

Deep Learning Models for Breast Cancer Classification

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Abstract— Breast cancer (BC) is a common disease that majorly affects women, which underline the importance of awareness, understanding of risk factors, and regular screenings to ensure early detection and proper treatment. The complexities of breast cancer require correct health care guidance and family support to face the challenges. The main objective is to achieve early detection and correct diagnosis, to hasten patient care and improve health outcomes. This review explains different aspects used by various studies, including datasets, architectural frameworks, and performance metrics. The final objective is to find the efficient model for predicting accurate breast cancer detection. For this purpose, this paper intends to comparatively review and evaluate Convolutional Neural Networks (CNN) and Vision Transformers (ViT) on classification of images.

Index Terms—Breast Cancer, Deep Learning Models, CNN, Vision Transformer.

I. INTRODUCTION

Breast cancer is still a problem affecting the female population around the world. Women have to know the risk factors associated with this type of cancer, and it is therefore important for early detection by carrying out regular screening for appropriate treatment. Challenges seen in BC detection reveal the necessity of obtaining the right health professional advice and family support to cope with the illness and its proper treatment. There has been an emerging surge in the adoption of different Deep Learning (DL) architectures in BC research. Researchers use CNN and hybrid methods using various image datasets such as MRI, mammography, and ultrasound in the application of BC detection. The foremost objective being dual-fold, namely: achieve early detection and precise diagnosis. Early diagnosis aims at improving patient care and required medical intervention, hence improving health outcomes. By conducting an extensive review of the literature, we realized that many research articles on the subject of breast cancer detection.

Our review has recognized over 25 papers that are very relevant in this area. In our review, we have comprehensively examined the datasets, the proposed architectural frameworks, and the performance metrics used in each study. Our work is driven by the purpose of relating the most effective model that would help to identify BC accurately. In particular, we conducted a comparative study to identify the advantage of the Convolutional Neural Networks (CNN) and Vision Transformers (ViT) which are both essential in the topic of the image classification.

Application of DL models to preventive analysis has contributed greatly to cancer diagnosis and classification because it facilitates the automatic extraction of complicated patterns in medical image data.

DL techniques specifically convolutional neural networks (CNNs) and vision transformers (ViTs) can be used to diagnose breast cancer (BC) early and accurately, resulting in improved diagnostic performance and patient outcomes. The models are effective in deriving complex features out of multimodal data that include Magnetic Resonance Imaging (MRI) scans and consequently come up with a sound and accurate computer-aided diagnostic tool. Not only have they simplified the detection of tumours using novel DL architectures, but they have changed the medical imaging into a data-driven diagnosis [1], [2]. The recent literature has developed more advanced deep learning models to predict and classify breast cancer. CAD systems based on Vision Transformer architectures and improved CNN models such as DeepBreastCancerNet and DenseXtNet have been able to achieve accuracy figures of more than 99% [1]-[3]. Ensemble CNN and Mask R-CNN models are useful in enhancing the classification of lesions in MRI and prove that the methods based on the use of DLs perform better than other diagnostic tools in terms of reliability and accuracy [4], [5].

A large number of studies have used different deep learning models and imaging methods in the diagnosis and classification of BC. MRI datasets allow researchers to use the designed models such as BCCNN, BPBRW with the HKH-ABO optimization, DLA-EABA, and 3D CNN model, with the highest accuracy of 99.6% [9], [10], [13], [20]. Other works used mammography images, including hybrid CNN-BiLSTM, pretrained DL models with PCNNs, and the GAN-HOG method, with the highest accuracy of 98.77% [12], [14], [15]. Similarly, ultrasound-focused approaches such as ensemble meta-models, BreastUS transformer networks, and two-layer DNNs with VGG16 features demonstrated great results with an accuracy rate of about 90% [16], [21], [23]. In addition, two-network orthogonal low-rank learning with deployed pre-trained CNNs and E-SVM classifiers attained an accuracy of 97.7% on histologic images [22], and the ViT-DeiT model achieved an accuracy of 98.17% on histopathology images [24].

II. DL METHODS FOR BC CLASSIFICATION

Aggressive application of deep learning models to preventive analysis has develop advances in several types of cancer detection and classification. Deep-learning is an algorithm method of determining the complex trends of medical imagery. DL enhances the accuracy and effectiveness of diagnosis to a great extent. The BC the DL techniques are useful in the context of BC with early and precise identification and subsequent prompt intervention thus benefiting the patient in the end.

Deep Learning models of cancer diagnosis involve complicated procedures that involve convolutional neural networks (CNN) and visual transformation (ViT). These models take advantage of the fact that they extract multifaceted characteristics of varied data sets, especially brain magnetic resonance imaging (MRI) scans at different angles. Modern technology also enhances precision in the detection of the tumor and also plays a significant role in the construction of an outstanding and dependable diagnostic instrument.

A. Convolutional Neural Network (CNN)-based Models

Related to the medical imaging modalities like MRI, mammography, and ultrasound Convolutional Neural Networks represent the most widely used approach for the diagnosis of breast cancer. The studies [1]–[5], [9], [10], [13], and [20] were able to illustrate that CNN-based architectures can effectively detect lesions and classify tumor types into benign and malignant ones. The popular models involve BCCNN [9], which classified breast tumors into eight categories using various architectures such as Xception, InceptionV3, VGG16, MobileNet, and ResNet50, and a 3D CNN model [20] used for MRI-based detection of breast cancer. Similarly, DeepBreastCancerNet [2] was developed to combine convolution and inception modules with batch and cross-channel normalizations and yielded an accuracy of 99.35%. These CNN-based approaches show high precision in feature extraction and could provide the fundamental blocks of computer-aided automatic diagnosis of breast cancer.

B. Vision Transformer (ViT)-based Models

Recently, ViT models, which exploit attention mechanisms in an attempt to acquire global contextual information from medical images, have emerged as strong competitors to CNNs. Applications of ViT-based architectures for Computer-Aided diagnosis in the field of BC have utilized both ultrasound and histopathology images. The ViT-DeiT model [24] revealed an accuracy of 98.17% when classifying breast histopathology images as either benign or malignant. Similarly, BreastUS transformer models [21] realized strong performance on ultrasound datasets, further confirming transformer-based networks as suitable for visual understanding in oncology. Examples of such models include the following. They show that transformer architectures are gaining more importance toward better diagnosis interpretability and generalization.

C. Generative Adversarial Network (GAN)-Based Models

GANs have also been applied for the detection of BC by generating synthetic images and extracting features. [15] Introduced the GAN-HOG (Generative Adversarial Networks - histogram of oriented gradients) model, specifically designed for detecting and diagnosing breast cancer and out of all the approaches examined, this model performed and exhibited highest accuracy. GAN-based approaches are helpful for better data augmentation, enhanced visualization of lesions, and balancing of training datasets, which, in turn, could contribute to increasing the accuracy and robustness in classification performance for medical imaging applications.

D. Hybrid and Ensemble Deep Learning Models

Hybrid and Ensemble Learning techniques incorporate the strengths of several architectures for better predictive performance. Examples include the 99.6% accuracy achieved in MRI datasets by the Back Propagation Boosting Recurrent Wienmed model integrated with the Hybrid Krill Herd–African Buffalo Optimization mechanism [10], the enhancement in early detection by ensemble classification through the Deep Learning–Assisted Efficient AdaBoost Algorithm [13], and the hybrid CNN–BiLSTM[12], U-Net–VGG19[6], and ensemble meta-classifiers [8] that attained accuracies greater than 95%. This is how such combinations take full advantage of transfer learning, optimization algorithms, and multiple feature extractors to become more reliable and adaptive across different imaging modalities.

III. PERFORMANCE COMPARISON OF DL MODELS FOR BC CLASSIFICATION

A comparative review of different deep learning architectures has shown that the performance of a model for breast cancer classification highly depends on the quality of the data set, modality of images, and optimized hyperparameters, such as activation functions, filter size, loss functions, and network depth. Hybrid and ensemble models are mostly superior to traditional CNN architectures with better accuracy and stability. Models using the ViT have also shown outstanding precision and generalization capability; therefore, this might be a very promising direction for future research in automated BC detection.

TABLE I. PERFORMANCE OF DL MODELS ON BC CLASSIFICATION

References	Architecture	Accuracy	Precision	Recall	F1 Score
Azaf Raza[4]	DeepBreastNET of 24 layers	99.35	99.60	99.66	99.60
Alshehri[5]	DenseNet and optimized ResNeXt,	98.0	90.9	95.2	93.0
Yang Zhang [8]	Mask R-CNN., ResNet50	95.0	-	-	-
Silva [9]	VGG19, CustomNet, MobileNetV3Large, U-Net VGG-19	95.65	-	-	-
Zabit Hameed [10]	Xception Model	98.0	96.0	97.0	97.0
Abhishek Das [11]	CNN, CNN with EWT, CNN with VMD meta data	98.08	98.4	99.2	98.8
Abunasser [12]	CNN	98.30	98.39	98.30	98.28
Dewangan [13]	BPBRW with HKH-ABO	99.6	100	99.9	-
Abunasser [14]	Xception Model	97.6	97.60	97.60	97.58
Aslan [15]	CNN, BiLSTM	98.56	98.36	98.82	98.56
JING ZHENG [16]	DLA-EABA	97.2	-	-	-
Meteb M. Altaf [17]	PCNN	98.72	-	-	-
Anitha Ponraj [18]	GAN-HOG	98.43	-	-	-
Jyoti Kundale [20]	GoogLeNet+CNN	94.0	63.42	61.47	61.66
Zabit Hameed [21]	Full trainedVGG16+VGG19				
Fine-Tuned VGG16+VGG19	95.29	-	-	95.29	
Aljuaid [22]	ResNet, Inceptio-V3Net, ShuffleNet	97.81	-	-	-
Muhammad Saad [24]	Vision Transformer	97.0	97.0	97.0	96.0
WANG [25]	E-SVM	97.7	84.53	83.49	84.01
Hossain [26]	Transfer learning with VGG16	98.2	-	-	89.0
Amira Alotaibi [27]	ViT-DeiT	98.17	98.18	98.08	98.12

Table I indicates the comparison of several deep learning architectures applied for BC classification in various works. The DeepBreastNET developed by Azaf Raza [4] recorded the highest performance: accuracy 99.35%, precision 99.60%, recall 99.66%, and 99.60% F1-score. It indicates its strength in feature extraction and classification. The BPBRW model optimized using the HKH-ABO algorithm, by Dewangan [13], also resulted in an outstanding performance of 99.6% accuracy, indicating the potential of hybrid optimization mechanisms in

medical image analysis. Also, various other CNN-based models, including Abunasser [12] and Aslan [15], have shown very high accuracy levels of above 98% that culminates the performance of convolutional networks in BC image detection and classification.

Among transformer-based models, the best performances were recorded by the Vision Transformer of Muhammad Saad [24] and the ViT-DeiT architecture by Amira Alotaibi [27], which achieved generalization results with 97.0% and 98.17% accuracies, respectively. The GAN-HOG model of Anitha Ponraj [18], followed by the DLA-EABA algorithm by Jing Zheng [16], therefore contributed to high diagnostic precision at about 98% accuracy. Traditional or hybrid CNN variants, on the other hand, represented by GoogLeNet+CNN [20] and E-SVM [25], attained relatively lower classification performances at 94%–97.7%. This leads to the conclusion that DL models based on Transfer Learning and transformer networks are much better at classifying breast cancer. Indeed, these findings have verified that deep learning approaches pertaining specifically to hybrid CNNs and Vision Transformers have repeatedly yielded high diagnostic precision, precision, and reliability in detecting the presence of breast cancer early.

A. Performance Comparison of CNN and ViT on Two Class dataset

The input training dataset from Kaggle consists of images labeled with two different classes. The classifier is trained on this dataset to learn each class and evaluate the performance on a new dataset to predict the label for these two classes. The metrics such as accuracy, precision, recall and F1-score are used to show the model's performance. Taking into account the results of quantitative analysis, it will be possible to evaluate the performance of CNN model on two classes in a complex manner.

The classification report shows a comprehensive summary of the performance of the model in classification of two classes. The overall result of the classifiers demonstrates that the model achieved the accuracy of 99% i.e. it predicts 99 out of the 100 instances properly. Moreover, it is reported that ViT model provides a balanced score on all other measures. The fact that the high accuracy indicates that the model is accurate in terms of predicting between two classes which implied that the model has vigorous classification abilities. The performance demonstrates that ViT model is more precise in comparison to the CNN one.

TABLE II. CLASSIFICATION PERFORMANCE OF CNN MODEL

Class	Precision	Recall	F1-Score	Accuracy
0	0.94	0.95	0.95	
1	0.95	0.94	0.94	0.95

TABLE III. CLASSIFICATION PERFORMANCE OF ViT MODEL

Class	Precision	Recall	F1-Score	Accuracy
0	0.99	0.99	0.99	
1	0.99	0.99	0.99	0.99

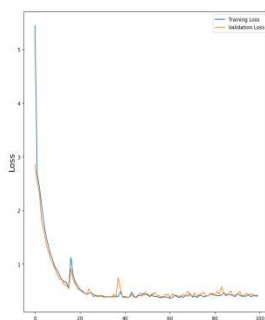


Fig.1 Performance of CNN

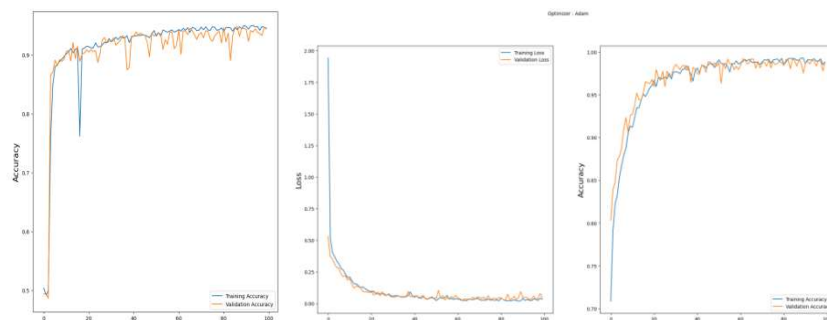


Fig.2 Performance of ViT

Tables II and III indicate the performance of two DL models in classification, in which Model 1 achieved a total accuracy of 95% and therefore, it accurately classified the images reliably well, and its precision and recall of the two classes were good. It was outperformed by model 2 with 99% accuracy showing high consistency in terms of precision, recall and F1-score of each of the classes and hence better generalization and strength with respect to breast cancer classification.

IV. CONCLUSIONS

In our research, we have critically examined a number of studies that applied the DL models to diagnose and classify BC. The literature review indicated the presence of CNN models to categorize breast cancer (BC), but ViT applications were less represented. The most preferred type of CNN-based models were mostly used in the research studies. Consequently, we have conducted a comprehensive comparison to analyze the performance of CNN and ViT models on many datasets. The training and testing of CNN and ViT models is part of the implementation. Our findings indicate that ViT model was able to perform at an impressive level on various datasets. Nonetheless, CNN performed better than ViT in cross-dataset testing, which is the comparison of models that were trained on one dataset with another dataset. These findings resulted in the appearance of a hybrid model that unites the strengths of the CNN and ViT architectures. We plan to build a hybrid architecture which can integrate the merits of CNN and ViT architecture in the future, retaining the particular benefits of both

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