MELANOMA SKIN CANCER CLASSIFICATION

CSE360-DEEP LEARNING

Hema Varsini R - E0322010

Sudharshini R - E0322019

Shreya S - E0322030

INTRODUCTION

- Skin cancer is among the most commontypes of cancer globally, and melanoma, though less prevalent, is the most deadly form due to its aggressive nature.
- Early and accurate detection plays a critical role in improving patient outcomes. With computer vision and deep learning advances, automated melanoma detection usingdermatoscopic images is now a promising reality.
- This project focuses on building a deep learning-based system for classifying skin lesions as melanoma or non-melanoma using multiple convolutional neural network architectures.
- The goal is to explore and compare these models to identify the most accurate andefficient architecture for skin cancerclassification.

PROBLEM STATEMENT

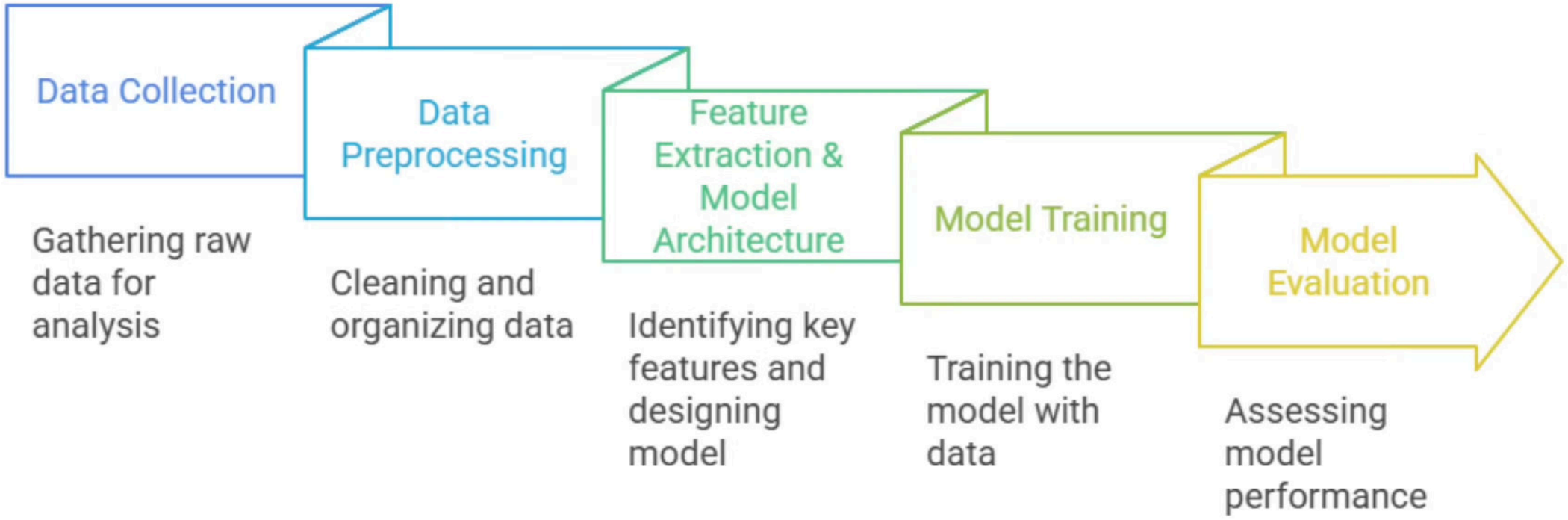
- Diagnosing melanoma accurately at an early stage is challenging due to the visual similarity of malignant and benign skin lesions.
- Dermatological examinations rely heavily on clinical expertise and biopsies, which can be invasive, time-consuming, and inconsistent across practitioners.
- The problem addressed in this project isdeveloping an automated, image-based melanoma classification system using deep learning.
- By leveraging convolutional neural networks, the aim is to reduce diagnostic errors, support dermatologists in decision-making, and improve early detection rates.

OBJECTIVE

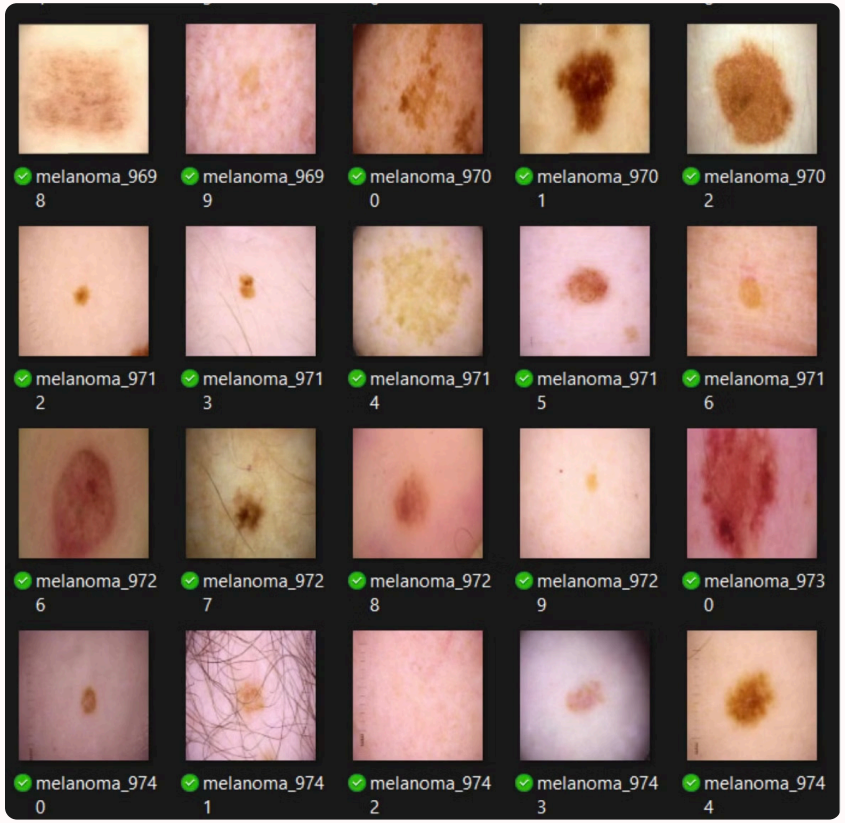
The primary objective of this project is to develop an efficient and accurate deep learning-based model for the classification of Melanoma. The project aims to:

- To develop an automated system for classifyingdermatoscopic images of skin lesions intomalignant and benign categories using deep learning techniques.
- To implement and evaluate multiple CNN architectures, including VGG16, ResNet50, EfficientNetB0, and a custom-designed CNN model, to determine the most effective model for accurate skin cancer detection.
- To apply transfer learning with pre-trained models and fine-tune them on the melanomadataset for improved learning efficiency andperformance.
- To compare model performance using metricssuch as accuracy, training and validation loss,and visualizations, identifying the architecturethat provides the best trade-off between accuracy and computational complexity.

METHADOLOGY



DATA COLLECTION AND PREPROCESSING



- The dataset used in this project comprises dermatoscopic images of skin lesions labeled as either malignant and benign.
- To prepare the data for training, all images wereresized to 224x224 pixels.
- The dataset was normalized by scaling pixel values to the range of 0 to 1, ensuring faster convergence during training.
- Additionally, data augmentation techniques such as rotation, flipping, zooming, and shifting were applied to artificially expand the dataset and help the model generalize better by learning from varied image patterns. The dataset was split into training, validation, and test sets to allow accurate performance evaluation.

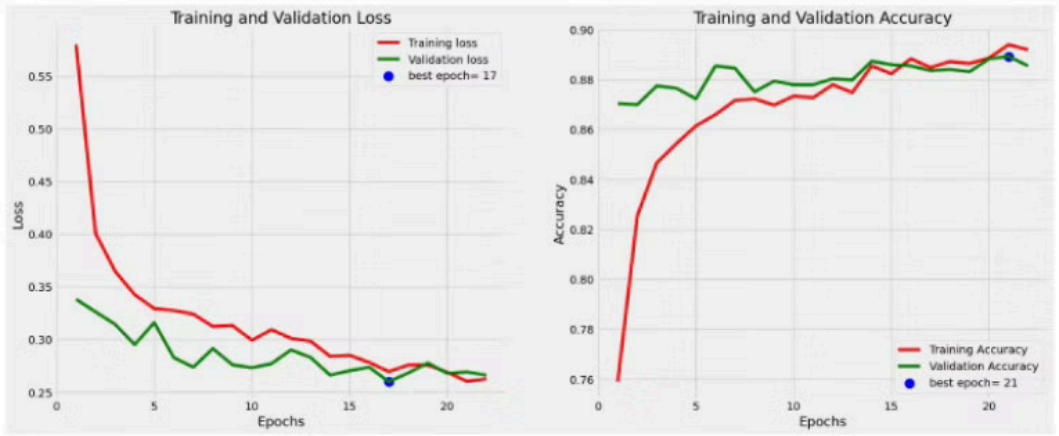
Layer (type)	Output Shape	Param #
resnet50v2 (Functional)	(None, 2048)	23,564,800
dense (Dense)	(None, 512)	1,049,088
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 64)	16,448
dropout_2 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 1)	65

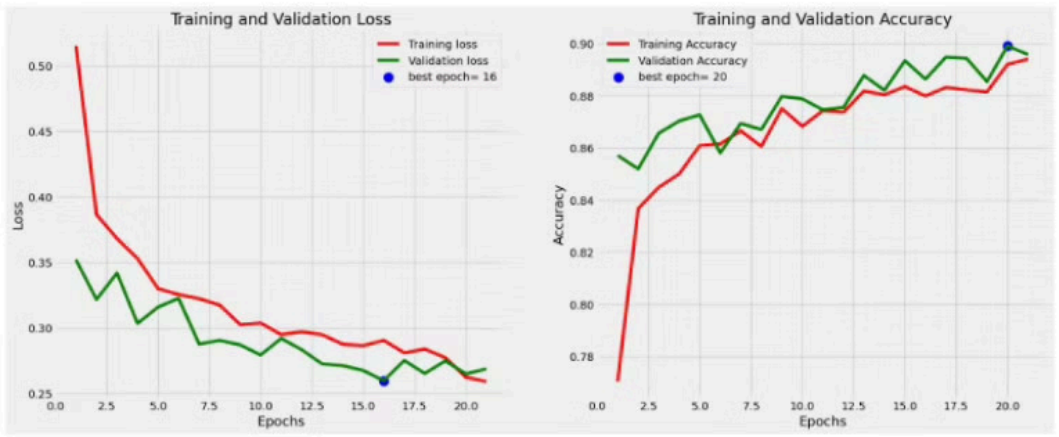
FEATURE EXTRACTION AND MODEL ARCHITECTURE

This project explores four different CNN architectures for melanoma classification: VGG16, ResNet50, EfficientNetB0, and a custom CNN model referred to as the Densemodel.

- Each of the pre-trained models was used with transfer learning by removing the topclassification layers and adding custom layerssuitable for binary classification.
- These layers included Global Average Pooling, Dense layers with ReLU activation, Dropout for regularization, and a final Dense layer with sigmoid activation.
- The custom CNN was built from scratch with convolutional, pooling, and fully connected layers.
- The goal of experimenting with different architectures was to identify the most effective one for accurately classifying dermatoscopic images.

MODEL TRAINING AND MODEL EVALUATION





- All models were trained using the Adam optimizer and binary crossentropy loss function. Training was conducted over multiple epochs, and early stopping was used to preventoverfitting by monitoring validation loss.
- A consistent batch size was applied across all models to ensure comparability. Throughout training, key metrics such as accuracy and loss were recorded for both training and validation sets.
- The custom Dense model, while simpler, served as a baseline to compare against the morecomplex, pre-trained architectures.
- Model performance was visually monitored through plotted accuracy and loss curves,providing insights into convergence and generalization.

APPLICATION

Risk Assessment:

- **Targeted Screening Programs:** Integrating automated image analysis can help identify high-risk individuals for more frequent skin screenings, enabling dermatologists to focus resources on patients who need it most.

Clinical Decision Support:

- **Enhanced Diagnostic Accuracy:** Deep learning-based classification systems can serve as second-opinion tools for dermatologists, reducing human error and increasing diagnostic confidence in distinguishing melanoma from benign lesions.

Healthcare Optimization:

- **Scalable and Accessible Solutions:** Automated skin lesion classification using mobile or web platforms can expand access to diagnostic tools in remote or underserved areas, making melanoma screening more scalable and cost-effective.

Educational Tool:

- **Training Support for Clinicians:** These AImodels can also be used in dermatology education, helping medical students and juniordoctors learn to identify and differentiate skinlesions more effectively.

RESULTS AND DISCUSSION

Best Performing Model:

The ResNet50 model outperformed all others, achieving the highest validation accuracy (~87.82%) in classifying melanoma from dermatoscopic images.

Performance Metrics:

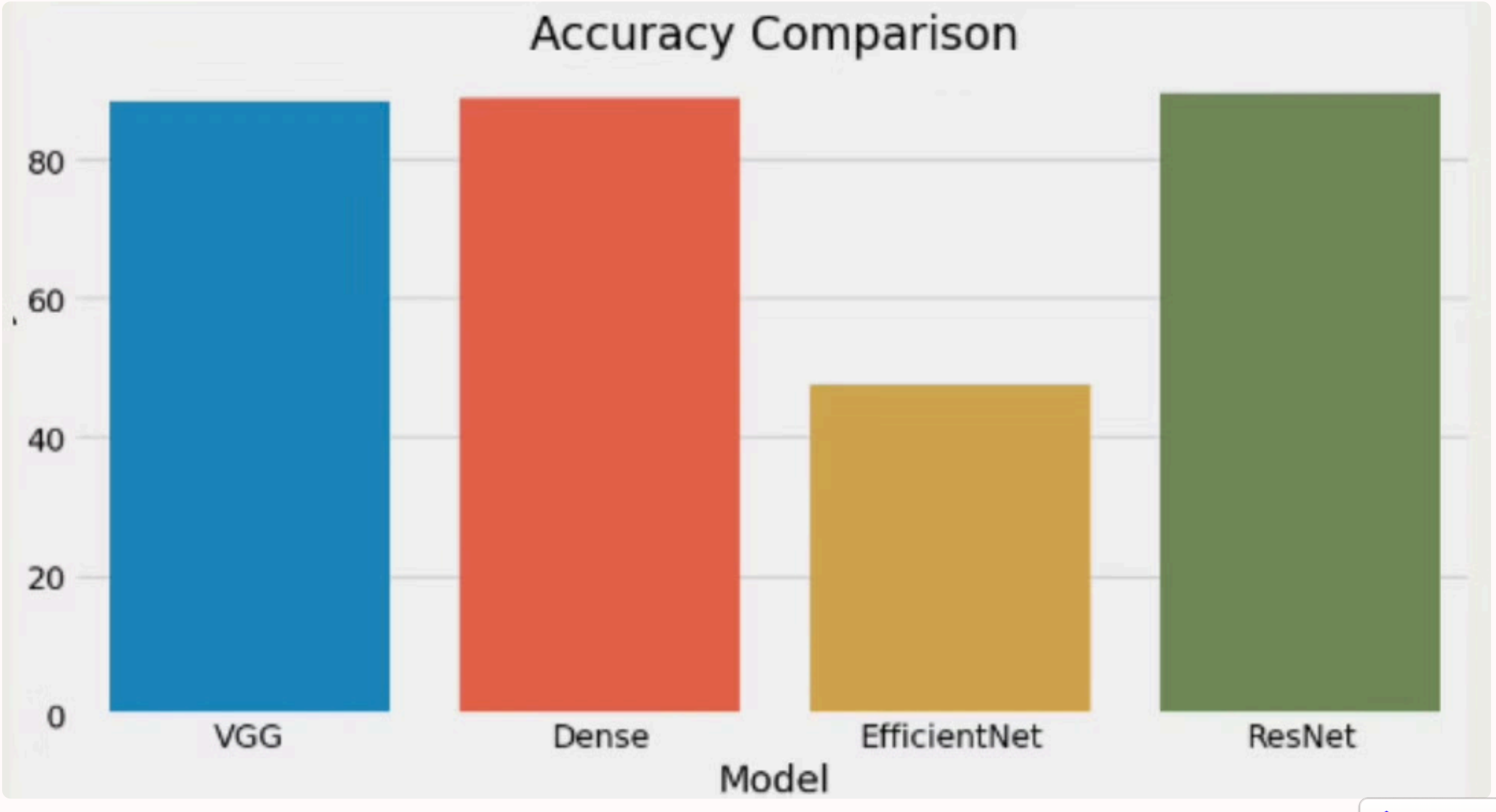
- Model accuracy and loss were monitored during training across both training and validation sets.Plotted performance curves revealed that ResNet50 maintained strong, consistent performance with minimal overfitting.
- In contrast, EfficientNetB0 showed significantly lower accuracy (~50%), indicating poor generalization.

Feature Learning:

- Pre-trained models like ResNet50 and VGG16 effectively captured essential features such as lesion asymmetry, border irregularity, and colour variation, which are critical in clinical melanoma diagnosis.

Insights:

The models demonstrated a strong capacity to distinguish between malignant and benign lesions. This suggests that AI systems like ResNet50 could assist dermatologists in early melanoma detection and reduce diagnostic errors.



CONCLUSION

- This study demonstrates that deep learning models, particularly those based on transferlearning like ResNet50, are highly effective inclassifying melanoma from dermatoscopicimages.
- Among the four architectures evaluated, ResNet50 emerged as the best-performingmodel, achieving the highest validation accuracy (~87.82%) and consistent performance. WhileDense and VGG16 also performed well, EfficientNetB0 showed poor results (~50%), highlighting that not all efficient architectures guarantee high accuracy in medical imaging tasks.
- The analysis underscores the critical importance of architecture selection when applying deep learning to medical image classification.

Future work may include:

- Expanding classification to multiple types of skin lesions.
- Optimizing models for edge devices to support real-time diagnostics.
- Integrating clinical metadata (e.g., patient history, lesion location) to enhance predictiveaccuracy and clinical relevance.

THANK YOU !