Optimized Genetic Algorithm for BreastCancer Detection and Classification using Back Propagated ANN

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Abstract - Breast cancer is common varieties of cancer resulting in over a million deaths of woman. It is found that if the Breast cancer is detected earlier, about one-third of cancers become preventable, another one-third newline become potentially curable. In medical imaging, detection of Breast cancer is one of the most challenging tasks, for identifying the cancerous cells location in this paper probabilistic kernel-based fuzzy c means clustering (PK-FCM) algorithm has developed with non-subsampled contourlet transform (NSCT) based image denoising and enhancements. Several state of art approaches used machine learning (ML) based support vector machine (SVM) approaches to assist interpretation of classification of type of cancer. These SVM based classification is an ineffective approach to achieve a range of quantitative goals such as disease detection at early stage and analysis of disease progression using various metrics. Thus, to attain a more reliable and accurate classification back propagated artificial neural network (BP-ANN) method with the usage of Gary level co-occurrence matrix (GLCM) for feature extraction is presented. In addition, genetic algorithm (GA) is utilized as a feature selection algorithm to enhance the accuracy of features. Extensive simulation results disclosed the effectiveness of proposed hybrid BP-ANN-GA approach as compared to conventional classifiers in terms of qualitative evaluation metrics.

Keywords: Mammography, breast cancer, image segmentation, NCT, PKFCM, GLCM, SVM and BP-ANN.

I. INTRODUCTION

Cancer is an unwanted cell with unusual property differs from normal cell of the breast tissue. This will spread rapidly and invade surrounding tissue and forms as tumor which occurs in both men and women. Breast cancer has become leading reason for tumors in women which increase the death rate. Since early 90's, due to breast cancer the death rates have been declining with larger decreases in women with younger age less than 50. The decrease in the ratio is because of the early detection of cancer through screening and it also increased the awareness among women as well as improved**.** Cancer cells normally begin in the duct of the breast then it happens on the lobule region and very less cases in the tissues of the breast region. Around 80% of the women are recognized with the breast malignancy called Invasive Ductal Carcinoma which means the cancer [1-2] has spread to the surroundings of breast tissues. Breast cancer usually starts in the region of duct and spread by penetrating to the duct wall and reaches the fatty tissues which in turn increase the severity of cancer. At times it eventually spread the cancerous cells to various parts of the body through the lymph node. This makes the clinical person to have screening for early detection and recognition of cancer. A suitable prognosis measures are required to avoid removal of breast, the impact of chemotherapy and radiations to increase the survival rate among human being. Since human life is involved, we need to detect the destructive malignant tissue using breast image at the most precision. Computer aided detection is used as an examination technique which could assist the radiologist in finding the malignancy which will decrease the false prediction and this technique is just to read the image again which could increase the clarity for the radiologist [3-4]. Thus, developing a computer aided tool to help the oncologist has become a great interest. Breast image is obtained from different imaging modalities and then it been transformed for further investigation of the image and to extract the features from the image. A women breast is specialized tissues that produces milk may consist of fatty tissues. An anomalous arrangement is created which multiplies and divide out of control which typically increases the start of the cancer [5-6]. Cancer in breast region begins in the gland cells and grows up to the milk ducts.

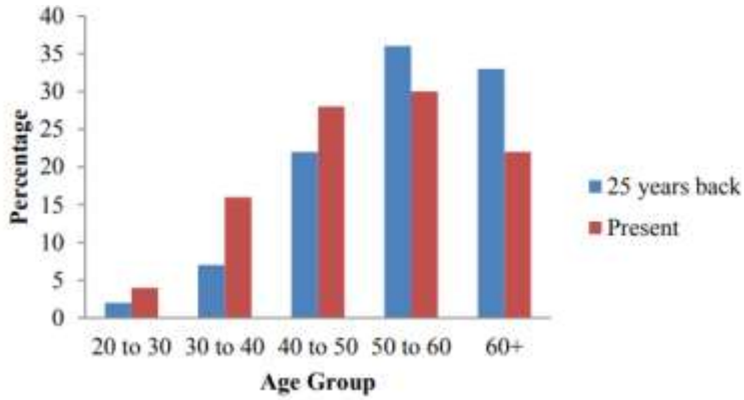


Fig. 1: statistics of breast cancer in India (http://www.breastcancerindia.net).

Fig. 1 shows the statistical information of breast cancer in India. Both men and women have breast tissue so it can happen but when it comes to the breast region most of them have a perception that women get breast cancer, so the discussion mainly focused on breast cancer in women. In India, around 3, 56, 256 women have been analyzed to have breast cancer.

Many researchers have addressed the issue of breast cancer detection from the past few years' later classification approaches also discussed and presented by several authors. A new breast cancer diagnostic system by employing PSO-SVM framework is presented in [7-9], where the PSO aimed at mitigating the simplification ability of the SVM classification by concurrently tackle the essential kernel constraint set and recognizes the majority discriminative characteristic feature separation. In scheming categorization accurateness, the object utility quantity of SVs and quantity of characteristic features are concurrently followed as deliberation. Principally, during a sequence of observed experiments on standard database, PSO-SVM organization not merely exploits the simplification presentation but too choose the majority revealing characteristic features. Author in [10-13] reviewed supervised deep learning (SDL) area of research, conceptual groups and analyzes various techniques. They have proposed two unconventional combinations; the primary is founded on SDL representation mechanism utilized for feature drawing out, while the subsequent utilizes the imperative drawing out method. The analysis is followed by a comparative evaluation of the algorithms are relative performance as measured by several metrics. They have concluded by highlighting the potential research directions, such as the need for rule extraction methods. The recognition scheme for classification of tumor lesions appearing in mammographic X-ray images is addressed in [14-17]. GA utilized FSS is defiant from clamor up to a definite stage and categorization rate is enhanced for GA used FSS method. FCM has separation the huge amount contour group clusters such that the level of alliance is burly for the features inside the similar groups and weedy for the features in dissimilar groups. GA explored the important contour features by concerning the magnificence of usual dispute. Utilizing three operatives like imitation, crossover and mutation, GA can choose important feature division. However, due to lack of accurate detection, efficient extraction of features and classification accuracy, conventional breast cancer diagnosis systems failed to produce acceptable outcome. In [18], authors investigated the proliferative action of bosom tumors, which was routinely evaluated by including of mitotic figures in hematoxylin and eosin recolored histology segments, was viewed as one of the most significant prognostic markers. In any case, mitosis checking was difficult, emotional and may experience the ill effects of low between onlookers understanding. With the more extensive acknowledgment of entire slide images in pathology labs, programmed image examination has been proposed as a possible answer for these issues. In [20], authors innovated hybrid ANN-based approach for breast cancer detection and classification using non sub-sampled shearlet transform with modified probabilistic FCM clustering algorithm for improved performance over existing ML-based approaches. However, no feature selection algorithm is applied in [20] and it needs to further improve the accuracy of hybrid ANN model. Therefore, this article presents optimized GA using BP-ANN with NSCT and PK-FCM. Additionally, GLCM also utilized for feature extraction.

To achieve this extensive research goal, specific objectives are set. The research objectives of this paper comprise of the following components.

- Implementation of NSCT to mitigate the artifacts and any noise components present in the mammographic X-ray images while image acquisition.
- Next, PK-FCM is employed for detection of breast cancer effectively with exact region of interest (ROI) extraction and feature extraction is done by utilizing GLCM approach with additional feature selection using GA.
- Finally, BP-ANN is applied to classify whether the patient is normal or abnormal then form abnormal the type of cancer is classified as benign or malignant.

Rest of the paper is planned as following Section 2 deals about the detailed architecture of proposed methodology with detailed operation of segmentation, feature extraction, feature selection and classification. Section 3 deals about results and discussion with comparison to the state of art methods using quantitative metrics. Section 4 deals about the conclusion and future enhancements of proposed methodology followed by bibliography.

II. PROPOSED METHOD

Figure 2 shows the proposed method of breast cancer detection and classification process. Initially query image applied from image acquisition unit, and then it is applied to preprocessing stage. Here, by using NSCT to remove the artifacts and noises and performs the image enhancement. Then PKFCM clustering applied for breast cancer detection and effective ROI extraction. Then by using the GLCM feature matrix to achieve the features and create the database using features. Then by applying the BP-ANN classification methodology to detect the normal and abnormal stage of cancer, at the same time type of classification also recognized.

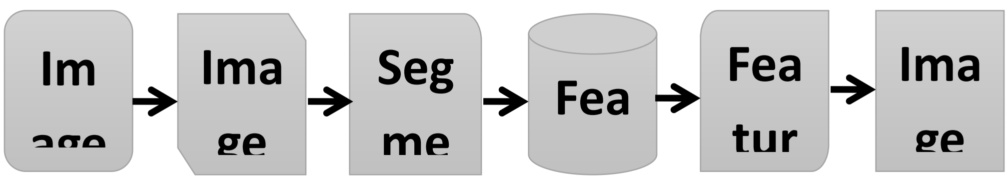


Fig. 2: Proposed methodology.

2.1 Image Preprocessing

Images are generally infected by noise. Usually, noise is nothing, but the unwanted by-product occurred during image capture. In general, noise occurs due to various reasons likes imperfect instruments, problems with the data acquisition process and interfering natural phenomena. Furthermore, noise is introduced by transmission errors and compression.The various types of noises are salt and pepper, impulse valued, spike, random, data drop out and independent noise. These clamors are happened because of the sharp and unexpected changes of image sign and residue particles in the image obtaining source or over warmed broken segments.

In pre-processing stage, the breast is partitioned in order to improve the search for abnormalities without undue influence from the background of the mammogram and some filtering or cropping is accomplished in order to improve the quality of the of the image and to reduce noise. Pectoral muscle is a portion of Mammogram similar to dense tissues; hence, removal of the pectoral muscle is necessary before searching any abnormalities in Mammogram. Mammograms contain some labels; those are equipment name, hospital name and mammographic view which do not give any details regarding abnormalities. Hence, they are removed by keeping the largest area in the Mammogram after NSCT thresholding and labeling the connected components.

NSCT role in preprocessing:New multilevel and multidirectional transform called NSCT, is developed efficiently to analyze the images with anisotropic features and various noise. The important characteristics or mathematical properties of NSCT are well localized, and they support the parabolic scaling, exhibit highly directional sensitivity, spatially localized and optimally sparse. The diagrammatic representation of NSCT is shown in Figure 3. It is mainly implemented, to overcome the disadvantages of wavelet transforms and NSST, which is not efficient, when dealing with the multidimensional images with edges and it also captures the merits of the curvelet and contourlet transforms.

NSCT frameworks are produced by utilizing one single capacity which is widened by an illustrative scaling and a shear grid and deciphered in the time space, and consequently they structure a relative framework. Contourlets are generated by applying three operations namely dilating, shearing and translating on a fixed generating function or on mother Contourlets. The exceptionally directional affectability of the shearlet change and its almost ideal estimate properties lead to the enhancements in many image handling applications. Moreover, Contourlets has completely analyzed the singular structures of piecewise smooth images and exactly, it computes the Contourlets coefficients, which is based on a multiresolution analysis. Henceforth, Contourlets structures a tight edge of very much restricted waveforms, at different scales and headings, and is ideally meager in speaking to images with edges. As a result, the Contourlets transform provides several advantages then conventional preprocessing methods.

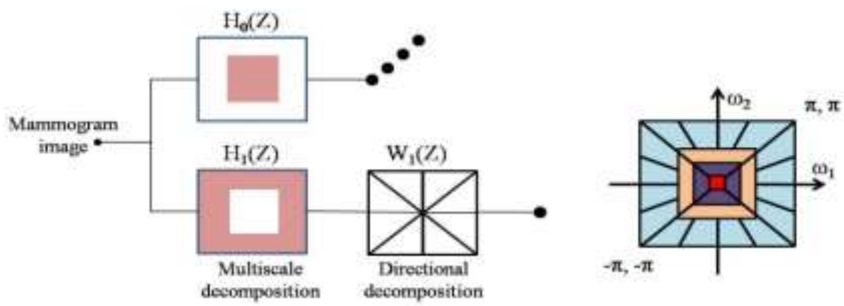


Fig. 3: NSCT operation.

NSCT is the combination of non-subsampled directional filter bank (NSDFB) and non-subsampled pyramid (NSP). By utilizing those contourlets in NSCT maintains the same size for each DFP and pyramid of original input image. NSP contains Laplacian pyramids for denoising the errors. DFB is the shift invariant filter bank; this is effectively used for image enhancement. The perfect data reconstruction achieved by

$$H_o(z)W_o(z) + H_1(z)w_o(z) = 1 \quad (1)$$

Where $H_o(z)$ is the frequency response of NSP ,$W_o(z)$ is the levels of NSP,$H_1(z)$ is the frequency response of NSDFB and $W_o(z)$ is the directions of NSP.

2.2 Segmentation and ROI extraction

PKFCM clustering algorithm efficiently overcomes the geometric allied problem in FCM algorithm, but due to the absence of efficient spatial information, FCM is sensitive to noise. In the proposed PKFCM algorithm, spatial information is incorporated in the form of kernel function which does not produce considerable effect on noise. Generally, the neighborhood pixels are highly correlated in spatial domain. Therefore, if the segmentation algorithm fails to incorporate the relationship between the neighborhood pixels, the performance of the algorithm would be minimized because of noise. To circumvent this shortcoming, in the proposed algorithm local neighborhood information is integrated in the similarity measure of objective function

The objective function of the proposed algorithm is defined as

$$J_{PKFCM} = \sum_{i=1}^{C} \left(\sum_{k=1}^{n} \mathrm{U}_{\mathrm{ik}}^{\mathrm{m}} \left| |\varphi_L(x_k) - \varphi_L(v_i)| \right|^2 \right) \quad (2)$$

The membership function U_{ik} is updated as

$$U_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{D_{ik}{}^2}{D_{jk}{}^2} \right)^{1/(m-1)}} \quad (3)$$

Where m is the fuzzy coefficient, and D_{ik} is the similarity measure which is given as

$$D_{ik} = ||\varphi_L(x_k) - \varphi_L(v_i)||^2 \quad (4)$$

Generally, c numbers of membership values are to be computed for the pixel under consideration while clustering an image into c clusters. Segmentation is achieved by assigning the pixel to any cluster i for which it possesses high membership value. From this, one can deduce that the segmentation results rely on the similarity measure which is utilized to calculate the membership value. Therefore, in the proposed algorithm novel spatial neighborhood information is incorporated in its similarity measure to overcome the effect of noise. Incorporating spatial neighborhood information in the similarity measure results in

$$D_{ik} = ||\varphi_L(x_k) - \varphi_L(v_i)||^2 g_{ik} \quad (5)$$

In above equation the term g_{ik} indicates the spatial information and is defined as

$$g_{ik} = (1 - \beta H_{ik}) \quad (6)$$

Here,H_{ik} indicates spatial function for ROI, and $\beta\epsilon[0,1]$ is neighborhood attraction parameter that controls the significance of neighboring pixels on center pixel x_k. The value of β between 0 and 1 indicates the influence of neighboring pixels on center pixel. If β value is 0, then the similarity measure tends to be that of PK-FCM algorithm without the above-specified spatial information.

The noise resistance capability of PK-FCM algorithm relies on the spatial function For any noisy center pixel x_k having large gray level difference with its neighboring pixel x_a , the spatial information H_{ik} computed will be large, and thus the spatial function in above Equation becomes small for all values β of other than zero. After the first iteration, the noisy pixel x_k will be attracted to the cluster i to which its closest neighbor x_a belongs. If the value of H_{ik} remains to be high till the last iteration, despite being its dissimilarity, the center pixel x_k will be forced to cluster it is clear that after each iteration, the similarity measure of noisy pixels as well as other pixels in a window tend to a similar value, ignoring the noisy pixels. In this case, the gray level value of noisy pixel is large when compared to other pixels within the window, but the spatial functiong_{ik} incorporated balances their similarity measure. The spatial function thus eliminates the effect of noise in the clustering process

Table 1: PK-FCM algorithm.

Input: mammogram image, output: U cancer detected image
1: for t = 1: do
2: Randomly initialize membership matrix U_{ik} on input image I
3: Compute the spatial neighborhood information using Equation (5)
4: Compute the probability similarity measure using Equation (4)
5: Compute the updated membership value using Equation (2)
6: Update objective function objective function J_{PKFCM}
7: end for
8: return U if the membership degrees of each pixel of the image to different clusters

2.3 Feature Extraction

For successful detection and classification of breast cancer, the feature extraction stage is especially important. Since, the feature extraction techniques improve the performance of the system. Feature extraction is an important component that decides performance of classification. Feature extraction is also called as description. Description deals with the process of extracting attributes, which produce some quantitative information of interest, in order to differentiate one class of objects from another. When the input data used for manipulation is complex, then it is converted into the group of characteristics called feature vector. It is process of collecting image information such as color, shape, and texture. Features comprise the appropriate information of an image and it is used in the image processing task (e.g. searching, retrieval, storing).

In GLCM, the relevance of radius and angle are the most crucial input parameters. Several First Order Statistics (FOS) texture features like mean, variance, energy skewness and entropy and Second Order Statistics (SOS) comprises of GLCM, contains features such as contrast, correlation, cluster prominence, cluster shade, dissimilarity, homogeneity, sum average, sum of squares, difference entropy and sum entropy are to be extricated from the segmented nodule. GLCM uses second order image statistics; it has an advantage that it considers the spatial properties. But it has limitation that it does not consider the primitive shapes. Hence, the performance of GLCM is amazingly effective in the classification of breast cancers compared to the other conventional features.

Texture measures based on FOS (or histogram based) are measured from the image pixel information and not considering the relationship between neighboring pixels. Intensity levels of the entire image are used in the texture analysis of histogram-based approaches. Several FOS based features includes mean, variance, average energy, skewness and entropy. Computation of histogram based gray level entails only single pixels. Histogram based method are easy to compute the gray level images. Using histogram-based features, the characteristics of the lung nodule can be found.

Spatial distribution of gray level images estimates the property of the image correlated to SOS which consider the correlation between pixels. The SO image histograms are defined by GLCM, which presents higher data concerning to periodicity; spatial dependency and inter pixel bond of gray level image. The GLCM is considered as the well-known, commonly used statistical technique for extracting texture features. It computes not only the single pixel but also the neighborhood properties for extraction of features. Based on joint probability distributions of pixel pair, this method can be employed. GLCM depicts how frequently the pixels are positioned in the geometric location in relation with another pixel.

GLCM of image $P(i,j)$can be expressed as

$$P(i,j) = count\left(\left(P_{x,y,z}, v\right)\left(P_{x,y,z}, \alpha\right)\right) \tag{7}$$

$$= j, \alpha \ \text{€} \ \{1,2,3, \dots \dots \dots \dots \dots \dots 26\}$$

where v is the function which takes one voxel from 26 neighboring voxels according to the index α, $P_{x,y,z}$ is the value of the voxel with xyz coordinates α is the i^{th} entry of the marginal probability matrix is achieved by the summation of the row of $P(i,j)$.

GLCM can be calculated from texture images using different values of θ and d and these probability values create the co-occurrence matrix $P\ (I, j, d|\ , \theta\ )$ as shown in figure 4. GLCM are considered for the orientations of 0°, 45°, 90°, and 135°; distance d =1,2,3 and 4 are calculated.

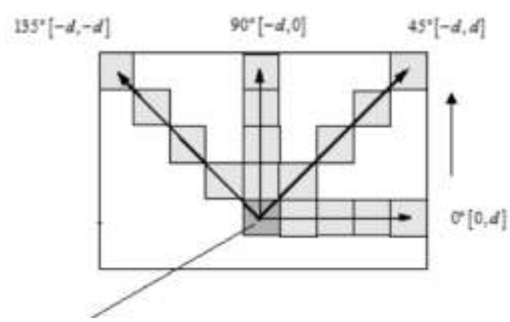


Fig. 4: Distances and Orientations to compute GLCM.

2.4 Feature selection

Normally, mammogram image contains enormous information in miscellaneous form. The usage of such variant information leads to an increase in feature vector dimensions and computation and as a result, the classification accuracy of the system gets decreased. In order to avoid that, consistent features are considered for the classification by eliminating the redundant and irrelevant information. Feature selection is a task of selecting small number feature subset from the original feature set. It is obtained by eliminating the irrelevant and redundant features from the original feature list. This selected feature subset is given as one of the inputs to the classifier and with the help of this; the breast mammogram image is classified as normal or cancerous. In this work, statistical texture features are extracted from each decomposed ROI. Statistical texture features are primary and are frequently used in medical image analysis. Here, GA is employed to find the optimal feature subset from statistics texture features. In this research work, GA is applied to select the optimal features with the help of the tournament selection method and the size of the tournament is 2.

The input value assigned for population size, initial population type and the number of generations is 20, bit string and 20 respectively as represented in Figure 5. Then the uniform mutation and arithmetic crossover operations are performed, and the probability of mutation and the probability of crossover are 0.1 and 0.8 respectively by using the fitness evaluation. The feature selection measure such as information gain, gain ratio, gain index results in over fitting problem. Whereas the solution satisfies Genetic algorithm is naturally inspired one and provide a stochastic optimization with existed criteria. GAs use probabilistic transition rules rather than deterministic rules over its selection. As the genetic algorithm is a stochastic optimization method, the genes of the individuals are usually initialized at random mutation. Genetic algorithms operate on a population of individuals to produce better and better approximations. They use processes of selection, cross-over, and mutation to get to optimal solutions. The subsets of variables selected by genetic algorithms are generally more efficient than those obtained by classical methods of feature selection, with large features. When compared with other feature selection techniques, genetic algorithm results in better performance, can manage data sets even with few features and GA itself a parallelized algorithm to further speed up the feature selection process.

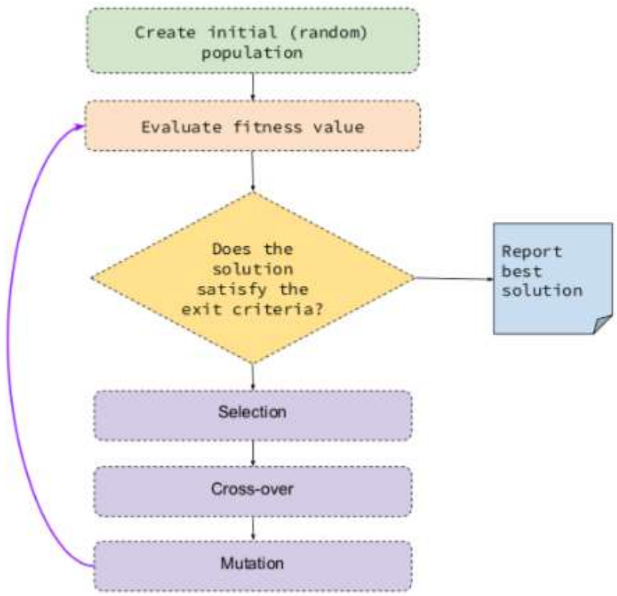


Fig. 5: Feature selection by using GA.

2.5 Cancer classification

Cancerclassification consists of training and testing phases as shown in Figure 6, in training phase thousands of images are trained using GLCM based GA selected features. In the testing phase, the query image features are extracted using GLCM based GA approach and then applied to BP-ANN. One of the most boundless NN models is the back-propagation model. The BP model incorporates five primary stages as shown in figure 7. Those are input layer, hidden layers, output layer, error computation and back propagated output layer. In the wake of choosing the system weights arbitrarily, the back-spread computation is locked in for figuring the necessary modifications. Back Propagation calculation feed forward ANN algorithm works well for feed-forward systems with ceaseless yield. In this system, the neurons are organized in layers and direct their signs the forward way. The mistakes delivered are spread the regressive way. The system gets the contribution by neurons of the info layer. The system output is given through the neurons on the feed backed output layer. Here, the system involves of one or, more than likely progressively moderate hid layers. Directed learning is used in the Back-Propagation algorithm for example. The cases of information and furthermore the yield to be determined is outfitted to the algorithm. The mistake during the contribution with the figured yield is processed. The system is qualified with irregular weights and after that the weights are receptive to accomplish fewer mistakes. The system will be immaculate when the blunder is less. In the back-propagation algorithm, the edges and weights are adjusted each time a model is introduced, with the end goal that the blunder dynamically diminishes. The input layer neurons have a steady weight and the weights have been assigned in the output and the hidden layer neurons by randomly choosing the weights.

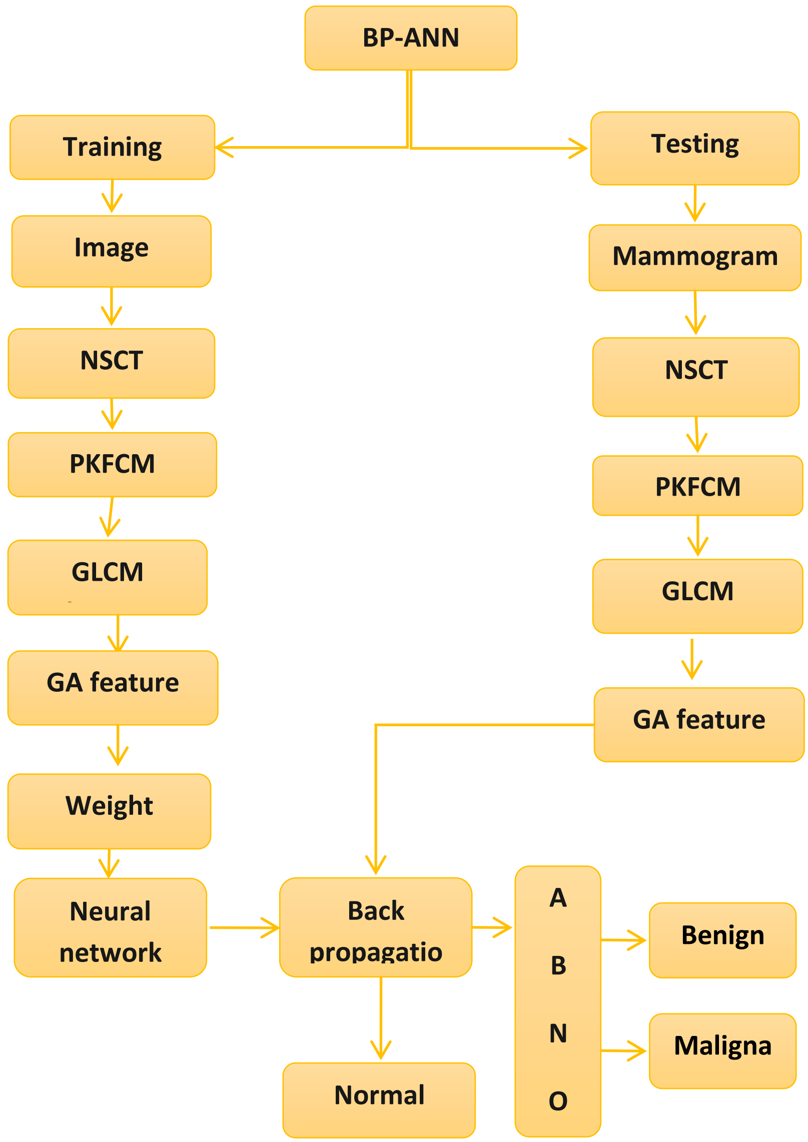


Fig. 6: Detailed architecture of Breast cancer detection and classification.

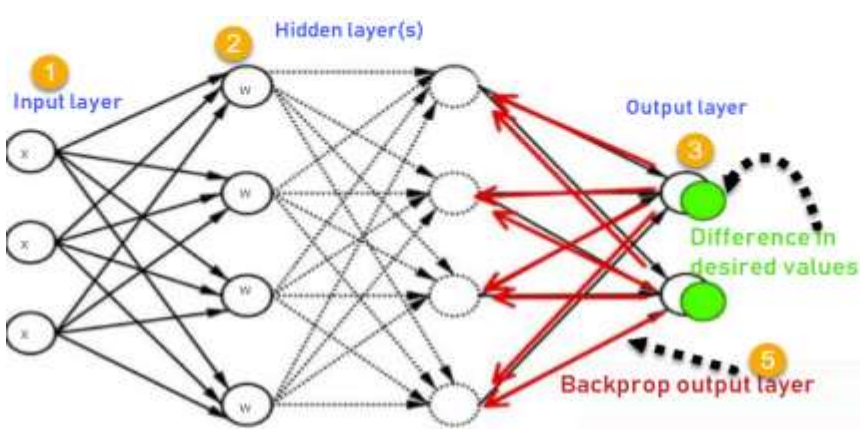


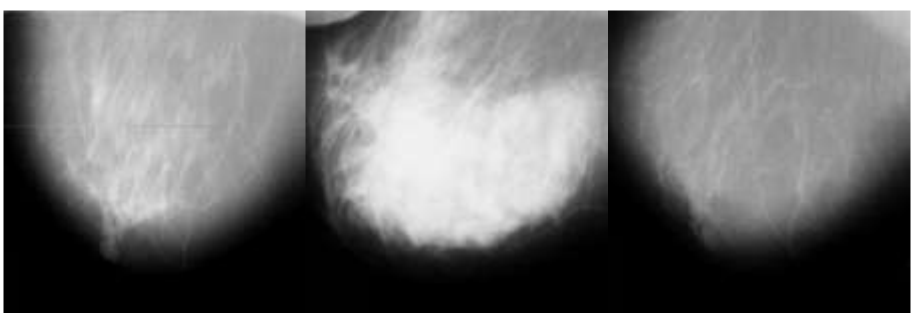
Fig. 7: back propagated ANN.

The BP-ANN is as a rule generally utilized in clinical image identification and acknowledgment. Contrasted with a few traditional image acknowledgment techniques, utilized for the examination of mammograms, or utilized for the partition of tumors into favorable and threatening, the neural system-based strategies have high acknowledgment precision and less processing time. Trials show that the neural system troupe can accomplish a high pace of ID as well as a low pace of bogus negative ID, for example a low pace of assessing malignant growth cells to be ordinary ones. While making a useful model of the organic neuron, there are three essential segments of significance. To begin with, the neurotransmitters of the neuron are demonstrated as loads. The quality of the association between info and a neuron is noted by the estimation of the weight. Negative weight esteems reflect inhibitory associations, while positive qualities assign excitatory associations. The following two parts model the genuine action inside the neuron cell. A path summarizes all the sources of info adjusted by their individual loads. This action is alluded to as direct mix. At last, an actuation work controls the abundancy of the yield of the neuron. A satisfactory scope of yield is ordinarily somewhere in the range of 0 and 1, or - 1 and 1. The result is 0 indicated as Normal mammogram image with no cancer. The result 1 indicates benign type of breast cancer, whereas result -1 indicates malignant type of breast cancer.

III. RESULTS AND DISCUSSION

3.1. Dataset

The Mammographic Image Analysis Society (MIAS) is an association of UK inquiries about gatherings inspired by the comprehension of mammograms and has created a database of computerized mammograms. Movies taken from the UK National Breast Screening Program have been digitized to 50-micron pixel edge with a Joyce-Loebl examining microdensitometer, a gadget straight in the optical thickness run 0-3.2 and speaking to every pixel with a 8-piece word. It additionally incorporates radiologist's "truth"- markings on the areas of any variations from the norm that might be available. The database has been decreased to a 200-micron pixel edge and cushioned/cut with the goal that all the images are 1024×1024. Mammographic images are accessible by means of the PEIPA at the University of Essex. The accomplishment of the proposed strategy is controlled by the degree to which potential anomalies can be separated from comparable to mammograms dependent on investigation of their image. The MIAS Database is utilized to assess the proposed procedure. Total 425 mammographic images are adopted for this experiment analysis where 150 of malignant, 150 of benign and 1250 of normal mammographic X-ray images with the consideration of patient mean age around 35.6year and ranging from 18 to 81. The breast grazes assortment from 2mm to 20mm in mass and several patients contain several grazes whereas some other patients might have merely one. Figure 6 shown the sample dataset images of each size 1024×1024 as shown in figure 8



(a) (b) (c)

Figure 8. Sample dataset images (a) Benign tumor. (b) Malignant tumor. (c) Normal.

3.2. Evaluation criteria

For valuation of classification outcomes, we utilized three qualitative metrics such as specificity, accuracy and sensitivity. The accuracy can be defined as out of certain random test cases, how many outcomes give the perfect classification output. The sensitivity is defined as individual classification accuracy, how much the method is sensitive towards the malignant and benign cancers. And specificity is defined as the how much accurately the location of tumor is recognized.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (8)$$

$$Specificity = \frac{TN}{TN+FP} \quad (9)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (10)$$

$$precision = \frac{TP}{TP+FP} \quad (11)$$

where TP conveys the amount of test cases properly recognized as malignant, FP conveys the amount of test cases improperly recognized as malignant, TN conveys the amount of test cases properly recognized as benign and FN is conveys the amount of test cases improperly recognized as benign.

Table2. Performance of quality metrics using existing and proposed hybrid BP-ANN-GA model.

Method	Accuracy (in %)	$F1$-score	Specificity (in %)	Sensitivity (in %)
SVM [17]	76.09	0.65	75.51	77.40
MK-SVM [18]	80.01	0.71	79.18	80.72
KNN [16]	80.42	0.78	80.18	81.81
Decision Tree [19]	81.20	0.84	80.72	82.26
Hybrid ANN [20]	95.91	0.954	95.81	96.34
Proposed	**96.57**	**0.963**	**96.77**	**97.29**

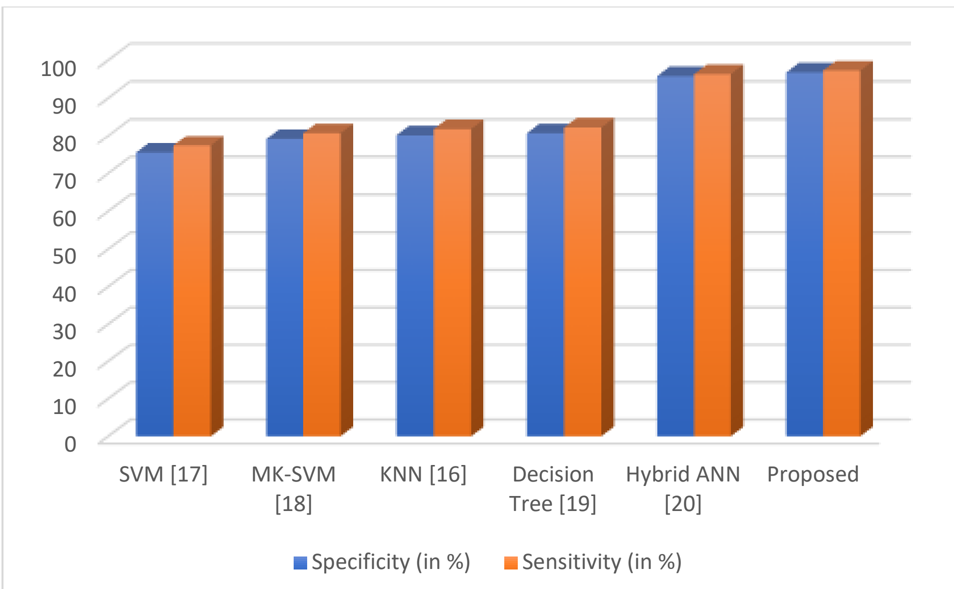


Figure 9. Comparison graph of proposed and existing methodologies with specificity and sensitivity.

In the training procedure, network limits were attuned by the preparation slaughter and after that the justification dataset would be utilized to check the matching amount of the attuned system. The matching curvatures of system depend on network testing slaughter and training loss slaughter. In order to additionally calculate the planned technique, we contrasted it with pair of NN-contained methods utilized in [14], [15]. For the categorization, we adopted SVM [17], multi-kernel SVM [19] and K-nearest neighbor (KNN) [16], CNN [13] and hybrid ANN [20] classifiers from the literature for comparison with the proposed hybrid BP-ANN-GA classifier model. Table 1 demonstrates that quality evaluation criteria of existing and proposed classifiers, where proposed hybrid BP-ANN-GA classifier outperforms the conventional SVM, MK-SVM, CNN and even that of hybrid ANN classifiers to distinguish the benign and malignant from the mammographic X-ray images. Figure 9 and Figure 10 represents the graphical representation of different comparison schemes in contrast with proposed method using the quantitative parameters such as accuracy, specificity, and sensitivity, respectively.

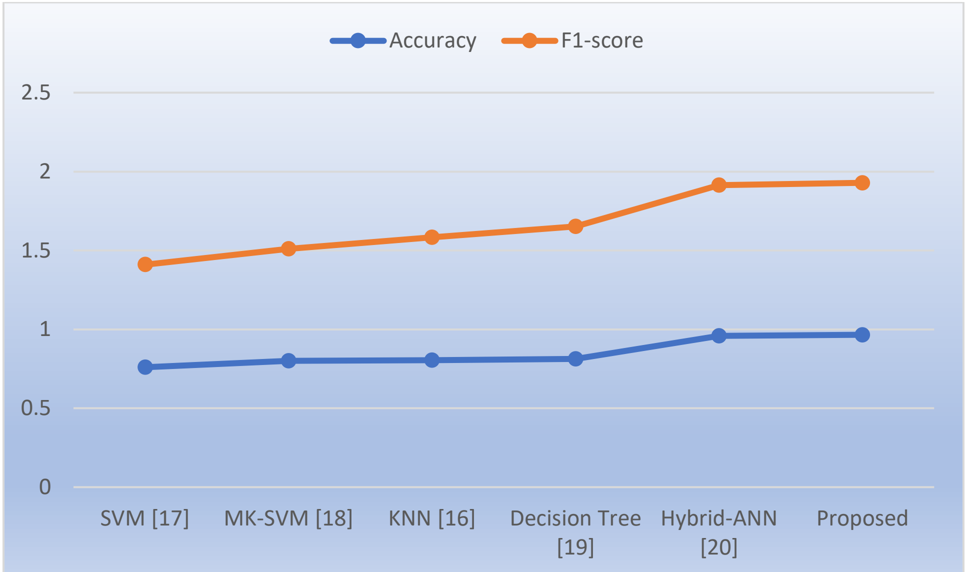


Figure 10. Performance of proposed hybrid BP-ANN-GA with accuracy and F1-score.

IV. CONCLUSION

In this paper a new method for breast cancer detection and classification has been presented as it results over a million deaths of woman. Initially, The NSCT based transformation methodology adopted for removal of noise and for image enhancements purposes. To overcome the drawbacks of FCM, an innovative PKFCM clustering algorithm has introduced for segmentation and ROI extraction, respectively. Then, after detecting the cancer cells from mammogram images, the features are extracted using GLCM filter. But to select the appropriate features to increase the classification accuracy GA algorithm has utilized effectively. For the classification of type of cancer and error resilient BP-ANN based deep learning methodology was developed, so the benign and malignant type of breast cancers classified with almost 97% accuracy. The qualitative evaluation was compared with several conventional approaches and proves that the proposed methodology has maximum accuracy.

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