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Mammogram Image Nucleus Segmentation and Classification using Convolution Neural Network Classifier

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Abstract: Breast Cancer is one of the dangerous diseases which lead in resulting deaths among women. This is due to the presence of cancerous cells that are produced in extra amount of proportion which can replace the neighboring non-cancerous cells or it can infect all over the body. As the breast cancer concerns women mostly at the age of 40, they are asked to attain the regular mammographic screening, since mammography is most reliable method for cancer detection at early stages. Mammogram is the most common method used for breast imaging. It helps in examine the presence of cancer at early stages and help in reducing the mortality rate by 25-30% in screened women. There occur many different types of breast cancer such as: mass, micro calcification clusters, architectural distortion and asymmetry breast tissue. This dissertation carries the masses problem and deals with its shape and texture feature for classification. Various type of techniques and methodologies are present in mammography which helps to find out the presence of cancer and also multiple ways to detect it in its early stage so that the patient affected by it could not lead to death. Mammography is the most common, safe and inexpensive methodology suggested whose standard image database could be used for training the learning machine. In this dissertation nucleus segmentation is used to find out the region of interest (ROI). The result of ROI is further used for extracting the valuable shape and textural features by using geometrical features, GLCM and GLDM for classifying the cancer through the machine learning approach i.e. CNN (Convolution neural networks). CNN remove the overlapping of features obtained after segmentation. Hence, CNN is used to evaluate the performance through defining accuracy, precision, and recall and also compare the results with existing logistic regression and neural network classification technique.

Keywords: Breast cancer, Mammogram, Convolution Neural Network (CNN), GLCM (Gray Level Co-occurrence Matrix), GLDM (Gray Level Difference Method).

I. Introduction

Breast cancer originates in human and mammals from the breast tissues, most commonly from inner lining of milk ducts that supply the ducts with milk. The reason for this cancer can be mutational changes, radiation effect, or hereditary. Mammogram is an effective technique for the screening of breast cancer screening and early detection of masses or abnormalities and this technique is known as mammography. Micro calcifications and masses are the most common abnormalities in breast cancer [1]. It has been detected that a mass screened on a mammogram image can be either benign or malignant tumor depending on its shape. Benign tumors usually have round shapes, while malignant tumor has a partially rounded shape with a spiked or irregular outline. Non-cancerous or benign tumors include fibro adenomas, cysts, and breast hematomas. A malignant tumor in the breast is a mass of breast tissue that grows in an abnormal way.

Normally, malignant masses appear brighter than any tissue surrounding it [2].

To accomplish the mass recognition process, the suspicious region is identified to obtain the region of interest (ROI) on mammogram image, extract the features, and distinguish the ROI between mass and normal tissue, and finally decide the classified mass into the benign or malignant. Mass segmentation is essential to the later feature extraction and classification. Different algorithms for the early detection of breast cancer have been widely studied, and the most common used are classical threshold method, active contour model, region growing, watershed, and template matching methods [3].
On the other side, CAD systems are inexpensive and easy to use the tools and by analyzing the digital mammogram images they can efficiently assist the radiologists in their decision making process. CAD systems are used earlier for screening mammogram and proved to be useful in the screening procedure of digital mammogram images and it is also useful in detection of early stage breast cancer. However, there exist controversial result and views against the usage of CAD systems due to their high false positive and false negative results in the breast cancer detection, which makes radiologist not really trust them. False negative results occur when the CAD system results a mammogram to be normal when the breast cancer is still present. The major cause of the false negatives results is the mass of the breast, as both dense tissues and tumor are appeared as white regions in the digital mammogram image which makes it difficult to distinguish between them. As women get older, their breasts become fatty and false negatives are less likely to occur. A false positive is the region in which the mammogram image that is benign but interpreted as the suspicious region by the CAD system. High false positive results occurs most commonly when it is analyzing that the digital mammogram images of the younger women occurs because of the similar reason of dense breast tissues [4].
The computer-aided detection (CAD) system could reduce the expert's workload and can improve the early cancer detection rate. Mass and microcalcification clusters are the most common signs of breast cancer, and MC clusters appear in 30–50 % of diagnosed cases. MCs are the calcium deposits having small dimensions and they appeared as a granular group of bright spots in a mammogram image [5].

To identify the presence of breast cancer, the detection of cancer can be done by retrieve the mammographic images available in database such as DDSM or MIAS database which helps in analyzing the type of tumor and according to the stage of that tumor there are many different ways of treatment of mass lesions. Many type of Breast cancer are present and the biggest problem regarding them is that it is impossible to detect it in its early stage. So there is a need to evolve some methods which helps in detecting cancer in beginning time of cancer. This research also draws the comparison between Support Vector Machine (SVM) classification technique and Artificial Neural Network (ANN) learning mechanism [6].

II. Literature Review

Afsaneh Jalalian et al [7] presented the approach which are applied to build up CAD systems on mammography to find out the tumor inside the breast and it is also applied on ultrasound images. The recital evaluation metrics of CAD systems are also review. Mammography is the best technique for breast imaging and detecting breast cancer. But the results that are obtained from mammography are not that reliable specially in dense breast so some another modalities like magnetic resonance imaging and ultrasound are recommended to achieve better results.

Daniel C. Moura et al [8] a novel descriptor invariant to turning round, histograms of gradient divergence (HGD), was urbanized to deal with round-shaped objects, such as masses. HGD was compare with unadventurous CAD features. HGD and 11 conventional image descriptors were evaluate using cases from two publicly obtainable mammography data sets, the digital record for screening mammography (DDSM) and the breast cancer digital depository (BCDR), with 1,762 and 362 instances, correspondingly.

Huda Al-Ghaib et al [9] **t**his author present a new machine learning algorithm, known as margin setting algorithm (MSA), to fragment the breast and pectoral muscle. In this investigate, they applied MSA to division the breast and pectoral muscle. The performance of their algorithm is compare with four different algorithms. These algorithms were tested on 554 mammograms from 125 patients. biased evaluation, by four researchers in the area of pattern recognition, was used to evaluate the outcomes. MSA outperformed NN algorithm in 84.21% of the mammograms. Also, MSA outperformed the other three algorithms in 98.12% of the mammograms.

Issam El-Naqa et al [10] this paper describes an advance to content based repossession of medical images from a database, and provides a introduction demonstration of our approach as applied to reclamation of digital mammograms. A study has been made and comparison has done on examples that are provided by different human observers. The result shows that the learning frame work can correctly predict the perceptual; the learning-based framework can radically outperform a simple distance-based similarity metric, the use of the hierarchical two-stage network can progress retrieval performance and relevance opinion can be effectively integrated into this learning.

Raul Ramos-Pollan et al [11] **t**his work explore the design of mammography based machine learning classifiers (MLC) and propose a new method to build MLC for breast cancer diagnosis. They particularly evaluated MLC configurations to classify facial appearance vectors extracted from segmented regions anthological lesion or normal tissue on craniocaudal (CC) or mediolateral oblique (MLO) mammography image views, providing BI-RADS diagnosis. The method can be used under different data acquisition conditions and exploits computer clusters to select well drama MLC configurations.

Abbas et al [12] anticipated a study in which they are using two major morphological operations: dilation and erosion. The proposed system will help the doctors to progress the diagnosis of the disease to detected cancer cells. The best result was obtain when using the (disk) formation element of disk with (15*15) mask. However, the worst is the (line) formation element of disk with (3*3) mask. The results that have been obtain by applying Mean Square Error and Peak Signal to Noise Ratio are a good pointer of image quality because they are easy to create and seemingly unbiased. The dataset of mammogram image were taken from Baghdad madina Al-tab andazadi hospital Kirkuk.

Liu et al [5] made studies on breast cancer and incorporated the possibilistic fuzzy c-means (PFCM) clustering algorithm and subjective support vector machine (WSVM) for the exposure of MC clusters in full-field digital mammograms (FFDM). The revealing performance is evaluated using ROC curves and FROC curves. For the selection of MC clusters, the proposed method is obtained for a high sensitivity of 92 % with a false-positive rate of 2.3 clusters/ image, and it is also improved than standard SVM with 4.7 false-positive clusters/image at the same sensitivity.

Pratiwi et al [3] anticipated a study in which there are three main process, which are pre-dispensation, feature removal, and classifier. This paper report and attempt on with RBFNN for mammograms classification based on GLCM texture based features. In this experiment both the breast images has been used as standard input and MIAS database is used. With the help of computational experiments it has been observed that RBFNN is better than BPNN in performing breast cancer classification.

Xie et al [2] offered a novel automatic detection dispensation in terms of mammographic images for micro calcification clusters recognition. The methods proposed in this paper attempt to resolve this problem by establish an automatic detection procedure of an input mammographic image. The comparison experiments and Cohen’s kappa coefficients all show that our proposed loom can potentially obtain better micro calcification clusters revealing results in terms of accuracy, kindliness and specificity.

Sharma et al [13]**:** propose a CAD system to classify wicked and nonmalignant mammogram patches. The variations in the results are observed by experiment with the low- and high-order Zernike moments. Experiments are performed with other well-known texture descriptors GLCM and DCT, and it is experiential that the proposed CAD system works well with Zernike moments. SVM with RBF kernel attains the highest understanding and specificity values at lower orders of Zernike moment. The projected CAD system improves the accuracy of analysis and promise to perform a second-reader role.

R. tipa, O. baltang et al [14] **t**he paper presents some new methods for early breast cancer finding using microwaves. On describe the subsequent methods and technique: microwave impedance tomography, thermograph and microwave radiometry, combined method - microwave and ultra-acoustic image and co focal microwave imaging. We make an examination of compensation and disadvantages of every method and also physical philosophy of microwave thermography.

Gisella Gennaro et al [15] **t**o evaluate the clinical act of digital breast tomosynthesis (DBT) with that of digital mammography (FFDM) in a diagnostic inhabitants. Clinical performance of DBT compared with that of FFDM was evaluated in terms of the variation between areas under ROC curves (AUCs) for BIRADS scores. Results: Overall clinical presentation with DBT and FFDM for malignant versus all other belongings was not considerably different (AUCs 0.851 vs. 0.836, p=0.645). The lower limit of the 95% CI or the dissimilarity between DBT and FFDM AUCs was -4.9%.

H.D. Cheng et al [16] In this survey paper, we recapitulate and evaluate the methods used in various stages of the computer-aided detection systems (CAD). In scrupulous, the improvement and segmentation algorithms, mammographic features, classifiers and their performances are studied and compared. Remaining challenge and future research directions are also discussed.

III. Design and Implementation

The previous chapter discussed the literature review. Researchers have implemented various techniques in breast cancer. In the current chapter, the algorithms would be designed and implemented with the help of implementation tool MATLAB. For the implementation, new algorithm is proposed.

Design

After the detailed study of breast cancer and mammography, the next objective is to implement the proposed algorithm. The algorithm is designed in this section.

Performance metrics

Comparison is done for the three parameters namely precision, recall and accuracy as shown in Table 4.1.

Table 1 Performance Metrics

Precision
Recall
Accuracy

Precision, Recall and accuracy are described in terms of TP, TN, FN and FP. The interpretation of these is described below:
True positive (TP): ill people are correctly diagnosed sick.
False positive (FP): healthy people are incorrectly diagnosed sick.
True negative (TN): healthy people are correctly diagnosed healthy.
False negative (FN): sick people are incorrectly diagnosed healthy.
The performance metrics are described below:

1. **Precision:** It is defined as the ratio of correct positive observations. In other words, it is defined as the ratio of true positive values to the true positive and false positive.

$$Precision = \frac{\mathrm{TP}}{TP + FP}$$

2. **Recall:** It is also known as sensitivity or true positive rate. In other words, it is defined as the ratio of true positive to the true positive and false negative.

$$Recall = \frac{\mathrm{TP}}{TP + FN}$$

3. **Accuracy:** Accuracy is perhaps the most intuitive performance measure. It is simply the ratio of correctly predicted observations. It is defined as ratio of true negative and true positive to the true negative, true positive, false negative and false positive.

$$Accuracy = \frac{\mathrm{TN} + \mathrm{TP}}{\mathrm{TN} + \mathrm{TP} + \mathrm{FN} + \mathrm{FP}}$$

Based on these performance metrics, the approaches under study are evaluated and compared.
The following section elaborates the steps to be followed for the proposed algorithm.

Steps of proposed approach

The new approach is implemented which is described using the following steps:

1. Input the image of MIAS database.
2. Images are segmented using nucleus segmentation.
3. Noise is removed using noise removal.
4. Extract the geometrical features, GLCM and GLDM from step 4 images.
5. Combine the feature set.
6. Label the feature set with three classes.
7. Train the NN, CNN and Logistic regression classifier using the training data.

8. Analyse the model by test process based on precision, recall and accuracy.
   The flow of the proposed algorithm is depicted in the Figure 4.1

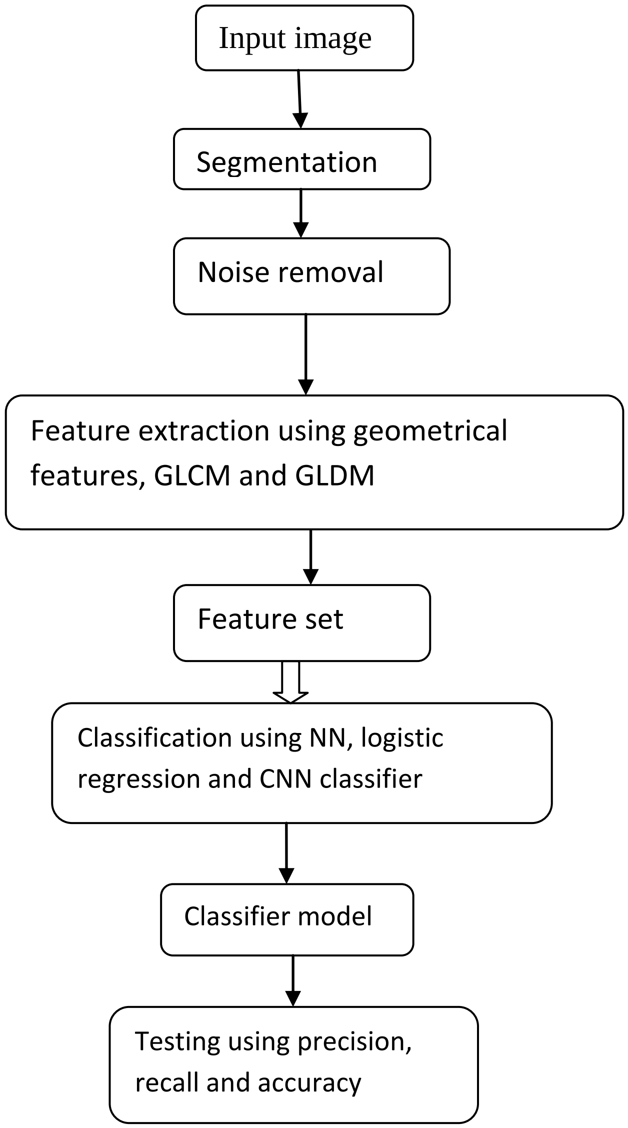

Figure 1 Flowchart of proposed approach

Pseudo code for proposed model

The pseudo code for the proposed algorithm is described as shown in Figure 2

```
Medical Image Classification (Images)
{
for i=1 to number of images
{
Apply the segmentation image [i]
Apply noise removal image [i]
Apply GLCM and GLDM image [i]
Apply geometric features image [i]
}
Make database of feature →.matfile
for i=1 to number of instances in .matfile
{
Apply convolution prediction
Apply learning kernel
```

The implementation of the proposed algorithm is discussed in the next section.

Implementation of proposed algorithm

Segmentation of the mammogram image is the most important step in image analysis and many algorithms have been proposed to solve this problem. In Figure 3 Input mammogram image is taken from the MIAS database to check the presence of cancer producing cells. In Figure 4 breast region segmentation is done to find out the region of interest (ROI) and it can remove the additional artifacts, labels and borders from the mammogram images. Finally the breast region is segmented using nucleus segmentation.

Figure 3 Input images from MIASdatabase.

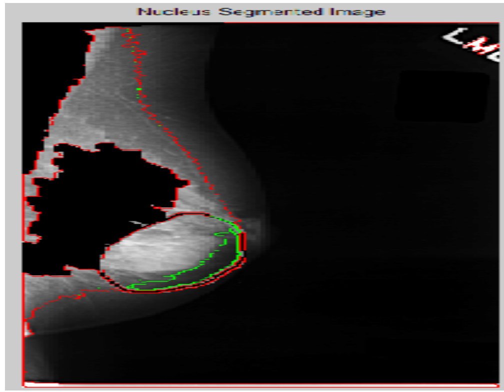

Figure 4 Segmentation and region of interest (ROI) by nucleus segmentation method.

In Figure 5 input mammogram image is taken from segmented image done in the previous step. In Figure 6 Masking out Image area using Binary Mask. In Figure 7 image is cropped after masking. In Figure 8 after cropping the image noise removal is removed in order to enhance the mammogram image.

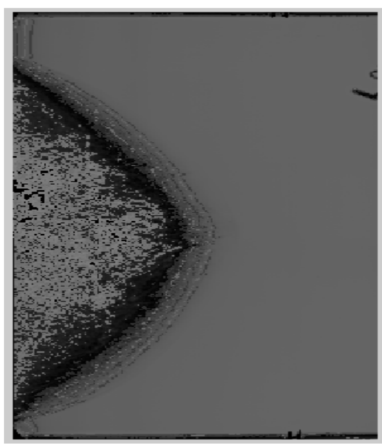

Figure 5 Input mammogram image

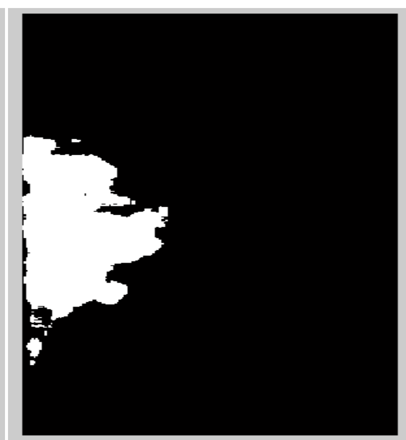

Figure 6 Masking image

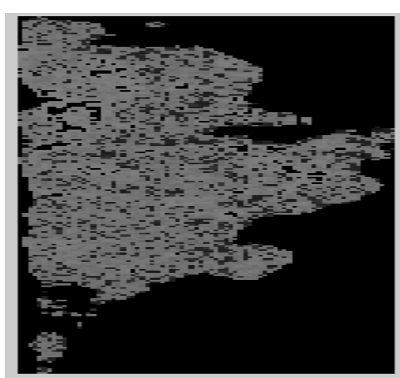

Figure 7 Cropped image

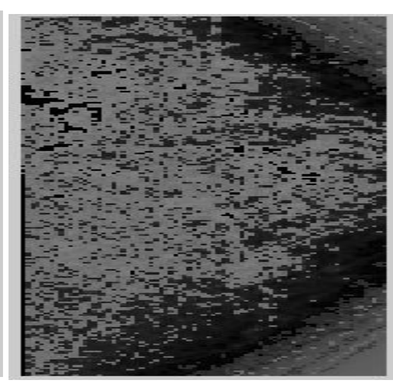

Figure 8 Noise removal image

More than one feature is used to analyze the presence of cancer and that features which are used in our research are geometrical features, GLCM and GLDM. The total features to be calculated are 40 out of them 7 features are geometric features which represents more efficiency in calculating the nature or shape of the presence of cancer. Those features are Eccentricity, Area, Equivalent Diameter, Euler Number, Inertia, X-axis and Y-axis. GLDM features are used to define the probability density functions and therefore, it includes 4 features which are used to define the changes occurs in the image density. This feature can be seen through plotting its density graph. After noise removal, extract the geometrical features - GLCM and GLDM, from mammogram image.

IV. Results and Discussions

The mammogram image dataset used in this research is collected from MIAS dataset. With the implementation of proposed approach results have been obtained. In this chapter, the results are analyzed and compared.

Results

Table 3 shows the convolution neural network (CNN) express by high accuracy, precision, recall because CNN remove the overlapping between features.

Table 2 Testing using true positive, true negative, false positive and false negative

Classifier	TP	FP	FN	TN
Neural network	9	9	4	8
Logistic regression	13	1	2	14
Convolution neural nwtwork	20	1	0	9

Table 2 shows that in neural network true positive number is 9, false positive number is 9, false negative number is 4, and true negative number is 8. In logistic regression true positive number is 13, false positive number is 1, false negative number is 2, true negative number is 14. In convolution neural network true positive number is 20, false positive number is 1, false negative number is 0, true negative number is 9.

Table 3 Highlights results of NN, logistic regression, CNN using precision, recall, accuracy parameters

Classifier	Accuracy	Precision	Recall
neural network	56.66	50	66.80
logistic regression	90	92.85	86.66
convolution neural network	96.66	95.23	99.86

Table 3 shows the results of neural network, logistic regression and convolution neural network using precision, recall and accuracy. The precision shows 50% results in neural network, logistic regression gives 92.85% and CNN gives 95.23%. The recall gives 66.80% results in neural network, logistic regression shows 86.66% results and CNN gives 99.86%. The accuracy achieved by neural network is 56.66%, logistic regression shows 90% accuracy and CNN shows the best result among them with 96.66%.

Accuracy

Figure 9 describes the accuracy performance using neural network, logistic regression and CNN. In this figure accuracy is compared between neural network, logistic regression, CNN in which CNN has the best accuracy. This figure shows the accuracy results by three classifiers. The neural network classifier has achieved accuracy of 56.66%, logistic regression shows the accuracy of 90% and CNN gives 96.66% results which show the best result.

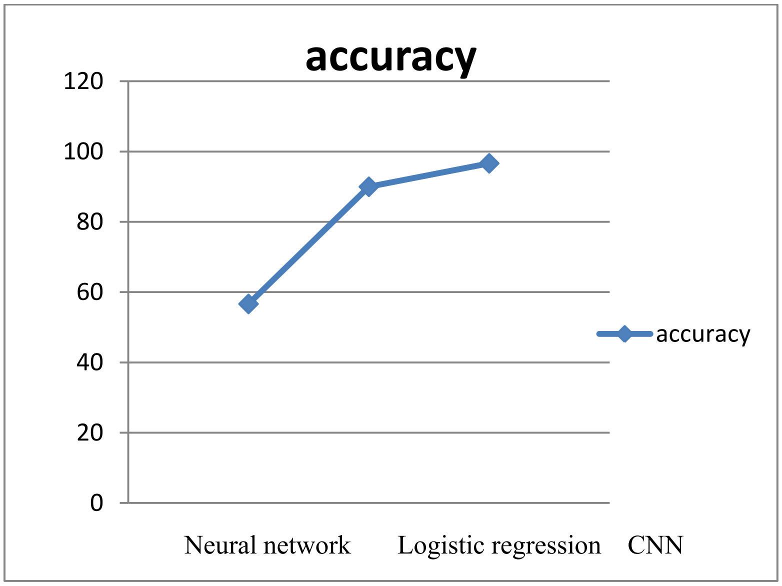

Figure 9 Accuracy comparison of Neural Network, Logistic regression and CNN

Precision

Figure 10 describes the precision performance using neural network, logistic regression and CNN. In this figure precision is compared between neural network, logistic regression, CNN in which CNN has the best result. This figure shows the precision results by three classifiers. The neural network classifier has achieved precision of 50% logistic regression gives 92.85% and CNN gives 95.23% results.

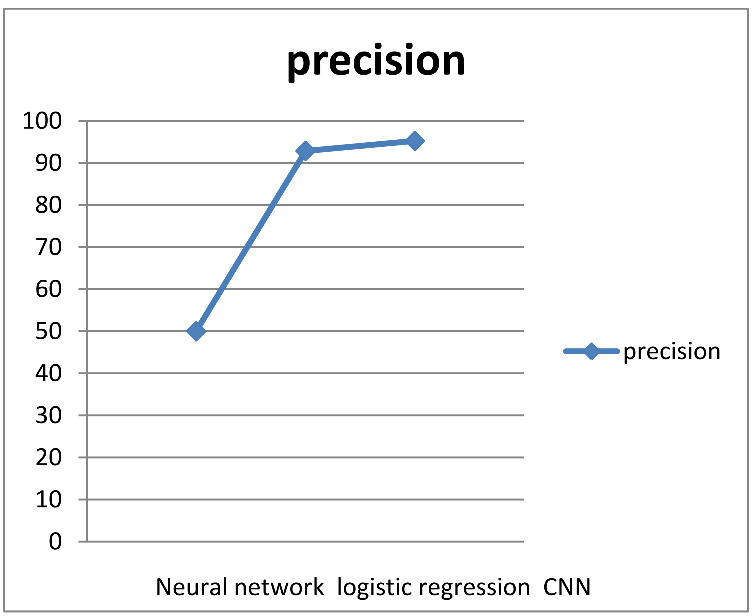

Figure 10 Precision comparison of Neural Network, Logistic regression and CNN.

Recall

Figure 11 describes the accuracy performance using neural network, logistic regression and CNN. In this figure recall is compared between neural network, logistic regression, CNN in which CNN has the best result. This figure shows the recall results by three classifiers. The neural network classifier has achieved recall of 66.80%, logistic regression shows the accuracy of 86.66% and CNN gives 99.86% results which show the best result.

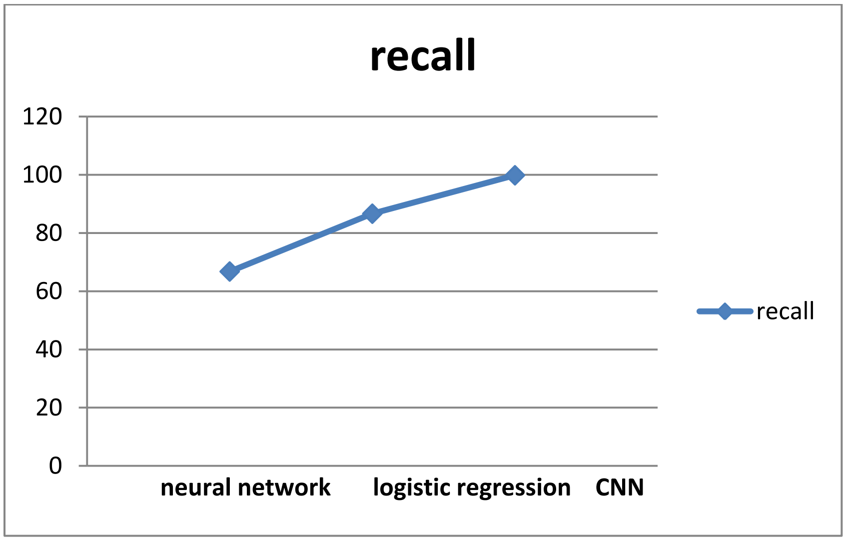

Figure 11 Recall comparison of Neural Network, Logistic regression and CNN.

Comparison

Figure 12 shows the comparison accuracy, precision, recall between neural network, logistic regression and CNN. This graph shows the accuracy, precision, recall results by three classifiers. Precision achieved by the neural network is 50%, logistic regression gives 92.85% results and CNN shows the best precision result by 95.23%. Recall achieved by the neural network is 66.80%, logistic regression shows 86.66% and CNN gives the best results 99.86%. Accuracy achieved by the neural network is 56.66%, logistic regression shows 90% and CNN gives 96.66% results which show the best result in accuracy.

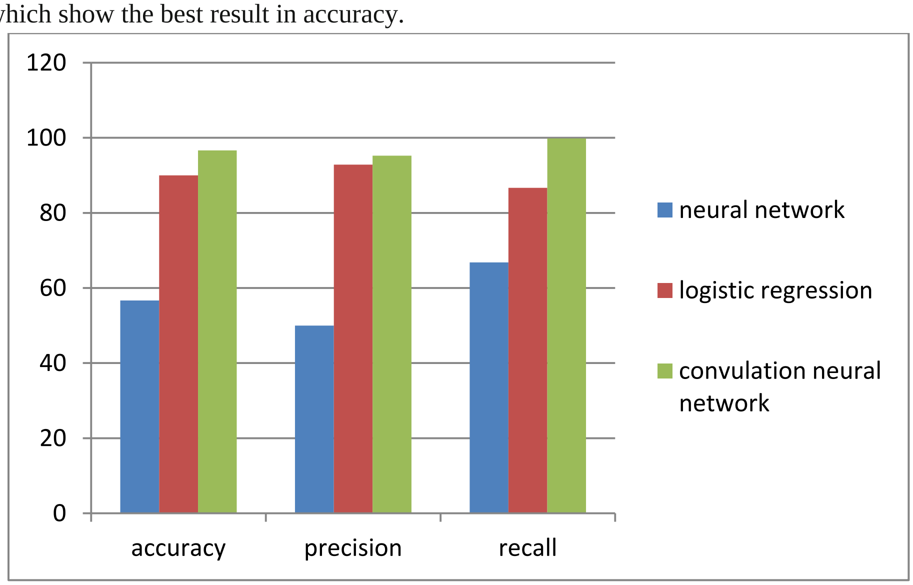

Figure 12 comparison between neural network, logistic regression, and CNN using accuracy, precision, recall.

Discussions

This work is conducted to get the highest accuracy using neural network, logistic regression and convolution neural network. Three parameters are used namely precision, recall and accuracy which are used for comparison between classifiers. There are many types of breast cancer but in this dissertation it takes only mass tumors which deal with its shape and texture feature for classification. There are many type of techniques which are present in mammography which helps to detect breast cancer in its early stage. Nucleus segmentation is used for segmentation which helps to find the region of interest in breast. The outcome of segmentation is used for extracting the shape and textural features by using geometrical features, GLCM and GLDM. The total features to be calculated are 40 out of them 7 features are geometric features which represents more efficiency in calculating the nature or shape of the presence of cancer. GLDM features are used to define the probability density functions. In Figure 5.4 comparisons is shown between classifiers and CNN shows the better results among all. CNN exhibits 96.66% accuracy and remove overlapping features which are obtained after segmentation.

Conclusion

The problem on which the research has been carried out has been solved using different measures like: the selection of mammographic images, use of more than one feature to analyze the presence of cancer and at the end calculating the percentage of getting the correct results from a large set of database. In earlier cases, the detection of cancer is processed through calculating the one of the different features descriptor, but there is a small approach is made i.e. instead of using single feature descriptors, the use of two different features in this case they are: shape and texture. Here 7 shape descriptors are used and 22 GLCM and 4 GLDM texture feature descriptors are used. Hence, by combining the features provides the better chances of analyzing the cancer type and character. Therefore, the conclusion of this research is that using more features builds the chances of spotting the cancer more effectively and compared it with the existing classification technique. Classifiers used in our research are neural network, logistic regression and CNN. Neural network results 56.66% which will give least accuracy, logistic regression results 90% and CNN classifier results 96.66% accuracy which shows that the CNN effect on accuracy and gives the best result among them.

Future scope

Each and every research has a needle through which something extra and new could be experimented and evolved. In this research there is a possibility to introduce new method of classification and ROI extraction so that the cancer could get detected in very early stages so that it can be cured easily and can't be reached to the malignant stage.

Therefore, there is outsized range for the further improvements in the field of Breast cancer detection as it is the most dangerous disease spreading among women and if not cured can get worse and affect the lives of people.

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