Comparative Analysis of Convolutional Neural Network (CNN) and Transfer Learning in Breast Cancer Detection*

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Abstract

Breast cancer is a type of cancer that is prevalent among women. Every year many women succumb to the fatality of breast cancer in Sub-Saharan Africa (SSA). The cancerous cells can metastasize to other parts of the body. Although preventive measures remain elusive to medical professionals, when detected in its early stages, measures can be taken to prevent fatality. However, health professionals make false positive and false negative diagnoses given that lumps are found within the breasts. In SSA, which is the focus of this research, most people mainly resort to physical examination predictive technique only, and often, during breast cancer awareness month. Additionally, individuals are not able to check on their own mammographs they have taken for the absence or presence of cancerous lumps. This research seeks to develop and integrate a machine learning model in a web application for detecting breast cancer when a mammogram is uploaded. To do this a comparison analysis is performed between two notable deep learning techniques; Convolution Neural Network (CNN) and Transfer Learning (TL) (MobileNetV2). Findings reveal the MobileNetV2 obtained a training and validation of 90.4% and 90.7% respectively. Greater than that of the CNN model which obtained training and validation of 88% and 88.7% respectively. Hence the MobileNetV2 model was integrated into the web application for easy accessibility to both health professionals and individuals. Furthermore, current result can be scaled to integrate more efficient techniques in the future scope.

Keywords: Breast Cancer, Deep Learning, Machine Learning, Transfer Learning, Web Application.

1 Introduction

Breast cancer stands as a significant contemporary health challenge, yielding profound repercussions for women (Aidossov *et al.*, 2023). This type of cancer manifests as a malignant growth within the breast tissue, potentially metastasizing to other parts of the body if diagnosed in its advanced stages (Pawar *et al.*, 2022). It ranks as the second most prevalent cancer among women globally and has high fatality rate. 2.1 million women were diagnosed with breast cancer in 2018 and it is projected that in 2024 the newly diagnosed breast cancer in women will be 19.5 million (Agyemang *et al.*, 2020). About 50% of women receive their diagnosis at a locally advanced stage. Reports from the American Cancer Society estimate that 31% of newly diagnosed cancer in women are breast cancer. About 1.2 million people die from breast cancer every year (Fatima *et al.*, 2020). Given the current state of knowledge, prevention mechanisms remain elusive, underscoring the importance of early detection for improving patient outcomes (Das *et al.*, 2023).

Presently, mammography serves as the established screening method for detecting breast cancer, albeit with inherent limitations like false positives and false negatives prediction by health personnel (Sajiv and Ramkumar, 2023). Deep Learning (DL) and Machine Learning (ML) methodologies have displayed significant promise in augmenting breast cancer detection (Alruwaili and Gouda, 2022). These models harness the capabilities of neural networks to discern intricate patterns and features within extensive datasets (Brancati *et al.*, 2022). Through the analysis of mammograms, DL provides prediction support for healthcare professionals.

Previous research has proven DL models' potential in breast cancer predictions. DL architectures like the Convolutional Neural Network (CNN) and Transfer Learning (TL) models such as VGG16 and MobileNetV2 have been explored (Das *et al.*, 2023). However, there needs to be a way for mammograms to be analysed by health personnel using these machine learning DL models. Also, individuals who would want to perform analysis of mammograms should be able to have access to a platform where they can confidently do that outside the presence of health professionals. Hence, a website needs to be developed for mammograms to be uploaded for models' integration to perform analysis, providing health professionals the readily available and ubiquitous verifiability and individuals the privacy of checking for the possibility of breast cancer.

Among the machine learning models to be used for detecting breast cancer, Convolution Neural Network and Transfer Learning are notable (Alhussan *et al.*, 2023; Bouzar-Benlabiod *et al.*, 2023). This paper performs a comparative analysis by training and testing CNN and TL (MobileNet) models on CBIS-DDSM and DDSM datasets. For ease of use, the implemented model is integrated

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into a web application built using Flask. The rest of this paper is organised as follows; literature review is performed in section 2, section 3 discusses the proposed methodology, results are discussed in section 4, a web interface is developed the model is integrated in section 5, and lastly, the conclusion in section 6.

2 Literature Review on ML and DL in Breast Cancer Prediction

ML has emerged as a formidable asset in healthcare, showing great promise in predicting and diagnosing diseases. This technique entails developing a model that learns from training data and can subsequently analyse other data to make accurate predictions (Sruthi *et al.*, 2022). Notable ML approaches for medical data analysis encompass Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), and Decision Trees (DT) (TIWARI *et al.*, 2020).

2.1 Machine Learning Algorithms for Breast Cancer Detection

In a study by (Jamal *et al.*, 2022), breast cancer prediction using machine learning classifiers was investigated. The objective was to identify breast cancer by assessing five ML algorithms, namely LR, DT, RF, SVM, and k-nearest neighbours (KNN); utilizing the Wisconsin Breast Cancer dataset. Random forest was the most accurate algorithm, with a prediction accuracy of 98.24%.

In another study, (Mangal and Jain, 2021) also conducted a study on breast cancer prediction using ML algorithms. They emphasized the importance of accurate prediction in combating breast cancer and applied four ML algorithms to a standardized dataset: SVM, LR, DT, and KNN. The SVM algorithm exhibited exceptional proficiency in forecasting breast cancer, attaining an accuracy rate of 96.92%.

In pursuit of creating a dependable computer assisted detection (CAD) system for diagnosing breast cancer, (Anklesaria *et al.*, 2022) amalgamated multiple ML algorithms. The authors approach included the utilization of SVM, LR, KNN, DT, RF, artificial neural network (ANN), and naive Bayes (NB) algorithms. Hyperparameters were fine-tuned for each algorithm through the random forest feature importance technique for optimal feature selection. Furthermore, to ensure dataset balance, they implemented both undersampling and SMOTE techniques on the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. The study found that SVM was the most effective algorithm, with an accuracy of 95.8%.

The authors in (Algarni *et al.*, 2021) acknowledged the significance of early breast tumour detection. They explored a DL architecture for breast tumour classification, comparing various ML techniques, including SVM, DT, LR, and CNN. They used the Wisconsin Carcinoma Dataset (WCD) to train and evaluate their models. Their proposed CNN model achieved the highest classification accuracy of 98%. However, the study also emphasized the challenges of developing accurate deep learning models for medical applications, advocating for further research.

The authors in (Bhise *et al.*, 2022) addressed the urgency of early breast cancer detection using both ML and DL methods. They compared CNN with traditional ML algorithms such as SVM, NB, KNN, LR, and RF. They used the BreaKHis dataset to train and evaluate their models. In the research, CNN outperformed the other models with an accuracy of 99% while the others had accuracy within 66% to 99%.

2.2 Mathematical Modelling

DL, is a subset of machine learning that employs artificial neural networks such as CNN to glean insights from data. These data include breast cancer images for predicting breast cancer (Mridha *et al.*, 2021). Research indicates that DL models, particularly those based on mammographic data, exhibit enhanced capabilities in predicting breast cancer (Khuriwal and Mishra, 2018).

Convolutional Neural Network (CNN) is a specialized type of neural network tailored to process grid-like data, such as images, where there exists a strong correlation among neighbouring elements. CNNs have demonstrated exceptional prowess and success in tasks related to images (Khuriwal and Mishra, 2018), particularly in the area of medical image analysis. The architecture of a CNN encompasses various layers, including convolutional layers, pooling layers, and fully-connected layers.

Convolutional layers are typically the initial layers employed to extract features from input images by employing a set of filters that traverse the image, each designed to identify a specific feature or pattern (Nawrocka *et al.*, 2023). These layers are complemented by pooling layers, which serve to decrease the spatial dimensions of the image, thereby simplifying processing and reducing required memory. On the other hand, the fully connected layers are positioned towards the conclusion of the CNN. They take the features gleaned by the convolutional and pooling layers to make predictions (Nawrocka *et al.*, 2023).

In a study conducted in 2019, (Ting *et al.*, 2019) utilized CNN to enhance the classification of breast cancer, employing the dataset provided by the Mammographic Image Analysis Society (MIAS) to achieve an accuracy rate of 90.5% in classifying breast cancer. (TIWARI *et al.*, 2020) employed deep learning techniques to predict breast cancer risk in women, incorporating both machine learning and deep learning models. The Artificial Neural Networks (ANN) model demonstrated the highest accuracy of 99.3%.

Addressing the critical importance of early detection of breast cancer metastasis, (Khan *et al.*, 2021) proposed a customized CNN model for distinguishing metastasis cells from non-metastasis cells in histopathological images. The model exhibited notable training and validation accuracies of 94.98% and 94.08%, respectively. Furthermore, the precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC) of the proposed CNN model collectively underscored its robustness in discriminating metastasis cells.

On the other hand, (Ali *et al.*, 2023) proposed a hybrid learning model for breast cancer detection, combining deep neural networks and machine learning techniques. Their approach involved feature extraction using the VGG-19 convolutional neural network and classification using SVM, neural autoregressive distribution estimation (NADE), and a hybrid SVM-NADE model. The method achieved efficient binary classification with improved accuracy compared to the individual SVM and NADE models. The study highlighted the advantages of this hybrid approach in accurately classifying breast cancer states, although it also noted the limitation of dataset size.

2.3 Transfer Learning in Medical Image Analysis

TL is a technique in which pre-trained CNN models are leveraged for classification tasks in the area of medical image processing. In this approach, a model previously trained on a specific task serves as the starting point for a new model intended for a different task as illustrated in Fig 1. This strategy can lead to efficient and accurate models in scenarios where collecting a large dataset for training from scratch may not be feasible or practical. MobileNetV2 is a convolutional neural network (CNN) architecture specially designed for efficiency and low resource requirements. It comes pre-trained on a vast dataset called ImageNet and is designed to take inputs of shape [224, 224, 3]. This architecture is preferred for image classification tasks on devices with restricted computational power, such as mobile devices and less powerful personal computers. It relies on a simplified convolutional layer structure. The MobileNet approach provides the advantage of reducing the network's size without compromising its accuracy, making it an excellent choice for applications with limited computational capabilities (Das *et al.*, 2023).

2.4 Transfer Learning for Breast Cancer Detection

Numerous studies have investigated the utilization of transfer learning in the detection of breast cancer (Voon *et al.*, 2022). Transfer learning entails training a machine learning model on a sizable dataset of images from a related task, followed by fine-tuning the model on a smaller dataset of images from the target task.

3 Proposed Methodology

The proposed methodology has four main steps which include data collection and preprocessing, model development, model training and evaluation and web application development. Data collection and preprocessing involve the collection of mammogram images and preprocessing through resizing, reshaping and pixel normalisation. Model development includes the development of CNN and the Transfer Learning model. The models are then trained on the two datasets and evaluated using accuracy, precision, recall and F1-score to determine the performance of the model's ability to make correct predictions. Finally, a web application is developed and the better-performing model is integrated as illustrated in Fig 2.

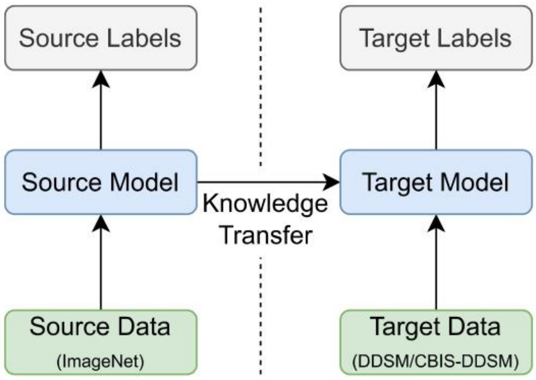

Fig. 1 Illustration of Transfer Learning Process

3.1 Data Preprocessing

This DDSM dataset, combines negative images sourced from the Digital Database for Screening Mammography (DDSM) with positive images from the Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM) datasets. The images have undergone preprocessing, with the region of interest (ROI) extracted and the dimensions standardized to 299 x 299 pixels.

The CBIS-DDSM dataset comprised 1,856 calcification studies and 1,712 mass studies. Each study has full mammography images, crops of abnormalities and ROI images.

To retrieve the images and their corresponding labels, a function was created. Two variables, “label_normal” and “label” were created to represent the labels in the dataset. The label normal variable indicates whether the image is negative (0) or positive (1). The tfrecords files were combined, and preprocessing techniques including reshaping, resizing, and conversion to a numpy array were applied. The data was randomized and the data was divided into 80% and 20% for training and validation respectively.

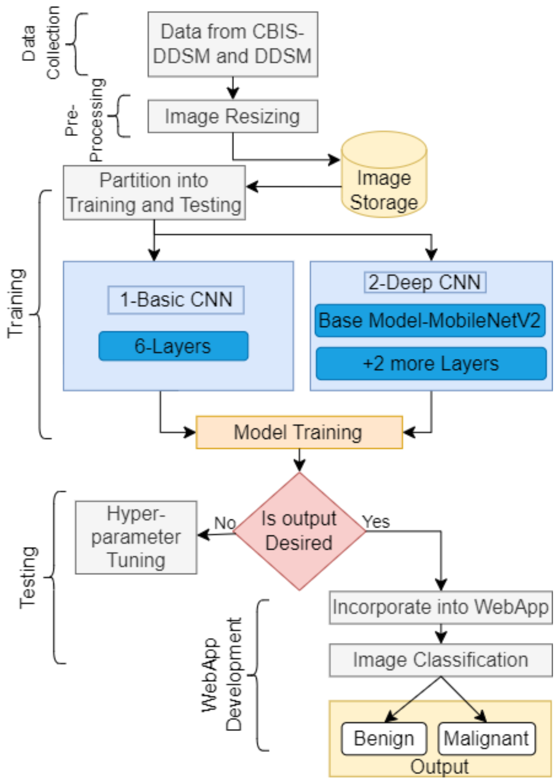

Fig. 2 Illustration of the Proposed Methodology

3.2 CNN Model Training

The straightforward CNN architecture was constructed with two convolutional layers for extracting features from the images. This was followed by max-pooling and dense layers responsible for classifying images as either benign or malignant. Subsequently, the model underwent compilation using the Adam optimizer and a binary cross-entropy loss function, both well-suited for binary classification tasks. In order to enhance model convergence, the learning rate was reduced to 0.001, and the batch size was lowered from 128 to 64.

3.3 Transfer Learning Model Training

In the transfer learning approach, the MobileNetV2 architecture was employed. The base model’s weights were frozen, and a custom output layer was introduced for binary classification. The model underwent fine-tuning using the Adam optimizer along with a binary cross-entropy loss function, mirroring the configuration used for the CNN. The learning rate was maintained at 0.001, and the batch size was set to 128.

4 Results and Discussion

4.1 Model Training Accuracy

On the larger DDSM dataset, the CNN achieved a training accuracy of 88.7% and a validation accuracy of 88% following 12 epochs as shown in Fig 3. As for the CBIS-DDSM dataset, the CNN attained a training accuracy of 94% and a validation accuracy of 66% after 12 epochs as shown in Fig 4.

Figure 4 illustrates the training progress of the MobileNetV2 model on the larger DDSM dataset, achieving a training accuracy of 90.4% and a validation accuracy of 90.7% following 5 epochs. On the CBIS-DDSM dataset, the transfer learning model based on MobileNetV2 demonstrated a training accuracy of 68% and a validation accuracy of 67% after 5 epochs, as Fig 5 depicts.

Hence more epochs were required by CNN model to obtain high accuracy values when compared to the MobileNetV2 model. However, training and validation values obtained from the MobileNetV2 model outperformed the CNN model.

An inherent class imbalance is realised, with significantly more benign samples than malignant ones.

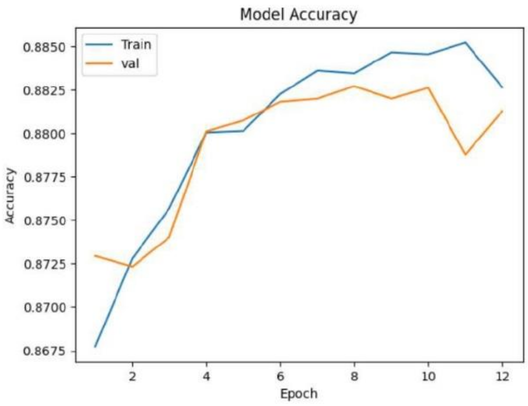

Fig. 3 CNN Learning Curve n DDSM Dataset

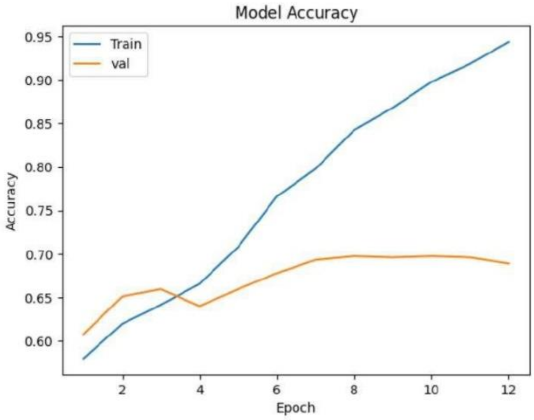

Fig. 4 CNN Learning Curve on CBIS-DDSM Dataset

4.2 Model Evaluation

Model evaluation was performed to analyse the performance and determine the effectiveness of the developed models on each dataset. Confusion matrix, precision, recall and f1-scoremetrics were used for evaluating the performance of the models. Fig 6 illustrates the confusion matrix, Equation (1), (2), (3) and (4) illustrate how precision, recall and F1-score and accuracy are calculated respectively.

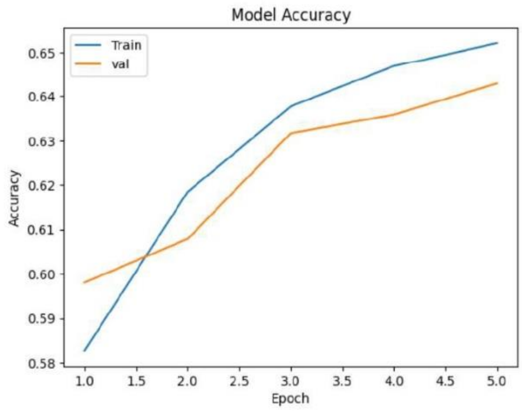

Fig 5. Transfer Learning Model's Learning Curve on CBIS-DDSM Dataset

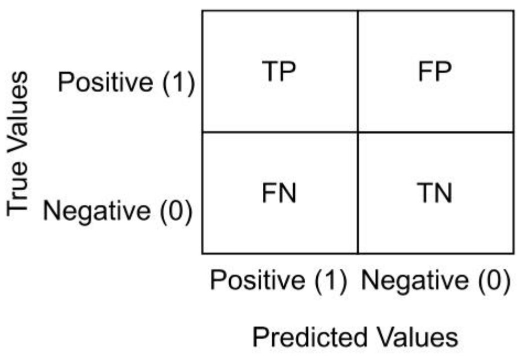

Fig 6 Illustration of Confusion Matrix

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (1)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negatives} \quad (2)$$

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total} \quad (4)$$

4.3 Evaluation of Model Performance on the DDSM Dataset

Using Equation (4) to calculate the accuracy, the confusion matrix of the CNN revealed a high accuracy of 96.7% for class 0 (benign), but a lower accuracy of 50% for class 1 (malignant), indicating some difficulty in correctly identifying malignant cases as can be seen in Fig 7. The model exhibited a precision of 0.99 for class 0, but only 0.5 for class 1, suggesting a higher rate of false positives in the latter. F1 scores of 0.5 for class 0 and 0.99 for class 1 indicated an imbalance in performance, while recall values of 0.68 for both classes demonstrated the model's ability to capture true positives effectively as seen in Table 1.

On the larger DDSM dataset, the MobileNetV2 model achieved a training accuracy of 90.4% and a validation accuracy of 90.7% after 5 epochs as illustrated in the confusion matrix in Fig 7. This indicates the model's ability to generalize well to unseen data. The confusion matrix revealed that 94.7% of benign images were correctly classified, but 8.8% of malignant images were misclassified as benign as illustrated in Fig 7. Precision values were 0.92 for class 0 and 0.78 for class 1, with F1 scores of 0.99 for class 0 and 0.49 for class 1. Recall values were 0.97 for class 0 and 0.56 for class 1 as seen in Table 2, demonstrating the model's effectiveness in capturing true positives for benign images.

4.4 Performance Evaluation of Model on the CBIS-DDSM Dataset

On the CBIS-DDSM dataset, the CNN achieved a training accuracy of 94% and a validation accuracy of 66% after 12 epoch as can be seen from Fig 8. Precision values were 0.75 for class 0 (benign) and 0.60 for class 1 (malignant), indicating the model's proficiency in correctly classifying samples for each class. F1 scores were 0.74 for class 0 and 0.62 for class 1, striking a balance between precision and recall. However, the validation loss increased to 0.92, suggesting potential overfitting and a need for further regularization.

The confusion matrix of the MobileNetV2 model however achieved an accuracy of 68% for training and a validation accuracy of 67% after 5 epochs. Precision values were 0.5 for class 0 (benign) and 0.99 for class 1 (malignant), and the F1scores were 0.65 for class 0 and class 1. The recall values were 0.99 for class 0 and 0.5 for class 1.

Fig 7 and 8 illustrate the confusion matrix for both models on the DDSM and CBIS-DDSM datasets respectively. Fig 9 and 10 depict a graphical representation of the performance metrics for the DDSM and CBIS-DDSM respectively.

Table 1 Evaluation of CNN

Mode	DDSM		CBIS-DDSM	
	Class 0	Class 1	Class 0	Class 1
Precision	0.99	0.50	0.75	0.60
Recall	0.68	0.68	0.75	0.64
F1-Score	0.50	0.99	0.74	0.62

Table 2 Evaluation of TL

Mode	DDSM		CBIS-DDSM	
	Class 0	Class 1	Class 0	Class 1
Precision	0.92	0.78	0.50	0.99
Recall	0.97	0.56	0.99	0.50
F1-Score	0.99	0.49	0.65	0.65

5 Web Application Interface

To make the implemented models accessible to more users, a web application was developed to deploy the model. The web application makes the prediction models readily accessible through a user-friendly user interface.

5.1 Deployment Process

Flask, a web framework for Python, was used as the backbone for the web application and for handling user requests. It renders the HTML templates and integrates the trained model into the web application for real-time predictions. The MobileNetV2 transfer learning model was used because of its better performance. The model is saved as an h5 file and loaded into the application using Tensorflow's Keras Library. The user interface (UI) is designed to be interactive. It used an HTML template, which was developed using Bootstrap CSS. There is a feature form where users upload their mammogram images and a "Predict" button to trigger the prediction process.

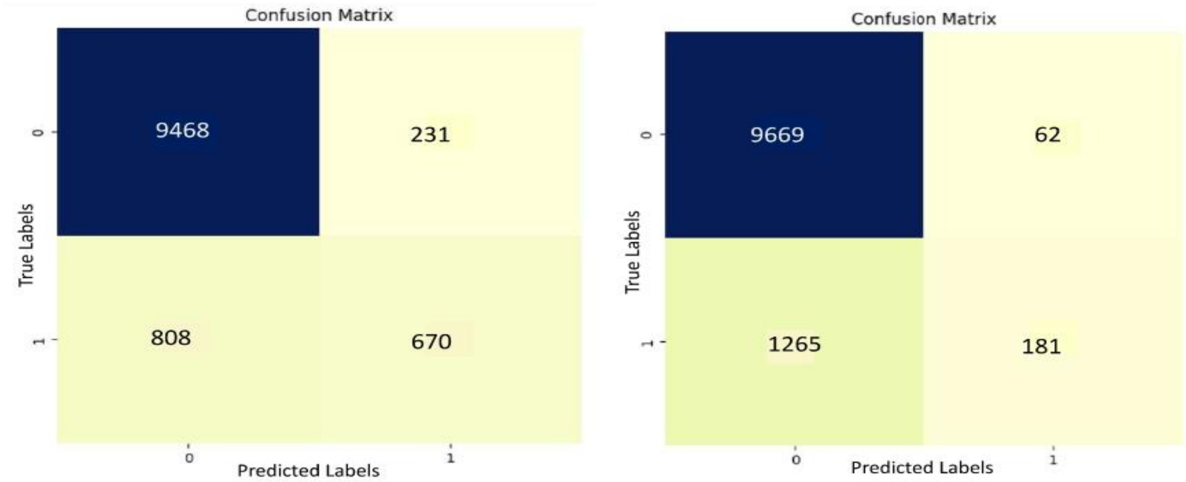

Fig 7 Confusion Matrix for TL and CNN Models on DDSM Dataset

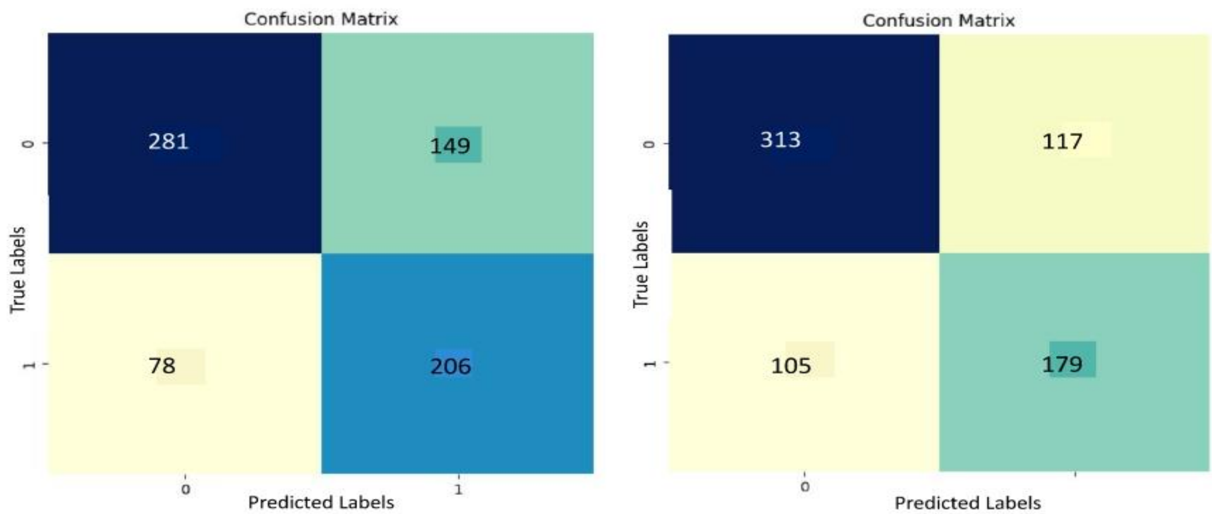

Fig. 8 Confusion Matrix for the Two Models on CBIS-DDSM Dataset

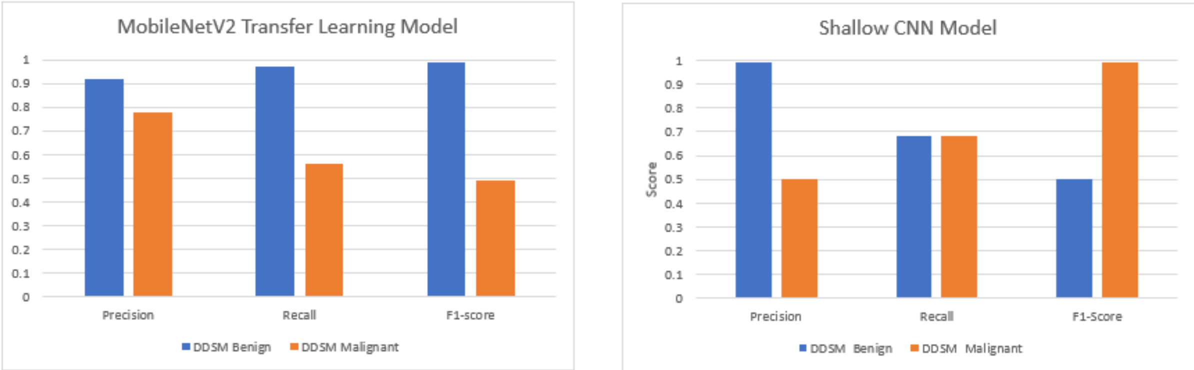

Fig 9 Performance Matrics for the Two Models on DDSM Dataset

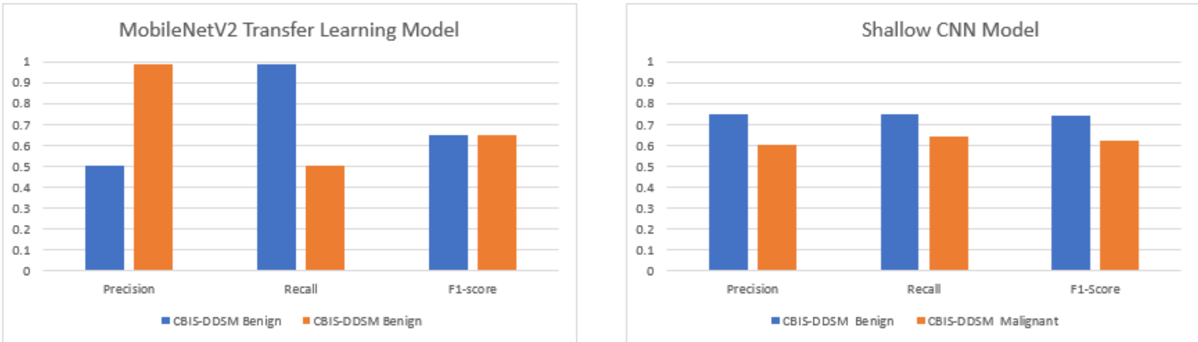

Fig. 10 Performance Matrics for the Two Models on CBIS-DDSM Dataset

Table 3 Comparison of Percentages

			DDSM		CBIS-DDSM	
Model	Learning Rat	Epochs	Training Accuracy	Validation Accuracy	Training Accuracy	Validation Accuracy
CNN	0.001	12	88.7%	88	94%	66
TL	0.001	5	90.4%	90.7%	68%	67%

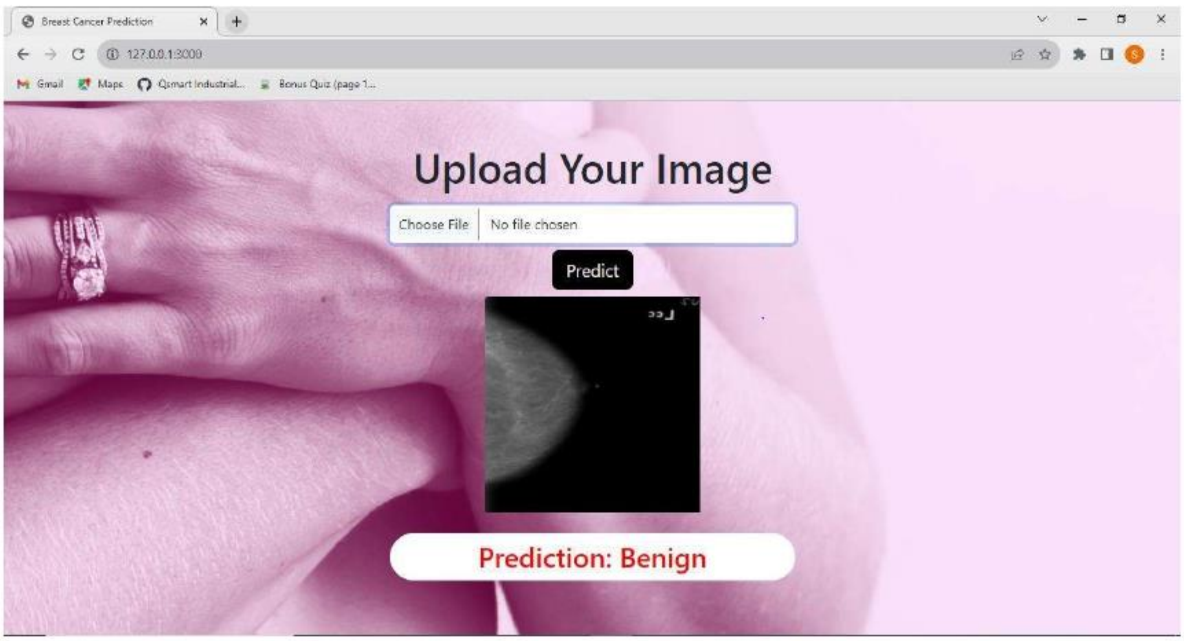

Fig. 11 User Interface for Web Application

When a user uploads their mammogram image, the web application preprocesses the image and feeds it into the model for a prediction to be made as either benign or malignant.

5.2 Deployment Process

Before a prediction is made, the uploaded mammograms are pre-processed to match the input requirements of the model. This is done by resizing the images to 224 × 224 pixels and applying normalization. There is a preprocess image function that handles this. Once the preprocessing is done, a function feeds the output image to the model to make the prediction. The prediction (benign or malignant) is dynamically displayed alongside the image using the Jinja templating engine. Fig 11 shows the user interface design for the web application.

6 Conclusion

This research provides a machine model for predicting benign or malignant lumps in breasts in a web application. It provides a model for predicting breast cancer. Two notable deep learning techniques, that is, CNN and TL (mobileNetV2) were compared to determine which would be suitable for breast cancer prediction in the web application. Training and evaluation were done using two popular datasets, DDSM and CBIS-DDSM. CNN had a validation accuracy of 88% and 66%, while, TL had a validation accuracy of 90.7% and 67% for DDSM and CBIS-DDSM respectively.

A web application which accepts mammograms for performing prediction was developed and integrated with the TL model because of its better performance. It is readily available for health professionals and non-health professionals who would want to check for the possibility of cancer. Current results can be scaled to integrate more efficient techniques for breast cancer prediction in future scope. Such as techniques that investigate advanced techniques such as Synthetic Minority Over-sampling Technique (SMOTE), to deal with class imbalance and improve model performance. Limitations include the inability of the application to take mammogram, hence users take mammograms at health centres before upload. Also, there is a lack of mobile application.

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