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Medical Image Retrieval using Dual Tree Complex Wavelet Transform and Principal Component Analysis with Haralick Texture Features

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Abstract*: Noise and distortion occurs in all types of medical images (Computed Tomography (CT), Magnetic Resonance Imaging (MRI.)..) and are unavoidable during the stages of image acquisition. We use medical image retrieval to extract the images from database by texture, shaptrix or color features. We use Dual Tree Complex Wavelet Transform (DTCWT) and Principal Component Analysis (PCA). DTCWT extracts the information of images. PCA compress the images. It also minimizes the feature vectors dimensions of all images. Haralick texture features are extracted from images with the co-occurrence matrix. This matrix describes the relationship of pixels. The similar images are found by calculating the similarity measure of the query image and all images in database by Mahalanobis distance. This method retrieves the similar images from database with respect to the input image provided by the user. The performance of the proposed algorithm can be found by precision and recall measures for evaluation. This system can be used in hospitals, clinics etc., for detecting diseases earlier.

***Keywords*: Dual Tree Complex Wavelet Transform (DTCWT), Haralick texture features, Medical Image Retrieval, Principal Component Analysis (PCA).**

I. INTRODUCTION

Development in technology during recent days inspired our day-to-day life and the method people store and communicates data. The people moved from traditional old methods to new techniques; this increases the digital medias' usage. Because of this greater increase of stored and captured digital images needs the novelty methods used for effectively classifying and retrieving similar images. Thus, Content Based Image Retrieval (CBIR) systems developed into a very trending systems for more effective and efficient techniques as CBIR systems can be used in crucial monitoring serving time applications in scientific, homeland security, among other apps [8].

Medical images plays a role in clinical (hospital) diagnosis and treatment. Every hospital acquire medical images, every day upto 10 GB. Lot of medical image informations are available on hospitals and clinics. It is impossible to manage the data in manual way. So we use medical image retrieval system.

Noise in images started with its generation, transmission, storage, signal conditioning etc. Digital Cameras that takes and stores photos in digital are used for the images' generation, with the help of sensors. Under unavoided circumstances, in medical images (US, MRI, X-Ray...), because of the generation wave nature, noise gets introduced in these images. The preprocessing step in images removes noise, which is an important step, to get better results of image processing in higher level such as secure image communication, fusion, recognition, identification, segmentation, compression [6].

We use DTCWT for decomposition of images. This wavelet basis is found in order to improve the system's performance[14]. We describe another method that is used for the compression of low frequency elements, with the help of standard principal components method. It helps to reduce images' dimension [4].

The medical images can be used to detect the nodule for treatment. Technique such as background anatomy of suppressing feeling in body that includes blood vessels, bronchi and ribs helps in detecting the disease procedure. A clear view presented in image that provides better region for nodule and features classification of images like shape, contrast and size.

This paper contains literature survey of 20 papers in second section, proposed architecture in third section, methods used in the system in fourth section, results found in fifth section followed by conclusion, future scope and some references.

II. LITERATURE SURVEY

Subasi A et al. (2019) analysed the problem of neuromuscular disorders, by Electromyographic (EMG) signals. They detected the problem by machine learning algorithms with the help of decision support system. They tested their proposed method with both simulated and clinical EMG data, from website of EMGLAB. They used Multiscale PCA (MSPCA) for the reduction of noise.

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They utilized the extraction of features by DTCWT, and recognized the signals by ensemble classifier rotation forest. They calculated standard deviation, kurtosis, skewness and mean by coefficients of wavelets obtained from DTCWT. This method used cross validation of tenfold with respect to classification accuracy, achieved better performance. The proposed method of EMG signals and Support Vector Machine (SVM) accured 96.6%, while Rotation Forest accured 99.7%.

Torbati N et al. (2019) solved the problem of volume based data misleading from Intra Vascular Ultrasound Sequence (IVUS) studies. They proposed image grating algorithm. They used DTCWT for phase information utilization that identifies the edge-like structures. They analyzed the DTCWT coefficients phase that detects the six motion signals. They chose best three motion signals by judging the properties for frequency of each and every signal. They filtered these signals by new bandpass Butterworth filter, and formed the gated sequence. They compared the four methods, and discovered that the accurate characteristics were in frequency than cardiac spectrum. The proposed method's extraction of gated sequence proved to be similar than the physicians' extraction of gated sequence. They found that the proposed method's direct application can act as pre-processing step for filtering, segmentation and reconstruction of images [2].

Padmavathi K et al. (2016) proposed a method for rerieving information of PET, CT, SPECT and MRI medical images. They used DTCWT for decomposing the low and high frequency characteristics, extracted features of informations from each type of image, and PCA for fusion rules and removing redundant information. DTCWT proved to be effective and shift invariant, preserved frequency and time information, and suited for fusion based applications. They applied PCA in each level to individual coefficients. They used five different data sets for five types of medical images. They analysed their method's performance with other methods, by Peak to Signal Noise Ratio (PSNR), Mean Squared Error (MSE), entropy, standard deviation and fusion factor. They plotted graphs and tabulated for each type of image to analyse the values of entropy, PSNR and MSE, for better retrieval. Their method showed the visual quality's improvement [3].

Lichtblau D et al. (2016) showed effective and simple method for saving images so that the retrieval of images can be accurate and fast. They extracted components of low frequency by Discrete Fourier Transform (DFT), compression by PCA and saving in k-D Trees. They started with the group of images, processed with filtering technique and extracted components of images. The MNIST digit suite illustrated the results' quality and applied on segmentation of chromosomes. They proposed automated method, no need of changing parameters or other offline processing for testing images. Wavelets alone or by in merge with Fourier technique for recognizing image at decreased speed cost. PCA compressed the image so that it suited for individual review. They demonstrated the utility of image recognition and classification of images. They proved that PCA performed better than other compression methods [4].

Amiot C et al. (2016) proposed efficient denoising and restoration algorithms, when the input images were of low contrast and high noise. The input images detected Poisson noise. They reviewed transforms of multiscale, used in previous years. They introduced motion compensation that detected and matched the objects and paired between frames. They used the method in multiscale space, filtered by spatial-temporal filter. They applied this filter in DTCWT domain. They compared their method with state of art. They analyzed recall curve in all types of curvelets and wavelets. They also tabulated the frangi, rotated filters, curvelets and DTCWT, that showed higher value of receiver operating characteristics (ROC). They demonstrated that qualitative and quantitative analysis on both real fluoroscopic and synthetic images, helps with the reduction of noise and performed effective [5].

Malini S et al. (2015) differentiated the images by correlation between signal and noise by PCA. It included the retention of the characteristics of high frequency with curves, edges etc. and the local requirements in analysis phase. This method operated on the multi resolution environment. This method maintained the visual characteristics of the image. The resulting more proved to be more informative. They proposed the combination of multi-resolution technique and PCA for denoising of images. The method provided a better efficiency and effectiveness. The method presented proved to be taken less significant time. Different variances and zero mean in Gaussian noise was tested in the original image. SSIM and PSNR ratio was calculated for four images. The results of the denoising by the wavelet thresholding are provided [6].

Bhateja V et al. (2014) proposed medical fusion of CT scan and MRI images, that retrieves the information for treatment and diagnosis purposes. They discovered that DTCWT provided directionality and shift invariant, together with spectral content preservation. DTCWT also were localized in frequency and time, and were designed with respect to time span. This method provided phase information by combining coefficients of wavelets. The images after decomposition of DTCWT, used fusion rules of PCA that reduced the redundancy and improved the resolution of images. They retained the features, by keeping the components that provide higher variance. They tested the results by fusion of one CT image and one MRI image, as input images. They simulated and experimented the results with fusion factor and entropy as fusion metrics. They justified the effectiveness while compared with others [7].

Anantrasirichai N et al. (2013) solved the video surveillance problem by image restoration, disturbed by atmospheric turbulence. They used region of interest for reducing the noise effects in video. They proposed efficient and effective selection of frames technique to choose ROIs from frames of good quality. They registered ROI in each and every frame, for reducing distortions. They answered the problem of distortion, by DTCWT on region level fusion. DTCWT helped them by higher directional selectivity over the Discrete Wavelet Transform (DWT), and remains shift invariant. They applied contrast enhancement after DTCWT, reduced haze interference. They also proposed metrics on learning for assessment of image quality, a new metric, QSVR, in both no-reference and full environment. They showed that the proposed method outperforms already used methods, in respect to enhancement in video surveillance [8].

Fierro M et al. (2013) presented algorithms that reduces noise and enhance images, using random sampling method.

They used DTCWT for data distinction in transform space. They limited the analysis to non-enhanced and enhanced images' luma channel. They computed standard deviation for each transform level among the six directions of DTCWT, and normalized the images. They concluded with the directional structured map of non-enhanced image. The directional map shrinked the enhanced image coefficients. They found that non enhanced image coefficients and shrunk coefficients behave to data directions. They produced enhanced noise reduced image by inverse transform. They retrieved the results of first and second decomposition levels and values were compressed. They plotted the graph according to performance of the proposed system. Numerical analysis was done by the researchers, to find the proposed method's validity [9].

Kaur A R et al. (2013) presented PCA and extraction of features for images of lung cancer. They preprocessed the images with histogram equalization and retrieved features with PCA. They enhanced the images from interference or corruption and noise. They obtained segmented images' features by Masking and Binarization method. They calculated matrix based on occurrence of gray levels to find the brightness pixel values. From GLCM, they obtained the features of it named, energy, homogeneity, maximum probability, entropy and contrast. They tried to combine GLCM and binarization to check whether the images in database and query image were abnormal or normal. They found image accuracy and quality as the important factors of their presented method. The proposed method performed well when compared to other feature extraction methods. This method produced high rate of survival and decreased the risk [10].

Yan Y H et al. (2012) proposed fusion method on images by DTCWT and PCA. They used DTCWT that decomposed the input images in many direction and multi scale way, and PCA fusion of rules that collects all information together. They named their method, DTWCT-PCA fusion technique. They described all tools on multi resolution development, on DTCWT. They tested the method on remote and multifocal images. They compared with other methods, by calculating Mean Cross Entropy (MCE), sharpness, Root Cross Entropy (RCE) and entropy. RCE and MCE indicated the difference between combined and original images. Entropy represented images' quantity of information. Sharpness indicated the clarity of fused image. All these factors helped their method to be clear and informative. They demonstrated the results, experimented and proved that their proposed method was efficient and effective [11].

Yildizer E et al. (2012) proposed a new technique of content based image retrieval by grouping and numbering wavelets. They explained clustering by k-means with indexing by B+- tree algorithm. They derived and extracted feature vectors by Daubechies wavelet transform. They tested and implemented 1000 JPEG format images, each category 10 images of 100 datasets. Their proposed system contains extraction of features, construction of models and query by image retrieval. They checked the similarity with the help of distance measure, and sorted the first five retrieved results, according to the input image provided by the user. All the techniques explained in this system using step-by-step algorithm and diagrams. This method improved the efficiency without damaging the accuracy of the system. They proved that their presented system has achieved higher performance than the other methods [12].

Caralavan M et al. (2011) proposed a method for biological 3-D living specimens that provides good resolution images with Poisson noise. They also proposed deconvolution methods that reduced the noise, and discussed methods that improve the solution. They presented common materials required in confoscal microscopy images.They introduced two techniques to find the poisson noise parameters, improved estimators of images and presented the deconvolution problem as the problem's minimization. They expressed the minimization by poisson distribution's likelihood and required no approximation. They solved constrained and unconstrained problems by direction methods that are wavelet transforms and total variation. They used DTCWT for their proposed problem. They finally presented results on 3-D real and 2-D synthetic images by TV and DTCWT transform. They provided an efficient algorithm for the large database of confocal images [13].

Dua S et al. (2011) classified the glaucomatous images by wavelet features. They surveyed the wavelet features calculated from the biorthogonal, symmlets and daubechies filters in wavelets. These features plotted in graph with the filters mentioned in the system. They subjected the images to equalize the pixels in histogram. They first performed extraction of images. Then, they discussed a novel method to obtain the ranks of features by sequential optimization, Bayes classification, random forest and SVM techniques. They calculated detailed and approximate coefficients of images by low pass and high pass filters. The features and their values were tabulated with normal and glaucoma images. They obtained 93% accuracy, with respect to detailed coefficients, to define the proposed method's effectiveness, with the help of cross validations in tenfold manner [14].

Kwitt R et al. (2009) proposed probabilistic retrieval in wavelets. They discussed various performance disadvantages that prevented applications from attaining better retrieval results. They discovered new retrieval method on featuring coefficients in wavelet transforms on marginal distributions. They used different statistical methods for the wavelet coefficients and DTCWT. They plotted the histogram on coefficient magnitudes of wavelets. They found the measurement of similarity between the query image and images in database using Kullback-Leilber divergences. They provided analysis based on the parameter estimation, like gamma and Weibull parameters, and arithmetic operations count for similarity. They discussed issues of parameter estimation. They concluded with brief of open problems and main advantages of the proposed method. They produced the results with less cost of computation [15].

Liu C C et al. (2009) presented DTCWT on face recognition. They proved this method to be efficient and effective for the representation of geometrical features, i.e., contour, orientation, strength and various singularities, with lesser redundancy in facial images. They proved to be different than old DTCWT methods, as it discuss only of the single scale information and reduce to one-eighth dimensions. They verified experimentally the method, and discovered it to be powerful than Gabor and discrete wavelet transform, in feature extraction versus the illumination and shift variations. They also proposed clip technique for the reduction of singular intrinsic extraction features. They used FERET database of eight bit grayscale 14051 images with various poses and expressions.

They discovered DTCWT to be traditional, can substitute with other wavelet transforms, based on attributes of transform [16].

Coria L E et al. (2008) proposed watermarking scheme that prevents piracy in camcorder. They presented the videos with watermark, so the compliant player only can detect it. They discovered the watermark should be strong to geometric distortions, i.e., cropping, rotation and scaling, and should use lossy compression, to separate block access content, for the video. These properties proved the proposed algorithm to be less cost and less complexity. They introduced algorithm for watermarking in playback control, which provides benefits of the DTCWT properties.

The DTCWT applied, retrieve transformation coefficients that are attached to video sequence. The DTCWT transform in the method they used, provides the benefits such as good directional selectivity, effective reconstruction and shift invariance. They provided an efficient implementation, and proved that this method performed better than other methods, by calculating geometric distortion features [17].

Yu R et al. (2008) analyzed in dual tree wavelet transform with complex wavelets. They explained the scaling functions and transformation functions. Separation of other properties from analyticity was done. These provided a unique treatment for the wavelet generation. Theorems and proofs were explained for scaling functions of wavelets. They proposed functions of scaling with respect to its transformation functions and also they derived scaling relationship on the filters. The discovered relationship was checked for analyticity with the help of functions. The functions were applied in Fourier transform to determine the relationship of wavelets. Transformation functions were also checked for biorthogonal and orthonormal wavelets in easier way. Their method can be studied and applied in complex wavelet forms, where dual tree is proposed. They proved the method as effective and efficient [18].

Chen Q et al. (2008) described PCA algorithm for gastroscopic image retrieval. First HSV color space quantized and clustered, calculated each color in main block with use of partitioning-weighted spatial method and the image retrieved by color correlogram. They used PCA to reduce dimension of the feature vector included the high spatial and color information. They implemented and designed query by example algorithm. The proposed approach proved to be effective in gastroscopic images. They combined the information of color and space to retrieval and integrated the retrieval system. The proposed methods proved to have better applications to gastroscopic images. They applied relevant feedback for next retrieval to provide better performance. This method proved to be feasible that integrated the two methods to provide information of space and color and the results proved this point [19].

Sjostrand K et al. (2007) presented a technique of connecting clinical data with spatial features. They did the extraction of variables using the method Principal Component Analysis (PCA) and they established variables with relation by model of regression. They used 569 images as datasets of brain images. PCA used two methods, one was the derivation of wavelets and the other regression of the original variables. They calculated Sparse PCA, derived from approximations of least squares, and decomposed the centered and spherical data. They analysed the connection between outcome variables and loading vectors. They tabulated the results for each mode of deformation and tested the t-significance value for the output variables, while this was time-consuming, they proposed methods like original variables analysis and wavelet transform decomposition. Their system's results can be seen as patterns of variation in anatomy [20].

III. PROPOSED ARCHITECTURE

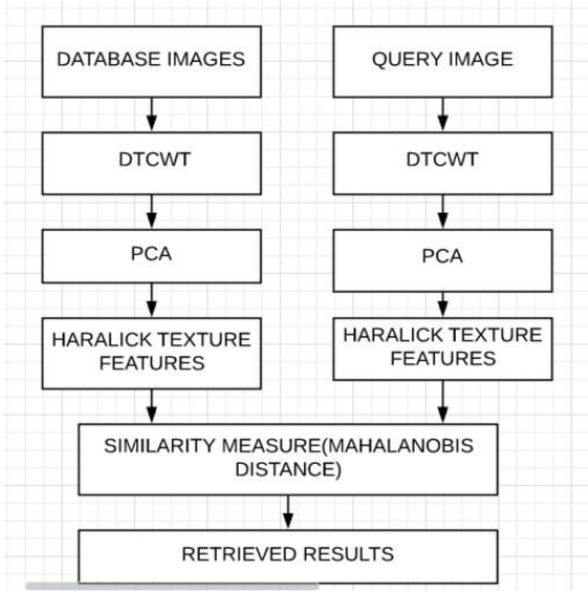

Fig. 1. Proposed architecture of the system

Fig.1. represents the proposed architecture of the system. In a multimedia era, the description of retrieval to represent a database full of images, which is established as a feature vectors derived from information of textures by DTCWT. PCA applied to both query and database image to reduce the dimension of images. We extract information from the images by Haralick texture features. At the time of query request, we measure the similarity between the images, using Mahalanobis distance, that are stored in the database and a user provided image is calculated and compared to find the result to report most similar images. As we take database for medical images, the experimental results of image retrieval are obtained.

IV. FRAMEWORK AND METHODOLOGIES

A. Image retrieval

An image retrieval system is used for large databases by browsing, searching and retrieving information. The first image retrieval system was developed at the MITs in year 1990s. Image retrieval- a kind of search to retrieve the images. For the search, the user provides a query image so that this retrieval system helped to find the similar images in database. Image retrieval divided in two types: Image Meta search- searches the images with respect to keywords and text present in the image, and CBIR- searches the images with respect to color, shape and texture of the image. Image Meta Search takes a lot of time and the text cannot be captured to explain the images. CBIR tem was originated by Kato in 1992. Features applied for both input user provided image and the database images to identify the similar image.

B. Dual Tree Complex Wavelet Transform (DTCWT)

Discrete Wavelet Transform (DWT) has been an establishing stone for all uses of computerized images handling: from denoising image to design acknowledgment, going through encoding image and then some. With the complete and (semi) invertible change of 2D information, the DWT offers to do a new technique known as "checkerboard" design,

which provides that information direction on the investigation is unthinkable. Besides, the DWT isn't invariant shift, making it less helpful for strategies dependent on the calculation of invariant highlights.

While trying to take care of these two issues influencing the DWT, Freeman and Adelson first presented the idea of Steerable channels, which can be utilized to break down a picture into a Steerable Pyramid, by methods for the Steerable Pyramid Transform (SPT). But, the SPT is an over-complete portrayal of information, it allows the capacity to properly recognize information directions just as being shift-invariant. However, the SPT isn't without issues: specifically, channel configuration can be chaotic, impeccable remaking is unimaginable and computational proficiency can be a worry. Along these lines, a further advancement of the SPT, including the utilization of a Hilbert pair of channels to register the vitality reaction, has been practiced with the help of Complex Wavelet Transform (CWT). So also as the SPT, so as to hold the whole Fourier interval range, the change should be over-finished by a factor of 4, for example there are 3 complex coefficients for every genuine one. While the CWT is additionally productive, since it tends to be figured through distinguishable channels, despite everything it does not have the Perfect Reconstruction property.

In this manner, Kingsbury likewise presented the Dual-tree Complex Wavelet Transform (DTCWT), which has the additional trait in Perfect Reconstruction at the expense of invariance in better move. Since the point is incredibly tremendous, just a short presentation of the 2D DTCWT is given. The peruser is published by Selesnick et al. for an extensive inclusion on the DTCWT and the relationship it imparts to different changes. The 2D DTCWT can be actualized utilizing two particular arrangements of divisible bases in wavelets of 2D, demonstrated as follows.

$$\psi_{1,1}(x,y) = \varphi_h(x)\psi_h(y), \tag{1}$$

$$\psi_{1,2}(x,y) = \psi_h(x)\varphi_h(y), \tag{2}$$

$$\psi_{1,3}(x,y) = \psi_h(x)\psi_h(y) \tag{3}$$

$$\psi_{2,1}(x,y) = \varphi_g(x)\psi_g(y), \tag{4}$$

$$\psi_{2,2}(x,y) = \psi_g(x)\varphi_g(y), \tag{5}$$

$$\psi_{2,3}(x,y) = \psi_g(x)\psi_g(y). \tag{6}$$

In (1) to (12), φ_h and ψ_h represents scaling wavelet coefficients passed through high pass filter, φ_g and ψ_g represents scaling and wavelet coefficients of low pass filters, in both dimensions x and y respectively.

$$\psi_{3,1}(x,y) = \varphi_g(x)\psi_h(y), \tag{7}$$

$$\psi_{3,2}(x,y) = \psi_g(x)\varphi_h(y), \tag{8}$$

$$\psi_{3,3}(x,y) = \psi_g(x)\psi_h(y), \tag{9}$$

$$\psi_{4,1}(x,y) = \varphi_h(x)\psi_g(y), \tag{10}$$

$$\psi_{4,2}(x,y) = \psi_h(x)\varphi_g(y), \tag{11}$$

$$\psi_{4,3}(x,y) = \psi_h(x)\psi_g(y). \tag{12}$$

In 2D wavelet transform, the wavelets provide six subbands with coefficients at each level, that will be in various orientations at angles +15°, +45°, +75°,-15°, -45° and -75°.

But in 2D complex wavelet transform, real and imaginary coefficients exists at each level, so six subbands for real and six subbands for imaginary coefficients will be available to find the detailed information of images.

(13) and (14) represents low and high filter relationship:

$$g_0(n) \approx h_0(n-1), forj = 1 \tag{13}$$

$$g_0(n) \approx h_0(n-0.5), forj > 1 \tag{14}$$

where j is the decomposition level. g_0 is low pass filter and h_0 is high pass filter for the trees.

At the point when consolidated, the bases offer to 2 arrangements of genuine, two-dimensional, situated wavelets.

$$\psi_i(x,y) = \sqrt{2}\left(\psi_{(1,i)}(x,y) - \psi_{(2,i)}(x,y)\right) \tag{15}$$

$$\psi_{(i+3)}(x,y) = \sqrt{2}\left(\psi_{(1,i)}(x,y) + \psi_{(2,i)}(x,y)\right) \tag{16}$$

$$\psi_i(x,y) = \sqrt{2}\left(\psi_{(3,i)}(x,y) + \psi_{(4,i)}(x,y)\right) \tag{17}$$

$$\psi_{(i+3)}(x,y) = \sqrt{2}\left(\psi_{(3,i)}(x,y) - \psi_{(4,i)}(x,y)\right) \tag{18}$$

The above equations (15) to (18) have combined the two seperable wavelets of (1) to (12) that provides two sets of two-dimensional, real and oriented wavelets, that results in Hilbert pairs.

The DTCWT is an ongoing improvement to the discrete wavelet change. The change was first proposed by Kingsbury so as to alleviate two principle burdens, in particular, the absence of move invariance and poor directional selectivity, of the DWT.

This change is a variety of the first DWT with the principle contrast being that it utilizes channel trees of two rather than one. In1-D signal, the utilization of channel trees brings about double the quantity of coefficients in wavelets as the first DWT. The coefficients created by these two trees structure two sets that can be joined to shape one lot of complex coefficients of the structure.

For 2-D signals, DTCWT requires a 4:1 increment in the quantity of coefficients and gives variance's estimated move in the level and vertical ways.

As 2-D DWT provides sub-bands of three at each level, comparing to Low-High(LH), High-High (HH), and High-Low (HL) filters, orientation shifting (0 , 45 , 90 , seperately), 2-D DTCWT provides sub-bands of six that relate to the yields of six directional channels.

C. Principal Component Analysis

PCA reduces two dimension to one dimension data in subspace of feature vector called eigen space obtained from matrix' covariance. The PCA is an analysis of images' method produced from Karhunen-Loueve (KL) transform. This transform was initially presented as expansion in series for random processes.

KL series expansion's equivalent is PCA. PCA converts discrete correlated set to uncorrelated set and also for the transformation of digital data from higher to lower dimensions. Data are arranged in higher order of significance. In the denoising area, PCA separates the signal from noise. The PCA values and Eigen values are related. PCA operates as filter of low pass and removes the noise of important features in images. After transformation in PCA, smaller magnitudes of noise related to signal are distributed over full data in case of noisy images. The components of PCA are in subspaces that are right angle to other components. The initial PCA is in higher variance and the following PCA's are of low variances. They are orthogonal to the other in subspaces.

PCA first calculates the co-variance and mean of the given data. Let the data matrix be X [The mean is represented by (19):

$$M = \frac{1}{N}\left[X_1 + X_2 + \ldots + X_N\right] \tag{19}$$

Shifting data in origin is solved by (20), difference of data and mean by

$$\hat{X} = data - M \tag{20}$$

The matrix of covariance C_A is calculated in (21):

$$C_A = \frac{1}{N-1}\hat{X}\hat{X}^T \tag{21}$$

Next is to evaluate eigen values and vectors of matrix C_A. The $p \times p$ matrix formed by matrix in diagonal and eigen values formed by eigen values. The values of eigen vectors and diagonal matrix are to be in descending order. The matrix resulted are principal component values. The initial PC values are of greater eigen values and the following PC values are lesser. Deleting the unimportant PC values and lesser values in matrix, reduction of dimensionality has achieved. Change of variables $A = (PC)Y$ discovered by orthogonal matrix PC that the uncorrelated variables $y_1, y_2, \ldots, y_p$ sorted of descending variances. Y in relation with X represented by (22):

$$Y_k = \left(PC^{-1} X_k\right) \tag{22}$$

The covariance matrix to be arranged in diagonal matrix of descending order.

D. Feature Extraction

Feature extraction lessens the resources amount required to define huge data. It begins with initial data and derived features needed to be non-redundant and informative leads to better human perceptions. The texture features are analyzed by representing Gray Level Co-occurence Matrix (GLCM).

Dataset collection

Datasets of type, CT and MRI images has been collected. Among them, different types of medical images exists in each type. We take 50 brain and 50 lung cancer images from each type, that consists 200 images totally. Here, we retrieve only top ten similar images from the database.

GLCM

The square matrix referred as co-occurrence matrix corresponds the occurrence pairs of gray level pixels which is known as GLCM. It is also known as co-occurrence distribution. For texture analysis, it is the statistical second-order method. An image has intensity for each pixel (a particular gray level), the GLCM is a table of how often various combinations of gray levels are in image region or the whole image. Calculation of texture features uses the GLCM contents which measures the variation in intensity at the pixel we choose from an image.

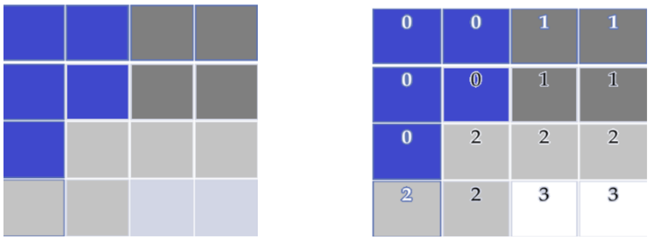

Image **GLCM matrix**

Fig. 2. GLCM

Fig. 2 shows how GLCM matrix is formed for an image according to the brightness of the pixels. The blue color represents the gray value 0 as it is most bright; the dark gray represents the gray value 1 as it is the second bright pixel; the gray represents 2 and white represents 3 according to the brightness of the pixels.

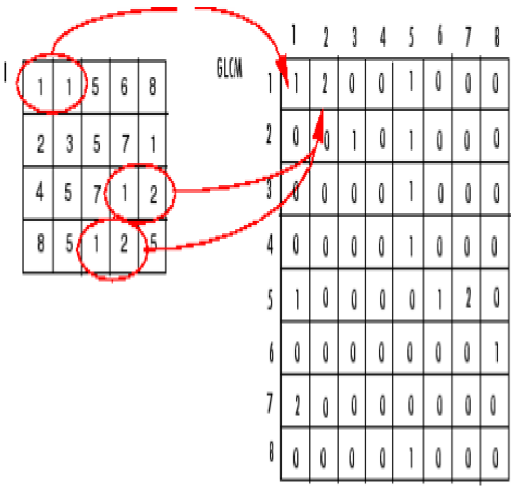

Fig. 3. GLCM Example

Fig. 3 represents 4 by 5 image with the GLCM matrix. Element (1, 1) contains 1 in GLCM because there is only one instance where two adjacent horizontal pixels have the 1 and 1 values in image. It follows the processing to fill other values in GLCM.

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Four directions are derived to explain the content of texture in the adjacent zero degree, the left diagonal 135 degree, right 45 degree and vertical 90 degree. If I is a binary image, co-occurrence matrix scales two values in the image. It scales eight levels if it is an intensity image. The image texture is completed when represented by the co-occurrence matrix computed in four directions. The information of texture from these matrices provides the structure of the texture.

Haralick texture features

Texture provides information on the colour spatial arrangement or intensities of selected portion of image or the intensity of whole image. It is defined as entity containing group of pixels and mutually related pixels.

It has different dimensions in which the image can be viewed.

Statistical methods are the most importantly used in medical images. These methods define texture on the distribution of space of gray values calculating features at images' each point and from the distribution of features, set of statistics derived.

Second order statistics which I use below are co-occurrence matrix and the gray level method defines the relationship between pixels of images. Second order methods provide higher discrimination rates than any other methods. Haralick et al have introduced textural features which were obtained from matrices of co-occurrence in 1973. The 14 Haralick features are explained.

1. *Energy*

Energy is derived from the **Angular Second Moment (ASM)**. It measures the gray levels' uniformity. When the pixels are similar, this value will be large.

$$ASM = \sum_i \sum_j P_d^2(i,j) \quad (23)$$

Equation (23) describes the sum of squares of all values in the GLCM with respect to rows and columns.

2. Contrast

The local images' quantity are measured by contrast. It shows the reflection of the sensitivity of textures in relation with changes in the intensity. It provides the intensity contrast measured between the region of interest and its neighbourhood pixel in images. For constant image, contrast is zero. If the gray level differs, contrast becomes large.

$$Contrast = \sum_{n=0}^{N_g-1} n^2 \sum_{|i-j|=n} P_d(i,j) \quad (24)$$

Equation (24) describes the sum of all values in GLCM with respect to rows and columns.

3. Correlation

The linear dependency of gray levels in the co-occurrence matrix is known as correlation.

$$Correlation = \sum_i \sum_j P_d(i,j)\frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y} \quad (25)$$

where μ_x, μ_y and σ_x, σ_y are the means and deviations in (25) which can be expressed as

$$\mu_x = \sum_i \sum_j i\, P_d(i,j)$$

$$\mu_y = \sum_i \sum_j j\, P_d(i,j)$$

$$\sigma_x = \sqrt{\sum_i \sum_j (i-\mu_x)^2 P_d(i,j)}$$

$$\sigma_y = \sqrt{\sum_i \sum_j (i-\mu_y)^2 P_d(i,j)}$$

4. Sum of Squares-Variance

Variance is square of standard deviation represented in (26).

$$Variance = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i-\mu)^2 P_d(i,j) \quad (26)$$

5. Homogeneity

Also called as **Inverse Difference Moment**. The similarity of pixels measured is known as homogeneity. A gray co-occurrence matrix of diagonal provides homogeneity of one. If local images have minimal changes, the homogeneity becomes large. In (27), contrast value is used to determine homogeneity.

$$Homogeneity = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{P_d(i,j)}{1+|i-j|} \quad (27)$$

6. Sum Average (sav)

$$sav = \sum_{i=2}^{2N_g} i\, p_{x+y}(i) \quad (28)$$

7. Sum Variance (sva)

$$sva = \sum_{i=2}^{2N_g} (i-sen)^2\, p_{x+y}(i) \quad (29)$$

8. Sum Entropy (sen)

$$sen = -\sum_{i=2}^{2N_g} p_{x+y}(i)\log\{p_{x+y}(i)\} \quad (30)$$

From (28) to (30), x and y are the co-occurrence matrix co-ordinates , and $p_{x+y}(i)$ is the co-occurrence matrix's probability with its co-ordinates adding to $x+y$.

9. Entropy

Entropy provides the randomness of images' intensity. It is the degree of disorder present in image. Entropy becomes large when values of co-occurrence matrix are all same. Entropy is represented in (31):

$$Entropy = -\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_d(i,j)\log(P_d(i,j)) \quad (31)$$

10.Difference Variance (dva)

$$dva = \sum_{i=0}^{N_g-1} i^2\, p_{x-y}(i) \quad (32)$$

11. Difference Entropy (den)

$$den = -\sum_{i=0}^{N_g-1} p_{x-y}(i)\log(p_{x-y}(i)) \quad (33)$$

where $p_{x-y}(i)$ is the probability of co-occurrence co-ordinates difference to $x-y$. (32) and (33) are similar with sva and sen.

12. Information measures of Correlation 1

$$imc1 = \frac{HXY-HXY1}{max(HX,HY)} \quad (34)$$

13. Information measures of Correlation 2

$$imc2 = [1-\exp(-2(HXY2-HXY))]^{1/2} \quad (35)$$

where

$$HXY = -\sum_i \sum_j p(i,j)\log\{p(i,j)\}$$

HXY1 is same except log (p(i,j)) it will be $\log p_x(i)p_y(j)$. Now, HXY2 is same except p(i,j)and log(p(i,j)) it will be $p_x(i)p_y(j)$. and $\log p_x(i)p_y(j)$

p_x and p_y. 's entropies are HX and HY.

14. Maximal Correlation Coefficient

$$mcc = (\text{second largest eigenvalue of } Q)^{1/2} \quad (36)$$

where

$$Q(i,j) = \sum_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(k)}$$

Equation (34) to (36) calculated due to computational instability.

Energy, variance, homogeneity, entropy and correlation are the five Haralick features that are used to define certain properties of gray level's spatial relationship between pixels, among 14 Haralick texture features. Since texture has dimensions different, they are not independent to each other features. For example, the energy derived from the matrix is also known as uniformity, heterogeneity's measure known as variance and homogeneity's measure is inverse difference moment. Thus, selecting features' subset from co-occurrence matrix of gray levels for an application, the features should not be independent of the other, as it is usually hard to find.

E. Similarity Measure

A similarity measurement is selected to check the closeness of one vector with another. It is also called as metric distance. The problem can convert to compute the issue between two vectors x, y ∈ Rd. Once images are extracted, we find measurement of similarity between features of database images and features of query image. Various distance measures in image retrieval are there. In that, we used Mahalanobis distance here.

Mahalanobis distance

It is an important case derived from quadratic with metric distance in the matrix ransformation that is solved by matrix of co-variance provided with feature vectors' training set. i.e. A= inverse of ∑. The feature vectors are considered as variables in random X={x0, x1, x2…1}. Then, the matrix of correlation is provided by R with row i and column j, given by the mean of the random variable x multiplied with mean of i and j. The co-variance matrix is solved by $\Sigma = [\sigma_{ij}^2]$ where $\sigma_{ij}^2 = r_{ij} - E\{x_i\}E\{x_j\}$. The Mahalanobis distance defined in (37)by Q and T feature vectors is solved by x_Q=Q and $x_T = T$, that provides

$$d_{mah} = [(x_Q - x_T)\Sigma^{-1}(x_Q - x_T)]^{\frac{1}{2}} \quad (37)$$

The distance of Mahlanobis in efficient form in (38):

$$d_{mah}(Q,T) = \frac{\sum_{i=0}^{N-1}(Q_i - T_i)^2}{\sigma_i^2} \quad (38)$$

It gives smaller variance with respect to more dimension weight and larger variance to less weight of dimension.

Mahalanobis distance can also be measured between x, y and training vector (xi) as shown in (39):

$$d(x,y) = \sqrt{(x-y)^t S^{-1}(x-y)} \quad (39)$$

where sample co-variance S is $S = \frac{1}{n}\sum_{i=1}^{n}(x_i - u)(x_i - u)^t$ and mean vector is Equation

$$u = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Mahalanobis distance is a form of Euclidean distance which mainly takes the co-variance of the data into account. It is computed to check the similar distance between the datasets as it provides bigger weight to the components that are noisy. It is mainly used to find the outliers of data. Detecting outliers is very important, as the expectation happens to be the data should be normally distributed. Outliers contributes to the data that are skewed, so they have to be removed.

Mahalanobis distance performs better than Euclidean distance. Euclidean distance does not looks good for all datasets. As the data finds the squares of two points and add, then taken square root of the answers at the last. So, it takes more time and complexity is large. It is found that histogram distance performs lesser than other similarity measures. The histogram intersection takes out the dissimilar elements by matching of the feature vectors in two. This can be selected for matching of object-to-image as it removes the features part irrelevant to object. However, it causes huge mistake in image-to-image and object-to-object matching. Although, quadratic distance measure takes the each feature element relationship with other elements of feature, it produces same weight to each element in relationship. We use Mahalanobis distance for better retrieval effectiveness and efficiency.

F. Evaluation Metrics

The images can be evaluated by the performance of precision and recall. Precision is called as true positive predictive values and recall is called as sensitivity. Both metrics are based on measure of relevance and understanding the images. Higher precision is described that an step-by-step procedure returns more relevant than irrelevant results are retrieved. High recall describes that a step-by-step procedure returns the results which are mostly relevant.

Precision:

Precision is described as the retrieved similar images' count to the retrieved similar an dissimilar images' count in (40). Suppose, t_p is the number of retrieved similar images and f_p is the count of retrieved dissimilar images. So, the total number of retrieved similar and dissimilar images is t_p+f_p. Precision is described as:

$$precision = \frac{t_p}{t_p+f_p} \quad (40)$$

Recall:

Recall is described as the total count of retrieved similar images to the whole count of similar images in database in (41). Recall is solved by:

$$recall = \frac{t_p}{t_p+f_n} \quad (41)$$

Precision-Recall graphs:

Precision-Recall graphs determine the accurate result of the image retrieval discussed above. They have also used these graphs in the evaluated performance of search engines such as documents or text. They are also used in the machine learning performance evaluation through ROC (Receiver Operating Characteristic) Curves.

The graphs are suited for data and document retrieval. In the image retrieval, given the query image, the graph measures how similar the image is to query image with the remaining images in database. Each of the images in database has similarity measures related with query image and then the similarities has to be ordered in descending order. The relevant images appears first then the irrelevant images appears next which proves that this is good image retrieval system.

Precision and recall are related inversely. Because, if precision increases then recall decreases. And, if the recall increases then precision decreases.

The retrieved results include relevant images and irrelevant images. So it causes the decrease in precision.

V. RESULTS AND DISCUSSION

Medical images from Cancer Imaging Archive has been collected for datasets. Among them, they has different medical images in each section. The top ten similar images has been retrieved. For evaluation of the system, the precision and recall computed to find the similar images retrieved that are relevant and irrelevant. Likewise, the top 10 images has been added every time. At each step of adding images, the precision and recall was calculated. And a query image can be provided by the user to find the similar images.

At each step of adding images, the precision and recall was calculated. And a query image can be provided by the user to find the similar images. Some of the similar images with respect to query for different diseases has been shown below:

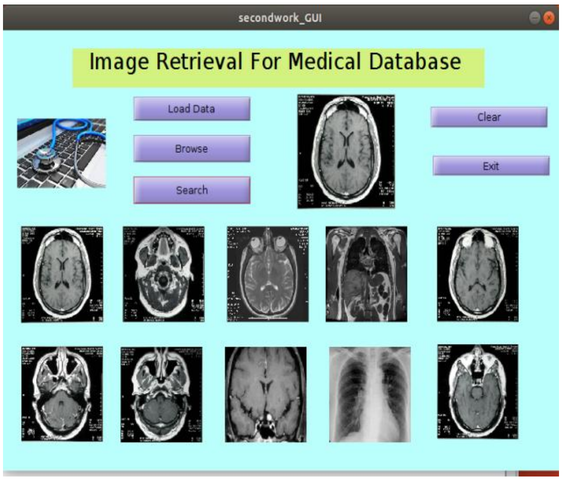

Fig.4. Retrieved results -1

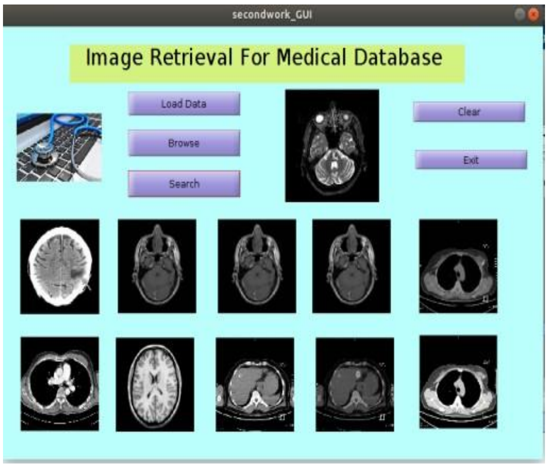

Fig.5. Retrieved results -2

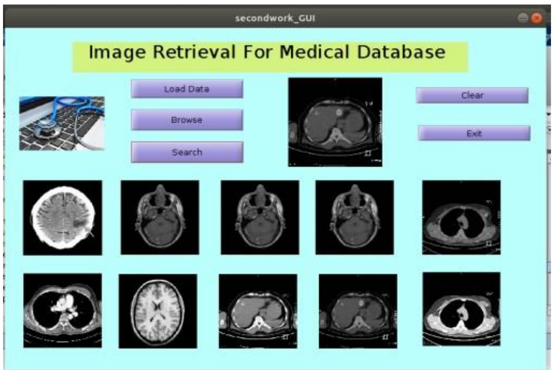

Fig.6 Retrieved results -3

Similar to Fig. 4, Fig.5 and Fig.6, we can retrieve relevant images from database.

Table 1.Number of images retrieved vs. Precision values

No. of Images Retrieved	Precision
10	0.9
20	0.85
30	0.8

40	0.76
50	0.71
60	0.68
70	0.65
80	0.6
90	0.58
100	0.5

Table 1. represents the number of images retrieved vs. precision values of the similar images retrieved with respect to the query image.

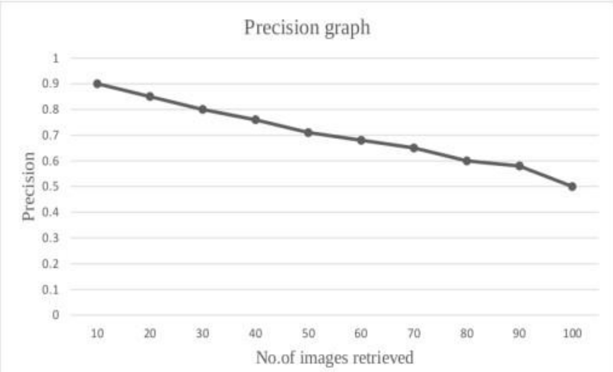

Fig.7. Precision graph

Fig.7. represents the precision graph for the table of values given with respect to the number of images retrieved.

Table 2. Number of images retrieved vs. Recall values

No. of Images Retrieved	Recall
10	0.45
20	0.65
30	0.7
40	0.85
50	0.89
60	0.91
70	0.93
80	0.95
90	0.96
100	0.98

Table 2.represents the number of images retrieved vs. recall values of the similar images retrieved with respect to the query image.

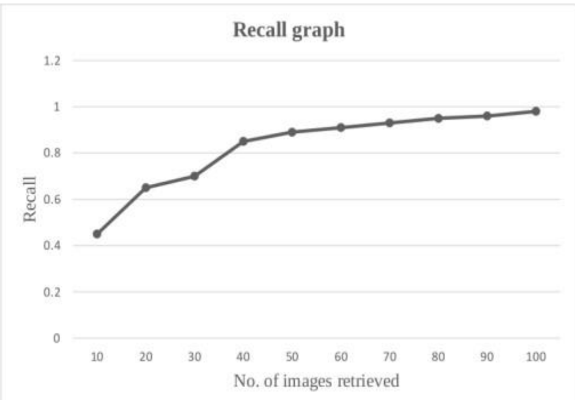

Fig.8. Recall graph

Fig.8. represents the recall graph for the table of values given with respect to the number of images.

VI. CONCLUSION

Medical image retrieval has been proposed for detecting disease at an early stage. This retrieval used DTCWT for decomposition, PCA for compression and Haralick Texture Features for feature extraction. DTCWT has been applied here with combination of PCA. GLCM has been found to extract the spatial relationship of pixels and Haralick texture features are derived from GLCM. The similarity measure Mahalanobis distance has been calculated and performance can be evaluated. The proposed method can be used in hospitals, clinics etc., and by doctors, physicians, patients etc. This medical image retrieval can be extended to calculate accuracy and compare this system's accuracy with other methods.

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