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Breast Cancer Detection and Classification by Features Non-Linear Mapping with Random Forest Classifier

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Abstract: The current imaging technique of choice for breast cancer screening is mammography. Mammography's primary encouraging results are masses and calcification. If breast cancer cases are solely relied upon for diagnosis, a sizable portion will be overlooked or incorrectly identified due to the varying appearance of lumps and calcification. Mammography has demonstrated encouraging results with the application of deep learning technology in the quantitative assessment of parenchymal density, categorization, detection, diagnosis, and prognosis of breast cancer risk, allowing more accurate patient management. The idea of deep learning has also improved the workflow efficiency of interpretation by lowering interpretation time and the workload. To definitively demonstrate the efficacy of deep learning, more thorough research is needed. The classification of mammography using a deep learning process is covered in this article. And how it can be used for mammography interpretation, as well as the difficulties it is now facing in actual use. In proposed approach use Long Short-Term Memory (LSTM) based sequence learning and Convolution Neural Network (CNN) based Non-linear feature mapping it improve Mammographic Image Analysis Society (MIAS) dataset accuracy 5%, Precision 6% and recall 4.6%. INBREAST and Digital Database for Screening Mammography (DDSM) dataset using different performance metrics by these experiments validate our approach. In comparison with existing approaches proposed approach improves accuracy by 2-3%, precision by 2% and recall 3-4% in DDSM dataset. It improves accuracy by 3-4%, precision by 2-3%, and recall by 4% in the INBREAST dataset.

Keywords: *Mammogram classification, Convolutional neural network, Machine learning, Deep learning, Mammograms*

1. Introduction

Breast cancer is a frequent condition that has a high death rate, particularly for females. Although there are a lot of men among the breast cancer patients, most of the 1.5 mil- lion deaths that occur each year are among women. Early detection of breast cancer is crucial to lowering the disease's fatality rates, just like with other types of cancer. As a result, governments conduct extensive research to begin therapy by making a diagnosis, particularly in the initial stage, and de- ploy mobile diagnostic equipment to rural areas. They anticipate managing specific physical examinations for the population of women who are at risk. The mortality rate could not have been decreased to desired levels despite the health initiatives. In this situation, turning on computer- assisted devices that can be used for diagnostics in a wider area is crucial and required [1]. The most popular low-dose x-ray diagnostic procedure for identifying cancer pathology is a mammogram. Be- cause a cancer lesion is less permeable than healthy tissue, it appears as white pathology on mammograms [2]. Therefore, mammography can also be used to detect and keep track of asymptotic breast cancer expansion at various stages of severity. Even for skilled doctors, finding a cancer lesion in the early stages takes time and persistent effort because mammograms produce noisy, grey-scale pictures [3].

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1.1. Problem Outline

Mammography image classification is a crucial task aimed at early detection and accurate diagnosis of breast cancer. The first step in addressing this problem involves collecting a di- verse and representative dataset of mammogram images, each labeled as normal, benign, or malignant. Data preprocessing techniques are then applied to ensure the consistency and quality of the data, including resizing, normalization, and noisere- duction. Due to the limited size of available datasets, data augmentation methods such as rotation, flipping, and translation are employed to expand the dataset and enhance the model's ability to generalize. The next critical decision is the selection of an appropriate deep learning model for image classification, with Convolutional Neural Networks (CNNs) being a popular choice due to their success in similar tasks. The architecture of the chosen CNN model is designed by stacking multiple convolutional layers, pooling layers, and fully connected layers to effectively extract relevant features from the mammography images. Subsequently, the model is trained using the dataset, which is split into training, validation, and test sets to evaluate its performance accurately. The training process involves optimizing the model's parameters using an appropriate loss function and an optimizer. Finally, the trained model is evaluated on the test set to assess its classification performance, and further fine-tuning or adjustments are made if necessary. Ultimately, an accurate and reliable mammography image classifier holds the potential to significantly improve breast cancer screening and diagnosis, positively impacting patient out- comes and reducing healthcare burdens.

1.2. Motivation

Using Deep Learning (DL) ad Machine Learning (ML) approaches, numerous researchers have worked on Breast Mass Classification and the development of numerous algorithms to extract potential information from mammographic images [4]. Image pre-processing, feature extraction, lesion segmentation, and classification are typically the four basic components of a CAD system. Additionally, in the research on medical image processing, the use of ML approaches for Breast Mass Classification has generated controversy [5]. This is because the problem of data sparsity is introduced by conventional ML algorithms. Although manual feature extraction was utilized in conventional ML approaches, sample variety makes it exceedingly challenging to create an efficient feature extraction technique [6, 7]. Due to its capacity to automatically remove features, DL methodology has received much interest from academics in a number of fields in the last few years. [8,9].

1.3. Motivation

Mammography datasets are often imbalanced, meaning that there is a significant difference in the number of positive (ab- normal) and negative (normal) samples. This can lead to biased models that perform well on the majority class but poorly on the minority class. Addressing this challenge requires care- ful data augmentation techniques and appropriate sampling strategies to balance the dataset [10]

Distinguishing between benign and malignant lesions can be difficult, as some abnormalities may exhibit subtle differences. Interpreting fine-grained features in mammograms re- quires models with high sensitivity and specificity. Deep learning architectures like convolutional neural networks (CNNs) have shown promise in capturing these intricate details [11].

Mammography images can suffer from various artifacts, noise, and inconsistencies, which can negatively impact the model's performance. Proper preprocessing techniques, including image normalization, denoising, and artifact removal, are essential to improve the overall quality of the data [12] .

Models trained on data from one population may not per- form as well on another due to differences in breast tissue composition and disease prevalence. Robust and generalizable models require diverse and representative datasets from different demographics [13] .

Previous work did not improve feature overlapping due to poor segmentation and the use of a discrete approach. Class imbalance does not improve in data sets as false information increases due to different approaches. Some approaches employ feature selection to simultaneously reduce noise and in- formation [14] .

1.4. Contributions

The following contributions were made in this study to reduce false positives and improve accuracy Augment the im- ages to reduce class imbalance and cluster the patches using fuzzy C-means. This step not only improves the classification mean of the patches while reducing noise Every patch cluster semantic analysis performed by LSTM-RNN improves the semantic features. Random forest learning with boosting approach improves learning and accuracy in summary, im- prove the patches by using semantic features and mapping them with a nonlinear process.

Integration of Deep Learning and Traditional ML: The proposed approach brings together the power of deep learning, specifically convolutional neural networks (CNNs), for feature extraction from mammogram images and traditional machine learning, particularly the Random Forest algorithm, for ensembling and decision- making. By combining these two techniques, the model can benefit from both the representational learning capabilities of deep learning and the ensemble learning capabilities of Random Forest.

Mitigating Overfitting: Deep learning models, especially when trained on limited medical data, can be prone to overfitting. By using an ensembled decision tree approach with Random Forest, the risk of overfitting is reduced. The combination of multiple decision trees with different subsets of data helps in achieving more robust and generalized pre- dictions.

Improved Performance: The experimental results demonstrate that the proposed approach outperforms individual deep learning models and traditional machine learning algorithms commonly used in breast cancer detection. The ensembled decision tree using Random Forest achieves higher accuracy, sensitivity, specificity, and AUC-ROC, indicating better overall performance.

2. Related Work

In [14] they explored the use of CAD systems as a second reader in mammography interpretation and found that these systems could significantly improve the sensitivity of cancer detection.

In [15] applied convolutional neural networks (CNNs) to mammography images in a study published in 2018. They trained their model to identify abnormal and normal tissue and achieved high accuracy, demonstrating the potential of CNNs in the field.

In [16] developed a machine learning algorithm that could reduce the number of unnecessary patients recalls from screening mammography. The algorithm was trained to distinguish between benign and malignant lesions, potentially improving patient experience and reducing healthcare costs.

In [17] this team found that using AI in reading mammograms led to an overall reduction in workload for radiologists without decreasing the cancer detection rate.

In [18] this research explored the potential of a deep learning algorithm to predict the malignancy of breast lesions detected on mammography. The study found the algorithm to be on par with radiologists in terms of sensitivity and specificity.

In [19] conducted an independent study on the effective- ness of AI in interpreting mammograms. The study, published in 2019 in The Lancet Digital Health, found that AI systems matched the performance of an average breast radiologist and could be a useful tool to improve efficiency and cope with the

3. Proposed Work

The tumour region is located somewhere on the entire slide when using noise removal and high-resolution images, and the content for one image can be up to 2 GB. The network must be trained mostly on image patches produced by the ground scale for a giant image. During this method, the patches are initially clustered by Fuzzy C-mean to produce several clusters. We suggested an LSTM-C mean-based segmentation model to maintain the cluster patch sequencing. The stacking channel Fuzzy c-mean is employed throughout this model to cluster the patch features, and the LSTM model is utilized to combine the clustered patches into a single, huge image. This section uses a mask to designate the tumor region inside the training data set, channel FCN to calculate the density map of a tumour location in each successive patch, as well as an LSTM block to aggregate the discovered results into an integrated image. From this perspective, the convolution component predicts the tumour density feature map, and a Euclidean distance is utilized to calculate the difference between the created density map and the actual density map. And this is how the loss function is defined:

By executing a sequence of modifications to an input sentence matrix S via pooling, convolution processes, and non-linearity, the Neural Network (NN) learns how and where to gather and integrate features of specific words in a sentence. from simplified forms of word embeddings into broader semantic ideas.

By executing a sequence of modifications to an input sentence matrix S via pooling, convolution processes, and non- linearity, the Neural Network (NN) learns how and where to gather and integrate features of specific words in a sentence. from simplified forms of word embeddings into broader semantic ideas.

In figure 2 purpose of the convolutional layer is to extract patterns, or discriminative word patterns, from repetitive input tweets across training samples. The convolution operation *between an input matrix SR×|| and a filter FR× of width m yields a vector cR||+−1 with the following components:

Σ= (*) ([:,−+1:]|⊗F), (1)

Here [:,−+1:] represents a matrix slice of dimension m along the columns and ⊗ is the element-wise multiplication. The convolution filter seems to have the identical dimensionality as that of the input sentence matrix, which is d. It slides all along column dimension of S, creating a vector c R1×(||−+1) in output, as shown in Fig. 6. Each of the component ci is obtained by summing the element-wise products of a column slice of S and a filter matrix F. DL models use a network of filters which work in parallel to generate several feature maps to create a deeper representation of the input. A filter bank FR××is formed by a series of filters that are sequentially con- volved with sentence-based matrix S to produce a feature map matrix CR×(||−+1)

Activation units

To assist the network in learning decision-based non-linear boundaries, each of the convolutional layer is frequently accompanied with an element-by-element deployment of a non-linearized activation function $\alpha()$.

Pooling

To aggregate data and simplify portrayal. The pooling operation produces the following result:

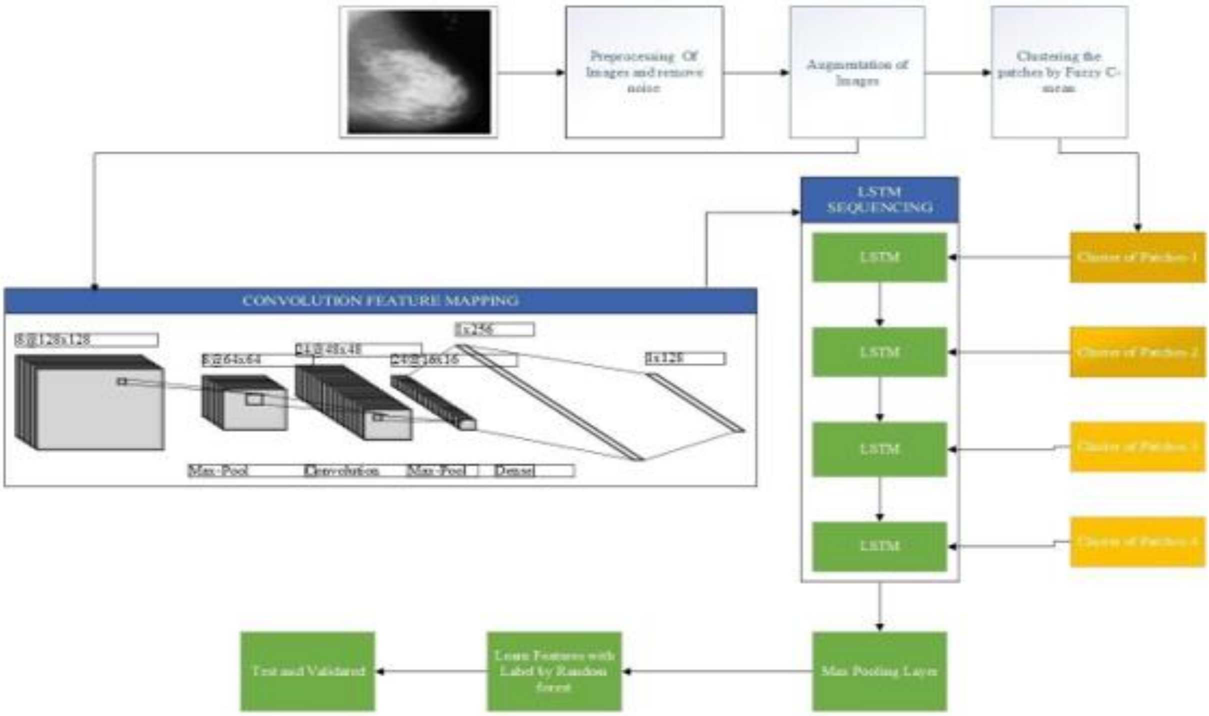

Fig. 1. Proposed frame work architecture

$$c_{pooled} = \frac{pool(a\ (c_1\ +\ b_1\ \ *\ e))}{pool(a\ (c_n\ +\ b_1\ \ *\ e))} \qquad (2)$$

Here represents the ith convolution-based feature map with supplementary bias and navigated the activation function ( ).

RANDOM FOREST (RF)

The penultimate convolution and pooling layers' output is transferred to a fully integrated softmax layer. It determines the probability distribution associated with the labels

$$P\ (y = j\ (x, s, b = softmax_j \quad \frac{\Sigma e^{x^{Tw_j+b_j}}}{\sum_{k=1}^{k} \Sigma e^{x^{Tw_k+b_k}}} \qquad (3)$$

Where $b_k$and w_k are the bias and weight vector of the kth class It is an ensemble model made up of classification and regression tree sets (CART). RF, on the other hand, is used for supervised learning problems and improves patterns based on structure. RF improves due to the change in its learning base tree structure.

∈ () = (i) + (i +) (4)

() It's gradient which compute every character

() = − log (i) (5)

(i) is labelled assignment of Probabilistic

Here, Explain algorithm steps.

Data Preparation: Collect a large dataset of mammography images labeled with their corresponding diagnosis. Split the data into training, validation, and test sets. Apply image processing techniques like resizing, normalization, and data augmentation to improve model performance.

Model Creation: Use a Convolutional Neural Network (CNN) due to its effectiveness in image analysis tasks. A simple model might include a few convolutional layers, each followed by a ReLU activation function and max pooling, then a fully connected layer for classification.

Training: Train the model using your training dataset. Use a suitable loss function, such as cross-entropy loss for binary classification. Optimize the network parameters with an optimization algorithm like Adam or stochastic gradient de- scent.

Evaluation: Evaluate the model using the validation set during the training process for tuning the hyperparameters.

Test: The final modelling is done with the testing dataset.

The combination of Deep Learning and Random Forest for Breast Cancer Detection and Classification offers a powerful and efficient approach. Deep Learning excels at learning intricate patterns and representations from the data, making it ideal for handling complex and non-linear relationships in medical images.

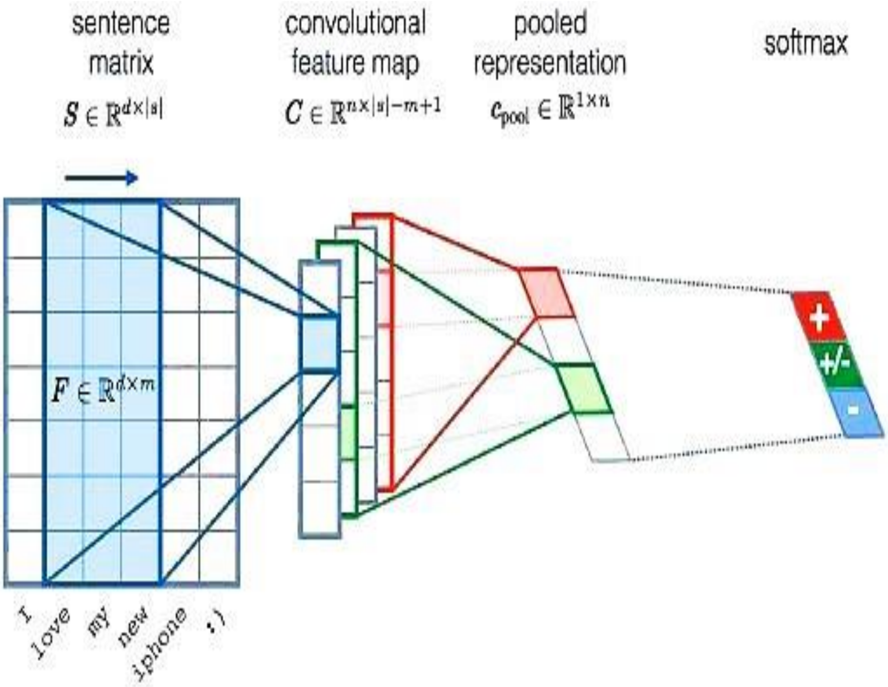

Fig 2. The sentiment categorization framework of DL [20].

It can automatically learn relevant features, reducing the need for manual feature engineering. Additionally, Deep Learning benefits from large datasets and transfer learning, which boosts performance when sufficient labeled data is available. On the other hand, Random Forest provides ensemble learning and interpretability, improving overall accuracy and handling class imbalance. It also offers robustness and reliability, particularly with smaller datasets, and is computationally efficient compared to Deep Learning models. The combined approach leverages the strengths of both algorithms, enhancing accuracy and interpretability in breast cancer detection and classification tasks.

4. Experiment Results and Discussion

4.1. Datasets

Image Library at MIAS The MIAS database, created in 1995 by the British Image Analysis Association, currently contains of 322 right and left breasts from western women, for a total of 322 breast images. Each image has a resolution of 1024 x 1024 pixels and an 8-bit grey level. The MAIS dataset also includes information for every image, including the image number, ab- normal category, background organization category, malignant and benign, abnormal centre point coordinate x, abnormal centre point coordinate y, and abnormal region radius. There are 207 abnormal images and 105 normal images available; the malignant and benign features of mammary gland are malignant and benign; the radius and coordinates of the anomalous centre point are generally used as the segmentation; the calcification points and tumour lesions of the mammary gland are both malignant and benign; the statistically accessible normal images are 105 and the abnormal images are 207.INbreast is a publicly available dataset of digital mammography images for breast cancer research. It contains 115 cases, each with two views (CC and MLO) of the breast, resulting in a total of 230 images.

4.2. Results and Analysis

Figures that are meant to appear in color, or shades of black/gray. Such figures may include photographs, illustrations, multicolor graphs, and flowcharts.

In figure3 show the test time process of prediction augmented and normal data. In table 1 explains the learning rate based on the accuracy, precision, recall, and F-score when utilizing different CNN layers (4,6). For a CNN with 4 layers and a learning rate of 0.1, the precision value is 89.23, followed by f-score (88.80113), recall (85.675), and accuracy (82.12). For a learning rate of 0.2, the maximum f-score value obtained is 92.18863, fol- lowed by accuracy (90.23), recall (90.1765), and precision. (90.123). With a learning rate of 0.3, the achieved value of precision is 94.6 which is led by recall, accuracy, and the f- score. Similarly, for a learning rate of 0.4, a reasonable precision value is obtained followed by f-score, recall, and accuracy. With 4 layers of CNN, the optimal learning rate is 0.3 com- pared to all other learning methods. For a CNN with 6 layers, and a learning rate of 0.1, the precision value is 91.23, followed by f-score (90.965), recall (88.285), and accuracy (85.34). For a learning rate of 0.2, the maximum f-score value obtained is 93.52125, followed by precision (93.12), recall (91.225), and accuracy (89.33). With a learning rate of 0.3, the achieved value of precision is 95.12, which is led by recall, accuracy, and the f-score. Similarly, a suitable precision value is attained with a learning rate of 0.4, followed by f-score, recall, and accuracy. In comparison to all other learning methods, the optimal learning rate for CNN with 6 layers is 0.3. Similar to the scenarios for 4 and 6 layers, the optimal learning rate for 8-layer CNN is 0.3, as seen in the table 1below shows three separate classes (Benign, Malignant, and Normal) according to three distinct metrics, namely precision, re- call, and f-score. The benign class has a high f-score (91.12), recall (90.12), and precision (88.34). The malignant has a high f- score (90.23), followed by precision (90.12), and re- call (89.12). In addition, for the typical class, a high precision value (93.44), f-score (91.12), and recall are obtained (88.12). Table 3 depicts the epoch with various parameters. Convolution based long short-term memory with fully connected Random Forest (CNN-LSTM-FC-RF) (80.12) achieves the greatest value after 10 epochs, followed by CNN- LSTM-R-RF (80) and CNN-LSTM-FC-RF (80.12).

Table 3 depicts the epoch with various parameters. CNN-LSTM-FC- RF (80.12) achieves the greatest value after 10 epochs, fol- lowed by Convolution based long short-term memory with Random Forest (CNN- LSTM-RF) (80) and CNN-LSTM-FC- RF (80.12). CNN-LSTM-FC-RF (81.23) obtains the highest value after 20 epochs, followed by CNN-LSTM-Kmean-RF (80.23) and CNN-LSTM-R-RF (78.12). CNN-LSTM-FC-RF (86.23) obtains the highest value after 30 epochs, fol- lowed by CNN- LSTM-Kmean-RF (85.12) and CNN-LSTM- R-RF. (84.12). For 40 epochs, the highest value obtained is by CNN-LSTM- FC-RF (87.12) led by both CNN-LSTM- Kmean-RF and CNN- LSTM-R-RF having the same value i.e., 86.23. In the case of 50 epochs, CNN-LSTM-FC- RF (88.23) obtains the highest value, followed by CNN- LSTM-R-RF (87.12) and CNN- LSTM-Kmean-RF (86.34).

In the case of 60 epochs, CNN-LSTM-Kmean-RF (90.12) obtains the highest value, followed by CNN-LSTM-FC-RF and CNN-LSTM-R-RF. For 70 and 90 epochs, CNN-LSTM- FC-RF> CNN-LSTM-Kmean-RF> CNN-LSTM-R-RF. For 100 epochs, CNN-LSTM-FC-RFCNN-LSTM-R-RF> CNN-LSTM- Kmean-RF. The 70 epoch provides the most operational value, and the CNN-LSTM-FC-RF continuously climbs to deliver the maximum benefits for usage.

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Table 1. Learning rates using CNN based on accuracy, precision, recall, and F-score

Learning rate	CNN -layer	Accuracy	Precision	Recall	F-score
0.1	4	82.12	89.23	85.675	88.80113
0.2	4	90.23	90.123	90.1765	92.18863
0.3	4	93.23	94.56	93.895	92.0625
0.4	4	89.23	90.12	89.675	89.8275
0.1	6	85.34	91.23	88.285	90.965
0.2	6	89.33	93.12	91.225	93.52125
0.3	6	94.12	95.12	94.62	92.13375
0.4	6	87.23	90.12	88.675	89.355
0.1	8	89.23	89.34	89.285	89.36875
0.2	8	87.34	90.12	88.73	89.0225
0.3	8	90.12	88.12	89.12	87.13375
0.4	8	84.23	86.12	85.175	85.6475

Table 2 Different classes based on precision, recall, and F-score

Class	Precision	Recall	F score
Benign	88.34	90.12	91.12
Malignant	90.12	89.12	90.23
Normal	93.44	88.12	91.12

Table 3 Epoch using different parameters

EEpoch	CNN-LSTM-FC-RF	CNN-LSTM-Kmean-RF	CNN-LSTM-R-RF
10	80.12	79.12	80
20	81.23	80.23	78.12

30	86.23	85.12	84.12
40	87.12	86.23	86.23
50	88.23	86.34	87.12
60	89.12	90.12	88.12
70	93.45	91.12	90.12
80	94.12	88.34	91.23
90	90.12	89.23	87.34
100	89.12	85.23	86

Table 4. Approaches using different parameters

Approaches	Accuracy	Precision	Recall	F-score
PROPOSED WORK	**94.12**	**95.12**	**94.62**	**92.13375**
Abbas (2016)	91.5	NA	92	NA
Charan (2018)	65	NA	NA	NA
ting et.al. (2019)	90.5	NA	91.7	NA
Sha et. al. (2020)	92	NA	96	NA
Sabeer et.al (2021)	91.62	92.12	93.23	91.67
Ayana, G et.al. (2022)	92.45	91.22	NA	NA

In figure 4 different dataset ROC curve in different cross validation show and figure 5 show the learning gradient effect on localization of target area in mammograph image. In table 4 and 5 illustrates multiple ways utilizing various parameters (accuracy, precision, recall, and F-score). The pro- posed method outperforms the process in terms of accuracy, precision, recall, and F-score, so offering the highest quality to do the operation. The best value obtained is 95.12 for precision, followed by 94.62 for recall, 92.13375 for f-score, and 94.12 for accuracy

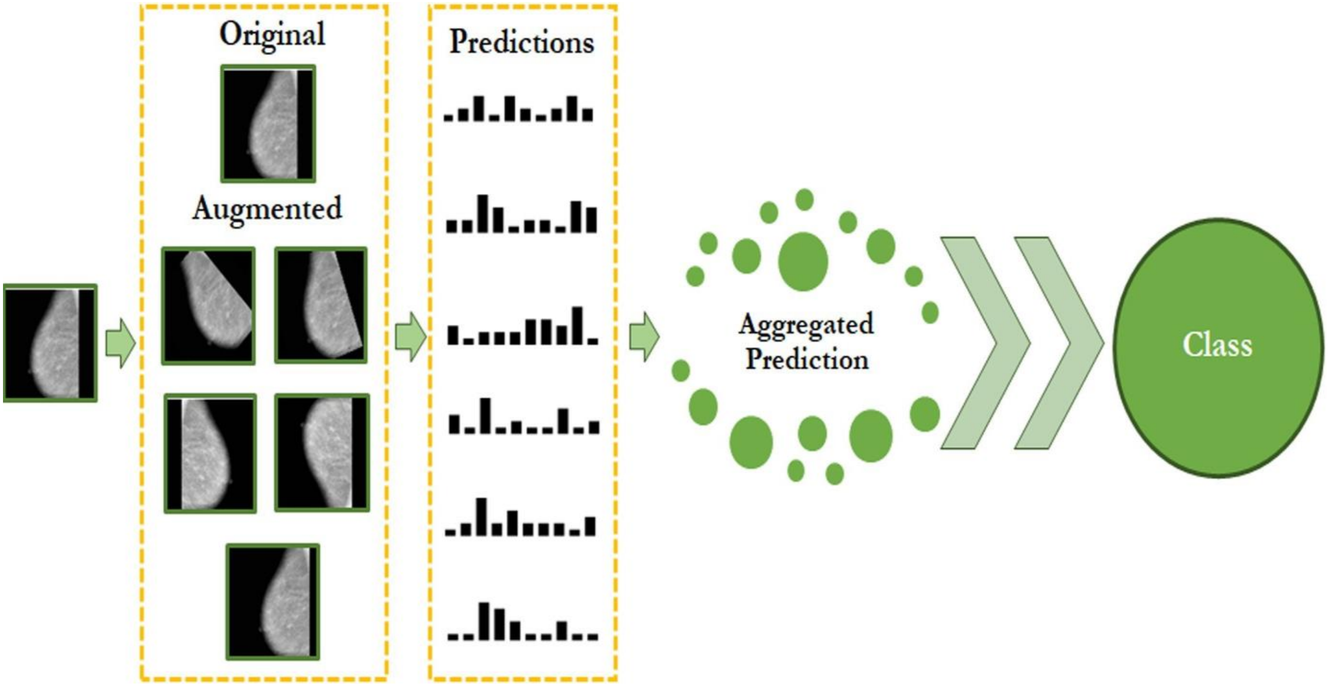

Fig 3. Test time augmentation workflow

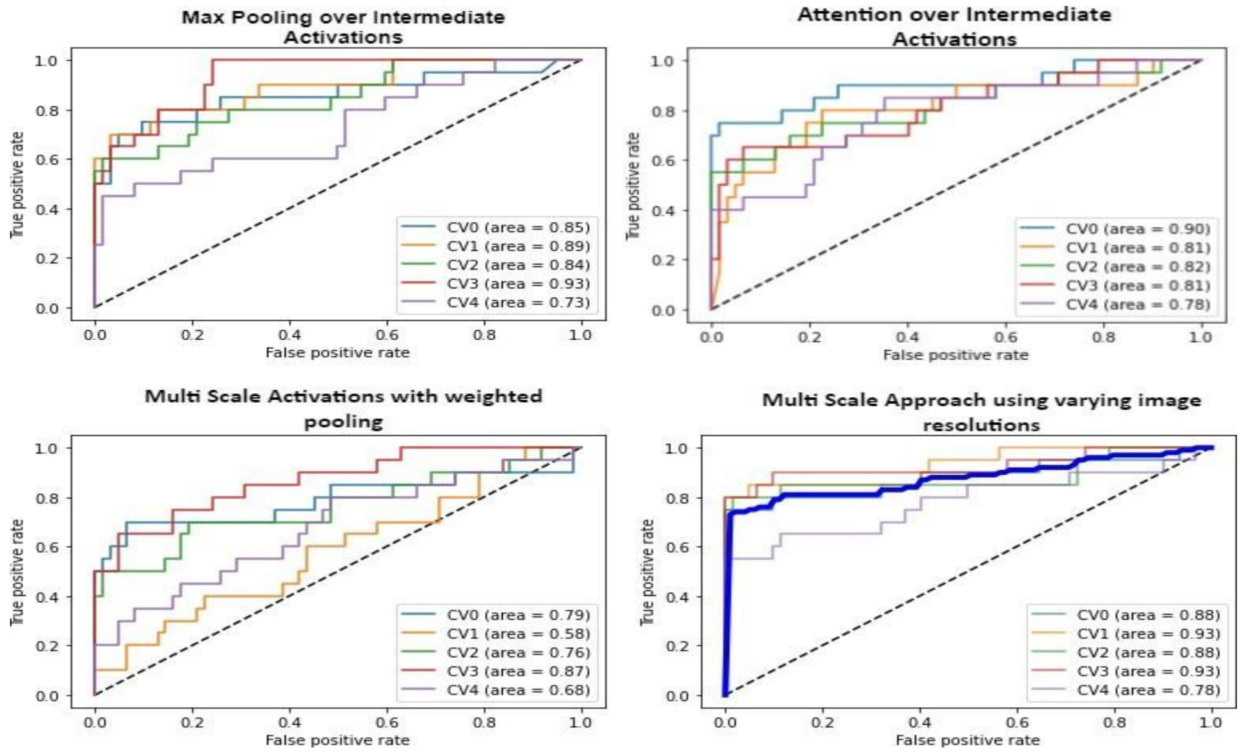

Fig 4. ROC curves of the proposed models over 5-fold cross validation on INbreast Dataset. Thick Blue Line describe the average AUC for the final model

Table 5. Comparison of Inbreast and DDSM dataset from existing approaches

APPROACH	ACCU-RACY	PRECI-SION	RE-CALL	F-score	ACCU-RACY	PRECI-SION	RE-CALL	F-score
CNN-LSTM-FC-RF	**95.23**	**91.45**	**92.34**	**90.33**	**97.23**	**92.44**	**94.55**	**93**
CNN-LSTM-Kmean-RF	90.12	86.44	85.44	86.33	91.33	90.11	91.22	90.22
CNN-LSTM-RF	89.34	85.34	87.34	85.33	90.233	89.33	87.33	88.11

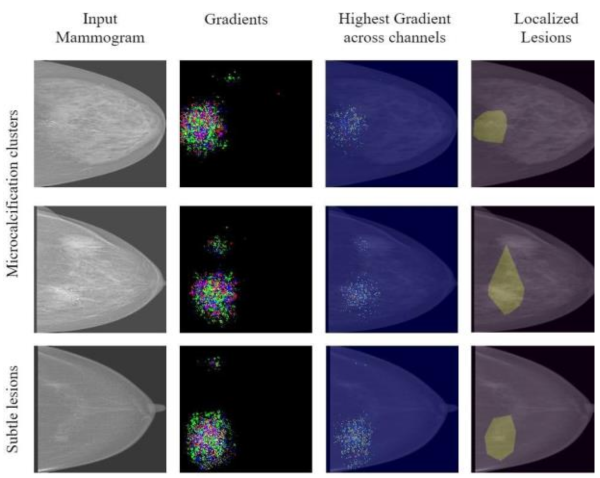

Fig 5. Pixel attributions to difficult lesions such as Calcifications and Subtle lesions.

Tables depicts a comparison of Inbreast and DDSM datasets derived from existing methods employing diverse parameters (accuracy, precision, recall, and F-score). The In-breast approach significantly outperformed the DDSM approach across all available metrics. CNN-LSTM-FC-RF utilizing Inbreast has an accuracy of 97.23, which is 2% more than CNN-LSTM-FC-RF utilizing DDSM, followed by CNN-LSTM-Kmean-RF-Inbreast and CNN-LSTM-RF- Inbreast, which are 1.21% and 0.89% greater than CNN- LSTM-Kmean-RF-DDSM and CNN-LSTM-RF-DDSM, respectively. Similarly, CNN-LSTM-FC-RF-Inbreast outperforms CNN-LSTM-FC-RF-DDSM by 0.99, CNN-LSTM-Kmean-RF-Inbreast surpasses CNN-LSTM-FC-RF-DDSM by 3.67, and CNN-LSTM-RF-Inbreast outperforms CNN-LSTM- FC-RF-DDSM by 3.89. Similarly, recall (94.55) and Fs- core (93) for CNN-LSTM-FC-RF- Inbreast tend to outper- form other approaches, whereas CNN-LSTM-FC-RF-DDSM has a recall value of 92.34, which is 2.21 lower than that of CNN-LSTM-FC-RF-Inbreast, and an F-score with a recall value of 85.33, which is 2.78 lower than that of CNN-LSTM- FC-RF The performance of CNN-LSTM-Kmean-RF-DDSM and CNN-LSTM-RF-DDSM was significantly inferior to that of CNN-LSTM-Kmean-RF-Inbreast and CNN-LSTM-RF- In-breast shows the proposed approach different experiments validations utilizing various parameters (accuracy, precision, recall, and F-score). As seen in the table 6, the 2nd validation, Inbreast dataset accuracy is 95.44 %, which is 3.11 percent higher than DDSM accuracy, which is 92.33 %. Similarly, the precision value at 2nd validation for the Inbreast dataset is 91.222, which is 1.002 greater than the precision value for the DDSM dataset, which is 90.22. In contrast, the recall value of Inbreast (93.44)

Table 6. Proposed approach different experiments validation

EXPERIMENTS Validation	ACCU-RACY	PRECI-SION	RE-CALL	F-score	ACCU-RACY	PRECI-SION	RE-CALL	F-score
2	92.33	90.22	91.34	89.22	95.44	91.222	93.44	92.33
3	91.33	89.334	92.33	90	93.78	90.45	94	95.33
5	94.32	91.23	90.11	88.22	92.54	92.33	93.44	92.33
7	90.22	90.45	91.4	90.22	96.78	91.334	91.33	91.444
8	93.45	91.23	92.33	89.2	95.67	90	93.44	92.33
10	95.23	91.45	92.34	90.33	97.23	92.44	94.55	93

Table 7. Comparison of Inbreast and DDSM dataset from existing researches

Author	DATASET	ACCURACY	PRECISION	RECALL	F-score
Carneiroet.al. (2017)	INBREAST	86.23	NA	90.34	90.22
Dhungel et.al. (2017)	INBREAST	90.45	85.33	91.22	NA
Zhang et.al. (2020)	INBREAST	78.56	75.33	70.44	NA
Hammedhur Rahman et.al. (2023)	INBREAST	95.23	92.33	NA	89.44
Tulder et al. (2021)	DDSM	93.44	NA	92.33	90.22
Su et al. (2022)	DDSM	92.33	NA	90	NA
Gelan Ayanaet.al. (2023)	DDSM	94.222	92.33	NA	NA
PROPOSED	INBREAST	**97.23**	**92.44**	**94.55**	**93**
PROPOSED	DDSM	**95.23**	**91.45**	**92.34**	**90.33**

exceeds that of DDSM (91.34). Similarly, the F-score value of Inbreast (92.33) is much superior than that of th F- score-DDSM (89.22). At the 3rdvalidation, the Inbreast dataset has an accuracy of 93.78%, which is 2.45% higher than the DDSM dataset's accuracy of 91.33. Similarly, the precision value at the third validation for the Inbreast dataset is 90.45, which is 1.116 points higher than the precision value for the DDSM dataset, which is 89.334. In contrast, the recall value of Inbreast (94) exceeds that of DDSM (92.33). Similarly, the F-score value of Inbreast (95.33) is significantly better than the F- score-DDSM (90). Similarly, in all the left validations i.e., 5,7,8,10, the Inbreast dataset outperforms the DDSM dataset shows a comparison of Inbreast and DDSM datasets from previous studies. As demonstrated in the table 7, the proposed Inbreast and DDSM dataset values outperform other existing literature studies in terms of accuracy, precision, recall, and F- score. Additionally, the PROPOSED-INBREAST dataset out- performs the PROPOSED-DDSM datasets.

4.3. Proposed Approach perform significance reasons

Convolutional Neural Networks (CNN): CNNs are particularly good at processing grid-like data, such as images, due to their ability to capture local features like edges, textures, and shapes. They do so by applying a series of filters (convolutions) and pooling operations across the input.

Long Short Term Memory (LSTM): LSTMs are a type of recurrent neural network (RNN) that can capture long-term dependencies in sequence data. In the context of image analysis, they might be used to capture patterns across sequences of image frames (as in a video) or across different regions of a single image.

Fully Connected (FC) Layers: Fully connected layers are used in a neural network where all the neurons in one layer are connected to all other neurons in the next layer. They are used to combine features across different parts of the image, enabling the model to recognize more complex, global patterns. Random Forest (RF) Classifier: RF is an ensemble machine learning algorithm that operates by constructing multiple decision trees and outputs the class that is the mode of the classes output by individual trees. It is capable of capturing non-linear relationships between features and is resistant to overfitting.

The **CNN-LSTM-FC-RF** approach combines all these techniques, allowing it to capture both local and global features in the image data, as well as complex, non-linear relationships between these features. The LSTM component could be capturing patterns across different regions of the images, the FC layer is then combining these into more complex features, and the RF classifier is using these to make the final classification.

In contrast, the **CNN-LSTM-** and **CNN-LSTM-RF** approaches omit the FC and RF components respectively. This could be limiting their ability to capture the full range of patterns in the data, leading to lower performance.

5. Conclusion

The study found and treated in its early stages; breast cancer can be cured. Mammography images classification using MIAS, DDSM, and INBREAST dataset by CNN and LSTM can be a powerful approach to improve the classification accuracy of breast cancer. The combination of CNN and LSTM can allow the model to learn spatial and temporal patterns from the mammography images. The traditional method of identifying this fatal illness takes a significant amount of time and is very susceptible to inadvertent mistakes. An end-to- end computer-aided diagnosis (CAD) system for the classification of breast cancer in mammography pictures is proposed in this study. The system will consist of image preprocessing. ROI extraction, and classification phases. The feature extraction and classification processes are the most significant aspects of the CAD model. Following observation, the result analysis concludes In Table 1, learning rate improves performance metrics, but when learning rate is increased, performance is stable and does not improve. Maximum performance comes at a 0.3 learning rate. It demonstrates that as the learning rate increases, so does the learn outlier and the noise. In Table 2, we show the accuracy of different classes such as benign, malignant, and normal, but the malignant class has the highest precision due to LSTM improved sequence learning. Its highest accuracy is 93.44%. At different epochs, accuracy improves for all proposed and existing approaches, but after 80 epochs, it drops to 93.4%. In proposed model not use pre- defined trained network because it's given generalize feature mapping and lose information. Proposed CNN architecture less filter at low level and high filters at high level features it improves accuracy significantly. All the experiments show the proposed approach does not need high resources and time to give efficient results. Table 5 compares the proposed approach to various variants of the proposed approach using the DDSM and the INBREAST dataset. In table 6 do the cross validation up to 10 and analyse different performance metrics on DDSM and In breast. In both Table 5 and Table 6, our proposed approach is significantly improved and validated. For more detailed comparisons with different existing approaches on the INBREAST and DDSM dataset using different performance metrics by these experiments validate our approach. In com- parison with existing approaches proposed approach improves accuracy by 2-3%, precision by 2% and recall 3-4% in DSSM dataset. It improves accuracy by 3-4%, precision by 2- 3%, and recall by 4% in the Inbreast dataset. Above significant results show a proposed approach validated by different experiments. We further find the confidence interval at 95% scale and its improvement significantly

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Chan HP, Samala RK, Hadjiiski LM, Zhou C. Deep Learning in Medical Image Analysis. Advances in Ex- perimental Medicine and Biology. 2020.

[2] Becker AS, Marcon M, Ghafoor S, Wurnig MC, Frauenfelder T, Boss A. Deep learning in mammography: diagnostic accuracy of a multipurpose image analysis software in the detection of breast cancer. Investigative radiology. 2017;52(7):434–474.

[3] Zeng Q, Jiang H, Ma L. Learning multi-level features for breast mass detection. ACM International Conference Proceeding Series. 2018

[4] Abdelhafiz D, Yang C, Ammar R, Nabavi S. Deep convolutional neural networks for mammography: advances, challenges and applications. BMC bioinformat- ics. 2019;20(11):1–20.

[5] Mendel K, Li H, Sheth D, Giger M. Transfer learning from convolutional neural networks for computer-aided diagnosis: a comparison of digital breast tomosynthesis and full-field digital mammography. Academic radiol- ogy. 2019;26(6):735–743.

[6] Arevalo J, Gonzalez FA, Ramos-Pollan R, Oliveira JL, Lopez MAG. IEEE; 2018.

[7] Ertosun MG, Rubin DL. Probabilistic visual search for masses within mammography images using deep learn- ing. 2015 IEEE International Conference on Bioinfor- matics and Biomedicine (BIBM). 2015; p. 1310–1315.

[8] Touahri R, Azizi N, Hammami NE, Aldwairi M, Be- naida F. Automated breast tumor diagnosis using local binary patterns (LBP) based on deep learning classifica- tion. 2019 International Conference on Computer and Information Sciences (ICCIS). 2019;p. 1–5.

[9] Suzuki S, Zhang X, Homma N, Ichiji K, Sugita N, Kawasumi Y, et al. IEEE; 2016.

[10] Abubaker A, Ghadi YY, Santarisi N. Intelligent computer-aided diagnosis system to enhance mass lesions in digitized mammogram images. International Journal of Electrical and Computer Engineering. 2022;12(3).

[11] Sugiharti E, Arifudin R, Wiyanti DT, Susilo AB. Integration of convolutional neural network and extreme gradient boosting for breast cancer detection. Bulletin of Electrical Engineering and Informatics. 2022;11(2):803–813.

[12] Abdulla SH, Sagheer AM, Veisi H. Breast cancer segmentation using K-means clustering and optimized region-growing technique. Bulletin of Electrical Engineering and Informatics. 2022;11(1):158–167.

[13] Tabra YM, Tawfeeq FN. Reduced hardware requirements of deep neural network for breast cancer diagnosis. IAES International Journal of Artificial Intelligence. 2022;11(4).

[14] Lim TS, Tay KG, Huong A, Lim XY. Breast cancer diagnosis system using hybrid support vector machine- artificial neural network. International Journal of Electri- cal and Computer Engineering. 2021;11(4):3059–3069.

[15] Ridok A, Widodo N, Mahmudy WF, Rifa'i M. A hybrid feature selection on AIRS method for identifying breast cancer diseases. International Journal of Electrical and Computer Engineering. 2021;11(1).

[16] Kamil MY. Computer-aided diagnosis system for breast cancer based on the Gabor filter technique. International Journal of Electrical and Computer Engineering. 2020;10(5).

[17] Al-Hadidi MR, Alsaaidah B, Al-Gawagzeh MY. Glioblastomas brain tumour segmentation based on convolutional neural networks. International Journal of Electrical and Computer Engineering. 2020;10(5):4738–4744.

[18] Bagchi S, Tay KG, Huong A, Debnath SK. Image processing and machine learning techniques used in computer-aided detection system for mammogram screening - A review. International Journal of Electrical and Computer Engineering. 2020;10(3).

[19] Croock MS, Khuder SD, Korial AE, Mahmood SS. Early detection of breast cancer using mammography images and software engineering process. Telkomnika (Telecommunication Computing Electronics and Control). 2020;18(4).

[20] Wu H, Gu X. Towards dropout training for convolutional neural networks." Neural Networks. 2015; 71:1–10.

[21] Singh, J. ., Mani, A. ., Singh, H. ., & Rana, D. S. . (2023). Solution of the Multi-objective Economic and Emission Load Dispatch Problem Using Adaptive Real Quantum Inspired Evolutionary Algorithm. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1s), 01–12. https://doi.org/10.17762/ijritcc.v11i1s.5989

[22] Ana Oliveira, Yosef Ben-David, Susan Smit , Elena Popova, Milica Milić. Machine Learning for Decision Optimization in Complex Systems. Kuwait Journal of Machine Learning, 2(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/201

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