A Hybrid Deep Learning Based Assist System for Detection and Classification of Breast Cancer from Mammogram Images

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Abstract: *The most common cancer disease among all women is breast cancer. This type of disease is caused due to genetic mutation of ageing and lack of awareness. The tumour that occurred may be a benign type which is a non-dangerous and malignant type that is dangerous. The Mammography technique utilizes the early detection of breast cancer. A Novel Deep Learning technique that combines the deep convolutional neural networks and the random forest classifier is proposed to detect and categorize Breast cancer. The feature extraction is carried over by the AlexNet model of the Deep Convolutional Neural Network and the classifier precision is increased by Random Forest Classifier. The images are collected from the various Mammogram images of predefined datasets. The performance results confirm that the projected scheme has enhanced performance compared with the state-of-art schemes.*

Keywords: *Breast cancer, mammogram, alexnet, deep convolutional neural networks, random forest*.

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1. Introduction

Breast cancer is rated as the second most common cancer found in women and it stands next to lung cancer. A recent survey done by American Institute for Cancer Research and World health organization states that approximately 2 million women are spotted with this disease every year. Out of 15% of total cancer deaths are because of breast cancer. And it is also reported that 85% of the women affected by this breast cancer do not have any genetic link and less than 15% of the women are having genetic history. The main cause of breast cancer is due to genetic mutation because of the ageing process. In developing countries, 50% of breast cancer patients are in stages 3 and 4 of the cancer of which 90% will lead to death [24]. The mortality caused by breast cancer is due to a lack of awareness and delay in diagnosis [4]. The tumour that occurred may be benign which is considered non-dangerous or non-cancerous or malignant which has the possibility of being dangerous [35]. The benign tumours are normal and they grow very slowly they do not spread to the other parts of the body or invade any tissues and will be in a proper edged shape. But malignant tumour grows rapidly and invades the nearby tissues and spreads beyond the tumour and affects the other parts of the body they do not have a proper shape and be visible in abnormal shapes [6].

Mammography is considered one of the best methods for the early detection of breast cancer.
Mammography is a method of using reduced energy X-ray to examine the breast for diagnosis. A mammogram is used for spotting the presence and absence of the disease in the breast using an X-ray image [1]. Because through mammograms we can visibly find four major signs of breast cancer are Mass, Micro calcification, Architectural distortion and bilateral asymmetry [10]. But still, it is difficult for a radiologist to interpret because the sensitivity of the mammogram is seriously affected by the image quality. Double reading was introduced through which the mammogram reading will be done by two radiologists, though this system increases the sensitivity of the diagnosis it is not an economical method of diagnosis [11]. Many types of research were done for improving the sensitivity in an economical way [2]. This led to Computer-Aided Diagnosis (CAD) schemes being developed which acts as an assist i.e., supporting material for the radiologists to improve the accuracy in detecting breast cancer [12]. There are many states of the art CAD techniques like Deep Convolutional Neural Networks (DCNN), Recurrent Neural Network (RNN), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) etc., are available for detecting breast cancer from mammogram images with good accuracy and performance.

Section 2 deals with the related works. The materials and methods used for classifying the disease are explained in section 3. Section 4 deals with the experimental results and discussions related to disease classification. Conclusion and the future scope are discussed in section 5.

2. Related Works

The Classification of breast cancer is a very important task in recent days because of the mortality observed in recent days. Much research has been done in this area and a few states of the art researches which helped in performing our proposed method of detecting and classifying the disease using mammogram images are discussed in this section.

A deep learning oriented scheme [25] has been proposed for detecting and classifying breast cancer from mammogram images. In this method, they have used a k-means clustering algorithm for performing the feature extraction for speed up robust features and they have used the multiclass support vector machine classifier for classification of the mammogram into three different classes such as normal, benign and malignant with an accuracy of 95%, 94% and 98%. A bibliographic review [20] of cancer diagnosis using deep learning algorithms have performed here different deep learning algorithms such as Convolutional Neural Networks (CNN), Generative Adversarial Network (GAN), Deep Adversarial Network (DAN), Restricted Boltzmann Machine (RBM), Sparse Auto Encoder (SAE), Computer-Aided Engineering (CAE) and different variants of Convolutional neural networks were studied for the application of algorithms in various cancer diagnosis such as breast cancer diagnosis [17], lung cancer diagnosis and brain tumour diagnosis were discussed for making the readers perform research in the field of cancer detection using deep learning and artificial neural networks [19].

A computer-aided diagnosis technique [37] has been implemented to diagnose breast cancer from the mammogram in its early stage. In this proposed technique they use CNN for extracting the features such as morphological, texture and density features along with the unsupervised Extreme Learning Machine (ELM) [27]; later using the ELM classifier with the extracted features the system classifies the mammogram as benign, Malignant or Normal. And finally, the method is compared with the SVM classifier and the accuracy sensitivity and specificity shows the superior performance of the proposed system [43]. A deep learning technique [29] has been developed which can predict breast cancer from the mammogram images more accurately by using the lesion annotations only in the initial training period and in the later stages they use image-level labels by avoiding the lesion annotations.

The classification was done using CNN classifier and classified the mammogram into five different classes which are benign calcification, malignant calcification, benign masses, malignant masses and background. A new computer-aided detection system [18] has been developed for classifying the mammogram as benign, malignant and normal. Here they have used two different approaches for segmentation where the first identifies the region of interest manually and the second uses the thresholding method [8]. The feature extraction was done using the deep CNN with AlexNet architecture and the fully connected layer of CNN AlexNet is replaced with SVM classifier [23] for getting better accuracy. Investigated results illustrate that SVM with linear kernel function and threshold and region-based segmentation provides more promising results. The experimented three states have developed the art machine learning algorithms such as SVM, Artificial Neural Network (ANN) and naive bayes algorithms [13] for classifying Breast cancer using Wisconsin Diagnostic Breast Cancer (WDBC) dataset. The algorithms were integrated with the feature extraction methods and their performance was evaluated based on reduced dimensionality features which are done by linear discriminate analysis. Later these reduced feature datasets are applied to the Support Vector Machine classifier to improve the accuracy [16].

The CNN based breast cancer classification [5] has been proposed with a special pre-processing technique to reduce the uncertainty in diagnosis. In this technique, the image dataset is incorporated into a special pre-processing such as median filtering, histogram equalization and data argumentation to improve the accuracy of the classification. The breast cancer diagnosis using CNN [39] with two different training scenarios one is with pre-trained weights and other is initialized with the random process which is tested on two diverse datasets. Investigational results illustrate that pre-trained networks perform their work in a superior manner. The new CAD method has been implemented [15] for classifying breast cancer using Decision Tree (DT) algorithms by subjecting the image to the longest line detection algorithm for pectoral muscle which helps in classifying more accurately [5].

The improved CAD technique for diagnosing breast cancer has been used [32]. It uses an optimized region growing technique where preliminary seed points and thresholds are optimized using Dragon Fly Optimization (DFO), surface highlights are mined utilizing GLCM and GLRLM techniques and arranged to utilize Feed Forward Neural Networks (FFNN) classifier [14] which is trained using backpropagation algorithm and archived a sensitivity and specificity of 98.1% and 97.8% respectively. The classification of breast cancer [35] classes using Neural Networks [28] such as Multi-Layer Perceptron (MLP) [9], Radial Basis Function (RBF) [42] and SVM [21] is being carried out. The diagnosis of breast cancer is based on the state-of-the-art classification algorithms [33] such as CNN, Principle Component Analysis (PCA) and K Nearest Neighbourhood algorithms through different datasets of Mammogram images are also performed [36]. As mammogram [30] has been used in identifying breast cancer their methods to diagnose breast cancer [7] use ultrasound images, MRI images [26], histo-pathological images and Ectopic breast tissue. Similarly, Machine learning can be used for classifying other cancers such as lung cancer [22], brain tumour [15], skin cancer [31] and other lung disorders [16]. The comparison of the proposed technique with the relevant techniques in terms of classification is demonstrated in Table 1.

Table 1. Comparison of the proposed system with other state of the art classification techniques.

Reference Number	Technique used for Feature Extraction	Method for Breast Cancer Classification	Accuracy
[25]	K-mean clustering for Speed-Up Robust Features (SURF) selection	Multiclass Support Vector Machine	Normal stage - 95% Benign stage- 94% Malignant stage - 98%
[37]	CNN deep features	Unsupervised Extreme Learning Machine	Benign stage- 86.5% Malignant stage – 82.5%
[18]	A Deep Convolutional neural network	SVM	Method 1-Cropping ROI: Benign and Malignant Stage- 79% Method 2- Threshold and Region based Segmentation: Benign and Malignant Stage- 80.05%
[3]	GLCM is used to extract texture features	Decision tree Classifier	Detect the presence of Breast Cancer with accuracy of 98.14%
[14]	Otsu Thresholding for feature extraction and segmentation	SVM Classifier	Normal- 90.03% Benign- 90.3% Malignant- 90.8%
[35]	Multi-Layer Perceptrons (MLP)and Radial Basis Functions (RBF)	SVM Classifier	Detect the presence of Breast Cancer with accuracy of 96.20%
[28]	Cuckoo search algorithm to select optimal feature split points	Association Rule Agreement-Based Classifier model	Detect the presence of Breast Cancer with accuracy of 93.33%
[42]	Two methods are proposed 1) Convolutional Neural Network-Discrete Wavelet (CNN-DW) • Image Decomposition into 4 sub bands by two-dimensional discrete wavelet transform (2D-DWT) • Dense Scale Invariant Feature (DSIFT) for all subbands is extracted using CNN 2) Convolutional Neural Network-Curvelet Transform (CNN-CT). • Image Decomposition into sub bands byDiscrete Curvelet Transform (DCT) • Dense Scale Invariant Feature (DSIFT) for all subbands is extracted using CNN	SVM Classifier	CNN-DW Accuracy – 81.83% CNN-CT Accuracy- 83.74%
Proposed Method	Convolutional Neural Networks-AlexNet is utilized for Feature Extraction	Random Forest Classifier	Normal stage - 98% Benign stage- 98.4% Malignant stage – 98.3%

3. Materials and Methods

In this section we discus about the datasets used in this research and various steps involved in classifying the breast cancer in to three different classes such as Benign in Figure 1, Malignant in Figure 2 and Normal mammogram images using the proposed method.

But most of these techniques involve more steps such as image enhancement, image segmentation, feature extraction, feature evaluation and at the last the final classification and evaluation will be done.

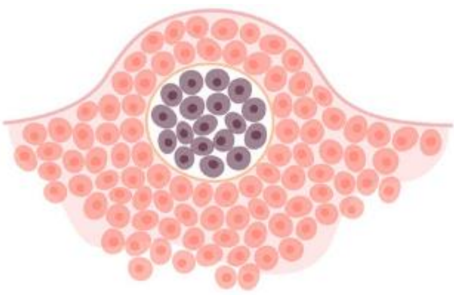

Figure 1. Benign breast cancer.

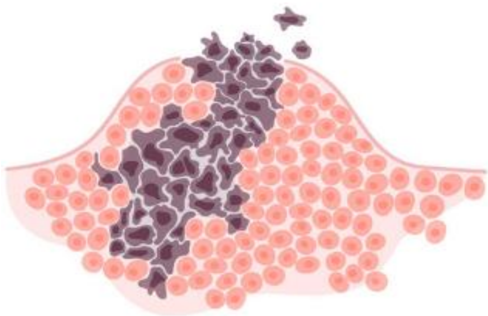

Figure 2. Malignant breast cancer.

All these steps are time-consuming processes and the complexity of the system is getting increased simultaneously. To avoid these issues a novel hybrid method is proposed in this research which combines the DCNN and the Random Forest classifier (RF) which are the state of the art classifiers. Initially, the image is pre-processed to remove the unwanted noise from the mammogram image and extract the Region Of Interest (ROI), using the ROI the AlexNet model of feature extraction can be done using DCNN and as per the principle of the transfer learning the fully connected layer of CNN is replace by the Random Forest Classifier this improves the accuracy of the classifier in Figure 3. This proposed techniques is utilized as AlexNet CNN can automatically extract various features in the images without any intervention of a human and at the same time Random forest has an advantage of bringing down the variance by combining multiple trees to an collective form and can work in any environment as it does not requires the Graphical Processing unit which become computationally less expensive. While combining these two techniques the accuracy is increased in the aspects of robustness to noisy images, general ability of classification of disease and reduces the over fitting problem.

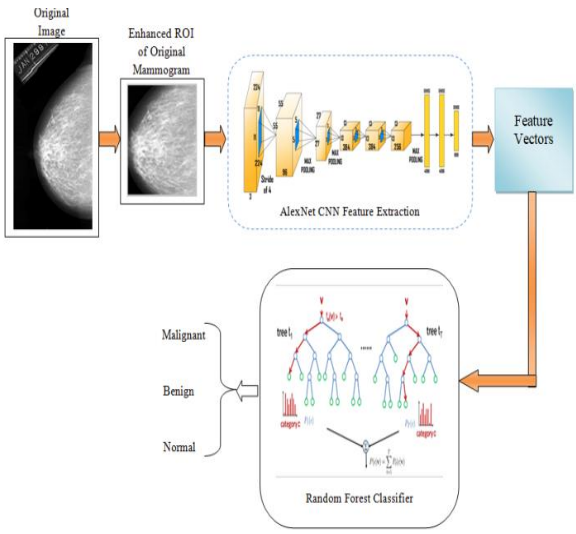

Figure 3. Proposed hybrid CNN and RF based breast cancer classification

3.1. Mammogram Dataset and Augmentation

As breast cancer is a very common type of cancer and the second most common disease found in women all over the world, many researchers were going on to find an optimal solution to spot breast cancer in its beginning phases. Due to this reason, the datasets for the proposed system is mammogram images which are very easily available from various online dataset repository [40]. In this research, we obtained datasets from three different sources. The first source is from Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM) which consist of 2620 digital mammogram images. The second source is from Mammographic Image Analysis Society (MIAS) with 322 images of which 208 is normal 51 are malignant and 63 are Benign images. The third source is from the Iterative Refinement Meta-Assembler (IRMA) database which consist of 2796 patch images all of these datasets is composed of Benign, Malignant and Normal Images with verified pathological information as shown in Table 2. Though these datasets are publicly available for research purposes the quantity of the image is not sufficient to perform deep learning [41].

Table 2. Data collection report from different sources.

	No of Original Images	No of Augmented Images	Total No of Images
CBIS-DDSM Dataset	2620	9800	12420
MIAS Dataset	322	1566	1888
IRMA Dataset	2796	10,490	13,286

On the other hand, fewer amounts of data would lead to an overfitting problem that is if the model learns the problem well and if it performs very well on a training dataset, it will not predict the test accurately and which may reflect in the performance of the system. This problem has increased variance and less bias. Increasing the dataset with new unseen new data and noise added images in the training dataset is the only way to fix these issues, this can be done by introducing image augmentation in such a way that the original images are rotated, and mirrored to acquire different interpretation of the original dataset images.

3.2. Image Pre-Processing and ROI Extraction

Image pre-processing is the process of removing the unwanted noise and redundant signals present in the image which will affect the accuracy of the classification in the later stage. Adaptive Contrast Enhancement (AHE) is very commonly used for image enhancement. In this research an efficient Contrast Limited Adaptive Histogram Equalization (CLAHE) is used which is one of the AHE techniques which are capable of improving the contrast of the image and extracting more details from the image in Figure 4.

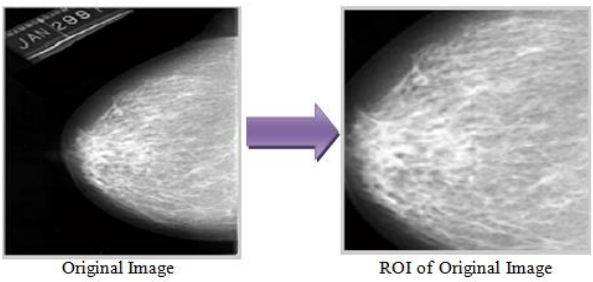

Figure 4. ROI Extraction from the mammogram image.

In MATLAB we have a function to perform the CLAHE which is J=adapthisteq(I) this function enhances the contrast by transforming the values [34]. We use filtering for improving the quality of the image by removing the noise from the enhanced image using MATLAB functions. There are many filtering techniques available in MATLAB such as median filters and mean filters which make the subsequent process such as feature extraction and classification of both normal and medical images more reliably. In this proposed work we use a median filter instead of the mean filter as the performance of the median filtering is better for mammogram images [38]. The effectiveness of the noise removal is based on the size of the filter. After enhancing the input image to improve the efficiency of the anticipated CAD technique it is required to separate the mass areas from the whole mammogram image. As the mammogram images will be containing labels, patient details and dates those details have to be removed before performing the feature extraction as it may reflect in the classification process and its efficiency.

ROI is extracted by boundary Pixels is hoarded in B array (2-dimensional array). The first column and second column of a B array signify X-coordinate and Y-coordinate values of Boundary Pixels. Here n is used to represent the number of boundary pixels. The boundary pixel on the topmost and bottommost of the y column in B is named Top Most (TM) and Bottom Most (BM) respectively. The TM and BM are represented using Equations (1) and (2). The half Euclidean distance between the two points TM and BM is denoted using e. The bottommost pixel on boundary pixels between TM-e and TM points is found out using Equation (3) and its X-coordinate value is allocated to A1. Similarly, the topmost pixel on boundary pixels between BM and BM+e points is found out using Equation (4) and its X-coordinate value is allocated to A2. The rightmost column position of A1 and A2 rows of ROI are evaluated using equations 5 and 6 respectively. Their results are hoarded in RM1 and RM2. Here RM1 has the rightmost breast pixel Y- coordinate value in the A1th row. In the same way, RM2 has the rightmost breast pixel Y-coordinate value in the A2th row. To enhance the ROI size, Algorithm (2) is used.

Algorithm 1: Region of Interest

Input : A_1, A_2, RM_1, RM_2
Output : A_1, A_2, RM_1, RM_2
begin
$TM_1 \leftarrow A_1 - 1;\ BM_1 \leftarrow A_2 - 1$
while $TM_1 < A_2$ *or* $BM_1 > A_2$ *do*
begin
$Z \leftarrow A_2 - A_1;\ P_1 \leftarrow RM_1 - y\,;\ P_2 \leftarrow RM_2 - y\,;\ P \leftarrow min(P_1, P_2)$
if $Z < P$ *then return*
else begin
$r \leftarrow P/Z$
if $RM_1 < RM_2$ *then*
begin
$RM_3 \leftarrow \{min(c)\,|B[c,1) == TM_1\ \forall c = 1\ to\ TM\ \}$
if $RM_3 - RM_1 > (r * (TM_1 - A_1))$ *then*
begin $RM_1 \leftarrow RM_3;\ A_1 \leftarrow TM_1$ *end*
$TM_1 \leftarrow TM_1 + 1$
end
else begin
$RM_4 = \{max(c)\ |\ B[c,1] == A_2 \quad \forall c = BM\ to\ n$
if $RM_4 - RM_2 > (r * (A_2 - BM_1))$ *then*
begin $RM_2 \leftarrow RM_4;\ A_2 \leftarrow BM_1$ *end*
$BM_1 \leftarrow BM_1 - 1$
end
end
end
end

$$\mathrm{TM} = \{\min(a)\ |\ \mathrm{B}[a,2]\} == y \qquad \forall a = 1,2,\ldots.n \tag{1}$$

$$\mathrm{BM} = \{\max(b)\ |\ \mathrm{B}[b,2]\} == y \qquad \forall b = 1,2,\ldots.n \tag{2}$$

$$\mathrm{A}_1 = \arg(\max_i(\mathrm{B}[i,1]) \quad where\ \ i = \mathrm{TM} - e, \mathrm{TM} - e + 1 \ldots..\mathrm{TM} \tag{3}$$

$$\mathrm{A}_2 = \arg(\max_j(\mathrm{B}[j,1]) \quad where\ \ j = \mathrm{BM} - e, \mathrm{BM} - e + 1 \ldots..\mathrm{BM} + e \tag{4}$$

$$\{\min(c)\ |\mathrm{B}[c,1) == \mathrm{A}_1\} \qquad \forall c = 1 \text{ to TM} \tag{5}$$

$$\{\min(c)\ |\mathrm{B}[c,1) == \mathrm{A}_2\} \qquad \forall c = \text{BM to n} \tag{6}$$

3.3. Feature Extraction

There are many feature extraction techniques available in the recent days of that DCNN is considered as one of the best techniques due to its superior performance. This proposed DCNN feature extraction technique was built using three different which are the Convolutional layer, Max pooling layer and the Fully Connected (FC) layer. There are many types of CNN techniques available such as AlexNet, ResNet, VGG16, VGG19, Google Net and LeNet. In this proposed method we use AlexNet because of its superior performance when compared with the other techniques. AlexNet Consist of five Convolutional layers in which each neuron calculates the dot product of its weights and the area attached to it locally, three max-pooling layers this layer performs the down-sampling operation which is used to lessen the computational intricacy and increases the robustness and two fully connected layers is connected with all the previous layer neurons which are shown in Figure 5.

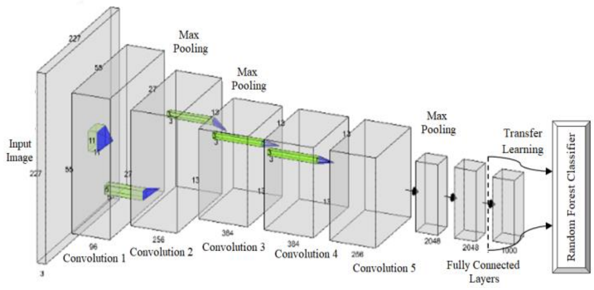

Figure 5. AlexNet CNN Architecture for feature extraction.

The yield of the first convolution layer is associated with a Max pooling layer. Similarly, it forms a layer of convolution and max-pooling the input image size in length, width and the depth is 227x227x3 with 96 kernels of size 11x11, next layer is connected with the max-pooling layer which is followed by similar layers and the 3rd, 4th and the 5th convolution layers are interconnected with each other the 5th layer is the output layer with size 13x13x 256. These arrangements of convolution and max-pooling layer close with the completely associated layers in which the third completely associated layer addresses the number of classes. As the implementation is done on Matlab software there is some default function available to import the AlexNet which is net=AlexNet, and layers =net layers; will pull I AlexNet layers.

3.4. Transfer Learning

The AlexNet CNN is pre-trained using the ImageNet database to perform the classification of the three publicly available datasets from IRMA, MIAS and DDSM. The pre-trained AlexNet can classify the given image as one of the thousand predetermined categories as any moving objects such as vehicles flowers and animals to more complicated medical images but it cannot classify the disease in the medical image. But we can use AlexNet to classify it as a medical image and train it on the images of the mammogram instead of starting training the dataset from the scratch. This process of having a pre-trained network, modify it and retrain it on a new set of dataset is called the transfer learning.

This transfer learning is considered as a very effective way to handle many deep learning problems when there are limited amount of training dataset. In this proposed method we used AlexNet as a pre-trained network and the last dense part is removed and it is replaced with a new model in our case we use Random forest classifier now we can train this with a relatively smaller dataset. As the layers before the fully connected layer is already been trained which needs no training and we require little training for the new network added. In this proposed method we keep two fully connected layer and eliminate the final fully connected layer and restore the detached layer along Random forest classifier as shown in the Figure 4, through this complexity is reduced, training time is reduced and at the same time the accuracy of the classification is also good.

3.5. Random Forest Classifier

This section explains the final step of the classification process this step the image is classified as either one of the classes which are benign, malignant or normal. There are many classification algorithms available to perform this classification step such as ANN, SVM, Decision Tree Algorithm, Random Forest Classifier, K nearest Neighbourhood Algorithm and Naive Bayes Classifier.

In this proposed method we use RF classifier falls under a supervised algorithm that learns from the labelled images and classifies the images which are not labelled in this work the algorithms uses the deep features extracted from the CNN for the classification and the last fully connected layer fc7 is replace with the RF Classifier. The RF Classifier works as a large collection of uncorrelated decision trees that is by using multiple weak classifiers to form a powerful classifier by the process of voting which is called ensemble learning which is shown in Figure 6.

This ensemble method can be implemented in many ways such as Bagging, Boosting, Stacking and cascading. In this proposed work we have used the Bagging method otherwise called as Bootstrap Aggregating method here the sampling is done with sampling with replacement. If the model changes frequently with changing training data then the variance will be high. Bagging is used to reduce the variance in the model without disturbing the bias.

Algorithm 2: Random Forest Classifier

Step 1: Select Random L features from the features extracted from the CNN.
Step 2: For Each y in L

1) *The Information gain is calculated as*

a. Gain (a, y) = E(a) – E(a,y) (7)

b. $E(a) = \sum_{i=c}^{c} -P_i \, log_2 P_i$ (8)

c. $E(a,y) = \sum_{c \in y} P(c)E(c)$ (9)

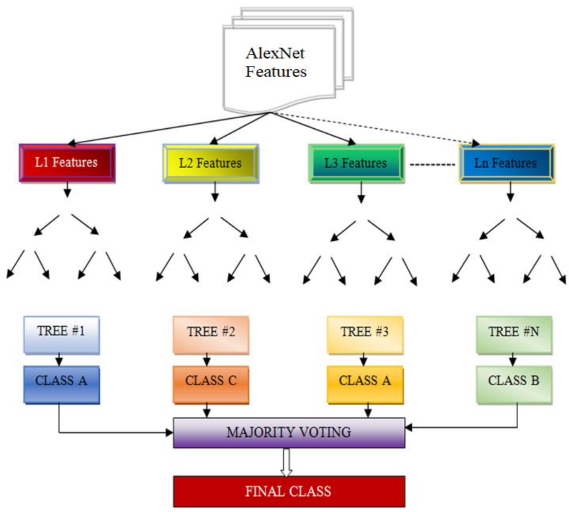

Figure 6. Random forest classifier.

2) *Here E(a) is the entropy of two classes, E(a,y) is the entropy of feature y.*
3) *Select Node h which has the maximum information gain.*
4) *Divide the nodes in to sub-nodes.*
5) *Iterate the step I, II, III to build the tree until it achieve the least number of samples necessary to be divided.*

Step 3: Reiterate the step 1 and 2 for N time for building the forest with N trees.

4. Experimental Results and Discussions

Here we present a hybrid Deep Learning (DL) based breast cancer finding using CNN and Random Forest Classifier which is implemented in Matrix laboratory (Matlab) R2017b Software version 9.3. The technique is validated with the three different mammogram datasets from a database such as IRMA, MIAS and DDSM with 5738 images.

The input image shown in Figure 7 is first pre-processed and the ROI is extracted as shown in Figure

8, which this ROI as input the Deep features are extracted using AlexNet CNN and the last fully connected layer is replaced with the RF Classifier which classifies the input image as Normal, Benign or Malignant.

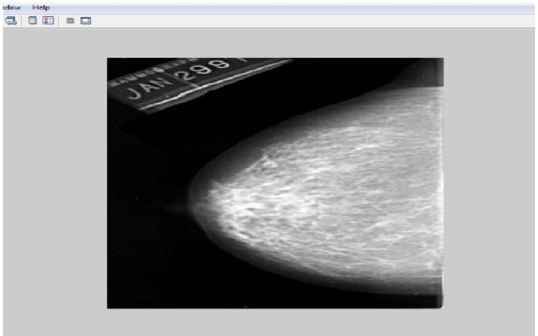

Figure 7. Input image from MIAS dataset.

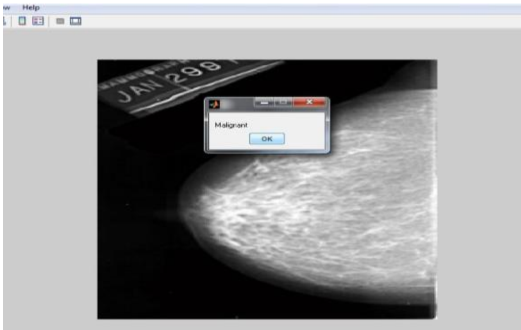

Figure 8. MIAS dataset test image classified as malignant.

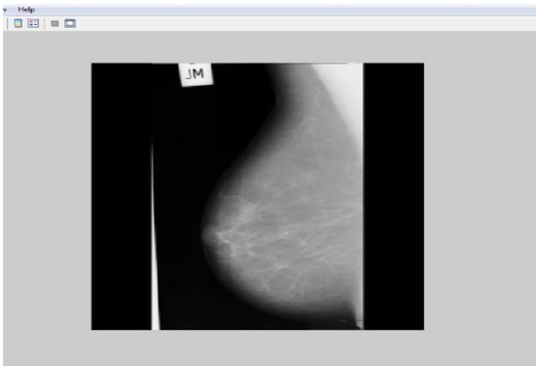

Figure 9. Input image from DDSM dataset.

The classified output is shown in Figuer 9 which shows the input image classified as Malignant and Figure 10 shows the input image classifies as Benign. The basic evaluation tools available for the deep learning process are confusion matrix, Accuracy, Sensitivity, Specificity, Precision, F1 score, ROC curve and Area under the Receiver Operating Characteristic curve (ROC) Curve.

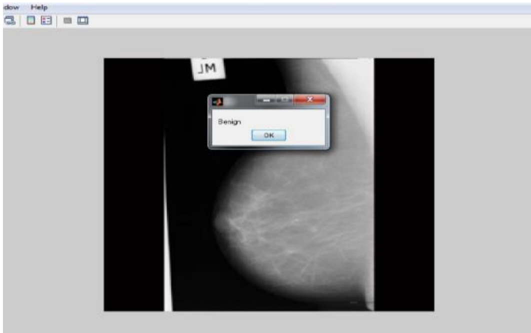

Figure 10. DDSM dataset test image classified as malignant.

Confusion matrix in Table 3 that is comprised of the four possible outcomes they are:

- True Positive (TP): here the system forecasts True; and the real classification is also true.
- True Negative (TN): here the system forecasts False; and the real classification is also False.
- False Positive (FP): here the system forecasts True; But the real classification is not True.
- False Negative (FN): here the system forecasts False; But the real classification is not False.

Table 3. Confusion matrix.

Actual/Prediction		**Prediction**		
		Benign	**Malignant**	**Normal**
Actual	Benign	0.98	0.01	0.02
	Malignant	0.02	0.97	0.03
	Normal	0.02	0.10	0.88

The following are the equations for calculating the performance metrics.

$$Accuracy = \frac{TN+TP}{Total} \times 100 \quad (10)$$

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

$$Recall\ (or)\ Sensitivity = \frac{TP}{TP+FN} \quad (12)$$

$$F1\ Score = \frac{2*Precision*Recall}{Precision+Recall} \quad (13)$$

$$Specificity = \frac{TN}{TN+FP} \quad (14)$$

Table 4. Summary of results

Classifier	Accuracy	Precision	Recall	Specificity	F1 Score
Random Forest	98.6%	0.94	0.98	0.99	0.96

From above Table 4 the accuracy of the proposed model is 98.3% and the other parameters such as precision, recall specificity and F1 score are 0.94, 0.98, 0.99 and 0.96 respectively.

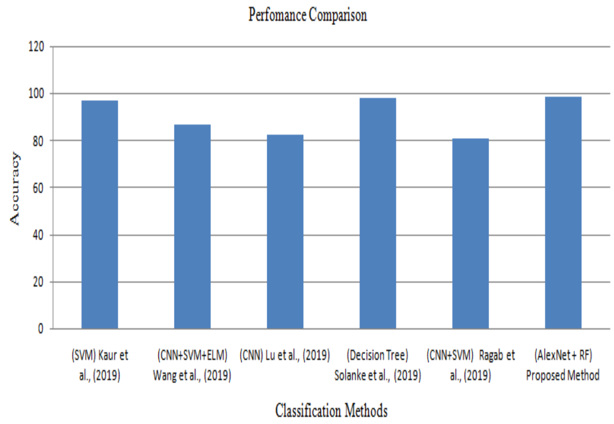

Figure 11. Comparison of accuracy with other state of the art classifiers.

The accuracy of the proposed scheme is contrasted with the other efficient classifiers such as CNN+SVM+ELM [39], SVM [25], CNN+SVM [18], CNN+Softmax [13] and Decision Tree [29] classifiers. The results show that the proposed process shows the superior performance when compared with the other state of the art classifiers which is shown in Figure 11.

5. Conclusions

Breast cancer is considered as one of the most deadly diseases which are very common among women and stands second, next to skin cancer which is 15% of the total cancer infected women. The main cause of breast cancer is due to mutations and ageing factors. In this research, we propose a novel deep learning-based technique to detect breast cancer in the earlier stage and classify the mammogram image as Normal, Benign or Malignant. In this proposed method we utilize the efficiency of the pre-trained neural network CNN AlexNet for extracting the feature and the last fully connected layer is replaced with the random forest classifier. Through this method, we achieve an accuracy of 98.6% with a precision of 98%, Specificity of 99%, Recall of 98% and F1 score of 96% this hybrid method is compared with the other existing leading classifiers and the experimental results show that the proposed method is best suited for the detection of Breast Cancer in its early stages. The future development of this work will be creating a handy device for women which can extract the mammogram image from the breast and classify the image using this proposed method so that women can diagnose instantly and take necessary treatments.

- Conflict of Interest Statement

The authors declared that they have no conflict of interest.

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