Breast Cancer Detection Based on Hybrid Deep Learning Models

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***Abstract*— Early breast cancer diagnosis and detection are very important. It may greatly enhance treatment results and save a life. The absence of early cancer signs makes early identification challenging. Cancer continues to be one of the health subjects that many researchers work to advance. This study proposed a new hybrid model for classifying breast cancer images. The proposed framework consists of preprocessing stage and the proposed two models stage. For the preprocessing, we downsized every image from its original 50x50 to 32x32 pixel size, rotating and flipping all positive images for the Histology Images. The proposed hybrid model consists of a CNN model created from scratch and transfer learning based on EfficientNetB0 (CNN+ EfficientNetB0) to classify Invasive ductal carcinoma (IDC) into benign and malignant. According to tests, the CNN + EfficientNetB0 model has the highest accuracy compared to the other deep learning models. This model achieves 96% accuracy, 95% precision, 82.5% recall, and 88.3% F1- score.**

Keywords*— *Invasive Ductal Carcinoma, Breast Cancer, Deep learning, Data Processing, Pre-trained Model.

I. INTRODUCTION

Breast cancer comes in second place after lung cancer and is one of the leading cancers for women [1-2]. The World Health Organization predicts that 2.3 M women will be diagnosed with breast cancer worldwide in 2020 and that 685 000 will die. By the end of 2020, there will have been 7.8 million women diagnosed with breast cancer in the preceding 5 years, making it the most prevalent cancer globally. Breast cancer accounts for one in every four cancer cases and one in every six cancer fatalities [3-4]. The survival rate can be increased by as much as 80% through early detection and accurate diagnosis [5-6]. Invasive ductal carcinoma (IDC) is the subtype of breast cancer that is most common, comprising almost 80% of them [7-8].

Medical imaging has increasingly utilized deep learning technology in recent years. In general, deep learning has been employed for disease diagnosis and detection. Convolution Neural Network (CNN) architectures are among the most remarkable classifiers due to their accuracy in classification and feature extraction [9-10]. They can aid a radiologist in reducing the time and effort required for interpreting BC-IDC images and providing a second opinion for disease diagnosis. We conducted transfer learning on deep learning models that produced the best results and had higher efficiency in classifying 1000 classes of the ImageNet dataset, such as the EfficientNetB0 architecture, which accepts input with image resolutions ranging from 32x32 to 224x224. Because EfficientNetB0 has 5.3 M parameters, it is the smallest model and will be employed in this study [11,12].

This research presents a novel artificial intelligence (AI) method for breast cancer detection. Therefore, the significance of our research rests in incorporating a deep-learning model for breast cancer tumor detection. The following are the main contributions of the current research:

- Suggest a CNN model and a new hybrid model that combines CNN with the EfficientNetB0 for identifying breast cancer. Compared to other learning approaches, performance was acceptable for identifying BC-IDC tissues in breast cancer whole slide images (WSI).
- Due to the imbalanced data size of the dataset, we utilized and applied flip and rotate modifications to the training images that were already accessible.
- Analyzing and contrasting the suggested model's performance with other deep learning models to demonstrate how much better or more effective in accuracy, precision, recall, and F1-Score.
- Using the information from the pre-trained model to improve the detection and classification of IDC (+, -) tissues in the histology images dataset.

The rest of this paper is organized as follows. The literature review is explained in Section 2. The proposed framework is represented in Section 3. After that, Section 4 represents the experimental result. Finally, the conclusion and future works are presented in Section 5.

II. RELATED WORK

An overview of earlier research on breast cancer diagnosis is presented in this section. Healthcare systems use a variety of deep learning techniques. Deep learning may be used to identify diseases using visual data. Convolutional neural networks (CNN) were employed in this study to extract features.

Gupta et al. [13] presented a technique for categorizing BC-IDC in the histology images into IDC (+) or IDC (-) based on deep learning. Convolutional Neural Networks (CNN) of 10, 19, and 20 layers were employed in this model. According to the experimental research, a 19-layer_CNN model has a high accuracy of 87% compared to alternative designs. On a portion of the whole dataset, this strategy employed CNNs. In order to address the issue of class imbalance, Barsha et al. [14] proposed a model to identify IDC breast cancer based on DenseNet-121, DenseNet-169 and Test time augmentation (TTA) was then applied to the images with an accuracy of 92.70%. This model offered several pre-trained architectures. Humayun et al. [15] provide a deep-learning model for forecasting breast cancer risk. Transfer learning is the foundation of the suggested technique. The experiment achieved 91% accuracy, which helped to enhance the classifying process. Two deep-learning techniques were presented by Abdolahi et al. [16] for classifying IDC in histopathology images. Train a simple CNN called baseline model on these images as part of the first technique. The second method classified breast pathology images using feature extraction and fine-tuning on the pre-trained VGG-16 model. For the automated classification of IDC (+, -), the baseline model performed better with an accuracy of 85%. With large amounts of data, this approach could perform better and be robust. A technique for the automated identification of IDC-based MSRCNN-SVM was put out by Zhang et al. [17]. The WSI is separated into patches based on coordinates after the data augmentation and normalization as pre-processing. For feature extraction, the patches are entered into MSRCNN. The IDC (+) and IDC (-) regions are then shown on the WSI once the features have been input into the SVM for classification. The MSRCNN-SVM model automatically detected IDC by classifying tiny slices with an average accuracy of 87.45. Working with huge data yielded poor accuracy for this strategy. In order to accomplish the pre-processing, Wang et al. [18] introduced a hybrid model (CNN-GRU) based on deep learning for the automated identification of BC-IDC (+, -) using whole slide images (WSIs). The accuracy of the performance indicator is 86.21%. ResNet-50 and DenseNet-161 are two deep-learning models that have already been trained by Celik et al. [19]. The Automated Detection of Invasive Ductal Carcinoma (IDC) for experimental research employed the histopathology dataset, and the first model produced accuracy values of 91.57% and 90.96% utilizing ResNet-50 architecture. Singh et al. [20] presented a hybrid model for studying histopathology images, which aids early diagnosis, and combines classic machine learning techniques with transfer learning. The combination of the DenseNet and Logistic Regression experiment produced an F1-score of 81%. Using a Convolutional Neural Network (CNN) as a classifier, Kundale et al. [21] offered a comparison of two approaches: the first is feature extraction using a traditional handcrafted based model, and the other is a transfer learning-based model (Pre-trained). VGG16, VGG19, ResNet50, and GoogLeNet were utilized in the pre-trained model to extract features, and the pre-trained GoogLeNet+ CNN model provided 94% accuracy.

Traditional methods may not effectively analyze large volumes of medical data, leading to time-consuming and inefficient diagnosis processes. In contrast, the proposed methods utilize computer-aided detection and diagnosis (CAD) algorithms, which are capable of efficiently analyzing whole slide images (WSIs) for the presence of invasive ductal carcinoma (IDC). This enables the timely and accurate detection of positive (IDC) and negative (non-IDC) tissue, enhancing the overall efficiency of the diagnosis process.

Furthermore, previous methods may need help to achieve high accuracy rates and avoid false positives or negatives. The proposed methods tackle this challenge by employing convolutional neural networks (CNNs) as the underlying model. CNNs are renowned for extracting meaningful features from medical images, leading to improved accuracy in classification tasks.

The proposed work consists of two models; the first is a CNN model created from scratch, and the second model combines CNN with pre-trained deep learning architecture to enhance the classification performance of IDC or non-IDC and aid radiologists in identifying breast cancer from BC-IDC images to overcome the abovementioned problems. The suggested approaches also perform better than existing algorithms.

III. Proposed Framework

The proposed framework uses two models the CNN architecture only and CNN with the pre-trained model. The proposed framework is shown in Fig. 1. The proposed work consists of two models the first is a CNN model created from scratch, and the second model integrates CNN with the transfer learning method used by EfficientNetB0 to classify IDC (-) and IDC (+). Deep learning methods have significantly advanced in the area of tumor classification. This work evaluated the suggested model's performance on breast histopathology images with existing Deep Learning Models.

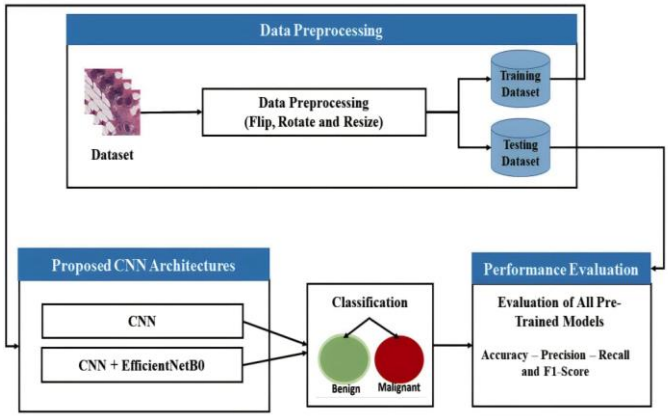

Fig. 1. Proposed framework for classification BC-IDC based on deep learning architecture

A. Breast Cancer Histology Dataset

In this research, the dataset used to assess the effectiveness of the suggested framework was taken from the Kaggle website [22]. The collection included 162 breast cancer whole mount slide images, each of which had 277,524 images of size 50 x 50 pixels separated into 78,786 IDC (+) and 198,738 IDC (-) and scanned at 40 X. We divided the test sample, choosing 30% of the images for testing and 70% for training.

B. Data Preprocessing

Dealing with imbalanced datasets is a common challenge in breast cancer detection, where the number of positive cases (invasive ductal carcinoma) is often significantly lower than the number of negative cases (non-IDC). This class imbalance can negatively impact the performance of machine learning models, as they tend to favor the majority class and struggle to accurately classify the minority class. Data augmentation techniques are employed to augment the samples in the low-number class to address this issue. In the proposed methods, data augmentation is applied specifically to the positive (IDC) images to increase their diversity and quantity. By using techniques such as rotation and flipping, the dataset for the positive class is expanded, thereby balancing the distribution of positive and negative samples. This augmented dataset helps to alleviate the class imbalance problem. It enables the models to learn more effectively from the available data, improving classification performance and more accurate detection of invasive ductal carcinoma.

This stage will be divided into two steps: resizing and augmentation. First, we downsized every image from its original 50x50 to 32x32 pixel size because the large data volume affects the computational resources of the Colab and makes the RAM full; therefore, we had to repeat the training from the beginning, so we reduced the dimensions of the images to avoid this problem and downsizing the images can help mitigate overfitting. Data preparation is one method for lowering the computational complexity of the models. We performed image augmentation in the second step by rotating and flipping all positive images. The class imbalance between positive and negative cases was addressed using this approach. We raised the positive images in the dataset and enhanced the accuracy and dependability of the model's predictions by flipping and rotating the positive images.

C. The First Model (CNN)

The proposed CNN model was created from scratch. The input image for the first model is 32 x 32 pixels, with 1,242,770 parameters. The summary of CNN architecture consists of the following:

- Convolutional Layer 1: `model_1 = Convolution2D(32, (3,3),padding='same'), this layer performs a 2D convolution operation with 32 filters of size 3x3 on the input image and the 'same' padding ensures that the spatial dimensions of the input and output feature maps remain the same.
- Activation Function 1: `model_1 = Activation('Relu'),` the Rectified Linear Unit (ReLU) activation function is applied to allow the model to perform better and learn faster.
- Batch Normalization 1: `model_1 = BatchNormalization()` helps stabilize the learning process by bringing the activations within a similar range.
- Convolutional Layer 2: `model_1 = Convolution2D(32, (3, 3),padding='same'),` another convolutional layer with 32 filters of size 3x3 is applied to the previous output. The 'same' padding is used to maintain the spatial dimensions.
- Batch Normalization 2: `model_1 = BatchNormalization()` is applied to the output of the second convolutional layer.
- Activation Function 2: `model_1 = Activation('Relu')` is applied to the output of the second batch normalization layer.
- Max Pooling Layer: `model_1 = MaxPooling2D(pool_size=(2, 2),padding='same')` is performed on the previous output. Max pooling downsamples the feature map by taking the maximum value within each pooling window. The 'same' padding is used to maintain the spatial dimensions. A dropout rate of 0.2 is applied to the output of the max pooling layer, which helps prevent overfitting.

The above steps are then repeated to add convolutional layers, batch normalization layers, activation functions, max-pooling layers, and dropout layers. The filters gradually increase, starting from 32 and doubling to 64, 128, and 256. The padding used is 'the same' to maintain the spatial dimensions, and the dropout rate of 0.2 is consistently applied to each dropout layer.

Finally, the output of the last convolutional layer is flattened into a 1D vector using the `Flatten()` operation and passed through two dense layers with 64 and 16 units, respectively, and a SoftMax activation function for BC-IDC classification into IDC(+) or IDC(-).

D. The Second Hybrid Model (CNN + EfficientNetB0)

The proposed hybrid model consists of a CNN and transfer learning based on EfficientNetB0 (CNN+ EfficientNetB0). The input image for the second model is 32 x 32 pixels, with 5,374,261 parameters. The summary of the proposed hybrid model is shown in Table I. The customized CNN model architecture consists of multiple convolutional layers, activation functions, batch normalization, and max pooling operations. The model starts with a convolutional layer with 32 filters and a kernel size (3, 3). A ReLU activation function and batch normalization follow it. Another convolutional layer with 32 filters and a kernel size of (3, 3) is applied, followed by batch normalization and ReLU activation. Max pooling with a pool size of (2, 2) and padding is then performed. Dropout regularization with a rate of 0.2 is applied.

This model continues with additional layers following a similar pattern. It includes convolutional layers with increasing numbers of filters (64, 128, and 256) and corresponding batch normalization and ReLU activation functions. Dropout is applied after each convolutional layer. Max pooling is performed after the 64 and 128 filter layers, and the 256 filter layer is followed by a convolutional layer with 256 filters and batch normalization. ReLU activation and dropout are applied again before max pooling with a pool size of (2, 2), padding same, and stride 1. Finally, a flattened layer transforms the output into a vector representation for further processing in subsequent layers.

Conversely, the EfficientNetB0 [23] is a pre-trained model to benefit from the previously learned pre-trained experience and weights. The EfficientNetB0 has 28 layers, including 13 convolutional layers, 10 pooling layers, and 5 fully connected layers. The convolutional layers use a depth-wise separable convolution, which reduces the number of

parameters and computation required. The pooling layers use max pooling, a simple and efficient operation. For binary classification, the output from each branch is combined and sent through two dense layers and a SoftMax activation function. The binary cross-entropy loss function and the Adam optimizer are used to train the model. Fig. 2 is the first and last portion of the second proposed hybrid model that shows visualization between combining the CNN model with the EfficientNetB0 model.

The proposed hybrid method achieved the highest accuracy by leveraging several key techniques and model architectures. Firstly, utilizing a hybrid model that combines a convolutional neural network (CNN) and the EfficientNetB0 model allowed for the extraction of powerful and discriminative features from breast cancer images. The CNN part of the model employed multiple convolutional layers with different filter sizes, activation functions, batch normalization, and max pooling operations. This architecture enabled the model to learn complex spatial patterns and capture important features relevant to breast cancer detection.

Additionally, integrating the EfficientNetB0 model, one of the state-of-the-art pre-trained models, further enhanced the performance of the proposed hybrid method. The EfficientNetB0 model acted as a feature extractor, capturing high-level representations and semantic information from the input images. By leveraging the pre-trained weights of the EfficientNetB0 model, the proposed hybrid method benefited from transfer learning and avoided the need to train the entire model from scratch; this led to faster convergence and improved accuracy.

Both the feature vector from the EfficientNetB0 model and the output of the CNN part are concatenated together. This combined representation is passed through two fully connected layers with sigmoid activation functions. The final output layer consists of two units with softmax activation, representing the binary classification of breast cancer.

Furthermore, data augmentation techniques were applied to address the challenge of imbalanced datasets. Specifically, augmentation was performed on the low number class to artificially increase the number of samples, thereby balancing the dataset. This approach helped prevent the model from being biased toward the majority class and improved its ability to accurately classify both classes.

Moreover, the proposed methods used advanced optimization algorithms, such as the Adam optimizer with tuned hyperparameters, to efficiently update the model's parameters during training. This optimization technique helped the model to converge faster and reach a more optimal solution.

Lastly, comprehensive evaluation metrics, including accuracy, precision, recall curve and F1-score, were employed to assess the performance of the proposed methods. By considering multiple evaluation metrics, the authors thoroughly analyzed the model's performance. They demonstrated the hybrid model's superiority in achieving high accuracy compared to previous breast cancer detection methods.

Collectively, the combination of a hybrid model, leveraging both CNNs and the EfficientNetB0 model, data augmentation techniques, advanced optimization algorithms, and comprehensive evaluation metrics contributed to the highest accuracy achieved by the hybrid model.

TABLE I. THE SUMMARY OF SECOND PROPOSED HYBRID MODEL

Layers	**K_Size**	**Input**	**Act_Function**	**Output**
Conv2d_1	3 X 3	(32,32,3)	Relu	(32,32,32)
Dropout = 0.2	-----	(32,32,32)	-----	(32,32,32)
Conv2d_2	3 X 3	(32,32,32)	Relu	(32,32,32)
Max_pooling_1	2 X 2	(32,32,32)	-----	(16,16,32)
Dropout = 0.2	-----	(16,16,32)	-----	(16,16,32)
Conv2d_3	3 X 3	(16,16,32)	Relu	(16,16,64)
Dropout = 0.2	-----	(16,16,64)	-----	(16,16,64)
Conv2d_4	3 X 3	(16,16,64)	Relu	(16,16,64)
Max_pooling_2	2 X 2	(16,16,64)	-----	(8,8,64)
Dropout = 0.2	-----	(8,8,64)	-----	(8,8,64)
Conv2d_5	3 X 3	(8,8,64)	Relu	(8,8,128)
Dropout = 0.2	2 X 2	(8,8,128)	-----	(8,8,128)
Conv2d_6	3 X 3	(8,8,128)	Relu	(8,8,128)
Max_pooling_3	2 X 2	(8,8,128)	-----	(4,4,128)
Dropout = 0.2	-----	(4,4,128)	-----	(4,4,128)
Conv2d_7	3 X 3	(4,4,128)	Relu	(4,4,256)
Dropout = 0.2	-----	(4,4,256)	-----	(4,4,256)
Conv2d_8	3 X 3	(4,4,256)	Relu	(4,4,256)
Max_pooling_4	2 X 2	(4,4,256)	-----	(2,2,256)
Dropout = 0.2	-----	(2,2,256)	-----	(2,2,256)
Flatten_CNN	-----	(2,2,256)	-----	1024
Flatten_1 eff	-----	(1,1,1280)	-----	1280
Concatenate	-----	(1024,1280)	-----	2304
Dense1	-----	2304	Sigmoid	64
Dense2	-----	64	Sigmoid	16
Output Dense3	-----	16	Softmax	2

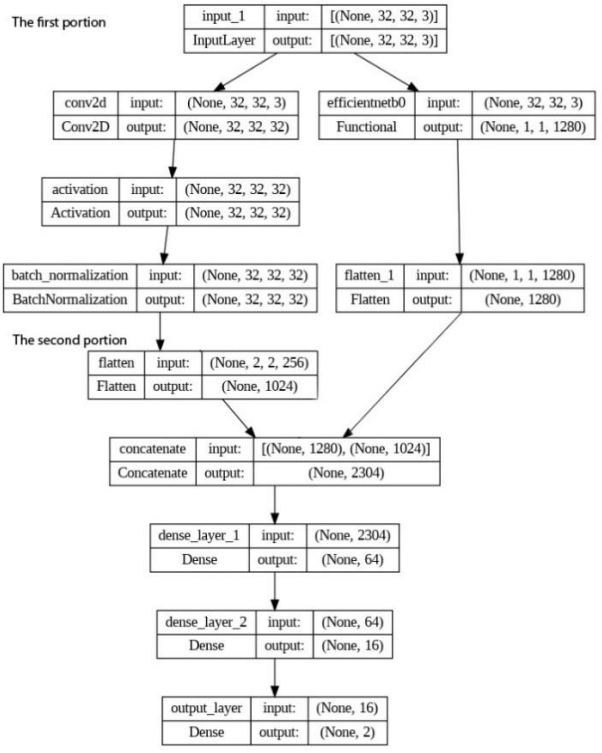

Fig. 2. The first and last portion of the second proposed hybrid model

IV. EXPERIMENTAL SETUP

This model was executed using Tensorflow with the Keras package in Python. We evaluated the suggested model using the IDC datasets. Then, we compared the suggested model with previous work. The experiment's configuration used a Tesla K80 GPU and 12 GB of RAM, disk space of about 78 GB, which was run on Google Colab. The training

time for the CNN model took about 2 hours, and the hybrid model took about 3 to 3.5 hours. To test out our models, we calculate the following evolutions metrics:

$$P = \frac{TP}{TP + FP} \quad (1)$$

$$R = \frac{TP}{TP + FN} \quad (2)$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$F1\_Score = 2 * \frac{P * R}{P + R} \quad (4)$$

Where P= Precision, R= Recall, ACC= Accuracy and F1-Score, True Positives=TP, False Positives=FP, False Negatives=FN, True Negatives =TN.

V. Results and Analysis

The experimental study was conducted by the CNN model and hybrid deep learning model CNN+EfficientNetB0. The results of these models were compared using a histology dataset. Fig. 3 shows the accuracy curve; Fig. 4 shows the loss curve of the CNN model; Fig. 5 shows the accuracy curve; Fig. 6 shows the loss curve of the hybrid model, and Fig. 7 shows the performance analysis of this model during prediction.

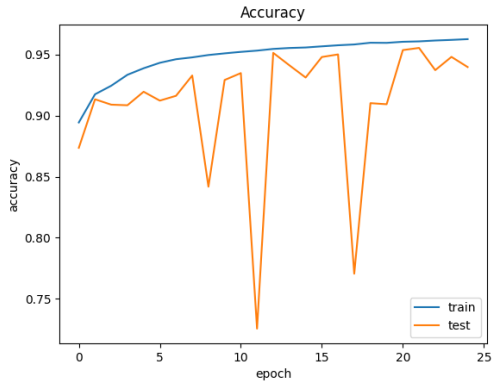

Fig. 3. The accuracy curve of CNN model

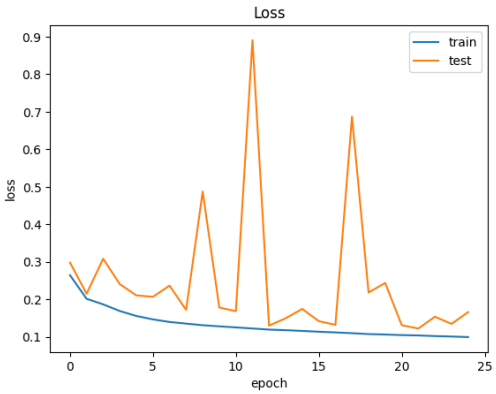

Fig. 4. The loss curve of CNN model

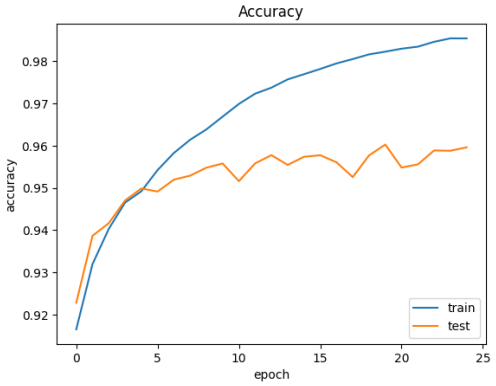

Fig. 5. The accuracy curve of hybrid model (CNN+EfficientNetB0)

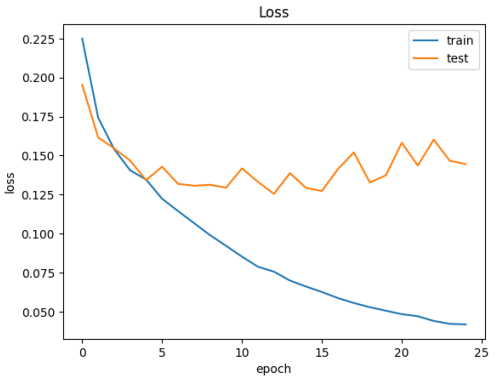

Fig. 6. The loss curve of hybrid model (CNN+EfficientNetB0)

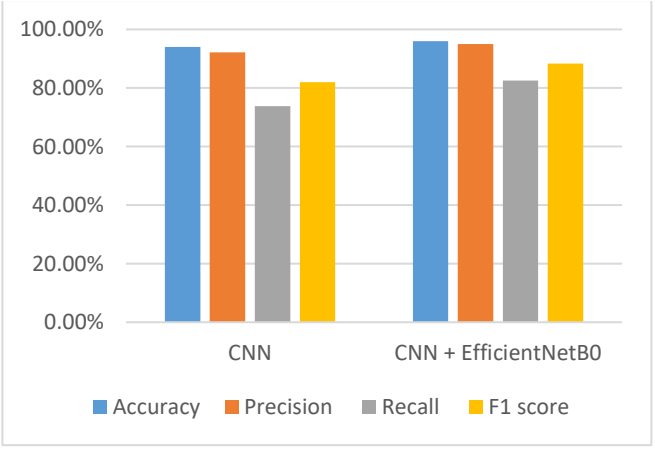

Fig. 7. The performance analysis of the proposed models

The outcomes demonstrate the accuracy of the CNN + EfficientNetB0 model, which is 96%, Precision of 95%, Recall of 82.50%, and F1 score of 88.30%.

The confusion matrix shows the classification results of IDC (+, -) where the achieved Predicted model 104614 IDC (-) and already IDC (-). Fig. 8 shows it as follows: predict 3442 IDC (-) but is IDC (+), predict 1662 IDC but is IDC (-) and predict 20811 IDC (+) and already IDC (+). The results demonstrate how effective the CNN + EfficientNetB0 model.

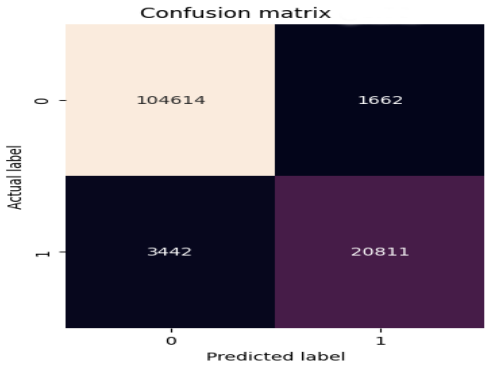

Fig. 8. The Confusion Matrix

According to tests, the CNN + EfficientNetB0 model has the highest accuracy compared with the CNN model and the other deep learning models, as shown in Table II. Our performance's accuracy, precision, recall, and F1-Score are 96%, 95%, 82.50%, and 88.30%, respectively.

TABLE II. PERFORMANCE COMPARISON BETWEEN THE PROPOSED MODEL WITH EARLIER MODELS USING BC-IDC DATABASE

Author	Approach	Accuracy
Gupta et al. [13]	CNN	87%
Barsha et al. [14]	DenseNet-121 and DenseNet-169	92.70%
Humayun et al. [15]	InceptionResNetV2	91%
Abdolahi et al. [16]	CNN	85%
Zhang et al. [17]	Alexnet, MobilenetV2, and Resnet50	87.45%
Wang et al. [18]	CNN-GRU	86.21%
Celik et al. [19]	ResNet-50 and DenseNet-161	91.57%
Singh et al. [20]	DenseNet + Logistic Regression	81%
Kundale et al. [21]	GoogLeNet+ CNN	94%
First Model	CNN	94%
Second Hybrid Model	CNN + EfficientNetB0	96%

VI. DISCUSSION

From the previous results mentioned in section V, we can observe that the second proposed method (the combination of CNN and EfficientNetB0) achieved better accuracies than the first method (the CNN) using the histology images dataset. Therefore, we confirmed the second method to be our method. We can also observe from the results that the second method obtained high accuracy of 96% on histology images, making it more robust and efficient than other deep learning methods.

A. Limitations of the second Proposed hybrid Method

While the proposed second method presents several advantages for breast cancer detection and classification, it is important to acknowledge its limitations. These limitations include:

- Dataset Bias: The performance of any machine learning model heavily relies on the quality and representativeness of the training dataset. If the training dataset is biased or limited in terms of diversity, the proposed hybrid method may inherit these limitations. It is crucial to ensure that the training dataset is diverse and balanced to mitigate potential biases.
- Computational Requirements: Hybrid models, especially those incorporating large-scale pre-trained models like EfficientNetB0, can be computationally demanding during training and inference. The increased number of layers and parameters may require substantial computational resources, including high-performance GPUs or specialized hardware, which could limit the accessibility and feasibility of the proposed hybrid method in resource-constrained environments.
- Hybrid models often involve a combination of different architectures, each with its own set of hyperparameters. Tuning these hyperparameters effectively can be challenging, requiring extensive experimentation and computational resources, and suboptimal choices may lead to subpar results.
- Lack of Clinical Validation: While the proposed hybrid method shows promising results in accuracy and performance metrics, it is crucial to validate its effectiveness and clinical utility in the real world.

VII. CONCLUSION AND FUTURE WORK

CAD solutions enable the patient and the doctor to get a second opinion and greatly assist in the automated decision process in medical images. In this study, we utilize breast cancer images (the histology images dataset) classified as benign and malignant using a CNN model and a new hybrid model based on a customized CNN model with a transfer learning method. According to the comparison, the proposed hybrid model has the highest accuracy compared to CNN and other deep-learning models.

In future work, combining multiple datasets with hand-crafted features will be used to evaluate the proposed framework. Also, combine various pre-trained models such as VGG16, Xception, and MobileNetV2 for breast cancer classification.

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