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Improved Breast Cancer Detection Through Hybrid Deep Learning Algorithm

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Abstract
The objective of this paper is to design a breast cancer detection model using hybrid deep learning. The design model encapsulates pre-processing, feature extraction, and classification. Convolutional neural networks (CNN) and recurrent neural networks (RNN) are the names of the two deep learning architectures. Furthermore, the tumour-segmented binary image is regarded as input to CNN, and both GLCM and GLRM are regarded as input to RNN. It is demonstrated that the AND operation of two classifier outputs will produce diagnostic accuracy that is superior to that of conventional models. We compare the proposed model with contemporary neural network systems. The proposed model outperforms the contemporary neural network model with a substantial prediction accuracy of 99.11%. The major contribution of this work is the development and application of a deep forest model for breast cancer classification. The proposed model was simulated in MATLAB 2018R software. For the validation of algorithms, tested two reputed datasets, such as DDMS and MIAS. The analysis of the results suggests that the proposed algorithm is very efficient in terms of existing algorithms for breast cancer detection.
Keyword: *BCD, Deep Learning, LSTM, CNN, Feature Extraction MIAS*

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I. Introduction

Breast cancer can grow when the genetic material in cells changes and causes them to start multiplying in an uncontrolled manner. Two functional factors are generated, such as lumps and nodules, after some time. The changes in cells depend on several factors, such as women's age, hormones, and many mothers. There are several approaches to the classification of breast cancer, the most common of which is the TNM system. TNM (T-tumor, N-lymph node, and M-metastasis) [1]. The processing of breast cancer is categorised in different ways, such as being benign or malignant. Computer-aided diagnosis (CAD) of breast cancer saved millions of lives. CAD is an automatic detection method for breast cancer using a medical imaging system. Automatic breast cancer detection helps medical professionals detect cancer at an early stage. Accuracy and precision are the two most important factors in automatic breast cancer detection. Accurate detection of cancer saves women's lives and allows them to proceed as normal humans. Recently, for automatic breast cancer detection, several machine learning and deep learning algorithms were employed[2]. The performance of algorithms depends on several factors, such as the mapping of features, the extraction of features, and the training of sample images of breast cancer[3,4,5]. Several studies have looked into AI techniques to enhance breast cancer detection through mammography. The majority of methods employed in earlier research include decision tree (DT), biogeography-based optimisation (BBO), wavelet energy entropy (WEE), cross validation (CV), k-nearest neighbour (kNN) algorithm, fractional Fourier transform (FrFT), particle swarm optimisation (PSO), support vector machine (SVM), and particle swarm optimisation (PSO). For instance, experimented with various classifiers, such as SVM, kNN, and Naive Bayes. Five-fold CV and receiver operating characteristic analysis were used to choose the best classifier. The authors discovered that support vector machines produced the best results (SVM). BBO and PSO hybridization (also known as HBP). CNN, deep neural network (DNN), and stacked autoencoder (SAE) are the three types of deep neural networks that are proposed for use in the classification of benign and malignant tumours in the lung nodules framework . Multiple maps are present in each layer of CNN, and each map is made up of a single convolutional kernel combined with a variety of neural units. Every input layer, hidden layer, and output layer in the DNN is interconnected[5,6,7]. The input and output layers of the SAE have equal numbers of neurons and are composed of fully connected layers. Because there is less data available, CNN produces better results than DNN and SAE, according to the results. For this reason, the neural network's layer size is kept small. Deep learning has now surpassed other traditional approaches in a wide range of fields. In a variety of fields, including medical imaging, deep learning techniques have demonstrated amazing performance, such as vertebrae segmentation. Tumours from an infected breast can now be more easily detected and classified thanks to image processing techniques. A deep learning-based model for CNN-based breast cancer classification was proposed by the authors in. After generating patches from the images, the model feeds the training set to CNN. Because of the straightforward architecture offered by this model, costs are decreased. However, the lack of experimental data, which drives up experiment costs, limits the scope of this study. This paper proposes a hybrid deep learning algorithm for the detection of breast cancer. The proposed hybrid algorithm for breast cancer improves the detection ratio by a high percentage and decreases the mortality rates of women worldwide. The rest of the paper organized as in Section II. Related work is in Section III, proposed methodology, in Section IV, experimental analysis, and finally concluded in Section V.

II. Related Work

This section describes related work in the area of breast cancer detection based on recently developed methods. Recently developed methods improved the performance of accurate detection of breast cancer and saved millions of lives worldwide. In [1] authors, to enhance precision and the area under the receiver operating characteristic curve, this technique outperforms RELIEF. These measurements are, respectively, 98.1% and 0.9650 for the classification of normal from abnormal, whereas they are, respectively, 95.2% and 0.9200 for the classification of benign from malignant. In [3], this study also sets the framework for creating a reconstruction method based on deep learning for radiologists to use when interpreting images. In [4], segmentation is employed for accurate skin cancer region detection. Finally, a back-propagated artificial neural network was created for the classification of skin cancer using spatially grey-level dependency matrix features in order to attain the highest classification accuracy. In [5], the segmentation task's mean average precision is between 0.80 and 0.75. The accuracy of the radio leaks was 0.80 to 0.88. Radiologists may benefit from the proposed study's potential assistance with breast mass categorization and segmentation of the malignant zone. In this work, methods for image processing have been developed in order to identify vibrational experimental observations completely automatically. These technologies might reveal intriguing traits and anticipate tissue disease. In identifying and categorising breast cancer cells, CNN outperforms MLP. The majority of studies suggest that CNN offers good accuracy because of the incorporation of layers like convolutional, pooling, and fully linked layers. CNN and MLP are nearly as effective, although CNN displays findings with a better degree of accuracy. In [9], the best algorithms have consistently shown positive outcomes for the majority of the performance indicators examined in this study, including accuracy levels above 99. In [10], in a pilot investigation, we sought to create a novel technique called BDR-CNN-GCN, combining two sophisticated neural networks to achieve a sensitivity of 96.202.90%, a specificity of 96.002.31%, and an accuracy of 96.101.60% for the detection of malignant lesions in breast mammograms. In [11], the methodology outlined in the research has an accuracy rate of 81.5% for prescribing the right course of treatment. The suggested methodology would make treatment recommendations accessible even in the most remote locations where cutting-edge amenities, such as specialist consultation, are not readily accessible. In [12], the proposed method uses mammography images to identify breast cancer, which lessens the need for chemotherapy or breast excision and saves lives by identifying breast cancer in its early stages. In [13] Using this technique, medical professionals can identify breast cancer more quickly and accurately. We evaluated the multi-variant analysis and prediction rate for the suggested strategy using an Anova test. In [14], the model exhibits 100% accuracy when categorising breast cancer patients and healthy individuals using the Adam optimizer. We think the model will help medical professionals screen patients more effectively and quickly, and it will help spread the word about breast cancer. In [15] According to the experimental findings, this method has an accuracy rate of 89% for classifying data sets containing breast cancer photos, a substantial improvement over existing methods. In [16], the proposed model performs significantly better than the current neural network model, with a prediction of 99.11%. This work's main contribution is the creation and use of the deep forest model for categorising breast cancer. In [17], the proposed model has an accuracy of 86% and was tested on the entire dataset of slide histopathology images, which includes images from four independent data cohorts. The suggested method automatically learns the optimal characteristics, outperforming previously proposed deep learning methods and usually being superior to traditional ones. In [18], the model was trained to classify images into five scenarios: normal, benign calcification, benign mass, malignant calcification, and malignant mass. However, the model's performance under data settings was not as accurate as its achieved accuracy of 91.039%. Balanced is not the right word. [19] employed AI techniques in breast imaging is the strict standardisation of best practices, which calls for accreditation of the AI tools before they can be used regularly in breast imaging facilities. In [20], the accuracy of the proposed model was 98.48%, outperforming the alternatives, and its area under the curve (AUC) value was 0.7999. Research findings have linked a few of the retrieved comics to breast cancer prognosis and survival. In [21], the investigators' success in identifying the data and providing training was evident. In comparison to CCNN, our work demonstrates that QNN performs better in terms of successfully training and providing a willing model for smaller data sets. In [22], does the proposed approach make use of the ResNet50-

pertained CNN model? The proposed model did better than the current best methods when using the CBIS-DDSM dataset, achieving 98.32% accuracy, 98.56% sensitivity, and 98.40% specificity. This is good for classification performance. In [23], the obtained findings are contrasted with the results obtained using already-developed CAD systems in previously published studies utilising the same dataset to illustrate the utility of the proposed approach. The results imply that the suggested technology is suitable for in-the-moment therapeutic applications. In[24] For hard voting, we used a majority-based voting mechanism, and for soft voting, we used voting mechanisms based on the average, product, maximum, and minimum of probabilities. Comparing the hard voting mechanism to the most advanced WBCD algorithm, the hard voting mechanism performs better with 99.42%. In [25] This study further examines the importance of feature selection and its effect on the anticipated result. Comparing the multilayer perceptron model to the other supervised machine learning models, it had a high accuracy of 94.7%. In [26], the impacts of radiomics and gene transcriptomics on BRCA molecular subtype prediction were explored. Gene transcriptomics produced better prediction results than radiomics, but from a clinical standpoint, radiomics was easier and more practical. In [27], these techniques for decreasing mammography mass detection have false positive findings. This false-positive reduction algorithm's major goal is to tell which perceived blobs are genuinely real and which are just regular parenchyma. In [28], we go over some of the ways that BP nanomaterials are used to treat breast cancer, including drug delivery, drug coding, photodynamic therapy, photothermal therapy, combination therapy, gene therapy, immunotherapies, and multidrug resistance reversal. In [29], the proposed ResHist model classifies histopathological images with an accuracy of 84.34% and an F1-score of 90.49; additionally, this method does so with an accuracy of 92.52% and an F1 score of 93.45% when data augmentation is used.

III. Proposed Methodology

This section proposes a breast cancer detection algorithm. In the proposed algorithm design hybrid classifier, the design classifier employed convolutional neural networks (CNN) and long-term short memory (LSTM). The proposed classifier detects the input images as normal or malignant. The proposed model is presented in Figure 2. Before employing a hybrid classifier, the cancer image dataset proceeds through a median filter and processing for the extraction of features. The process of feature extraction employed GLCM methods. Convolutional neural network (CNN), is deep learning algorithm for image data classification. The processing of CNN[29] is linear and non-linear function of fully connected layer (FC), the CNN model consists of nonlinear function with an activation function. Every element of the input and pooling layer is affected by this nonlinear function, which also reduces the size of the final results. To analyse the image inputs, multiple perceptron's are used, and they are trained with bias values and learnable weights that can be used to separate pixel values in different parts of an image. The fact that CNN uses a local spatial domain for the input images, along with a small number of shareable parameters and fewer weights, is one of its main advantages. Due to its simpler computations and less memory usage than other models, this method generally performs better. The CNN is set of input layer, convolutional layer, pooling layer, fully connected layer and output layer. The varying capacity o layers robust the CNN classifier for the classification and detection of data. consider that the input features of CNN are map of layer x is Mx(M0=F). now the convolutional process can be expressed as

$$Mx = f(M_{x-1} \otimes Wx + bi) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(1)$$

Here Wx is the convolutional kernel weight vector of the x layer, the symbol $\otimes$ represents convolutional approach, bi is the offset vector of x layer. F(x) is the activation function. By providing various window values, the convolutional layer extracts various feature information from the data matrix Mi1 and various feature information from the data using various convolution kernels. By sharing the same weight and offset throughout the convolution operation, the same convolution kernel adheres to the notion of "parameter sharing," significantly reducing the number of parameters used by the complete neural network. Following the convolutional layer, the pooling layer typically samples the feature map using various sampling algorithms. The pooling layer may be written as follows if Mx is the input and Mx+1 is the output of the pooling layer.

$$M_{x+1} subsampling(Mx) \dots\dots\dots\dots\dots\dots.(2)$$

The window region's mean or maximum value is typically chosen by the sampling criterion. The pooling layer primarily minimizes the feature's size, which lessens the impact of redundant features on the model.

LSTM [24]

The LSTM is a type of RNN that is connected to other nodes in the same layer to enhance learning by eradicating and retaining particular information. The LSTM model's flow graph is shown in Figure 1. It consists of a dropout layer with a rate of 0.5 after the first LSTM layer with a 128 kernel and Adam activation function. A dense layer with a sigmoid function receives input from a fully connected layer that receives output from the dropout layer and uses it to classify normal or malignant.

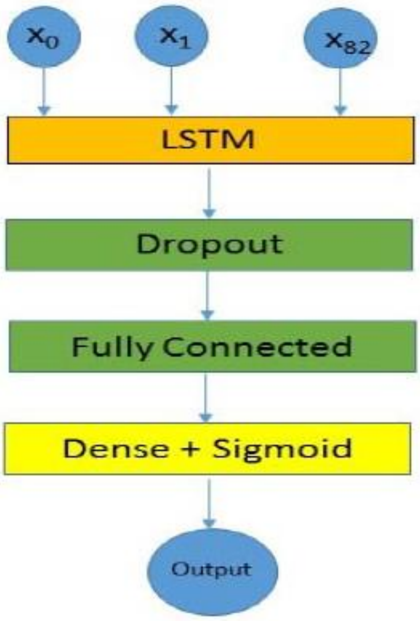

Figure 1 LSTM model for processing of features

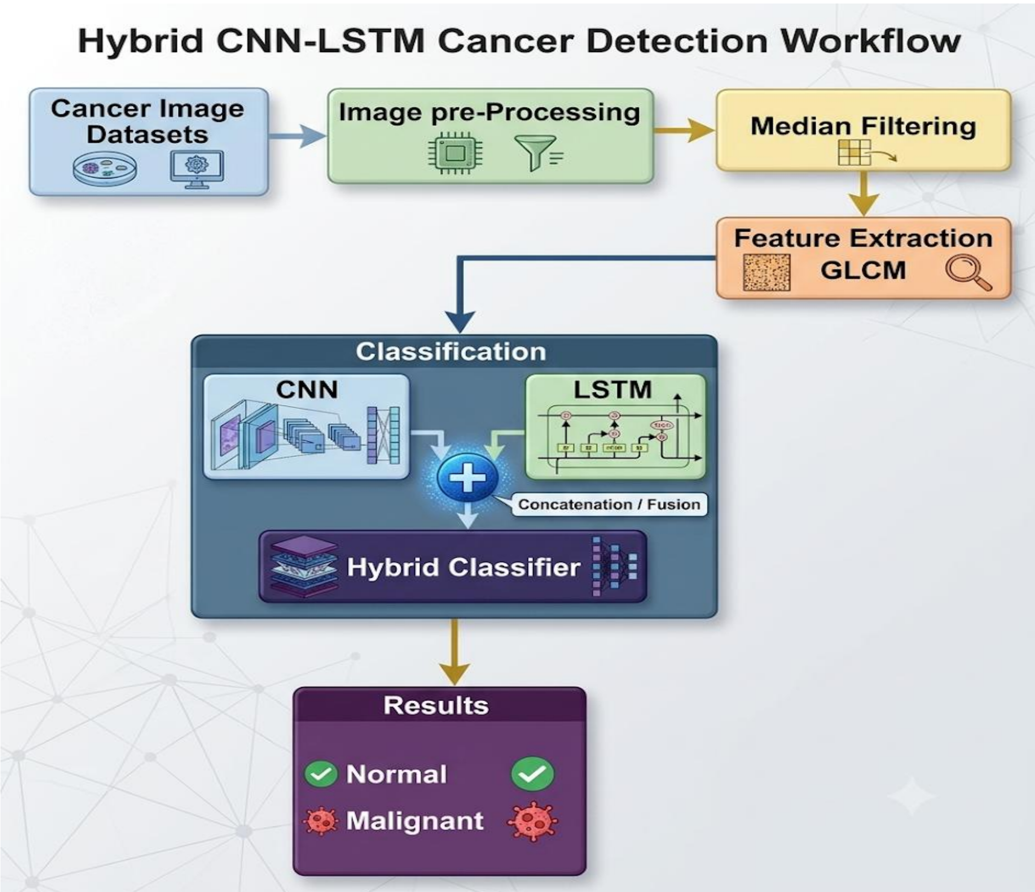

Figure 2 Proposed Model of Breast Cancer Detection Using Hybrid Classifier

IV. Experimental Analysis

To evaluate the performance of the proposed algorithm for breast cancer detection simulated in MATLAB software with version 2018R, the MATLAB software provides several functions for machine learning algorithms and image processing of breast cancer images. For the validation of algorithms, two standard datasets of breast cancer, such as DDSM, were employed. The DDSM dataset consists of 2620 mammography images; these images consist of normal, benign, and malignant images. Another dataset is the MIAS breast cancer dataset, with 330 total images. The total of 330 images in the MIAS dataset consist of all classes, such as malignant, normal, and benign. evaluation of results measured as accuracy, specificity, sensitivity, MCC, and F1. The process of evaluation also evaluates the existing methods of breast cancer detection, such as CNN, MLP, ELM, and ensemble. The estimation of results formula is mentioned here [25,26,27,30].

$$Accuracy = \frac{Total\ No.of\ Correctly\ Classified\ Instances}{Total\ No.of\ Instances} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

$$F1 = \frac{2TP}{2TP + FN + FN}$$

$$MCC = \frac{TP\ XTN - FP\ X\ FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

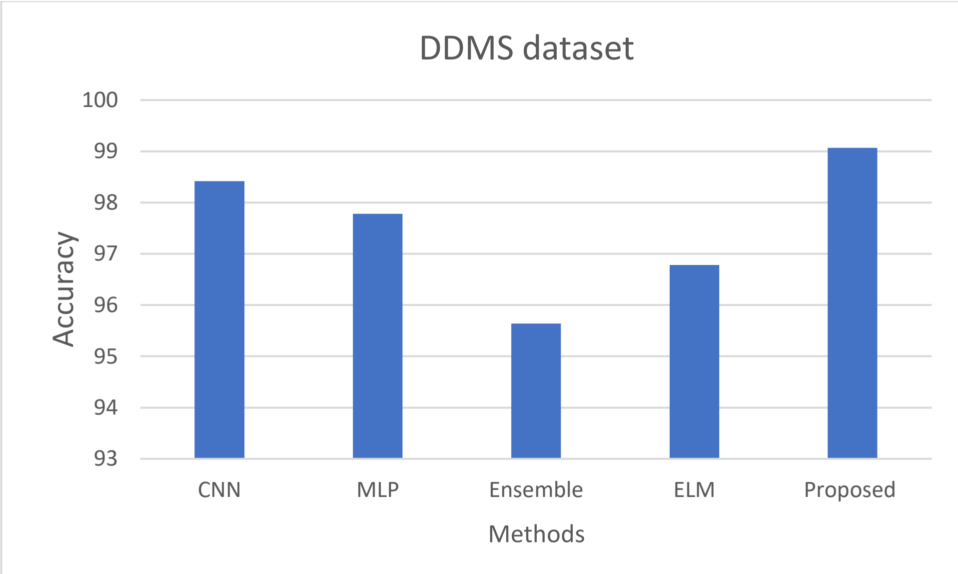

Figure: 3 Comparative Performance analysis of accuracy using proposed, CNN, MLP, ELM, and Ensemble for DDSM dataset.

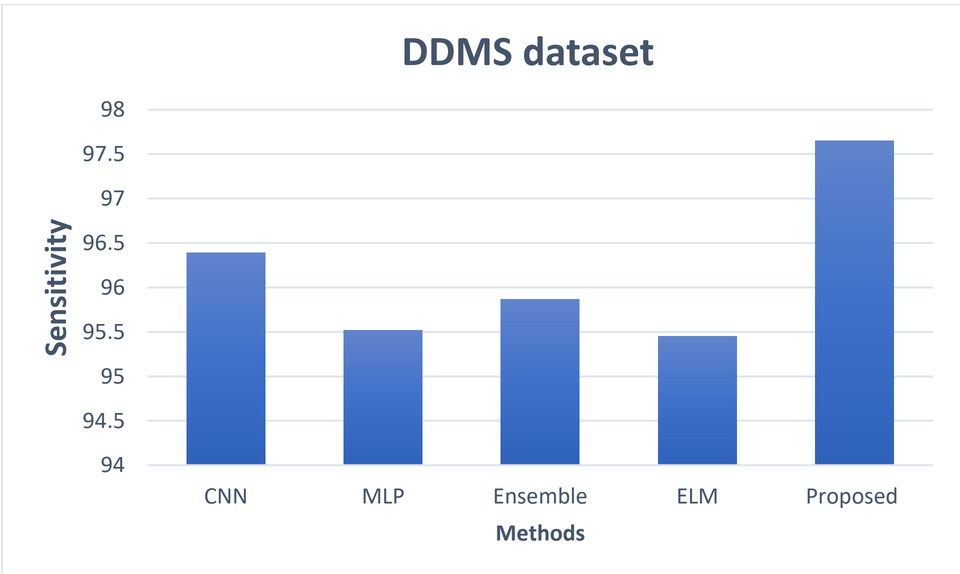

Figure: 4 Comparative Performance analysis of Sensitivity using proposed, CNN, MLP, ELM, and Ensemble for DDSM dataset.

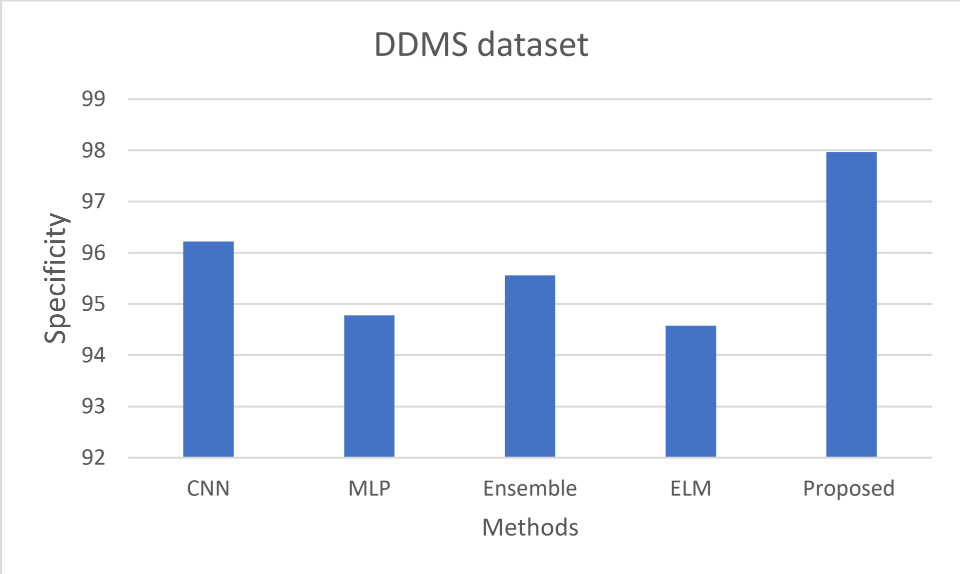

Figure: 5 Comparative Performance analysis of specificity using proposed, CNN, MLP, ELM, and Ensemble for DDSM dataset.

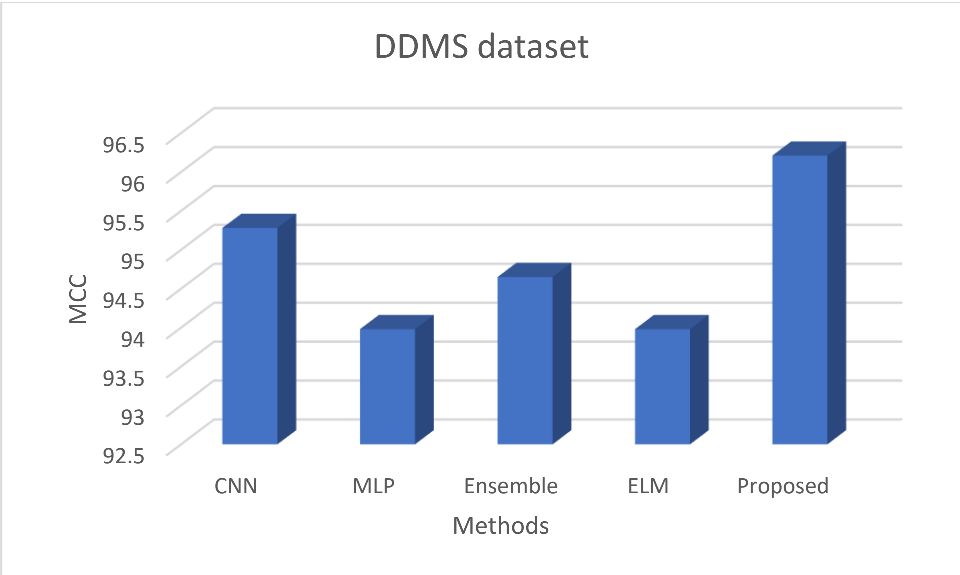

Figure: 6 Comparative Performance analysis of MCC using proposed, CNN, MLP, ELM, and Ensemble for DDSM dataset.

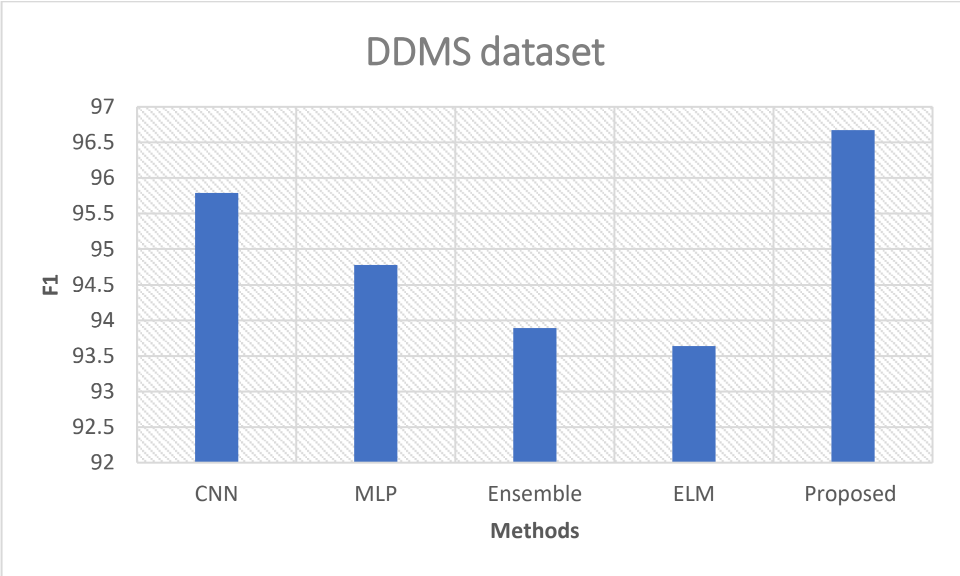

Figure: 7 Comparative Performance analysis of F1 using proposed, CNN, MLP, ELM, and Ensemble for DDSM dataset.

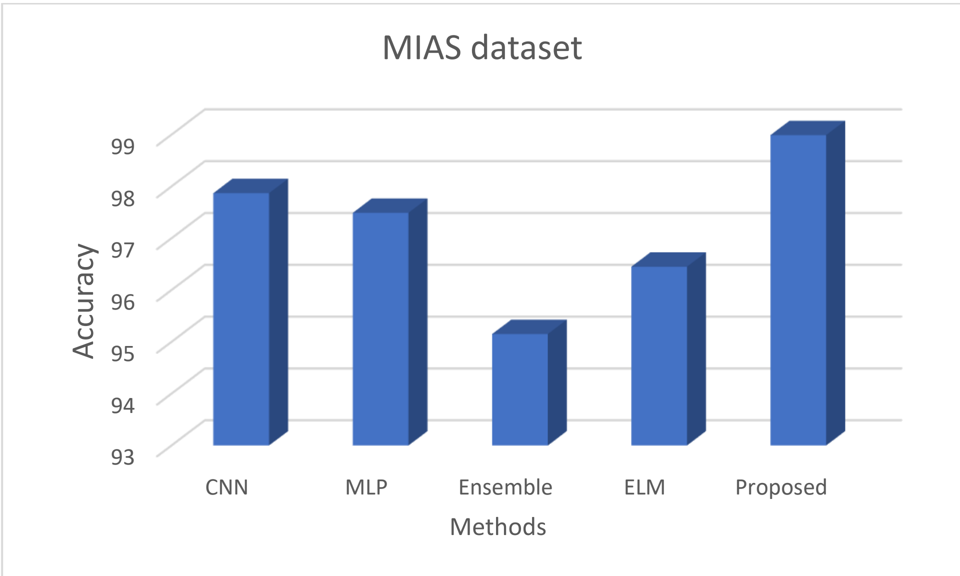

Figure: 8 Comparative Performance analysis of accuracy using proposed, CNN, MLP, ELM, and Ensemble for MIAS

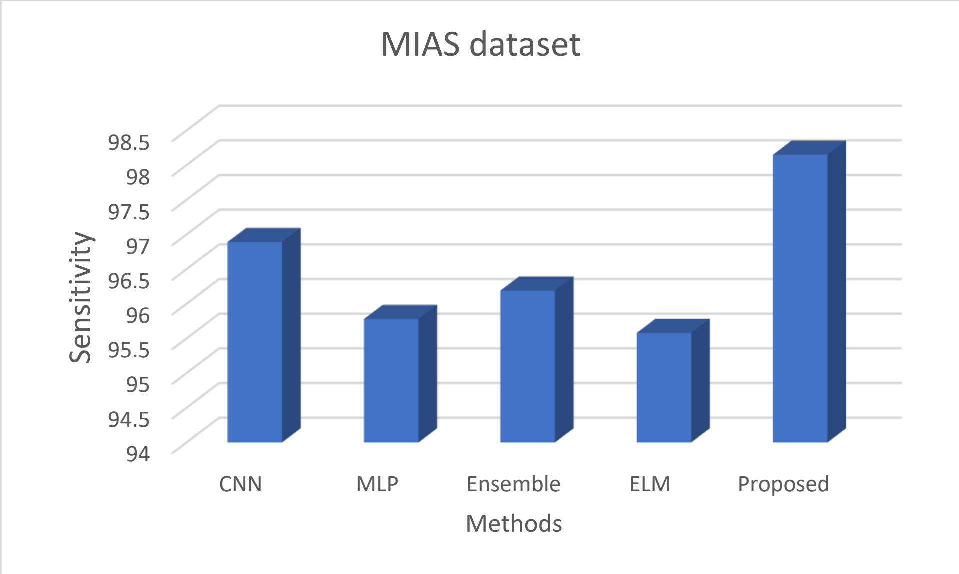

Figure: 9 Comparative Performance analysis of sensitivity using proposed, CNN, MLP, ELM, and Ensemble for MIAS

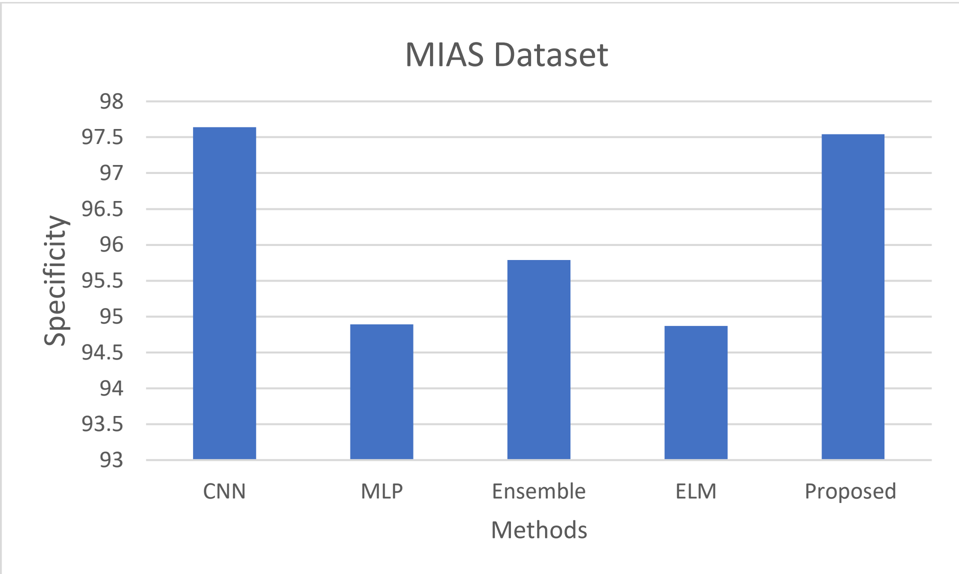

Figure: 10 Comparative Performance analysis of Specificity using proposed, CNN, MLP, ELM, and Ensemble for MIAS dataset.

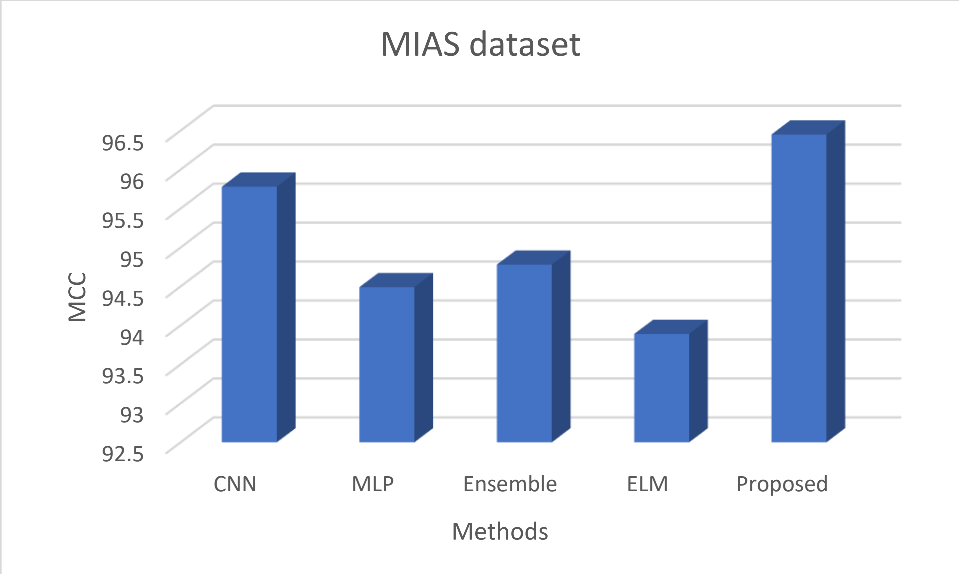

Figure: 11 Comparative Performance analysis of MCC using proposed, CNN, MLP, ELM, and Ensemble for MIAS dataset.

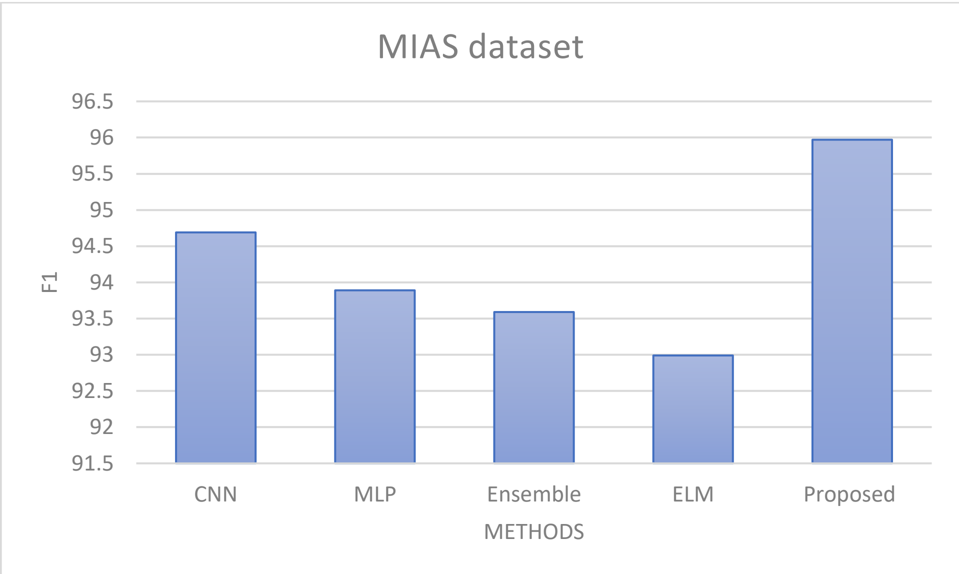

Figure:12 Comparative Performance analysis of F1 using proposed, CNN, MLP, ELM, and Ensemble for MIAS dataset._

V. Conclusion & Future Work

Sure The proposed algorithm underwent pre-processing of breast cancer images and applies a median filter for the removal of local intensity of noise. After the median filter employed the GLCM feature extractor, The GLCM feature extractor is a pixel-based feature extraction approach. The proposed method detects breast cancer using mammogram images, which reduces the need for chemotherapy or breast removal and saves lives by detecting breast cancer at an early stage. In this work, we used the median filter at the pre-processing stage for noise removal. Even though the median filter has several benefits, such as being straightforward and offering sensible noise removal performance, it has the drawback of removing blurred image details and thin lines even at low noise densities. The proposed algorithm is simulated in MATLAB software with estimated standard parameters. The proposed algorithm compares with existing algorithms for breast cancer detection, such as CNN, MLP, ELM, and ensemble classifiers. In the future, we will extend the model to all categories of breast cancer detection.

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