ISSN:2731-538X | E-ISSN:2731-5398
Vol. 17 No. 02 (2023)

BREAST CANCER DETECTION USING DEEP LEARNING ALGORITHMS

Amol Naraya Dumbare
Department of Computer Science and Engineering, Research Scholar, Madhyanchal Professional University, Bhopal, MP (India), amoldumbare12@gmail.com

Vijay Bhandari
Professor, Department of Computer Science & Engineering, Madhyanchal Professional University, Bhopal, MP (India), vijaysirt@gmail.com

Abstract

Breast cancer is a common malignancy among women and ranks as one of the most common malignant malignancies after lung cancer. Breast cancer detection is based on mammography film. Mammography films can be used to diagnose breast cancer in the female population. However, mammograms do not allow accurate diagnosis of breast cancer, resulting in misdiagnosis. Hence, a critical need arises for an integrated system employing a deep learning approach to comprehensively classify breast cancer type, sub-type, and grade. The implementation of such a system holds the potential to alleviate the substantial workloads of pathologists and mitigate the risk of misdiagnoses. The MATLAB software provides several functions for machine learning algorithms and image processing of breast tumor images. The study demonstrates improved accuracy compared to established algorithms and models. The algorithm employs Swish, LeakyReLU, ReLU, and Sigmoid activation functions for activation. The model achieves high accuracy rates for benchmark datasets and avoids overfitting, incorporating multiple variations for CNN training algorithms.
Keywords: - BCD, deep Learning, CNN, RNN, LSTM

Introduction

Breast cancer, a prevalent form of cancer among women, originates in breast cells and ranks as one of the most common malignancies after lung cancer. This life-threatening disease is diverse, with various types distinguished based on microscopic analysis of cell appearance. The primary classifications are (1) invasive ductal carcinoma (IDC) and (2) ductal carcinoma in situ (DCIS). DCIS, characterized by slow evolution, generally poses minimal impact on the daily lives of patients, accounting for a low percentage of cases (20% to 53%). Conversely, IDC is a more perilous type, as it encompasses the entire breast tissue. The majority of breast cancer patients, approximately 80%, fall within the IDC category [1]. The most effective approach to reduce breast cancer mortality lies in early-stage diagnosis and prompt treatment. Achieving early detection necessitates a precise and reliable diagnostic method. Mammography stands out as a widely adopted and popular technique among various methods for diagnosing breast cancer. Implementing systematic screening through mammograms in the female population not only facilitates early-stage breast cancer detection but also enhances survival prospects for patients while minimizing adverse effects of necessary treatments. However, the reliance on mammography film for breast cancer diagnosis presents certain challenges. Issues such as film damage or unsuitable images for diagnosis may arise, and over time, the film quality deteriorates,

ISSN:2731-538X | E-ISSN:2731-5398
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reducing the likelihood of accurate revision. Additionally, the sole reliance on visual observation by physicians for lesion diagnosis introduces potential errors. One such error involves presenting the same radiograph twice to a physician or radiologist, potentially leading to differing diagnoses if unaware of the duplicate images. Another error arises when showing an image to two different physicians or radiologists, each with a distinct diagnosis. Although mammography remains a predominant method for breast cancer diagnosis, certain cancer classes may elude detection through this approach. To address this limitation, the integration of computer-aided systems proves efficient in detecting malignant lesions. The existing models in the literature designed to identify the type, sub-types, and grades of breast cancer often exhibit limitations, either being specialized for a single purpose or characterized by complexity, computational intensity, and restricted performance tied to the magnification factor of histopathological images. A critical need arises for an integrated system employing a deep learning approach to comprehensively classify breast cancer type, sub-type, and grade. Such a system is pivotal for determining appropriate clinical treatment strategies and aiding in surgical planning. Additionally, the implementation of such a system holds the potential to alleviate the substantial workloads of pathologists and mitigate the risk of misdiagnosis. Deep learning techniques, with their ability to automatically discern patterns, extract features, and represent images in an abstract form, offer promise in efficiently distinguishing between different types of breast cancer. Recent models in the literature have proposed deep neural network (DNN) approaches for diagnosing breast cancer using histopathological images. For instance, a deep convolutional neural network (CNN) employing a patch-level voting model and merging model achieved an accuracy of 87.5% in classifying breast tissues biopsy images as normal, benign, malignant, or invasive carcinoma. Similarly, a combination of deep CNN and gradient-boosted tree method reported an accuracy of 93.8 ± 2.3% for classifying breast cancer into basic types and 87.2 ± 2.6% for the same classification using a different methodology. Other studies implemented a CNN as a feature extractor and a support vector machine as a classifier, achieving accuracies of 77.8% for four classes and 83.3% for distinguishing carcinoma (in situ and invasive) from non-carcinoma (normal and benign). Furthermore, the adaptation and fine-tuning of the Inception-v3 convolutional neural network for patch classification, coupled with majority voting for whole slide classification, yielded an accuracy of 85% for the four classes and 93% for the binary classification of non-cancer versus malignant cases. These advancements in deep learning models demonstrate promising outcomes in the automated classification and diagnosis of breast cancer using histopathological images [13–19].

II. Related work

The adoption of deep learning algorithms in medical imaginary systems enhances the performance of critical disease analysis. This section describes a recently employed and proposed deep learning algorithm for breast cancer detection. In [1], the goal is to enhance the precision of breast cancer diagnosis through the use of CNN. The study introduces an automated tool for identifying IDC, aiming to minimize human errors in diagnosis. It investigates the impact of different CNN architectures on the proposed system without specifying any particular limitations. [2] explores deep learning models that automatically learn hierarchies of related attributes. A multiple-activation DNN model is suggested for breast cancer classification, employing Swish,

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LeakyReLU, ReLU, and Sigmoid activation functions. The study demonstrates improved accuracy compared to established algorithms and models. [3] claims higher accuracy in breast cancer detection than traditional methodologies. It discusses the use of ANN for diagnosis, highlighting its potential lower reliability compared to radiologists. Doctors must pre-diagnose the input images for training. The study suggests that ANN can reduce errors, save time in diagnosis, and alleviate the burden on individual doctors examining numerous patients. [4] utilizes the Database for Masto logy Research with Infrared Image (DMR) for breast cancer detection. It evaluates the impact of adding lateral images and personal/clinical data to 14 different models, presenting a multi-input CNN achieving 97% accuracy and a ROC-curve area of 0.99. [5] introduces a risk predictive component, represented by MLP-Classification, offering a risk score for predicting cancer development and mammography-perceivable cancer. In [6], adopts a stacked ensemble approach to enhance breast cancer histopathology image classification accuracy. It uses deep learning-based models for feature extraction, training three CNNs as base learners. The study incorporates empirical wavelet transform (EWT) and variational mode decomposition (VMD) for dataset decomposition, outperforming state-of-the-art methods. [7] is the first study exploring the application of Efficient Net to MBC classification. It introduces a new data augmentation method, Random Centre Cropping (RCC), aiming to improve Efficient Net's performance through technical advancements. The study suggests potential applications in other biomedical diagnostic areas, limited to testing on the RPCam dataset. In [8], a new automated method for breast cancer diagnosis in mammogram images is proposed, using phylogenetic diversity indexes for image classification and demonstrating higher precision compared to other techniques. [9] applies deep learning networks to differentiate breast cancer molecular subtypes on MRI, achieving higher accuracy using recurrent networks with CLSTM compared to conventional CNN. However, limitations include a small case number and low accuracy for multi-class differentiation. [10] integrates global and local information for high diagnostic performance in breast cancer histology images. The study uses a hierarchical voting method, learning transfer, and data augmentation strategies to stop overfitting and get better results with the CNN architecture (AlexNet) that was proposed. [11] designs a hybrid model based on pulse-coupled neural networks (PCNN) and deep CNN, utilising transfer learning (TL) with small-sized datasets. The complex model achieves high accuracy rates for benchmark datasets and avoids overfitting, incorporating multiple variations for PCNN training algorithms. [12] highlights limited work on deep learning-based solutions for breast tumor detection and localization from MI systems. The study presents a deep learning framework that outperforms other techniques in detection accuracy, tumor localization, and characterization. [13] develops Android software for breast cancer classification using CNN, achieving high processing performance with 96 % accuracy. [14] addresses the effective prediction of breast cancer without providing specific details. [15] proposes a new cascaded CNN, UBCNN, for mitotic cell detection, achieving improved results compared to existing algorithms. [16] focuses on screening large-scale female breast cancer using various diagnostic methods and establishing a comprehensive database for breast cancer information. [17] proposes a novel approach for breast cancer detection using multi-channel merging, demonstrating measurable improvements compared to state-of-the-art methods. [18] employs CNN in deep learning for breast cancer classification, designing a network structure for coronal and cross-section input fusion, and

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integrating image and text information for improved classification and discrimination. [19] introduces an integrated system for breast cancer type, sub-type, and grade classification, reducing pathologists' workload and improving accuracy. The resolution-independent system serves as a decision-support system for clinical settings. [20] proposes a novel method for automatic detection of breast cancer using UWB, achieving a high accuracy of 94%. [21] develops a deep-learning-based algorithm for automated diagnosis of breast masses, specifically identifying TN-breast cancer. The algorithm contributes to non-invasive clinical tools for ultrasound diagnosis. [22] suggests an automated system for histopathological image analysis using an ensemble of CNNs, optimizing network selection through a genetic algorithm, and demonstrating favourable outcomes. [23] introduces a deep learning approach for breast cancer diagnosis from biopsy microscopy images, incorporating preprocessing techniques and proposing an ensemble technique for improved classifier accuracy. In [24], a deep-CNN method for feature extraction of breast cancer masses is presented, utilizing an SVM classification algorithm for defining ROI and achieving 97.8% accuracy. [25] explores deep learning techniques for breast cancer segmentation and classification using ultrasound images, achieving high accuracy despite variations in cancer size and characteristics. [26] develops a patient-specific dose prediction model using deep learning, outperforming conventional knowledge-based planning and highlighting the need for diametric features to increase accuracy. [27] utilizes an attention gate module in a modified VGG16 architecture for breast lesion classification, introducing a new loss function and integrating local and global features for improved performance. In [28], we discuss the proportionality of pathologist reports in clinical laboratories with the predicted population and the shortage of pathologists in certain regions. [29] explores genetic changes in cancer drivers and symptoms of breast cancer, using CNN for thermographic testing with novel ROI segmentation. The study emphasizes preprocessing-augmentation techniques and the evaluation of findings in future studies. [30] develops a CNN-CAD methodology for breast cancer diagnosis using thermography, emphasizing the importance of unbiased methodologies, smaller and less complex CNN architectures, and hyperparameter optimization for increased model performance. The study acknowledges limitations in information (thermal images) and the black-box nature of CNN models. The rest of the paper is organised as follows: section II: related work in the area of breast cancer detection using deep learning; section III: methodology of breast cancer detection; section IV: experimental analysis of breast cancer dataset; and section V: conclusion and future work.

III. Methodology

The deep learning is advance version of artificial neural network and its consist of three layers such as input, hidden, and output. The input and output layer are single layer and hidden layers may be extended to multiple layers depending on the complexity of the processing algorithm. the development of deep learning model represents in figure (1)[20]

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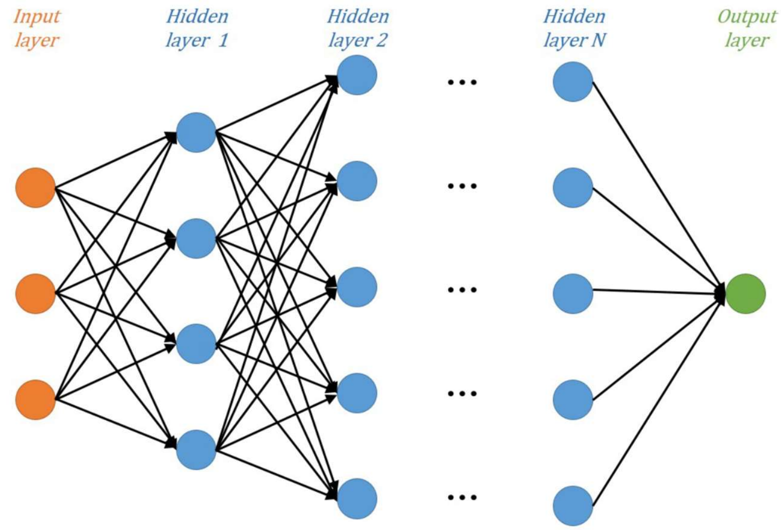

Figure 1 development of deep neural network model

There are two important factors of the relation between adjacent layers are linear and nonlinear. The linear relationship connects input layer and output layer with operators of multiplication and addition. Instead of that non-linear relation handle the process of activation function

Consider that output of the (x-1)th layer is Yn-1, the weight matrix of the xth layer is Wn, the bias vector is bn and the oupt of the n-th layer yn can be expressed as

$$y_n = f(w_n . y_{n-1} + b_n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

The performance of deep learning algorithms depends on activation function. Deep learning consists of several activation function such as sigmod function, tanh functions, and rectified linear unit (ReLU). The majors of deep learnings have convolutional neural network (CNN), recurrent neural network (RNN), deep neural network (DNN), and long- short term memory networks.

b.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

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 user. consider that the input features of CNN are map of layer x is Mx(M0=F). now the convolutional process can be expressed as

$$Mx = f(C_{x-1} \otimes Wx + bi) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Here Wx is the convolutional kernel weight vector of the x layer, the symbol ⊗ 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 Channel 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 Cx is the input and Cx+1 is the output of the pooling layer.

$$C_{x+1} subsampling(Cx) \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

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

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features on the model.

2 LSTM

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 2. 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 interference fee subchannel allocation[27].

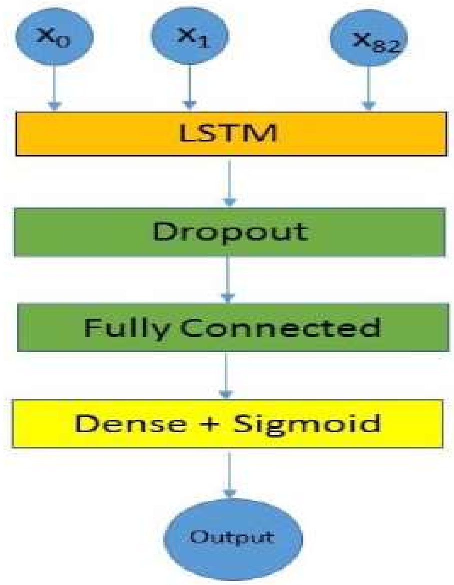

Figure 2 LSTM model for resource optimization

b.3 RNN

Recurrent neural networks (RNNs) are a subset of supervised learning algorithms. They can model sequential data for estimation and recognition. RNNs are made up of higher-dimensional hidden layers made of artificial neurons with non-linear feedback loops. As a result, RNNs have two inputs: the current sample and the recent past sample, as illustrated in Figure, where the recent input is the non-looping input to each neuron and the recent past is the output that loops back into the network[26]. The hidden layers can act as memory for the network state at a given point in time, which is dependent on its previous state. This design allows RNNs to save, recall, and process previously complex data for an extended period of time. RNNs can also map a specific input to an output sequence during the current time period and forecast this sequence during subsequent time periods. The dispersion of a transmitted signal through a fading channel produces an expanded signal with long-term dependencies between its samples. These dependencies differ from one signal to the next and do not follow a consistent pattern. Using a feed-forward (FF) neural network to model long-term dependencies will necessitate a high-dimensional feature space and a large number of neurons, which will result in over-fitting and sub-optimality. Figure 3 represent the processing of RNN network.

ISSN:2731-538X | E-ISSN:2731-5398
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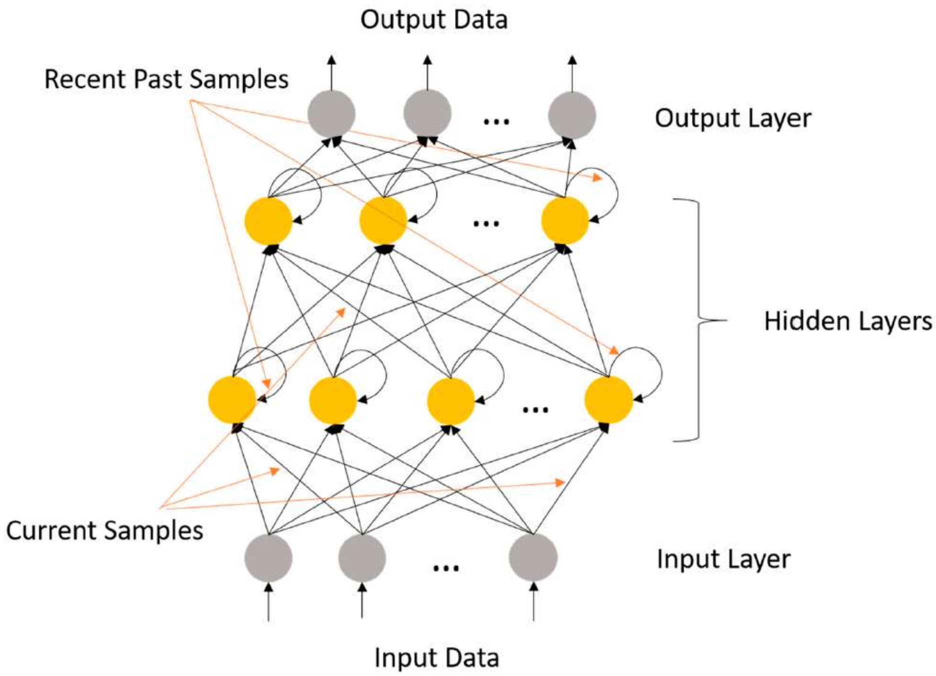

Figure 3: The processing block of RNN networks.

IV. Experimental analysis

To evaluate the performance of the deep learning 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].

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

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

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

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

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

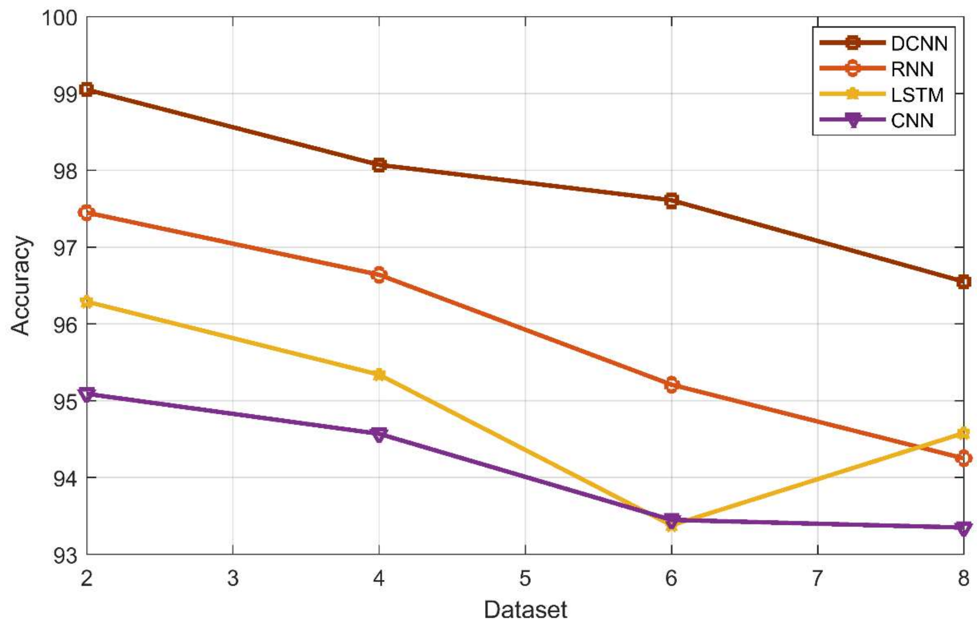

Figure: 4 Comparative performance analysis of accuracy using DCNN, RNN, LSTM, and CNN for DDSM dataset.

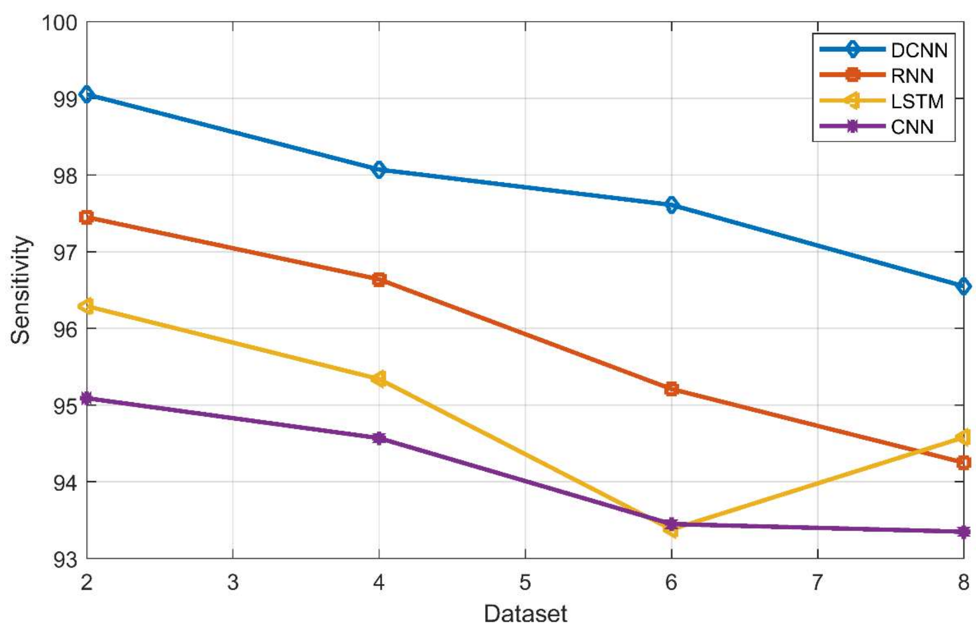

Figure: 5 Comparative performance analysis of sensitivity using DCNN, RNN, LSTM, and CNN for DDSM dataset.

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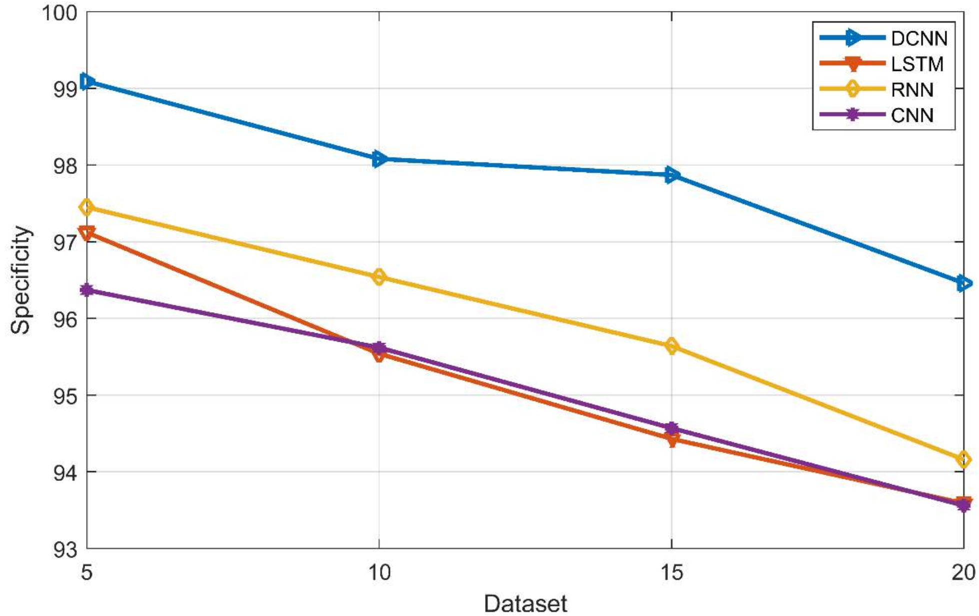

Figure: 6 Comparative performance analysis of specificity using DCNN, RNN, LSTM, and CNN for DDSM dataset.

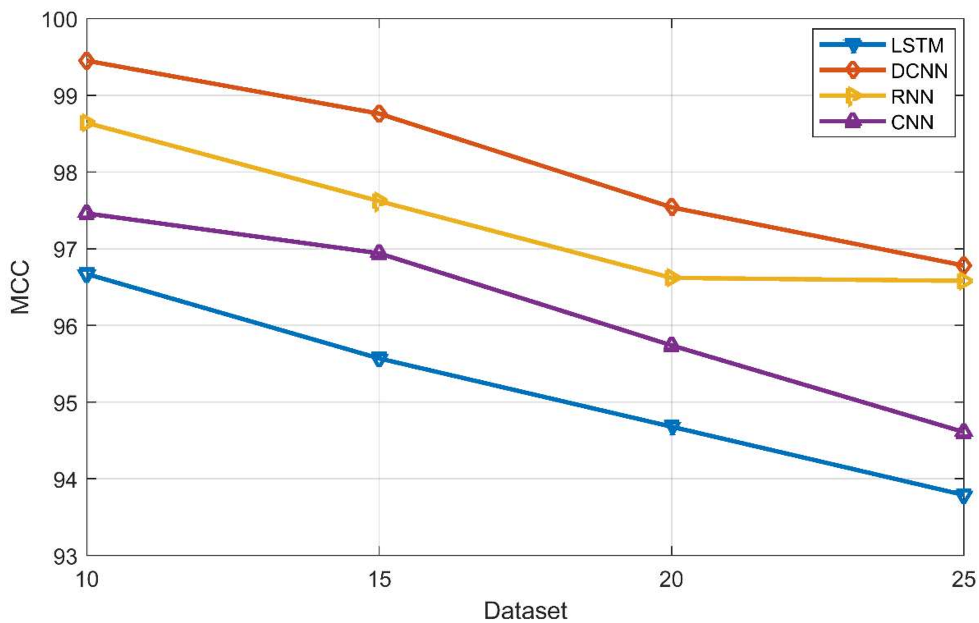

Figure: 7 Comparative performance analysis of MCC using DCNN, RNN, LSTM, and CNN for DDSM dataset.

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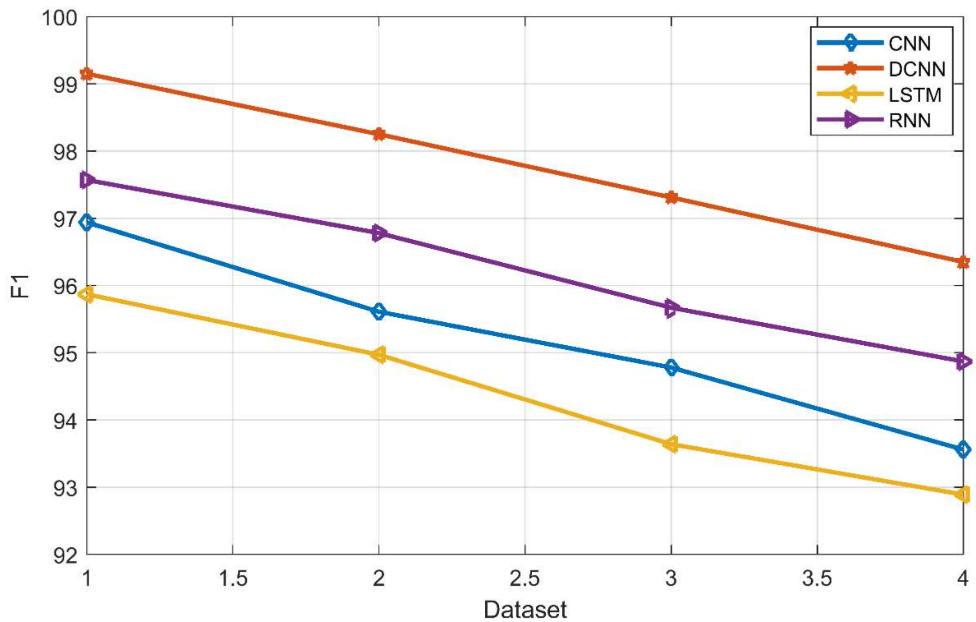

Figure: 8 Comparative performance analysis of F1using DCNN, RNN, LSTM, and CNN for DDSM dataset.

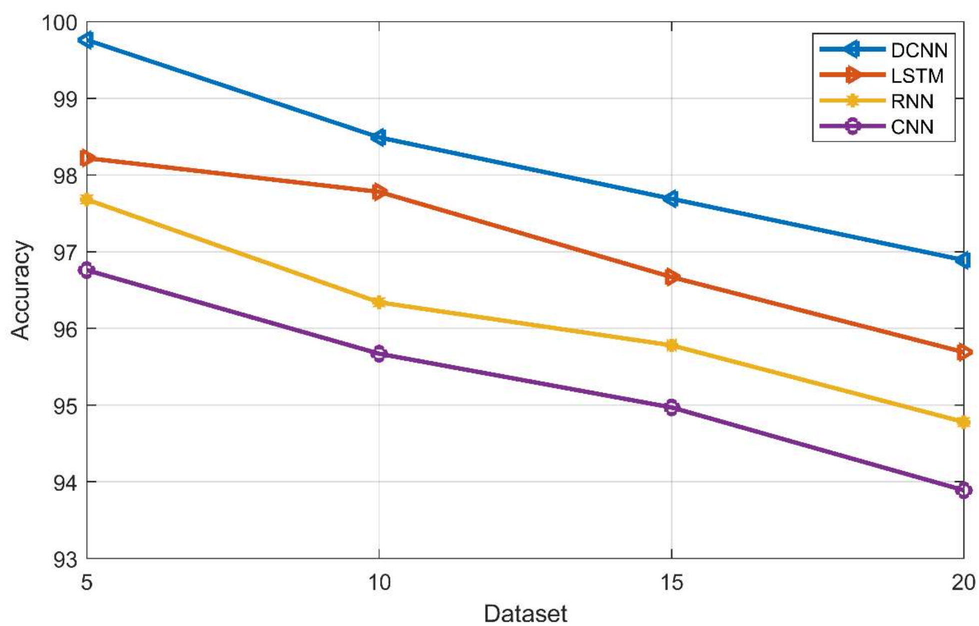

Figure: 9 Comparative performance analysis of accuracy using DCNN, RNN, LSTM, and CNN for MIAS dataset.

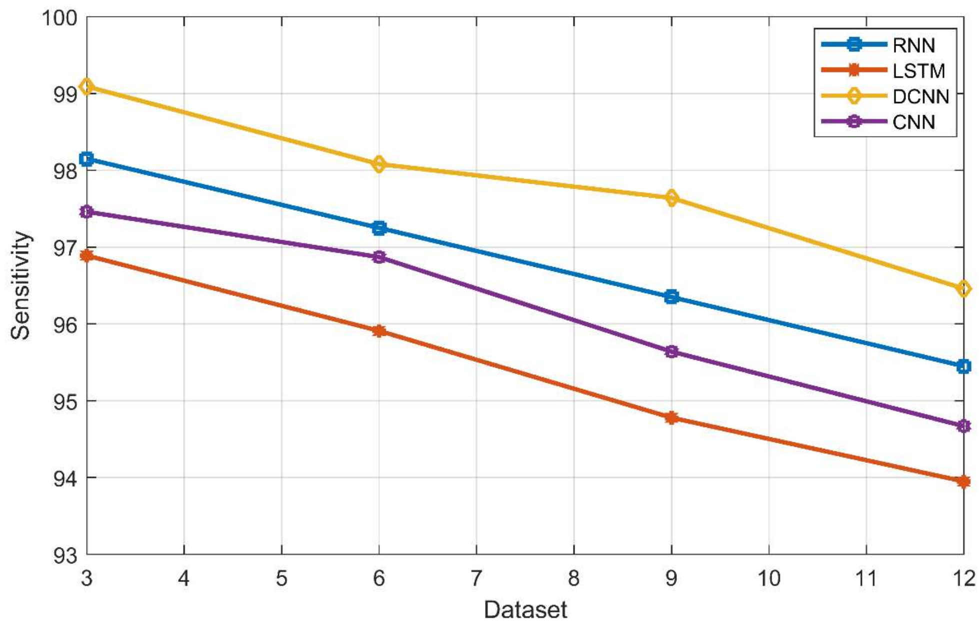

Figure: 10 Comparative performance analysis of sensitivity using DCNN, RNN, LSTM, and CNN for MIAS dataset.

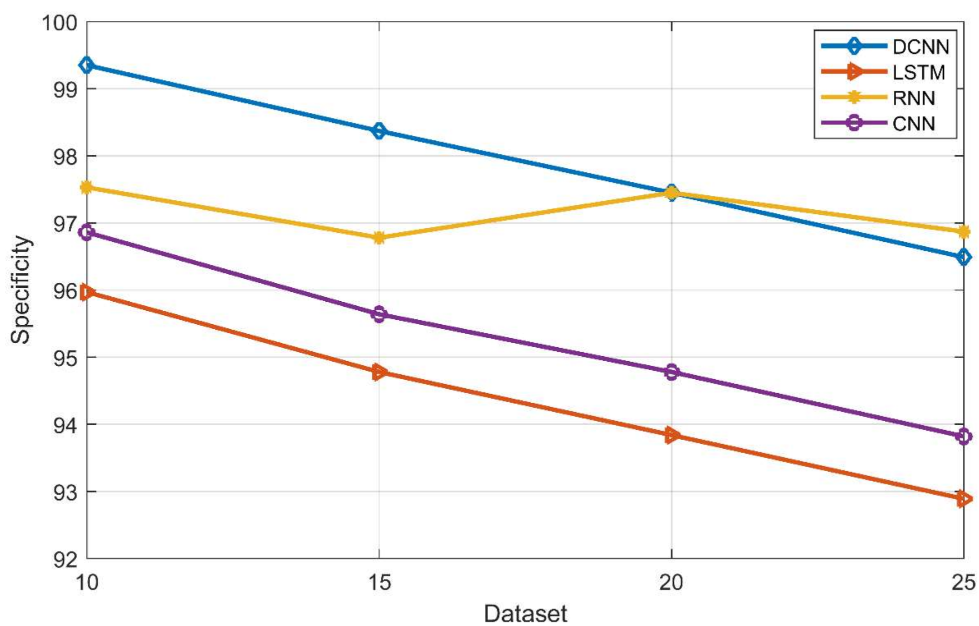

Figure: 11 Comparative performance analysis of specificity using DCNN, RNN, LSTM, and CNN for MIAS dataset.

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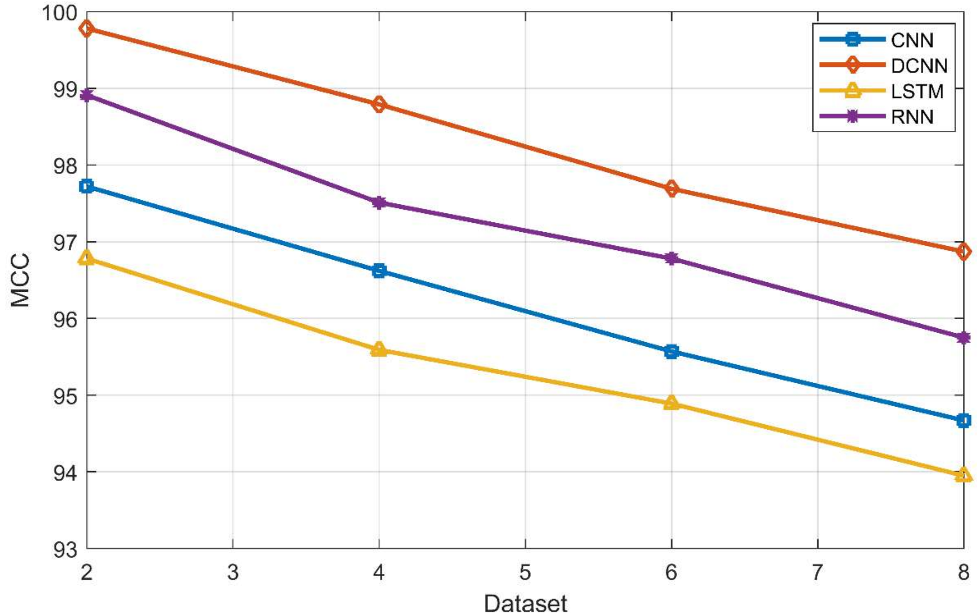

Figure: 12 Comparative performance analysis of MCC using DCNN, RNN, LSTM, and CNN for MIAS dataset.

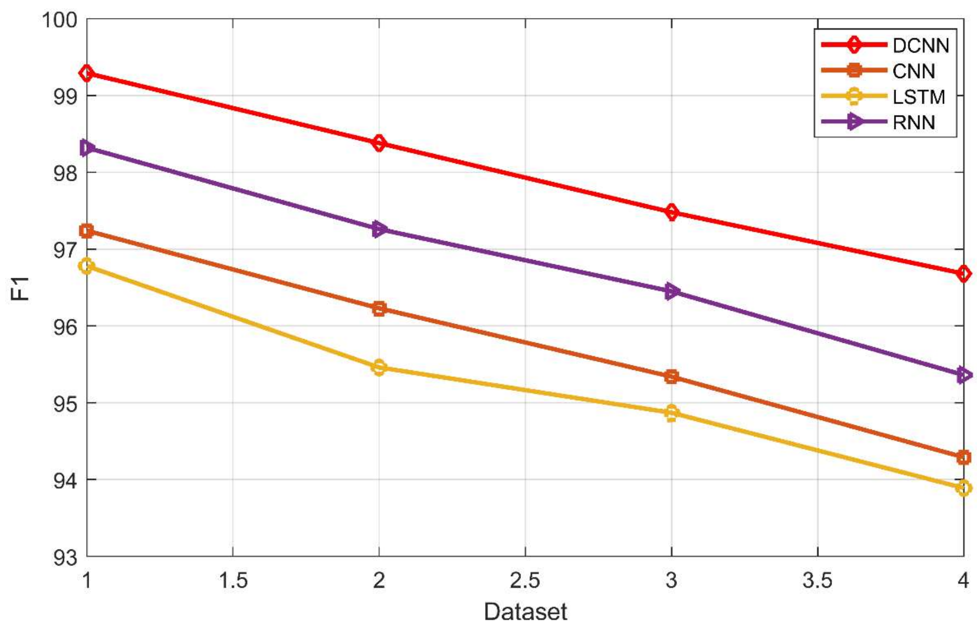

Figure: 13 Comparative performance analysis of F1 using DCNN, RNN, LSTM, and CNN for MIAS dataset.

V. Conclusion & Future Work

This study introduces a deep learning algorithm aimed at enhancing breast cancer detection performance. Leveraging the auto feature extraction capability of a deep learning-based Convolutional Neural Network (CNN) model, we employ pre-stage data processing algorithms to convert the one-dimensional row and column pixels of image data into two-dimensional decomposed modes. Training the CNN model with these decomposed modes yields superior

ISSN:2731-538X | E-ISSN:2731-5398
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performance compared to direct dataset training. To further enhance accuracy, a Recurrent Neural Network (RNN) is employed as a meta classifier, achieving an impressive 98.08% validation accuracy, surpassing existing state-of-the-art methods to the best of our knowledge. The metadata generated from the stage one classifiers comprises one-dimensional data, encompassing the combination of prediction probabilities and corresponding predicted labels. Suitable meta classifiers for processing this type of data include RNN, Deep Convolutional Neural Network (DCNN), and Long Short-Term Memory (LSTM). While our method demonstrates superior performance in a simulation-based environment, it is crucial to note that hardware implementation is pending verification, and the study does not encompass the validation of other types of breast cancer. Future considerations may include exploring the algorithm's applicability to different breast cancer types and implementing hardware verification.

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