HYBRID CNN-RNN FUSION FOR ENHANCED BREAST CANCER DETECTION IN EARLY STAGE

V. Krishna Sree, A. Pavan Dheeraj and S. Shyamala
Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India
E-Mail: shyamalasammoji2003@gmail.com

ABSTRACT

One of the most prevalent cancers in women and one with a high death rate is breast cancer. Since determining the actual origin of breast cancer is challenging, early detection of the illness is essential to lowering the death rate from breast cancer-related causes. Recently, the medical industry has benefited from the application of deep learning techniques for disease classification and identification. This research uses an ultrasound image dataset to provide a hybrid deep learning method for breast cancer diagnosis. The model classifies ultrasound images into three classes normal, benign, and malignant. In contrast to the widely used serial technique to extract image features by a convolutional neural network (CNN) and then giving them as input into a recurrent neural network (RNN), our model extracts image features using a structure made up of a CNN and an RNN with LTSM layer and as an extra layer, we have added RELU with softmax. ReLU helps the first hidden layer receive errors from the last layer to adjust all weights between layers and the softmax layer which will divide each class prediction into probabilities and the class with the highest probability will be the best prediction and help in enhancing accuracy. The obtained results indicate that the suggested method outperforms the others in terms of evaluation criteria like an accuracy of 99.35%. In this manner, the proposed hybrid model helps in breast cancer detection.

Keywords: breast cancer, hybrid deep learning, convolutional neural network (CNN), recurrent neural network (RNN), softmax.

Manuscript Received 27 April 2024; Revised 10 August 2024; Published 12 October 2024

1. INTRODUCTION

Breast cancer is among the most common diseases that occur in women globally, and is a danger to public health. Due to the rapid growth of tumor-like cells in the breast tissue, it may be potentially lethal if not identified and treated quickly. Breast cancer is a well-known disease due to its high prevalence and negative impact on patients, their families, and healthcare systems. Medical doctors believe that abnormal cell growth in the breast causes breast cancer, which then spreads to lymph nodes and other parts of the body. Consequently, it is critical to recognize and stop the growth of these unwanted cells as soon as possible to avoid the consequences of the subsequent phase. Finding out if a tumor is benign or malignant is the doctor's first step after discovering one. Because different strategies for treatment and prevention are needed for the two types of tumors. Benign cells lack both of these properties, but malignant cells can move to other parts body. When a disease is discovered in its early stages,it is often curable with minimal human intervention. Deep learning models for medical decision support assist oncologists in managing the disease more efficiently and economically. A prediction system that can detect breast cancer at an early stage can be developed using clinical data and computer-aided automated diagnosis techniques. Comparing this type of diagnostic technique to other current surgical procedures, needless harsh therapies, and expensive treatment costs, it is more affordable, safer, quicker, and easier. In this paper breast cancer prediction using a hybrid model (CNN and RNN) is proposed. The proposed model yields extremely accurate results for disease prediction.

2. METHODOLOGY

We used a hybrid model on the ultrasound image breast cancer dataset. This tactic entails boosting and bagging. The first step in doing this is gathering data. After selecting characteristics through pre-processing, the data was divided, allocating 80% for training and 20% for testing. To build a model, the training data is subjected to several supervised classification approaches and the dataset has been labeled with normal, benign, and malignant states. The hybrid model is used to offer accurate results to identify breast cancer.

Figure-1. Flow chart representing methodology.

VOL. 19, NO. 14, JULY 2024 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

2.1 Data Collection

In our study, we used ultrasound images of breast cancer to classify the considered data into normal, benign, and malignant states. This data set captures features primarily from the center of breast mass images. The dataset consists of 1560 ultrasound images, where 874, 420, and 266 are labeled as benign, malignant, and normal respectively.

2.2 Data Pre-Processing

Pre-processing techniques like normalization, shuffling, and splitting of data are performed. The data is split into training and testing modules with 80% and 20% respectively. Table-1 shows the training and testing data splitting in the above ratio. The model was trained using training sets, and its effectiveness was evaluated on test data. The values of the various qualities will determine whether or not the individual is affected. Collecting the data needed for pre-processing is the initial step towards improving the quality of the data.

Table-1. Splitting data into training and testing data.

Label	Category	Number	Training data	Testing data
0	Benign	874	699	175
1	Malignant	420	336	84
2	Normal	266	212	54
Total		1560	1247	313

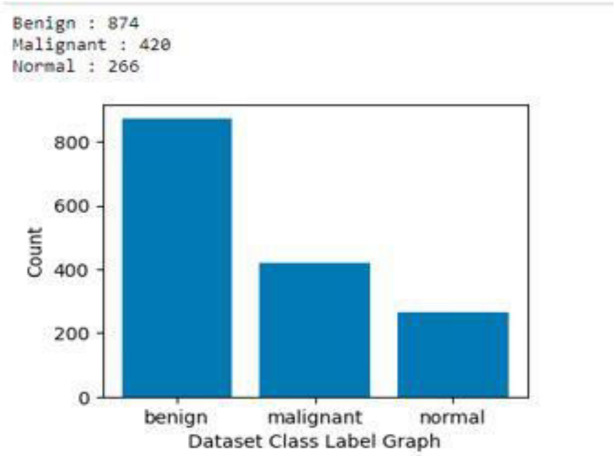

Figure-2. Labeling of data in the dataset.

2.3 Approach

CNN is a redesigned deep neural net variant that relies on the correlation between adjacent pixels. During training, it starts with input consisting of randomly specified patterns and modifies them. These updated patterns are used by the network after training to forecast and validate the outcome during testing and validation. Thanks to CNN's established structure that conforms to the image's data point distribution, convolutional neural networks have shown success in solving the image classification challenge. For automatic feature extraction, CNN is thus used in numerous image processing tasks. CNN is widely utilized in both medical image processing and image segmentation applications. Two major transformation types are present in the CNN architecture. The first method involves convolving pixels using a filter or kernel. The dot product between the kernel and the image patch is provided in this stage. The filter's depth is equal to the input's depth, and its breadth and height can be adjusted based on the network. Subsampling is a second crucial change that can be applied in several ways (max, min, and average pooling), depending on the needs. The user can adjust the pooling filter's size, which is often taken in odd numbers. The pooling layer is used to reduce the data's spatial dimensions and is a great tool for minimizing overfitting. The output can be obtained by combining convolution and pooling layers and then passed into RNN. It could be difficult for an ordinary RNN to learn long-term dependencies because it only has one hidden state that is carried across time. Long Short Term Memory (LSTMs) is a type of RNN to addresses the vanishing gradient problem and better captures long-term dependencies. Additionally, LSTMs can be used with other neural network architectures, such as CNNs, to process images.

We have developed a combination of CNN and LSTM (RNN) to detect breast cancer disease and as an extra layer, we have added RELU with Softmax. ReLU helps the first hidden layer receive errors from the last layers to adjust all weights between layers and the Softmax layer which will divide each class prediction into probabilities and the class with the highest probability will be the best prediction and help in enhancing accuracy.

Combining CNN and LSTM

Combine the CNN's retrieved features with the LSTM network's output.

Before sending these features to the categorization layers, you can concatenate or combine them.

The model can use both temporal and spatial information for breast cancer detection thanks to this merging of elements.

Classification

ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

On top of the combined features for categorization, add fully connected layers.

Dropout regularization should be used to avoid overfitting.

A sigmoid activation function may be used in the final output layer for classification.

Training and evaluation

Split the dataset into training, testing, and validation sets. Train the hybrid CNN-LSTM model on the training set, using a suitable loss function.

Validate the model's performance on the validation set and adjust hyperparameters as needed.

Evaluate the final model on the test set to assess its generalization performance.

3. RESULTS AND DISCUSSIONS

Figure-3 shows that CNN with LSTM and Softmax obtained 99.35% accuracy and can see other metrics like precision, recall, etc. In the confusion matrix, the x-axis shows predicted labels and the y-axis shows true labels. The diagonal boxes of the confusion matrix show the correct predictions and the blue boxes show the incorrect predictions. In ROC the x-axis stands for the false positive rate and the y-axis for the true positive rate. If the blue line of the ROC AUC curve falls below the orange line then all predictions are incorrect.

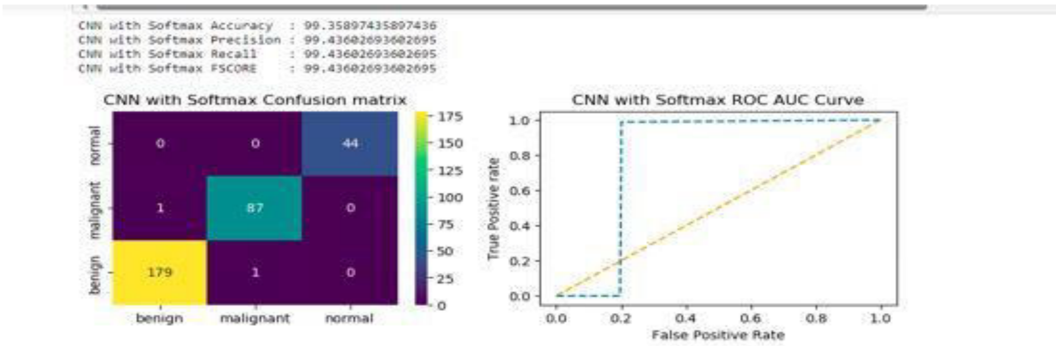

Figure-3. Results of the proposed model.

The graph plotted between validation accuracy and epochs gives us a conclusion that validation accuracy increases with epochs. After 11 epochs accuracy reaches its saturation level. The number of layers in our model is taken by experimental results. Maximum accuracy was obtained near 14 layers. Below are the graphs showing changes in validation accuracy and validation loss with epoch count.

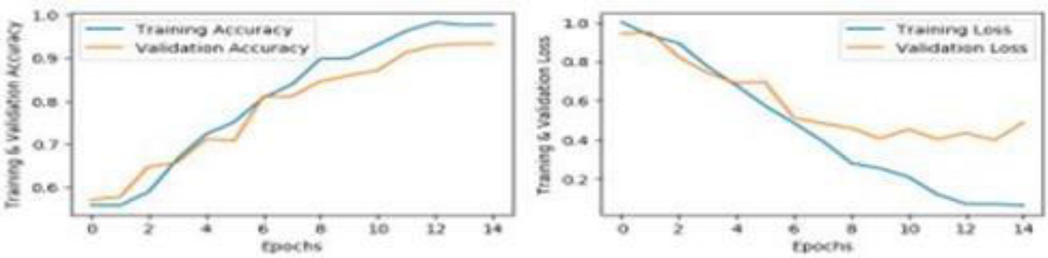

Figure-4. Training and validation results of the proposed model

Figure-4 is a graph that shows the accuracy and loss values for CNN training and validation. The training epochs are represented by the x-axis, and the accuracy and loss are shown by the y-axis in separate lines. The graph shows that as the number of epochs increases, accuracy increases and loss decreases.

Change in training and validation accuracy with epochs

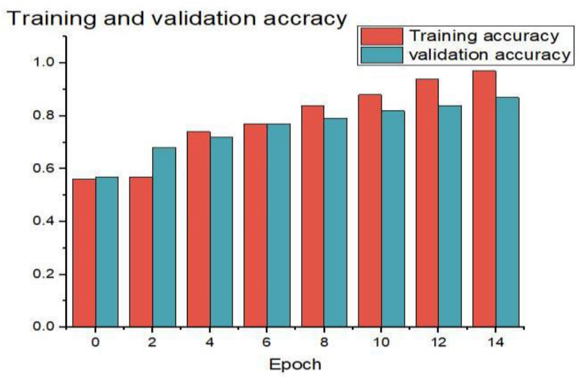

Figure-5. Change in validation and training accuracy with epochs.

ARPN Journal of Engineering and Applied Sciences

Change in training and validation loss with epochs

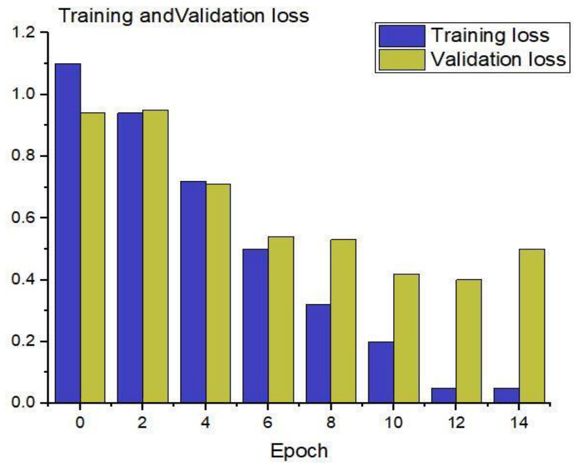

Figure-6. Change in validation and training accuracy with epochs.

Test images and predicted results

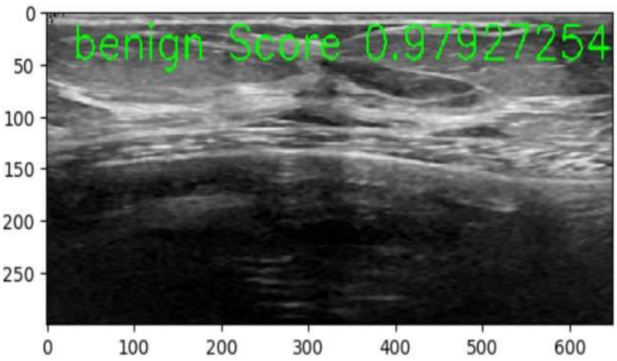

Figure-7. Expected results of testing benign.

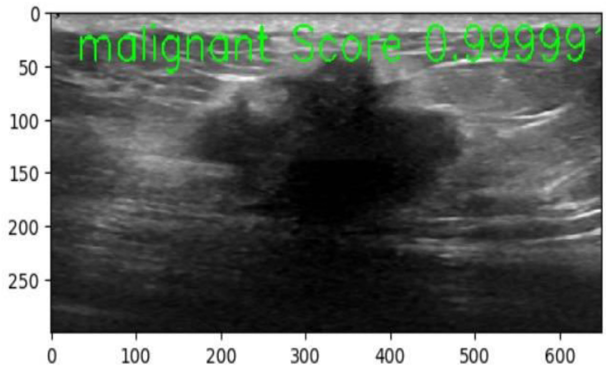

Figure-8. Expected results of testing malignant.

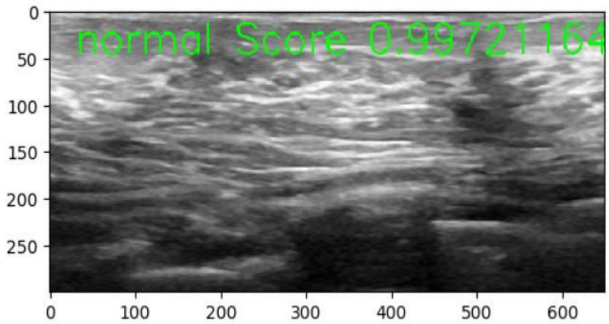

Figure-9. Expected results of testing normal.

Comparison of different Models

Table-2. Comparison report with other models.

Proposed Model	Classification Accuracy
Recurrent neural network (RNN)	63.15%
CNN + Gated recurrent units (GRU)	86.21%
5 layer Convolutional neural network (CNN)	87%
Proposed Model (CNN + RNN)	99.35%

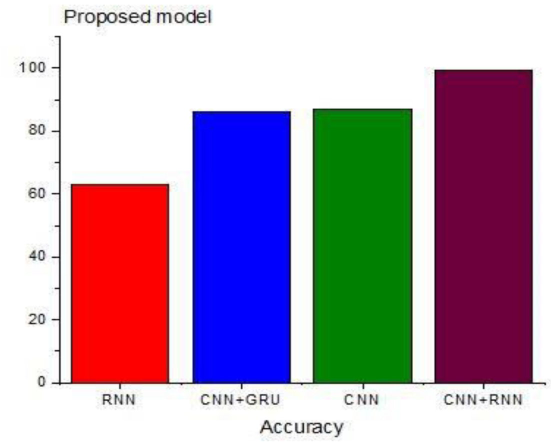

Figure-10. Model vs accuracy for disease classification.

4. CONCLUSIONS

In this work, we have used the hybrid model to diagnose and classify diseases in breast cancer like benign, malignant, and normal achieving a classification accuracy of 99.35% and, a precision of 99.43%. Our model helps in the early detection of breast cancer and with highly accurate results.

REFERENCES

Jiang Y., Chen L., Zhang H., Xiao X. 2019. Breast cancer histopathological image classification using convolutional neural networks with a small SE-ResNet module. PLoS ONE, 20, e0214587.

Gurcan M. N., Boucheron L., Can A., Madabhushi A., Rajpoot N., Yener B. 2009. Histopathological image analysis: A review. IEEE Rev. Biomed. Eng. 2, 147.

Liu M., Cheng D., Yan W. 2018. Classification of Alzheimer's Disease by Combination of Convolutional and Recurrent Neural Networks Using FDG-PET images. Front. Neuroinform. 12, 35.

Sannasi Chakravarthy S. R. & Rajaguru H. Automatic detection and classification of mammograms using improved extreme learning machine with deep learning. Irbm. 43(1): 49-61.

Oza P., Sharma P., Patel S. & Kumar P. Deep convolutional neural networks for computer-aided breast cancer diagnostic: A survey. Neural Comput. Appl. 34(3): 1815-1836.

Nahid A. A., Mehrabi M. A., Kong Y. 2018. Histopathological breast Cancer image classification by deep neural network techniques guided by local clustering. BioMed Res. Int. 2018, 2362108.

Yin Q., Zhang R., Shao X. 2018. CNN and RNN mixed model for image classification. In Proceedings of the 2018 International Joint Conference on Metallurgical and Materials Engineering (JCMME 2018), Wellington, New Zealand.

VO D. M., Nguyen N. Q., Lee S. W. 2019. Classification of breast cancer histology images using incremental boosting convolution networks. Inf. Sci. 482, 123-138.

Alom M. Z., Yakopcic C., Nasrin M. S., Taha T. M., Asari V. K. 2019. Breast Cancer Classification from Histopathological Images with Inception Recurrent Residual Convolutional Neural Network. J. Digit. Imaging. 1-13.

Huang G., Liu Z., Van Der Maaten L., Weinberger K. Q. 2017. Densely connected convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA. pp. 4700-4708.

Wang J., Peng B., Zhang X. 2018. Using a Stacked Residual LSTM Model for Sentiment Intensity Prediction. Neurocomputing. 322, 93-101.

M. Masud, A. E. Eldin Rashed and M. S. Hossain. 2020. Convolutional neural network-based models for diagnosis of breast cancer. Neural Computing and Applications. Vol. 5.

L. Tsochatzidis, P. Koutla, L. Costaridou, and I. Pratikakis. 2021. Integrating segmentation information into CNN for breast cancer diagnosis of mammographic masses. Computer Methods and Programs in Biomedicine. 200: 105913.

M. Malathi, P. Sinthia, F. Farzana and G. Aloy Anuja Mary. 2021. Breast cancer detection using active contour and classification by deep belief network. Materials Today: Proceedings.

M. Desai and M. Shah. 2021. An anatomization on breast cancer detection and diagnosis employing multi-layer perceptron neural network (MLP) and Convolutional neural network (CNN). Clinical eHealth. 4: 1-11.

G. Murtaza, L. Shuib, A. W. Abdul Wahab et al. 2020. Deep learning-based breast cancer classification through medical imaging modalities: state of the art and research challenges. Artificial Intelligence Review. 53(3): 1655-1720.

D. Singh, S. Singh, M. Sonawane, R. Batham and P. A. Satpute. 2017. Breast cancer detection using convolution neural network. International Research Journal of Engineering and Technology. 5(6): 316-318.