

Comparison of Breast Cancer Detection using Probabilistic Neural Network and Support Vector Machine

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ABSTRACT - Cancer is one of the deadliest diseases that the human beings are encountered. Of all the types of cancers found the breast cancer is the most common disease that has highest death rates in women. The traditional approaches that are used to diagnose a cancer mainly depends upon the doctor's experience, investigation and visualization. The error rate is high because human eye can't recognize the patterns so easily therefore there is need for accurate diagnosis of mammogram images. The main objective of this work is to develop an automated system which identifies a tumour in digital mammograms images. For this purpose, machine learning algorithms can be used. Certain adaptive filters along with segmentation needs to be done before the classification is done. Neural networks will aid in the training process and then the prediction can be done appropriately. The tumor are classified into the following classes benign, malign and normal. By this classification process it can be found if the cancer cells will spread or not. This will also help in increasing the efficiency of the process of identification of breast cancer.

Keywords: Image Classification, Segmentation, GLCM, PNN, SVM.

1. INTRODUCTION

The medical field keeps on improvising in ways by which they can fight several diseases and this field has seen exponential unidirectional growth. Majority of research focus has been towards developing ways to counter deadly diseases such as cancer. A disease where a set off cells tend to concentrate into one particular region thereby leading to formation of lump or tumour is termed to be as cancer. Out of ninety million, the count of those that have been infected by cancer has been twelve million which accounts to close to fifteen percent of the total count. The major general types of cancer that are found are lung cancer, colon cancer, breast cancer, pancreatic cancer, prostate cancer, ovarian cancer, brain cancer. Breast tumour is major causes for death caused due to these cancerous cells especially amongst women. According the report available by World Health Organization of the International Agency for Research on Cancer (IARC), out of the eighteen million women that were identified who are suffering from breast cancer nine million patients pass away. Lung, breast and colorectum cancers are deemed to be the ones that are more frequent, contributing around eleven percent of the over-all cancer occurrence problem.

There are four stages in cancer namely stage 1, stage 2 a, b and c, stage 3 and stage 4. Stage 1 contains small tumor and spreads slowly in the formation of lymph can causing infections. Stage 2a as well as 2b consists of always larger than 2cm it is not part of lymph that was spread in stage 1. There is a large tumor caused separately. In stage 2c cancer will be due to lymph nodes then can spread along with connecting tissues. The lymph spreads along with muscles and may spread till bones when it is stage 3. In stage 4 the tumor will spread in all body parts such as brain and liver.

Therefore, there is a need to decrease the impact caused by cancer. When it comes to reducing the impact there are two ways by which it can be achieved. One way is finding new innovative ways to diagnose the disease thereby reducing the treatment time. In second method, the tumour can be detected at an earlier stage thereby reducing the damage caused on the body. In this project we are formulating a method by which we can detect the lumps or tumor by using machine learning techniques and we are restricting the project to breast cancer. Breast cancer was chosen because it is common and more people suffer due to this disease, the more the people suffer the greater is the need to find a solution. Machine Learning techniques can be utilized iteratively to find a solution to identify the existence of any cancerous lump present in any body part with a greater extent of accuracy and reliability.

2. LITERATURE SURVEY

Cancer is a disorder, the cure should be the major objective through technical examination. Disease curing at initial stages can be useful. Many techniques from the literature are accessible for detecting cancer. Researchers have discovered and implemented many ideas related to detecting of cancers. The works of literature mainly discuss current cancer recognition methods. Numerous fields and ideas have applied in discovery of cancer. The foremost fields in recognizing the technique incorporate image processing, neural networks, and, etc. Mammogram image system is being used since very long time and researches have been carrying out.

2.1. Image Enhancement

It is a method which is provoked from reality that tumors be inclined to be optimistic than the neighboring as specified

by Tang et al. (2009) [7]. Simple awareness is to utilize approaches to increase the disparity of tumor areas. This approach has developed to increase the value and mammograms readability.

2.1.1. Direct contrast enhancement methods

The researchers in 2014, illustrated applications of morphology mathematics processes in the area of digital image processing. In the continuation, it presents as well as discusses about the latest algorithm depending on arithmetical morphology operators, can capable to identify the micro calcification in mammograms images [8]. Applications of few operators to shape an algorithm applied to digital images. Rebuilding with isotropic organizing element using erosion operation, followed by contrast improvement in segmentation to discover novel dominant algorithms. It is more effective to identify contrast enrichment and also the micro calcification was benign or malignant in mammography imagery. They have then used added algorithm to obtain minimal areas from the image.

2.1.2. Wavelet enhancement methods

The researchers selected the move towards for finding malignancy in a mammogram image. As it improved the SNR portion of the lesion being identified and eradicated the false-positive conclusion [9]. Thus an algorithm is proposed for mammograms improvement that had refining intention segmentation of dissimilar mammograms structures. The enrichment method utilized wavelet decomposition, restoration, morphological methods, local scaling. Following improvement, separating areas was performed and from each of the segmented regions, a group of features computed. A ranking system is used for classification.

The researchers in 2009, it deals with two problems and solution for it: Detection of tumor as doubtful areas with an extremely feeble dissimilarity to the surroundings and feature extractions that classify tumor [10]. The tumor identification method works as (a) enhancement of Mammogram (b) tumor part segmentation (c) feature extraction by segmented tumor part (d) usage of SVM classifier. Image excellence and understandable level is improved. The mammogram improvement method comprises of top hat action, discrete wavelet transform and filtering. Contrast stretching gives rise for improving image contrast. Mammogram segmentation of image plays a main part for improving recognition, analysis of breast cancer. Popular segmentation process made use is thresholding. From segmented breast area, the features are removed. Later phase classifies the area by using the SVM classifier. 75 images were tested.

Balakumaran et al. (2010), they have projected an algorithm for spotting microcalcification in a mammogram. The suggested microcalcification exposure comprises mammogram superiority development utilizing multi

resolution investigation [11]. It can be feasible to identify modular segments like micro calcification precisely by presenting shape data. The efficiency of algorithm for microcalcification identification was definite by investigational results.

2.2 Region based algorithm

Region growing algorithm Bocchi et al. (2008), declared that the micro calcification is primitive indications of breast cancer. Here a method is proposed to identify and categorize microcalcification. So as to determine microcalcification bunches, specific attention to the exploration of noticed lesions. To define the mammographic image a fractal model is used [12]. It allows the usage of a coordinated filtering phase to improve micro calcification in opposition to the framework. An algorithm, linked by a neural classifier, finds out existing lesions. Consequently, another fractal model is made use of to investigate their collection.

Shanmugavadivu et al. (2014), projected a Wavelet Transformation which makes use of morphological pre-processing, area properties and seed area emerging to take away the digitization noises, for removing the inner tissue and to overcome radiopaque artifact, therefore segmenting irregular masses perfectly [13]. The joined possible of region growing and wavelet benefits to active masses segmentation which guarantees for the worth of projected method.

2.2.1. Region of Interest Method

Alofe et al. (2008), confirmed that collections of micro calcification are premature indications of cancer that tends for improving a CAD framework which aids for the radiologist in analyzing micro calcifications patterns in computerized mammograms before and quicker than regular selection programs [14]. The suggested approach is performed in 3 phases: (a) the region of interest choosing of 32×32 pixels size, (b) feature taking out step depends on wavelet decomposition for locally preprocessed image to figure the relevant each bunch features and (c) the categorization stage that classifies among normal and micro calcification patterns. In the this stage, 4 techniques are used, K-Nearest Neighbor classifier (K-NN), fuzzy classifier, Neural Network (NN) classifier and Support vector machine (SVM) classifier.

Mohd Khuzi et al. (2009), stated that digital mammogram, effective technique for early breast detection modality. It is directly stored in a computer to grow automatic framework. Digital image processing approaches used to increase the images quality [15]. Extra data consists of a masses location centers and masses radius. The taking out from features of texture about ROIs is achieved by applying grey level co-occurrence matrices (GLCM). The result shows GLCM @ 0, 45, 90 and 135 degree, which provide important texture data toward classify among masses.

Rabi Naraiyan Pandya et al. (2009), says usual concurrent choice for early discovery of breast tumor in women. Although, the view of the physician has a conspicuous impact on the mammogram elucidation. The advanced study aims to improve an image processing algorithm for identification of micro calcification also mass lesions to support early exposure of breast tumour [16]. Work suggested here deals with the drawing out features like microcalcification also mammograms mass lesions for early on recognition of breast tumour. The advanced procedure is depended on a 3-step process: (a) Regions of Interest (ROI) projected requirement, (b) Extraction of feature based on OTSU thresholding (c) two-dimensional wavelet transformation. Research recommended exposing of micro calcification and mass tumor from mammogram picture segmentation, examination were tested on a number of images from mini-MIAS. The algorithm implementation was using Matlab and it executes effectively on computer, a digital mammogram as gathered information for evaluation.

2.3 Probabilistic Neural Network

Al-Timemy et al (2009) mentioned about the arrangement of threatening and kind breast tumor relied upon Fine Needle Aspiration Cytology (FNAC) and Probabilistic Neural Network (PNN). This data set includes 30 features where input layer is represented to PNN. Mass spectrometry-based proteomics provides an accomplished approach for perfect analysis of various disorders. However, there are issues in the "mass spectral data" like complexity of, noise presence that makes the examination of proteomic model extremely complex.

Neural network-dependent framework is projected by Xuu et al (2009) for proteomic pattern examination. This method chiefly includes 3 phases namely selection of feature on the basis of statistical test, categorization from RBFNN a PNN, lastly results in optimization over ROC study.

Ankita Satyendra Singh (2017), in this paper, designed and obtain the outcomes of breast masses categorization using a data set of 322 images as well as considering 20 malignant and 20 benign constrained masses, gambled, architectural misrepresentation and 20 usual mammograms. Subsequently the ROI abstraction, respectively mass is characterized with 22 features of texture. Previously categorization, choosing of feature was accomplished by 60 ROIs. The PNN classifier made use of 60 images to categories over PNN classifier, Accuracy, Specificity, Sensitivity are accomplished.

2.4 Support Vector Machine Learning methods

An innovative mechanism for recognition of clustered micro calcification in mammogram are recommended by Xinnsheng Zhag et al (2009). Correct recognition of micro calcifications is important reason in CAD outline. Hence to improve the presentation of detection, a Bagging then

Boosting depended Twin Support Vector Machine (BB-TWSVM) is proposed to detect micro calcifications. The process contains 3 parts particularly pre-processing of image, extraction of feature and also the BB-TWSVM part. At first, straightforward physical object elimination filter and a well-made high-pass filter are utilized for every micro calcification preprocessing. Then collective pictures extractors of feature are utilized to extort 164 features of image. Within the collective area of image features, the micro calcifications identification process is projected as a supervised learning and categorization drawback.

Fathma Edaoudi and Regragui Fakhita (2011) declared cancer representation of the foremost often analyzed cancer in ladies. So as to diminish death, primitive identification of breast cancer is significant; as a result of identification is a lot of doubtless to achieve success within the primary phases of sickness, given a novel methodology for automatic recognition of clustered micro calcifications in computerized mammograms. This innovative methodology makes use of the textures coding of mammographic pictures on idea of that Haralick options are calculated for SVM classification intention. With the help of examination outcomes those got within the literature, strategy of coding is tried which tremendously decreases the estimating time of Haralick vector parameters released. In advance, rates of categorization originated by victimization, the coded images enhanced a lot.

Xeen Zhang Sheng (2014) projected to categorize and discover Mcs. Classification issues are developed as distributed feature study dependent mostly categorization. The visual data-rich terminology of training samples is physically created by a collection of samples that incorporate Mcs elements. From the earlier Mcs position truth in mammograms, distributed feature learning is assimilated by the regular fact of Mcs in mammograms, distributed characteristic learning is obtained by spare feature study dependent mostly Mcs categorization algorithmic rule by using Twin Support Vector machine (TWSVM). Projected technique is applied 2 DDSM dataset and then equated with SVMs for exploring its performance with identical dataset. Tests depicts that performance of projected technique is further economical, higher than state-of-art strategies.

3. PROPOSED METHODOLOGY

This section deals with the collection of MRI mammographic images and different algorithm used for identification and recognition of tumors. Picture units of distinct mammograms picture utilized in the examination were accumulated by the Mammographic Image Analysis Society (MIAS) is an association of UK investigation organizations engaged with the acknowledgment of mammograms additionally has made a database of computerized mammograms. The database holds 322 digitized mammograms also been decreased to a 200-micron pixel frame and the images are 1024x1024.

A community that consists of a sum of 321 mammographic images, 206 signify normal images, 51 malignant including 62 benign images. The models in the MIAS database are collected in the Portable Gray Map setup. Each image is 8-bit grey level range images among 256 various grey levels (0–255). In this analysis utilized 20 benign, 20 normal also 20 malignant mammograms which are thick, fat and fatty-glandular moreover have irregularities like surrounded asymmetry, masses, ill-defined masses moreover all the mammograms are changed toward .JPG format. The below figure shows the 40 malignant which is a type of cancerous. The cells are anomalous and distribute randomly also 40 benign and 40 normal which a type is of the non-cancerous group.

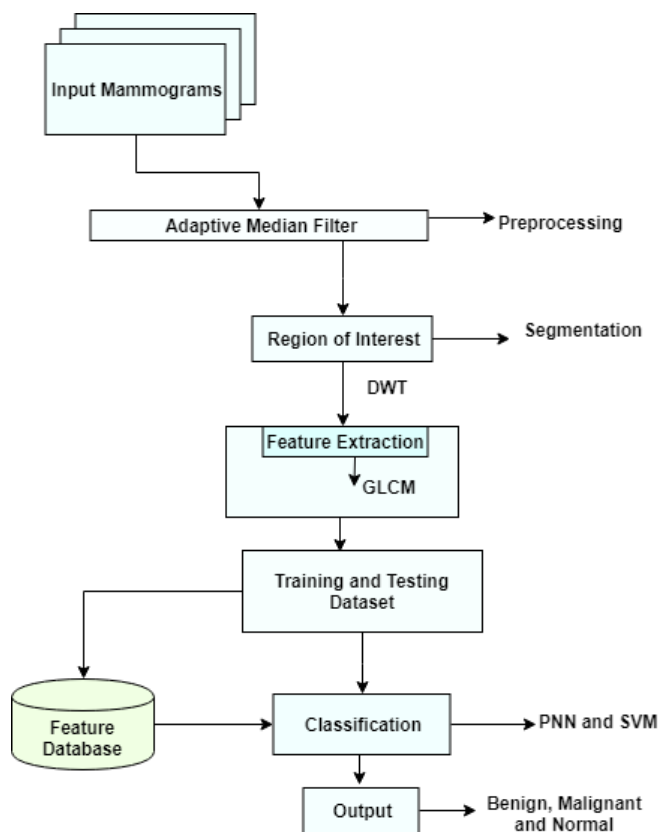


Figure 3.1 Flow of System Architecture

3.1. Preprocessing

Preprocessing is measured as important step so as to find the orientation of the mammogram images and to enhance the standard of the image. The breast images collected will be subjected to preprocessing for noise removal using adaptive median filtering technique so that the result is more suitable than the original image for a specific application.

The adaptive Median Filter classifies picture elements as noise by comparing every pixel within the image to its close neighboring pixels. The dimensions of the neighborhood is adjustable, because the threshold. A picture element that's

completely different from a majority of its neighbor, which are not structurally aligned with those pixels to that it's similar, is labelled as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels within the neighborhood that have passed the noise labelling test.

3.2 Extracting Region of Interest

The challenging part for image analysis is extracting ROI from image. There are several classical types of segmentation process is applied to extract ROI. The identified regions are analyzed to detect various types of defects which has covered over a mammography images. In suspicious abnormality the ROI is extracted and cropping operation is applied. By referring the abnormal area, the ROI take approximate pixel range of circle surrounding the abnormal region. Hence, the extracted ROI is free from the background information and noises.

3.3 Gray-Level Co-occurrence Matrix (GLCM)

The transition between two pixels of gray level is used in gray-level co-occurrence matrix to extract the texture of the image. It also provide joint distribution of neighboring pixels of gray level pairs within an image. For classification of the breast malignancy a descriptors from the matrix is extracted. For the computation of GLCM, established the spatial relationship between two pixels i.e. reference pixel and neighbor pixel so it form a different combination of gray pixel values in an image. Let the element of the GLCM for a given image be $q(i, j)$ of size $M \times N$ containing gray levels G ranging from 0 to $G-1$. Hence, the element $q(i, j)$ is defined as:

$$q(i, j) = \sum_{x=1}^M \sum_{y=1}^N \begin{cases} 1, & \text{if } f(x, y) = i \text{ and } f(x + \Delta x, y + \Delta y) = j \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Where the locations of reference pixel and its neighboring pixel are (x, y) and $(x + \Delta x, y + \Delta y)$ respectively. And $q(i, j | \Delta x, \Delta y)$ is relative frequency of two pixels in a given neighborhood of distance $(\Delta x, \Delta y)$ having gray level values. In an image, the two pixel with intensities i and j separated between two neighboring resolution cells with a distance D . And the direction of neighboring pixel w.r.t the pixel reference denoted by θ .

The extracted texture features are:

- Energy: It is the sum of the square values in the GLCM.

$$\sum_{i=1}^G \sum_{j=1}^G \{p(i, j)\}^2 \tag{2}$$

•**Contrast:** It measure the variation in the matrix distribution, a local change in an image in a number, imitating the image clarity and shadow depth of texture.

$$\frac{\sum_{i=1}^G \sum_{j=1}^G (i,j) p(i,j) - \mu(x) \mu(y)}{\sigma(x) \sigma(y)} \dots\dots\dots (3)$$

•**Entropy:** It measure the randomness of an image texture and the minimum value is achieved when co-occurrence matrix is equal for all the values.

$$-\sum_{i=1}^G \sum_{j=1}^G p(i,j) \log(p(i,j)) \dots\dots\dots (4)$$

•**Correlation Coefficient:** It measure the joint probability existence of the quantified pixel pairs.

$$\sum_{i=2}^{2G} (i - \text{sum entropy})^2 p_{x+y}(i) \dots\dots\dots (5)$$

•**Homogeneity:** It measure the distribution of closeness element in the GLCM to the GLCM diagonal.

$$\sum_{i=2}^{2G} ip(x+y)[i] \dots\dots\dots (6)$$

3.4. Probabilistic Neural Network

PNN is made up of 3 layers of nodes including input, where activation function are hidden and output. In input, the input data is set which is nonlinearly transformed into a high dimensional hidden layer by the basic functions then linear transformation of the hidden output layer.

The below figure shows the architecture for PNN that classifies K equal to two classes, however it can be prolonged to any number of K classes. On the left side the input layer comprises N nodes of the N input feature vector. In the hidden layer nodes, receives the wide range of input features X. And in the output layer node for each feature vector a Gaussian function is grouped to feed their functional values. Therefore k output nodes will be presented.

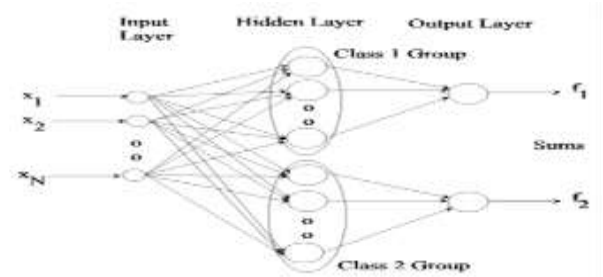


Figure 3.2: PNN Architecture.

For the class K, Gaussian values are been summed and scaled so that the probability of the sum function is unity and forms probability density function. Assume there are P example feature vectors {x: p =1... P} labelled as class 1 and Q (p) example features vectors {y: r=1... R} labelled as class 2. Therefore, in the class 1 represent P nodes and in the class 2 represent R nodes. Each Gaussian is centered on the particular class 1 and class 2 points x and y i.e., feature vectors as shown in the equation.

$$g_1(x) = [1/\sqrt{(2\pi\sigma^2)^N}] \exp\{-\|x - x^{(p)}\|^2/(2\sigma^2)\}$$

$$g_2(y) = [1/\sqrt{(2\pi\sigma^2)^N}] \exp\{-\|y - y^{(q)}\|^2/(2\sigma^2)\} \dots\dots\dots (7)$$

The output node k is sum of the values established after the hidden nodes in the k group called Gaussian mixed model. The sums are defined by

$$f_1(x) = [1/\sqrt{(2\pi\sigma^2)^N}] (1/P) \sum_{(p=1,P)} \exp\{-\|x - x^{(p)}\|^2/(2\sigma^2)\}$$

$$f_2(y) = [1/\sqrt{(2\pi\sigma^2)^N}] (1/Q) \sum_{(q=1,Q)} \exp\{-\|y - y^{(q)}\|^2/(2\sigma^2)\} \dots\dots\dots (8)$$

Where input feature vector is denoted by x, σ1 and σ2 are the standard deviations for Gaussian in class1 and class2, the dimension of input vectors denoted by N, the number of center vector in class1 denoted by P, the number of center vector in class2 denoted by R, the centers of class1 and 2 respectively denoted by x (p) and y(r) and the Euclidean distance between x and x (p) is denoted by ||x-x(p)||.

The maximum value of f1(x) and f2(x) will decides which classes it belong to. There is no computing weights or iteration for each class may be it reduced by thinning which are close to one another by making σ larger. Here the PNN recognize three different classes namely benign, malignant and normal based on feature database.

4. RESULT & DISCUSSION

We have used Matlab, R2014a, 64-bit for the experimental set up. The RGB image of size 256x256 is considered for experimental purpose. The comparison between SVM and PNN classifier is done respectively.



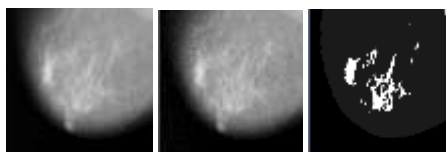
Figure 4.1: Display the different stages when the program is executed.

The above figure indicates format of the resulting image display. Firstly input image should be uploaded. After image is been uploaded Adaptive Median Filter, Segmentation, and classifier for the input image and class will be identified and final processed and resulting image will be displayed on the right hand side.



Figure 4.2: Selecting of input image from the database.

The above figure depicts the uploading of the image from the computer for processing and classification of the type of disease, it will be done after processing using the algorithm or the code.



(a) (b) (c)

Figure 4.3: a. Benign input image b. Preprocessed image c. Segmented image.

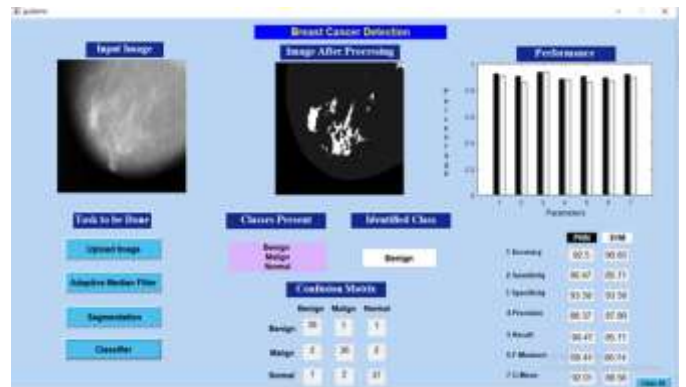


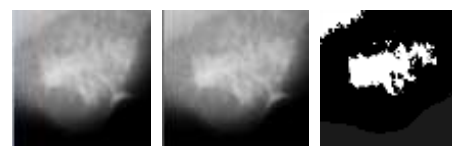
Figure 4.4: This shows the performance evaluation of PNN & SVM.

The above figure depicts the image after performing segmentation, classification through using PNN and SVM. The class of the image will be identified after processing the image through all the three steps i.e. adaptive median filtering, Segmentation and classifier. So the result is obtained which is same as the predicted one.



Figure 4.5: Indicates the uploading of malignant image for processing and identifying the class.

The above figure depicts the uploading of the known example malignant class cancer image and verifying the same image and finding out the class through different steps of processing.



(a) (b) (c)

Figure 4.6: a. Malign input image b. Preprocessed Image c. Segmented image.

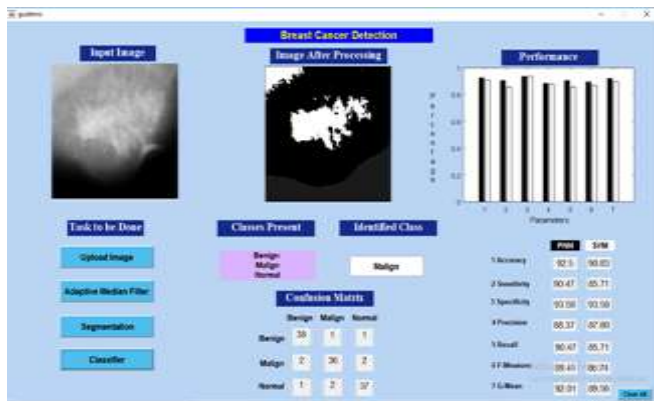


Figure 4.7: Indicates the image undergoing classifier block for processing and identification of the cancer class.

The above figure depicts the image after processing in the segmentation block, classification is done through the 2 types that is PNN and SVM, steps are carried out through the two classifier processes also and cancer class will be identified for the uploaded image.

	Benign	Malign	Normal
Benign	38	1	1
Malign	2	36	2
Normal	1	2	37

Table 4.1: Confusion Matrix

Finally from the 120 images was considered which included 40 images of benign, 40 images of malignant and 40 images of normal. After classification 38 images of benign images were properly classified, 36 images from malignant images were appropriately classified and 37 images from normal images were correctly classified as shown in the table 4.1.

	PNN	SVM
Accuracy	92.5	90.83
Sensitivity	90.47	85.71
Specificity	93.58	93.58
Precision	88.37	87.80
Recall	90.47	85.71
F-Measure	89.41	86.74
G-Mean	92.01	89.56

Table 4.2: Performance measurement of the PNN and SVM

Compared the classifier between PNN and SVM. Accuracy, Sensitivity and so on obtained by PNN was higher than SVM, which clearly depicts that applying PNN would give higher accuracy than SVM. Finally PNN is used as a classifier to distinguish mammogram and classify it into normal or malignant class.

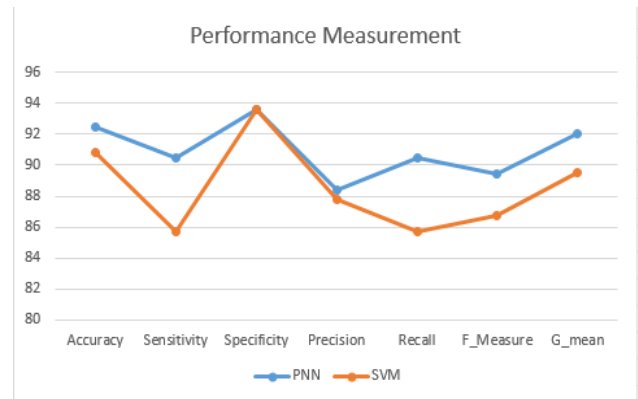


Figure 4.8: Comparison graph between PNN and SVM.

The Performance of the PNN and SVM is as shown in the above figure some the parameter such as Sensitivity obtained by applying PNN was 90.47 and SVM was 86.71. Precision obtained by using PNN was 88.37 and SVM was 87.80. Precision obtained by PNN was higher than SVM. Accuracy obtained by using PNN was 92.5 and SVM was 90.83 which clearly depicts that applying PNN would give higher accuracy than SVM.

5. FUTURE SCOPE

Detection of breast cancer is a field in which there is a constant scope for enhancement. The detection process can be done using several other detection methods and new image processing tools can be used.

Classification and prediction can be done using new decision-making algorithms. Multiple algorithms can be used to generate more accurate results and at the same time the speed of detection can also be increased.

The performance measurement parameters need to be maximized as much as possible, this will ensure that the detection is of higher quality and the results given while detection can become more reliable.

The dataset can be altered and more appropriate images can be added. The better the quality of the dataset the better will be the performance parameters. All the images added must be unique and of better detailing in order to produce to desired result.

6. CONCLUSION

In this proposed work, it has become evident it is possible to predict the presence of tumor and at the same time it can classify if the tumor present is benign or malign. This will also help in diagnosis to identify, if the cancer will spread to other parts of the body. The classification is done using Probabilistic Neural Network and based on the network formed the training process is also done. The classification is done after the completion of two vital processes. Firstly, the

Adaptive Median Filter is applied to the image followed by which segmentation needs to be done.

Training is done using a set of one hundred and twenty images which comprises of three classes namely: normal, benign and malign. Each class is built up with forty images. Testing can be done with any random image that will fall into any one of this class and that image will be classified into the right class. In case there are more images that need to be added to the base dataset it can be done by performing the Probabilistic Neural Network training to the entire set of images. Performance measure is also calculated and displayed in the user interface that was created solely for this purpose. And in the classification for the benign images 38 images of benign were properly classified, 36 images from malignant images were appropriately classified and 37 images from normal images were correctly classified. There is also a graphical representation of the performance measure. The performance measure does include the following parameters that are displayed: accuracy, sensitivity, specificity, precision, recall, g-mean, f-measure.

This software like setup can be used to aid in detection of cancer. It can help in reducing certain painful acts such as biopsy and can make the detection process much simpler. It will help prevent mental stress that the patients with tumor or lumps will undergo.

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