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Research Article

Performance Comparison of Deep Learning-based Models on Breast Cancer Detection

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Abstract – Breast cancer is one of the most common types of cancer among women and early detection can significantly reduce mortality rates. Traditional methods such as mammography can have difficulties in detecting small and benign tumors and increase the risk of misdiagnosis. This study utilizes artificial intelligence technologies for early detection of breast cancer. Because of this, it uses deep learning models to analyze data from established imaging technologies such as mammography, MRI, and ultrasound, and improved diagnostic accuracy is demonstrated. As a result of the experimental results using Convolutional Neural Networks (CNN), EfficientNet, ResNet, and DenseNet models, the highest success rate was achieved in the CNN model with an accuracy of 84.5%. As a result, this study aims to support and accelerate the process of doctors' evaluation of patients by creating a model with high accuracy, sensitivity, and specificity rates from deep learning models. This will allow diagnosis to become more efficient and accessible while aiming to reduce medical errors and early diagnosis.

Keywords – Breast Cancer, Deep Learning, Mammogram, Cancer Diagnosis, Early Detection

I. INTRODUCTION

Breast cancer is the most common cancer in women worldwide and has a significant impact on global health [1]. According to the 2020 report of the International Agency for Research on Cancer (IARC), both new cancer cases and mortality rates have increased compared to 2018. This shows that the global cancer burden is gradually increasing. 2020 statistics reveal that breast cancer is the most commonly diagnosed cancer with approximately 2.3 million new cases. Breast cancer surpassed lung cancer (11.4%), colorectal cancer (10.0%), prostate cancer (7.3%) and stomach cancer (5.6%). Lung cancer was the leading cause of cancer-related deaths (18%), followed by colorectal (9.4%), liver (8.3%), stomach (7.7%) and breast cancer (6.9%). This data emphasized the critical role of early detection in reducing breast cancer mortality rates and the urgent need to develop effective global cancer control strategies [2].

Radiological imaging techniques, especially mammography, have been widely used in the diagnosis of breast cancer for many years. However, mammograms have sensitivity limitations and some limitations. This can make early detection of cancer difficult, especially in young women and patients with dense breast tissue. This study investigates the use of deep learning models to improve early detection of breast cancer. Deep learning (DL) models have the ability to solve complex problems by learning from large datasets [3].

Researching the literature, Lidia et al. [4] investigated the generalization capabilities of DL models for breast cancer detection across several FFDM datasets, including OPTIMAM, INbreast, and BCDR. Their analysis highlighted the effectiveness of eight object detection models, with Deformable DETR showing the highest generalization with an AUC of 0.79. Yoon and Kim [5] examined the use of DL-based artificial intelligence algorithms on mammography images. These algorithms showed promising results in the quantitative assessment of parenchymal density, breast cancer detection, and risk estimation. In experiments, DL models highly aligned with radiologists' BI-RADS density assessments, showing a 94% concurrence in routine clinical practices. DL algorithms used pixel-based information in mammographic images to detect details missed by the human eye and demonstrated high potential with an overall accuracy rate of 72% in predicting breast cancer risk. Hepsağ et al. [6] conducted a pioneering study in 2017 using the Mammographic Image Analysis Society (Mini-MIAS) and Breast Cancer Digital Repository (BCDR) datasets to examine the effectiveness of DL models with Convolutional Neural Networks (CNN) in breast cancer classification. The study evaluated CNN's capacity to automatically extract features from complex image data and distinguish between benign and malignant lesions. The research findings revealed that when the Mini-MIAS dataset was used, the model exhibited a performance of 68% accuracy, 59% precision, 55% recall, and 57% F-score. Hekler et al. [7] worked on the classification of histopathological melanoma images in Germany. In the study, DL techniques were used, and the results were compared with expert physicians. This research considered an innovative contribution to the field, allowed the evaluation of the precision and effectiveness of DL algorithms. The study used a CNN model built on the pre-trained ResNet50 architecture to train on a dataset of 595 melanoma images. CNN achieved 76% precision, 60% specificity, and 68% accuracy across 11 test cases. In comparison, the group of 11 pathologists participating in the study recorded lower scores, with 51.8% precision, 66.5% specificity, and 59.2% accuracy. Khameneh et al. [8] present an innovative machine-learning solution for the analysis of breast cancer images. This work made a significant contribution to the scientific literature by developing methods for effectively segmenting, classifying, and evaluating complex images. The technique consists of three critical steps. Support vector machine (SVM)-based feature learning classifier is developed to distinguish tumor and stromal regions using superpixel techniques as the first step. Second, membrane structures in the classified epithelial regions were segmented using a CNN. The last step is to combine these segments and make an overall score for each slide. This research, through experiments conducted on 127 slides, has shown that the proposed method exhibits superior performance compared to other DL techniques.

This study applies model analysis and provides a web framework for the detection of breast cancer to assist radiologists and physicians. For this, it is used a dataset consisting of both cancerous and non-cancerous mammography images. Preprocessing steps were applied to the dataset that included extensive measures to remove blur from the images. Models such as DenseNet121, EfficientNetB0, CNN and ResNet50 were selected for training. During the model training phases, the Image Data Generator was used to augment the data, and early stopping techniques were used to prevent overlearning. The contribution of this study:

- Compared to traditional methods, DL-based models can detect subtle details not visible to the naked eye, allowing for earlier detection of cancerous lesions.
- A user-friendly interface significantly speeds up and simplifies the diagnostic process for radiologists and physicians, reducing the risk of misdiagnosis.

The methodology and materials used in the study are described in detail in the second section "Materials and methods". The results of the experimental study are discussed in the third section, while the experimental results are discussed in the fourth section. The final section outlines the conclusions of this study and discusses future research directions.

II. MATERIALS AND METHOD

Studies using artificial intelligence techniques to diagnose breast cancer more effectively and accurately make early diagnosis easier. In this study, it is suggested to detect cancerous cells in mammography images using DL-based models. Used datasets for detection is subjected to processes such as cleaning, removing blur in the image, and adjusting the contrast to increase the likelihood of successful results. Different DL-based models were trained by fine-tuning, and the most successful DL-based model was selected according to the results. The methodology of our system is shown in Figure 1. The success of DL-based models is analyzed through the training-testing phase.

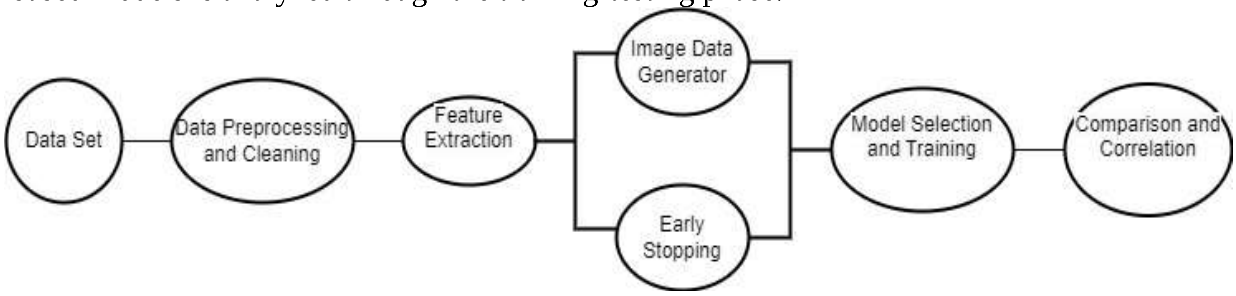

Figure 1. Methodology of this system

DL-based model selection was made by evaluating the "keras.io" site and literature studies. Model selection was made by evaluating the literature studies of the "keras.io". Among the many DL-based models, those listed in Table 1 have been selected [9].

Table 1. The features of the selected model [9]

Model	Size (MB)	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth	Time (ms) per inference step (CPU)	Time (ms) per inference step (GPU)
DenseNet121	33	75.0%	92.3%	8.1M	242	77.1	5.4
EfficientNetB0	29	77.1%	93.3%	5.3M	132	46.0	4.9
Resnet50V2	98	76.0%	93.0%	25.6M	103	45.6	4.4

II.I Dataset

CBIS-DDSM[1] and "Breast Histopathology Images"[2] datasets were utilized in this study. The CBIS-DDSM dataset includes mammogram images that have been converted to DICOM format and are accompanied by ROI masks with pathological outcomes, encompassing normal, benign, and malignant conditions. The other dataset, Breast Histopathology Images contains samples predominantly of invasive ductal carcinoma (IDC), the most common subtype of breast cancer. This dataset is extensively used for the precise delineation of IDC regions, which are crucial for pathologists when classifying the aggressiveness of cancer in breast tissue. Comprising 162 fully assembled slide images scanned at 40x magnification, this dataset provides 277,524 patches; 198,738 are labeled as IDC-negative and 78,786 as IDC-positive. Each patch is identified by file names containing x and y coordinates, enhancing the accuracy of the analysis. Both datasets significantly contribute to the accurate analysis and classification of various breast cancer conditions, supporting the development of enhanced diagnostic and treatment options.

II.II Deep Learning-based Models

II.II.I CNN

The CNN model architecture receives a breast cancer image as input. Convolutional layers identify various features within the image. Max pooling reduces the dimensionality of the feature maps, decreasing computational load while preserving essential information. Flattening transforms these feature maps to be compatible with fully connected layers. These layers utilize the features to classify the image

[1] https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset
[2] https://www.kaggle.com/datasets/paultimothymooney/breast-histopathology-images

as cancerous or non-cancerous. Dropout layers are incorporated to ensure the model is robust against overfitting. The classification process in the final layer employs a SoftMax activation function [10].

II.II.II DenseNET

DenseNet (Densely Connected Convolutional Networks) enhances learning efficiency by increasing the spacing between layers in deep neural networks. Each layer inputs the feature maps from all preceding layers, facilitating the accumulation of information and the reuse of learned features across layers. DenseNet achieves high performance with fewer parameters, making it particularly suitable for medical image processing. In this field, DenseNet excels in capturing details of varying sizes and generalizing effectively due to typically limited datasets [11].

II.II.III EfficientNet

EfficientNet scales network architectures of various sizes (width, depth, resolution) in a unified manner to achieve effective performance enhancement. This architecture is designed to perform well in various tasks and at different scales. EfficientNetB0 is particularly effective for therapeutic image analysis and is loaded with its weights on large datasets like ImageNet. This transfer learning allows the model to adapt to new datasets quickly. The core structure of the model consists of MBConv blocks and feature vectors are obtained through global average pooling. The model yields results with a SoftMax activation function. The training process uses data enhancement changes, learning and speed adjustments, and early stopping rates to prevent overfitting. EfficientNetB0, with its architecture scaled in a balanced manner across depth, width, and resolution, adapts to different types of data packages and computing resources, demonstrating performance. EfficientNet is noted for its programming efficiency and high accuracy rate. Especially in image annotation tasks, it is one of the main reasons for eliminating the preference for high accuracy with less computing resource usage [12].

II.II.IV ResNet

ResNet employs skip connections to train deeper networks by addressing the vanishing gradient issue, which helps maintain training accuracy with increased depth. This architecture is particularly beneficial for complex tasks like medical image analysis, where preserving feature integrity is crucial. In breast cancer detection, ResNet50 excels due to its ability to capture subtle distinctions in mammography images, making it highly effective for applications requiring precise diagnostic capabilities with limited datasets [13].

III. RESULTS

III.I Analysis of Deep Learning-based Models

Mammogram images are classified to support the early diagnosis of breast cancer in this study. The performance of various DL-based models used for breast cancer detection is evaluated, including DenseNet121, ResNet50, EfficientNetB0, and a CNN model. The effectiveness of each model is measured through extensive tests conducted on a large dataset, and the results are presented in confusion matrices and accuracy changes during the training process, as shown in Figure 2.

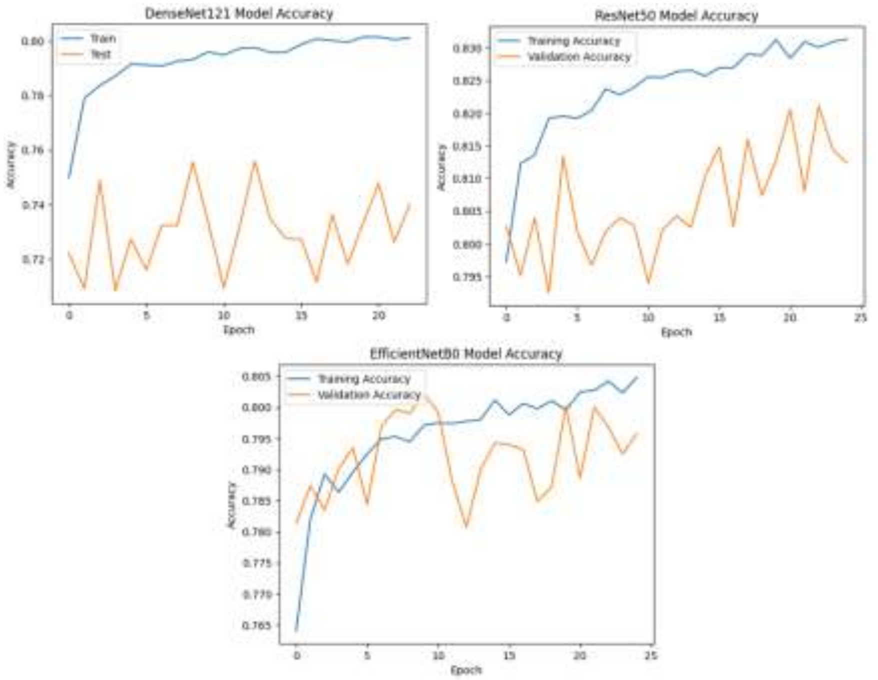

Figure 2. The accuracy graphs of DL-based models

Table 2 details the performance metrics of four DL-based models (CNN, EfficientNetB0, DenseNet121, and ResNet50), focusing on accuracy and loss rates after training and testing. Among them, the Convolutional Neural Network (CNN) shows superior performance, achieving the highest accuracy of 0.8450 and the lowest loss of 0.3745 in both the training and validation phases.

Table 2. Outputs of the models used

Model	ACC	LOSS	VAL_ACC	VAL_LOSS
CNN	0.8450	0.3745	0.8450	0.3745
EfficientNetB0	0.8048	0.4246	0.8047	0.4345
DenseNet121	0.7716	0.5076	0.7716	0.5075
Resnet50	0.8201	0.4074	0.8201	0.4074

The below graph showing the training (blue) and validation (orange) accuracy of the CNN model as percentages is presented in Figure 3. Both values change over time, dependent on the number of epochs during the training period. According to the graph, both accuracy metrics increase over time, indicating that the model continues to learn and its performance consistently improves.

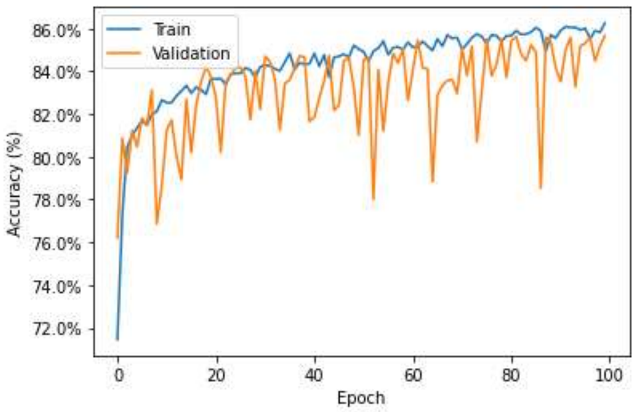

Figure 3. Accuracy graph of the CNN model

The model's loss on the training dataset starts very high at the first epoch and rapidly decreases thereafter. After the initial few epochs, the loss significantly reduces and stabilizes at an almost constant level. This indicates that the model begins learning quickly from the training data and is well-fitted to the training set. The closeness of the training and test losses in the graph suggests that there is neither overfitting nor underfitting occurring. If the training loss were low while the test loss remained high, it would indicate that the model was overly fitted to the training data and failed to generalize, thus exhibiting an overfitting problem. The loss rates of the CNN model on training and test data are shown in Figure 4.

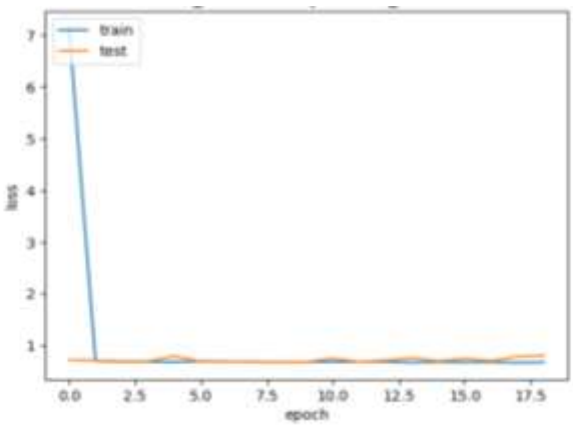

Figure 4. The loss rate of CNN on training and test data

The CNN model achieves a True Positive (TP) rate of 86.3% for class 1, with a corresponding False Negative (FN) rate of 13.7%, demonstrating its effectiveness in identifying class 1 samples correctly. For class 0, it shows a True Negative (TN) rate of 82.7% and a False Positive (FP) rate of 17.3%, indicating occasional misclassification of class 0 as class 1. Overall, the model exhibits robust classification performance with accuracy rates for both classes exceeding 80%, though it tends to misclassify class 0 as class 1 more frequently than misclassifying class 1 as class 0. The confusion matrix detailing these results is shown in Figure 5 below.

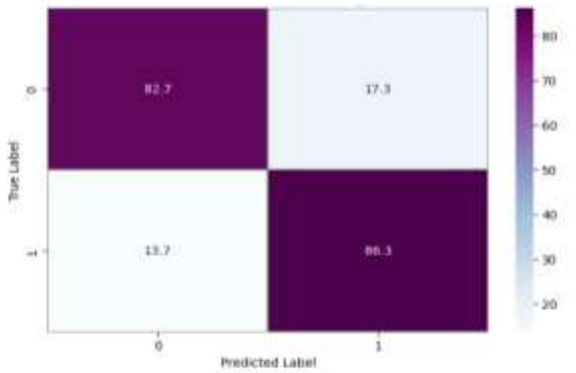

Figure 5. Confusion matrix of the CNN model

III.II Demo of Framework Platform

This section discusses the display of trained models within the web interface. As depicted in Figure 6, the Breast Cancer Detection Model Results Screen facilitates the uploading of mammography images for analysis by an artificial intelligence model. The interface includes a 'Choose File' button for uploading images, an 'Upload' button to initiate processing, and a 'Clear' button to reset selections. The interface's simple design and pink color palette enhance usability and support breast cancer awareness themes.

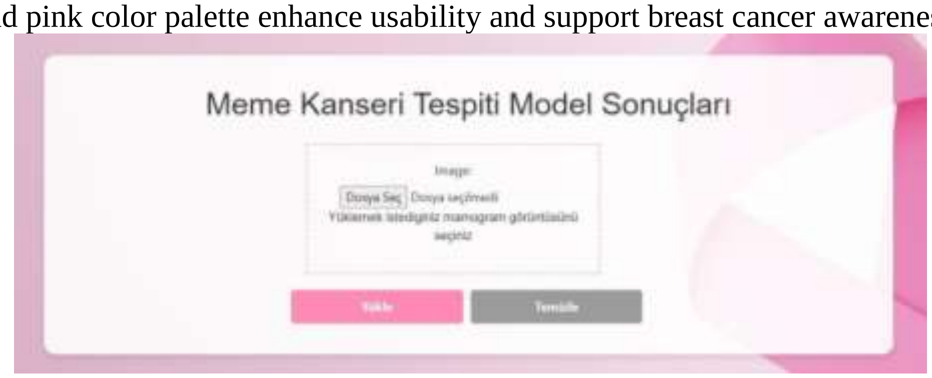

Figure 6. Breast Cancer Detection Model Results Screen

When the analysis of the uploaded cancerous image in Figure 7, our model returned this result: 'Cancerous cells have been detected!

Figure 7. Recommendation to consult a doctor according to the output on the user panel

As shown in Figure 8, the Breast Cancer Detection Model Results Display shows the successful results of various DL-based models over the mammogram images uploaded by the administrator. At the bottom of the page, there is a table under the heading 'Model Predictions'; this table contains whether different models (CNN, DenseNet121, ResNet50, EfficientNetB0) detect cancer and the probability values of these predictions. Whether each model detected cancer and the associated probability scores are listed.

Figure 8. Outputs displayed on the screen as a result of a cancer detection in the admin panel

IV. DISCUSSION

This study conducts an in-depth analysis of the impact of various DL-based models on the detection of breast cancer. The comparative performance of different models indicates that CNN, achieving a particularly high accuracy rate, may be superior in this field compared to other models. However, a detailed examination of how model selection and configuration interact with different datasets and preprocessing techniques is necessary. Such an analysis would help identify the strengths and weaknesses of each model, guiding the selection of the most appropriate model under specific circumstances.

Moreover, when these findings are compared with previous studies, they enhance our understanding of how DL-based models used in breast cancer detection have evolved and which innovations have significantly contributed to the field.

V. CONCLUSION AND FUTURE WORK

In this study, various DL-based methods have been employed to develop a user-friendly support system for the early diagnosis of breast cancer. It involved two main datasets: Initially, the "CBIS-DDSM: Breast Cancer Image Dataset" was utilized to categorize and process images based on mass and density. Images from this dataset were enhanced through mammography improvements, deblurring, and sparse coding techniques specifically aimed at extracting low-level features from grayscale images. During the training phase, CNN, DenseNet121, EfficientNetB0, and ResNet50 models were utilized and optimized using techniques such as "Image Data Generator" and "Early Stopping." The second dataset, "Breast Histopathology Images," underwent preprocessing steps such as separating cancerous from non-cancerous samples, feature extraction, and converting labels to one-hot encoding. The trained models were also tested on this dataset, with the CNN model achieving the highest success rate of 84.5% accuracy. Additionally, a user-friendly web interface designed using the Django framework has been deployed to make these models accessible to end-users. This interface aids in diagnosing cancer-based on selected mammogram images.

Future studies aim to enhance the model's accuracy by utilizing larger datasets and conducting clinical validation trials. The scope of the web interface will be expanded to foster greater voluntary participation from both users and administrators. Furthermore, to broaden our reach, interfaces compatible with mobile platforms will be developed.

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