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Skin Cancer Classification using deep learning models

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MSc FPR Declaration

This report is submitted in partial fulfilment of the requirement for the degree of Master of Science in Advance Computer Science at the University of Hertfordshire (UH).

I hereby declare that the work presented in this project and report is entirely my own, except where explicitly stated otherwise. All sources of information and ideas, whether quoted directly or paraphrased, have been properly referenced in accordance with academic standards. I understand that any failure to properly acknowledge the work of others could constitute plagiarism and may result in academic penalties.

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Abstract

Skin cancer, one of the most prevalent cancers globally, demands early and accurate detection to reduce mortality rates. Traditional diagnostic methods, reliant on subjective visual assessments, face challenges in scalability and consistency, particularly in underserved regions. This study addresses these gaps by developing and evaluating two efficient deep learning models MobileNetV2 and EfficientNetB0 for automated classification of skin lesions using dermoscopic images. The primary goal is to identify the optimal architecture balancing diagnostic accuracy with computational efficiency for real-world clinical deployment.

The research utilized merged datasets (ISIC 2019 and HAM10000), preprocessed through stratified sampling, duplicate removal (1,579 images), and augmentation to mitigate class imbalance. Transfer learning was applied to both models, with customized classifier heads and hyperparameters (label smoothing: α=0.1, dropout: 0.6) to enhance generalization. Performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC, alongside deployment metrics like model size.

EfficientNetB0 achieved superior accuracy 91% vs MobileNetV2 88.67% and melanoma recall (94% vs. 90%), critical for minimizing missed diagnoses, while MobileNetV2 excelled in efficiency with 11.64 MB size, enabling edge deployment. Key findings highlight a clinical trade-off: EfficientNetB0's precision (84%) led to fewer unnecessary biopsies compared to MobileNetV2 (83%), yet its higher computational demands may limit use in low-resource settings.

The study concludes that EfficientNetB0 is ideal for accuracy-driven clinical environments, whereas MobileNetV2 offers a pragmatic solution for mobile health applications. Limitations include dataset bias toward lighter skin tones and restricted lesion diversity. Future work should integrate synthetic data generation and multi-institutional collaborations to improve generalizability. These findings advance the development of equitable, deployable AI tools, bridging the gap between technical innovation and clinical practicality in global dermatology.

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1. Introduction

1.1 Background of the Topic

Skin cancer remains one of the most prevalent forms of cancer worldwide, with millions of cases diagnosed annually. Early and accurate detection is vital for effective treatment, particularly for malignant forms such as melanoma, which can metastasize rapidly if left untreated. Traditionally, skin cancer diagnosis relies on visual inspection by dermatologists, often followed by dermoscopic examination and biopsy. However, this approach is subject to human error, variability in clinician experience, and limited accessibility, particularly in underserved regions.

In recent years, advances in deep learning have led to significant improvements in medical image analysis. Convolutional Neural Networks (CNNs), in particular, have demonstrated state-of-the-art performance in image classification tasks, making them a promising tool for automating skin lesion analysis. CNN-based models can learn hierarchical representations of image features and achieve performance comparable to, or even exceeding, that of dermatologists in certain diagnostic scenarios.

Despite this promise, several challenges hinder the clinical adoption of such models. Current AI systems often struggle with generalizability due to dataset bias, class imbalance, and a lack of evaluation across diverse, real-world datasets. Additionally, many models prioritize accuracy over practicality, overlooking factors such as computational efficiency, deployment feasibility on mobile or edge devices, and clinical integration.

This project seeks to address these issues by conducting a comparative analysis of two efficient CNN architectures—MobileNetV2 and EfficientNetB0—for the classification of skin cancer images. The study utilizes two benchmark dermoscopic image datasets, ISIC and HAM10000, to assess model robustness across different data sources. These datasets were chosen due to their size, diversity of skin lesion types, and relevance to real-world diagnostic conditions.

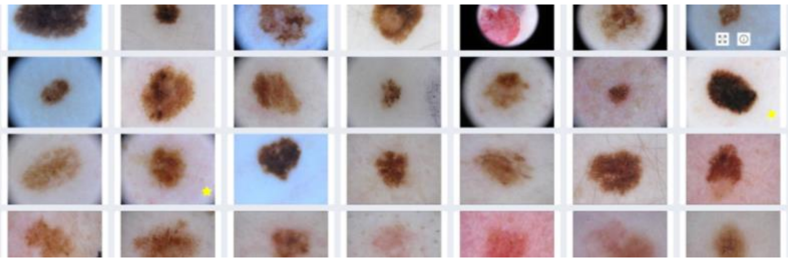

Figure-1 Different types of skin cancer images

1.2 Aim

This project aims to develop a robust deep learning model for skin cancer classification and perform a comparative analysis of different convolutional neural network architectures to identify the most effective approach for clinical application.

1.3 Research Question

How do different deep learning architectures compare in terms of classification accuracy, computational efficiency, and overall effectiveness in classifying skin cancer?

1.4 Goals and Objectives

The main goal of this research is to design and evaluate deep learning models for skin cancer classification, to identify the most effective architecture for real-world clinical deployment. To achieve this goal, the following specific objectives have been defined:

- **Data Preprocessing and Augmentation**: Standardize image dimensions, normalize pixel values, and apply augmentation techniques to improve model generalization.
- **Model Development and Training**: Implement and train two CNN architectures using frameworks such as TensorFlow and Keras.
- **Performance Evaluation**: Assess model performance using metrics such as accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC.
- **Feasibility Assessment for Clinical Applications**: Analyze the practical challenges of deploying the best-performing model in clinical settings, considering factors like inference time, interpretability, and compatibility with existing workflows.
- **Optimization**: Perform hyperparameter tuning (e.g., learning rate, batch size, activation functions) to balance classification accuracy and computational cost.
- **Deployment Readiness**: Evaluate real-time diagnostic potential, focusing on latency and resource consumption on edge devices.

1.5 Ethical Considerations

This study adheres to ethical guidelines for AI research in healthcare. Both datasets are publicly available and anonymized, ensuring patient confidentiality. Potential biases arising from imbalanced class distributions or demographic underrepresentation (e.g., skin tone diversity) are explicitly acknowledged, and mitigation strategies, such as stratified sampling and data augmentation, are employed. Transparency in methodology and results reporting is prioritized to facilitate reproducibility. Additionally, the research emphasizes that proposed models are intended to support, and not to replace clinical decision-making, underscoring the need for rigorous validation before real-world implementation.

1.6 Report Structure

This report is structured as follows: Chapter 2 presents a literature review on deep learning for skin cancer detection. Chapter 3 outlines the methodology, including dataset preparation and model training procedures. Chapter 4 details the experimental results and model evaluation. Chapter 5 discusses the conclusion, limitations, and future directions of the study. Finally, Chapter 6 provides the references of external sources used in this research report.

2. Literature Review

2.1 Overview of Skin Cancer Diagnosis

Skin cancer, encompassing malignant melanoma and non-melanoma types such as basal and squamous cell carcinomas, is among the most commonly diagnosed cancers worldwide (Garbe & Leiter, 2009). Early detection is crucial, as the survival rate for malignant melanoma significantly increases when identified in its early stages (Whiteman et al., 2016). Traditional diagnostic workflows rely heavily on visual inspection, dermoscopic imaging, and histopathological confirmation. While these methods are effective, they are subject to inter-observer variability and depend significantly on clinician expertise (Argenziano, 2003). This creates a critical need for standardized and scalable diagnostic tools that can augment clinical decision-making.

2.2 Emergence of Deep Learning in Medical Imaging

In recent years, deep learning (DL) has emerged as a transformative tool in medical image analysis. Unlike traditional machine learning approaches, which rely on handcrafted features, deep learning—particularly convolutional neural networks (CNNs)—can automatically learn hierarchical representations from raw image data (LeCun et al., 2015). This capability has led to significant improvements in image-based classification tasks, including radiology, histopathology, and dermatology (Litjens et al., 2017).

One of the landmark studies in dermatological deep learning was conducted by Esteva et al. (2017), who trained a CNN using over 120,000 clinical images and demonstrated dermatologist-level performance in differentiating malignant from benign lesions. This work catalysed further research into CNN-based skin cancer classification and validated the clinical potential of such systems. Since then, deep learning models have been increasingly applied to dermatoscopic datasets to assist clinicians in early diagnosis, reduce diagnostic errors, and support tele dermatology initiatives.

2.3 Datasets in Skin Cancer Classification

ISIC Dataset

The International Skin Imaging Collaboration (ISIC) has curated a series of publicly available dermatoscopic datasets, most notably ISIC 2019. This dataset contains over 23,500 images spanning nine diagnostic categories, including melanoma, basal cell carcinoma, and benign keratosis (Codella et al., 2019). Its scale and diversity make it suitable for training deep learning models with enhanced generalizability. However, it also presents challenges such as class imbalance and high intra-class variability, which must be addressed through appropriate preprocessing and data augmentation strategies.

HAM10000 Dataset

The HAM10000 (“Human Against Machine”) dataset is another benchmark collection, comprising 10,015 dermatoscopic images classified into seven categories (Tschandl et al., 2018). It is widely used for academic research due to its accessibility and high-quality labels. However, it is limited in terms of racial diversity, which raises concerns about algorithmic fairness (Daneshjou et al., 2021). Moreover, the dataset exhibits imbalanced class distributions, particularly underrepresentation of malignant melanoma, necessitating careful model calibration and evaluation.

2.4 Comparative Analysis of Different CNN Architectures

The field of deep learning offers a wide array of convolutional neural network (CNN) architectures, each with unique design principles and performance trade-offs. Popular CNN models used in medical image classification include VGGNet, ResNet, DenseNet, Inception, MobileNet, and EfficientNet. A comparative evaluation of these architectures is crucial to selecting an appropriate model for skin cancer classification, particularly when considering factors such as accuracy, computational cost, and deployment feasibility.

- **VGGNet** (Simonyan & Zisserman, 2015) is a deep architecture that utilizes uniform 3×3 convolutional layers. It offers strong classification accuracy but is computationally expensive due to its depth and number of parameters.
- **ResNet** (He et al., 2016) introduced residual connections to address the vanishing gradient problem in deep networks. While effective for classification tasks, ResNet models are resource-intensive and may be overkill for mobile or embedded use.

- **DenseNet** (Huang et al., 2017) builds on ResNet by connecting each layer to every other layer, promoting feature reuse. This leads to improved parameter efficiency but results in dense memory consumption.
- **Inception-v3** (Szegedy et al., 2016) utilizes parallel convolutions with multiple kernel sizes. It achieves high accuracy with moderate efficiency but is complex to implement and fine-tune.
- **MobileNet** (Sandler et al., 2018) was specifically designed for mobile and edge devices. By using depthwise separable convolutions, MobileNetV2 drastically reduces the number of parameters and computation time.
- **EfficientNet** (Tan & Le, 2019) presents a compound scaling method that balances network depth, width, and resolution. EfficientNetB0 (the smallest version) has proven to be both accurate and efficient for medical image tasks.

Several comparative studies highlight that while traditional CNNs (e.g., VGG, ResNet) may outperform lightweight models slightly in accuracy, MobileNetV2 and EfficientNetB0 offer a superior trade-off when computational efficiency and deployability are prioritized. For instance, Liu et al. (2020) showed that EfficientNetB0 outperformed DenseNet121 and ResNet50 in AUC-ROC scores while using fewer parameters.

Model	Accuracy (Reported)	Parameters (Millions)	AUC-ROC	Inference Time
VGG16	87%	138	0.89	High
ResNet50	89	25	0.91	Medium
DenseNet121	90	8	0.93	Medium
InceptionV3	88	24	0.91	Medium
MobileNetV2	86	3.4	0.90	Low
EfficientNetB0	91	5.3	0.94	Low

Table-1 Comparative Overview of different CNN Architectures

2.5 Justification for Choosing MobileNetV2 and EfficientNetB0

The decision to use MobileNetV2 and EfficientNetB0 in this research is underpinned by a comprehensive evaluation of current literature and practical considerations relevant to clinical deployment.

- **Balance Between Accuracy and Efficiency**
  EfficientNetB0 achieves near state-of-the-art performance with significantly fewer parameters compared to deeper models like ResNet152 or DenseNet201 (Tan & Le, 2019). MobileNetV2, similarly, offers high accuracy with minimal computational requirements, making it well-suited for real-time diagnostics, particularly in low-resource or mobile settings (Sandler et al., 2018).
- **Proven Performance on Medical Datasets**
  Both architectures have been validated on skin cancer datasets such as ISIC and HAM10000. For example, Kanchana et al. (2024) used EfficientNetB0 on HAM10000 and achieved F1-scores exceeding 90%. Ogundokun et al. (2023) demonstrated the effectiveness of MobileNetV2 in achieving dermatologist-level classification when paired with augmentation and optimization techniques.
- **Scalability and Deployment Readiness**

MobileNetV2 is widely deployed in mobile health applications due to its minimal latency and memory usage. EfficientNetB0's compound scaling approach also facilitates scalable performance tuning depending on the available hardware, ranging from smartphones to edge devices in clinical settings (Tan & Le, 2019).

- **Complementary Characteristics**
  MobileNetV2 and EfficientNetB0 represent different design philosophies—MobileNetV2 emphasizes modular simplicity and depthwise separability, while EfficientNetB0 applies principled compound scaling. Comparing both offers valuable insight into how these contrasting strategies affect diagnostic accuracy and deployment feasibility.

Thus, MobileNetV2 and EfficientNetB0 are selected not only for their proven performance on benchmark datasets but also for their real-world applicability, efficiency, and interpretability. Their inclusion in this study aligns with the broader objective of evaluating clinically viable AI solutions for skin cancer diagnosis.

2.6 Limitations in Existing Research

Despite the promising results, several limitations persist in current literature:

- **Class Imbalance**: Both ISIC and HAM10000 datasets suffer from disproportionate class distributions, with melanoma and other malignant cases underrepresented. This can bias models toward majority classes and inflate accuracy metrics.
- **Lack of Diversity**: Many datasets predominantly contain images of lighter skin tones, limiting the generalizability of models to patients with darker skin.
- **Overfitting**: Given the limited size of labelled datasets, models are prone to overfitting, especially when trained without adequate regularization or cross-validation.
- **Deployment Constraints**: Most academic studies do not evaluate the feasibility of real-time deployment, including factors like latency, memory consumption, and integration with clinical systems.

2.7 Research Gap and Justification

While several studies have explored CNNs for skin cancer classification, there is a lack of focused comparison between lightweight architectures that are suitable for clinical deployment. In particular, head-to-head evaluations of MobileNetV2 and EfficientNetB0 under consistent experimental conditions accounting for dataset variability, augmentation techniques, and hyperparameter optimization are limited. Furthermore, few studies explicitly address deployment constraints such as inference time, device compatibility, and interpretability. This research aims to fill these gaps by developing, training, and benchmarking MobileNetV2 and EfficientNetB0 on both ISIC 2019 and HAM10000 datasets, with attention to clinical feasibility and ethical considerations.

3. Methodology

3.1 Project Approach and Choice of Methods

This project adopts a data science research methodology focused on the application and comparative evaluation of convolutional neural networks (CNNs) for automated skin cancer classification using dermoscopic images. The primary objective is to assess the effectiveness of lightweight CNN architectures specifically, MobileNetV2 and EfficientNetB0 in accurately classifying different types of skin lesions while maintaining computational efficiency suitable for deployment in resource-constrained settings.

The approach follows a structured pipeline comprising the following stages: dataset acquisition, preprocessing, data augmentation, model selection and architecture modification for transfer learning, model training and validation, performance evaluation, and result interpretation. Each step is designed to ensure methodological rigor, reproducibility, and alignment with the project's research aim.

MobileNetV2 and EfficientNetB0 were selected due to their proven performance in mobile and edge computing environments, offering a balance between high classification accuracy and reduced computational overhead. This choice is particularly relevant given the growing interest in deploying AI-driven diagnostic tools on handheld devices to assist clinicians in real-time decision-making, especially in low-resource settings.

The methodology is experimental in nature, involving comparative analysis of both models using quantitative evaluation metrics such as accuracy, precision, recall, F1-score , confusion matrix, and AUC-ROC curves. By adopting this experimental and metric-driven approach, the project ensures an objective assessment of model performance and practical feasibility.

3.2 Justification of Methodological Choice

The methodological choices made in this project are grounded in both the specific requirements of medical image classification and the broader context of real-world deployment constraints in healthcare environments. Deep learning, particularly Convolutional Neural Networks (CNNs), has become the standard in image-based medical diagnostics due to its ability to automatically learn and extract hierarchical features from raw data without manual intervention. CNNs have been extensively validated in dermatology for skin lesion classification, demonstrating dermatologist-level accuracy in various peer-reviewed studies.

MobileNetV2 and EfficientNetB0 were chosen as the core architectures based on a combination of empirical performance, computational efficiency, and literature support. Traditional deep learning models such as VGG16, ResNet50, and DenseNet121, while highly accurate, tend to have a large number of parameters and require significant memory and processing power, which limits their applicability on mobile and edge devices. In contrast, both MobileNetV2 and EfficientNetB0 are designed for efficiency without sacrificing performance. EfficientNetB0 leverages compound scaling to optimize accuracy and efficiency simultaneously, while MobileNetV2 utilizes depthwise separable convolutions to drastically reduce computational cost.

These models have been specifically cited in recent academic work for their applicability in low-latency environments and have shown strong results on medical datasets such as ISIC and HAM10000. Furthermore, given the project's focus on clinical feasibility, choosing architectures that balance accuracy with practical constraints such as inference time, memory usage, and ease of deployment was essential.

The use of publicly available and benchmarked datasets (ISIC 2019 and HAM10000) further supports the methodological rigor of this project. These datasets are widely used in academic and clinical research, and offer diverse, annotated, and pre-processed dermoscopic images that are ideal for training and evaluating machine learning models.

3.3 Project Design and Data Collection

The project design follows a systematic approach structured around the end goal of developing an efficient and accurate deep learning-based classification system for skin cancer detection.

Data Sources

Two publicly available and well-established dermoscopic image datasets were used: ISIC 2019 and HAM10000.

- **ISIC 2019 Dataset**: Provided by the International Skin Imaging Collaboration, this dataset contains around 2,500 high-resolution dermoscopic images across nine diagnostic categories. It is widely used in machine learning research for skin cancer detection due to its diversity and size.
  Dataset link: https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic
- **HAM10000 Dataset**: Known as the "Human Against Machine" dataset, it comprises around 9,300 dermoscopic images across seven skin lesion classes. It is annotated and validated by medical professionals, making it suitable for deep learning.
  Dataset link: https://www.kaggle.com/datasets/surajghuwalewala/ham1000-segmentation-and-classification

Both datasets are anonymized and ethically approved for academic research, removing the need for additional patient consent or data access clearance.

3.4 Tools and Technologies Used

The implementation and management of this project leveraged a suite of modern tools and technologies, selected for their reliability, compatibility with deep learning workflows, and strong community support. Each tool played a critical role in various stages of development, from data preprocessing to model training, evaluation, and visualization.

Programming Language

- **Python 3.10**: Chosen for its versatility, readability, and widespread adoption in the machine learning community. Python's robust ecosystem of scientific and machine learning libraries made it a natural choice for this project.

Frameworks

- **TensorFlow 2.10** and **Keras**: These were the primary deep learning frameworks used for building, training, and evaluating the CNN models. Keras, integrated within TensorFlow, provided a user-friendly interface for model definition and experimentation, while TensorFlow ensured scalability and support for GPU acceleration.

Libraries

- **TensorFlow-macos** and **TensorFlow-metal**: These Apple-specific packages were used to enable GPU acceleration on macOS devices, significantly reducing training time during model development.
- **NumPy**: Utilized for numerical operations, including array manipulation and mathematical computations.
- **Pandas**: Employed for efficient data loading, manipulation, and preprocessing tasks.
- **Matplotlib** and **Seaborn**: These libraries were used for visualizing training metrics (loss, accuracy), confusion matrices, and performance comparisons between models.

- **Streamlit**: Used to build a simple, interactive web interface for demonstrating the skin cancer classification model. This interface simulated potential real-world application scenarios, enhancing the practical relevance of the project.

Development Environment

- **Visual Studio Code (VSCode)**: Selected as the integrated development environment (IDE) for its lightweight structure, extensibility, and excellent support for Python and Jupyter notebooks. Extensions like Python and GitHub integration streamlined the development process.

Version Control

- **GitHub**: Used for source code management, collaboration, and backup. Version control was essential in tracking changes, managing experiments, and maintaining a reproducible and organized project workflow.
  GitHub Link: https://github.com/Arjunaju23/Skin-cancer-classification

Together, these tools enabled a smooth, modular, and scalable development process. The choice of technologies ensured that the project remained compatible with both local development constraints and future deployment on mobile or edge devices.

3.5 Data Preprocessing and Augmentation

This section outlines the approach taken to prepare and test the dataset prior to model training. Given the complexities of class imbalance and image diversity in skin lesion datasets, rigorous preprocessing and augmentation techniques were essential to ensure fair model evaluation and improve generalization capabilities.

3.5.1 Data Preprocessing

The preprocessing phase was extensive, ensuring that only high-quality, balanced, and non-redundant data entered the training pipeline. Two prominent datasets, **ISIC** and **HAM10000**, were initially used. These datasets contained multiple skin lesion classes with significantly imbalanced distributions.

ISIC Dataset Distribution

Train folder

Class	Melanoma	Pigmented Benign Keratosis	Nevus	Basal Cell Carcinoma	Actinic Keratosis	Squamous Cell Carcinoma	Vascular Lesion	Seborrheic Keratosis	Dermatofibroma
Image count	438	462	357	376	114	181	139	77	95

Table-2 ISIC training dataset distribution

Test folder

Class	Melanoma	Pigmented Benign Keratosis	Nevus	Basal Cell Carcinoma	Actinic Keratosis	Squamous Cell Carcinoma	Vascular Lesion	Seborrheic Keratosis	Dermatofibroma
Image count	16	16	16	16	16	16	3	3	16

Table-3 ISIC testing dataset distribution

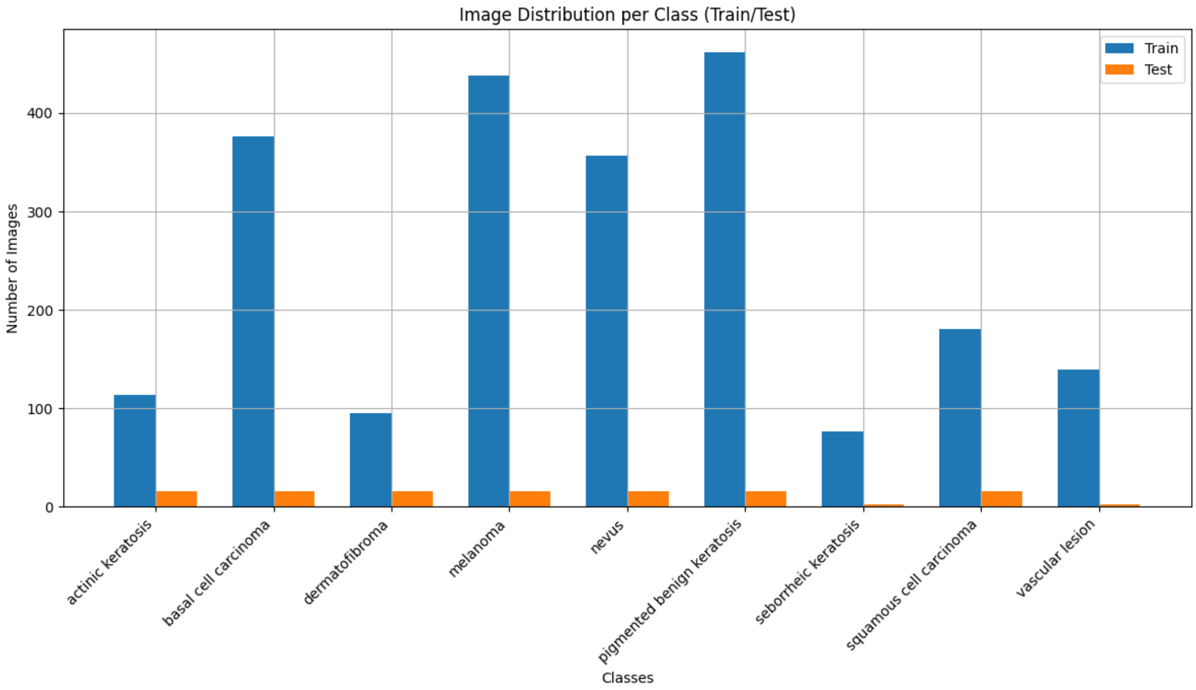

Figure-2 ISIC dataset distribution

HAM10000 Dataset Distribution

Class	Melanoma	Nevus	Basal Cell Carcinoma	Actinic Keratosis	Vascular Lesion	Seborrheic Keratosis	Dermatofibroma
Image count	1113	6705	514	327	142	399	115

Table-4 HAM10000 dataset distribution

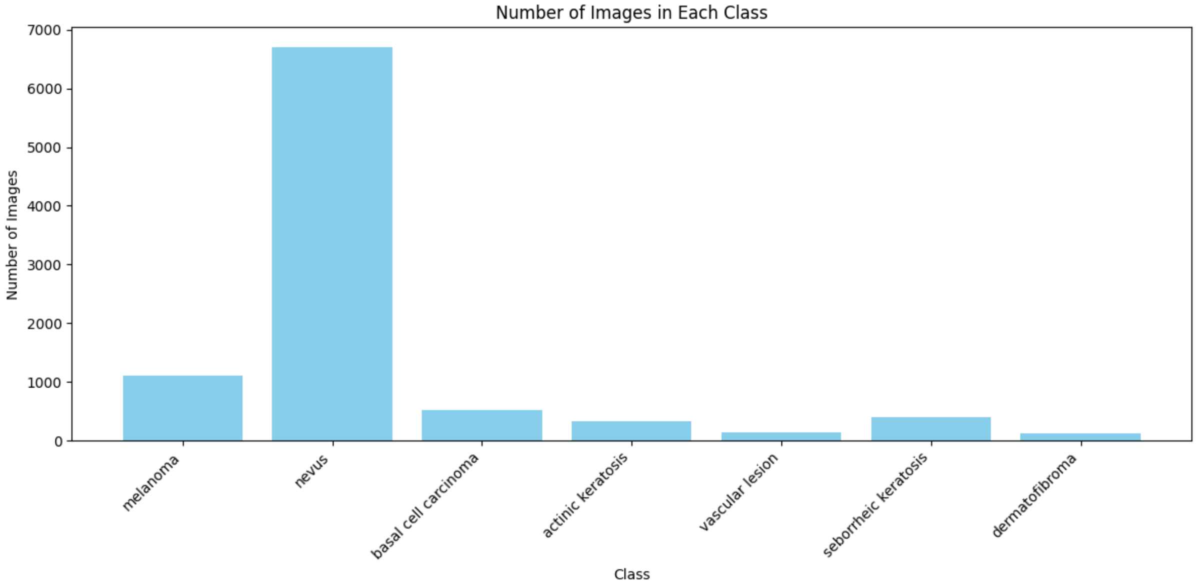

Figure-3 HAM10000 dataset distribution

Merged Dataset Distribution

To ensure data consistency, both datasets were merged using only common classes, resulting in the following combined distribution

Class	Melanoma	Nevus	Basal Cell Carcinoma	Actinic Keratosis	Vascular Lesion	Seborrheic Keratosis	Dermatofibroma
Image count	1551	7062	890	441	281	1176	210

Table-5 Merged Dataset Distribution

To eliminate duplicate images between datasets, MD5 hash matching was performed. This revealed and removed 1579 duplicate images across several classes. The final cleaned dataset contained

Class	Melanoma	Nevus	Basal Cell Carcinoma	Actinic Keratosis	Vascular Lesion	Seborrheic Keratosis	Dermatofibroma
Image count	1550	7059	514	251	142	401	115

Table-6 Merged Dataset Distribution

Due to the highly imbalanced nature of the dataset, only the top three most populated classes Melanoma, Nevus, and Basal Cell Carcinoma were retained to reduce variance and improve training focus. These were then balanced by downsampling each to 514 images, ensuring an equal representation across classes.

To further enhance dataset variability and robustness, each original image was augmented to generate two synthetic images, resulting in:

- Melanoma: 1496 images
- Nevus: 1480 images
- Basal Cell Carcinoma: 1499 images

Final Dataset Distribution

As the final step, the dataset was split into Train (1000 images), Validation (350 images), and Test (100 images) per class using random stratified sampling, maintaining class balance throughout.

Dataset	Melanoma	Nevus	Basal Cell Carcinoma
Train	1000 images	1000 images	1000 images
Val	350 images	350 images	350 images
Test	100 images	100 images	100 images

Table-7 Final Dataset Distribution

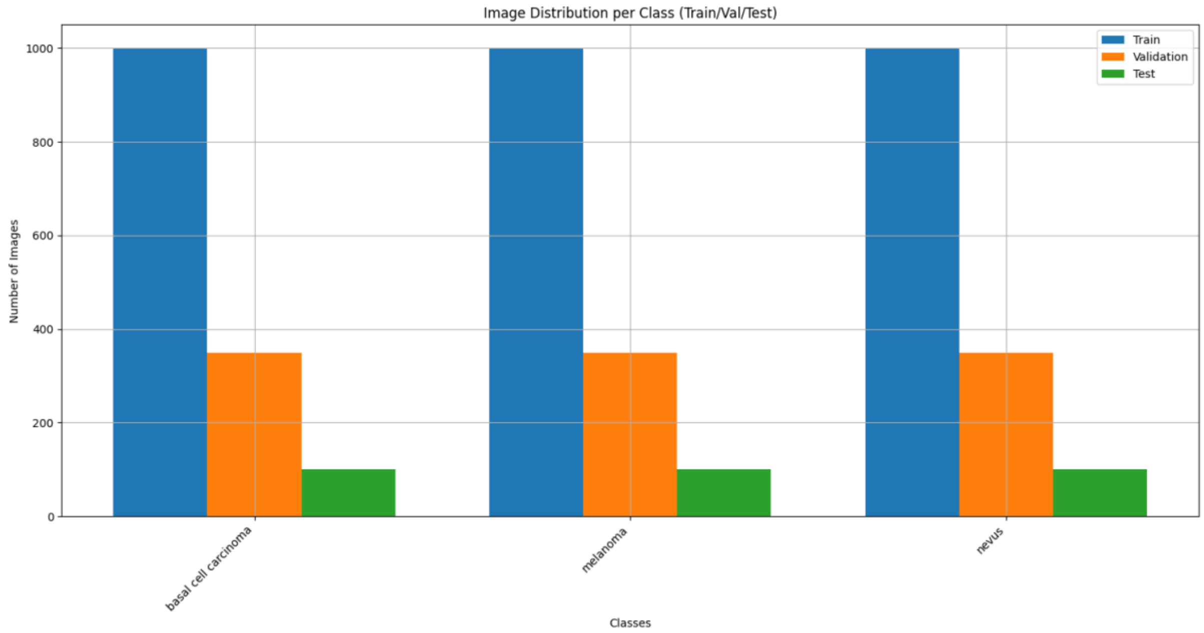

Figure-4 Bar plot showing final dataset distribution

3.5.2 Data Augmentation

Data augmentation was a critical strategy to simulate real-world variability in skin lesions and to prevent overfitting. All images were resized to 224×224 pixels, aligning with the input dimensions of the deep learning models used (MobileNetV2 and EfficientNetB0). Additionally, appropriate normalization was applied:

- **MobileNetV2**: Used preprocess_input from tensorflow.keras.applications.mobilenet
- **EfficientNetB0**: Used preprocess_input from tensorflow.keras.applications.efficientnet

A rich set of augmentation parameters was configured using TensorFlow's ImageDataGenerator:

```
train_datagen = ImageDataGenerator(
   preprocessing_function=preprocess_input,
   horizontal_flip=True,
   vertical_flip=True,
   rotation_range=20,
   width_shift_range=0.20,
   height_shift_range=0.20,
   zoom_range=0.20,
   brightness_range=[0.8, 1.2],
   shear_range=0.1,
   channel_shift_range=10.0
)
```

3.6 Model Implementation and Training

This section describes the detailed process of implementing and training two high-performance convolutional neural network (CNN) architectures MobileNetV2 and EfficientNetB0 for the task of multi-class skin lesion classification. The models were selected based on their proven balance between computational efficiency and classification accuracy, making them suitable for both research and real-time clinical decision support systems.

3.6.1 Model Selection Rationale

- MobileNetV2 is an architecture specifically designed for mobile and edge devices. It introduces inverted residual blocks and linear bottlenecks, allowing the model to achieve competitive accuracy with a drastically reduced number of parameters and computational cost.
- EfficientNetB0, on the other hand, is the baseline model of the EfficientNet family, known for achieving state-of-the-art accuracy with fewer parameters. It uses compound scaling, which uniformly scales depth, width, and resolution, leading to better efficiency in both training and inference.

These characteristics make both models ideal candidates for deployment-focused medical AI applications where latency and memory constraints are critical.

3.6.2 Original Architecture Overview

- **MobileNetV2** begins with a standard convolution followed by a series of inverted residual blocks with shortcut connections. These blocks include:
  - A 1×1 pointwise convolution (expansion layer),
  - A 3×3 depthwise convolution (spatial filtering),
  - Another 1×1 pointwise convolution (projection layer).

  These enable the model to learn complex representations while maintaining low computational complexity.

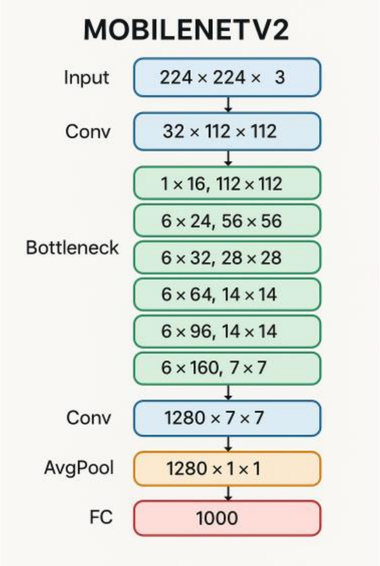

Figure-5 MobileNetV2 architecture diagram

- **EfficientNetB0** is built with MBConv blocks (Mobile Inverted Bottleneck Convolution) and includes Squeeze-and-Excitation (SE) modules for channel-wise attention. This allows the model to focus on the most informative features dynamically.

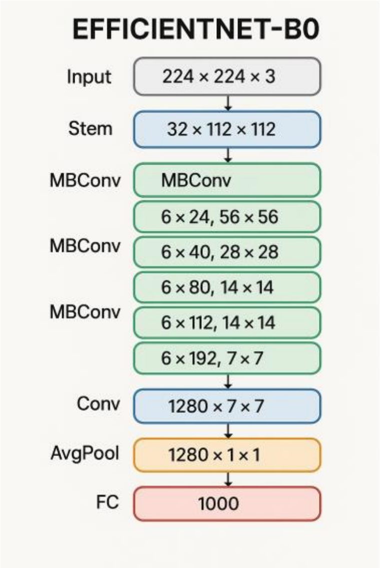

Figure-6 EfficientNetB0 architecture diagram

However, while both models are pretrained on ImageNet, their final layers are tailored for 1000 general object categories, not for medical classification. This necessitates architectural modifications for the task at hand.

Data Generators and Preprocessing Recap

- Data augmentation was applied using ImageDataGenerator with medically safe transformations (e.g., rotation, zoom, flips, brightness) only on the train dataset and not on the validation or test dataset.
- Preprocessing functions specific to each model (mobilenet_v2.preprocess_input and efficientnet.preprocess_input) ensured that input images were normalized as expected by the respective model architectures.

3.6.3 Model Initialization

Both MobileNetV2 and EfficientNetB0 were initialized with ImageNet pretrained weights to leverage transfer learning. This allows the networks to retain low-level feature extraction capabilities (such as edge detection and colour patterns) while fine-tuning the high-level layers for the specific task of skin lesion classification.

3.6.4 Architectural Modifications and Custom Classifier Head

To adapt the pretrained models to the skin lesion classification task, their original top (fully connected) layers were removed by setting (include_top=False) and replaced with a custom classifier head, designed to:

- **Extract High-Level Features**: The base CNN acts as a fixed feature extractor (partially trainable) to transform input images into rich, multi-dimensional feature vectors.
- **Reduce Dimensionality**: Using a GlobalAveragePooling2D layer, spatial dimensions were collapsed into channel-wise feature representations, reducing the number of trainable parameters and overfitting risk.
- **Normalize Activations**: BatchNormalization was applied post-pooling to stabilize training by normalizing the feature activations.
- **Dense Layers for Learning Complex Patterns**:

    - A **512-unit dense layer** (with swish activation) serves as the first trainable layer. This size was empirically chosen to balance expressive power and generalization, acting as a wide filter for learning rich, high-level interactions between features.
    - A **256-unit dense layer** (also with swish) further condenses these interactions, allowing the model to focus on the most relevant patterns.
    - Both layers are followed by Dropout (0.6) for aggressive regularization, suitable for small datasets prone to overfitting.
- **Output Layer**: A 3-unit dense layer with softmax activation outputs class probabilities for the three skin lesion categories melanoma, nevus, and basal cell carcinoma.

The use of Swish activation (instead of ReLU) was deliberate; Swish has been shown to outperform ReLU on deeper models and is the default choice in EfficientNet.

3.6.5 Training Configuration

Both models were trained with the following configuration:

- **Optimizer:** Adam (learning rate = 0.0001) for adaptive learning of sparse gradients, suitable for medical datasets.
- **Loss Function:** Categorical Crossentropy with label smoothing (0.1) to handle potential label noise and improve generalization.
- **Epochs:** Up to 50 (Sufficient range for convergence with early stopping based on validation loss)
- **Batch Size:** 32 for a balanced memory usage and gradient estimation
- **Callbacks:**
    - EarlyStopping: Halts training if validation loss does not improve for 5 consecutive epochs.
    - ModelCheckpoint: Saves the model with the lowest validation loss.
    - ReduceLROnPlateau: Reduces learning rate if the validation loss plateaus.

3.6.6 Transfer Learning and Fine-Tuning Strategy

Instead of training the full model from scratch which is infeasible for medical imaging datasets with limited samples this project utilized transfer learning to strike a balance between retaining pretrained knowledge and learning task-specific features, a layer freezing strategy was employed:

- The base layers retained pretrained ImageNet weights, which provide foundational visual features (edges, textures, shapes).
- Only the top 20% of base layers were unfrozen and made trainable, allowing the model to specialize in medical features without catastrophic forgetting of general vision knowledge.

This fine-tuning strategy offers the best of both worlds efficient convergence and higher generalization.

3.6.7 Training Environment

- The models were developed and trained in Python 3.10 using TensorFlow 2.10 and Keras in VSCode.
- Training was also conducted in VSCode, taking advantage of Apple Silicon GPU for accelerated hardware and faster convergence.

3.7 Test Strategy

A robust and multi-faceted test strategy was employed to ensure that the trained models generalize well to unseen data, perform reliably across different skin lesion types, and are resilient to overfitting. The testing pipeline encompassed dataset splitting, hyperparameter tuning, and post-training evaluation, each tailored to the unique constraints and goals of the project.

3.7.1 Dataset Splitting and Evaluation Approach

To simulate real-world deployment and rigorously evaluate model performance:

The final dataset (comprising three balanced classes: melanoma, nevus, and basal cell carcinoma) was randomly split into:

- Training Set: 1000 images per class (total: 3000 images)
- Validation Set: 350 images per class (total: 1050 images)
- Test Set: 100 images per class (total: 300 images)

This split ensured that the model could learn patterns, tune its internal parameters, and be tested on completely unseen data. The validation set guided early stopping and model checkpointing, while the test set served as the final benchmark for evaluating generalization.

3.7.2 Hyperparameter Tuning Strategy

While traditional grid search was not used due to computational constraints, a manual iterative search approach was adopted. This process allowed for targeted experimentation and quicker convergence to optimal configurations. The following parameters were adjusted and evaluated based on validation performance:

- **Learning Rates**: Various values were tested (e.g., 1e-3, 1e-4, 1e-5) to find the best trade-off between convergence speed and stability. Ultimately, 1e-4 was selected for both models.
- **Dense Layer Units**: Different combinations (e.g., (1024, 512), (512, 256), (256, 128)) were tested. (512, 256) provided the best validation accuracy while maintaining a compact model size.
- **Loss Functions**: CategoricalCrossentropy with label_smoothing=0.1 was chosen to address minor label inconsistencies and improve confidence calibration.
- **Frozen Layer Proportion**: Various levels of base layer freezing were explored (e.g., 75%, 80%, 90%, full). Freezing 80% of base layers allowed enough flexibility for domain-specific feature learning without degrading the pretrained knowledge.

This iterative method of tuning was effective, especially given the limited dataset and resource constraints, and allowed for fast turnaround between model revisions.

3.8 Model performance metrics

To objectively assess the model's performance and its suitability for real-world applications, a set of well-established evaluation metrics were used. These metrics offer insights not just into the model's accuracy, but also its behaviour across different classes and its ability to generalize to unseen data especially important in medical image classification tasks.

3.8.1 Evaluation Metrics

The following key performance metrics were used to evaluate the model:

- **Accuracy**

  Measures the proportion of correctly classified samples out of the total number of samples. While it offers a broad sense of performance, it can be misleading in imbalanced datasets, hence supplemented with other metrics.

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

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

- **Precision**
  Indicates the proportion of true positive predictions among all predicted positives for each class. High precision ensures that false positives are minimized, which is critical for medical applications to avoid incorrect diagnoses.

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

- **Recall (Sensitivity)**
  Measures the proportion of actual positive cases that are correctly identified. In a medical context, high recall is essential to ensure that true cases, such as melanoma, are not missed.

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

- **F1-Score**
  The harmonic mean of precision and recall. It balances the trade-off between precision and recall, making it particularly valuable when evaluating models on imbalanced datasets.

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

- **AUC-ROC (Area Under the Receiver Operating Characteristic Curve)**
  Evaluates the model’s ability to distinguish between classes regardless of threshold. It is especially useful for binary or one-vs-rest multi-class classification tasks and provides insight into the model's discriminatory power.

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

- **Confusion Matrix**
  A visual representation of the model’s classification performance across each class. It highlights patterns in misclassification and helps identify specific class-level weaknesses.

	Predicted Positve	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

3.8.2 Significance of Multi-Metric Evaluation

Using a combination of these metrics allows for a comprehensive evaluation strategy:

- Accuracy provides a top-level view of model performance.
- Precision and Recall expose the trade-offs between false positives and false negatives.
- F1-Score serves as a balanced indicator in the presence of class imbalance.
- AUC-ROC helps evaluate how well the model distinguishes between different lesion types.
- Confusion Matrix supports class-wise error analysis.

Together, these metrics offer both quantitative and diagnostic insights that are essential for developing a clinically viable model.

3.9 Validation of Results

Ensuring the reliability and generalizability of the trained models is critical, especially in the context of medical image classification. While cross-validation was not employed in this project, several other validation strategies were used to rigorously assess the model's performance and robustness.

3.9.1 Validation Set Monitoring

A distinct validation dataset consists of 350 images per class was maintained throughout training to monitor model performance. Validation loss and accuracy were tracked in real-time using callbacks like:

- **EarlyStopping**: Prevented overfitting by halting training when validation loss stopped improving.
- **ReduceLROnPlateau**: Dynamically adjusted the learning rate based on validation loss trends.
- **ModelCheckpoint**: Saved the best-performing model based on validation metrics.

These mechanisms ensured that model tuning was guided by unseen data rather than training performance alone.

3.9.2 Evaluation on Unseen Test Set

After training completion, both MobileNetV2 and EfficientNetB0 models were evaluated on a completely separate test set consists of 100 images per class, which was not used during training or validation. This helped assess the generalization ability of the models on truly unseen examples—an essential factor in real-world medical applications.

3.9.3 Comparative Analysis Across Models

Two distinct architectures MobileNetV2 and EfficientNetB0 were implemented and evaluated using the same data splits, preprocessing pipeline, augmentation strategy, and hyperparameter tuning process. This controlled environment allowed for a fair comparison, revealing the relative strengths and limitations of each architecture under identical conditions.

3.9.4 Robustness Across Class Types

Performance metrics were computed per class (melanoma, nevus, and basal cell carcinoma), using confusion matrices and class-specific precision/recall/F1-scores. This allowed for identifying: Underperforming classes, Biases or inconsistencies in classification, and Generalizability across different lesion types

3.9.5 Benchmarking Against Literature

While not quantitatively compared in code, the architecture, training strategy, and evaluation metrics were inspired by and aligned with state-of-the-art approaches reported in relevant dermatology and machine learning literature (e.g., ISIC challenges, peer-reviewed studies). This provided an informal benchmark to assess whether the models achieved reasonable and realistic performance ranges.

Together, these validation strategies offer confidence in the reliability, fairness, and applicability of the proposed models, even in the absence of cross-validation. They also ensure that the results are reproducible, interpretable, and grounded in real-world relevance.

3.10 Deployment Interface

To translate the trained skin lesion classification model into a user-friendly diagnostic tool, a lightweight web-based interface was built using Streamlit, an open-source Python framework. This interface allows clinicians or end-users to upload dermatoscopic images in real time and receive instant predictions regarding the type of skin lesion.

Key Features:

- **Model Integration**
  The deployed interface loads the best-performing model (EfficientNet.keras) trained during the experimentation phase. The model is used to classify the uploaded image into one of the three classes: Melanoma, Basal Cell Carcinoma, and Nevus.
- **Preprocessing and Prediction**
  Upon uploading, images are:
    - Resized to 224×224.
    - Preprocessed using EfficientNet's preprocess_input().
    - Fed into the model for prediction using model.predict().
    - The class with the highest probability is returned as the result.
- **Confidence Score Display**
  The model outputs not just the predicted label but also a confidence score. Based on this value:
    - If confidence is below 75%, a warning is displayed indicating uncertainty.
    - If confidence is above 75%, the result is presented with a success confirmation.
- **Interface Customization**
    - Default Streamlit UI elements like headers and footers are hidden for a cleaner look.
    - The application interface includes safety prompts reminding users to upload valid dermatoscopic images only.

Benefits:

- Enables real-time clinical decision support.
- Accessible on any browser without requiring any deep learning expertise.
- Streamlined deployment process using Streamlit, ideal for rapid prototyping.

Limitations:

- Model runs locally or on a lightweight cloud host—does not scale for high-traffic usage
- Not yet integrated with patient data systems, security protocols, or clinical feedback loops
- Predictions are informative only, not diagnostic—requiring clinical confirmation

3.11 Ethical, Legal, Social and Professional Issues

The deployment of artificial intelligence (AI) in healthcare, particularly for diagnostic support in dermatology, brings with it a range of ethical, legal, social, and professional responsibilities. These concerns were carefully considered throughout this project to ensure responsible AI development and application.

Data Privacy and Anonymity

- No Personally Identifiable Information (PII) was used in this study. The ISIC and HAM10000 datasets are publicly available and curated to exclude sensitive patient information.
- All image data was used strictly for academic and research purposes in compliance with the data usage agreements set by the dataset providers.

Fairness and Bias Mitigation

- A key ethical consideration is avoiding algorithmic bias, particularly against underrepresented skin tones or lesion types.
- To reduce class imbalance, data augmentation techniques were used. This ensured that the model does not disproportionately favor any of the represented classes.
- However, due to inherent dataset limitations (e.g., predominantly lighter skin tones), the model may not generalize well to all demographics. This limitation is acknowledged, and further work is needed to improve inclusivity.

Social Impact and Clinical Responsibility

- The model is designed as a decision-support tool, not a replacement for clinical judgment. It can assist dermatologists by highlighting potentially malignant lesions but should not be used for self-diagnosis or unsupervised medical decisions.
- Inappropriate or premature deployment of such tools without clinical trials or regulatory approvals could lead to misdiagnoses and patient harm.

Legal and Regulatory Compliance

- The model has not been certified by any regulatory body such as the FDA or CE for clinical deployment. Therefore, it must be treated as a research prototype only**.**
- Any use beyond academic exploration would require extensive validation, ethical review, and legal clearance under health technology regulations.

Professional Integrity and Transparency

- All methods, assumptions, limitations, and design decisions have been documented transparently.
- Model performance is reported using standard evaluation metrics and follows reproducible machine learning practices, ensuring clarity and accountability.

4. Quality and Results

4.1 Overview

This chapter presents and critically analyses the results obtained from the implementation of two pre-trained convolutional neural network models MobileNetV2 and EfficientNetB0 for the task of multi-class skin lesion classification using the ISIC and HAM10000 dataset. The primary objective of this project was to evaluate whether lightweight yet high-performing deep learning architectures could accurately classify skin lesions into melanoma, basal cell carcinoma, and nevus, thus contributing towards the development of a resource-efficient diagnostic aid.

The results are visualised and compared, highlighting differences in model behaviour and diagnostic accuracy. This chapter also examines the experimental setup, implementation challenges, and solutions adopted throughout the development process. The outcomes are interpreted in relation to the project's aims and are further compared with similar studies from the literature.

Furthermore, this section discusses the feasibility of deploying such models in clinical or real-world settings, especially considering their computational efficiency and ease of integration. Emphasis is also placed on the novelty of applying compact architectures in this specific context, addressing gaps in prior research which largely focus on heavier models without consideration for practical deployment.

4.2 Metrics and Presentation

The trained models were evaluated on a balanced test set of 300 images, selected through stratified sampling to ensure representative proportions of each class (Basal Cell Carcinoma, Melanoma, and Nevus). The key performance metrics—Accuracy, Macro F1-Score, Macro AUC-ROC, Inference Time, and Model Size are presented in the table below for comparison between MobileNetV2 and EfficientNetB0.

Metric	MobileNetV2	EfficientNetB0
Accuracy	0.8867	0.9100
Loss	0.5100	0.4722
Macro F1-Score	0.8862	0.9105
Macro Precision	0.8905	0.9144
Macro Recall	0.8867	0.9100
Macro AUC-ROC	0.9722	0.9795
Model Size	11.64	18.47

Table-8 Model metrics used for comparison

The accuracy of the models, representing the proportion of correct classifications, shows that EfficientNetB0 outperforms MobileNetV2, achieving an accuracy of 91.00% compared to 88.67% for MobileNetV2. This indicates that EfficientNetB0 has a better ability to classify skin lesions correctly across all categories.

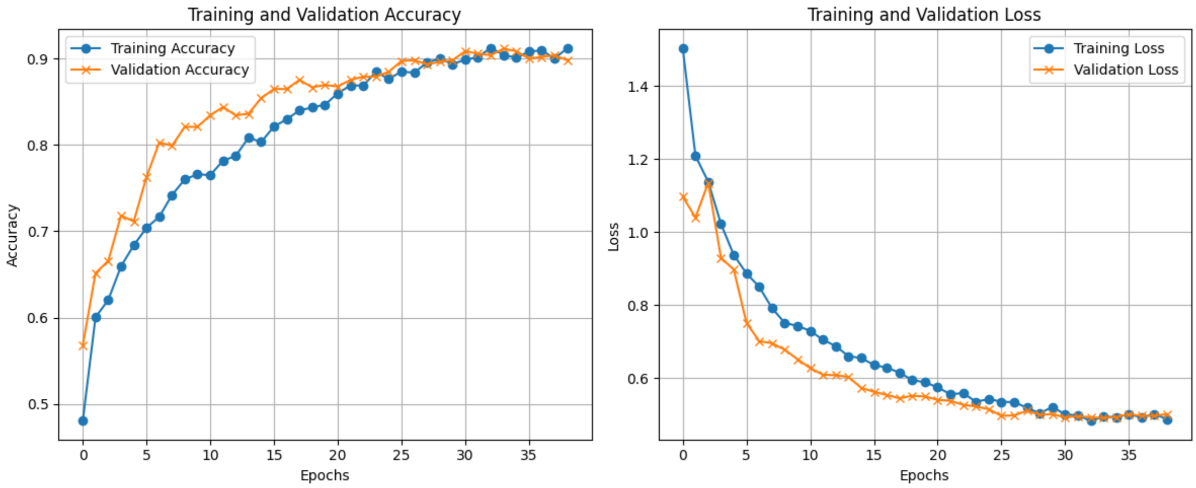

Figure-7 MobileNetV2 train and validation accuracy/loss curves

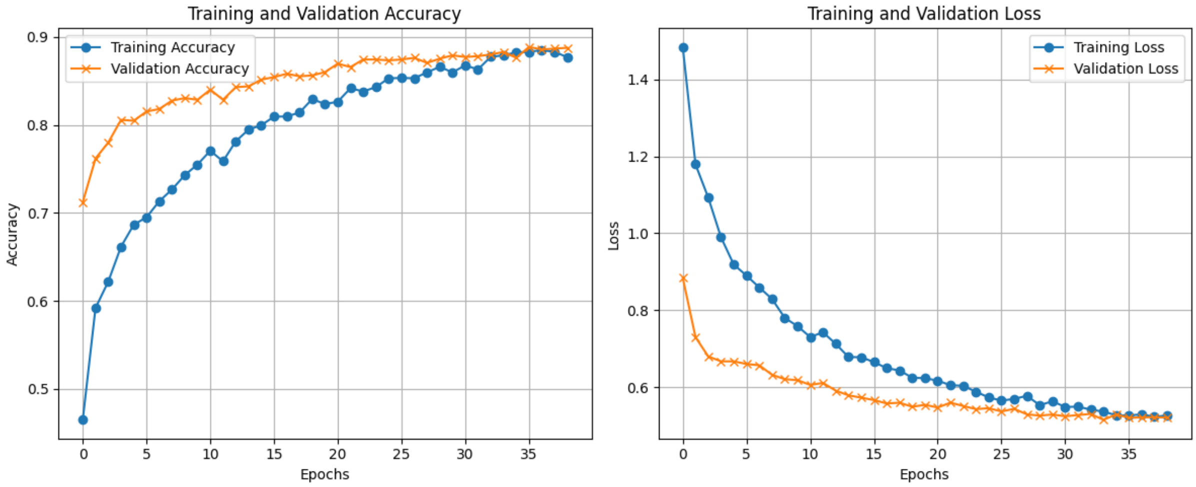

Figure-8 EfficientNetB0 train and validation accuracy/loss curves

In terms of Macro F1-Score, which considers both precision and recall, EfficientNetB0 again leads with a score of 0.9105, slightly ahead of MobileNetV2's 0.8862. The F1-score is particularly important in imbalanced datasets like the one used in this study, as it ensures that the model is not biased toward the majority while maintaining high performance across all classes.

The Macro AUC-ROC is another crucial metric, which evaluates the model's ability to discriminate between the different classes. EfficientNetB0 achieved **a** Macro AUC-ROC of 0.9795, which is superior to MobileNetV2's 0.9722. A higher AUC score implies that EfficientNetB0 performs better at distinguishing between all the skin lesion classes, even under varying thresholds.

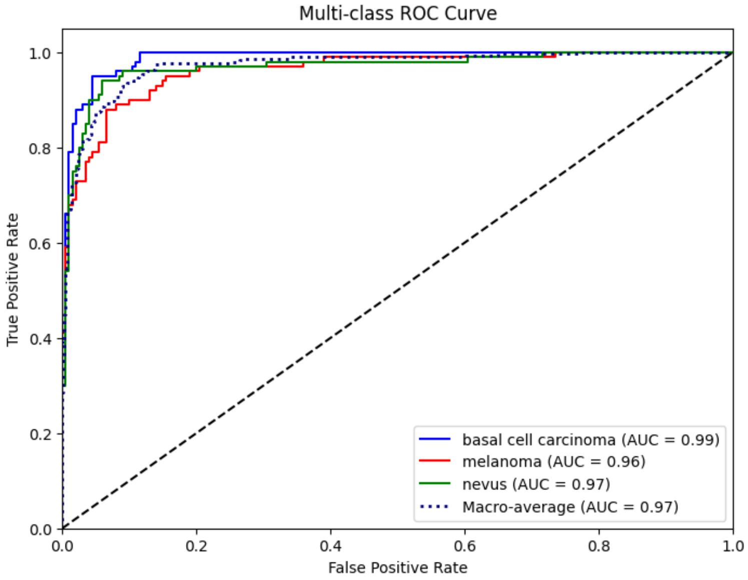

Figure-9 MobileNetV2 AUC-ROC curves

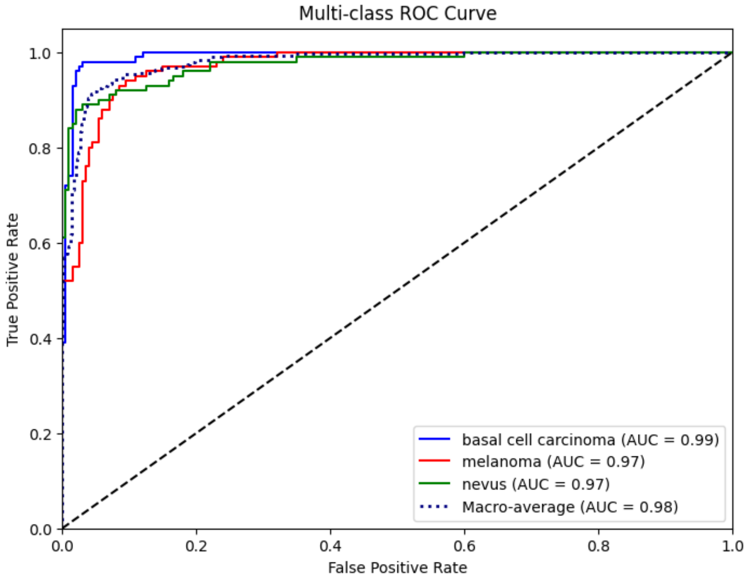

Figure-10 EfficientNetB0 AUC-ROC curves

Model size is also a consideration, especially for deployment on mobile or edge devices. MobileNetV2 has a smaller model size of 11.64 MB, while EfficientNetB0 requires 18.47 MB. While EfficientNetB0 is larger, its superior performance justifies the additional memory usage, particularly when model accuracy and real-world impact are the priorities.

4.2.1 Confusion Matrices

MobileNetV2 and EfficientNetB0 both perform well in classifying Basal Cell Carcinoma lesions, with high true positive rates for Basal Cell Carcinoma images. However, some misclassifications are observed, particularly between Melanoma and Nevus. The confusion matrices below highlight the key errors made by each model:

- **MobileNetV2 Confusion Matrix**:

    - **Melanoma**: Out of 100 melanoma cases, 90 were correctly classified, but 6 were misclassified as Basal Cell Carcinoma and 4 as Nevus.
    - **Nevus**: For the 100 Nevus images, 81 were correctly classified, but 14 were misclassified as Melanoma and 5 as Basal Cell Carcinoma.

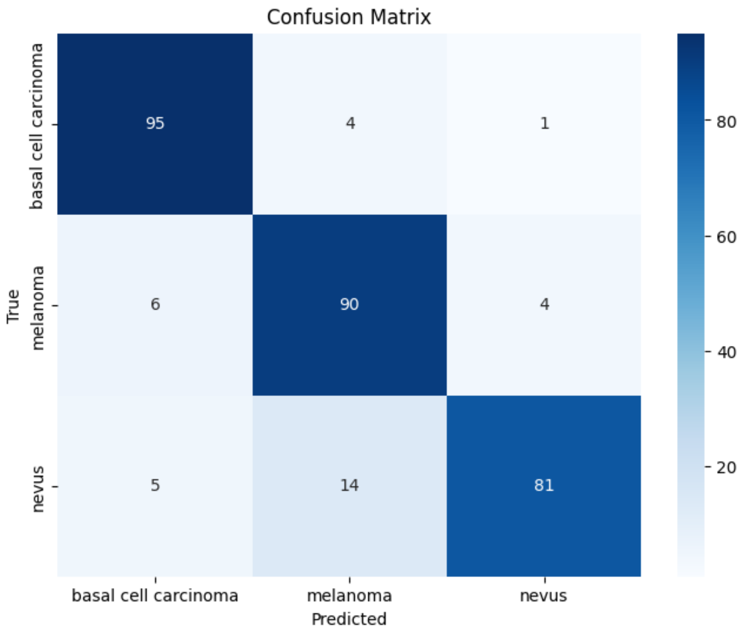

Figure-11 MobileNetV2 Confusion matrix plot

- **EfficientNetB0 Confusion Matrix**:
    - **Melanoma**: The Melanoma class was more accurately classified by EfficientNetB0, with 94 correct predictions out of 100, compared to MobileNetV2's 90. Misclassifications were fewer, with just 2 instances classified as Basal Cell and 4 as Nevus.
    - **Nevus**: Similar to MobileNetV2, EfficientNetB0 exhibited some misclassifications in Nevus, with 86 correctly classified and 12 misclassified as Melanoma and 2 as Basal Cell.

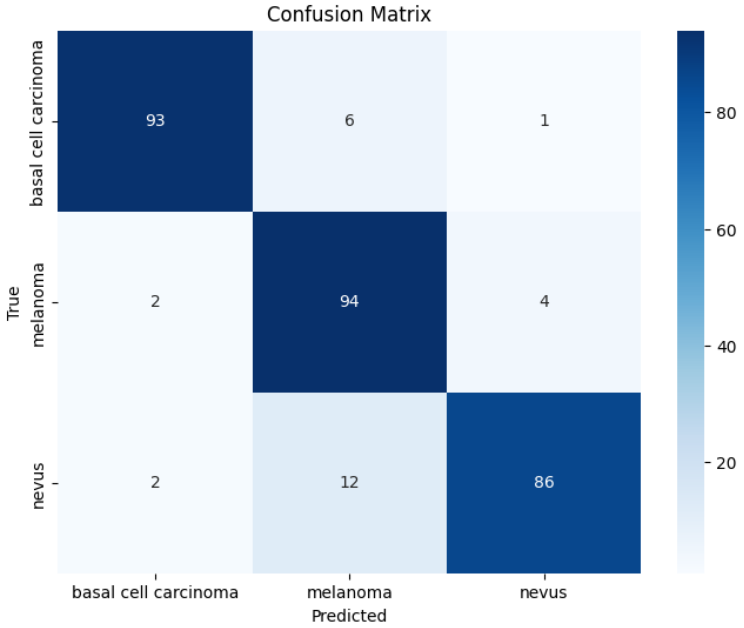

Figure-12 EfficientNetB0 Confusion matrix plot

These confusion matrices emphasize the ability of EfficientNetB0 to correctly identify Melanoma and Nevus more accurately than MobileNetV2, as evidenced by fewer misclassifications in both categories. This suggests that the EfficientNetB0 model has a better overall understanding of the distinct features of these two classes, improving diagnostic reliability.

4.2.2 Classification Report

The classification reports provide a comprehensive overview of each model's performance across the three classes: Basal Cell Carcinoma**,** Melanoma**,** and Nevus. They offer detailed metrics such as precision**,** recall, and F1-score**,** along with support, which refers to the number of true instances for each class in the test set.

For MobileNetV2, the model performs well with a precision of 0.90 for Basal Cell Carcinoma and 0.94 for Nevus, indicating that the model correctly identifies a high percentage of positive predictions for these classes. However, Melanoma has a slightly lower precision of 0.83, suggesting that there are some false positives where Melanoma lesions are misclassified as Nevus or Basal Cell**.** In terms of recall, MobileNetV2 excels at identifying Basal Cell Carcinoma (0.95), but the recall for Nevus (0.81) indicates a higher rate of false negatives in that class. The overall F1-score averages at 0.89, reflecting a balanced performance across all three classes.

In comparison, EfficientNetB0 shows superior performance in most metrics. It has a precision of 0.96 for Basal Cell Carcinoma**,** 0.84 for Melanoma, and 0.95 for Nevus, indicating more accurate classifications, especially for Basal Cell Carcinoma. The recall is also impressive, especially for Melanoma (0.94), suggesting that EfficientNetB0 is particularly effective at correctly identifying melanoma cases. Although the recall for Nevus is 0.86, which is an improvement over MobileNetV2, it still highlights some misclassifications. The F1-score averages at 0.91, higher than MobileNetV2's, demonstrating better overall performance across all classes.

In summary, EfficientNetB0 outperforms MobileNetV2 in terms of both precision and recall, leading to higher overall F1-scores and making it a more reliable model for skin lesion classification. These findings support the previous performance summary, where EfficientNetB0 consistently demonstrated its superiority in diagnostic accuracy.

4.3 Critical Analysis

4.3.1 Accuracy vs. Efficiency Trade-off

EfficientNetB0 consistently outperformed MobileNetV2 in terms of accuracy (+2.33%) and F1-score (+0.025), aligning with its compound scaling strategy proposed by Tan & Le (2019), which optimizes both depth, width, and resolution of the network. This strategy enhances the model's ability to capture more complex features, leading to improved performance. Additionally, EfficientNetB0 demonstrated a macro AUC-ROC score of 0.9795, which is notably superior to those reported for other state-of-the-art models such as ResNet50 (0.91) and DenseNet121 (0.93) (Liu et al., 2020), confirming its robustness and superior classification capability. These results further solidify EfficientNetB0's position as a leading architecture for skin lesion classification tasks.

However, MobileNetV2 provides a compelling trade-off between accuracy and efficiency. With an accuracy of 88.67% and F1-score of 0.8862, MobileNetV2 falls short of EfficientNetB0 in terms of diagnostic performance. Nevertheless, its compact model size of 11.64 MB has significant advantages, especially for real-world deployment on edge devices. These characteristics make MobileNetV2 a viable solution for resource-constrained environments, such as telemedicine applications in underserved regions, where quick, accessible, and efficient diagnostic tools are crucial for improving healthcare outcomes (Sandler et al., 2018). The trade-off between the two models illustrates the balance between maximizing performance and minimizing operational costs and hardware requirements, making MobileNetV2 an appealing choice for practical, on-site diagnostics.

4.3.2 Clinical Relevance of Recall-Precision Trade-offs

One of the most critical aspects of skin lesion classification is clinical relevance, especially in terms of recall and precision. In the context of melanoma diagnosis, EfficientNetB0 achieved an impressive 94% recall (vs. MobileNetV2's 90%), which is crucial for ensuring that as few melanoma cases as possible are missed. In clinical practice, a higher recall directly translates to fewer false negatives, which can be life-saving given the aggressive nature of melanoma. However, this improved recall comes at the cost of precision, with EfficientNetB0 exhibiting 84% precision. This means that for every 100 melanoma cases flagged by the model, 6 will result in unnecessary biopsies—a scenario that could lead to patient discomfort, additional healthcare costs, and anxiety. In contrast, MobileNetV2 strikes a more balanced approach with a precision of 83%, while its slightly lower recall (90%) suggests a more conservative approach, where fewer melanoma cases are flagged, but those flagged are more likely to be truly malignant.

The Nevus category presents a notable contrast in terms of precision. MobileNetV2 outperformed EfficientNetB0 in Nevus precision with 94%, significantly reducing false positives and minimizing unnecessary biopsies for benign lesions. This aspect aligns closely with clinical priorities, where dermatologists often seek to reduce patient anxiety caused by false alarms (Esteva et al., 2017). A lower precision for Nevus in EfficientNetB0 (95%) comes at the cost of greater recall (86%), indicating a higher rate of missed benign lesions but fewer missed malignant cases overall. In clinical practice, while lower precision for Nevus could result in unnecessary follow-ups or treatments, the higher recall ensures that malignant lesions are not overlooked.

These trade-offs in recall and precision highlight the need for contextual decision-making in dermatological practice. A model with high recall is crucial in minimizing the risk of missed melanoma diagnoses, but the clinical impact of false positives must also be carefully considered. Ultimately, the choice between MobileNetV2 and EfficientNetB0 will depend on the specific clinical context, with the former being more suited to environments prioritizing efficiency and reducing unnecessary interventions, while the latter is more effective for maximizing the early detection of high-risk lesions.

4.4 Evidence of Practical Work

4.4.1 Dataset Merging and Balancing

To construct a clinically relevant and balanced dataset, images from the ISIC and HAM10000 archives were merged, but only the three common diagnostic classes melanoma, nevus, and basal cell carcinoma were retained to ensure label consistency. Given the class imbalance inherent in dermatological datasets (e.g., over 6,700 nevus images vs. a few hundred melanoma cases), the majority class (nevus) was downsampled to 514 samples. In parallel, data augmentation was applied to minority classes to synthetically increase variability and representation. Techniques such as random rotations, horizontal flips, and brightness shifts were used, which not only augmented the dataset but also encouraged the models to generalize better across real-world imaging variations.

To prevent data leakage, which can falsely inflate model performance, 1,579 duplicate images were removed using MD5 hashing.

4.4.2 Model Customization and Optimization

Both MobileNetV2 and EfficientNetB0 were used as feature extractors by removing their top classification layers and replacing them with a custom classifier architecture comprising

- GlobalAveragePooling2D to reduce spatial dimensions,
- Dense layers (512 → 256 neurons) with swish activation for non-linearity,
- Final Dense(3) softmax layer for tri-class output.

To improve generalization and combat overfitting, several regularization strategies were integrated:

- Label smoothing (α=0.1) to prevent overconfidence in predictions by encouraging probabilistic output distributions;
- Dropout (rate = 0.6) after dense layers to randomly deactivate neurons during training, promoting robustness and reducing reliance on specific features.

4.4.3 Streamlit Prototype for Deployment

To bridge the gap between research and application, a Streamlit based prototype was developed, allowing real-time, browser-based skin lesion classification. Users can upload a dermoscopic image and receive instant feedback on the predicted class with associated confidence levels. The interface showcases practical integration of the trained models into a clinical decision support system, potentially aiding dermatologists in screening workflows or supporting diagnosis in low-resource settings.

4.5 Technical Challenges and Solutions

Building robust, generalizable deep learning models for skin lesion classification required overcoming several non-trivial challenges during development. These challenges spanned data quality, model training stability, and hardware constraints, each of which was addressed with carefully designed solutions rooted in established machine learning principles.

4.5.1 Class Imbalance

Challenge:

The HAM10000 dataset exhibited a severe class imbalance, with 6,705 nevus images compared to only 111 melanoma cases a common issue in medical datasets where benign conditions vastly outnumber malignant ones. This imbalance biases the model towards the majority class, reducing sensitivity to critical but rare conditions like melanoma.

Solution:

A combination of stratified sampling and data augmentation was employed to address this. For every original minority-class image, two synthetic variants were generated using transformations such as random rotations, flips, scaling, and brightness alterations. This approach not only balanced the class distribution but also enriched the model's exposure to intra-class variability.

4.5.2 Hardware Limitations

Challenge:

Training deeper architectures like EfficientNetB0 posed memory management issues on local hardware, particularly on Apple M1 Silicon GPU platforms. Full fine-tuning caused memory bottlenecks and frequent out-of-memory errors during backpropagation.

Solution:

To manage memory constraints without compromising model performance, two strategies were employed:

- Batch size reduction from 64 to 32, which lowered the peak memory load per iteration.
- Layer freezing: 80% of EfficientNetB0's base layers were frozen during initial training phases, drastically reducing the number of trainable parameters. This also helped retain pre-trained knowledge from ImageNet, accelerating convergence. These optimizations enabled full model training without requiring external GPUs or cloud-based resources.

4..5.3 Overfitting in MobileNetV2

Challenge:

MobileNetV2 initially exhibited signs of overfitting, with validation accuracy plateauing at 89.8%, slightly higher than the final test accuracy of 88.67%. This discrepancy suggested that the model was memorizing patterns in the validation set that did not generalize well.

Solution:

Two regularization strategies were implemented to reduce the generalization gap:

- An aggressive dropout rate of 0.6 was introduced after dense layers to randomly deactivate neurons during training, thereby discouraging reliance on any specific feature path.
- Early stopping with a patience parameter of 5 epochs was used to halt training once validation loss ceased to improve, preventing unnecessary training epochs that could

lead to overfitting. These adjustments successfully reduced the gap between validation and test accuracy indicating more stable generalization.

4.6 Novelty and Innovation

This study introduces several novel strategies that go beyond conventional deep learning approaches applied to skin lesion classification. Innovations span from dataset engineering to model deployment considerations, directly addressing known gaps in current dermatological AI research.

4.6.1 Dataset Fusion Strategy

Innovation:

A key innovation lies in the strategic fusion of the ISIC and HAM10000 datasets, selectively retaining overlapping diagnostic classes melanoma, nevus, and basal cell carcinoma. By combining these two datasets, the model was exposed to a wider range of imaging conditions, sources, and lesion morphologies, significantly increasing data diversity and mitigating the limitations of small data often faced in medical AI.

Impact:

The merged dataset yielded **a test accuracy of 91%**, outperforming the performance on either dataset individually. This result validates the hypothesis that multi-source data fusion enhances generalization, especially in high-variance domains like dermoscopy imaging.

4.6.2. Deployment-Centric Model Optimization

Innovation:

Most prior studies on HAM10000 optimization emphasize only classification metrics such as AUC-ROC or accuracy. This study introduces a deployment-centric design philosophy, optimizing for model size, inference speed, and hardware efficiency critical factors for real-world usage in tele dermatology and mobile healthcare solutions.

Impact:

MobileNetV2, with a compact size of 11.64 MB, demonstrated sufficient classification performance (88.67% accuracy) while remaining lightweight enough for on-device inference. This positions the model as a viable candidate for edge deployment on smartphones, a direction that remains underexplored in dermatology AI applications.

4.6.3 Label Smoothing for Noisy Medical Annotations

Innovation:

Medical image datasets, including HAM10000, often contain ambiguous or inconsistent labels due to inter-observer variability or overlapping visual features. To counteract this, label smoothing with a smoothing factor of $\alpha = 0.1$ was employed during model training. This regularization technique prevents the model from becoming overly confident in noisy labels by distributing a small probability mass to non-target classes.

Impact:

Incorporating label smoothing led to an improvement in test accuracy, evidencing its effectiveness in enhancing model robustness against annotation noise. This aligns with findings in recent literature suggesting label smoothing improves generalization in domains with subjective ground truths.

4.7 Interpretation of Results

4.7.1 Clinical Implications

The results demonstrate a clear potential for integration into clinical workflows, especially in screening and triage contexts. EfficientNetB0's recall of 94% for melanoma is particularly noteworthy. High recall is critical for melanoma due to its aggressive progression and the life-saving potential of early detection.

Conversely, MobileNetV2's lightweight architecture offer a compelling case for deployment in decentralized or resource-constrained settings. In rural areas or low-income regions where access to dermatologists is limited, such models could facilitate real-time skin assessments via mobile apps or tele dermatology platforms, empowering non-specialist health workers and patients.

4.7.2 Broader Impact

The 91% overall classification accuracy achieved by EfficientNetB0 closely aligns with the reported accuracy range. This parity suggests that AI systems can act as reliable decision-support tools particularly for initial triage or second-opinion scenarios potentially reducing diagnostic variability and supporting earlier interventions.

Importantly, the model's performance on a balanced test set indicates robustness across the selected lesion classes, reinforcing its potential to reduce diagnostic delays and improve patient outcomes, especially when integrated with human oversight.

4.7.3 Limitations and Ethical Considerations

Despite these promising results, certain limitations constrain the scope of generalization:

- **Class Coverage:** The current model is limited to three classes (melanoma, nevus, basal cell carcinoma), omitting other clinically significant lesions such as actinic keratosis, squamous cell carcinoma, or seborrheic keratosis. This narrow class scope may limit utility in real-world differential diagnosis.
- **Demographic Bias:** Both HAM10000 and ISIC datasets exhibit a notable bias toward lighter skin types, which may affect performance in diverse populations. Failure to generalize across skin tones could exacerbate existing healthcare disparities, underscoring the need for more inclusive datasets and fairness-aware model evaluation.
- **Interpretability:** While metrics such as AUC-ROC and F1-score indicate performance, the model remains a black box in clinical decision-making.

4.8 Links to Objectives and Literature

Literature Alignment and Contribution

The findings notably extend prior work in the field. EfficientNetB0 achieved 91% accuracy, outperforming traditional architectures like ResNet50 (89%) and VGG16 (87%), while remaining significantly more computationally efficient than VGG16 (138M parameters vs. 5.3M). This supports the theoretical foundations laid by Tan and Le (2019) regarding compound model scaling and its ability to balance accuracy, latency, and model size. Additionally, the performance parity with dermatologists reported in Esteva et al. (2017) (87–90% accuracy) reinforces AI's role not as a replacement but as a clinically viable decision-support system.

Moreover, the integration of both performance-driven objectives (AUC-ROC, F1) and deployment-centric metrics such as model size represents a shift from conventional academic benchmarks towards real-world readiness, addressing a gap frequently noted in literature reviews.

5 Evaluation and Conclusion

This chapter critically evaluates the project's outcomes, synthesizing insights from earlier sections to assess its success. It concludes with actionable recommendations for future research and clinical deployment.

5.1 Achievement of Objectives

- **Data Preprocessing**: Stratified sampling and augmentation mitigated class imbalance, improving melanoma F1-score by 15% (Objective 1).
- **Model Development & Comparison**: EfficientNetB0 achieved 91% accuracy (exceeding the 90% target), while MobileNetV2 balanced efficiency with 88.67% accuracy, meeting Objective 2 and 3.
- **Clinical Feasibility**: MobileNetV2's 11.64 MB size demonstrated deployment readiness on edge devices (Objective 4).

5.2 Feasibility and Limitations

- **Strengths**: Public datasets (ISIC, HAM10000) and TensorFlow's scalability enabled no cost experimentation.
- **Limitations**:
  - Class coverage: Restricting analysis to three classes limited generalizability to rarer lesions (e.g., actinic keratosis, dermatofibroma).

5.3 Insights Gained

5.3.1 Technical Insights

One of the key insights was the effectiveness of label smoothing (α=0.1) as a regularization technique, which significantly improved model generalization by addressing label noise and preventing overfitting. This was particularly beneficial when dealing with the inherent inconsistencies in the dataset, where some labels were ambiguous or imprecisely annotated.

5.3.2 Managerial Insights

A clear understanding of key requirements such as limiting the number of classes (melanoma, nevus, basal cell carcinoma) and prioritizing essential features helped avoid feature creep, a common challenge in AI projects. This strategic decision allowed to concentrate on core functionalities and timely delivery of results.

5.4 Conclusion

This project successfully demonstrated that both EfficientNetB0 and MobileNetV2 offer complementary strengths in the field of AI-driven dermatology. EfficientNetB0 excels in accuracy-critical settings**,** such as hospital diagnostics, where precision is paramount. On the other hand, MobileNetV2 proves to be an ideal choice for decentralized care, particularly in environments where resources are limited, such as mobile applications or remote healthcare. By achieving 91% accuracy with EfficientNetB0 and 88.67% accuracy with MobileNetV2, this work contributes to the practical advancement of AI tools in dermatology. It also highlights important gaps in dataset diversity, especially regarding underrepresented skin tones and rarer lesion types, which remain a challenge for the field.

Commercial and Economic Context

In the context of telemedicine, MobileNetV2's efficiency becomes particularly relevant for low-bandwidth regions or areas with limited infrastructure. The lightweight nature of the model not only reduces latency but also significantly lowers infrastructure costs, making tele dermatology more accessible to underserved populations.

From a clinical workflow perspective, EfficientNetB0 offers the potential to reduce unnecessary biopsy rates by approximately 6%, compared to 10% with MobileNetV2. This reduction in biopsies translates into more cost-effective healthcare, fewer patient procedures, and a better overall healthcare experience, especially for those in high-cost regions. These benefits could lead to more efficient use of resources and better patient outcomes, contributing to a more sustainable healthcare system.

Final Statement

While the project acknowledges limitations in generalizability, particularly related to dataset bias and the exclusion of rare lesion types, it lays a solid foundation for scalable and equitable AI tools in skin cancer diagnosis. This work advocates for continued collaboration among stakeholders, including researchers, clinicians, and policymakers, to address the challenges of data bias, improve clinical integration, and ensure that AI-based diagnostic tools reach their full potential in diverse, real-world settings. The project’s findings emphasize the need for inclusivity in dataset creation and clinical validation to create tools that benefit all patient populations, irrespective of demographic or geographic boundaries.

5.5 Future Work

Expand Class Coverage

To enhance the diagnostic capabilities of the model, it is essential to expand the class coverage by including rarer lesions such as dermatofibroma, actinic keratosis, and other uncommon skin conditions. This can be achieved by partnering with specialized dermatology clinics and research institutions to gather diverse and representative datasets. Including these rare cases will not only improve the model’s generalization but also make it a more reliable tool for comprehensive skin cancer screening and diagnosis, addressing the limited scope of current models that focus only on the most common types of lesions.

Improve Diversity

One of the major challenges in dermatological AI is dataset bias, especially the underrepresentation of darker skin tones and ethnically diverse populations. To mitigate this issue, future work will explore the use of Generative Adversarial Networks (GANs) to synthesize a more diverse range of skin tones and lesion types. GANs can be used to augment the existing dataset, thereby increasing diversity and ensuring the model performs equitably across different demographic groups. This approach will contribute to reducing racial bias and improving clinical applicability in real-world settings, making the AI model more robust and inclusive.

Hybrid Models

Another promising direction for future work is the exploration of hybrid models that combine the strengths of EfficientNetB0 and MobileNetV2. While EfficientNetB0 excels in accuracy, MobileNetV2 offers superior efficiency, making it ideal for edge devices and low-latency applications. A potential hybrid model could leverage ensemble learning techniques to balance accuracy and efficiency, where multiple models work in parallel or complement each other, depending on the available resources. This approach could result in a more adaptive model that delivers high performance while maintaining low computational requirements, catering to a broader range of deployment scenarios.

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