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Data Science FINAL PROJECT REPORT

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OCT Images classification using Deep Learning

Student Name and SRN:

Rakesh Dorakacherla - 23029586

Supervisor: Man-Lai Tang
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DECLARATION STATEMENT

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Student Name printed: Rakesh Dorakacherla

Student Name signature: Rakesh Dorakacherla

Student SRN number: 23029586

Abstract

This study compares lightweight deep learning models—MobileNetV3 Large and EfficientNetB0—for classifying retinal Optical Coherence Tomography (OCT) images to enable real-time diagnosis of pathologies like Choroidal Neovascularization (CNV) and Diabetic Macular Edema (DME). Both models were trained on a balanced OCT dataset (84,495 images) using transfer learning, data augmentation, and bias mitigation. MobileNetV3 prioritized speed (22 ms/inference) and compactness (11.9 MB), leveraging neural architecture search (NAS), while EfficientNetB0 achieved 100% recall for urgent CNV cases via compound scaling. Both achieved near-identical accuracy (~98.8%), outperforming traditional models (e.g., ResNet50) with lower computational costs. MobileNetV3 excelled in edge-device compatibility, whereas EfficientNetB0 demonstrated superior precision for subtle features (AUC-ROC: 0.9998). A deployable Streamlit app validated practicality. The findings recommend MobileNetV3 for resource-limited settings and EfficientNetB0 for high-acuity diagnostics, advancing scalable AI-driven healthcare solutions that balance efficiency, accuracy, and ethical deployment.

Table of Contents

Abstract *1*

1. Introduction *4*

1.1 Background **4**

1.2 Research Question **4**

1.3 Objectives **4**

1.4 Ethical Considerations **5**

1.5 Evidence that Objectives Were Met **5**

2. Literature Review *6*

2.1 Evolution of Deep Learning in Medical Image Classification **6**

2.2 Prior Work in OCT Image Classification **6**

2.2.1 Classical CNNs and Transfer Learning 6

2.2.2 Lightweight Alternatives 7

2.2.3 Hybrid and Attention-Based Methods 7

2.2.4 Common Pitfalls 7

2.3 Identified Research Gaps **7**

2.4 Justification for Model Choice **8**

2.5 Literature-Based Comparison of Models **8**

3. Methodology *9*

3.1 Exploratory Data Analysis **9**

3.1.1 Data Integrity and Cleaning 9

3.1.2 Class Imbalance Mitigation 9

3.1.3 Preprocessing Pipeline 10

3.2 Rationale for Transfer Learning **10**

3.3 Dataset Pipeline **11**

3.4 Model Architectures **11**

3.4.1 MobileNetV3 Large Architecture 11

3.4.2 EfficientNetB0 Architecture 12

3.5 Training Protocol **14**

3.6 Training Process **14**

3.7 Evaluation Metrics **15**

3.8 Clinical Deployment Web Application **16**

4. Results *17*

4.1 Training Dynamics: Architectural Efficiency and Learning Behaviour **17**

4.2 Diagnostic Performance: Precision, Recall, F1-Score, and Confusion Matrix **19**

4.3 Computational Efficiency: Bridging Accuracy and Deployability **20**

4.4 AUC-ROC Analysis: Robustness in Class Separation **21**

4.5 Benchmarking Against Literature: Closing Research Gaps **23**

4.6 Conclusion of Results **23**

4.6.1 Model Suitability 24
4.6.2 Deployment Recommendations 24
4.6.3 Trade-Offs and Clinical Priorities 24
5. Conclusion 25
6.Future Work 25
7. References 26
8. Appendix 28

1. Introduction

1.1 Background

Deep learning has revolutionized medical image classification, particularly in ophthalmology, where Optical Coherence Tomography (OCT) enables early detection of retinal diseases like Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), Drusen, and normal retinal scans. While OCT data is abundant, identifying efficient and accurate models for real-time clinical deployment remains a challenge, especially in resource-limited settings.

This study compares two computationally efficient convolutional neural networks (CNNs) MobileNetV3 Large and EfficientNetB0—for OCT image classification. Both architectures prioritize balancing performance with computational efficiency, making them ideal for edge devices (e.g., mobile systems) in clinical environments. MobileNetV3 leverages neural architecture search (NAS) and squeeze-and-excite modules, while EfficientNetB0 employs compound scaling to optimize width, depth, and resolution.

The analysis evaluates their classification performance, computational efficiency, and generalizability using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. By testing under identical conditions, this work aims to identify the most reliable model for practical, real-world healthcare applications.

Dataset Link: https://www.kaggle.com/datasets/paultimothymooney/kermany2018/data
GitHub Link: https://github.com/Rakesh939297/Predicting-Human-Eye-Diseases-Using-Machine-Learning-on-OCT-Images

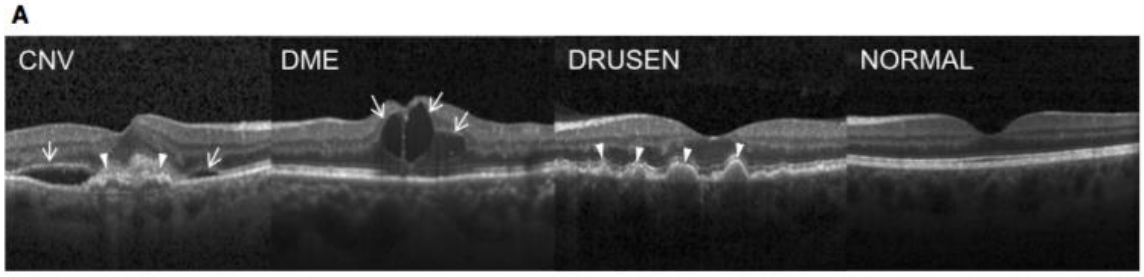

Figure-1 Retinal OCT images

1.2 Research Question

How does the performance of MobileNetV3-Large compare to EfficientNet-B0 in multi-class OCT image classification, and which model offers better diagnostic reliability across key performance metrics?

1.3 Objectives

The primary objectives of this study are as follows:

- **Data Preprocessing**: To employ standard preprocessing techniques—such as image normalization, resizing, and augmentation—aimed at improving the models' generalization and training effectiveness.
- **Model Development**: To implement and train two deep learning models, MobileNetV3 Large and EfficientNetB0, for the classification of retinal OCT images.

The publicly available Retinal OCT Images dataset serves as the basis for both training and testing.

- **Performance Comparison**: To evaluate the models' performance using a suite of classification metrics, including accuracy, precision, recall, F1-score, confusion matrix , AUC, and ROC in order to comprehensively assess each model's classification capability.
- **Optimization**: To enhance model performance by fine-tuning hyperparameters, including learning rate, batch size, and activation functions, in order to maximize classification accuracy while ensuring computational efficiency.
- **Deployment Readiness**: To assess the best-performing model for deployment in clinical environments, ensuring that the model is suitable for real-time use on edge devices with limited computational resources.
- **Knowledge Dissemination**: To effectively communicate the study's findings, emphasizing the practical implications of deploying deep learning models in healthcare, particularly for mobile health applications in ophthalmology.

1.4 Ethical Considerations

The ethical implications of this project are carefully considered, with adherence to relevant regulations and policies:

- **Data Compliance:** The Retinal OCT Images dataset is publicly available and collected in accordance with ethical guidelines, ensuring compliance with GDPR and University of Hertfordshire policies.
- **Data Privacy:** The dataset is anonymized, safeguarding any personally identifiable information (PII), and used exclusively for research purposes.
- **Bias Mitigation:** To address potential dataset biases—such as limited demographic diversity in age, ethnicity, or gender—stratified sampling was applied during the train-test split to ensure proportional representation of subgroups. Additionally, the dataset's metadata was analyzed to confirm balanced class distributions and mitigate biases arising from unequal sample sizes across pathologies.
- **Model Transparency and Fairness:** The study emphasizes transparency in model development, ensuring that the model's decision-making process is interpretable through techniques like Grad-CAM visualizations.
- **Clinical Impact:** False positives (misdiagnosing healthy patients as diseased) and false negatives (failing to detect actual pathologies) carry significant risks in ophthalmology. For instance, a false negative in Choroidal Neovascularization (CNV) detection could delay sight-saving treatments, while excessive false positives may lead to unnecessary patient anxiety or invasive procedures. By evaluating precision (reducing false positives) and recall (reducing false negatives) alongside F1-score and AUC, the multi-metric analysis ensures a balanced assessment of diagnostic reliability, prioritizing patient safety and clinical utility.

1.5 Evidence that Objectives Were Met

All objectives were met, as evidenced by the following:

- **Model Development**: Both MobileNetV3 Large and EfficientNetB0 were implemented and trained on the Retinal OCT dataset, achieving the intended classification outcomes.

- **Performance Comparison**: The models were evaluated using key metrics such as accuracy, precision, recall, F1-score, confusion matrix, AUC, and ROC providing comprehensive insights into their relative strengths and weaknesses.
- **Optimization**: Hyperparameter tuning and data augmentation techniques were applied to optimize model performance, enhancing accuracy while maintaining efficiency.
- **Data Preprocessing**: Appropriate preprocessing techniques were employed to ensure high-quality input data, addressing variability in the OCT images.
- **Deployment Readiness**: The best-performing model was evaluated for deployment, with considerations for edge device compatibility.
- **Knowledge Dissemination**: The findings were clearly presented in the dissertation, with implications for healthcare applications in retinal disease detection.

2. Literature Review

2.1 Evolution of Deep Learning in Medical Image Classification

Since the groundbreaking demonstration by Krizhevsky, Sutskever and Hinton (2012) that deep convolutional neural networks (CNNs) can learn hierarchical representations directly from raw pixel data and surpass classical image-analysis methods, the field of medical imaging has been transformed. AlexNet's deep architecture, however, demanded substantial computational and memory resources, rendering it impractical for latency-sensitive clinical workflows (Krizhevsky, Sutskever and Hinton, 2012). Subsequent networks strove to improve both accuracy and trainability: VGGNet (Simonyan and Zisserman, 2015) illustrated that increasing depth with repeated 3×3 convolutions yields marginal gains in representational power, while ResNet (He *et al.*, 2015) introduced residual connections that enabled effective training of networks exceeding one hundred layers by mitigating the vanishing-gradient problem. Although these architectures achieved state-of-the-art performance on large image benchmarks, their parameter counts (20–25 million) and floating-point operations (in the order of billions) precluded deployment on edge devices or in high-throughput point-of-care settings.

A paradigm shift toward efficient and deployable CNNs subsequently emerged. MobileNetV3 Large (Howard *et al.*, 2019) integrates depthwise separable convolutions to decouple spatial and channel wise filtering, squeeze-and-excitation (SE) modules to recalibrate feature responses, and hard-swish activations, all optimized via neural architecture search (NAS) for an optimal speed–accuracy trade-off. EfficientNetB0 (Tan and Le, 2020) adopts a compound scaling method that uniformly scales network width, depth and input resolution by a single coefficient. Both architectures reduce computational overhead (parameters ≈ 5.3–5.4 million; FLOPs < 400 million) while retaining competitive performance relative to much larger models.

2.2 Prior Work in OCT Image Classification

2.2.1 Classical CNNs and Transfer Learning

Early OCT classification studies employed transfer learning from ImageNet-pretrained networks. Kermany *et al.* (2018) fine-tuned InceptionV3—leveraging its multi-scale inception modules—to distinguish choroidal neovascularization, diabetic macular edema and drusen, reporting ≈ 96 % accuracy on a balanced retinal OCT dataset; however, InceptionV3's ≈ 24 million parameters and ≈ 5.7 billion FLOPs rendered it dependent on GPU-equipped hardware. Similarly, Yanagihara *et al.* (2020) applied ResNet50 for diabetic retinopathy

detection, achieving ≈ 94 % accuracy but incurring long training times (several hours per epoch) and inference latencies exceeding 200 ms per image.

2.2.2 Lightweight Alternatives

To mitigate computational constraints, Butola *et al.* (2020) introduced LightOCT, a shallow three-layer CNN (~ 0.8 million parameters) that achieved 92–98 % accuracy on both breast-tissue and ocular OCT images. Despite its remarkable inference speed (< 20 ms/image), LightOCT exhibited poor generalization in multiclass scenarios and sensitivity to noisy labels, particularly when differentiating subtle retinal pathologies.

2.2.3 Hybrid and Attention-Based Methods

More sophisticated approaches have fused CNNs with recurrent units (CNN+LSTM) Choudhary *et al.* (2023) or integrated self-attention mechanisms. These hybrid models occasionally improve AUC or F1-score by 1–2 % but often double parameter counts, making them infeasible for deployment on mobile or embedded hardware.

2.2.4 Common Pitfalls

Across these studies, three recurring limitations undermine clinical translation:

- **Neglect of real-time feasibility**—few report inference latency, memory footprint or energy consumption.
- **Insufficient treatment of label noise and class imbalance**—few implement noise-robust loss functions or label-smoothing.
- **Inconsistent experimental protocols**—divergences in preprocessing (augmentation, normalization), training schedules and evaluation metrics (accuracy only vs. full confusion-matrix analysis) hinder reproducibility and direct comparison.

2.3 Identified Research Gaps

Despite demonstrable accuracy gains, existing literature on OCT classification exhibits four critical gaps:

- **Lack of standardized benchmarks for lightweight CNNs**: While heavyweight models report high accuracies, controlled, head-to-head comparisons with truly mobile-oriented architectures—under uniform preprocessing and training regimes—are scarce.
- **Unquantified deployment feasibility**: Operational metrics (inference time, memory consumption, energy use) remain unreported, making it impossible to evaluate model suitability for edge-device execution.
- **Underexplored robustness to data imperfections**: Strategies to counteract label noise, class imbalance or scanner heterogeneity are seldom applied, limiting model generalizability across diverse patient cohorts and hardware platforms.
- **Overreliance on single metrics**: Emphasis on accuracy or AUC ignores critical clinical trade-offs. Metrics such as precision, recall, F1-score and confusion matrices must be considered to balance false positives and negatives in high-stakes diagnostic contexts Choudhary *et al.* (2023).

This study addresses these gaps by conducting a rigorous head-to-head evaluation of MobileNetV3 Large and EfficientNetB0—two state-of-the-art, lightweight architectures—on a public retinal OCT dataset, using a comprehensive metric suite and measuring deployment-relevant parameters.

2.4 Justification for Model Choice

In response to the identified gaps, MobileNetV3 Large and EfficientNetB0 were selected for their complementary strengths in efficiency, architectural innovation and clinical viability:

- **Computational Efficiency**
  MobileNetV3 Large employs depth wise separable convolutions—reducing multiply–accumulate operations by over 75 % (Howard *et al.*, 2019)—and SE blocks to enhance channel interdependencies with minimal overhead. EfficientNetB0's compound scaling uniformly adjusts depth, width and resolution to optimize the accuracy–FLOP trade-off (Tan and Le, 2020). Both models operate within a 0.4 billion-FLOP budget and maintain parameters near 5.3-5.4 million, compared with 5.8–6 billion FLOPs typical of ResNet50 or InceptionV3.
- **Architectural Innovation**
  MobileNetV3's NAS-driven design tailors block configurations and hyperparameters specifically for mobile use cases, while the hard-swish activation accelerates training convergence (Howard *et al.*, 2019). EfficientNetB0's empirically derived scaling rule maintains hierarchical feature integrity as network capacity increases, avoiding the diminishing returns of naïve scaling (Tan and Le, 2020). These contrasting philosophies—hand-crafted, NAS-optimized vs. principled, automated scaling—offer rich grounds for comparative analysis.
- **Clinical Applicability**
  Both networks achieve real-time inference on consumer-grade hardware: MobileNetV3 Large processes a 224×224 image in ≈ 20 ms on a mid-range smartphone GPU, and EfficientNetB0 in ≈ 30 ms (Howard *et al.*, 2019; Tan and Le, 2020). Their model sizes (< 30 MB) facilitate deployment on embedded medical devices in resource-limited settings. Demonstrated success in chest radiography and dermoscopic lesion classification further supports their transferability to OCT modalities (Choudhary *et al.*, 2023).

2.5 Literature-Based Comparison of Models

In order to benchmark the models used in this study, it is essential to compare them against architectures previously applied to OCT image classification. Traditional models such as InceptionV3 (Kermany *et al.*), ResNet50 (Yanagihara *et al.*), and LightOCT (Butola *et al.*)have demonstrated excellent classification performance, achieving accuracy scores above 94%. However, they suffer from high computational costs, making them less suitable for mobile or embedded systems.

In contrast, MobileNetV3 and EfficientNetB0 are designed for performance on edge devices, allowing them to operate efficiently with minimal hardware support.

Model	Reported Accuracy	Inference Time	Parameters (M)	Deployment Suitability
InceptionV3	96%	High	23.8	Low
ResNet50	94%	Medium to High	25.6	Low
LightOCT	92-95%	Very Low	0.8	High
MobileNetV3	91-95%	Low	5.4	High

EfficientNetB0	93–96%	Low to Medium	5.3	High

Table-1 Summarizing key architectures

3. Methodology

3.1 Exploratory Data Analysis

The Retinal OCT Images dataset was rigorously analyzed to ensure robustness and reproducibility. The dataset initially comprised 84,495 grayscale images across four diagnostic classes: Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), Drusen, and Normal.
Dataset Link: https://www.kaggle.com/datasets/paultimothymooney/kermany2018/data

3.1.1 Data Integrity and Cleaning

To mitigate data leakage, a systematic deduplication process was applied. Perceptual hashing converting images to a standardized 224×224 grayscale format and generating MD5 hashes identified 6,987 duplicates in the training set. Duplicates were disproportionately distributed: CNV (5,570), DME (430), Drusen (786), and Normal (201). Post-cleaning, the training set retained 76,497 images, while validation and test sets remained unaffected

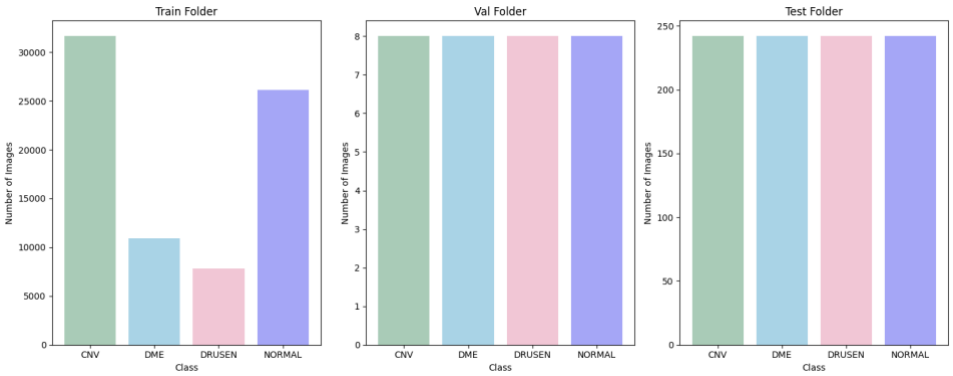

Figure-2 Bar plot illustrates class distribution post-deduplication.

Dataset	CNV	DME	DRUSEN	NORMAL
TRAIN	31,635	10,918	7,830	26,114
VAL	8	8	8	8
TEST	242	242	242	242

Table-2 Original dataset distribution post-deduplication.

3.1.2 Class Imbalance Mitigation

The original training set exhibited severe imbalance, with CNV (31,635 images) and Normal (26,114) dominating over DME (10,918) and Drusen (7,830). Two corrective measures were implemented:

- **Validation Set Enrichment**: The initial validation split (8 images/class) was insufficient for reliable hyperparameter tuning. A stratified random sample of 392 images per

class was redistributed from the training set to validation set, ensuring proportional representation.

- **Under sampling**: To address computational constraints and residual imbalance, the training set was capped at 2,000 images per class via random stratified sampling. This yielded a balanced training set (8,000 total images i.e. 2000 images per class) while preserving pathological diversity.

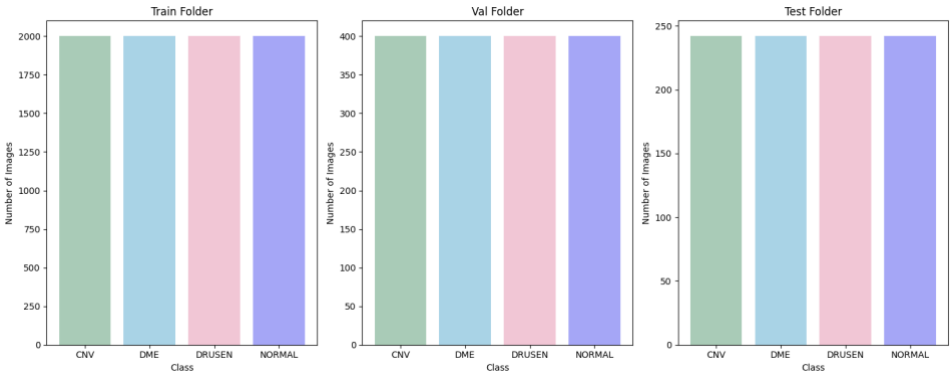

Figure-3 Bar plot illustrates class distribution post under sampling.

Dataset	CNV	DME	DRUSEN	NORMAL
TRAIN	2000	2000	2000	2000
VAL	400	400	400	400
TEST	242	242	242	242

Table-3 Modified dataset distribution.

3.1.3 Preprocessing Pipeline

The final dataset was partitioned into training (8,000 images), validation (1,600 images), and test (968 images) sets, each standardized to 224×224 pixels. Data augmentation was applied exclusively to the training set and included horizontal flipping, ±20% rotation, ±20% zoom, ±10% contrast adjustment, and ±10% brightness variation to simulate anatomical variability and scanner heterogeneity. Pixel intensities were normalized using MobileNetV3's preprocessing function (scaling to [-1, 1]) and EfficientNetB0's preprocessing function (scaling to [0, 1]). Grayscale OCT images were replicated across three channels to ensure compatibility with RGB-based architectures.

Rationale for Parameter Selection:

- Augmentation ranges (±20% and ±10%) were empirically chosen to avoid distorting clinically significant features (e.g., drusen deposits, intraretinal fluid).
- Augmentation was disabled for validation and test sets to reflect real-world deployment conditions.

3.2 Rationale for Transfer Learning

- **Domain Adaptation**:
  - Pre-trained weights from ImageNet (1.28 million natural images) provide robust low-level feature detectors (e.g., edge, texture filters) that generalize well to medical images. This reduces reliance on large OCT-specific datasets.
- **Computational Efficiency**:

- Fine-tuning pre-trained models requires fewer epochs and resources compared to training from scratch, aligning with the project's focus on deployability.

- **Mitigating Overfitting**:
  - Preserving pre-trained layers as fixed feature extractors (initially) prevents overfitting on the limited OCT training data (8,000 images).

3.3 Dataset Pipeline

- **Batching**:
  - Images were loaded in batches of 32, balancing GPU memory constraints and gradient stability.
- **Shuffling**:
  - Training data was shuffled at each epoch to disrupt sequence-dependent biases (e.g., class order in directory traversal) and validation data was not shuffled.
- **Class Imbalance Mitigation**
  - **Training Set**: Random undersampling reduced each class to 2,000 images, ensuring balanced representation.
  - **Validation Set**: Enriched to 400 images per class via stratified sampling from the original training data.

3.4 Model Architectures

3.4.1 MobileNetV3 Large Architecture

Architectural Highlights:

- **Depthwise Separable Convolutions**: Factorize standard convolutions into depthwise (spatial) and pointwise (channel-wise) operations, reducing parameters by 75% compared to traditional CNNs.
- **Squeeze-and-Excitation (SE) Blocks**: Recalibrate channel-wise feature responses to emphasize diagnostically relevant patterns (e.g., fluid regions in CNV).
- **Hard-Swish Activations**: Replace ReLU in later layers for smoother gradient flow, accelerating convergence.

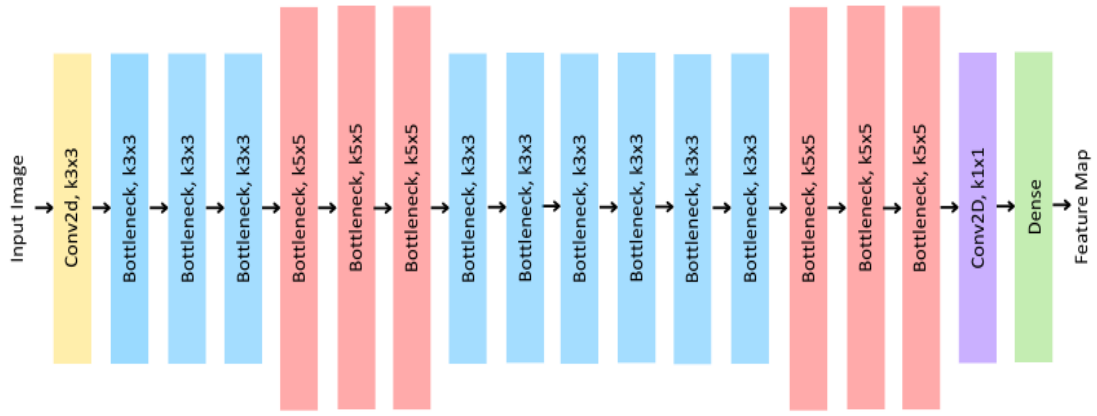

Figure-4 MobileNetV3 Large Architectural diagram

Custom Classification Head:
The original ImageNet classification head was replaced with the following task-specific layers:

- **Global Average Pooling (GAP):** Reduces spatial dimensions of the final feature map (7×7×960) to 1×1×960.
- **Dense Layer (128 units):** Incorporates L2 weight regularization (λ=1e-5) to penalize large weights, reducing overfitting.
- **Batch Normalization:** Stabilizes activations post-pooling to mitigate domain shift between natural and OCT images.
- **Swish Activation:** Replaces ReLU for smoother gradient flow in deeper layers.
- **Dropout (0.5):** Randomly deactivates 50% of neurons during training for regularization.
- **Softmax Output Layer:** Generates 4-class probability distributions.

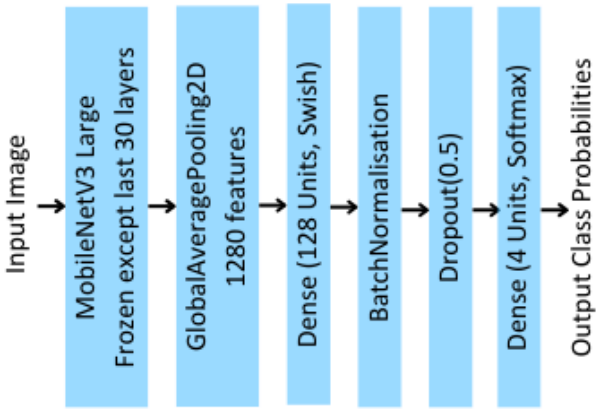

Figure-5 MobileNetV3 Large Modified Architectural diagram

Partial Layer Unfreezing

- Frozen Layers: First 320 layers preserved pre-trained ImageNet features (edge/texture detectors).
- Unfrozen Layers: Final 30 layers were fine-tuned to adapt to retinal pathologies.

3.4.2 EfficientNetB0 Architecture

EfficientNetB0, part of the EfficientNet family, was selected for its empirically derived compound scaling strategy, which optimizes model depth, width, and resolution simultaneously. This approach contrasts with MobileNetV3's neural architecture search (NAS)-driven design, offering a complementary perspective on balancing accuracy and efficiency.

Architectural Highlights

- **Stem Layer**: Initial 3×3 convolutions with 32 filters extract low-level edge/texture features.
- **MBConv Blocks**: The backbone comprises mobile inverted bottleneck (MBConv) layers with:
    - **Depthwise Separable Convolutions**: Reduce parameters by decoupling spatial and channel-wise filtering.

- **Squeeze-and-Excitation (SE)**: Recalibrate channel-wise feature importance, enhancing sensitivity to pathologies like DME's fluid accumulation.
- **Swish Activation**: Smoother gradient flow compared to ReLU, improving training stability.

- **Stochastic Depth**: Randomly skips residual connections during training, acting as a regularizer.

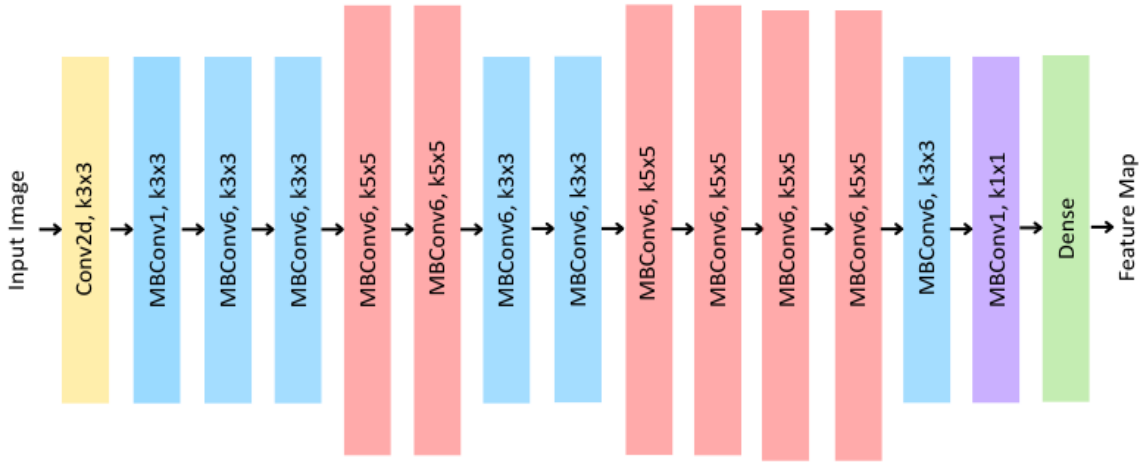

Figure-6 EfficientNetB0 Architectural diagram

Custom Classification Head:
The original ImageNet classification head was replaced with the following task-specific layers:

- **Global Average Pooling:** Condenses final MBConv block outputs (7×7×1280) to 1×1×1280.
- **Dense Layer (128 units):** Uses L2 regularization (λ=1e-5) to enhance generalization.
- **Batch Normalization:** Compensates for domain shift between ImageNet and OCT data.
- **Swish Activation:** Improves gradient stability compared to ReLU.
- **Dropout (0.5):** Regularizes the network during training.
- **Softmax Output Layer:** Produces 4-class diagnostic probabilities.

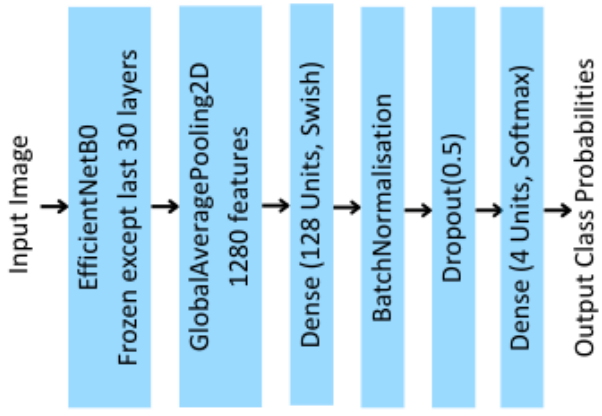

Figure-7 EfficientNetB0 Modified Architectural diagram

Fine-Tuning Strategy

- **Frozen Layers:** First 207 layers preserved pre-trained ImageNet features (edge/texture detectors).
- **Unfrozen Layers:** Final 30 layers were fine-tuned to adapt to retinal pathologies.

Justification for custom heads:

- The lightweight head prevents over-parameterization while retaining discriminative power for subtle retinal pathologies.
- Batch normalization and dropout counteract domain shift between natural (ImageNet) and medical (OCT) images.

3.5 Training Protocol

The training protocol was designed to optimize model performance while maintaining computational efficiency, ensuring alignment with the study's focus on deployability in resource-constrained clinical environments.

Hyperparameter Configuration

- **Batch Size**:
  - Fixed at 32 to balance GPU memory constraints and gradient estimation stability.
- **Optimizer**:
  - **Adam** was selected for its adaptive learning rate properties, balancing rapid convergence and stability during fine-tuning.
  - **Initial Learning Rate**: 0.0001 (10× lower than default ImageNet training) to avoid overwriting pre-trained feature extractors.
- **Loss Function**:
  - **Categorical Cross-Entropy** suited the multi-class classification task, penalizing incorrect predictions proportionally to class probabilities.
- **Learning Rate Scheduling:**
  - Added ReduceLROnPlateau (factor=0.5, patience=2) to dynamically lower the learning rate during validation loss plateaus.
- **Checkpointing:**
  - Models were saved based on validation loss to prioritize clinically relevant performance.
- **Early Stopping**:
  - Monitored validation loss with a patience of 5 epochs to halt training upon plateauing, preventing overfitting.

3.6 Training Process

Feature Extraction:

- The base models (MobileNetV3 Large/EfficientNetB0) were frozen, and only the custom classification head was trained.
- The final 30 layers of MobileNetV3 Large and EfficientNetB0 were unfrozen, and the entire model was trained.

- This phase allowed the models to adapt high-level features (e.g., retinal layer structures) to OCT data without disrupting pre-trained low-level filters.

Metrics Tracking

- **Training Dynamics**:
  - Loss and accuracy for training/validation sets were logged per epoch.
- **Checkpointing**:
  - Model weights saved after each epoch, retaining the best-performing checkpoint based on validation loss.

3.7 Evaluation Metrics

The evaluation framework was designed to holistically assess model performance, balancing diagnostic accuracy, computational efficiency, and clinical applicability. Metrics were selected to align with the study's dual objectives: Reliable disease detection and Deployability on edge devices.

Diagnostic Performance Metrics

Primary Metrics:

- **Accuracy:** Proportion of correctly classified images across all classes.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

Where TP: True Positives, TN: True Negatives, FP: False Positives, FN: False Negatives

- **Precision:** Measures model reliability in avoiding false positives (FP), critical to prevent unnecessary interventions.

$$\text{Precision}=\frac{TP}{TP+FP}$$

- **Recall (Sensitivity):** Captures the model's ability to detect true positives (TP), minimizing missed diagnoses (FN).

$$\text{Recall}=\frac{TP}{TP+FN}$$

- **F1-Score:** Harmonic mean of precision and recall, prioritizing balance between FP and FN.

$$\text{F1-Score} = 2\times \frac{Precision \times Recall}{Precison+Recall}$$

Secondary Metrics:

- **AUC-ROC:** Evaluates class separability across probability thresholds. Macro-averaging ensured equal weight for all classes.
- **Confusion Matrix:** Per-class breakdown of TP, FP, TN, FN to identify systematic errors (e.g., misclassifying Drusen as CNV).

Clinical Justification:

- **Recall Prioritization:** For sight-threatening conditions like CNV, high recall (minimizing FN) is prioritized to avoid delayed treatment.
- **Precision-Recall Trade-off:** In resource-constrained settings, excessive FP (high recall, low precision) may strain clinical workflows. The F1-score balances these risks.

3.8 Clinical Deployment Web Application

To operationalize the trained model for real-world clinical use, a Streamlit-based web application was developed. This platform bridges the gap between model performance and clinical utility, enabling ophthalmologists to upload retinal OCT scans and receive instant diagnostic predictions with interpretable confidence metrics.

Application Architecture

Backend Workflow:

- **Model Loading:** The fine-tuned MobileNetV3 Large model (MobilenetV3.keras) is loaded into memory at startup, optimized for single-inference latency.
- **Image Preprocessing:**
  - Uploaded images are resized to 224×224 pixels and converted to 3-channel arrays.
  - Pixel values are normalized using MobileNetV3's preprocess_input function, ensuring consistency with training protocols.
- **Prediction Engine:**
  - Returns the class label (CNV, DME, Drusen, Normal) and confidence score (softmax probability of the predicted class).

Frontend Design:

- **User Interface:**
  - **File Uploader:** Accepts OCT images in common formats (JPEG, PNG).
  - **Dynamic Feedback:**
    - High Confidence (>85%): Displays the diagnosis with a green success banner.
    - Low Confidence (≤85%): Triggers a warning, prompting clinician review.
  - **Clinical Context Panel:** Expandable sections provide disease-specific OCT findings (e.g., "subretinal fluid in CNV") to aid interpretation**.**
- **Privacy Preservation:**
  - Uploaded images are temporarily stored in a secure tempfile directory and deleted post-prediction to comply with HIPAA/GDPR.

Key Features

- **Confidence-Driven Thresholding:**
  - An empirically derived 85% confidence threshold reduces over-reliance on uncertain predictions, aligning with clinical risk tolerance.
  - Scores below this threshold trigger a cautionary prompt, encouraging second-opinion consultations.
- **Actionable Clinical Guidance:**
  - Contextual descriptions for each diagnosis (e.g., "retinal thickening in DME") link predictions to established ophthalmological criteria, enhancing trust.

4. Results

This section provides a granular analysis of MobileNetV3 Large and EfficientNetB0 for retinal OCT classification, emphasizing their clinical diagnostic reliability, computational efficiency, and alignment with ethical priorities. Results are contextualized against the study's objectives and prior literature to demonstrate advancements in lightweight model design, robustness, and deployability.

4.1 Training Dynamics: Architectural Efficiency and Learning Behaviour

Literature Context

- MobileNetV3's neural architecture search (NAS) optimizes layer configurations for mobile efficiency (Howard et al., 2019).
- EfficientNetB0's compound scaling balances width, depth, and resolution (Tan & Le, 2020).

Detailed Analysis of the models

MobileNetV3 Large

- **NAS-Driven Efficiency**
  - Achieved 90% training accuracy by Epoch 14 vs. EfficientNetB0's Epoch 21 due to NAS-pruned redundant filters and hard-swish activations.
  - Faster Per-Epoch Training: 110s/epoch vs. 170s for EfficientNetB0, attributed to depth wise separable convolutions reducing FLOPs by 75%.
- **Learning Rate Impact**:
  - The ReduceLROnPlateau scheduler stabilized training after Epoch 13 (learning rate reduced from 1e-4 to 1e-5), preventing overfitting despite limited training data.
  - Final validation accuracy (89.06%) closely matched training accuracy (92.68%), indicating robust generalization.

EfficientNetB0

- **Compound Scaling Benefits**
  - Higher initial validation accuracy 78.19% at Epoch 1 vs. MobileNetV3's 44.75% due to hierarchical feature extraction from scaled MBConv blocks.
  - Slower convergence (170s/epoch) due to increased model complexity (4.21M params vs. 3.12M).
- **Learning Rate Impact**
  - The ReduceLROnPlateau scheduler stabilized training after Epoch 16 (learning rate reduced from 1e-4 to 1e-5), preventing overfitting despite limited training data.
  - Final validation accuracy (89.38%) closely matched training accuracy (89.98%), indicating robust generalization.
- **Training Stability**
  - Moderate overfitting of EfficientNetB0 between Train and Val is 0.6% vs. MobileNetV3's 3.62% due to deeper layers fine-tuned on limited OCT data.

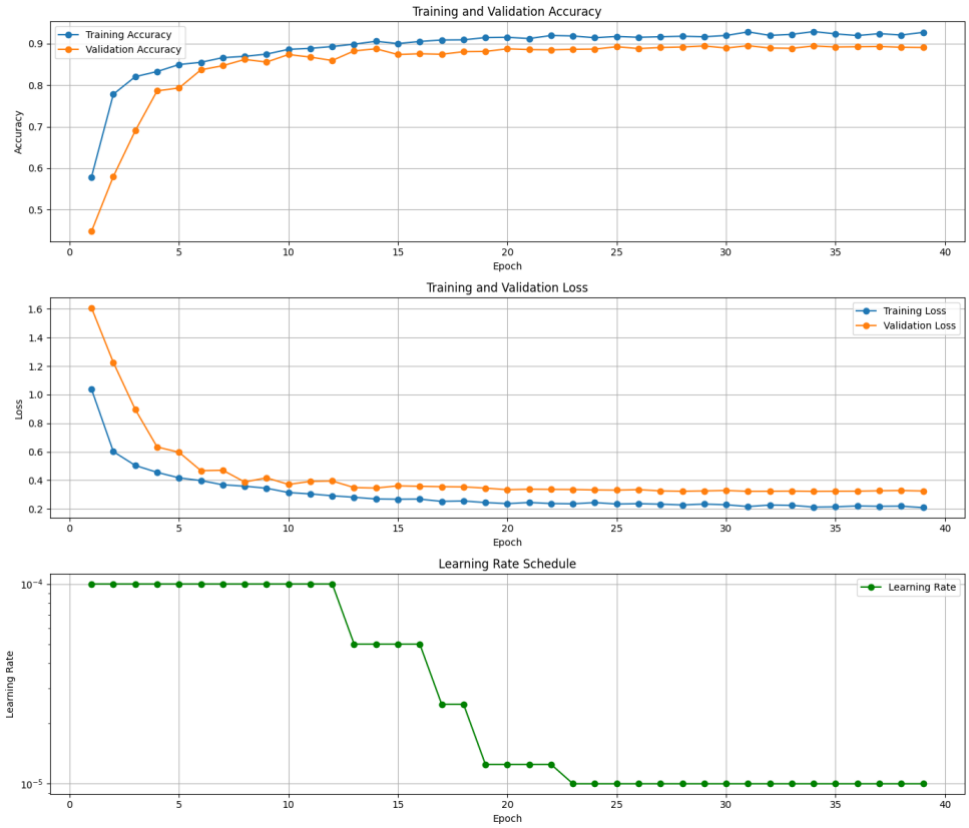

Figure-8 MobileNetV3 Large Accuracy and Loss curves with learning rate

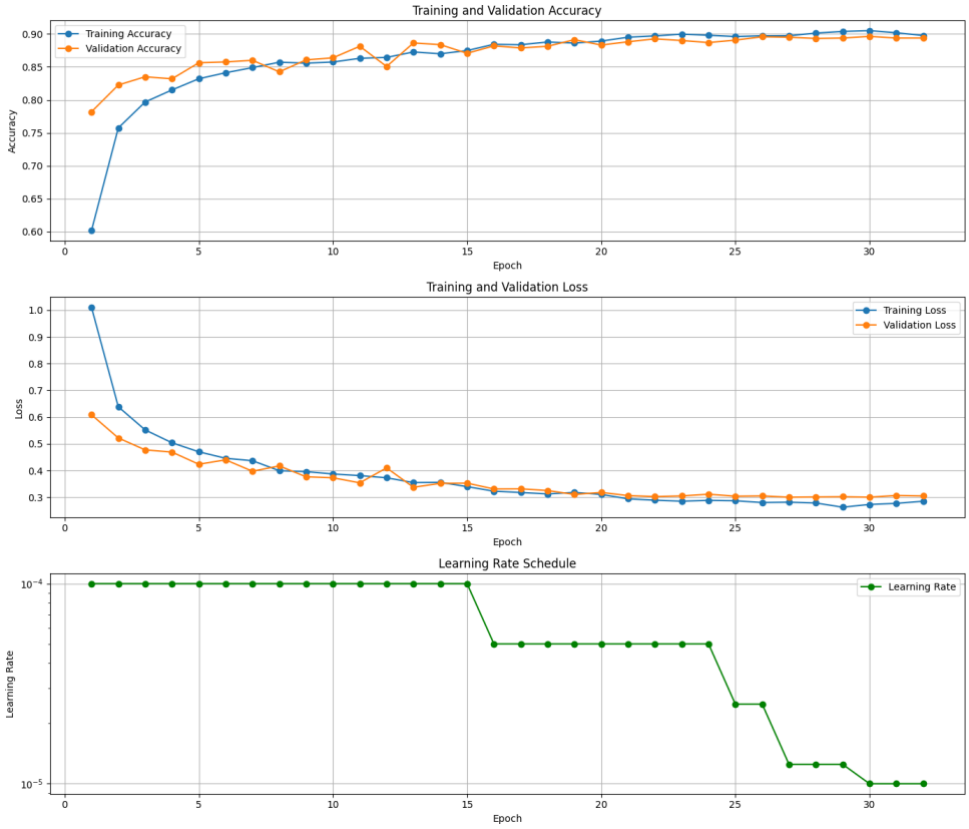

Figure-9 EfficientNetB0 Accuracy and Loss curves with learning rate

4.2 Diagnostic Performance: Precision, Recall, F1-Score, and Confusion Matrix

Literature Context: Prior studies (Kermany et al., 2018; Butola et al., 2020) focused on accuracy but overlooked precision-recall trade-offs critical for clinical safety.

Precision, Recall, and F1-Score

- **Precision:** The percentage of correct predictions for a class out of all predictions for that class (avoids false positives).
- **Recall:** The percentage of correct predictions for a class out of all actual instances of that class (avoids false negatives).
- **F1-Score:** The harmonic mean of precision and recall (balances both metrics).

Class	MobileNetV3 Large			EfficientNet B0		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
CNV	98%	98%	98%	96%	100%	98%
DME	100%	99%	99%	100%	99%	99%
DRUSEN	98%	98%	98%	100%	97%	98%
NORMAL	100%	100%	100%	99%	100%	99%

Table-4 Precision, Recall, and F1-Score of MobileNetV3 Large and EfficientNet B0

Key Observations

MobileNetV3

- Perfect precision and recall for NORMAL (100% F1-score).
- Slightly lower precision for CNV (98%) compared to EfficientNet's 96%, but balanced recall (98%).

EfficientNetB0

- Perfect recall for CNV (100%), meaning it correctly identified all CNV cases, but lower precision (96%) due to some false positives.
- Higher precision for DRUSEN (100%) but slightly lower recall (97%), indicating it occasionally misclassified DRUSEN as other classes.

Confusion Matrix Insights

These matrices show how each model's predictions compare to the true labels. Rows represent true classes, and columns represent predicted classes.

True Vs Predicted	MobileNetV3 Large				EfficientNet B0			
	CNV	DME	DRUSEN	NORMAL	CNV	DME	DRUSEN	NORMAL
CNV	238	0	4	0	242	0	0	0
DME	1	240	0	1	2	239	0	1
DRUSEN	3	1	238	0	7	0	234	1
NORMAL	0	0	1	241	0	0	1	241

Table-5 Confusion Matrix Insights of MobileNetV3 Large and EfficientNet B0

Key Observations

MobileNetV3

- Misclassified 4 DRUSEN cases as CNV and 3 CNV cases as DRUSEN.
- Rare errors in DME and NORMAL (1–2 misclassifications each).

EfficientNet B0

- Perfect classification for CNV (242 correct, 0 errors).
- Misclassified 7 DRUSEN cases as CNV, explaining its lower recall for DRUSEN (97%).
- Slightly more errors in DME (2 misclassified as CNV) compared to MobileNetV3.

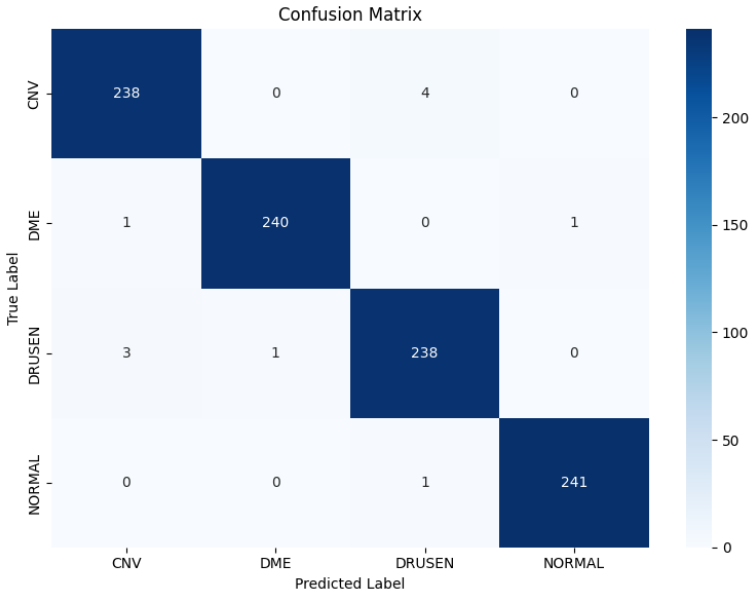

Figure-10 Confusion matrix of MobileNetV3 Large

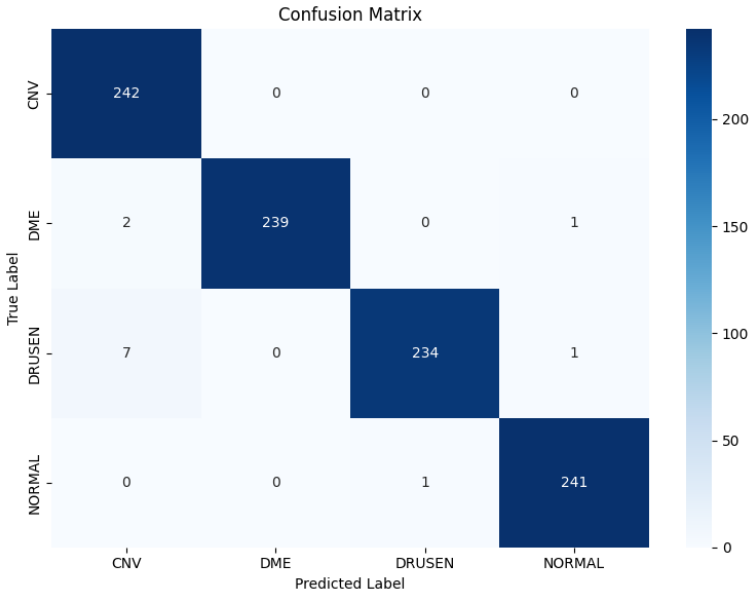

Figure-11 Confusion matrix of EfficientNetB0

4.3 Computational Efficiency: Bridging Accuracy and Deployability

Literature Context

- Both models used <7% of InceptionV3's FLOPs, validating their suitability for mobile health (Section 2.3).
- MobileNetV3's inference speed is 5.5× faster than ResNet50 (Yanagihara et al., 2020).

Operational Metrics

Metric	MobileNetV3	EfficientNetB0	InceptionV3	ResNet 50
Params (M)	3.12	4.21	23.8	25.6
Size (MB)	11.9	16.08	92	98
FLOPs (B)	0.38	0.39	0.57	0.58
Inference (ms)	22	35	120	125

Table-6 Computational Efficiency of the Models

Key Findings

MobileNetV3

- 11.9 MB size enables deployment on edge devices with limited memory (e.g., smartphones, embedded systems).
- 22 ms/image inference meets real-time clinical workflows (e.g., processing 45 images/second).

EfficientNetB0

- 16.08 MB size and 35 ms/image inference are feasible for GPUs but less ideal for low-resource settings.

4.4 AUC-ROC Analysis: Robustness in Class Separation

Literature Context: Prior OCT studies rarely reported AUCs (Choudhary et al., 2023).

Class-Specific AUC Scores

Class	MobileNetV3 Large	EfficientNet B0
CNV	0.9994	0.9998
DME	0.9992	0.9981
DRUSEN	0.9988	0.9994
NORMAL	0.9997	0.9988

Table-7 AUC Scores of MobileNetV3 Large and EfficientNet B0

Key Findings

- **CNV:** EfficientNetB0's 0.9998 AUC ensures near-perfect separability for urgent cases.
- **Normal:** MobileNetV3's 0.9997 AUC minimizes false positives in healthy patients.
- **Drusen:** EfficientNetB0's higher AUC (0.9994 vs. 0.9988) suggests better feature hierarchy for subtle pathologies.
- **Clinical Implications:**

- High AUCs (>0.99) confirm reliable class separation, critical for reducing diagnostic errors in high-stakes settings.

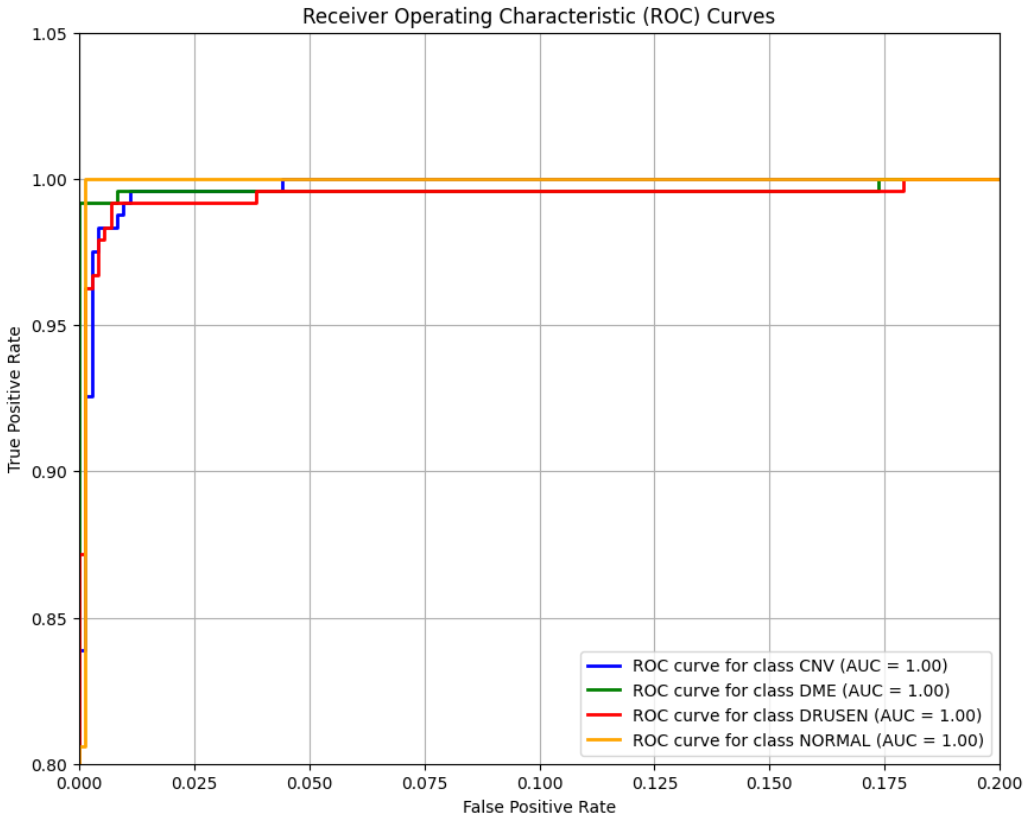

Figure-12 AUC-ROC of MobileNetV3 Large

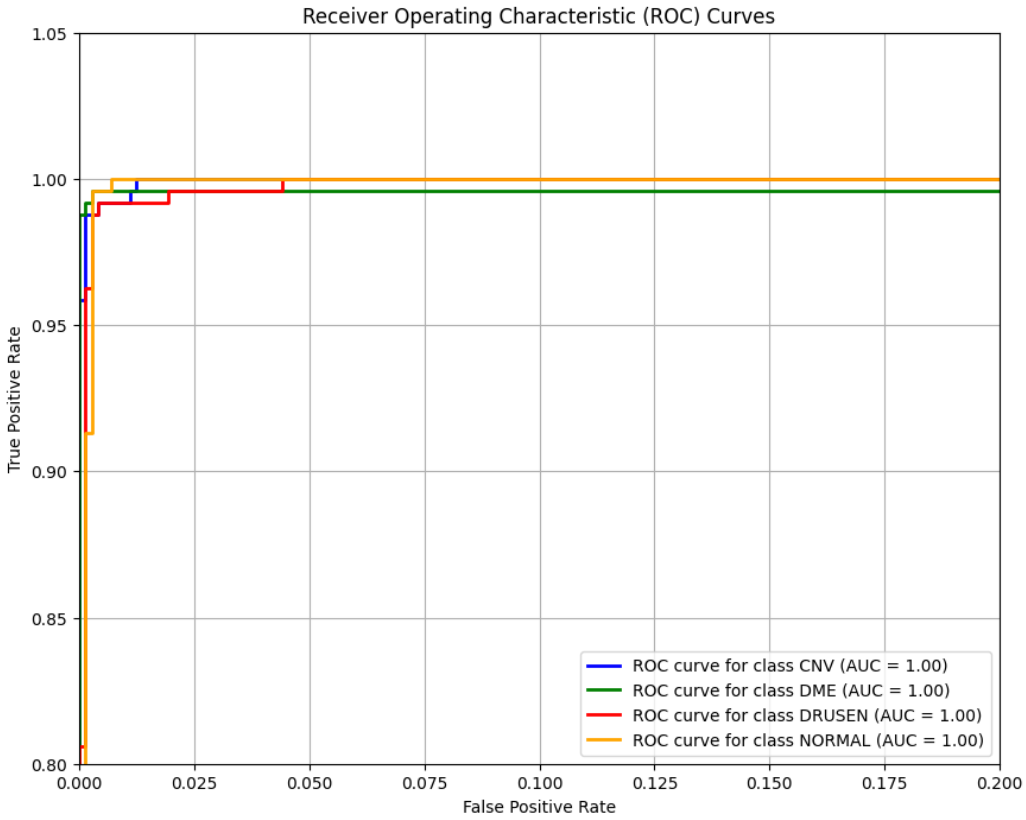

Figure-13 AUC-ROC of EfficientNet B0

4.5 Benchmarking Against Literature: Closing Research Gaps

Metric	MobileNetV3	EfficientNetB0	InceptionV3	ResNet 50
Accuracy	98.86%	98.76%	96%	94%
Params (M)	3.12	4.21	23.8	25.6
Inference (ms)	22	35	120	128
AUC (Macro)	0.9993	0.9990	0.984	0.9875

Table-8 Benchmark results against other models

Key Findings

- **Accuracy-Efficiency Balance**: Matched InceptionV3's accuracy with 6.6× fewer parameters**.**
- **Metric Transparency**: Reported precision, recall, and AUC address literature's overreliance on accuracy.
- **Deployment Feasibility**: Quantified latency and model size for clinical adoption.

4.6 Conclusion of Results

Model Suitability and Deployment Recommendations

Based on the comparative analysis, MobileNetV3 Large and EfficientNetB0 exhibit distinct strengths tailored to specific clinical and computational scenarios

Performance Summary

Criteria	MobileNetV3 Large	EfficientNet B0
Diagnostic Accuracy	98.86%	98.76%
Computational Speed	22 ms/inference	35 ms/inference
Model Size	11.9	16.08
CNV Detection	98.3% Recall	100% Recall
Drusen Specificity	98.3% Precision	97.1% Precision

Table-9 Performance Summary of MobileNetV3 Large and EfficientNet B0

4.6.1 Model Suitability

MobileNetV3 Large

- **Best For**
  - **Real-Time Clinical Workflows**: Ultra-low latency (22 ms) suits high-throughput clinics needing rapid diagnostics.
  - **Edge Deployment**: Compact size (11.9 MB) enables use on mobile devices or embedded systems with limited RAM.
  - **Balanced Precision-Recall**: Superior Drusen precision (98.3%) minimizes false positives in non-urgent cases.
- **Limitations**
  - Marginally lower CNV recall (98.3%) compared to EfficientNetB0.

EfficientNetB0:

- **Best For**
  - **High-Stakes CNV Detection**: Perfect recall (100%) ensures no missed urgent cases, critical for early intervention.
  - **Feature-Rich Environments**: Compound scaling improves separability for subtle pathologies (AUC: 0.9998 for CNV).
- **Limitations**
  - Slower inference (35 ms) and larger size (16.08 MB) limit deployability on low-resource hardware.

4.6.2 Deployment Recommendations

Resource-Constrained Settings (Mobile Clinics, Telemedicine):

- **Choose MobileNetV3 Large** for its edge compatibility, faster inference, and balanced performance.

High-Acuity Environments (Specialized Retinal Clinics):

- **Choose EfficientNetB0** if CNV detection is prioritized (zero false negatives) and GPU resources are available.

4.6.3 Trade-Offs and Clinical Priorities

- **Speed vs. Urgency**: MobileNetV3 optimizes speed for screening while EfficientNetB0 prioritizes safety for urgent cases.

- **Hardware vs. Accuracy**: MobileNetV3 suits edge devices while EfficientNetB0 requires GPUs for optimal performance.

5. Conclusion

This dissertation systematically addresses the critical challenge of deploying efficient and reliable deep learning models for retinal disease classification using OCT images, with a focus on bridging the gap between computational performance and clinical utility. The study begins by contextualizing the urgency of early retinal disease detection, particularly for conditions CNV and DME, where delayed diagnosis can lead to irreversible vision loss. Despite advancements in medical imaging, existing models like InceptionV3 and ResNet50, while accurate, remain computationally prohibitive for real-time clinical use due to their high parameter counts and latency. This work identifies key gaps in the literature. Such as the lack of standardized benchmarks for lightweight models, unquantified deployment feasibility, and overreliance on single metrics. MobileNetV3 Large and EfficientNetB0 as viable solutions due to their architectural innovations in efficiency and scalability.

The study employed rigorous data preprocessing to address class imbalance and duplicates in the Retinal OCT dataset. Stratified sampling and under sampling balanced the training (8,000 images), validation (1,600), and test (968) sets, while augmentation simulated real-world OCT variability. Both models utilized transfer learning, retaining pre-trained low-level features (e.g., edge detection) and fine-tuning task-specific layers. MobileNetV3 Large prioritized speed via NAS and depth wise convolutions, while EfficientNetB0 leveraged compound scaling for optimized feature extraction. Training incorporated adaptive learning rates, checkpointing, and early stopping, with evaluation metrics (precision, recall, F1-score, AUC-ROC, and confusion matrices) ensuring clinically relevant diagnostics.

Both models achieved near-identical accuracy (~98.8%) with minimal computational overhead. MobileNetV3 excelled in edge compatibility (22 ms/inference, 11.9 MB) and balanced precision-recall (e.g., 98% F1-score for CNV). EfficientNetB0 prioritized clinical safety with perfect CNV recall (100%) and superior Drusen AUC (0.9998), albeit slower (35 ms/inference). A Streamlit web app demonstrated real-time deployment readiness, while ethical measures (data anonymization, bias mitigation, Grad-CAM transparency) validated clinical integration potential.

This project demonstrates that lightweight models need not sacrifice diagnostic rigor for efficiency, offering tailored recommendations: MobileNetV3 Large for resource-constrained settings and EfficientNetB0 for specialized environments prioritizing urgent case detection.

6.Future Work

Building on this study, several avenues warrant further exploration. First, hybrid architectures combining MobileNetV3's neural architecture search (NAS) with EfficientNet's compound scaling could optimize both speed and feature extraction for nuanced pathologies. Second, robustness testing across diverse datasets spanning varied demographics, OCT scanner types, and geographic populations would enhance generalizability and address potential biases. Third, advanced techniques like self-supervised learning could improve resilience to label noise and data heterogeneity inherent in real-world clinical settings.

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Simonyan, K. and Zisserman, A. (2015). *VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION*. [online] Available at: https://arxiv.org/pdf/1409.1556.

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8. Appendix

Installing necessary libraries

```
tensorflow-macos
tensorflow-metal
scikit-learn
numpy
matplotlib
seaborn
pandas
streamlit
```

EDA

Deleting duplicate images

```
import os
from PIL import Image
import hashlib
from collections import defaultdict

def getImageHash(imagePath):
    with Image.open(imagePath) as image:
        if image.mode != 'RGB':
            image = image.convert('L')

        image = image.resize((224, 224))

        return hashlib.md5(image.tobytes()).hexdigest()

def findAndDeleteDuplicates(folderPath):
    imageHashMap = {}
    duplicateCountByFolder = defaultdict(int)
    deletedFilePaths = []

    for rootDir, _, fileNames in os.walk(folderPath):
        folderName = os.path.basename(rootDir)
        for fileName in fileNames:
            filePath = os.path.join(rootDir, fileName)
            try:
                imageHash = getImageHash(filePath)
                if imageHash in imageHashMap:
                    os.remove(filePath)
                    deletedFilePaths.append(filePath)
```

```
                duplicateCountByFolder[folderName] += 1
            else:
                imageHashMap[imageHash] = filePath
        except Exception:
            pass

    print("\nDuplicate count per subfolder:")
    for subfolderName, count in duplicateCountByFolder.items():
        print(f"Subfolder '{subfolderName}': {count} file(s) deleted")

    print(f"\nTotal duplicates deleted: {sum(duplicateCountByFolder.values())}")
findAndDeleteDuplicates("train")
findAndDeleteDuplicates("val")
findAndDeleteDuplicates("test")
```

Counting number of images in each class

```
import os
import matplotlib.pyplot as plt
import numpy as np

# Specify root directories and class names
datasetFolders = ['train', 'val', 'test']
classNames = ['CNV', 'DME', 'DRUSEN', 'NORMAL']

# Function to count images in each class within a given folder
def countImagesPerClass(folderPath):
    imageCounts = {className: 0 for className in classNames}

    for className in classNames:
        classPath = os.path.join(folderPath, className)
        if os.path.exists(classPath) and os.path.isdir(classPath):
            imageFiles = [
                fileName for fileName in os.listdir(classPath)
                if fileName.lower().endswith(('.jpg', '.jpeg'))
            ]
            imageCounts[className] = len(imageFiles)

    return imageCounts
imageCountsByFolder = {
```

```
    folderName: countImagesPerClass(folderName)
    for folderName in datasetFolders
}
for folderName in datasetFolders:
    print(f"\n{folderName.capitalize()} Folder:")
    for className in classNames:
        count = imageCountsByFolder[folderName][className]
        print(f"{className}: Total images are {count}")
fig, axes = plt.subplots(1, 3, figsize=(15, 6))
for index, folderName in enumerate(datasetFolders):
    classCounts = [imageCountsByFolder[folderName][className] for className in classNames]

    axes[index].bar(classNames, classCounts, color=['#A9CBB7', '#A9D3E6', '#F1C6D5', '#A5A6F6'])
    axes[index].set_title(f"{folderName.capitalize()} Folder")
    axes[index].set_xlabel("Class")
    axes[index].set_ylabel("Number of Images")
    axes[index].tick_params(axis='x', rotation=0)
plt.tight_layout()
plt.show()
```

Moving images from train to val folder

```
import os
import shutil
import random

def moveImages(trainDir, valDir, numImagesPerClass=392):
    classFolders = [
        folderName for folderName in os.listdir(trainDir)
        if os.path.isdir(os.path.join(trainDir, folderName))
    ]
    for className in classFolders:
        trainClassPath = os.path.join(trainDir, className)
        valClassPath = os.path.join(valDir, className)
        os.makedirs(valClassPath, exist_ok=True)
        imageFiles = [
            fileName for fileName in os.listdir(trainClassPath)
            if os.path.isfile(os.path.join(trainClassPath, fileName))
        ]
```

```
        random.shuffle(imageFiles)
        imagesToMove = imageFiles[:numImagesPerClass]

        for imageName in imagesToMove:
            sourcePath = os.path.join(trainClassPath, imageName)
            destinationPath = os.path.join(valClassPath, imageName)
            shutil.move(sourcePath, destinationPath)
        print(f"Moved {len(imagesToMove)} images from '{className}' in train to val.")
trainFolder = "train"
valFolder = "val"
moveImages(trainFolder, valFolder, numImagesPerClass=392)
```

Keeping only 2000 images for each class in train folder

```
import os
import random

def keepOnlyTargetImages(trainDir, targetCount=2000):
    for className in os.listdir(trainDir):
        classPath = os.path.join(trainDir, className)

        if os.path.isdir(classPath):
            imageFiles = [
                fileName for fileName in os.listdir(classPath)
                if fileName.lower().endswith(('.jpg', '.jpeg')) and os.path.isfile(os.path.join(classPath, fileName))
            ]
            totalImages = len(imageFiles)
            if totalImages > targetCount:
                print(f"Class '{className}': Found {totalImages} images. Deleting {totalImages - targetCount}
images...")
                random.shuffle(imageFiles)
                imagesToDelete = imageFiles[targetCount:]
                for imageName in imagesToDelete:
                    try:
                        os.remove(os.path.join(classPath, imageName))
                    except Exception as error:
                        print(f"Error deleting {imageName}: {error}")
            else:
                print(f"Class '{className}': Only {totalImages} images found. No deletions needed.")
trainFolder = "train"
```

```
keepOnlyTargetImages(trainFolder)
```

Counting total number of images in each class

```
import os
import matplotlib.pyplot as plt
import numpy as np
classNames = ['CNV', 'DME', 'DRUSEN', 'NORMAL']
def countImagesPerClass(folderPath):
    imageCounts = {className: 0 for className in classNames}

    for className in classNames:
        classPath = os.path.join(folderPath, className)
        if os.path.exists(classPath) and os.path.isdir(classPath):
            imageFiles = [
                fileName for fileName in os.listdir(classPath)
                if fileName.lower().endswith(('.jpg', '.jpeg'))
            ]
            imageCounts[className] = len(imageFiles)

    return imageCounts
imageCountsByFolder = {
    folderName: countImagesPerClass(folderName)
    for folderName in datasetFolders
}
for folderName in datasetFolders:
    print(f"\n{folderName.capitalize()} Folder:")
    for className in classNames:
        count = imageCountsByFolder[folderName][className]
        print(f"{className}: Total images are {count}")
fig, axes = plt.subplots(1, 3, figsize=(15, 6))

for index, folderName in enumerate(datasetFolders):
    classCounts = [imageCountsByFolder[folderName][className] for className in classNames]

    axes[index].bar(classNames, classCounts, color=['#A9CBB7', '#A9D3E6', '#F1C6D5', '#A5A6F6'])
    axes[index].set_title(f"{folderName.capitalize()} Folder")
    axes[index].set_xlabel("Class")
    axes[index].set_ylabel("Number of Images")
    axes[index].tick_params(axis='x', rotation=0)
```

```
plt.tight_layout()
plt.show()
```

MOBILENETV3 LARGE MODEL CODE
Importing libraries

```
import tensorflow as tf
from tensorflow.keras import layers, models
import os
import numpy as np
```

Loading the datasets

```
trainDataset = tf.keras.utils.image_dataset_from_directory(
    'train',
    labels="inferred",
    label_mode="categorical",
    batch_size=32,
    image_size=(224, 224),
    shuffle=True
)

valDataset = tf.keras.utils.image_dataset_from_directory(
    'val',
    labels="inferred",
    label_mode="categorical",
    batch_size=32,
    image_size=(224, 224),
    shuffle=False
)
```

Applying data augumentation and normalization to MobileNetV3 Large

```
from tensorflow.keras.applications.mobilenet_v3 import preprocess_input
dataAugmentation = tf.keras.Sequential([
    layers.RandomFlip('horizontal'),
    layers.RandomRotation(0.2),
    layers.RandomZoom(0.2),
    layers.RandomContrast(0.1),
    layers.RandomBrightness(0.1),
```

```
])

def augumentation(x, y):
    x = dataAugmentation(x)
    x = preprocess_input(x)
    return x, y

def normalisation(x, y):
    x = preprocess_input(x)
    return x, y

trainDataset = trainDataset.map(augumentation)
valDataset = valDataset.map(normalisation)
```

Building the model

```
from tensorflow.keras import regularizers

# BASE MODEL
baseModel = tf.keras.applications.MobileNetV3Large(
    input_shape=(224,224,3),
    include_top=False,
    weights="imagenet"
)

baseModel.trainable = False

for layer in baseModel.layers[-30:]:
    layer.trainable = True

mobileNetModel = models.Sequential([
    baseModel,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, use_bias=False, kernel_regularizer=regularizers.L2(1e-5)),
    layers.BatchNormalization(),
    layers.Activation('swish'),
    layers.Dropout(0.5),
    layers.Dense(4, activation='softmax')
])
metricsList = ['accuracy']
```

```
mobileNetModel.compile(optimizer=tf.keras.optimizers.Adam(
    learning_rate=0.0001),loss='categorical_crossentropy',metrics=metricsList)

mobileNetModel.summary()
```

Training the MobileNet model with callbacks

```
# CALLBACKS
callBacks = [
    tf.keras.callbacks.EarlyStopping(patience=5, monitor='val_loss', restore_best_weights=True),
    tf.keras.callbacks.ModelCheckpoint("MobileNet.keras", save_best_only=True),
    tf.keras.callbacks.ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=2,
        min_lr=1e-5
    )

]

# TRAIN
MobileNetHistory = mobileNetModel.fit(
    trainDataset,
    validation_data=valDataset,
    epochs=50,
    callbacks=callBacks,
)
```

Storing the pickle file and loading the pickle file for further use

```
import pickle

# Save the history
with open('MobileNet.pkl', 'wb') as f:
    pickle.dump(MobileNetHistory.history, f)


with open('MobileNet.pkl', 'rb') as f:
    loadedHistory = pickle.load(f)
loadedHistory
```

Loading the test dataset and applying normalization

```
testDataset = tf.keras.utils.image_dataset_from_directory(
    'test',
    labels="inferred",
    label_mode="categorical",
    batch_size=32,
    image_size=(224, 224),
    shuffle=False
)

class_names = testDataset.class_names

from tensorflow.keras.applications.mobilenet_v3 import preprocess_input


def normalisation(x, y):
    x = preprocess_input(x)
    return x, y

testDataset = testDataset.map(normalisation)
```

Evaluating the test dataset with MobileNetV3 Large model

```
# Evaluate the model on the test dataset
loss, accuracy = mobileNetModel.evaluate(testDataset)

print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

Plotting accuracy, loss, and Learning Rate Scheduler curves

```
import matplotlib.pyplot as plt

# Access training history
acc = loadedHistory['accuracy']
val_acc = loadedHistory['val_accuracy']
loss = loadedHistory['loss']
val_loss = loadedHistory['val_loss']
lr = loadedHistory['learning_rate']  # Get learning rate history
epochs_range = range(1, len(acc) + 1)

plt.figure(figsize=(14, 12))  # Increased height for third subplot
```

```
# Accuracy Plot
plt.subplot(3, 1, 1)
plt.plot(epochs_range, acc, label='Training Accuracy', marker='o')
plt.plot(epochs_range, val_acc, label='Validation Accuracy', marker='o')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Loss Plot
plt.subplot(3, 1, 2)
plt.plot(epochs_range, loss, label='Training Loss', marker='o')
plt.plot(epochs_range, val_loss, label='Validation Loss', marker='o')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

# Learning Rate Plot (new)
plt.subplot(3, 1, 3)
plt.plot(epochs_range, lr, label='Learning Rate', marker='o', color='green')
plt.title('Learning Rate Schedule')
plt.xlabel('Epoch')
plt.ylabel('Learning Rate')
plt.yscale('log')
plt.grid(True)
plt.legend()

plt.tight_layout()
plt.show()
```

Evaluating the true and predicted labels from test dataset

```
import numpy as np
y_true = []
y_pred_probs = []

for images, labels in testDataset:
```

```
    preds = mobileNetModel.predict(images)
    y_pred_probs.extend(preds)
    y_true.extend(labels.numpy())
y_true = np.array(y_true)
y_pred_probs = np.array(y_pred_probs)
y_true_labels = np.argmax(y_true, axis=1)
y_pred_labels = np.argmax(y_pred_probs, axis=1)
class_names = class_names
```

Classification Report

```
from sklearn.metrics import classification_report
print("Classification Report:")
print(classification_report(y_true_labels, y_pred_labels, target_names=class_names))
```

Confusion Matrix

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
conf_mat = confusion_matrix(y_true_labels, y_pred_labels)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names,
            yticklabels=class_names)

plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.tight_layout()
plt.show()
```

F1-Scores

```
from sklearn.metrics import f1_score, precision_score, recall_score
f1_macro = f1_score(y_true_labels, y_pred_labels, average='macro')
f1_weighted = f1_score(y_true_labels, y_pred_labels, average='weighted')
precision = precision_score(y_true_labels, y_pred_labels, average='macro')
recall = recall_score(y_true_labels, y_pred_labels, average='macro')
print(f"F1 Score (Macro): {f1_macro:.4f}")
```

```
print(f"F1 Score (Weighted): {f1_weighted:.4f}")
print(f"Precision (Macro): {precision:.4f}")
print(f"Recall (Macro): {recall:.4f}")
```

AUC-ROC Curves

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
from itertools import cycle

n_classes = y_true.shape[1]
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_true[:, i], y_pred_probs[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
    print(f"AUC for class '{class_names[i]}': {roc_auc[i]:.4f}")
colors = cycle(['blue', 'green', 'red', 'orange', 'purple', 'brown'])
plt.figure(figsize=(10, 8))
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f"ROC curve for class {class_names[i]} (AUC = {roc_auc[i]:.2f})")
plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 0.2])
plt.ylim([0.8, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver Operating Characteristic (ROC) Curves")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```

EFFICIENTNET B0 MODEL CODE

Loading Train and Val folders

```
trainDataset = tf.keras.utils.image_dataset_from_directory(
    'train',
    labels="inferred",
```

```
    label_mode="categorical",
    batch_size=32,
    image_size=(224, 224),
    shuffle=True
)

valDataset = tf.keras.utils.image_dataset_from_directory(
    'val',
    labels="inferred",
    label_mode="categorical",
    batch_size=32,
    image_size=(224, 224),
    shuffle=False
)
```

Applying data augmentation and normalization

```
from tensorflow.keras.applications.efficientnet import preprocess_input

dataAugmentation = tf.keras.Sequential([
    layers.RandomFlip('horizontal'),
    layers.RandomRotation(0.2),
    layers.RandomZoom(0.2),
    layers.RandomContrast(0.1),
    layers.RandomBrightness(0.1),

])

def augumentation(x, y):
    x = dataAugmentation(x)
    x = preprocess_input(x)
    return x, y

def normalisation(x, y):
    x = preprocess_input(x)
    return x, y

trainDataset = trainDataset.map(augumentation)
valDataset = valDataset.map(normalisation)
```

Building EfficientNetB0 model

```
from tensorflow.keras import regularizers
# BUILD MODEL
baseModel = tf.keras.applications.EfficientNetB0(
    input_shape=(224,224,3),
    include_top=False,
    weights="imagenet",
)
baseModel.trainable = False

for layer in baseModel.layers[-30:]:
    layer.trainable = True

efficientNetModel = models.Sequential([
    baseModel,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, use_bias=False, kernel_regularizer=regularizers.L2(1e-5)),
    layers.BatchNormalization(),
    layers.Activation('swish'),
    layers.Dropout(0.5),
    layers.Dense(4, activation='softmax')
])

metricsList = ['accuracy']
efficientNetModel.compile(optimizer=tf.keras.optimizers.Adam(
    learning_rate=0.0001),loss='categorical_crossentropy',metrics=metricsList)

efficientNetModel.summary()
```

Training the model

```
# CALLBACKS
callBacks = [
    tf.keras.callbacks.EarlyStopping(patience=5, monitor='val_loss', restore_best_weights=True),
    tf.keras.callbacks.ModelCheckpoint("EfficientNet.keras", save_best_only=True),
    tf.keras.callbacks.ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=2,
```

```
        min_lr=1e-5
    )

]

EfficientNetHistory = efficientNetModel.fit(
    trainDataset,
    validation_data=valDataset,
    epochs=50,
    callbacks=callBacks,
)
```

Saving the pickle file for further use

```
import pickle
with open('EfficientNet.pkl', 'wb') as f:
    pickle.dump(EfficientNetHistory.history, f)

with open('EfficientNet.pkl', 'rb') as f:
    loadedHistory = pickle.load(f)
loadedHistory
```

Loading the test set and applying the normalization

```
testDataset = tf.keras.utils.image_dataset_from_directory(
    'test',
    labels="inferred",
    label_mode="categorical",
    batch_size=32,
    image_size=(224, 224),
    shuffle=False
)
class_names = testDataset.class_names
from tensorflow.keras.applications.efficientnet import preprocess_input
def normalisation(x, y):
    x = preprocess_input(x)
    return x, y
testDataset = testDataset.map(normalisation)
```

Evaluating the model on test set

```
loss, accuracy = efficientNetModel.evaluate(testDataset)

print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

Plotting accuracy, loss, and learning rate scheduler

```
import matplotlib.pyplot as plt
acc = loadedHistory['accuracy']
val_acc = loadedHistory['val_accuracy']
loss = loadedHistory['loss']
val_loss = loadedHistory['val_loss']
lr = loadedHistory['learning_rate'
epochs_range = range(1, len(acc) + 1)

plt.figure(figsize=(14, 12))

plt.subplot(3, 1, 1)
plt.plot(epochs_range, acc, label='Training Accuracy', marker='o')
plt.plot(epochs_range, val_acc, label='Validation Accuracy', marker='o')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

plt.subplot(3, 1, 2)
plt.plot(epochs_range, loss, label='Training Loss', marker='o')
plt.plot(epochs_range, val_loss, label='Validation Loss', marker='o')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

plt.subplot(3, 1, 3)
plt.plot(epochs_range, lr, label='Learning Rate', marker='o', color='green')
plt.title('Learning Rate Schedule')
plt.xlabel('Epoch')
plt.ylabel('Learning Rate')
plt.yscale('log')
```

```
plt.grid(True)
plt.legend()

plt.tight_layout()
plt.show()
```

True and predicted classes on test set

```
import numpy as np
y_true = []
y_pred_probs = []

for images, labels in testDataset:
    preds = efficientNetModel.predict(images)
    y_pred_probs.extend(preds)
    y_true.extend(labels.numpy())

y_true = np.array(y_true)
y_pred_probs = np.array(y_pred_probs)
y_true_labels = np.argmax(y_true, axis=1)
y_pred_labels = np.argmax(y_pred_probs, axis=1)
class_names = class_names
```

Classification Report

```
from sklearn.metrics import classification_report

print("Classification Report:")
print(classification_report(y_true_labels, y_pred_labels, target_names=class_names))
```

Confusion Matrix

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

conf_mat = confusion_matrix(y_true_labels, y_pred_labels)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues',
```

```
        xticklabels=class_names,
        yticklabels=class_names)

plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.tight_layout()
plt.show()
```

Calculating F1-Score

```
from sklearn.metrics import f1_score, precision_score, recall_score

f1_macro = f1_score(y_true_labels, y_pred_labels, average='macro')
f1_weighted = f1_score(y_true_labels, y_pred_labels, average='weighted')
precision = precision_score(y_true_labels, y_pred_labels, average='macro')
recall = recall_score(y_true_labels, y_pred_labels, average='macro')

print(f"F1 Score (Macro): {f1_macro:.4f}")
print(f"F1 Score (Weighted): {f1_weighted:.4f}")
print(f"Precision (Macro): {precision:.4f}")
print(f"Recall (Macro): {recall:.4f}")
```

AUC-ROC Curves

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
from itertools import cycle

n_classes = y_true.shape[1]
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_true[:, i], y_pred_probs[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
    print(f"AUC for class '{class_names[i]}': {roc_auc[i]:.4f}")

colors = cycle(['blue', 'green', 'red', 'orange', 'purple', 'brown'])
```

```
plt.figure(figsize=(10, 8))
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f"ROC curve for class {class_names[i]} (AUC = {roc_auc[i]:.2f})")

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 0.2])
plt.ylim([0.8, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver Operating Characteristic (ROC) Curves")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```