Breast Cancer Classification with Deep Learning

IE7615 - Project

Team -
Gokhale, Gargi
Paramel, Sree Reshma
Shainaj Nair, Nivedita

Problems addressed:

1

Our project uses CNNs like VGG16 and EfficientNet80 are used to analyze complex breast cancer images and to identify whether it is malignant or benign.

2

A misdiagnosis may result in treatment delays. Our project boosts early detection and saves lives by using deep learning to improve breast cancer diagnosis accuracy, speed, and accessibility.

3

Proper model training can’t be done due to small size of images in medical datasets like mammograms. The aim is to achieve high accuracy with less data by utilizing transfer learning with pre-trained models.

RELATED WORK

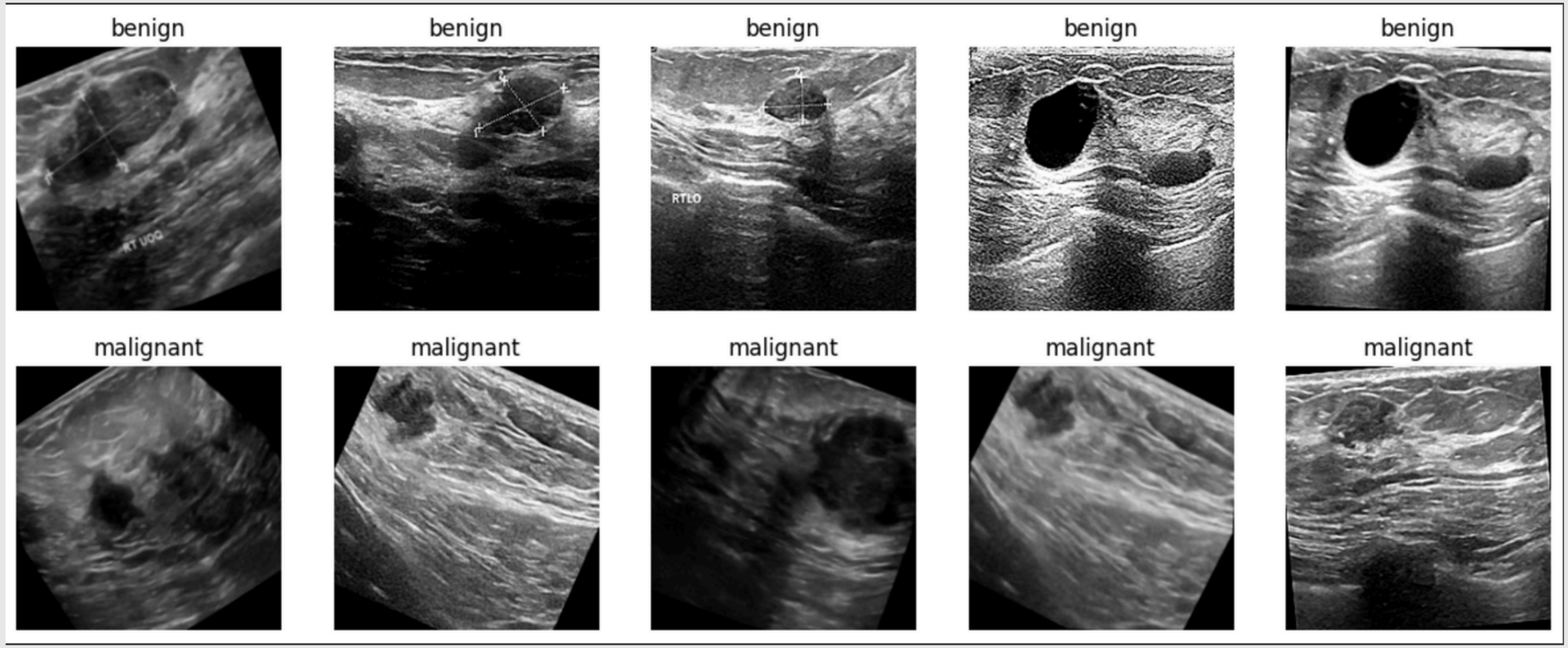
1. Advanced CNN models like ResNet and DenseNet are effective in analyzing high-resolution histopathology and mammography images as they provide higher accuracy rate.

2. Transfer learning has been widely used in breast cancer classification.

3. CNNs combined with Support Vector Machines (SVM) and Random Forests provides high accuracy.

DATASET USED

- **"Ultrasound Breast Images for Breast Cancer,"** dataset, includes ultrasound pictures aimed to differentiate between benign and malignant breast cancers. The pictures are in JPG or PNG.

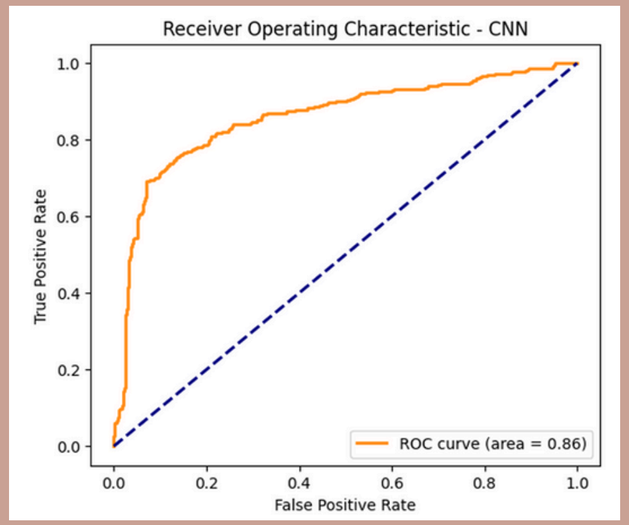


APPROACH

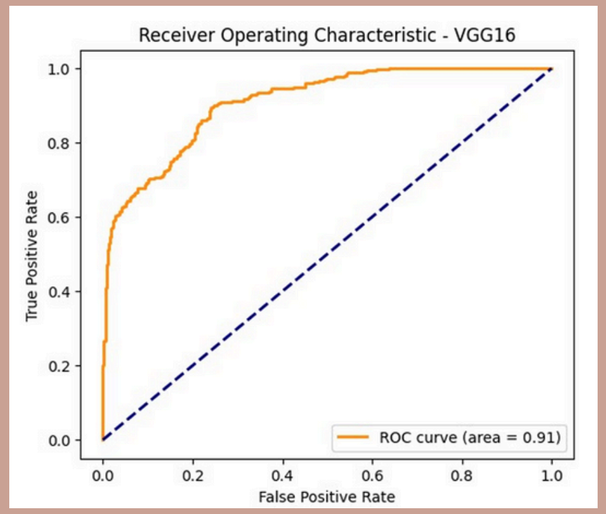
- Three different deep learning models - **CNN, VGG16** and **EfficientNet80** which are used for image classification were compared .

- Evaluation and visualization of performance of multiple models using ROC curves and AUC.

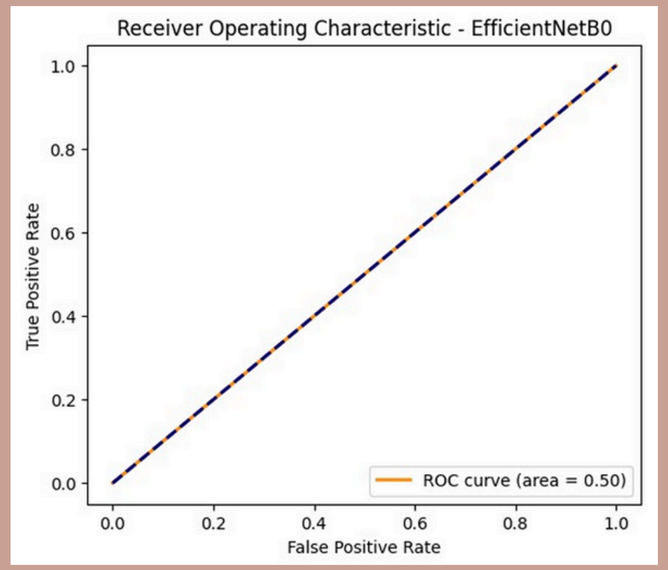
- The ROC curve is used to evaluate the various models and it displays the balance between the true positive rate (sensitivity) and false positive rate.



CNN

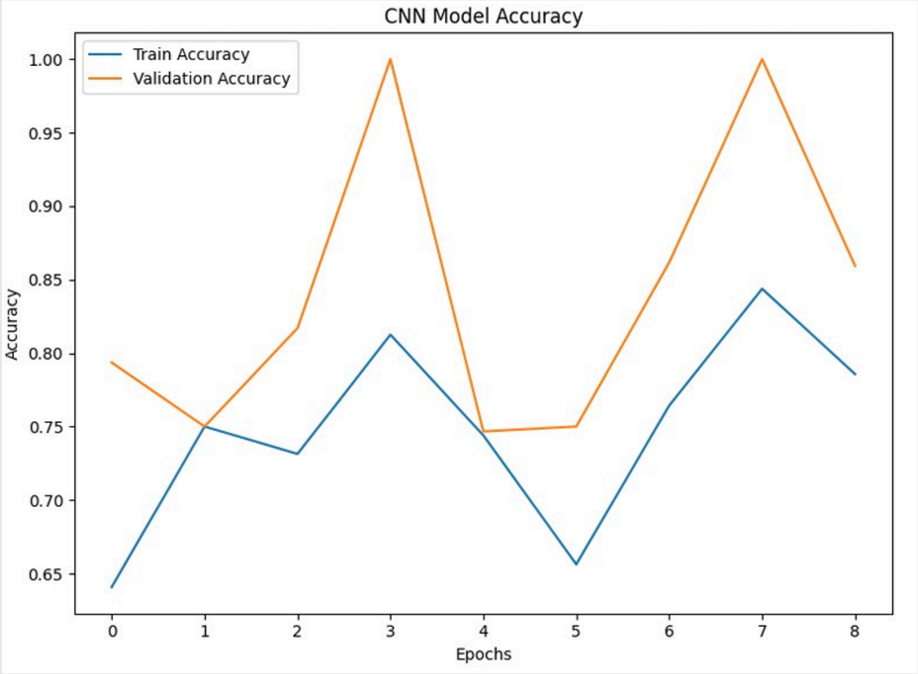


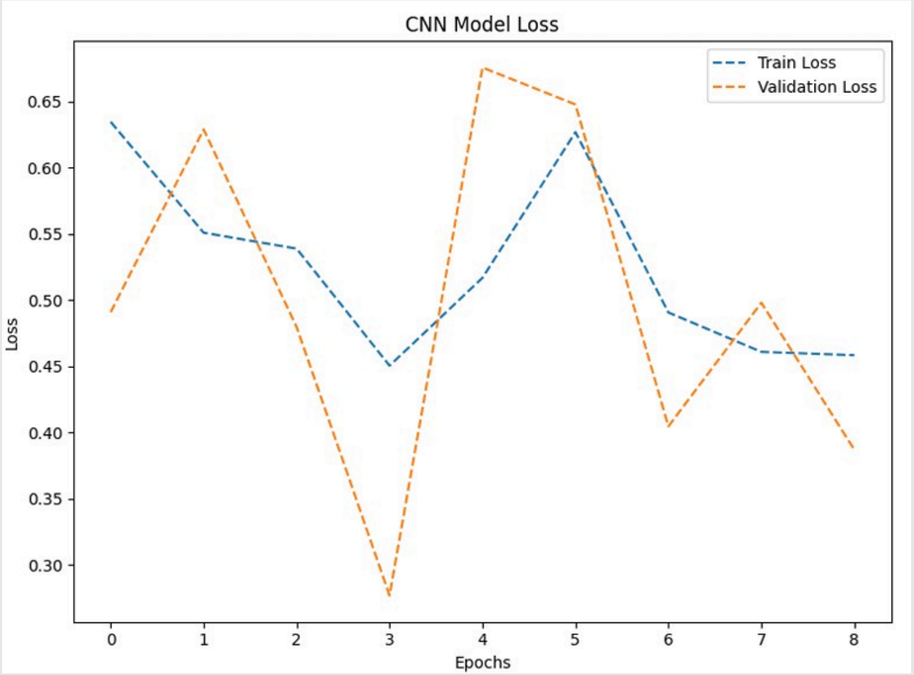
VGG16



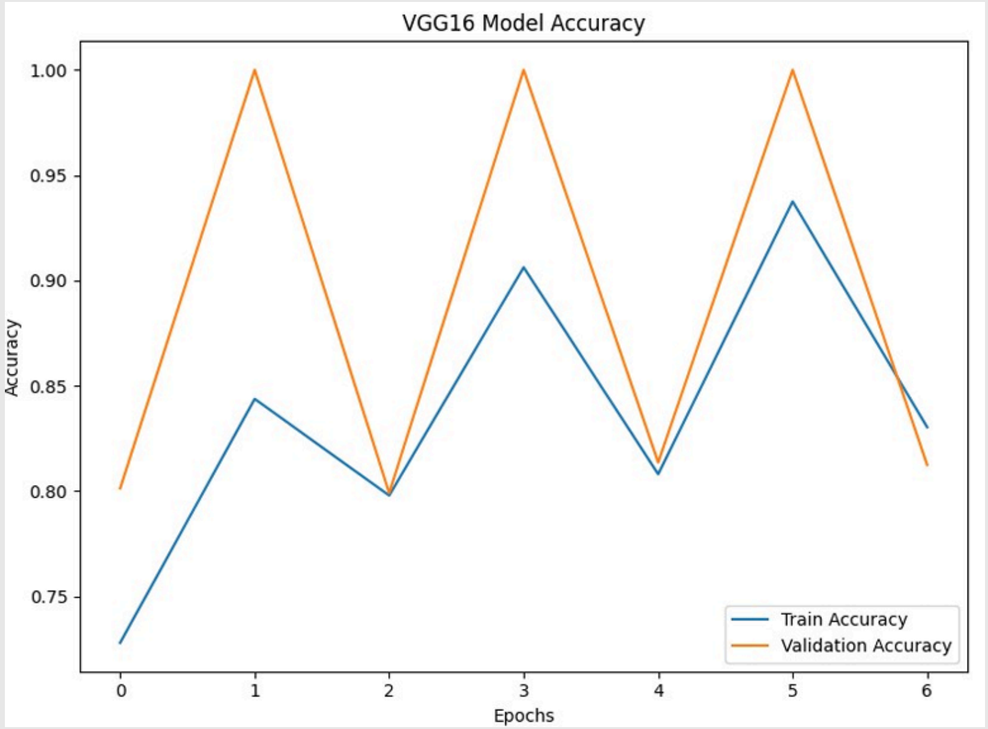
EfficientNet80

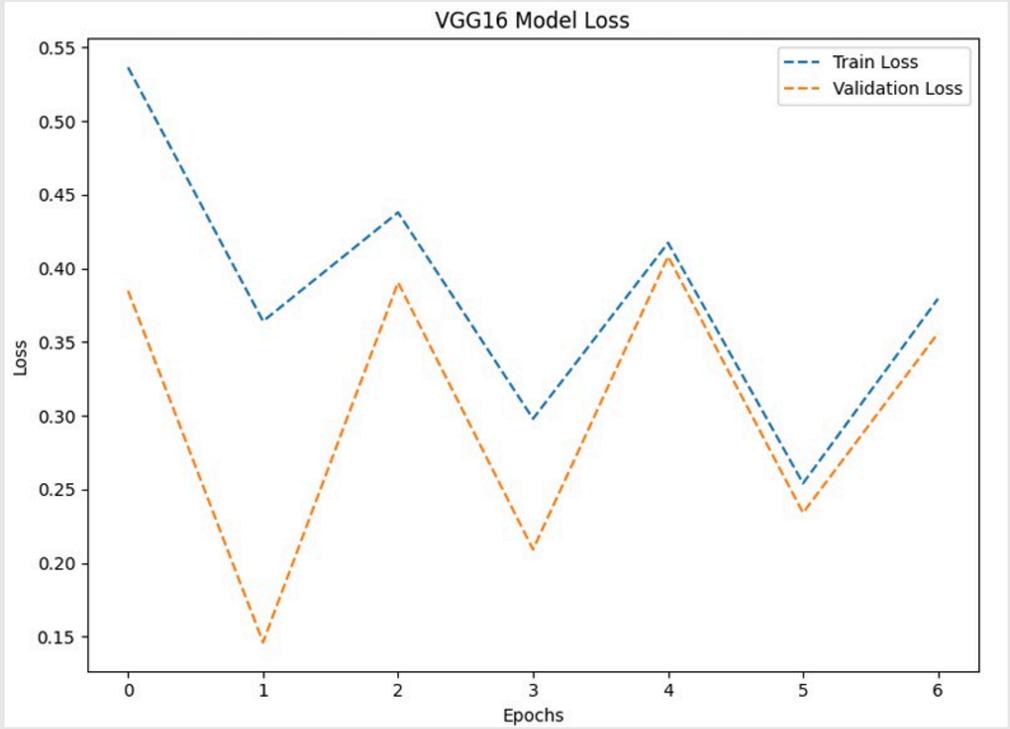
Graphs was plotted to visualize their accuracy and loss over the epochs for all three models. The purpose is to compare the performance of these models during training and validation.



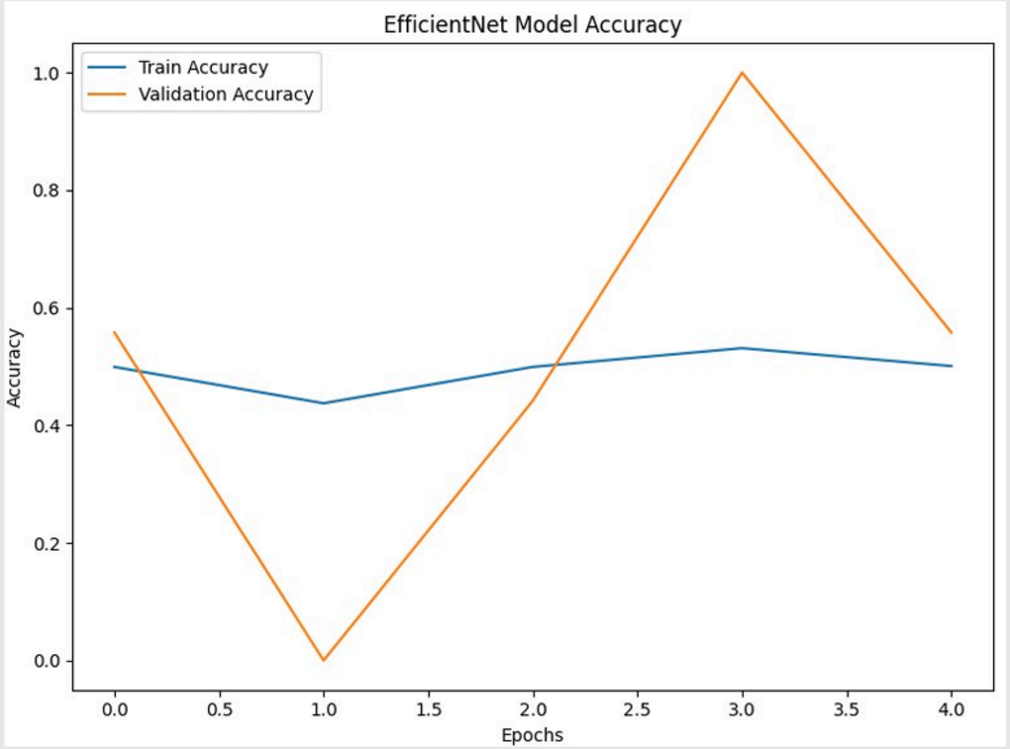


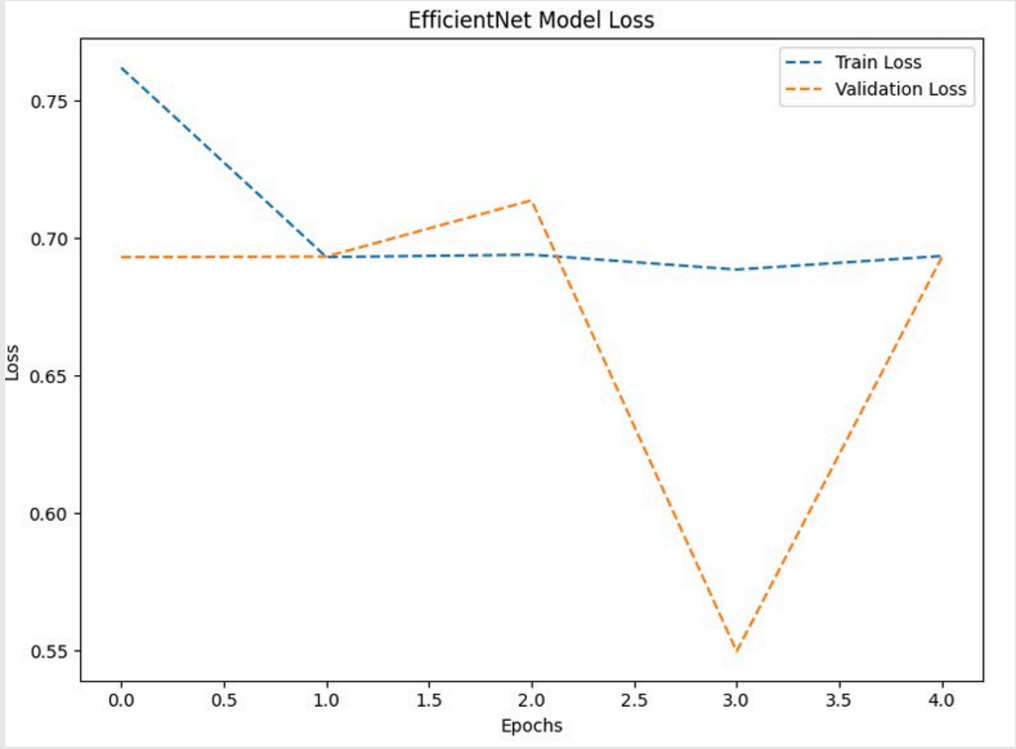
CNN Model


VGG16 Model Accuracy
Accuracy
Epochs
Train Accuracy
Validation Accuracy
1.00
0.95
0.90
0.85
0.80
0.75
0
1
2
3
4
5
6


VGG16 Model Loss
Loss
Epochs
Train Loss
Validation Loss
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0
1
2
3
4
5
6

VGG16 Model

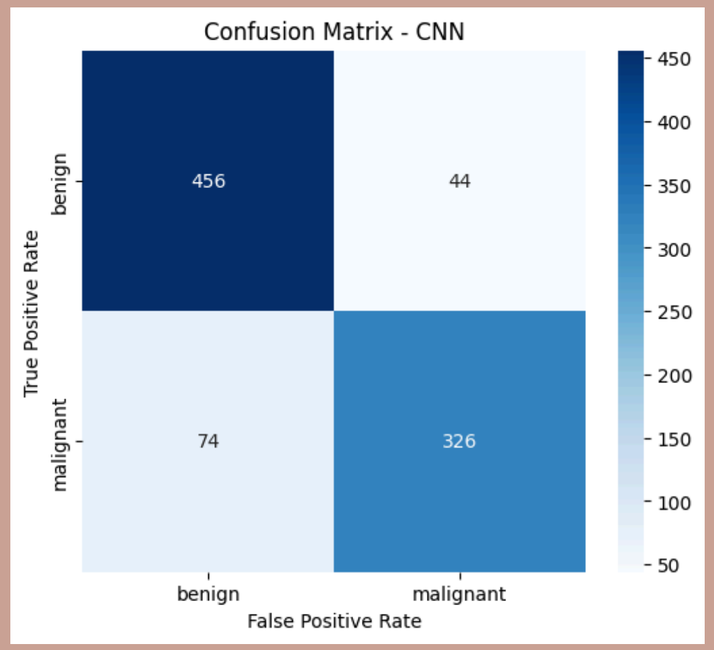




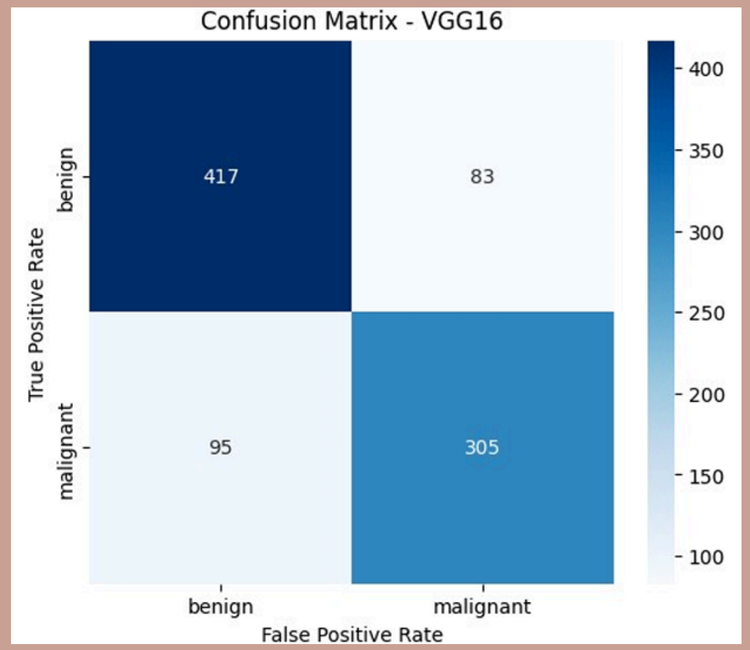
EfficientNet Model

RESULTS

A **heatmap** showing the confusion matrix with actual vs. predicted labels is plotted. A confusion matrix helps to understand how well the model is performing by comparing its predicted labels to the actual labels



CNN



VGG16

RESULTS

- The results show that **VGG16 and CNN is better** in classifying ultrasound images into malignant and benign, and it performs better than other model due to its effective feature extraction capabilities via transfer learning.

- **EfficientNet80 underperformed**, probably because of sensitivity of specific dataset tuning, whereas **CNN produced promising results.**

- These results demonstrate the promise of transfer learning in medical imaging, especially when using pre-trained models such as VGG16.

- **The best-performing model is VGG16 and CNN with a validation accuracy of 0.80 (80%)**

CONCLUSION

The results show that **VGG16 and CNN is better** in classifying ultrasound images into malignant and benign, and it performs better than other two models due to itThis project shows how transfer learning works well for categorizing ultrasound images. It achieves better results in terms of feature extraction and classification accuracy. In order to prevent overfitting and to get accurate results, additional data was essential. The potential of pre-trained models in medical imaging is highlighted by these results.

FUTURE DIRECTIONS

Exploring advanced architectures like combining CNNs with other deep learning models for better image feature extraction can improve performance.

Detection and Accuracy of the diagnosis can be improved by using additional datasets, like mammography or ultrasound pictures which evaluates model's robustness in various clinical settings.

Like Grad-CAM, experimenting with cutting-edge visualization approaches like LIME (Local Interpretable Model-Agnostic Explanations) can enhance understanding and ensure transparency in medical diagnostics.

THANK YOU