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Computer Aided Diagnosis of Breast Nodule Detection and Mammogram Enhancement Using Fuzzy Sets

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ABSTRACT

Breast cancer is widely used in many medical fields. The tumor pandemic drastically influences the health and well-being of the global population. In this proposed methodology, Fuzzy K-Nearest Neighbor Equality approach is performed. The extracted image of Breast cancer cannot be directly used for diagnosis. The captured image contains disturbances like noise, blurred image etc. To get a high-quality image from extracted panoramic. This approach is performed. To the extracted images, partitioning is performed to split up the images into samples. It helps for better recognition and classification. It shows the infected region of Breast cancer accurately. Before performing partitioning, the extracted image has to be preprocessed to clear out the disturbances in the image. After partitioning, feature extraction is performed by using GLCM and finally, classification is performed between the trained and test set data to produce a highly accurate image. It is done by using Fuzzy K-Nearest Neighbor Equality algorithm classifier. This processed image helps the dentist for good prediction. The objective of this work to improve the effectiveness and efficiency of the classification process. In this way to reduce the FP (false positive) rate. The proposed methodology accurately separating the benign and malignant region accuracy.

Keywords: Breast cancer, Computer-aided Diagnosis, Image enhancement, intuitionistic fuzzy sets, mammogram.

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INTRODUCTION

Image segmentation is an essential task in medical image processing, which is used to partition the image into the number of sectors with like characteristics using some predefined measurement criteria. In past decades several image segmentation has been proposed to improve the performance of segmentation. The goal of segmentation is that the pixels in the same region have similar qualities, i.e., pixels from the different region have different qualities. Breast cancer is the form of tumor that occurs almost entirely in women.

LITERATURE SURVEY

Image segmentation is an essential task in medical image processing, which is used to partition the image into the number of sectors with like characteristics using some predefined measurement criteria. In past decades several image segmentation has been proposed to improve the segmentation performances. The goal of segmentation is that the pixels in the same region have similar qualities, i.e., pixels from the different region have different qualities. Qingyong Li et al. [1] proposed an image segmentation on the vessel support region. It produces a fine segmentation, compared to the available methods but accuracy is less. This technique has the limitations to choose the threshold value to separate the image particles from the noisy images. To overcome these limitations Ronghua Shang et al. [2] suggested a new technique of image segmentation based on the key pixel. This method improves the overall segmentation performance and produced a reliable output. However, there are some limitations that, it is difficult to use image-level annotations to train segmentation. Liyilei Su et al. [3] introduced an integrated method of both region and boundary-based segmentation for x-ray images. It produces high accuracy. However, it concentrates only on the colour of the pixels and not bother about the other features of the image. To overcome these constraints Mengxuanzhang et al. suggested an unsupervised EA-based fuzzy clustering for image segmentation, this method does not require any prior information for segmentation [5]. However, this method is not working well in noisy images because of the lack of spatial information. To overcome this an FCM segmentation with spatial constraints for medical image Segmentation proposed [6], [7]. The spatial information derived from the images is used for the clustering process. However, there is a need for structural information and gradient information which provide better optimum segmentation at the edges. All these existing methods of segmentation has the limitations such as the fixing of the threshold value and curve function and finding the common borders of the clusters and choosing the opt parameters can be rectified by using the proposed Gradient Orientation Mapping Based Fuzzy C-Mean clustering method in which there is no need for any prior information like threshold value and curve function. In this new technique, both spatial and structural information are included for segmentation and also some image features such as edge which gives the boundary of the breast, the entropy which is used to classify the textures, intensity, Color, and Gradient features are also used to improve the performance of segmentation. Thus the various parts of the images are segmented elegantly. The breast has witnessed tremendous advances in all its medical field. With these advances, there is a need for a more precise diagnostic tool. Breast images have also found a place in modern dentistry. In this work, was used to extract the entire mouth in a single image. It made the complex work more accessible for examination. This paper is to review the trending advances in imaging technology and their uses in different disciplines of dentistry. For the precise prediction, a deep learning approach is used in the image for partitioning the breast and to get a high-quality image. Several approaches were used in the existing work but this proposed workout performs well compared to other work.

Wu et al., (2018) discussed the model-based breast assessment in the panoramic radiographs. In this work, they have used a set of parameters to obtain a piece of reliable information for the best treatment plan. ACVP and COA are new parameters that consume more time and difficult to find [1]. Gan et al., (2017) [4] they have discussed the segmentation of tooth region. They used the tooth contour propagation strategy for performing segmentation. By using this strategy, it suffers from serious accumulated error problem. Mao et al., (2018) [8] they have presented in detail about the Grab cut algorithm which is used for segmenting the breast image. Even though this algorithm is very fast and easy to implement. The drawback of this proposed work is, the result becomes unstable. To overcome this drawback. In this proposed methodology, the deep learning approach is performed in the breast image. Breast is chosen because it ionizes less radiation. It shows the image in a two-dimensional view. This breast tries to project the breast arch in orthogonal view. To the extracted panoramic image, a deep learning approach is utilized to achieve high accuracy. Researchers focus on increasing the accuracy of segmentation that can be achieved and proved by using this proposed segmentation algorithm.

3. PROPOSED SYSTEM

From figure 1 shows the schematic representation of the proposed methodology. Initially, the image is pre-processed by using the filter. Second, the pre-processed image can be given to the segmentation section of the system. This system consists of a fuzzy rule. Finally, features are extracted from the segmented region and provide the accuracy of the entire system.

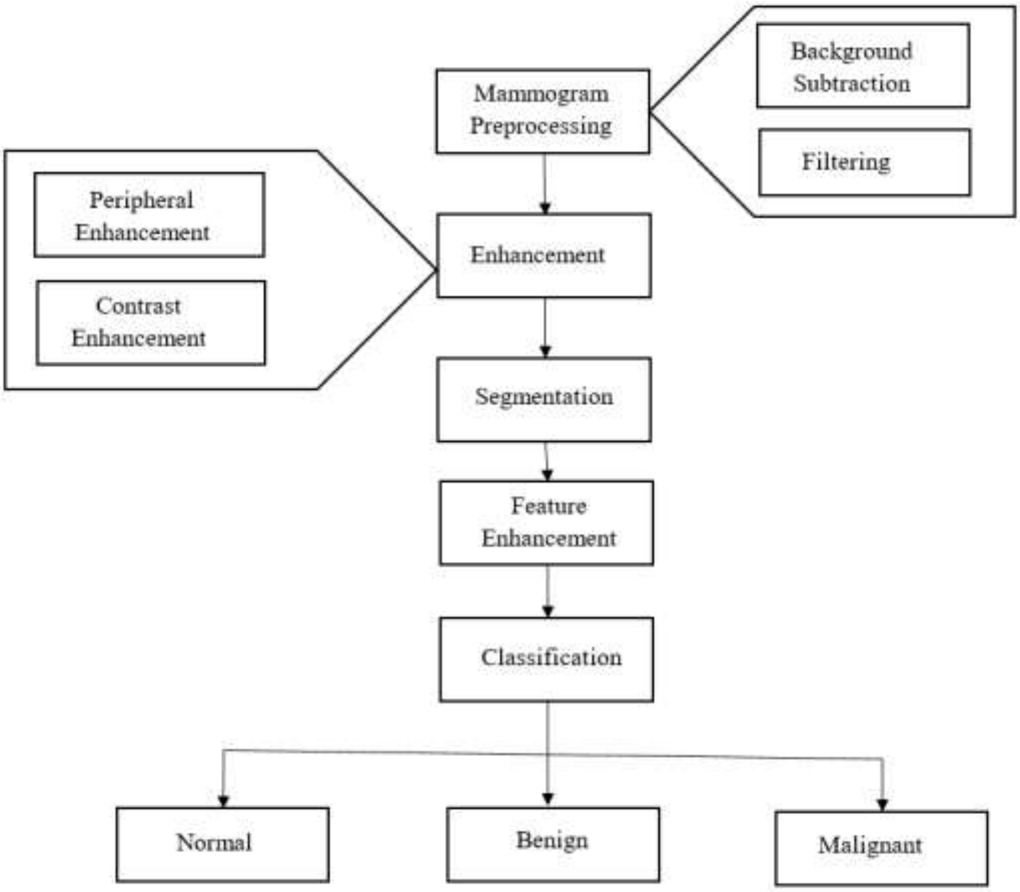

Figure 3.1: Diagrammatic flow of CAD system for breast abnormality

The input image is given to the pre-processing state to reduce the noise and crop the test data image from the input image. The then cropped image is converted into samples, it is achieved using the segmentation process. The correlation-based feature selection generates the trained data set. Both these features are compared using the proposed classifier.

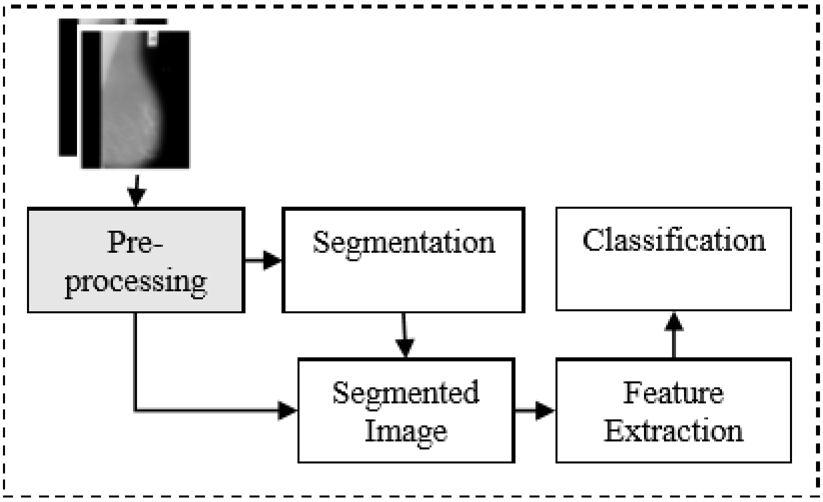

Figure 3.2: Framework of the preprocessing stage

Clustering is the route toward isolating information which focuses on image samples or clusters with the objective that the things in a similar class are comparable and things in various classes are disparate. Given the possibility of the data and the explanation behind which clustering is being used, particular measures of closeness may be utilized to place things into classes, where the likeness measure controls how the gatherings are surrounded. A couple of instances of measures that can be used as in gathering join separation of the image. In hard clustering, data are apportioned into specific gatherings, where each data segment has a place with precisely one group from the breast images. In fuzzy clustering, data parts can have palace with more than one gathering, which is more, accompanied with each segment is a course of action of membership levels. This exhibit the idea of the connection between that information part and a specific gathering of fuzzy clustering is an arrangement of propelling these enrolment levels, and subsequently utilizing them to apportion information parts to at least one get together. A champion among the most comprehensively used Fuzzy gathering tallies is the Fuzzy C-Means (FCM)

3.1 MIFS

Integrating the fuzzy filtering (based on IFSs) with nonlinear fusion operators, a new fuzzy enhancement scheme was developed called as MIFS, for mammogram enhancement. An original mammogram M(u) is separated into the foreground area $M_o(u)$ and background areas $M_B(u)$ for image enhancement via threshold. The filtered areas i.e $F_o(u)$ and $F_B(u)$ are achieved through fuzzy operations. Through normalization, the filtered mammogram D(u) is combined with the original image by using the fusions named as f1, f2 and f3 to acquire an enhanced mammogram E(u).

Steps for mammogram enhancement using an intuitionistic fuzzy algorithm are as follows.
Step 1: Separate a mammogram into the foreground area and background area. Step 2: Construct intuitionistic fuzzification generators of the foreground and background areas, and then convert the pixel plane into a membership plane. Step 3: Hyperbolize respective membership degrees of the foreground and background areas. Step 4: Re-transform the membership plane into a pixel plane, so achieve a filtered result through normalization. Step 5: Obtain an enhanced result by combining the filtered result with the original image.

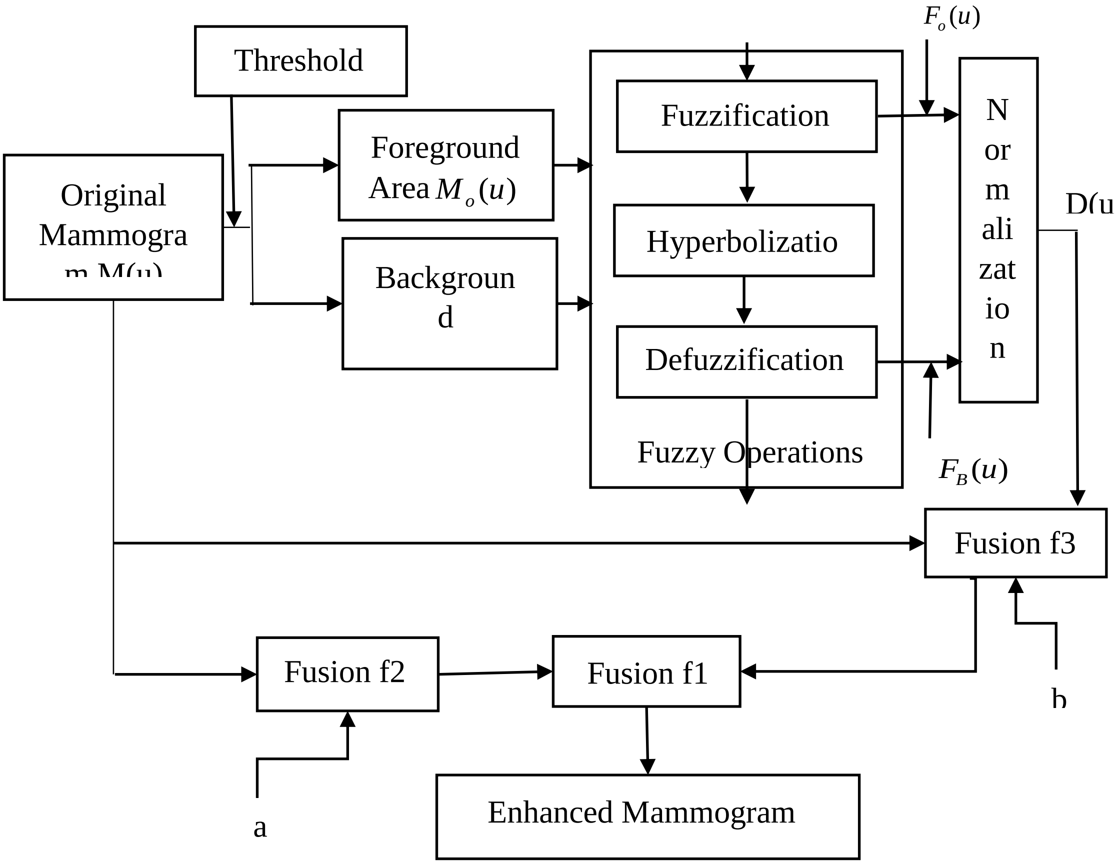

Figure 3.2: Diagrammatic representation of the MIFS scheme

3.1.1 Thresholding

Global thresholding is implemented because it is easy and also computationally less involved such as Ostu, minimum error and Parzen window estimate methods. A mammogram is automatically dividing into the foreground and background areas based on its iterative strategy. Input does not require to select foreground and background areas. For an input mammogram, the following iterative strategy is used to find a global threshold.

i) Initialize the global threshold T, T=0.5($I_{\max}$ + $I_{\min}$), where $I_{\max}$ and $I_{\min}$ denote the maximum and minimum gray values of the mammogram.

ii) Segment the mammogram using T. This engenders two groups of pixels: I_1 composing of all pixels with gray values ≥T, and I_2 consisting of pixels with values <T.

iii) Calculate the average gray values m1 and m2 for the pixels in I_1 and I_2, respectively.

iv) Compute a new threshold value: Ŧ=0.5($m_1 + m_2$).

v) If |T-Ŧ|>λ, let T=Ŧ and repeat Steps ii) through iv). Or else, achieve a final segmentation threshold Ŧ.

Algorithm:
1. Apply the Forward Curve-let transform into the noisy image.
2. Threshold the Curve-let coefficients to remove some insignificant curve-let coefficients by using a thresholding function in the curve-let domain.
3. Inverse Curve-let transform of the threshold coefficients to reconstruct a function.

Hierarchical Clustering: Hierarchical Clustering is used to implement a dendrogram (shows hierarchical relation between objects) with a grouping of patterns in nested form and to change groupings in combination with similar levels of the input breast images. In hierarchical clustering, the number of clusters need not be specified in prior where only local neighbours in each step are considered. To interpret the hierarchical clustering algorithm function two-dimensional data set is applied. The hierarchical clustering is subdivided into two categories, namely, the hierarchical agglomerative-algorithm and hierarchical divisive algorithm.

The hierarchical agglomerative method is stated below:
Step 1: In the database, each pattern is set as a cluster
Ci and distance in between all pair of patterns are computed with a proximity matrix.

Step 2: The common alike pair of clusters is found by using the proximity matrix and the two clusters are merged into a single cluster. Finally, modify the proximity matrix.

Step 3: Step 1 and 2 are repeated until all patterns in one cluster achieve the resemblance.

Algorithm Non-Local Means
Input 1: Image with Radom value impulsive noise
Output1: NLM (Denoised Image)
For each pixel i, where i$i \epsilon [1, N]$,
Do
For each pixel in N_k, where N_k is the square patch around the centre pixel k,
Do
Evaluate, normalization constant $Z(i) \sum_j e^{\frac{||v(N_i)-v(N_j)||^2}{h^2}}$ (3.1)
Where j refers to the $N_k$patches
Calculate, weight matrix W(I,j) $\frac{1}{z(i)} e^{\frac{||v(N_i)-v(N_j)||^2}{h^2}}$ (3.2)
Done
Denoise pixel i; NL[v] (i) $\sum_{j=1} w(i,j)v(j)$ (3.3)
Done

Feature Extraction

Features are unique properties of the information that help in separating the information patterns in the classification phase from the image. Features may be crude pixels for basic issues. Utilization of basic image pixels is not sufficiently clear. Changing the information on behalf of the arrangement of features is called Feature Extraction. Feature Extraction is typically distinguished as a diminished list of capabilities to speak to the errand. The portions of the components are colour histogram, zone and so on in the image. They are utilized for perceiving shapes and for the most part utilized as a global feature. Some different sorts of features are texture, intensity and so forth.

These elements tell about the spatial introduction and its degree. These features are called a local feature. It is important to recognize when to utilize global feature and local feature. By considering the portrayal of the significant functions the separated feature ought to give the attributes of the info to the classifier. Typically

Gray Level Co-Occurrence Matrix (GLCM): A notable procedure to extricate feature is to utilize Gray LevelCo-event Matrices (GLCMs), which have a place with measurable technique in breast analysis. The GLCM contain the second-arrange measurable data of spatial association the pixels of an image. The GLCM comprise data almost in what way frequently a pixel with the grey-level value I happen either vertically, on a horizontally, or diagonal to the neighbouring pixels with the value j, where i and j are the dark level values introduced in an input breast image.

Energy is a component that measures the smoothness of the input picture. Correlation is a grey tone measure of direct conditions in the picture. The parameter

Homogeneity, otherwise called 'inverse difference moment' measures picture homogeneity as it accepts bigger esteems for littler grey tone contrasts in combine components. Contrast for a bordering set of pixels is a measure of contrast between the most astounding and the least esteem in it. Hence GLCM using feature extraction is implements the potential component vectors for more image-based disease diagnosis. In general, GLCM deals with features of the image to be segmented. In our work, we are working with problem area segmentation. By this operation, feature calculation will be pointed in a particular region only so that output will be better than the existing approach.

Fuzzy K-Nearest Neighbor Equality (FK-NNE) Algorithm

A novel Fuzzy K-Nearest Neighbor Equality algorithm are discussed in this section. FK-NNE assigns class membership to a sample vector and the basis of the algorithm to assign membership as a function of the vector distance from its K-NN algorithm and those neighbour memberships in the possible classes. The mean distance is calculated from K-points to test the data. The minimized mean value distance is considered as output class values and it is stored.

Algorithm: Fuzzy K-Nearest Neighbour Equality (FK-NNE)
Input: x – Vector to be classified; K- Samples; (x_i, D^i), i = 1… n
Output: Class of Vector x

Step 1: **BEGIN**
Step 2: Input x, of unknown classification
Step 3: Set K, $1 \leq K \leq n$
Step 4: Initialize i =1
Step 5: DO UNTIL (K-nearest neighbours to x found)
Step 6: Compute distance from x to x_i
Step 7: IF ($i \leq K$) THEN
Step 8: Include x_i in the set of K-nearest neighbours
Step 9: ELSE IF (x_i closer to x than any previous nearest neighbour) THEN
Step 10: Delete the farthest of the K-nearest neighbours
Step 11: Include x_i in the set of the K-nearest neighbours
Step 12: END IF
Step 13: END DO UNTIL
Step 14: Initialize i = 1
Step 15: DO UNTIL (x assigned membership in all classes)
Step 16: Compute $\mu_i(x) = \dfrac{\sum_{j=1}^{K} \mu_{ij}\left(1/\|x - x_j\|^{2/(m-1)}\right)}{\sum_{j=1}^{K}\left(1/\|x - x_j\|^{2/(m-1)}\right)}$
Step 17: Increment i
Step 18: END DO UNTIL
Step 19: FOR each class value D^i DO //Fuzzy Equality Calculation
Step 20: Select the fuzzy K-Nearest Neighbours to x that belongs to D^i from the sample file
Step 21: Compute the mean distance from these k points to d, $\overline{d_{D^i}}$
Step 22: Output the class m^* with the minimized mean distance $\overline{d_{D^i}}$, among all the classes
Step 23: END FOR
Step 24: **END**

FK-NNE Classifier

Convolutional layers are neural system layers saving the spatial structure, which is the essential distinction from customary completely associated neural system layers. Having, for instance, 32 × 32 × 3 picture, rather than extending it to the one-dimensional vector of 3072things, the picture is kept in its unique 2D structure. By applying the convolutional channel, the information is changed into an alternate tensor called actuation map that additionally protects basic properties. Since enactment maps can be convolved again without loss of auxiliary data, stacked convolutional layers can be utilized for dimensionality decrease of spatial information into low-dimensional element rich vector space where regular completely associated systems can be applied.

The channels are little grids of numbers that are increased by districts of information. For each pixel in the info layer, the focal point of the channel is adjusted to it and the channel is increased with the area of contribution of a similar size as the channel. This procedure is rehashed for all pixels aside from those not having an adequately enormous neighbourhood, bringing about initiation guide of somewhat littler size.

Redundancy of applying the channel over the picture can be seen as a channel sliding over the picture, henceforth convolution. A channel consistently expands the first profundity of info.

Pooling Layer of FK-NNE Classifier: An elective way to deal with contract input volume region is to utilize pooling layer. Pooling layer performs collections over areas rather than duplication with channels of prepared loads. Typically performed conglomeration is limit of the area, giving the name of the maximum pooling layer.

The instinct behind successfully of the max-pooling layer in grouping task is that it doesn't make a difference where in the locale have to include been found as long as it has been found. Taking the limit of an area of actuation dismisses immaterial pieces of that district and reports nearness of the element in the entire locale. On the off chance that averaging were to be utilized rather than most extreme, the way that element was not recognized in the rest of the area would negatively affect noteworthy initiations. Pooling layer has no trainable parameters.

Most normal use of pooling layer is down-inspecting; thusly walk is set up so districts are not covering. A solitary channel is searching for a specific component in the information. There are numerous highlights to be found in a picture. In this manner, numerous channels are required. Thinking about the utilization of numerous channels, each channel brings about its enactment map, together yielding a heap of initiation maps called yield volume. Along these lines, an info picture can be changed into a lot further volume (remember the distinction between the profundity of volume meaning third measurement and profundity of the neural system as various layers). Instinctively, as info is being changed from input picture towards highlights over the system, the territory of information volumes is diminishing with an applied walk as well as pooling, while the profundity of info volumes can both increment and reduction dependent on the number of utilized channels in convolutions.

Structure of FK-NNE

FK-NNE Convolutional systems Structure is normally made out of three kinds of layers. The layer can be either Convolutional, Pooling or completely associated. For forward and error backward signal propagation impeach sort of layer has distinctive tenets. There are no exact standards on how the structure of individual layers ought to be composed. Anyway, with the special case of late advancement, FK-NNE is normally organized in two sections. An initial segment called feature extraction is utilizing mixes of convolutional and pooling layers. The second part called classification in utilizing completely associated layers.

In Cartesian coordinate the equation is given in Equation (3.4) as,

$$(x-a)^2 + (y-b)^2 = r^2 \qquad (3.4)$$

Deep learning technique is most annoying to detect the hidden layers and it classifies the specify cancerous cells from the larger microscopic dataset and the fitness value of an image is given by the equation (3.5),

$$f = \frac{W-K+2P}{S} + 1 \qquad (3.5)$$

Where W denotes the input volume size, K is the size of kernel field, S is a total number of pixels and P is the padded values to the image. The value of P is given at the Equation (3.6),

$$P = (K-1)/2 \qquad (3.6)$$

PERFORMANCE MEASURES

A cohort of 80 images was taken for analysis and it was modified by partitioning the breast into 256 samples. To train the image, partitioning of the breast in each mage was done for better performance. To be more effective, 80 image data set is taken. 50 images were used for training and the remaining 30 images were used for performing a deep learning approach. Finally, both trained and test set data were taken for comparison. By analogizing, it generates high accuracy.

Depending on the data type, the performance can be determined as to whether an image region is to be positive or negative. Confusion matrix also determined based on the correct decision of the four possible categories i.e. true positive (TP), true negative (TN), false positive (FP) and false-negative (FN).

$$accuracy = \frac{TP+TN}{TN+FP+FN+TP} \qquad (4.1)$$

$$sensitivity = \frac{TP}{FN+TP} \qquad (4.2)$$

$$specificity = \frac{TN}{TN+FP} \qquad (4.3)$$

$$Precision = \frac{TP}{TP+FP} \qquad (4.4)$$

$$F1score = \frac{2*Recall*Precision}{Recall+Precision} \qquad (4.5)$$

RESULT AND DISCUSSION

The results are estimated using by Convolution Neural Network algorithm are discussed in this section. The breast tumor images are obtained from the clinical database. Using MATLAB 2018a, the simulation results are estimated and the sample images of benign and malignant tumors are shown in Figure 5.1.

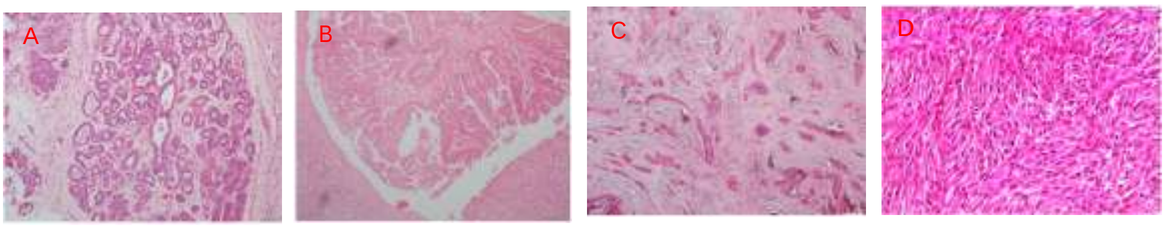

Figure 5.1 A: Benign sample dataset of breast cancer

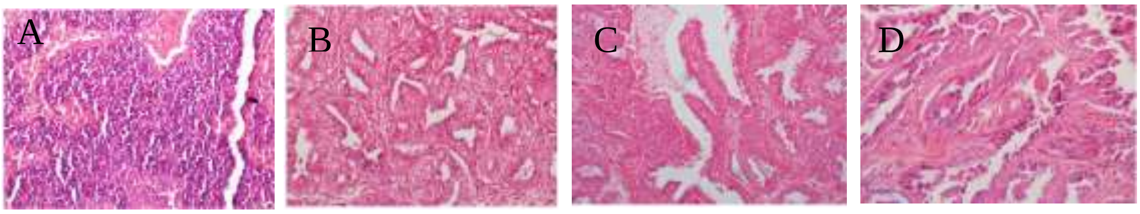

Figure 5.1 B: Malignant sample dataset of breast cancer

The proposed system is evaluated on a standard and challenging BreakHis dataset with 7909 images from 82 human breast cancer patients. The dataset is included both benign and malignant tumor set and its representation of histopathological images are shown in figure 5.2.

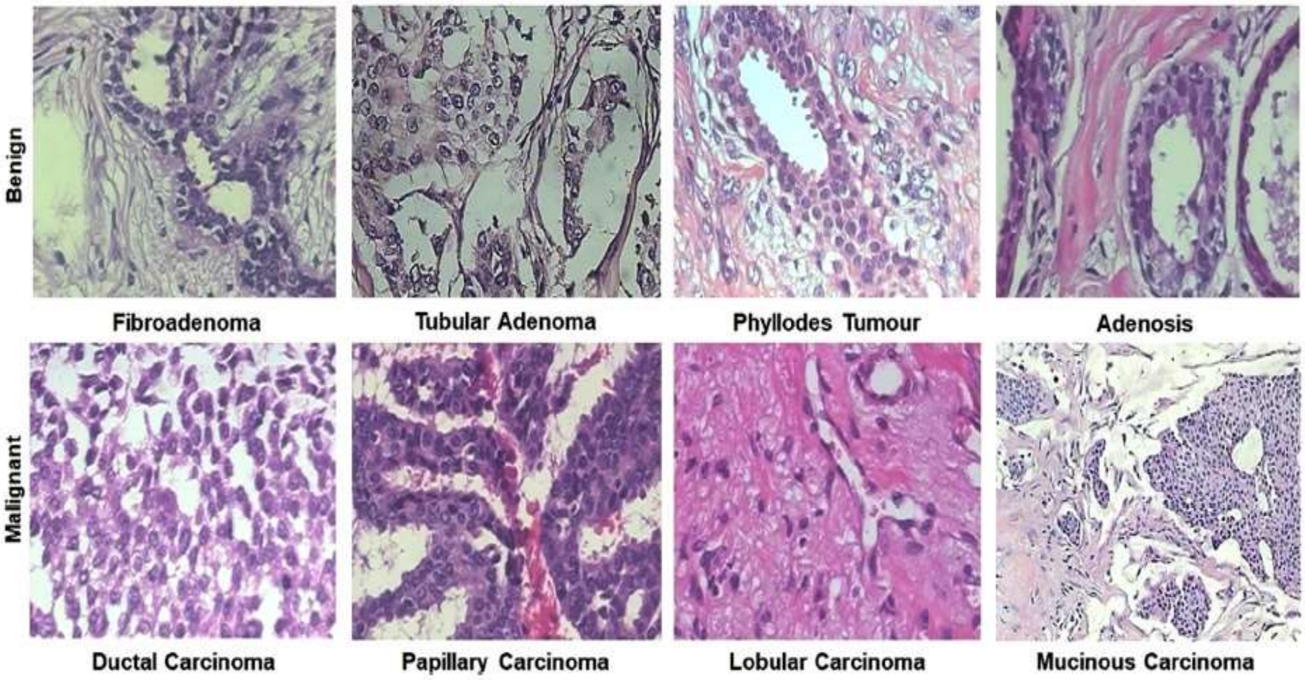

Fig 5.2: Representative H&E stained images from BreakHis dataset.

Mammogram cancer database can be captured by a digital camera equipped with a microscope. The captured images are compressed with JPEG 2000 format. This database can be utilized in the image acquisition process.

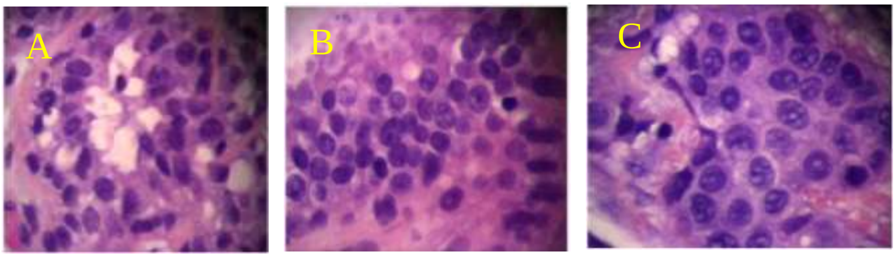

Figure 5.3: The representative breast cancer images: (A) normal; (B) uninvolved; (C) malignant.

Table I: Performance measures of different classifiers

Methods	Sensitivity	Specificity	Accuracy
K-NN	0.8986	0.8962	0.9125
K-NNE	0.9311	0.9436	0.9534
FK-NN	0.9084	0.9222	0.9342
FK-NNE	0.9446	0.9681	0.9652

Table I shows that the performance metrics of different classifier (K-NN, KNNE, FK-NN and FK-NNE). The proposed classifier provides higher accuracy.

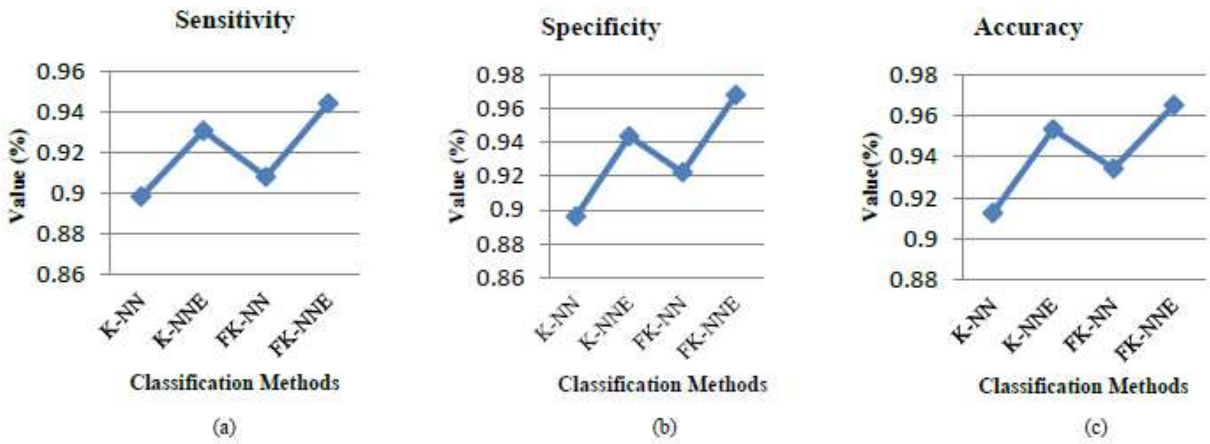

Figure 5.4: Performance of Sensitivity, Specificity and Accuracy of the Classifiers

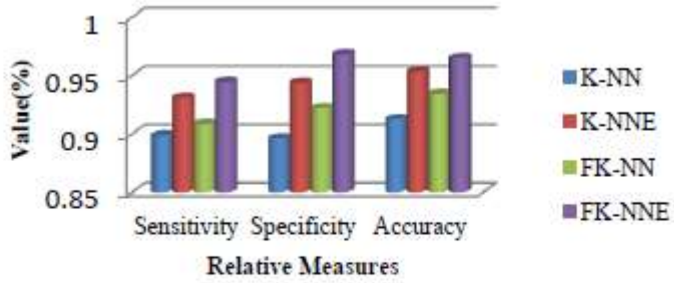

Figure 5.5: Relative Performance measures of the Classifiers

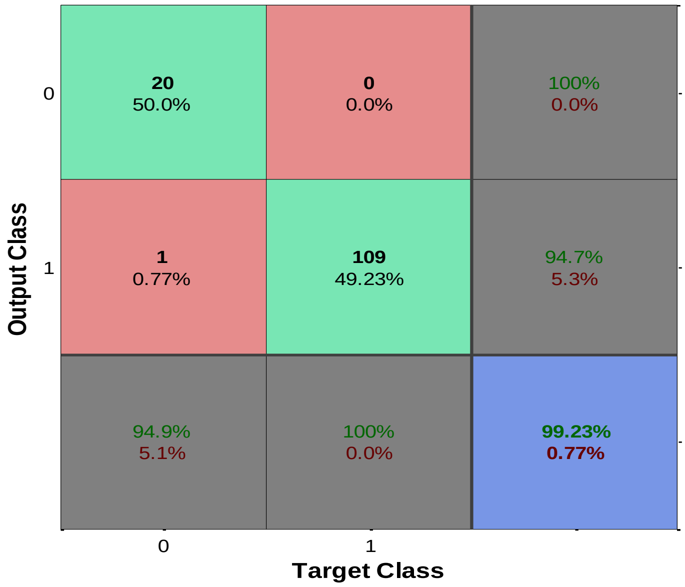

Figure 5.6: Fuzzy K-NN Equality classifier networks Confusion Matrix Plot

The confusion matrix output from the fuzzy K-NN Equality classifier (Figure 5.6). The benign category includes 444 mammogram images which are classified precisely. This corresponds to 63.5 % of all 699 mammogram images. On the contrary, the malignant category includes 238 cases that are classified accurately. Thus 34.0 % of all mammogram images have been categorized efficaciously. If 447 mammogram undergo prognosis, 99.3% are unerring and 0.7% is erring. When 252 Non- mammogram prognosis are involved, 94.4 % are unerring and 5.6% are erring. Out of 458 mammogram cases, 96.9 % is unerringly determined as benign and 3.1% are prophesied as malignant. Out of 241 mammogram cases, 98.8 % are accurately classified as mammogram and 1.2 % is classified as non- the mammogram. Overall, 99 % of the predictions are precise and 1% are erroneous.

Table II: Performance of Classification Algorithms using Area under Curve

Algorithms	Az Value
K-NN	0.9125
K-NNE	0.9634
FK-NN	0.9452
FK-NNE	0.9734

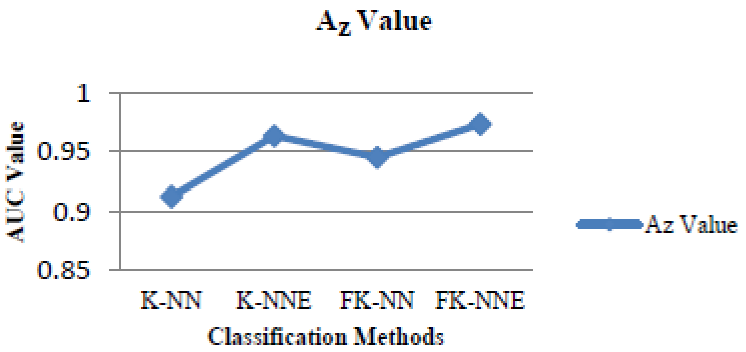

Figure 5.7: Areas (Az) under ROC curves for the classifier of K-NN, FK-NN, K-NNE and FK-NNE

CONCLUSION

In this study, we proposed an FK-NNE approach using MRI images obtained from breast and normal tumor patients to predict tumor patients automatically. The performance curve implies that the method outperforms the other existing method based on the closeness factors related to the True positive values. The accuracy of the proposed system is 99.23%, it is higher than the other classifiers. Moreover, the robustness of the proposed approach is verified by extensive simulations. The proposed classification accuracy is higher when compared to existing classifiers. The experimental result reveals that the proposed classifier achieves better classification accuracy than others. It could be a promising supplementary diagnostic method for frontline clinical doctors.

CONFLICT OF INTEREST

None

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