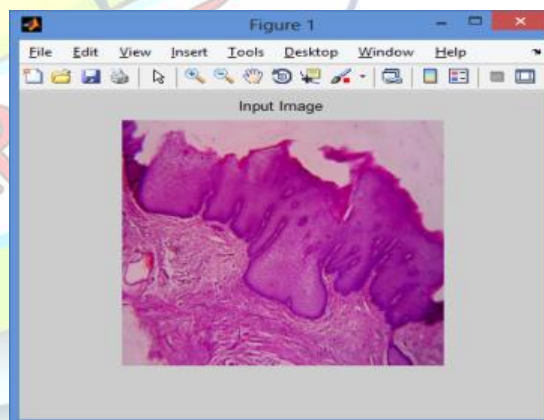


Fig.3. Correlation Input

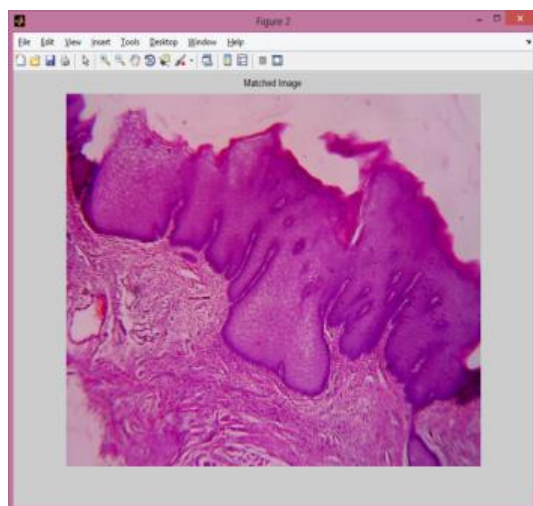


Fig.4. Correlation Output

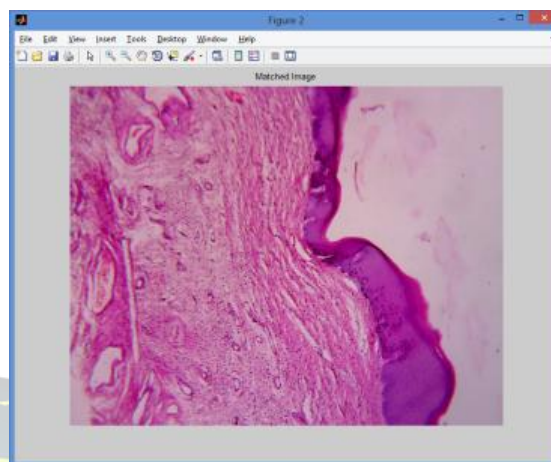


Fig.6. SVM Output

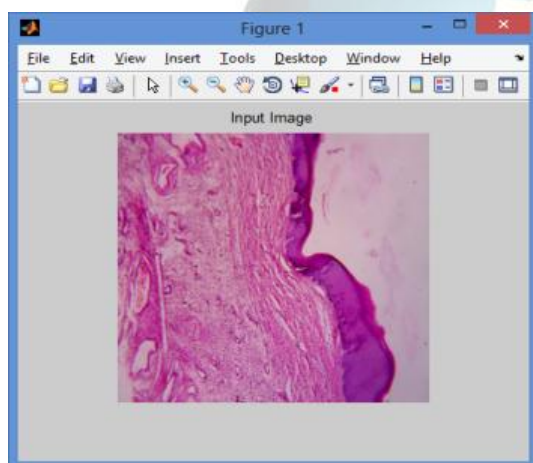


Fig.5. SVM Input

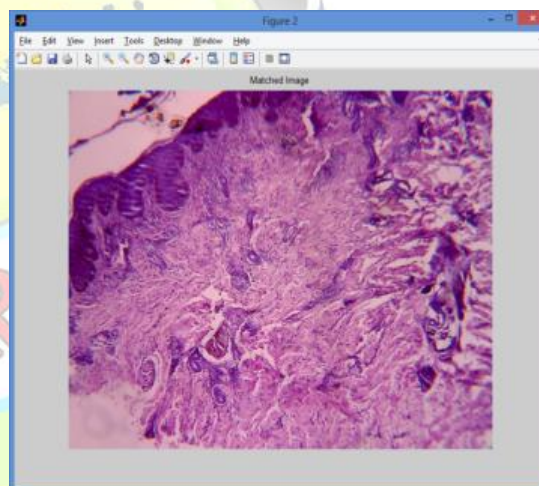


Fig.7. Euclidean Input

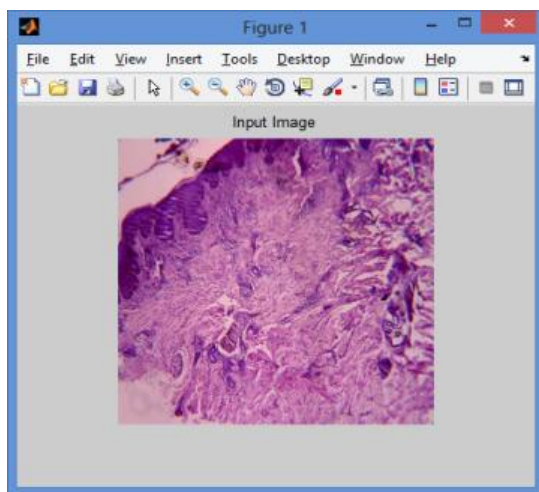


Fig. 8. Euclidean Output

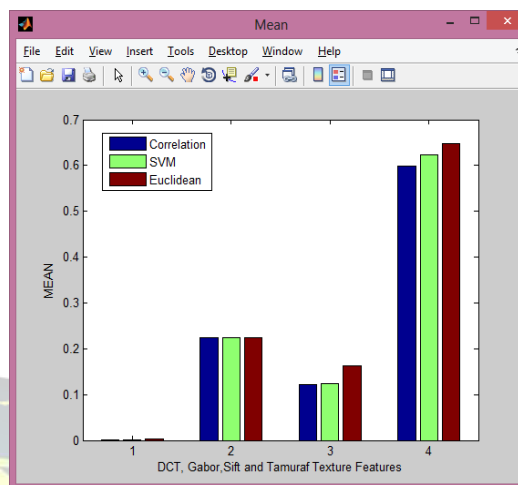


Fig.9.Comparison Chart

FEATURES	CORRELATION	SVM CLASSIFICATION	EUCLIDEAN DISTANCE
DCT	0.0010	0.0010	0.0028
GT	0.2247	0.2247	0.2247
SIFT	0.1219	0.1231	0.1621
TT	0.5984	0.6236	0.6485

TABLE.1.COMPARISON TABLE DCT,GABOR,SIFT & TAMURAF TEXTURE FEATURES WITH CORRELATION,SVM & EUCLIDEAN

## V.CONCLUSION:

Thus the MATLAB simulation has been done using the algorithms like Euclidean, Correlation and SVM in order to find an efficient algorithms for Medical image retrieval by comparing the performance of these 3 algorithms has been compared an certain parameters like **DCT,GT,SIFT** and **TT**. It is determined that the Euclidean algorithm stands high in all parameter, since it can slow good results in almost all extraction feature classifications. Hence Euclidean algorithm is the efficient algorithm for medical image retrieval especially for tissue images.

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