Breast Cancer Detection Using Neural Networks

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Abstract- Breast cancer is the second most common cancer in women worldwide, although it can be diagnosed in men too. Early detection and diagnosis are crucial in improving the survival rate of breast cancer patients. Traditionally, breast cancer is diagnosed using pathological evaluation, historical grading MRI screenings, and various estragon and progesterone receptors statuses. These manual screening tests leave a place for misdiagnosis and therefore delayed treatment. Recently, Artificial Intelligence, especially neural networks has shown great potential in the correct detection and early diagnosis of cancer cells in breast tissue. This research paper uses the Breast Cancer Wisconsin (Diagnostic) Data Set, which contains clinical and diagnostic features of breast cancer patients. This research paper studies various neural network architectures, including feedforward neural networks, convolutional neural networks, and recurrent neural networks to classify breast tumors as benign or malignant. In the result analysis, the convolutional neural network gives the highest accuracy of 98.2% among other models. This research paper highlights the potential of neural network models for breast cancer diagnosis, and the use of deep learning techniques can improve the accuracy of diagnosis.

Keywords- breast cancer, neural network, deep learning, diagnosis, Wisconsin Diagnostic Data Set.

1. Introduction

Breast Cancer is one of the most common types of cancer among women worldwide. Although breast cancer affects men alike, making early detection and correct diagnosis crucial for successful treatment [1]-[2]. There has been a lot of development in the field of screening and imaging techniques for breast cancer detection over the years, but correct diagnosis is still a challenge. Efficient, precise, and accurate analysis of these images is crucial for correct diagnosis. Traditionally, the medical industry uses mammography, ultrasounds, Magnetic Resonance Imaging (MRI), diagnostic mammogram, and biopsy for screening and diagnosis of breast cancer. Most of these methods include manual diagnosis from the images, leaving a chance for error. However, in the past years , neural networks have emerged as a powerful tool for detection and medical image analysis, which provides a great potential for correct diagnosis. This research paper aims to use neural networks for breast cancer detection. By using the capabilities of neural networks, one can seek improvement in the accuracy and efficiency of diagnosing breast cancer and consequently, it will result to better patient survival rates. Neural networks provide us with a tool for automation of the diagnosis process, enabling quicker, precise, and accurate diagnosis. In the recent years neural network techniques such as Convolutional Neural Network (CNN) have shown promising results in image analysis tasks. The hierarchical and non-Hierarchical nature of neural networks help us extract complex patterns and features from medical images. This ability is particularly useful for classification of cancer into benign or malignant lesions. The ability of neural networks to learn continuously from the data being fed to them , improves their accuracy more as a larger dataset is provided with time.

H. A. Abbass et al. [3] had developed a new evolutionary approach called MODE for multiobjective optimization. It extends the concept of differential evolution and uses a Pareto-based approach for implementing differential vectors. Comparative evaluations with existing algorithms show that MODE is more effective in finding accurate Pareto fronts with comparable efficiency. S. Bornholdt and D. Graudenz [4] have developed a learning algorithm for neural networks using genetic algorithms. They propose a model that explains inherited behavior and specifically focuses on a simplified brain model with sensory and motor neurons. Numerical simulations show that the network achieved through the algorithm reaches a stable state quickly. E. Heer et al. [5] did a population-based study, the number of premenopausal and postmenopausal breast cancer diagnoses globally in 2018 was roughly 645,000 and 1.4 million, respectively. The study also found that there were 490,000 fatalities in the postmenopausal group and more than 130,000 deaths in the premenopausal group. Given the rising incidence of breast cancer worldwide, their findings highlight the critical need for early detection, treatment accessibility, and all-encompassing preventative strategies. P. Henrot et al. [6] did research on the classification and interpretation of microcalcifications in breast imaging. They emphasize the need for a comprehensive analysis considering various factors such as associated signs, genetic context, distribution, and temporal changes. Their goal is to enhance the accuracy of identifying pathological processes associated with microcalcifications.

L. Wilkinson et al. [7] examined the importance of microcalcifications in mammography and how management has changed as a result of technological advancements. C. K. Bent et al. [8] retrospectively assessed the likelihood of malignancy in microcalcifications using BI-RADS descriptors in digital mammography. The study found that the morphologic and distribution descriptors were useful in predicting the risk of malignancy. The positive predictive value increased as the BI-RADS category advanced, indicating improved assessment of suspicious microcalcifications. Al-Antari et al. [9] used an integrated CAD system for digital X-ray mammogram screening, using deep learning methods for detection, segmentation, and classification of breast masses. Our approach utilizes You-Only-Look-Once (YOLO) for mass detection, a full resolution convolutional network (FrCN) for mass segmentation, and a deep CNN for mass recognition and classification as benign or malignant. The results of the proposed CAD system had a mass detection accuracy of 98.96% with an MCC of 97.62%, and an F1-score of 99.24% achieved with the INbreast dataset.

D. B. Fogel et al. [10] deployed a B-spline network for breast cancer detection. By using a tree-structured evolutionary algorithm and Particle Swarm Optimization, the hierarchical B-spline network model is optimized. The performance of the proposed approach was compared to Flexible Neural Tree (FNT), Neural Network (NN), and Wavelet Neural Network (WNN) using the same datasets. The results of the simulations indicate that the hierarchical B-spline network model achieves superior detection accuracy with a reduced number of variables and input features. S. Haykin's [11] book provides insight into how neural networks are used to build intelligent machines for signal processing, pattern recognition, and control. P. C. Pendharkar et al. [12] compared the performance of data envelopment analysis (DEA) and artificial neural networks (ANN) using discriminant analysis for mining breast cancer patterns. They used association rules to study the associations between female hormones and breast cancer occurrence. Their study had a successful contribution by proving the utility of data mining in the detection of breast cancer patterns. C. Szegedy, et al. [13] developed a deep convolutional neural network called Inception. The architecture of Inception focuses on efficiently utilizing computing resources by increasing the depth and width of the network while maintaining a constant computational budget. The design choices were guided by the Hebbian principle and the idea of multi-scale processing. The specific version of the network used in the challenge, called GoogLeNet, consists of 22 layers and excels in classification and detection tasks.

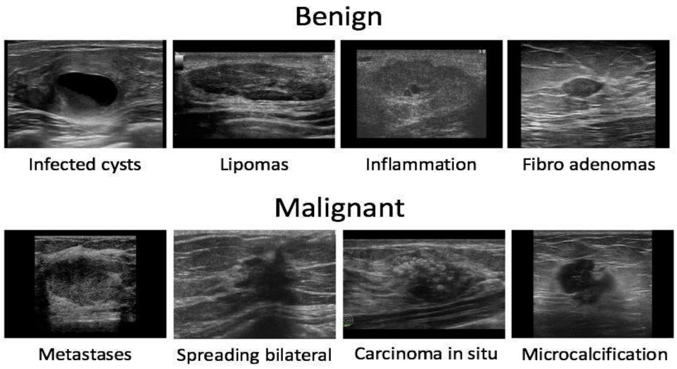

Fig 1: Benign and malignant breast lesions with different subtypes [14]

2. Background Study

Breast cancer is one of the leading causes of death among women worldwide. Early detection and accurate diagnosis of breast cancer are critical for improving patient outcomes. Neural networks have been extensively studied for breast cancer detection, with a particular focus on the use of evolutionary artificial neural networks (EANNs) to optimize network performance and architecture simultaneously. Traditional methods for determining a good neural network architecture, such as network growing and pruning, may suffer from slow convergence and long training times. EANNs offer a more successful platform for optimizing both network performance and architecture, but the trade-off between network architecture and generalization ability remains a challenge. The multi-objective optimization problem (MOP) has been proposed as a potential solution to this challenge, with evolutionary approaches in single-objective optimization proving successful in recent years. Applying a multi-objective approach to EANNs could improve the accuracy and reliability of breast cancer detection. This study aims to explore the use of the pareto-differential evolution (PDE) approach to optimize the architecture and generalization ability of EANNs for the purpose of breast cancer detection. EANNs are trained on large datasets of mammography images and patient data, with the goal of improving diagnostic accuracy and supporting early detection and treatment of breast cancer.

A.S. Becker et al. [15] did a study to assess the diagnostic efficacy of a multipurpose image analysis tool based on deep learning and artificial neural networks for the identification of breast cancer in a separate, dual-center mammography data set. M. Hassanin et al. [16] conducted a comprehensive survey on attention techniques in deep learning. They categorized and analyzed 50 attention techniques, providing insights into their strengths, limitations, and applications. The survey fills a gap in the literature and offers guidance for researchers interested in incorporating attention mechanisms into their models. M.G. Ertosun et al. [17] developed a deep-learning visual search system for localization in mammography images. Their system includes a classification engine and a localization engine. It achieved 85% accuracy in identifying images with masses and localizes 85% of the masses with an average of 0.9 false positives per image. The system has the advantage of working with entire mammography images without the need for pre-processing steps such as segmentation or cropping. It utilizes deep learning with unsupervised feature discovery, eliminating the need for hand-crafted image features. A. Rodriguiz-Ruiz et al. [18] did a study to compare the performance of radiologists reading mammograms unaided with an artificial intelligence (AI) system. The AI system provided decision support, lesion markers, and cancer likelihood scores. Results of the study showed that with AI support, the average area under the curve (AUC) increased compared to unaided reading (0.89 vs 0.87). Sensitivity improved (86% vs 83%), specificity showed a trend towards improvement (79% vs 77%) and reading time per case was similar. The AI system's AUC was similar to that of the radiologists. T. Schaffter, et al. [19] evaluated the use of artificial intelligence (AI) in mammography screening. While no single AI algorithm outperformed radiologists, combining top-performing algorithms with radiologist assessment improved overall accuracy. The study highlights the potential of AI and machine learning to enhance mammography interpretation and suggests the value of combining AI with human expertise for improved screening accuracy.

3. Methodology Used

The dataset used and the methodology used is explained in the subsequent sections.

3.1. Dataset Used

The data set used for this paper is taken from UCI website named Breast Cancer Wisconsin (Diagnostic) Data Set [20]. The dataset Characteristics are derived from digitized images of FNA (Fine Needle Aspirate) of breast mass. The attributes of the dataset are ID Number, Diagnosis (malignant or benign). There are also some features that are associated with each nucleus such as Radius, Texture, Parameter, Area, Smoothness, Compactness, Concavity, Concave points, Symmetry, Fractal dimension . The dataset contains a total of 569 data records with 357 benign and 212 malignant cases.

3.2. Data Pre-processing

The data is split into training and testing dataset it 70:30 ratio. Data pre-processing is also done by scaling the features using the Min-Max scaler. One-hot encoding is also performed on the target variable i.e. diagnosis , to convert it into a binary class.

3.3. Model Architecture

In this study, three different neural network architecture are applied to classify the data records in benign and malignant categories . The first technique is feedforward neural network. It was trained in tensor flow deep learning framework. The architecture consisted of two hidden layers with 64 and 32 neurons respectively. This layers where then followed by an output layer with an activation i.e. sigmoid function to predict the binary label, benign and malignant.
The activation of a neuron in a hidden or output layer is computed using an activation function, f.
For a hidden layer neuron i, denoted as h_i, the activation is calculated as:
$h_i = f(net_i)$
$net_i = sum\ (w_{ji} * x_j) + b_i$
w_{ji} represents the weight connecting the j-th input of neuron i, xj, and b_i is the bias term for neuron i.
For an output layer neuron k, denoted as y_k, the activation is computed similarly:

$y_k = f(net_k)$

They are followed by sigmoid activation function.

The formula for sigmoid function is: $\sigma(z) = \frac{1}{1+e^{-z}}$

The other technique is convolution neural network. It is mostly used for image classification; hence, it was a good pick for this study because the data sets consist of images of breast tissue. During pre-processing, since the images were already processed and reduced to a set of features, a modified approach of CNN is applied [21]. The initial layer of the model is applied with filters to extract unique features from the images relevant to the proposed study.

The relationship between Convolutional Layer C, filter F and Image I is, C=F*I, where * is convolution operation. Rectified Linear Unit ReLU (max(0,x)) is introduced to improve model's learning capability. Pooling layer is added to remove spatial dimensions and retain important features. Fully connected layers follow these convolutional layers. A dropout layer is added to remove overfitting by randomly disabling neurons. The last layer is dense, consisting of a sigmoid function.

The last technique used was the Recurrent Neural network [22]. They are typically used in sequential data , but it was applied to this dataset to see how it performs. To do so, features were treated as time step and fed into RNN sequentially.

4. Results

In this research paper, every neural network performed very well to diagnosis the type of breast cancer. The accuracy and precision for feedforward Neural network is 97.08% and 95.00% respectively . Similarly, for CNN it is 97.09 and 95.24 respectively. For RNN, precision is 90.91% and accuracy is 93.57%.

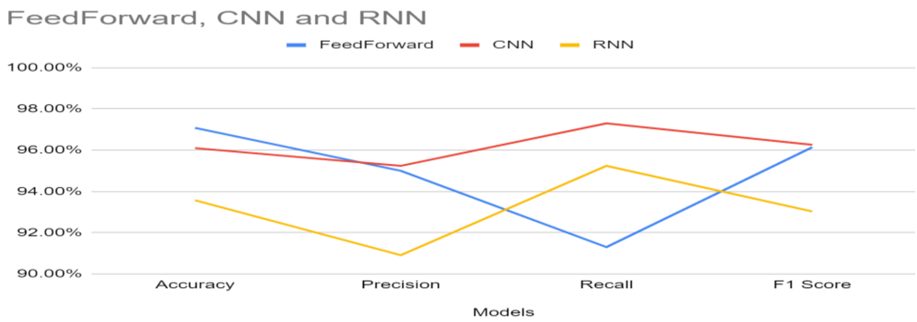

Fig 2: Training and Testing result analysis

In result analysis, comparison between CNN , RNN, and feedforward Neural network is done using accuracy matrix.

Table 1: Comparison of different evaluation metrics for different models.

Models	**Feedforward**	**CNN**	**RNN**
Accuracy	97.08%	97.09%	93.57%
Precision	95.00%	95.24%	90.91%
Recall	91.30%	97.30%	95.24%
F1 Score	96.14%	96.26%	93.03%

The accuracy indicated the percentage of cases that were classified correctly, and the precision measures the percentage of positive(malignant) predictions that were correct. These results indicate that the Convolution model performed very well on the dataset. It achieved a high level of precision and accuracy with a balanced F1 score. Feedforward neural network performed better than RNN.

5. Conclusion

Breast cancer is an ever-increasing problem today. It accounts for almost 25% of all types of cancers . The usage of neural networks in the identification of breast cancer has shown a lot of promise for improving the accuracy and dependability of diagnosis. AI is capable of helping medical practitioners overcome their difficulties in diagnosing, managing, and treating breast cancer, especially in the domain of breast cancer diagnostics. Early detection using neural networks have resulted in decline of mortality rates in breast cancer . In this study, convolutional neural networks and deep learning techniques are used to analyse mammography and biopsy images in order to detect breast cancer. The accuracy and reliability of breast cancer diagnosis can be further increased by using multi-objective optimisation techniques such as pareto-differential evolution. Usage of Neural networks can help in pattern finding amongst the breast tissue images which can be used to detect earlier signs. The application of neural networks in the diagnosis of breast cancer may result in earlier identification, better treatment results, and higher patient survival rates with more study and improvement. While this study shows promising results , a lot of other challenges are yet to overcome. The integration of multiple image screening techniques such as mammography , MRI ,ultrasound etc can increase the overall accuracy for diagnosis.

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