SKIN LESION BINARY CLASSIFICATION

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INTRODUCTION

SKIN CANCER, PARTICULARLY MELANOMA, IS A MAJOR GLOBAL HEALTH CONCERN. EARLY AND ACCURATE DIAGNOSIS IS CRITICAL FOR EFFECTIVE TREATMENT. TRADITIONAL DIAGNOSTIC METHODS RELY HEAVILY ON DERMATOLOGIST EXPERTISE, WHICH CAN BE SUBJECTIVE. DEEP LEARNING, PARTICULARLY DEEP CONVOLUTIONAL NEURAL NETWORKS (DCNNS), OFFERS PROMISING ADVANCEMENTS IN AUTOMATING AND ENHANCING THE ACCURACY OF SKIN LESION CLASSIFICATION.

AIM

- Develop a **robust deep learning model** for binary classification of skin lesion images (benign/malignant).

Objective:

- Research existing deep learning models.
- Prepare the dataset.
- Optimize model architectures.
- Address class imbalance using techniques like focal loss.
- Evaluate using accuracy, precision, recall, and F1 score.

LITERATURE REVIEW

AlexNet:

Esteva et al. (2017) successfully used AlexNet for skin cancer classification, achieving an accuracy of 81% on dermoscopic images, indicating potential for further improvements.

While AlexNet can capture complex features, its relatively shallow architecture compared to newer models limits its capacity to handle the variability in skin lesion images. Additionally, it struggles with class imbalance in datasets.

InceptionV3:

Authors: Menegola, A., Tavares, J., Fornaciali, M., Li, L., Avila, S., & Valle, E. Year: 2017

Conference: International Symposium on Biomedical Imaging (ISBI)

Summary: Menegola et al. utilized the Inceptionv3 model for skin lesion analysis, achieving an accuracy of 89% in classifying lesions as benign or malignant, demonstrating its superior performance in medical image analysis, despite its ability to process high-resolution images

Transfer Learning

Author:Brinker, T. J., Hekler, A., Enk, A. H., Berking, C.,
Year: 2019
Journal: European Journal of Cancer
Summary: This study fine-tuned the ResNet-50 model using a dataset of dermoscopic images specifically curated for melanoma classification. The approach demonstrated the potential of transfer learning to achieve high accuracy even when the available labeled data is relatively small.
Accuracy: The ResNet-50 model achieved an accuracy of around 86%, indicating that transfer learning can significantly improve the performance of skin lesion classification models with limited data.

•Ensemble Model

•Tan et al. (2021) utilized an ensemble of DCNNs, including AlexNet, ResNet, and Inception V3, for skin lesion classification.This approach achieved an accuracy of around 92%, demonstrating the benefit of combining multiple models.

•**Effectiveness**: Ensemble methods leverage the strengths of different models, resulting in improved accuracy and robustnessin classification tasks.

•**Limitations**: Ensemble models can be computationally expensive and require more resources for training and inference. The complexity of managing and integrating multiple models can also be challenging.

Skin Lesion Classification Challenges

• AlexNet: Limited generalizability due to shallow architecture, affecting effectiveness in diverse clinical settings.
• Inception V3: High computational demands, limiting deployment in resource-constrained environments.
• Transfer Learning: Limited by dataset size and diversity, affecting model's generalizability and reliability.

DATASET COLLECTION

- **Source**: ISIC Archive (International Skin Imaging Collaboration).
- **Training Set**: 7848 images (balanced between malignant and benign).
- **Validation Set**: 1962 images (balanced).
- **Test Set**: 600 images (ISIC 2017).

- **Image Preprocessing**:
- Resized to 224x224 pixels.
- Normalized pixel values for consistent input.
- **Data Augmentation**:
- Rotation, scaling, flipping, and cropping.
- Helps address the class imbalance issue.

Handling Class Imbalance

- **Problem**: The dataset had more benign than malignant cases.
- **Solution**:
    - **Focal Loss**: Adjusts the model's focus on harder-to-classify malignant cases.
    - **Class-weighted loss** to further balance sensitivity between classes.

MODEL SELECTION

Models Used:

- **AlexNet** and **Inception v3** for skin lesion classification.
- **Ensemble Models** combining **EfficientNet**, **DenseNet**, and **ResNet** to improve performance.

- **InceptionV3**:
- Pre-trained on ImageNet.
- Captures image features at multiple scales, ideal for varying lesion shapes and sizes.
- Added **Global Average Pooling (GAP)** to reduce dimensionality and prevent overfitting.
- Final classification layer uses **sigmoid activation** for binary classification.
- **AlexNet**:
- Focuses on extracting key features from skin lesion images using several convolutional and max-pooling layers.
- Ends with a **Dense layer** with one neuron and **sigmoid activation** for classification

- **ResNet50**:
- Residual connections allow deeper network training, crucial for capturing subtle lesion features.
- Global Average Pooling and a Dense layer are used to transform feature maps into a probability of malignancy .
- **DenseNet121**:
- Each layer is connected to all subsequent layers, promoting feature reuse.
- Efficient in parameter use and enhances feature extraction .
- **EfficientNetB0**:
- Pre-trained on ImageNet.
- Balances accuracy and computational efficiency.
- Uses **scalable architecture** for depth, width, and resolution to improve accuracy with fewer parameters .

Ensemble Model

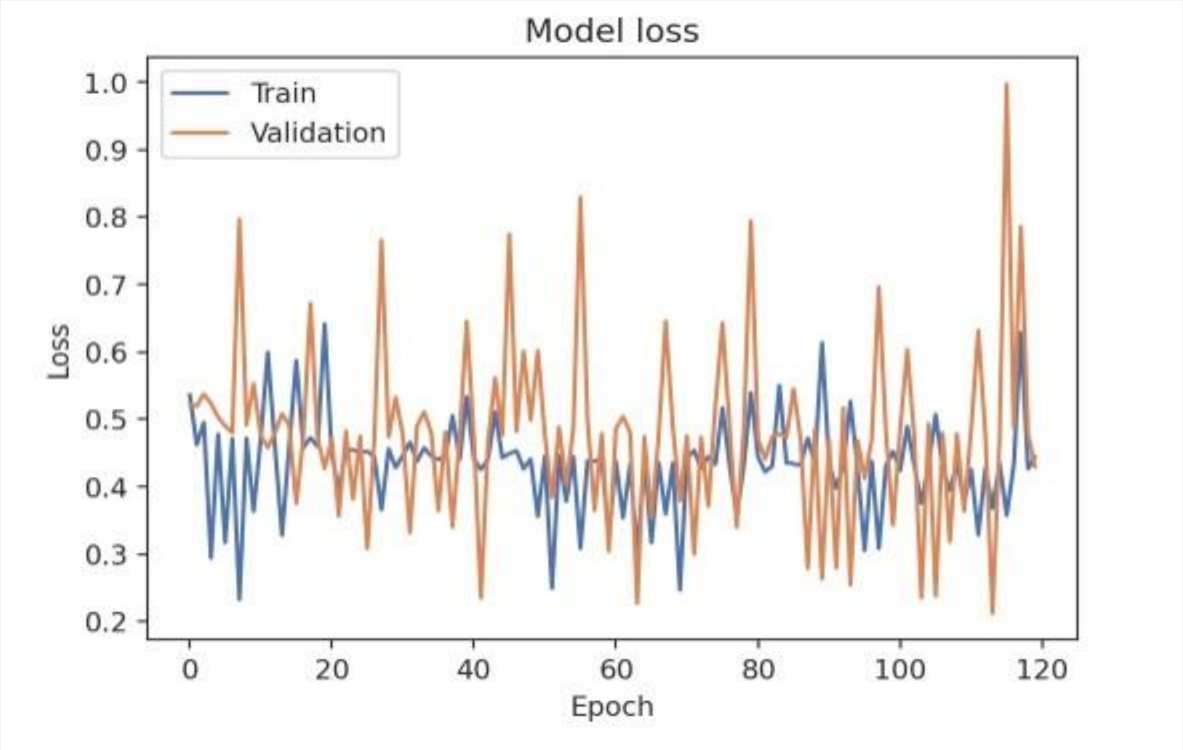
- **Ensemble Approach**:
    - Combines multiple models (InceptionV3, AlexNet, EfficientNet, DenseNet, ResNet) to enhance performance.
    - **Advantage**: Different models capture diverse aspects of the data, improving prediction accuracy and stability .

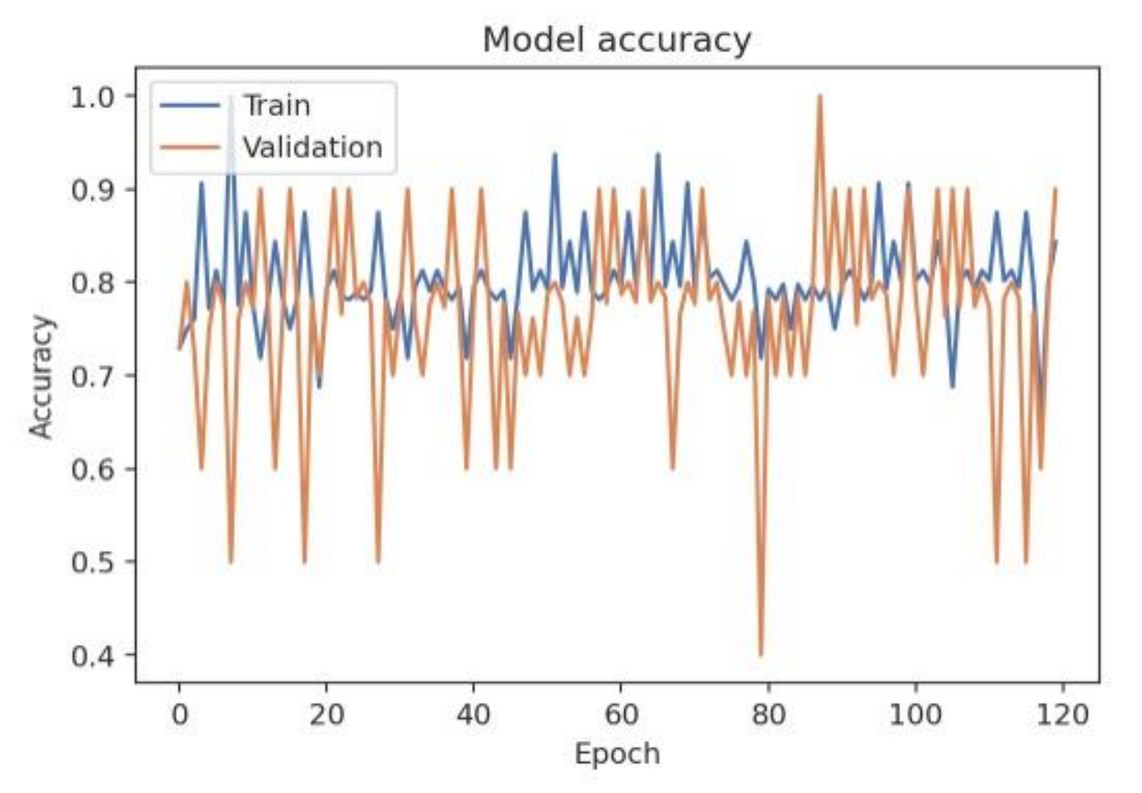
Model Compilation

- **Optimizer**: Adam optimizer (learning rate = 0.0001) used for all models to ensure faster and stable convergence.
- **Loss Function**: Binary cross-entropy for binary classification tasks.
- **Metrics**: Accuracy, Precision, Recall, F1 score .

EVALUATION

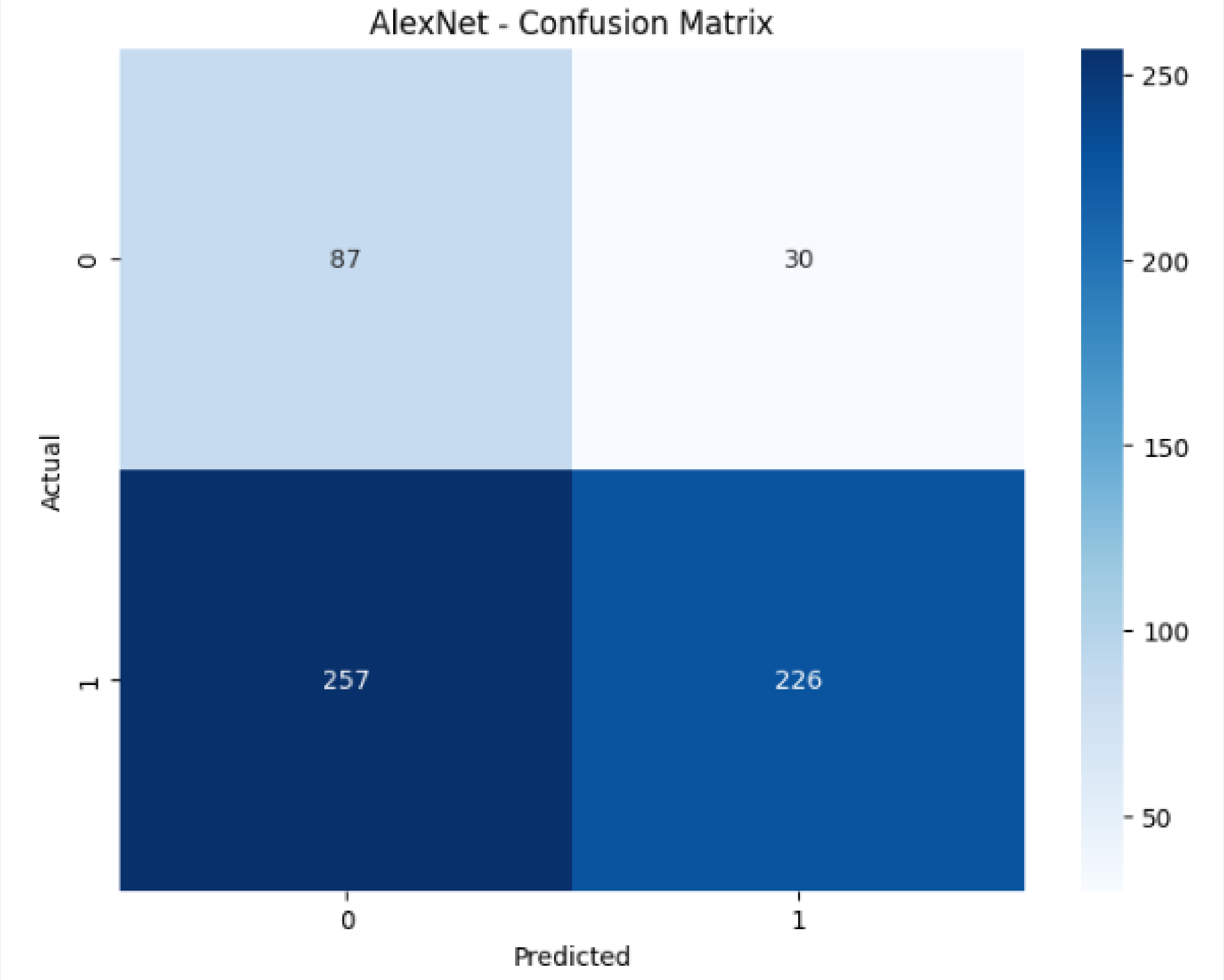
INCEPTIONV3

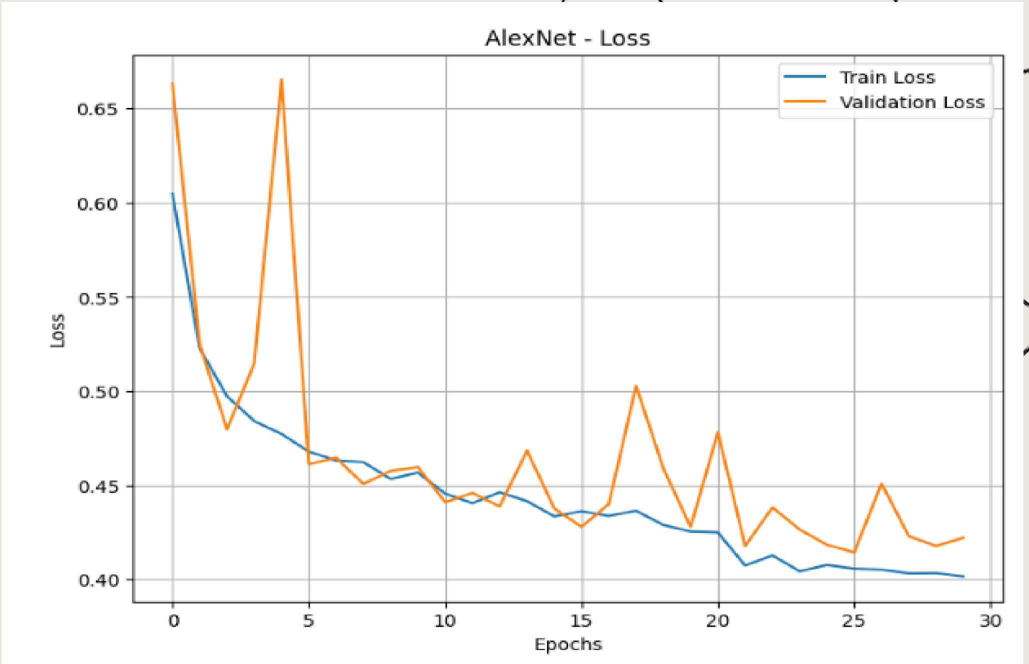


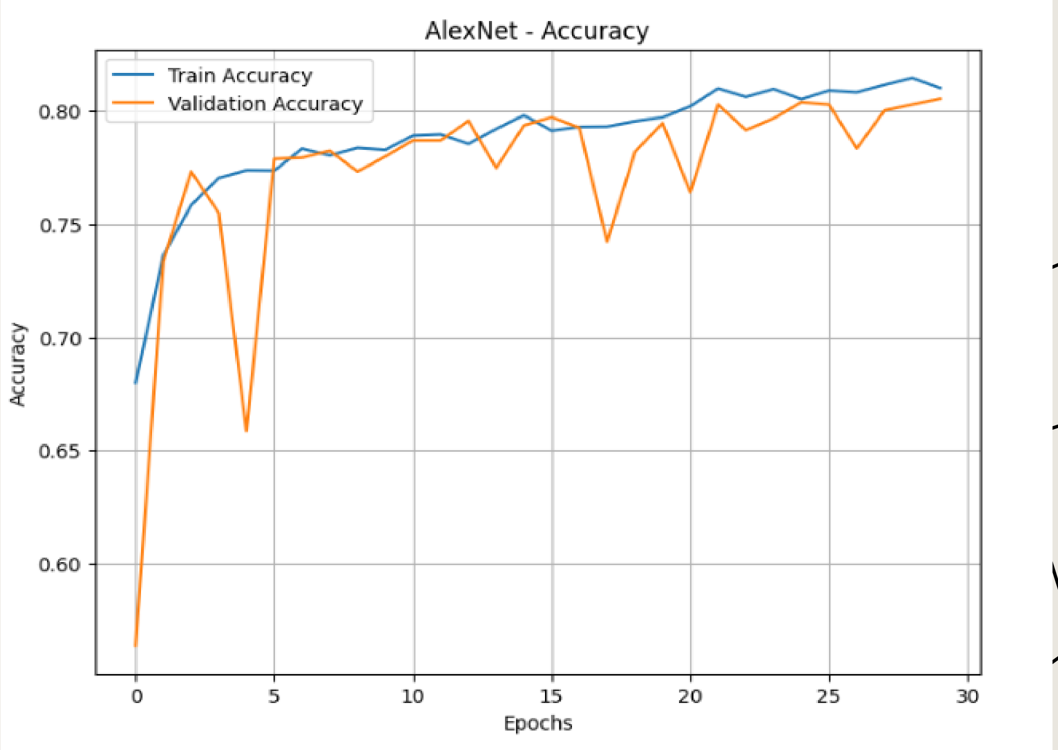


	precision	recall	f1-score	support
mel	0.21	0.29	0.24	117
oth	0.81	0.73	0.77	483
accuracy			0.65	600
macro avg	0.51	0.51	0.51	600
weighted avg	0.69	0.65	0.67	600

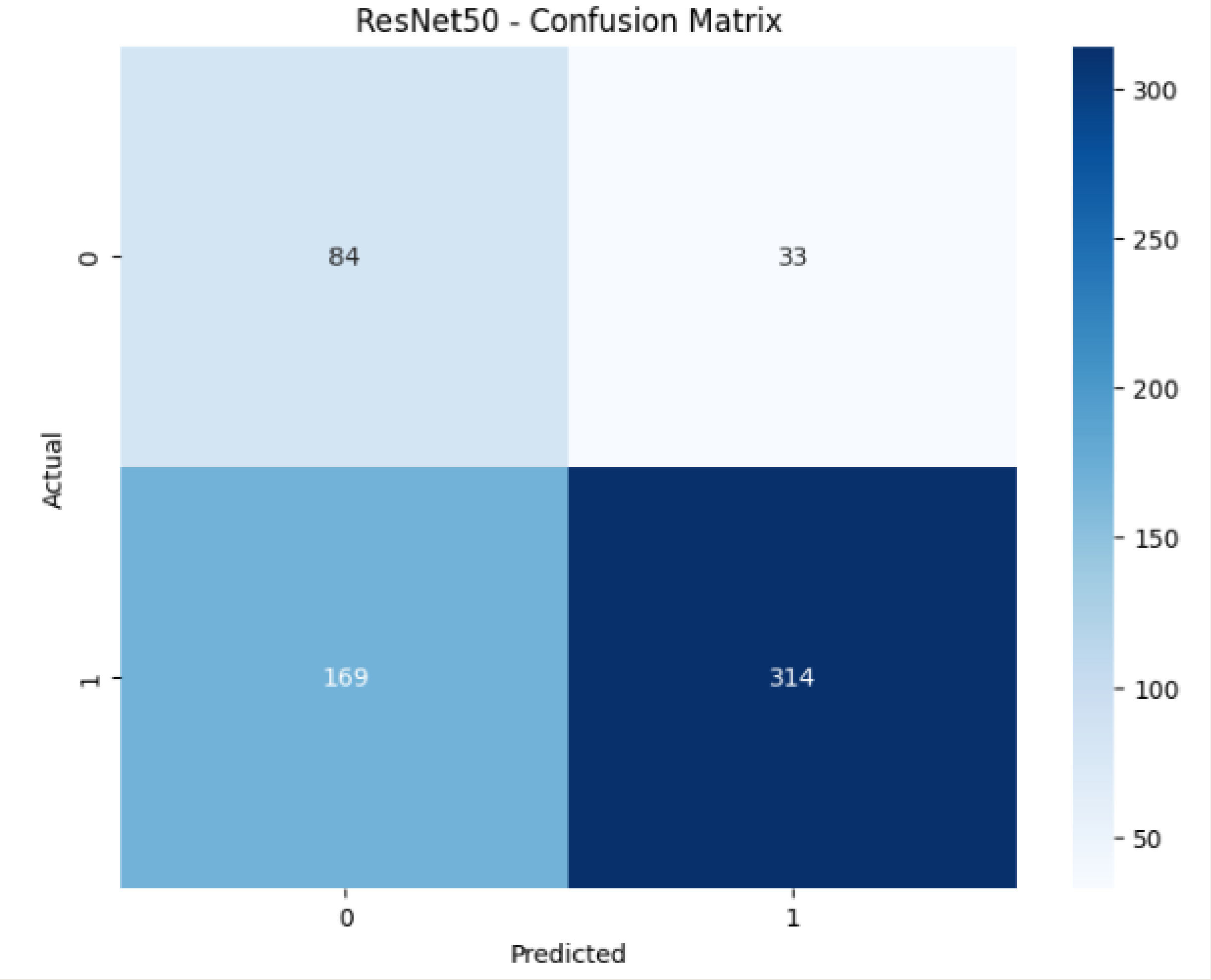
ALEXNET MODEL

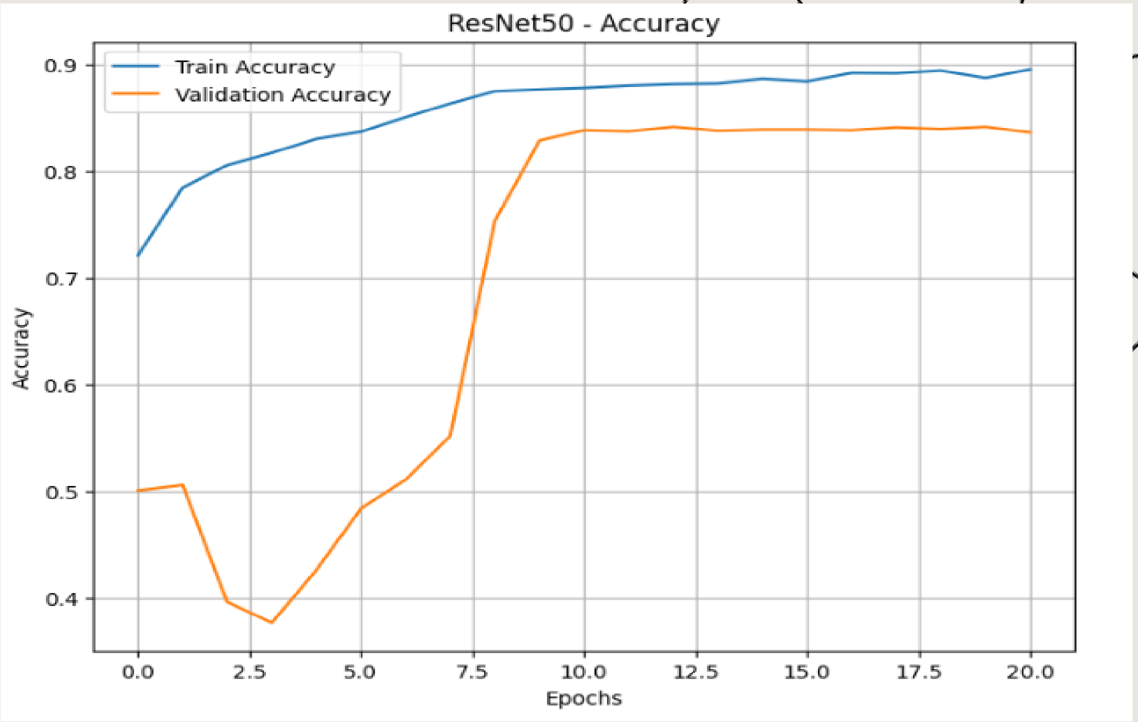


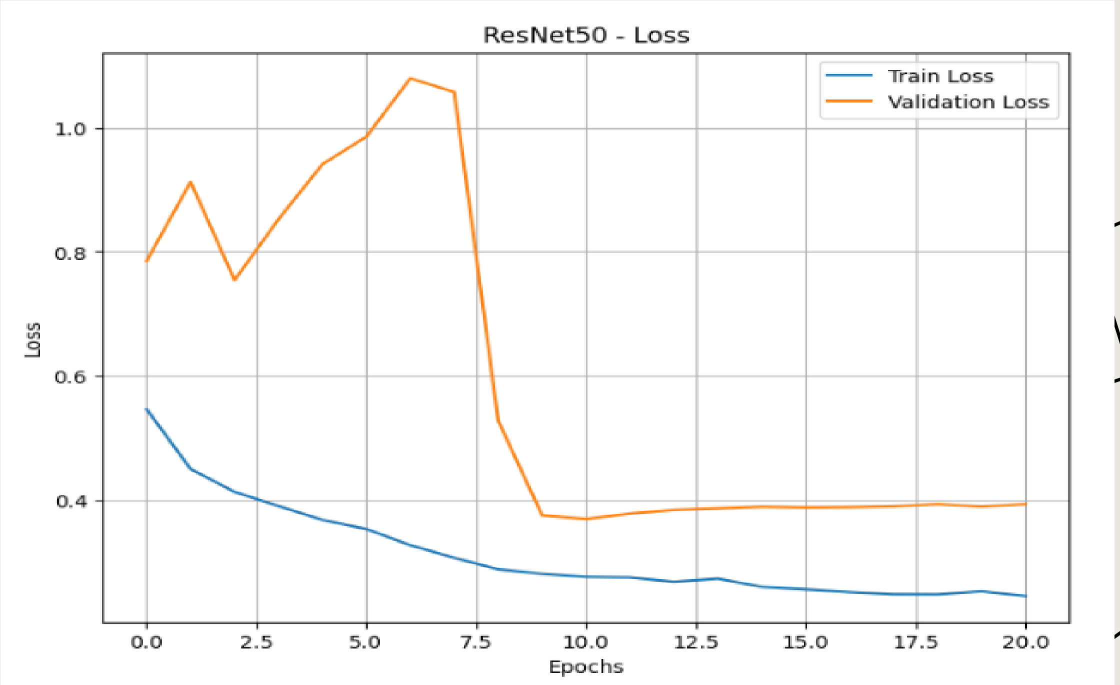




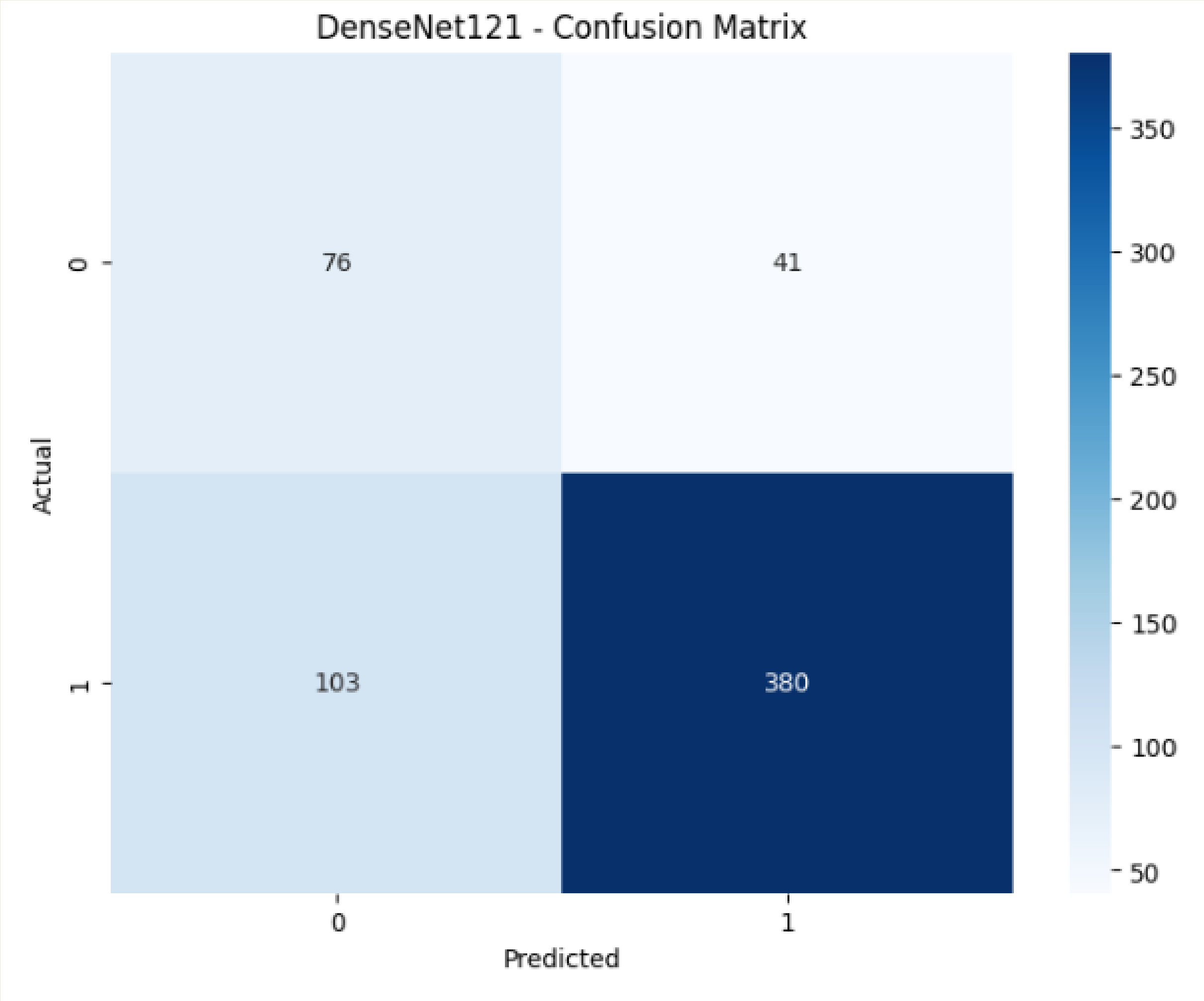
RESNET MODEL

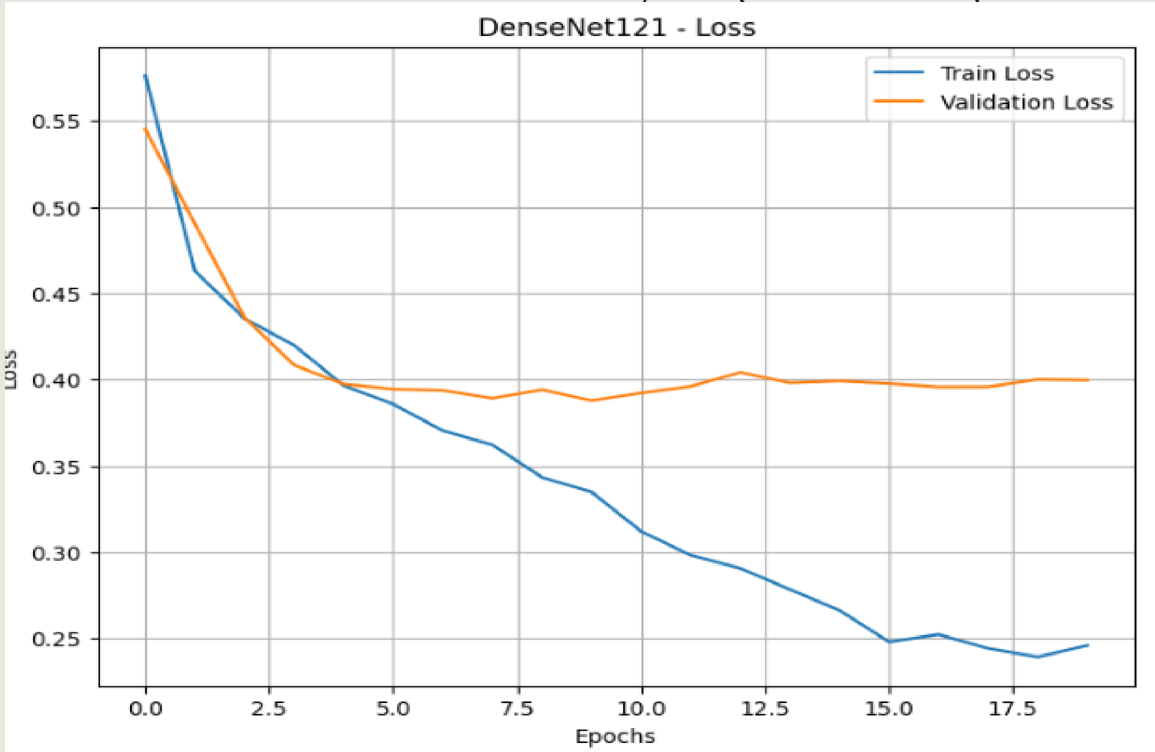


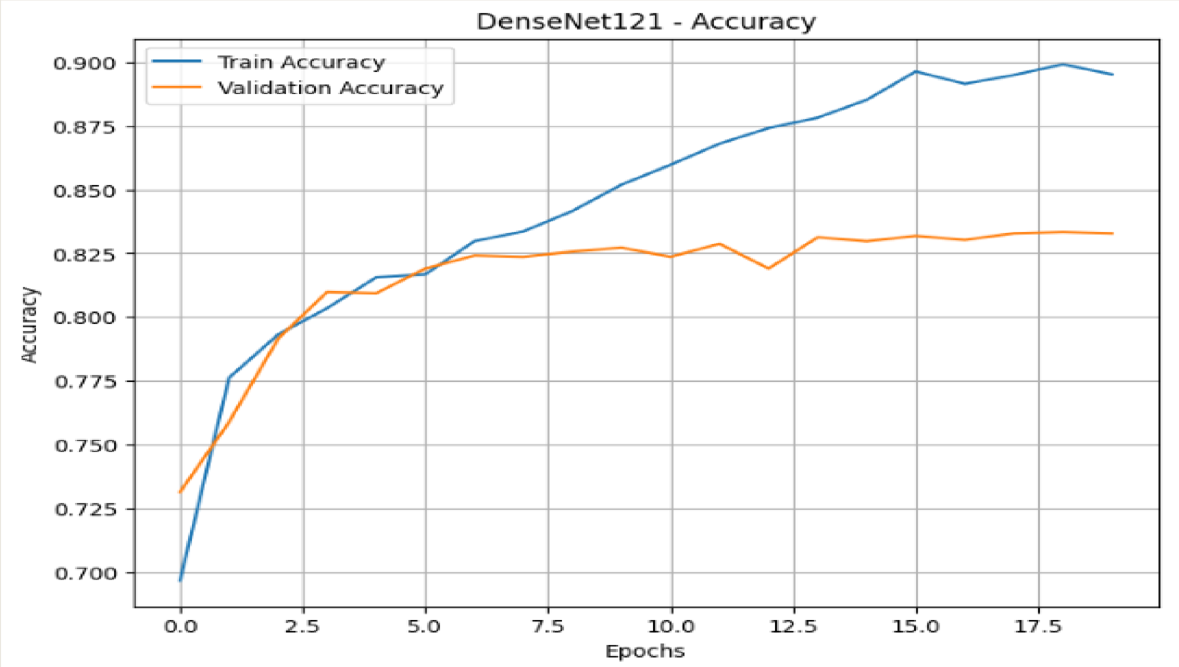




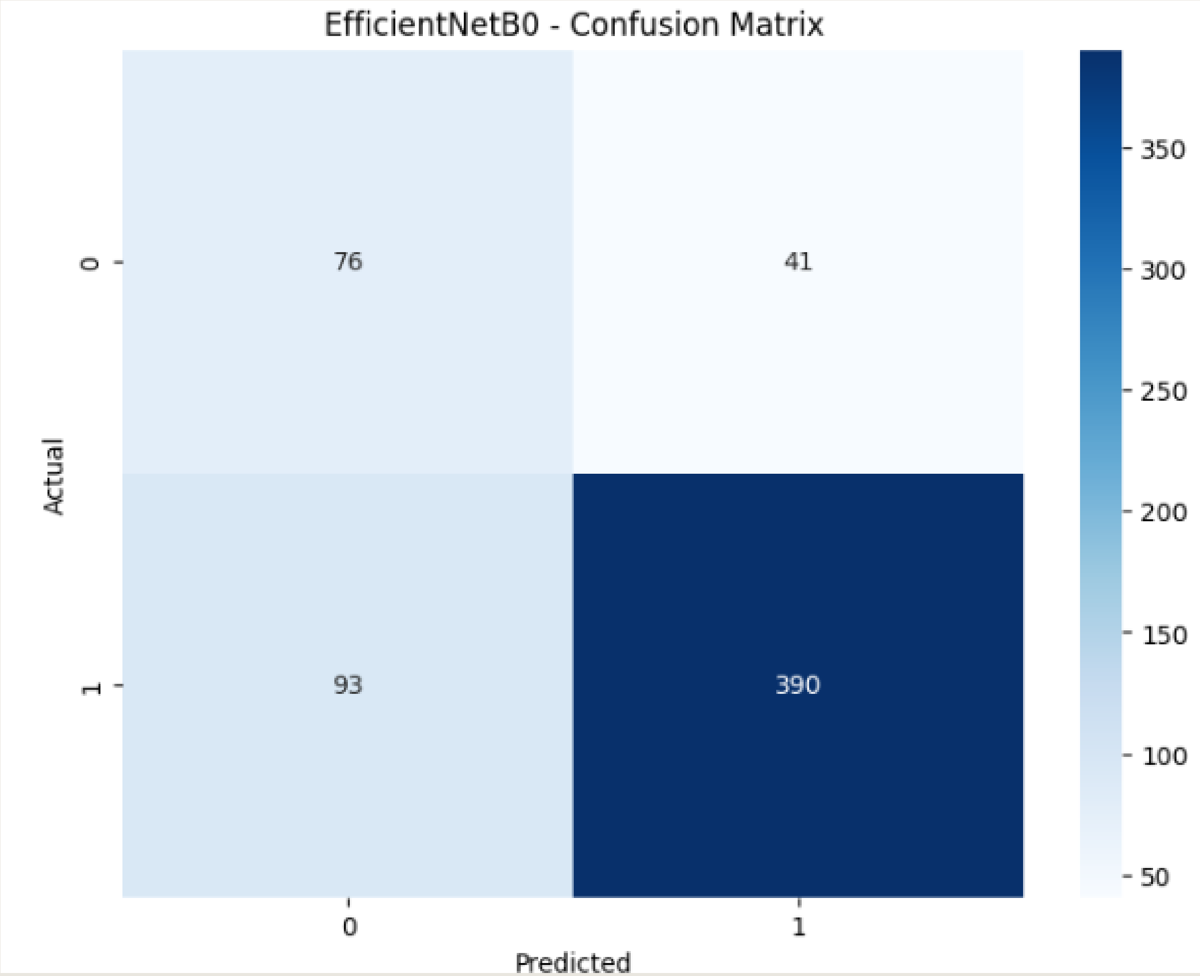
DENSENET MODEL

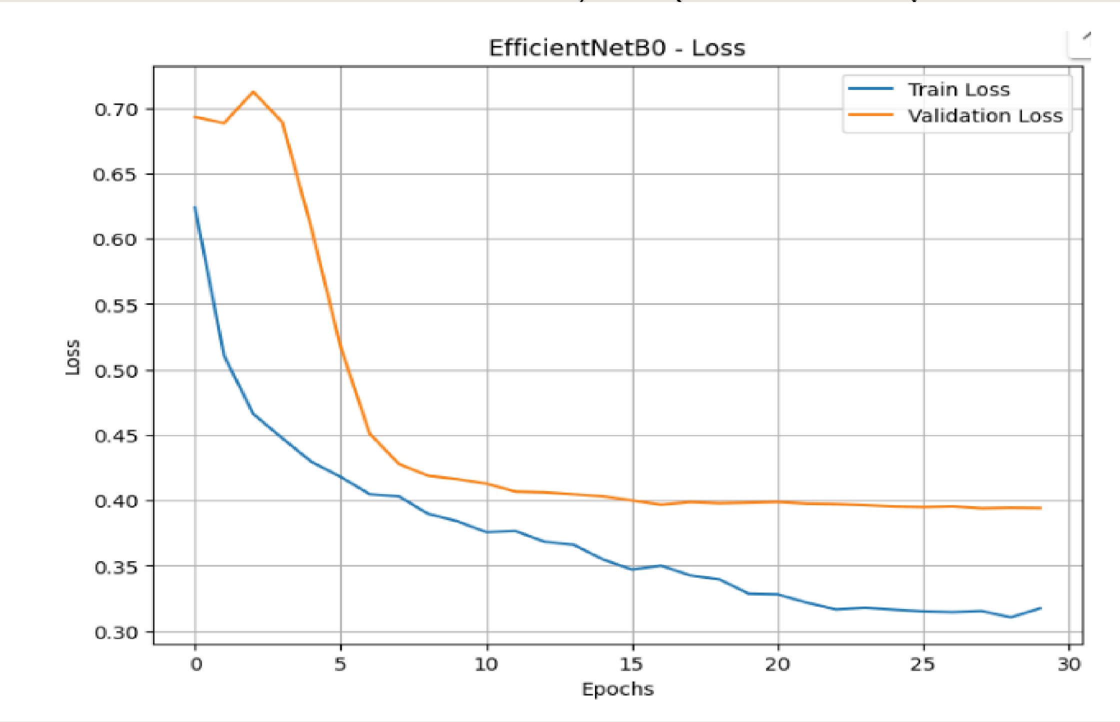


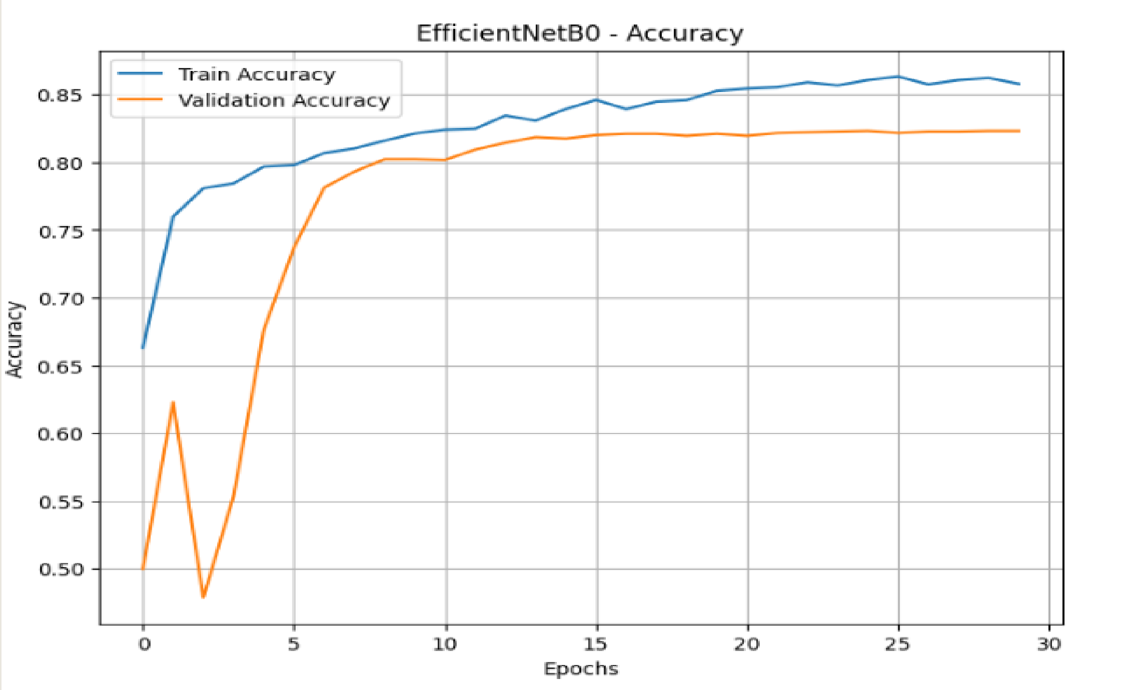




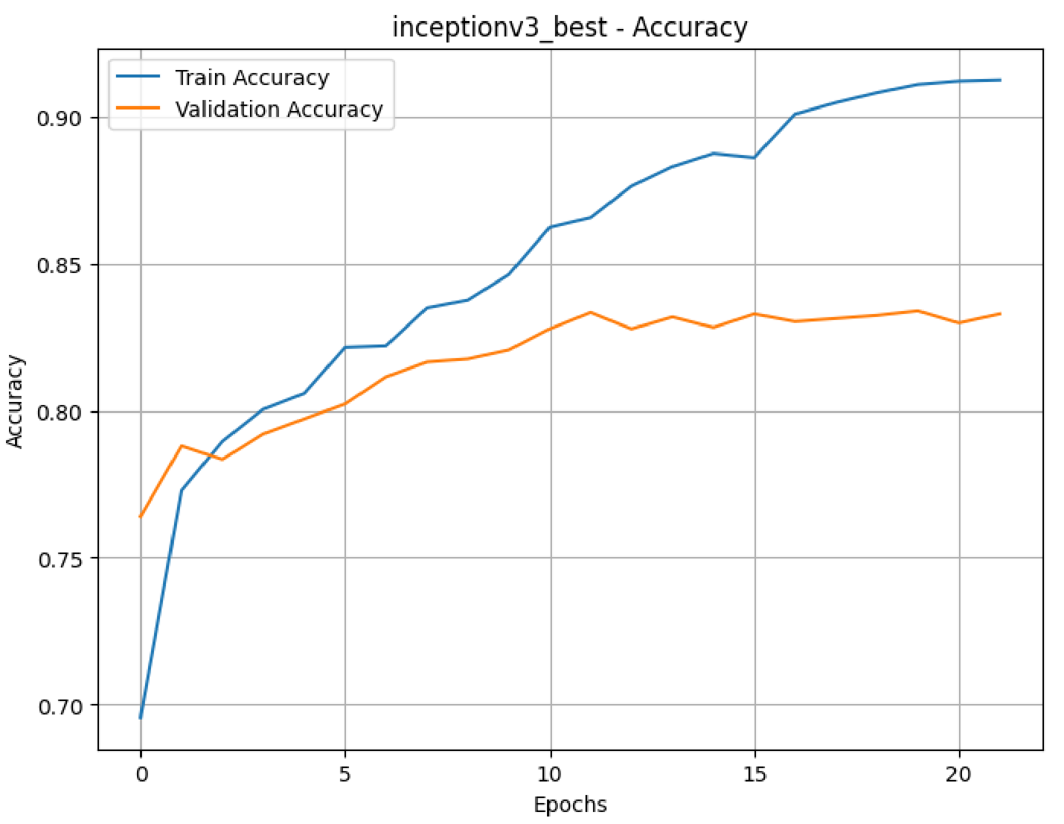
EFFICIENTNET MODEL

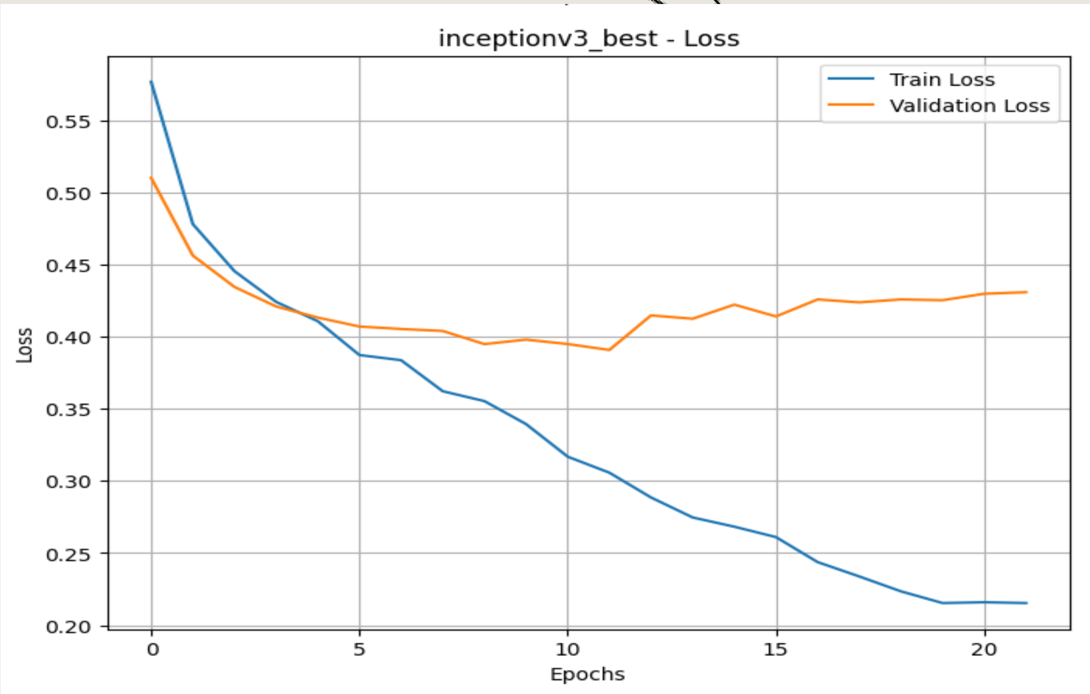






INCEPTIONV3 MODEL PERFORMANCE AFTER OPTIMIZATION(HYPERTUNING)

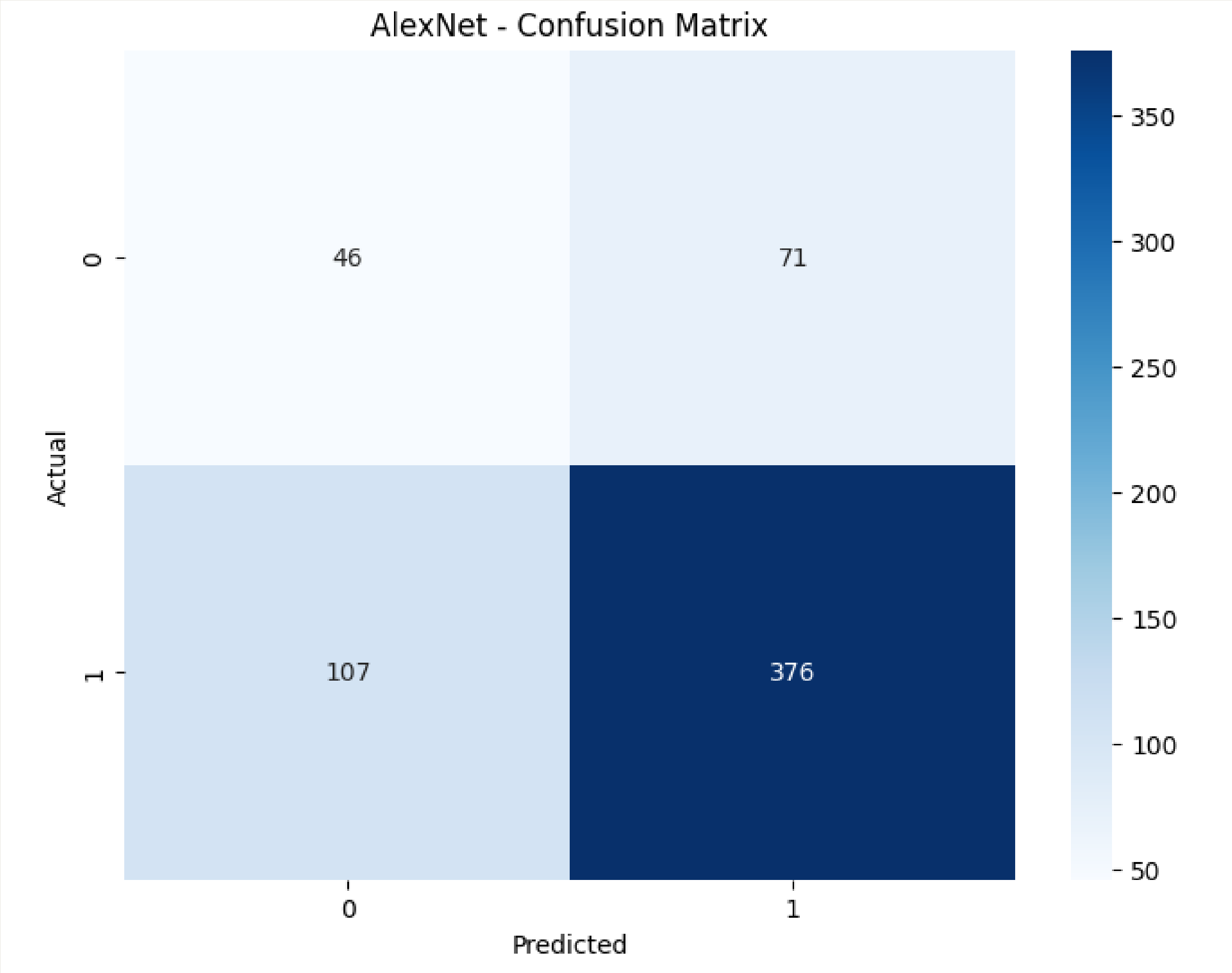


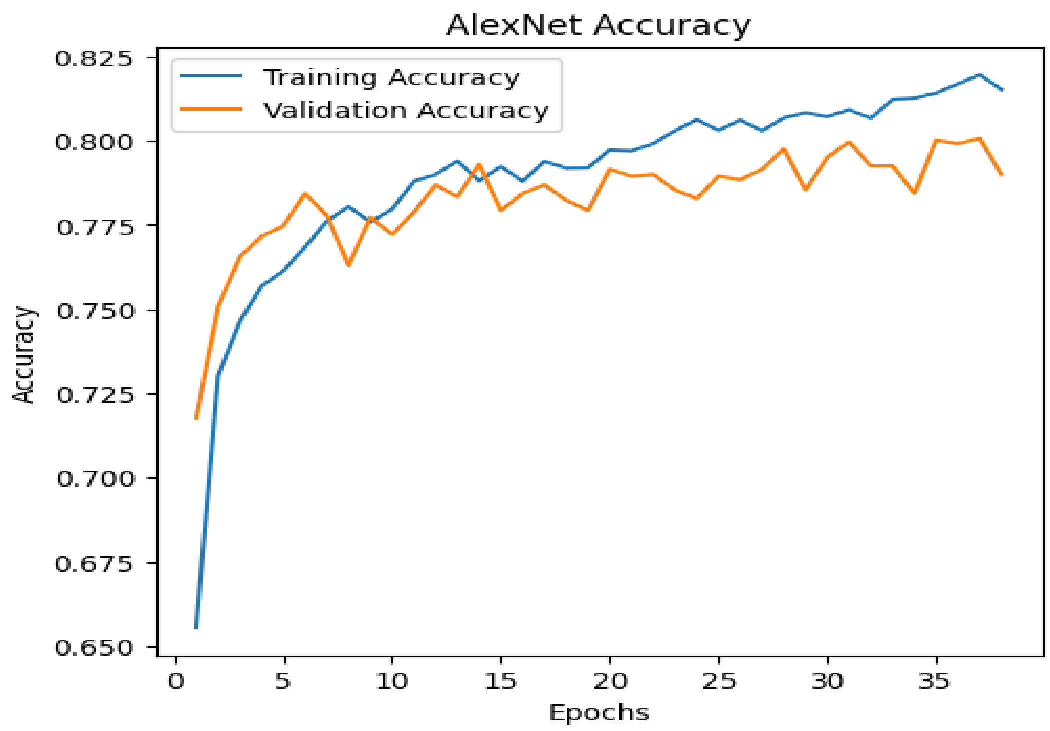


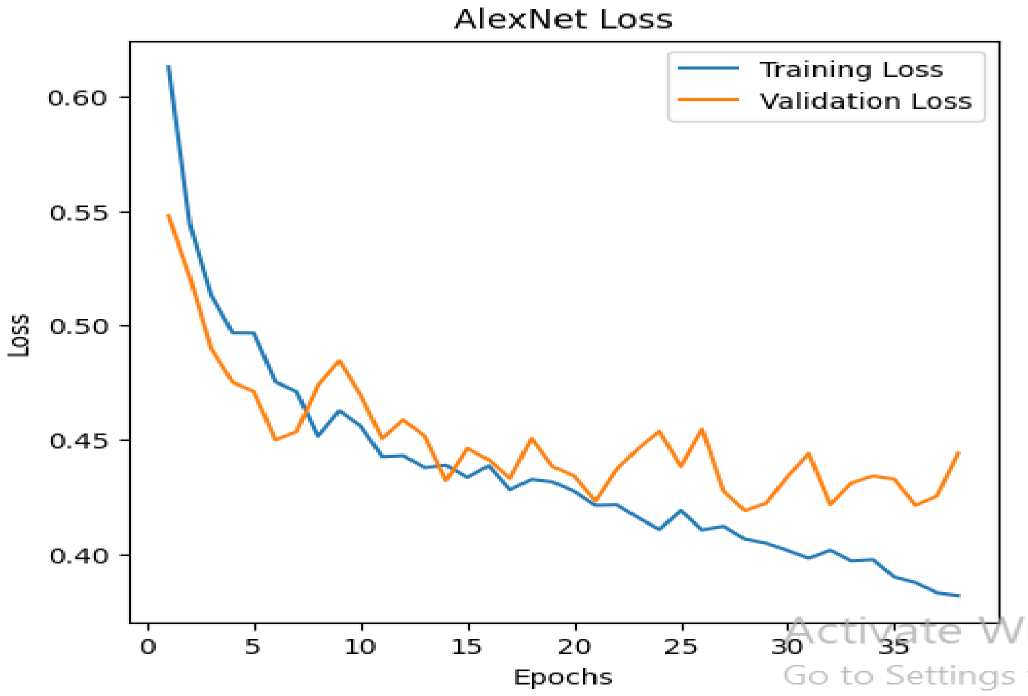
Classification Report for inceptionv3_best:

	precision	recall	f1-score	support
mel	0.40	0.56	0.47	117
oth	0.88	0.80	0.84	483
accuracy			0.75	600
macro avg	0.64	0.68	0.65	600
weighted avg	0.79	0.75	0.77	600

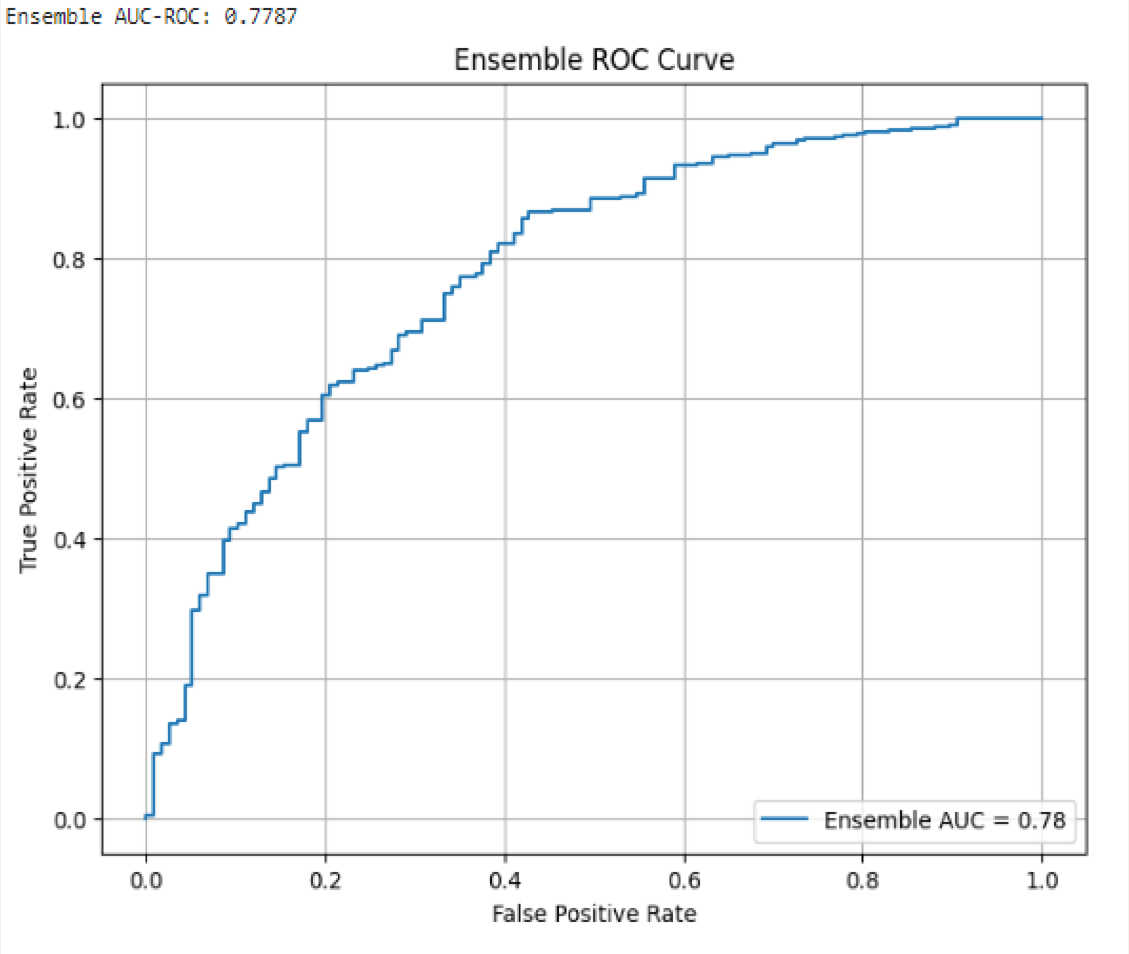
ALEXNET MODEL





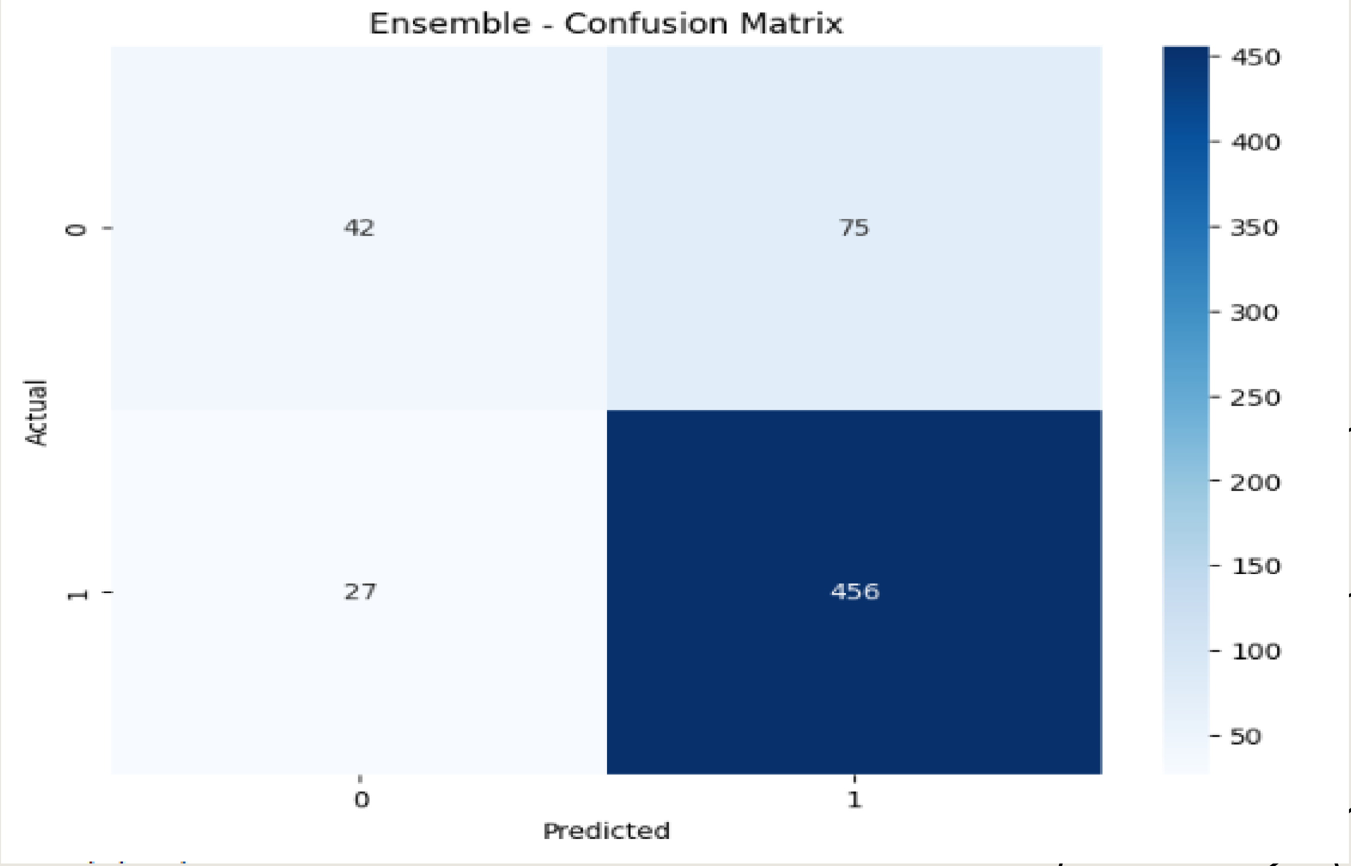


ENSEMBLE MODEL



Classification Report for Ensemble:

	precision	recall	f1-score	support
0	0.61	0.36	0.45	117
1	0.86	0.94	0.90	483
accuracy			0.83	600
macro avg	0.73	0.65	0.68	600
weighted avg	0.81	0.83	0.81	600



MODELS COMPARISON

Model	Accuracy	Precision	Recall	F1-Score	Precision	Recall	F1-Score
—-	—-	(Mel)	(Mel)	(Mel)	(oth)	(oth)	(oth)
InceptionV3	75%	0.40	0.56	0.47	0.88	0.80	0.84
AlexNet	70%	0.30	0.39	0.34	0.84	0.78	0.81
ResNet	66%	0.33	0.31	0.32	0.79	0.89	0.84
DenseNet121	76%	0.42	0.65	0.51	0.90	0.79	0.84
EfficientNet	78%	0.45	0.65	0.53	0.90	0.81	0.85
Ensemble	83%	0.61	0.56	0.58	0.86	0.94	0.90

Table 5.1: Performance Comparison of Models

CONCLUSION

- Developed effective deep learning models (AlexNet, InceptionV3, ResNet50, DenseNet121, EfficientNetB0) for skin lesion classification.
- **Class imbalance** addressed using focal loss and class-weighted loss, improving detection of malignant cases.
- **Ensemble models** provided the best accuracy and robustness by leveraging multiple architectures.
- Achieved **accuracy >80%** with optimized models (InceptionV3, AlexNet) and ensemble approach.
- **Challenges**: Class imbalance and limited dataset diversity remain significant hurdles.
- **Future Work**: Expand dataset, explore advanced architectures, and improve model generalizability for clinical use.

THANK YOU