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Prediction and Classifications of Breast Cancer Using Enhanced Convolutional Neural Network Approaches

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ABSTRACT

Breast cancer continues to be one of the major causes of mortality in women across the globe. Early diagnosis can significantly increase the survival rate among women. This study discusses the design and implementation of an Enhanced Convolutional Neural Network (ECNN) that effectively classifies the presence of breast cancer based on medical imaging. The enhancements are in terms of introducing Batch Normalization (BatchNorm), which stabilizes the training process, dropout for reduce overfitting, and appropriate hyperparameter tuning for optimal learning. The performance of the proposed method was evaluated on a publicly available dataset with a 70/15/15 training/validation/testing split. The ECNN achieved 97% accuracy, outperforming the traditional deep learning (DL) models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTMs), and Generative Adversarial Networks (GANs). Additionally, our model achieved superior precision, recall, and F1-score with the minimal false-negative rate. Thereby, ECNN proved to be robust and efficient in the early detection of breast cancer cases.

1. INTRODUCTION

Artificial Intelligence plays an important role in all aspects of regular life, and it is present in the medical field for predicting the severity of an issue, and accordingly, medical treatment can be taken for diagnosis. Machine learning (ML) contributes to the process of predicting breast cancer at an earlier stage and helps women to get healthy life. Various classification algorithms are used in the study conducted by Naji et al. [1], like K-Nearest neighbour (KNN), Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), and Support Vector Machine (SVM) for predicting, diagnosing breast cancer, and identified that SVM outstripped the rest of the classifiers and produced 97.2% highest accuracy. Biosensor and several ML approaches are investigated in the research [2] for earlier prediction of breast cancer, where ML doesn't require any pre-programmed models, it identifies patterns based on received data and forecasts outcomes by models, and biosensor quantifies organic characteristics of body fluids and tissues. Analysing breast cancer using genetic level is more expensive, and instead of that, histopathological image analysis is a common approach that is frequently used for cancer detection and analysis. Nassif et al. [3] processed a histopathological image using deep learning (DL), and previous works are reviewed to detect the seriousness of the disease. That provides opportunities for researchers to forecast the status of patients using Recurrent Neural Network (RNN) and LSTM methods.

Most research articles focus on the accuracy matrix, not on the confusion matrix, where it fails to distinguish false negative and false positive classifications, so it recommends that future research should concentrate on the confusion matrix for assessing the performance. Before introducing DL and ML approaches for detecting breast tumour by building models, a public data set was used for predicting and detecting the severity of the issue, and it gives a maximum of 99% accuracy using a Convolutional Neural Network (CNN). For creating a model, data should be analysed, and then it should be pre-processed with ML algorithms for measuring precision, recall, and accuracy. Khan et al. [4] divided the dataset into three portions—training, validation, and testing—with training conducted for 50 epochs. The model's performance improved progressively with each epoch, ultimately achieving 99% accuracy using a CNN. LR was employed for classification and sequential optimization. For performing automated diagnosis, recursive feature elimination is used for feature selection and CNNs as a classifier exemplary also various algorithms were compared in Bhise et al. [5] for accuracy and precision. Feature selection is the process of reducing ambiguity and reducing the complication of the dataset, also reducing data size and training time. Embedded methods, filter, and wrapper methods are commonly used feature selection methods, where the wrapper method is used by recursive feature selection, and in contrast, the filter–based method is used for identifying the largest score.

The proposed scheme distinguishes malignant and benign tumour with earlier rate. Pre-processing is not mandate extracting features inevitably, when a complicated classifier like CNN is used, and is more proficient because it screens significant parameters and works extremely well on image data. Naji et al. [6] incorporated a 10-cross-field procedure for identifying best classifiers in ML approaches using the voting ensemble technique. This scheme gives a maximum accuracy of 98.1 and a minimum error rate of 0.01 is fashioned. Parameters like sensitivity, accuracy, precision, and F-measures are compared for finding the best classification efficiency using the voting ensemble technique, and at the end, it produces a low error rate. Medical advancements like mammograms, histopathological imaging, Magnetic Resonance Imaging (MRI), and computed tomography are used for the detection of cancer in earlier and malignant states, but it is error prone and cost-effective.

A characteristic of DL is that it can analyse and extract features using high-dimensional correlated data. It has been utilized in the study [7] for the histopathological and radiographic images, classifying breast cancer image modalities like ultrasound, mammography, thermography, and MRI using DL, which is the main aim of the research with openly offered datasets. Methods like filters and DL simulations were incorporated in the study [8] to focus on the prominence of microcalcification in mammograms. Here, filters are used for filtering standard and unusual mammogram descriptions, and the riddled imageries are taken as input and given to the Yolov4 DL model for classifying standard and unusual mammogram images. To prove the significance of a filter in classifying images, it was implemented and classified without using a filter that gives a significant difference in the results. Yolov4 is a DL model that detects an object in a frame in real-time, by capturing 10% accuracy and 12% frames. As the number of images increases, the success ratio increases using a data augmentation technique that changes the brightness of images, rotates them, and scales the size of an image. A DL scheme was applied to images by converting them into one-dimensional data, which increased the performance of accuracy in classification [9]. In this work, DL is applied for both histopathological images and a genetic factor dataset, which is a one-dimensional dataset, and it uses the convex hull algorithm and disseminated stochastic neighbour technique. For an enlightening performance, the proposed method uses the dataset and its decomposition, whereas the previous method accesses the dataset directly for classification.

CNN-based classifiers, dissimilarity mode decomposition, are used for data decomposition along with wavelet transformation. Hybrid CNN-based cancer detection is incorporated in Sahu et al. [10], which reveals improved performance than base classifiers and threshold value, weight factor plays a vital role for hybridization. Unlike conventional DL models, a high-accuracy CNN performs well, not only for large datasets, even for smaller dataset too.

Though the use of DL models like ResNet, DenseNet, and EfficientNet in medical image analysis has shown remarkable success, these models demand extensive datasets and heavy computational power, making them less feasible for use in clinical settings. In addition to this, most conventional approaches emphasize accuracy but fail to take into account the rate of false negatives and the explainability of the model.

In an attempt to tackle these challenges, this study presents an Enhanced Convolutional Neural Network (ECNN) that offers computational efficiency, small sample size requirements, enhanced classification results, and comprehensive evaluation criteria. The proposed ECNN was selected as the core architecture because CNNs excel at automatically learning hierarchical spatial features from raw pixel data in medical images. Unlike RNN or Long Short-Term Memory (LSTMs), which are designed for sequential or time-series data (e.g., gene sequences), CNNs effectively capture local patterns, edges, textures, and spatial hierarchies present in mammograms, ultrasound, or histopathological images through convolutional filters and pooling layers. Hybrid models, while powerful, often demand substantially larger datasets and higher computational resources, whereas the lightweight ECNN achieves strong performance with limited data, making it more practical for real-world clinical deployment.

2. RELATED WORK

The earlier stage of breast cancer identified through a mammogram is the mainstay of clinical screening that greatly reduces mortality, it has well-known limitations, and nowadays magnetic resonance and ultrasound are adjunctive screening tools that support the enlarged risk of breast cancer. In Lee et al. [11], various screening tools like mammography, ultrasound, and magnetic resonance are discussed based on age, risk of the disease, which tool is appropriate, and how it can be used. Four ML schemes (Naïve Bayes, LR, SVM, and KNN) are compared using a data mining approach in Magboo et al. [12] with a high-dimensional, smaller dataset, and the results show that LR provides optimistic scores in almost all metrics. Followed by that, SVM and KNN produce optimal results next to LR, consecutively, where naïve bayes produce poor results in all aspects. In addition to the ML classification techniques like naïve bayes, LR, KNN and etc are incorporated in Nemade and Fegade [13], and ensemble methods like XGBoost, Adaboost on cancer are evaluated using various presentation procedures.

Even though numerous schemes are already available for breast cancer using ML algorithms, still several obstacles are lagging in accuracy, but this paper addresses this and concentrates on accuracy. An optimized neural network is proposed in Saleh et al. [14] for giving an accurate diagnosis scheme for medical representatives. An improved method is suggested in this work. Input, hidden, output, and dropout layers make up the RNN used by Keras - Tuner. The hidden layer optimizes the number of neurons, rate values of dropout layer, and a three-feature collection method is used for importing features from databases. Since manual detection of breast cancer is a time-consuming process due to laborious work, improper classification, and pathologist inaccuracies, those issues are addressed in Wang et al. [15] by incorporating a hybrid DL for automated detection using entire images from the Kaggle dataset. The proposed method in this article combines a CNN and GRU to detect breast cancer automatically, and a validation test is done using quantitative results. Here, various parameters like accuracy, sensitivity, precision, and specificity give the results like 86.2%, 85.50%, 85.60%, and 84.71% are, respectively.

The efficiency of the proposed results is compared with CNN-LSTM and BiLSTM ML approaches, and the results show that the hybrid model gives better performance. For detecting cancer, thermography imaging is one of the effective scheme in infrared technology, where in Mohamed et al. [16]

fully automated cancer detection system is incorporated. Firstly, the U-Net networking scheme is used to isolate the cancer area from the rest of the body by engendering the affected area as noise in the detection model. Secondly, a two-class DL model, which is accomplished from scratch, for the classification of usual and unusual breast tissues from thermal imageries. This is used to extract characteristics from the dataset that help in training the network and improving the efficiency of classification processes. For dense-breasted women, identifying breast cancer using mammography screening fails to identify the defective tissue. Comparison is done in the study [17] between the performance of mammography and ultrasound plus mammography in dense-breasted women with breast cancer. The result gives double the time higher than mammography in ultrasound mammography.

Rapid development of DL involves more in medical sciences, particularly in breast cancer detection and diagnosis. In the study [18], screening mammograms are used for breast cancer detection consuming an endwise training model, which professionally influences exercise datasets, which include whole medical comments of the whole image. Here, for the initial stages, lesion annotations are needed, whereas in subsequent stages, image-level tags are required. Compared to other methods, convolutional network schemes attained an excellent performance by incorporating screening mammograms. Cardinal Databank for screening mammography on sovereign assessment of digitized film mammograms. Accuracy of a single model is achieved with 0.88, and for four models it is achieved with 0.91 in the sovereign test of digitized film mammograms from the cardinal dataset.

Recent advancements [17-19] have explored CNN-Transformer hybrid architectures and multimodal fusion techniques for breast cancer detection. For instance, TransBreastNet integrates CNNs for spatial encoding with Transformer modules for temporal analysis, achieving high subtype classification accuracy while jointly modeling spatial, temporal, and clinical features. Similarly, other hybrid CNN–Transformer frameworks demonstrate superior performance by combining local and global features across imaging modalities. These studies highlight the potential of hybrid approaches, although they often require greater computational resources compared to the lightweight ECNN proposed in this work.

It is demonstrated that the entire image of the classifier was accomplished using an endwise methodology on digitized mammograms. This paper proposes high accuracy of dissimilar mammography daises and clutches, far-fetched potential for enlightening experimental trappings to decrease false affirmative and false negative mammogram broadcasting consequences. Prompt diagnosis of breast cancer detection is the need of the hour in the medical sciences to reduce complications and mortality in women. Recently, ML and DL have given the maximum of its contribution to the detection and diagnosis of breast cancer. In the study [19], a system is developed, where patients' breast cells are reported, and instant solutions are obtained for the beginning and malignant stages. The Wisconsin dataset is incorporated for carrying out this work from the UCI repository, and five ML classification algorithms were investigated and performs well obtaining accuracy of classification. Recent advancements [20-23] in breast cancer detection have explored transformer-based architectures such as Vision Transformers (ViT) and hybrid Convolutional Neural Network–Vision Transformer (CNN-ViT) models. Although these models achieve high accuracy, they require extensive computational resources and large annotated datasets. In contrast, the proposed Enhanced CNN model focuses on achieving comparable performance with lower computational complexity, making it more suitable for real-world clinical applications.

3. METHODOLOGY

The foremost purpose of this proposed work is to recognize an effective DL approach for detecting and diagnosing breast cancer in earlier and later stages, which is a subset of ML algorithms. Supervised Learning (SL), Unsupervised Learning (UL), and Reinforcement Learning (RL) are the major types of algorithms, whereas supervised learning is in need of a dataset for predicting the test data with a trained dataset with external supervision. It can be categorized into regression and classification. UL doesn't require any external supervision; it is trained using an unlabelled dataset, and it supports solving association and clustering-related problems. RL is completely different from the above-mentioned algorithms; it contains one agent, and it acts with an environment, according to the feedback received it takes decision. Here, Q-Learning is considered the main algorithm, and it is supported based on actions and rewards.

3.1 Deep learning for breast cancer detection

DL is the scope of ML that emphases on development and application of Artificial Neural Networks (ANN) with several layers. It is stimulated by the construction and purpose of the humanoid brain and aims to enable computers to learn and make decisions autonomously without explicit programming. DL algorithms have demonstrated promising results in predicting breast cancer risk by analysing various factors such as mammographic images, genetic data, and patient demographics. CNNs are commonly used in image analysis tasks. They learn to identify complex patterns within mammograms, such as micro calcifications, masses, and architectural distortions.

By training on large datasets, CNNs can learn discriminative features indicative of breast cancer presence or absence. Such algorithms enable risk stratification, assisting clinicians in identifying high-risk individuals who may require further screening or preventive interventions. CNNs are particularly effective in analysing images and have been widely used in medical imaging tasks. They can learn complex patterns and features from mammograms or other imaging modalities to aid in breast cancer detection and diagnosis. CNNs consist of multiple layers of interconnected units, including convolutional layers, pooling layers, and fully connected (FC) layers. The convolutional layers apply filters or kernels to the input images, which helps in capturing local patterns and features. The pooling layers reduce the spatial dimensions of the features, making the network more robust to translation and scale variations. Finally, the FC layers enable the network to make predictions based on the learned representations.

For CNNs for breast cancer prediction, a dataset of labelled images is required. This dataset typically consists of mammograms or other relevant imaging data, along with corresponding labels indicating the presence or absence of breast cancer. The CNN is trained on this dataset, where it learns to automatically extract discriminative features from the images and associate them with the cancer diagnosis.

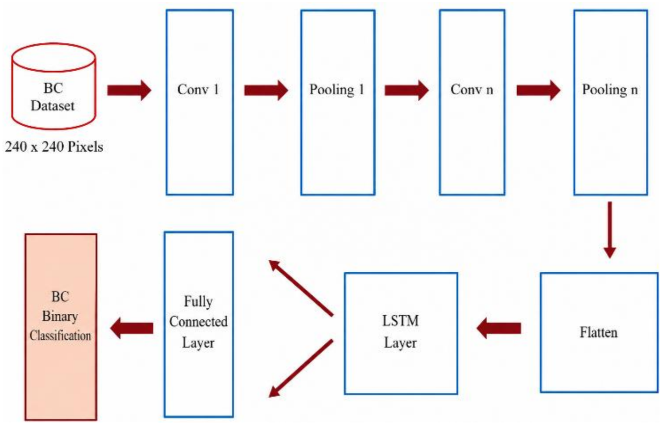

Figure 1. Deep learning (DL) Library model for the classification of deformities pipeline
Note: Long Short-Term Memory (LSTM).

In the above pictorial representation, Figures 1 and 2 show deformities of breast cancer using a CNN using DL. The proposed ECNN architecture consists of multiple layers designed to improve feature extraction and classification performance.

Input Layer: 224 × 224 grayscale images
Convolutional Layer 1: 32 filters, kernel size 3 × 3, ReLU activation
Batch Normalization
Max Pooling Layer: 2 × 2
Convolutional Layer 2: 64 filters, kernel size 3 × 3, ReLU activation
Dropout Layer: 0.25
Convolutional Layer 3: 128 filters, kernel size 3 × 3, ReLU activation
Max Pooling Layer: 2 × 2
Flatten Layer
Fully Connected Layer: 128 neurons, ReLU activation
Dropout Layer: 0.5
Output Layer: Softmax activation for binary classification (benign and malignant)
Training Parameters:
Optimizer: Adam
Learning Rate: 0.001
Batch Size: 32
Epochs: 50
Loss Function: Categorical Crossentropy

Note: Batch Normalization (BatchNorm); Rectified Linear Unit (ReLU); fully connected (FC).

Feature extraction, parameter sharing, spatial hierarchies, non-linearity and down-sampling are key responsibilities of the convolution layer in DL. Convolutional layers often include pooling operations, such as max pooling or average pooling, to down-sample the spatial dimensions of the feature maps. Pooling helps reduce the computational complexity of subsequent layers, provides local translational invariance, and helps the model to focus on the most salient features. Dimensionality reduction, feature selection, translation invariance robust to noise, and computational efficiency are the key responsibilities of the pooling layer in DL.

The pooling layer plays a crucial role in dimensionality reduction, translation invariance, feature selection, noise robustness, and computational efficiency within DL models. These responsibilities contribute to the effective extraction and representation of important features, enabling the network to learn and make accurate predictions. Parameter learning, classification, representation learning, and learning complex relationships are responsibilities of FC layers in DL. FC layer serves as the bridge between the preceding layers, responsible for learning complex relationships, introducing non-linearity, performing representation learning, producing the final output, and adapting the model's parameters during training. It plays a vital role in enabling the model to make accurate predictions or classifications based on the learned features.

Algorithm: Breast Cancer Prediction Using Deep Learning (DL) Model
Input: Breast cancer mammogram images (240 × 240 pixels)
Output: Binary classification (Benign/Malignant)

Step 1: Load the breast cancer dataset and preprocess the input images by resizing them to **240 × 240 pixels**, normalizing pixel values, and splitting the dataset into training and testing sets.
Step 2: Define and initialize the CNN architecture for feature extraction.
Step 3: Apply convolution layers to extract important image features:

output = Conv2D(input, filters, kernel_size, activation='relu')
Step 4: Apply max-pooling layers for dimensionality reduction:

output = MaxPooling2D(output, pool_size)
Step 5: Repeat convolution and pooling operations until sufficient feature maps are obtained.
Step 6: Flatten the extracted feature maps:

output = Flatten(output)
Step 7: Pass the flattened features through the LSTM layer to capture sequential dependencies:

output = LSTM(output, units)
Step 8: Add a fully connected dense layer for classification:

output = Dense(output, units, activation='relu')
Step 9: Add the output layer using sigmoid activation for binary classification:

output = Dense(output, 1, activation='sigmoid')
Step 10: Compile the model using binary cross-entropy loss and Adam optimizer:

model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics = ['accuracy'])
Step 11: Train the model using the training dataset until convergence is achieved:

model.fit(train_images, train_labels, batch_size, epochs)
Step 12: Evaluate the trained model using performance metrics such as accuracy, precision, recall, and F1-score:

model.evaluate(test_images, test_labels)
Step 13: Save the trained model for future prediction tasks:

model.save(model_filename)

Note: Convolutional Neural Network (CNN); Long Short-Term Memory (LSTM); fully connected (FC); Convolutional Two-dimensional Layer (Conv2D); rectified linear unit (ReLU); binary cross-entropy (BCE).

•Input (224 × 224 grayscale) → Conv layers + BatchNorm + ReLU + MaxPooling + Dropout → Flatten → FC layers → Softmax output
•Prepare dataset (70/15/15 split) and apply preprocessing
•Compile model: Adam optimizer (Lr = 0.001), Categorical

Crossentropy loss

•Train for 50 epochs (batch size = 32), monitor validation loss

•Evaluate on test set using accuracy, precision, recall, F1-score, confusion matrix, and Receiver Operating Characteristic–Area Under the Curve (ROC-AUC)

•Save the trained model

The above pseudocode illustrates the CNN algorithm that supports predicting the occurrence of breast cancer in earlier and later stages. Initially we should define CNN architecture and model model = Conv2D (input, filters, kernel_size, activation), and it is mandatory to add pooling layers for down-sampling. After flattening the output connection layers are activated with functions output = Dense (input, units, activation).

Then compiled using parameters like loss, optimizer, and metrics. Followed by that, the dataset is prepared, and it is trained using a CNN model. With the help of a trained model, the same procedure is repeated until the convergence of performance is achieved. After achieving the accuracy in the result, it is saved model.save (model_filename).

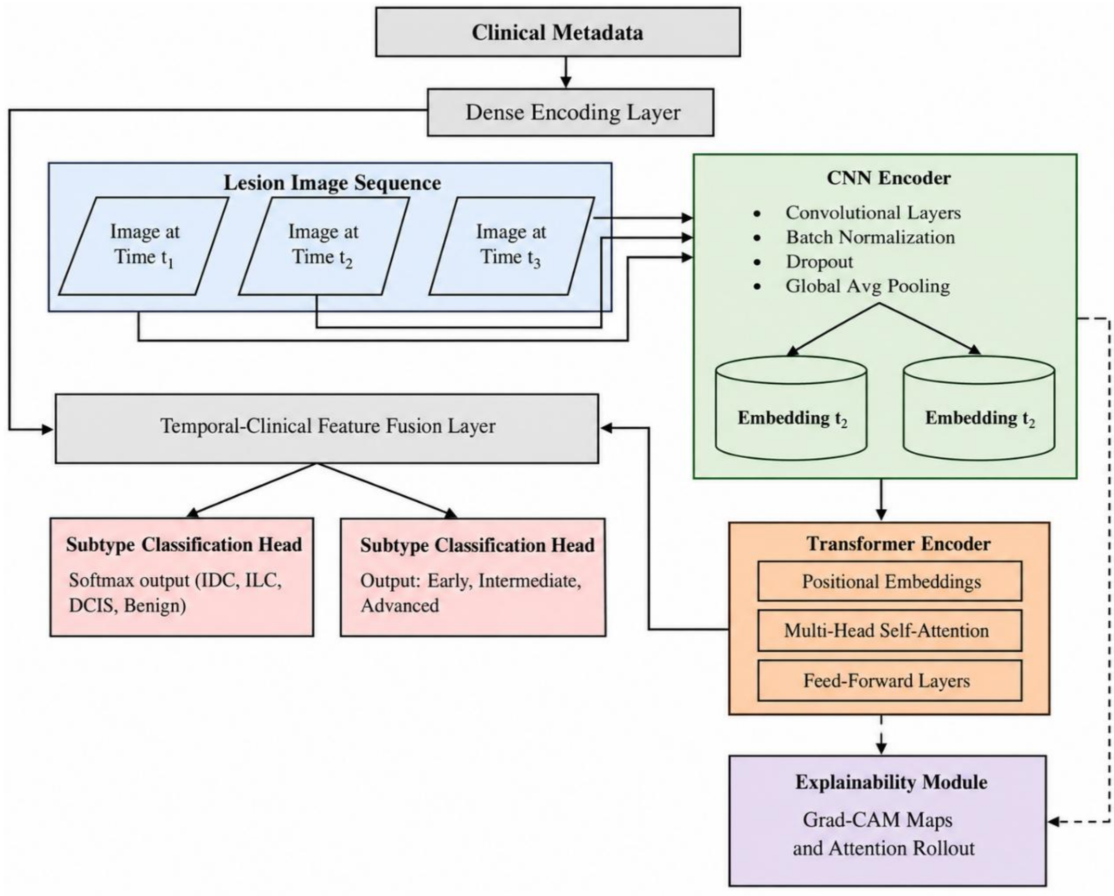

Figure 2. Enhanced Convolutional Neural Network (ECNN) architecture
Note: Convolutional Neural Networks (CNNs); Gradient-based class activation maps (Grad-CAM).

3.2 Data pre-processing

The dataset used in this research is the Breast Cancer Wisconsin Dataset acquired from the UCI ML Repository. It comprises 569 records, where 357 instances are benign, while the rest 212 are malignant. The dataset is split into training, validation, and testing datasets, accounting for 70%, 15%, and 15% of the dataset size, respectively. Traditional image operations (resizing, normalization, grayscale conversion, filtering) are applied first, followed by deep-learning-specific steps (convolutional feature extraction, Batch Normalization (BatchNorm), pooling, and dropout) within the ECNN model. This clear separation ensures that raw image quality is optimized before hierarchical feature learning.

Predicting breast cancer using a CNN involves medical image analysis, such as mammograms, and prediction is a complex task that requires extensive data pre-processing through various steps. Those steps are resizing, normalization, grayscale conversion, image filtering, and image enhancement.

$$Resized\ Image = Resize(Image, width, height) \tag{1}$$

$$Normalized\ Image = \frac{Image - Min}{Max - Min} \tag{2}$$

$$Grayscale\ Image = 0.2989 \times Red + 0.5870 \times Green + 0.1140 \times Blue \tag{3}$$

$$Output(x, y) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} Input(i, j) \times Filter(x - i, y - j) \tag{4}$$

$$Output(x, y) = \frac{CDF\big(Input(x, y)\big) - CDF_{min}}{M \times N - CDF_{min}} \times (L - 1) \tag{5}$$

In the above Eq. (1), the image is resized using parameters like image, height, and width. In Eq. (2), the resized image is normalized with its min and max values. In Eq. (3), the normalized image is converted into a grayscale image. In Eq. (4) and Eq. (5), the pre-processed image.

3.3 Feature extraction

Using CNN for image processing feature extraction involves mining relevant and discriminative features of images. CNN learns hierarchical representation of visual data and patterns of images. For detecting special features of images, CNN consists of multiple filters, and it supports computing element-wise estimation. Complex patterns are enabled by introducing activation functions; here, CNN includes the rectified linear unit (ReLU) that replaces negative values with zero. Spatial dimensions are reduced by pooling layers, and it supports for extracting more relevant information. Local Response Normalization (LRN) layers are used to normalize responses within a local region and promote against adjacent sectors. Feature maps are visualized to understand patterns in a specific layer, which helps to interpret network behaviour.

3.4 Image classification

Image classifications are done in breast cancer prediction using CNN DL model by considering various parameters like dataset preparation, data pre-processing, model architecture, training, validation, and hyper parameter tuning, interpretation, and deployment, and testing are considered carefully for various influences like data quality, architecture selection, and interpretation techniques. This technique analyses the model's predictions and investigates the learned features to gain insights into its decision-making process. The interpretation of mammography images can be improved by using interpretability approaches like gradient-based class activation maps (Grad-CAM) or occlusion sensitivity to pinpoint key areas that are crucial to the model's categorization. Once the model's performance has been validated, it can be used to classify breast cancer on fresh, previously unveiled mammography pictures.

4. RESULTS AND DISCUSSION

In this paper, for predicting breast cancer in patients in earlier and later stages, we incorporated four DL algorithms: CNN, LSTM, RNN, and Generative Adversarial Networks (GANs). We considered parameters like accuracy testing, gene sequence classifiers, image data classifiers, and malignancy detection, comparing with the above DL algorithms. CNN performs well in all parameters mentioned above. Because CNN has the ability to capture spatial information, relevant features from raw data are extracted automatically. CNNs were created primarily to take use of the spatial hierarchy of visual data. Local structures and slight anomalies in mammography pictures are frequently used to detect breast cancer.

Accuracy testing in predicting breast cancer using various DL algorithms is done in this paper, and our results in Figure 3 show that the modified CNN gives more accuracy than other algorithms. Results 0.93%, 0.95%, 0.96%, and 0.97% are given by the RNN, LSTM, GAN, and modified CNN, respectively. All compared models (ECNN/CNN, LSTM, RNN, and GAN) were trained under identical conditions for fair evaluation: 50 epochs, batch size of 32, Adam optimizer with learning rate 0.001, and the same 70/15/15 train/validation/test split on the Breast Cancer Wisconsin Dataset. This ensures that performance differences arise solely from model architecture rather than training hyperparameters.

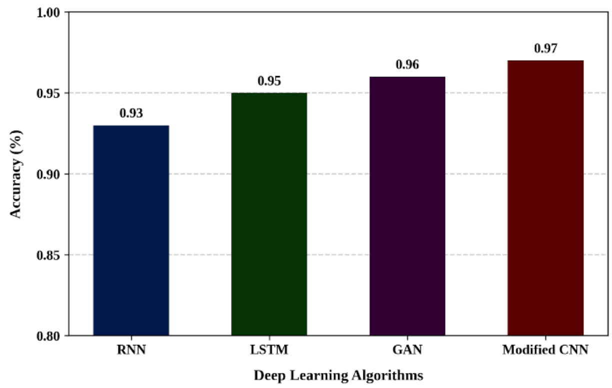

Figure 3. Accuracy testing vs. deep learning (DL) algorithms

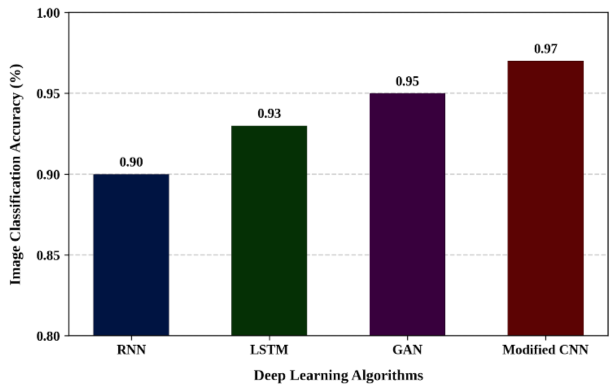

Figure 4. Image classifiers vs. deep learning (DL) algorithms

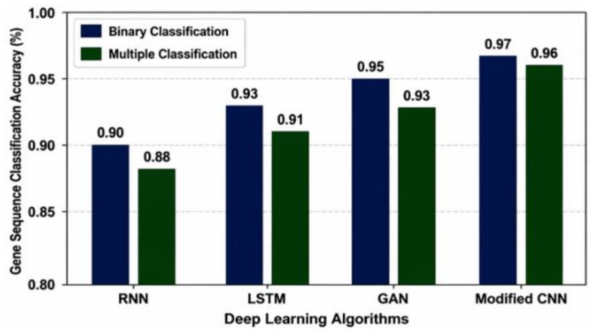

Figure 5. Gene sequence classifiers vs. deep learning (DL) algorithms

The models used in CNNs for classifying images into various groups or categories are known as image classifiers that consist of binary and multiple classification, as shown in Figure 4. Because they have the capacity to automatically learn and extract pertinent characteristics from unprocessed picture data, CNNs are highly suited for image classification applications.

DL gene sequence classifiers have produced encouraging results in a number of bioinformatics tasks. Gene sequence classification and analysis have both been effectively used to DL models, including RNNs, CNNs, and their derivatives. Figure 5 shows that CNN performs well in both binary and multiple classifications.

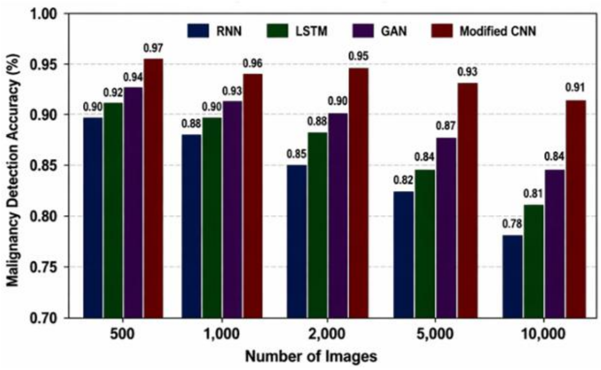

Figure 6. Malignancy detection vs. deep learning (DL) algorithms

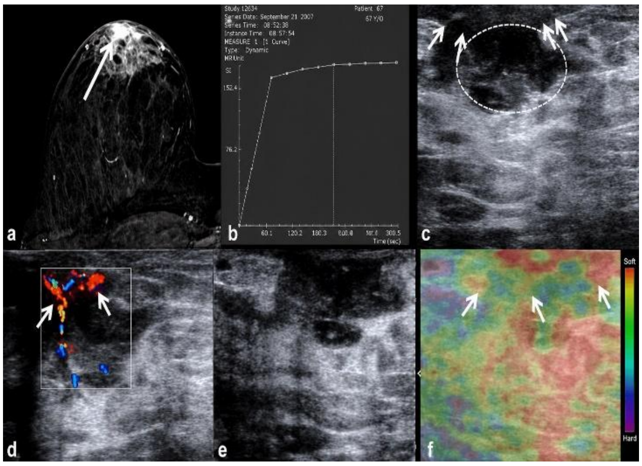

Figure 7. Prediction outcomes

CNN has become a potent tool for medical image processing, especially when used to detect breast cancer malignancy. In order to accurately detect malignancy in mammography pictures, CNNs have special capacities for learning and extracting pertinent information. In Figures 6 and 7, it is identified that compared to all algorithms, CNN gives significant performance. It also clarifies that when the number of images get increased, detection of malignancy gets reduced, CNN still performs well in all numbers of images. The performance of the proposed model is measured in terms of precision, recall, F1-score, confusion matrix, and ROC curve, in addition to accuracy. The confusion matrix proves the ability of the model to minimize false negatives and false positives. The ROC curve depicts the effectiveness of the classifier, where the area under the curve is 0.98.

There are various modifications that can be seen in the design of the Enhanced CNN when compared to the conventional CNN. BatchNorm is included in order to enhance learning efficiency and convergence rate. The model utilizes dropout regularization in order to prevent overfitting and ensure generalization. The use of data augmentation increases variation within the data set. All these factors help in improving the efficiency of the Enhanced CNN model.

5. DISCUSSION ON EXISTING DEEP LEARNING MODELS AND LIMITATIONS

The recent developments in the field of DL have enabled new architectures to be built that excel at solving medical image classification problems. For instance, ResNet uses residual connections that allow training of extremely deep neural networks and overcome the problem of the gradient vanishing. Similarly, DenseNet improves feature propagation through the connection of each layer to all others, which increases information exchange and decreases redundancies. EfficientNet scales the depth, width, and input resolution of a neural network, ensuring maximum performance and a minimal number of parameters.

However, there are some downsides to the use of these types of models for detecting breast cancer. The main one is the requirement of an enormous amount of annotated data for effective training. Moreover, due to complex architecture and the need to employ transfer learning, training of such models requires many computing resources, which makes using them in clinical practice unfeasible. In addition, they are likely to be overfitted on small or imbalanced datasets, which is common in medicine.

Conversely, the proposed ECNN employs a simple architecture supplemented by BatchNorm, dropout, and optimal hyperparameters. This allows the model to achieve high classification precision and low computational complexity, making it suitable even for smaller datasets without the risk of overfitting. In addition, ECNN puts special emphasis on minimizing false negatives, which is particularly important in breast cancer detection.

6. CONCLUSION

The proposed ECNN model effectively addresses key challenges in early breast cancer detection by achieving 97% accuracy, superior precision-recall-F1 scores, and a minimal false-negative rate on the Breast Cancer Wisconsin Dataset. The inclusion of BatchNorm and dropout layers significantly enhances training stability and generalization, demonstrating the model's robustness even with limited data. However, the study has limitations, including reliance on a single tabular/feature-extracted dataset and the absence of multi-modal inputs (e.g., combining mammograms with clinical/genomic data). Future extensions will explore integration with recent CNN-Transformer hybrid architectures and multimodal fusion techniques to further improve explainability and clinical applicability. Additional directions include handling imbalanced datasets, incorporating clinical and genomic data, and validating the model on larger, diverse real-world imaging repositories.

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