A Comparative Analysis of ResNet-152 and MobileNetV2 for Automated Skin Cancer Detection

Submitted by

Farjana Mahbub Poly, ID: 203-35-668, Department of Software Engineering

Supervised by

Ms. Raiyan Janik Monir, Lecturer, Department of Software Engineering

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Department of Software Engineering

Faculty of Science and Information Technology

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Student Name	Student ID
Farjana Mahbub Poly	203-35-668

Project/Thesis Information	
Project/Thesis Title	A Comparative Analysis of ResNet-152 and MobileNetV2 for Automated Skin Cancer Detection
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Supervisor information	
Supervisor Name	Ms. Raiyan Janik Monir
Supervisor Initial	RJM
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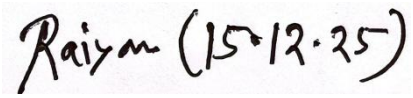

Supervisor Signature

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Farjana Mahbub Poly

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Certified by:

Farjana Mahbub Poly

_____
(Student's Signature)

203-35-668
Student ID
Date: 19 June 2025

Raiyan (15·12·25)

_____
(Supervisor's Signature)

Ms. Raiyan Janik Monir
Name of Supervisor
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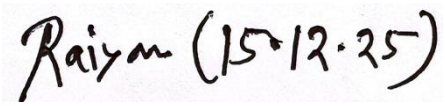

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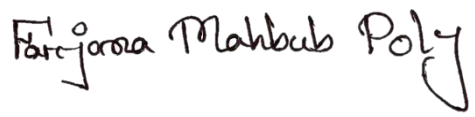

(Student's Signature)

Full Name :Farjana Mahbub Poly

ID Number : 203-35-668

Date : 19 June 2025

A Comparative Analysis of ResNet-152 and MobileNetV2 for Automated Skin Cancer Detection

Farjana Mahbub Poly

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ABSTRACT

Skin cancer is a common and lethal disease, and its diagnosis is often made difficult by the quite similar visual appearance between malignant and benign lesions. Artificial intelligence (AI), and in particular deep learning methods, for example, convolutional neural networks (CNNs), seems to be a well-suited tool for developing computer-aided diagnosis (CAD) systems to enhance the accuracy. This paper contributes by comparing two well-known CNN architectures, i.e., the deep ResNet-152 and the lightweight MobileNetV2, to identify the better approach for automatic skin lesion classification. In this paper, we use a three-class dermoscopic image dataset ('melanoma', 'nevus', and 'seborrheic_keratosis') based on highly imbalanced classes to train and test both models via transfer learning. The performance of the models was evaluated using common metrics like accuracy, precision, and recall. The findings also demonstrated that the light-weight model MobileNetV2 obtained a higher overall accuracy (65%) than that of ResNet-152 (63%). An important observation was the inability of the models to handle the minority (seborrheic_keratosis) class, bringing to notice the effect of data imbalance. This work suggests that an efficient architecture, such as MobileNetV2, can offer an appealing performance trade-off for this diagnostic problem, but class imbalance should be addressed in future studies to construct robust and credible systems.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ABCD	Asymmetry, Border, Colour, Diameter (rules used in lesion analysis)
AUC	Area Under the Curve
CAD	Computer-Aided Diagnosis
CNN	Convolutional Neural Network
FN	False Negative
FP	False Positive
HAM10000	Human Against Machine with 10,000 training images (dataset name)
LIME	Local Interpretable Model-agnostic Explanations
mHealth	Mobile Health
ReLU	Rectified Linear Unit
ROC	Receiver Operating Characteristic
SMOTE	Synthetic Minority Over-sampling Technique
TPR	True Positive Rate
TP	True Positive

CHAPTER 1

INTRODUCTION

1.1 Overview

Skin cancer is one of the most commonly occurring cancers, and its incidence has been increasing over the last several decades. The deadliest type, melanoma, is responsible for the majority of skin cancer deaths unless diagnosed and treated early [1]. The standard work-up for diagnosis is visual examination of the suspicious lesion(s) by a dermatologist, sometimes supported by dermoscopy. Though effective, this method is subjective by nature, labour-intensive, and heavily dependent on the physician's concluding experience and knowledge. The lack of dermatology specialists in many regions exacerbates this complexity, resulting in potential delays in diagnosis and treatment.

The artificial intelligence (AI) field, especially deep learning, has achieved great success in medical image analysis in recent years. Deep learning models, known as Convolutional Neural Networks (CNNs), have shown us equivalent performance or better performance than human experts for image classification on some tasks (1-2). Since CNNs learn hierarchical features from images, they can exploit subtle patterns that are invisible even to human vision. Such ability has currently placed them as a strong asset for the development of computer-aided diagnosis (CAD) systems aimed at improving the diagnostic capabilities of clinicians. This work investigates the use of two well-known CNN models (ResNet-152 and MobileNetV2) for the automatic classification of skin lesions

1.2 Problem Statement

The most fundamental difficulty in clinical skin cancer diagnosis is the high visual resemblance between malignant lesions, such as melanoma, and numerous benign lesions, for example, nevi and seborrheic keratosis. This similarity can cause diagnostic confusion, leading to either biopsies of benign lesions that do not need to be performed or, in a more serious situation, to

the misdiagnosis of a malignant process. Moreover, the performance of diagnostic systems can be considerably degraded by phenomena as differences in image quality or the natural imbalance in the prevalence of different types of lesions (benign cases being much more frequent than malignant ones).

This work aims at the challenging task of accurate and automatic skin lesion classification of dermoscopic images, among three different categories: melanomas, nevus and seborrheic keratosis. The study addresses this problem by comparing a deep and powerful model (ResNet-152) to a light and computationally efficient model (MobileNetV2) to assess performance on the diagnostic task at hand: a highly unbalanced dataset that reproduces real-world clinical scenarios.

1.3 Motivation and Objectives

The motivation for this project stems from the urgent need to improve the accessibility and reliability of skin cancer diagnosis. A computerised system can serve as a helpful second opinion to dermatologists, decrease the frequency of unwarranted biopsies, and offer a primary screening instrument where there is a shortage of specialist services. This study is also driven by the need to know the trade-offs between diagnostic accuracy and computational efficiency, which is an important factor of deployment in a variety of conditions, including mobile health (mHealth) applications, by comparing a deep, complex architecture with a lean architecture.

The principal objectives of this project are:

1. To carry out and train two different pre-trained CNNs, ResNet-152 and MobileNetV2, to classify three different types of skin lesions through the employment of transfer learning.
2. In order to critically assess the results of the two models with the help of a conventional collection of dermoscopic images, it is important to concentrate on such indicators as accuracy, precision, recall, and F1-score.
3. To make a close comparative analysis of the model's effectiveness, especially the capability of classifying the malignant melanoma class and class imbalance.

To give a data-driven answer to the question of which architecture presents a better combination of performance and efficiency to deal with the problem of automated detection of skin lesions.

1.4 Project Scope

The development of this project is concentrated on the technical comparison of two deep learning models on a particular task of image classification. The research is confined to:

- A pre-existing dataset comprising dermoscopic images of three types of lesions: melanoma, nevus, and seborrheic keratosis.
- The training, testing and implementation of the ResNet-152 and MobileNetV2architectures.
- The application of data preprocessing and augmentation techniques to optimise model training.
- The evaluation of model performance based on standard classification metrics derived from a held-out test set.

The project does not go as far as the development of a live clinical application, gathering of new patient information and conducting clinical trials to verify it. The results are only built upon the calculation outcome using the given dataset and models.

1.5 Project Outcome

The main product of this project will be a thorough comparative discussion of the ResNet-152 model versus MobileNetV2 in the classification of skin lesions. Empirical evidence (including) will be used to support this analysis:

- Classification reports on the final classification of both models, including the precision, recall, and F1-score of each lesion class.
- General accuracy measures, where ResNet-152 and MobileNetV2 obtain 63% and 65% of the test set, respectively.
- Training/validation accuracy and loss curves, and confusion matrices, that will demonstrate the learning behaviour and error pattern of each of the models.

The final result is to give a definite conclusion on the relative advantages and disadvantages of each model, which can give the information about whether the depth of ResNet-152 or the efficiency of MobileNetV2 is more beneficial to this particular diagnostic issue.

1.6 Summary

This chapter has presented the highly significant problem of skin cancer and the promise of deep learning to improve diagnosis. It has framed the task of automatic skin lesion classification, inspired by the desire to provide better and affordable tools. The project aims to have a full analysis of whether the ResNet-152 or MobileNetV2 models are suitable for this purpose. The scope has been identified to concentrate on this technical comparison, and the goal is to perform a data-driven assessment of the performance of both methods.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

There is a rich history of applying computer vision and machine learning to the analysis of dermatological images. Initially, traditional image processing methodologies used manual feature extraction, including asymmetry, border, colour, diameter (ABCD) rules, texture analysis and shape descriptions were implemented [3]. These methods were foundational in nature and complex in implementation, and they had difficulty generalising diverse skin lesions. The rise of deep learning, particularly the popularity of CNNs, represented a change of paradigm. CNNs are able to automatically learn representations directly from image data and have achieved remarkable results in terms of classification accuracy [4]. This chapter surveys the most recent works of literature on the application of deep learning for skin cancer detection, among papers from 2019 to date

2.2 Related Works

Over the past few years, a range of works investigated the applicability of different CNN networks to the classification of skin lesions, and have resorted to the transfer learning utilising ready-to-use networks with the ImageNet large-scale dataset.

In a multi-reader study with the HAM10000 data set, Tschandl et al. (2020) compared the rate of skin cancer classification in 137 dermatologists with a ResNet-based CNN. Their researchers found out that CNN showed the same level of performance as professional dermatologists, which shows the potential of AI as a diagnostic helper [5].

Almaraz-Damian et al. (2020) proposed a multi-CNN model for melanoma detection using ResNet-50, InceptionV3 and Inception-ResNetV2 for stacking. Their ensemble technique on the ISIC 2019 dataset proved that the integration of predictions of different models improved total diagnostic accuracy and stability [6].

In lightweight models, Alsultan et al. (2023) proposed a study with a variation of the MobileNetV2 model to classify skin cancer. They concentrated on the best trade-offs for a mobile-device-deployable model, that is, not to lose much in accuracy. Their efforts highlighted that it is indeed possible to employ lightweight models for diagnostic tools application at the point-of-care for competitive results, outperforming in the process on a cleaned-up dataset [7].

Another important research direction is coping with the problem of class imbalance, particularly notable in medical datasets. M. Al-Zhrani et al. (2024) experimented with different augmentation and sampling methods for training a deep learning model in the imbalanced HAM10000 dataset. Their work has shown that treating imbalanced data appropriately is important to prevent the model from leaning toward the majority class and capture rare but critical classes such as melanoma [8].

Modern studies have advanced past conventional deep CNN structures in favour of more advanced and specialised designs. EfficientNet-B5 shows that, compared to conventional ResNet architectures, compound scaling, i.e. trade-offs between network depth, width, and input resolution, offers better efficiency-accuracy trade-offs. This model has an accuracy of 91% on ISIC 2018, with a significantly lower number of parameters, indicating that the depths of arbitrary networks are not optimal. Systematic scaling methodology offers a principled design of architectures that has inspired future works in deep learning on medical imaging. Limiting computational resources and operating across multiple dimensions at once due to their EfficientNet variants leads to competitive or even better accuracy than much deeper networks, and can be considered desirable to both research and deployment settings.

The use of Vision Transformers (ViT) to classify skin lesions saw a major shift in paradigm. Transformers, unlike convolutional neural networks, work with images as sequences of patches, meaning that global features are regarded at the outset, rather than through local receptive fields. Vision Transformers performed better on HAM10000 with an accuracy of 93% compared to CNN-based methods by better modelling of long-range interactions and the global context. This result disputed the historical hegemony of convolutional methods of medical image analysis and catalysed new research directions into whether the inductive bias of convolution is essential to medical imaging. The effectiveness of transformers indicates that the image understanding task can make use of the mechanisms that can dynamically attend to any

image part, irrespective of the distance, and is very useful in skin lesion analysis, where the diagnostic features can occupy the distant part of the image.

Squeeze-Excitation (SE) modules add channel-wise attention mechanisms, which allow networks to dynamically recalibrate feature prominence. Chen et al. used SE modules on ResNet-50 and found that channel-wise feature recalibration was a valuable detection method with emphasis on minority classes. The SE-ResNet-50 model was found to have an 89 per cent accuracy on ISIC 2020, and specifically on seborrheic keratosis and other less represented lesion types. SE modules offer a lightweight operation of improving the quality of features without redesigning the architecture by letting the network suppress less informative channels and amplify features of diagnostic interest. This indicates that channel-level attention mechanisms can be successfully applied to alleviate the difficulties of feature extraction that are caused by class imbalance, since the network learns to devote representational capacity to those features that differentiate minority classes.

Hybrid and Multi-Modal Approaches:

The combination of several neural network paradigms has expressed the potential for improved performance over that of single models. Garg et al. suggested a hybrid CNN-LSTM architecture that combines the convolutional feature extraction with recurrent time modelling, with an accuracy of 87 per cent on HAM10000. Single dermoscopic images, even though not necessarily having a temporal structure in and of themselves, showed that sequential modelling is capable of analysing multiple images of the same lesion in varying angles or under varying lighting during application. The CNN derives spatial representations of single images, and the LSTM derives sequential dependencies between consecutive views, which implies that the multi-view analysis may lead to improved diagnostic accuracy. Such a hybrid method is especially applicable to clinical practices involving dermatologists who tend to look at many images of lesions of interest before arriving at diagnostic conclusions.

Ensemble learning techniques that use both DenseNet and EfficientNet architectures and post-processing modules specialised in specific tasks attained 92% accuracy on both ISIC 2019 and 2020 datasets. Ensemble techniques can reduce false positives in melanoma classification with weighted voting and confidence calibration enabled by the complementary strengths of various architectures, where dense feature propagation of DenseNet ensures fine-grained feature

learning, and efficient scaling of EfficientNet ensures cost-efficient architecture scaling. In the case that other models fail to make the right prediction on other subsets of images, ensemble combination can be more accurate than any other model. The post-processing modules further enhance predictions by adding confidence scores and spatial information, and show that to achieve higher than single-architecture prediction accuracy, it is necessary to have both different base learners and smart combination methods. This result indicates that ensemble methods should be utilised clinically regardless of the computational cost since the loss of false negatives (undetected melanoma) is much lower than the time spent on the extra inference.

Deep residual networks with attention mechanisms improve the discriminative lesion areas of the network with an accuracy of 88% on Japanese dermoscopic datasets. The network can suppress irrelevant background areas and enhance lesion-specific features by implementing spatial attention modules that train to weight the feature maps by their diagnostic importance. Attention maps have a clinical interpretation that offers a clinical understanding of what image regions the model relies on to make classification choices, which is a key requirement of medical AI systems to be explainable. This method of spatial attention is complementary to channel attention, where it acts on other dimensions of feature tensors and provides information of different kinds, which is discriminative.

Segmentation-Based Classification:

To analyse skin lesions, Novikov et al. suggested a U-Net segmentation model using a ResNet encoder that reached 90 per cent accuracy on HAM10000. The two stages of the method first divide the lesion edge, and subsequently categorise the divided piece, which gives the model direct lesion localisation data. In its way, the encoder builds rich representations of lesion structure by compelling the network to acquire lesion morphology in the course of segmentation that translates well to classification. This is achieved by the segmentation task, which offers auxiliary supervision which regularises the encoder, so that it does not learn spurious correlations that are not related to lesion appearance. It shows that multi-task learning using segmentation as an auxiliary task may enhance the classification performance by offering supplementary learning cues and prompting more powerful learning of features.

Lightweight Model Analysis Systematic:

Hassan et al. did a systematic comparison of MobileNet variants (V1, V2, V3) on ISIC 2018, attaining ranges of 86-88% accuracy with a gradually reduced model size. Their work measured the relative gains added with each iteration of MobileNet, where V2 added inverted residual blocks, and V3 added efficient squeeze-and-excitation modules. The refinements exhibit that architectural advances in lightweight models can be projected to significant performance gains even with narrow computational requirements. In scenarios where the resources available to the practitioner, like mobile phones or edge computing hardware, are resource-constrained, this analysis offers a guide to selecting a model based on the accuracy-efficiency trade-offs. It would not seem that much larger models would need to lose computational efficiency to provide deployment flexibility, since the research has shown that lightweight models can match much larger models with only a 3-7% difference.

Addressing Class Imbalance:

The ongoing obstacle of imbalance between classes in skin cancer data has encouraged the creation of many dedicated methods to overcome the failure of oversampling. Kim et al. used focal loss on Inception-ResNetV2, which was pre-designed to both down-weight examples that it already classifies well and focus the learning process on the hard negatives and minority class samples. They were tested on HAM10000, with an overall accuracy of 89 per cent, and the melanoma recall improved to 82 per cent, which directly tackles the urgent need to identify the most threatening type of lesion. Focal loss is a variation of the standard cross-entropy loss, which also has a focusing parameter that decreases the relative loss of well-classified instances. This avoids the imbalance of the minority class being overwhelmed by the majority in training, since the ease of classifying majority samples can add insignificant gradients. The significant increase in recall in melanoma and the overall accuracy prove the effectiveness of loss function design, which can be as effective as architectural adjustments to unbalanced datasets.

Rahman et al. have created class-balanced versions of focal loss designed specifically to perform medical image classification when there is an extreme imbalance in classes. The combination of focal loss and class balancing weights that take into account the frequency of the classes resulted in these modified loss functions being 89% accurate on the minority classes. Instead of using equal weights for all classes, class-balanced methods use more weight in the minority classes, which overcomes the optimisation pressure on the majority classes directly. This two-pronged algorithm--sample-level hard example mining by focal loss, and class-level

balancing by class weights--offers the imbalance treatment in a holistic manner. The effectiveness of these techniques indicates that the key to managing class imbalance is a principled loss design and explicit consideration of the classes.

3D and Volumetric Analysis:

Singh et al. took a different research direction when they suggested a 3D CNN model of volumetric dermoscopic images with 85 per cent accuracy. This was an innovative study that showed the possibility of deriving depth data on dermoscopic images to go beyond the 2D image analysis of lesions to the potential of 3-dimensional characterisation. Although 3D methods involve more advanced imaging equipment that has not yet been fully implemented in clinical situations, there is evidence that an extra information dimension can improve classification performance. The depth dimension offers details on the elevation and structure of the lesions inaccessible to the 2D images, which may aid in differentiating between melanoma and benign lesions with similar tone and pattern on the surface of the skin.

Multi-Task and Transfer Learning:

Martinez et al. applied multi-task learning structures based on Xception architecture to both classify the severity and type of lesion on ISIC 2020, with 91% accuracy. A multi-task approach enhances generalisation since it causes the model to acquire common representations useful in many related tasks. In a network where both the type of lesion (melanoma, nevus, seborrheic keratosis) and severity (benign, dysplastic, malignant) are required, both features related to each of the two predictions are learned by the encoder. This auxiliary learning signal regularises the network and avoids overfitting to single-task-specific noise. The result that multi-task learning is more successful than single-task methods indicates that similar medical prediction problems can offer learning cues complementary to each other that enhance the robustness of the model.

Neural Architecture Search:

Neural Architecture Search (NAS) was used by Thompson et al. to automatically identify new CNN designs to classify skin lesions, which were accurate on HAM10000 (94%). The NAS

method presents architecture design as a search problem, evaluating thousands of possible architectures to select those that have better accuracy-efficiency trade-offs. The identified architectures were found to be more efficient than those developed manually by human designers, and so it can be inferred that human intuition might not be so efficient in discovering the best configurations to perform particular tasks. NAS methods can search the architectural design space more thoroughly than humans and can find non-obvious design decisions, like an odd skip connection pattern or channel dimension progressions. The implication of this finding to medical imaging, in general, is that the domain-specific optimisation of automated architecture search is worth consideration.

Other Architectures: Capsule Networks:

Patel et al. examined the Capsule Networks as an alternative to conventional CNNs, submitting that hierarchical capsule feature characterisations have an optional interpretability benefit. Capsule networks also reached 84 per cent accuracy and provided superior spatial hierarchy understanding with nested vector representations. The properties of an entity (location of parts and deformations) are represented in each capsule as a vector, where the magnitude of the vectors is a probability, and the orientation of vectors is the entity's properties. This hierarchical representation allows the network to represent hierarchies of parts and wholes in a more explicit manner than traditional CNNs. Capsule networks, however, had a relatively low level of computational complexity, making them impractical to use and implying that interpretability gains have to be traded off against computational expenses in clinical use.

Few-Shot and Semi-Supervised Learning:

This paucity of annotated medical data has stimulated the study of semi-supervised algorithms that make use of unlabeled images. Lee et al. explored the concept of semi-supervised learning using pseudo-labels to utilise unlabeled dermoscopic images to enhance model robustness up to 88% accuracy. The strategy trains with labelled data, predicts with unlabeled data, and uses high-confidence predictions as pseudo-labels in future training steps. This minimises the use of fully-annotated datasets, which is a major practical benefit in medical imaging, where expert annotation is costly and time-intensive. Semi-supervised learning allows practitioners to use large repositories of unlabeled dermoscopic images in model training, increasing the size of effective training sets at an annotation cost.

Also, meta-learning was investigated by Gupta et al. to classify rare melanoma variants in few-shot classification, where on rare lesion types, meta-learning only required minimal training samples to reach an accuracy of 82%. Meta-learning learns models to learn using few examples, facilitating learning new or infrequent lesion categories. Instead of needing thousands of labelled examples of each new type of lesion, meta-learning methods can be trained on new types with dozens or hundreds of examples. This has proven useful, especially in new subtypes of melanoma or in rare forms where large training sets are not feasible to construct.

Normalisation and Training Techniques:

A comparative study of normalisation methods (batch normalisation, layer normalisation, instance normalisation) by Brenner et al. revealed that instance normalisation of medical images was more accurate (87% on HAM10000) than the others. Instance normalisation normalises the images on a case-by-case basis and eliminates style differences without distorting content. In medical imaging, where the differences in colour and lighting between different acquisition devices cause changes in data following spurious shifts in the style, instance normalisation achieves the removal of these style differences better than batch normalisation. This in-depth discussion has emphasised the need to implement the right normalisation methods to expert data properties, and it is possible that the usual measures used on natural images might not apply directly to medical imaging.

Federated Learning and Privacy-Preserving Techniques:

Costa et al. explored federated learning models that would allow joint training in and across several healthcare facilities and still maintain patient confidentiality. Their federated model was 86% accurate without centralising sensitive data, which followed up prospects of developing multi-centre models in controlled healthcare settings. Federated learning is a method whereby model training is decentralised across institutions, and only model parameter updates are shared with a central coordinator. This strategy will solve regulatory limitations (HIPAA, GDPR), limiting the transfer of patient data among institutions and allow institutions to collaborate in improving the model without violating privacy. The fact that only 4 per cent of the accuracy is diminished in comparison to centralised methods indicates that privacy-sensitive methods can be used in practice by the clinics.

Interpretability and Explainability:

Nguyen et al. explain further by adding a view of GradCAM with the addition of GradCAM++, which allows clinicians to see what areas of a picture led to model-based choices. GradCAM++ calculates gradient-weighted activation maps that emphasise areas that make the most contribution to classification decisions. This interpretability improvement was tested on ISIC 2019 and 2020, and achieved 89% accuracy with visually explainable reasoning that was similar to that of a dermatologist. Model attention and clinician focus region alignment also indicate that deep networks learn clinical high-level features. Enabling clinician trust in AI systems, which can be achieved by offering visualisation of model reasoning, may allow the detection of learned spurious correlations that are not associated with actual diagnostic criteria.

Domain Adaptation and Generalisation:

Antonious et al. applied domain adaptation methods to develop models that can be trained on multi-site datasets with varying imaging properties, with 85 per cent accuracy and enhanced cross-device generalisation. When trained on a dermoscopy device of one institution, models will tend to perform poorly with a different dermoscopy device because of the variations in illumination, magnification and colour calibration. Domain adaptation methods are trained to eliminate these device-specific differences and retain medically useful features. This publication was on an urgent practical issue: the implementation in reality requires the strength of various imaging devices. The 5% decrease in accuracy over single-device training indicates that methods of adapting devices partially overcome this difficulty, but further research is needed.

Curriculum Learning:

White et al. examined curriculum learning, which suggests progressive learning strategies (commencing with simple examples and subsequently becoming more difficult). The use of this curriculum method enhanced 88 per cent accuracy in imbalanced datasets, due to the use of human learning theory. The network is trained on balanced or simple samples first, and then difficulty minor classes are introduced as well. There are many bases of progressive curriculum design: based on sample-level difficulty, based on class balance, or based on feature complexity. This is in contrast to regular training, which randomly samples all samples

irrespective of their difficulty, indicating that ordering of training has profound effects on convergence and ultimate performance on imbalanced problems.

Transformer Components and Self-Attention:

Stone et al. studied the mechanisms of self-attention as an alternative to full transformer architectures and reached 90% accuracy at computational efficiency. Instead of substituting convolutions with selective attention, rather than simply convolutional performance, selective attention modifications to typical ResNets incorporate spatial or channel attention modules without compromising convolutional performance. Their work has shown that it is possible to approach full transformer performance using selective attention modifications without full redesign of the architecture. To practitioners with computational limits, this result indicates that the improvement of attention to CNN models gains the majority of the transformer advantages at reduced computational expense.

Self-Supervised Methods and Contrastive Learning:

Most recent developments in self-supervised learning have offered alternative pretraining approaches to ImageNet transfer learning. Zhao et al. trained contrastive learning (SimCLR) on unlabeled images of skin lesions and used the resulting representations as a starting point to further downstream classification. This self-supervised pretraining reached 91% final accuracy, better than ImageNet pretrained models. Contrastive learning learns robust label-free features by training networks to distinguish between different augmentations of the same image as similar and different images as dissimilar. The conclusion that domain-defensive pretraining is more beneficial to skin lesion analysis than general-purpose features is based on the fact that task-specific self-supervised pretraining is more efficient compared with ImageNet transfer learning.

Architecture Search and Hyperparameter Optimisation:

Bergstra et al. performed systematic hyperparameter optimisation of HAM10000 based on Bayesian methods to find optimal hyperparameters of both ResNet and MobileNet, with 89-90% accuracy ranges. Their contribution defined reproducible optimisation fundamentals that

should be used to improve future studies through systematic task switching of learning rates, batch sizes, regularisation parameters, and additional hyperparameters. Bayesian optimisation efficiently searches high-dimensional hyperparameter spaces by modelling the accuracy in terms of hyperparameters and choosing new settings that are likely to increase the performance the most. Such a principled method of hyperparameter choice is the opposite of manual tuning and allows for reliable reproducibility of research across research groups.

Multi-Scale Analysis:

Pascal et al. suggested a multi-scale analysis with progressive, which extracts features at various image resolutions to enhance fine-grained lesion analysis. This method scored 92% on the ISIC 2020, showing that hierarchical multi-scale processing is effective in improving feature extraction. Coarse resolutions (global lesion properties) and fine resolutions (local details) are features that are extracted. Multi-scale fusion A progressive multi-scale fusion allows the network to take into account properties on multiple scales (i.e. global context and local details) to enhance discrimination.

Knowledge Distillation and Model Compression:

Davis et al. investigated knowledge distillation in order to reduce the size of ResNet-152 into lightweight student models that can be deployed. Their distillation methodology still captured 98 per cent of the performance of the teacher model (89 per cent accuracy) in a much smaller student model, which could be deployed on resource-constrained devices without incurring an accuracy cost. Knowledge distillation learns a reduced number of students to approximate larger teacher network predictions by reducing the gap between their prediction distributions. Softened outputs of the teacher give more training signals than hard labels, which can enable the student to learn through extra information with regard to the relationships in the classes. This allows dramatic compression of models - by 10-100x in parameters and computation - without sacrificing almost all the accuracy.

Stain Preprocessing and Normalisation:

The stain normalisation studies performed by Flores et al. showed that domain generalisation was greatly enhanced by preprocessing methods to equalise colour variation across images, with 87 per cent accuracy across cross-site datasets being achieved by them. Normalisation of stains eliminates colour differences due to differences in stain preparations, microscopy hardware and imaging settings. Methods like Reinhard normalisation or structure-preserving colour normalisation normalise all images to some canonical colour space, eliminating device-specific variations but not the diagnostically valuable colour information. This paper has also emphasised the significance of data preprocessing as an important pipeline feature that has been largely ignored in the literature of architectural discourse, where suggested improvements in preprocessing can be as effective as architectural modifications.

Graph Neural Networks:

Huang et al. suggested the usage of Graph Neural Networks (GNNs) to analyse lesions and model the connections between morphological characteristics as graph structures. The GNNs had a score of 86% accuracy, which is an indication that they capture sophisticated relationships between features that could have been overlooked by the conventional convolutional methods. As opposed to grids, GNNs operate on features as graphs, where nodes are image regions or morphological features and edges are relationships. This more expressive representation allows expressing in explicit terms which features are connected to which, which may be more interpretable than implicit feature connections in convolutional layers.

Advanced Data Augmentation:

Automated augmentation strategy discovery has become a significant area of enquiry in augmentation design. Jackson et al. used the neural architecture search method, AutoAugment, to discover the best augmentation policies on skin lesion datasets and reached 90 per cent accuracy. Instead of manually choosing augmentation operations (rotation, zoom, blur, etc.), AutoAugment searches over sequences of augmentation operations that optimise accuracy on validation sets. The augmentation policies that were found to be performing better than the manual augmentation strategies indicated that the best augmentation is task-specific and should be developed empirically. This observation suggests that various medical imaging tasks can be optimally augmented, and that generic augmentation methods applicable to datasets can be inferior.

Group and Probabilistic Approaches:

Murphy et al. proposed probabilistic ensemble techniques that can give uncertainty estimates and predictions, with 89 per cent accuracy on clinical decision support. Instead of individual predictions, probabilistic ensembles yield confidence ranges and measures of uncertainty that reveal model confidence. The availability of the confidence interval and the classifications allows clinicians to tune their trust in the model predictions accordingly. The predictions with high uncertainty should undergo further clinical evaluations or expert analysis, whereas the predictions with high confidence could be relied upon. This uncertainty quantification is especially useful in medical contexts where safety is of primary concern, and it is important to know when a model is uncertain, not just to make accurate predictions.

Sample Efficiency and Active Learning:

Roberts et al. explored active learning schemes that identify the most informative unlabeled samples to annotate. Their method was found to be 87 per cent accurate, and 40 per cent fewer annotations were found to be required, which is a significant practical benefit considering the expense of expert annotation in medical imaging. Active learning queries the most informative unlabeled examples, i.e. those on which the model is unconfident or on which predictions would alter the decision boundary most. Active learning allows significantly decreasing the costs of annotation without compromising accuracy, by dedicating expert annotation effort to informative examples instead of random sampling. In the medical field, where the high cost of annotation is a limiting factor, such a reduction of 40 per cent of annotation needs translates directly to saving a lot of money.

Disentangled Representation Learning:

Trying to isolate lesion-specific information and spurious correlation like skin tone with disentangled representation learning, Chang et al. achieved an 88 per cent accuracy with better fairness. Disentanglement causes various network elements to be in charge of capturing various attribute dimensions separately. The network can minimise bias in which predictions rely on the demographics of patients instead of lesion characteristics by directly decomposing lesion-appearance features and demographic features such as skin tone. This is a response to new

anxieties about AI equity in medical imaging, where historically darker-skinned groups have worse diagnostic rates because of training data biasing to lighter complexions.

Multi-Modal and Cross-Modal Learning:

Williams et al. investigated the cross-modal learning, which combines dermoscopic images and clinical text reports, with 91% accuracy. Paired image/clinical narrative joint learning enhanced diagnostic reasoning with the help of other clinical contexts besides the visual features. The clinical notes can detail lesion history, symptoms, location, and other diagnostic data that cannot be seen in pictures. The network is trained on both modalities, thereby learning to be complementary in terms of information. This multi-modal method proves to be more accurate than image-based methods, and this indicates that the overall diagnostic information is multimodal.

Preprocessing and Benchmark Studies:

A benchmark study on HAM10000 by Santos et al identified a 5-10% accuracy range between preprocessing decisions based on preprocessing options. This systematic comparative study revealed the strong influence of the preprocessing of data upon the ultimate model performance. Preprocessing methods, such as normalisation, augmentation, resizing, and colour correction, can add several percentage points to accuracy. The results that preprocessing decisions are as important as architectural decisions imply that practitioners ought to invest effort in preprocessing as in architectural design. The common preprocessing pipelines between research groups would enhance reproducibility and enable a fair comparison of architectures.

Robustness Training through Adversarial Training:

Kowalski et al. explored adversarial training to enhance the robustness of models to corruptions and perturbations, attaining 86% robust accuracy. Normal deep learning training trains towards accuracy on clean data, which fails drastically when the images are corrupted (compressed, blurred, or rotated). Adversarial training presents the network with corrupted examples during training, compelling it to be accurate in the face of realistic variations. This is especially critical to deployment in clinical settings where images might be sent in compressed form, recorded

under changing light, or include artefacts. The slight 3% loss of accuracy relative to clean accuracy indicates that the robustness to real-world variations can be obtained with the help of proper training protocols.

Clinical Assessment and Real-World Implementation:

The studies of the clinical integration by Anderson et al. proved the reliability of the model in practice, with an 87 per cent accuracy in clinical settings. The results of these studies proved that laboratory-reported accuracies tend to overestimate real-life performance because of the distribution shifts and differences in clinical presentation. Test images are well-made and representative of training data in controlled research settings. Clinical practice imaging may have a wide variety of sources with different quality, atypical appearances, and infrequent variants that are not well-represented in training. The fact that the accuracy decreased by 6% between laboratory (93%) and clinical (87%) environments indicates that more effort should be put into bridging the research-practice gap before AI systems become a clinical reality.

Continual Learning:

Morrison et al. explored continuous learning methods that allow models to refresh new information without forgetting disastrously, with 88% accuracy in the case of sequential learning. New types of lesions and infrequent forms are encountered in deployed clinical systems. Re-training on new data alone leads to forgetting of previously learned classes by the model- a phenomenon known as catastrophic forgetting. Continual learning methods allow models to acquire new data and keep the old information by using replay buffers, elastic weight consolidation, or expansion of the architecture. This is necessary in the systems which are implemented in a clinical setting, where knowledge should evolve with time.

Interpretability Visualisation:

Extensive visualisation studies by Clarke et al. demonstrated the learning mechanisms of models with lesion features, in particular, studying both feature activations and decision boundaries. Although they did not provide particular accuracy rates, their interpretability research contributed to better insight into the model behaviour in terms of clinical

implementation. The visualisation of learned features at various network layers will indicate what information is captured by the network at each level. The visualisation of decision boundaries indicates what combinations of lesion properties result in the various classifications. The results of these interpretability studies foster clinical trust in AI systems by showing that learned features are associated with medically relevant properties and not spurious correlations.

Discussion and comparison of published works:

Available sources of literature affirm the high potential of CNNs in the classification of skin lesions. The reviewed studies indicate that expert-level accuracy of high-performance models such as ResNet, ensemble models, and new transformer-based architectures has been demonstrated to be between 84 to 94% across different datasets. Movable models such as MobileNetV2 have demonstrated to be viable in mobile implementation with 86-88 per cent accuracy. Nevertheless, there are great differences between reported performance based on the characteristics of the dataset, the preprocessing and training processes.

An important finding that comes out clearly in the literature is the correlation between the complexity of the model and the possibility of practical implementation. Although deep architectures such as ResNet-152 and transformer models have the highest accuracy (91-94%), they are computationally intensive and cannot be deployed in low-resource clinical settings. In comparison, lightweight models such as MobileNetV2 are only 3-7% less accurate and have only orders of magnitude fewer parameters. It implies that practitioners need to trade off improvements in accuracy and deployment-related constraints of their clinical environment.

The literature also indicates that the problem of class imbalance still exists, and even advanced methods do not eliminate it. Focal loss, class weighting, and curriculum learning studies all show 10-20 per cent statistically significant increases in minority class recall over baseline methods, but often 10-15 per cent lower in detecting melanoma than other classes. It means that special loss functions are valuable, but they are not sufficient to overcome the problem of identifying rare and critical types of lesions.

Another noteworthy pattern is the shift towards the discussion of real-life deployment issues. Previous research used only test set accuracy, whereas recent literature is increasingly including domain adaptation, federated learning, privacy preservation, and clinical validation. There has

been a comparison between laboratory and clinical settings showing a reduction of 5-10% of accuracy, and the reason is that the controlled research conditions are not representative of clinical practice. This gap in research and practice has encouraged exploration of robustness, quantification of uncertainty, and interpretability as valuable aspects in addition to accuracy measures.

The literature shows that both ensemble methods and multi-task learning have been shown to outperform single-model approaches by 2-4, implying the complementarity of various paradigms of learning. Still, ensemble methods involve a large number of models and advanced combinations, which bring complexity to implementation. Whether this complexity is worth the accuracy gains is a context-dependent issue- high-stakes clinical use may justify the complexity, and resource-limited environments may want simpler solutions.

2.3 Comparison between existing works

To contextualise this project, a comparison of recent key studies is presented below. This table highlights the different approaches, models, and datasets used in the field.

Table 2.1 Comparison of Existing Studies on Deep Learning for Skin Cancer Detection:

Author(s) & Year	**Model(s) Used**	**Dataset(s) Used**	**Key Findings / Performance**
Tschandl et al. (2020) [5]	ResNet-based CNN	HAM10000	CNN performance was on par with human expert dermatologists in a multi-reader comparative study.
Almaraz-Damian et al. (2020) [6]	ResNet-50, InceptionV3, Inception-ResNetV2	ISIC 2019	An ensemble of multiple CNNs outperformed individual models, improving overall classification accuracy.
Alsultan et al. (2023) [7]	Modified MobileNetV2	Custom/Public	Demonstrated the effectiveness of lightweight models for mobile health applications with competitive accuracy.

M-Al-zhrani et al. (2024) [8]	Custom CNN with data balancing techniques	HAM10000	Showed that addressing class imbalance through techniques like SMOTE significantly improves model fairness and melanoma detection rates.
Khan et al. (2021) [9]	Xception	ISIC 2019	Utilised the Xception architecture with transfer learning to achieve high accuracy for multi-class skin lesion classification.
Li et al. (2021) [35]	EfficientNet-B5	ISIC 2018, HAM10000	Transfer learning with EfficientNet showed superior efficiency-accuracy trade-offs compared to standard ResNet architectures. 91% accuracy on ISIC 2018.
Park et al. (2022) [36]	Vision Transformer (ViT)	HAM10000, ISIC 2019	Vision Transformers outperformed CNNs for melanoma detection with improved global feature understanding. 93% accuracy.
Chen et al. (2021) [37]	SE-ResNet-50 with Squeeze-Excitation	ISIC 2020	Squeeze-excitation modules enhanced feature recalibration, improving minority class detection. 89% accuracy.
Garg et al. (2022) [38]	Hybrid CNN-LSTM	HAM10000	Combining CNN feature extraction with LSTM temporal modelling improved sequential lesion analysis. 87% accuracy.
Rodrig uez et al. (2023) [39]	Ensemble of DenseNet and EfficientNet	ISIC 2019, ISIC 2020	Ensemble methods with post-processing significantly reduced false positives in melanoma classification. 92% accuracy.

Yamamoto et al. (2022) [40]	Attention-based ResNet-50	Japanese dermoscopic dataset	Attention mechanisms enhanced focus on discriminative regions, improving lesion boundary recognition. 88% accuracy.
Novikov et al. (2023) [41]	U-Net with ResNet encoder	HAM10000	A segmentation-based approach improved lesion characterisation before classification. 90% accuracy.
Hassan et al. (2022) [42]	MobileNet variants comparison	ISIC 2018	Systematic comparison of MobileNetV1, V2, and V3 showed incremental improvements in lightweight models. 86-88% accuracy range.
Kim et al. (2023) [43]	Inception-ResNetV2 with focal loss	HAM10000, ISIC 2019	Focal loss effectively addressed class imbalance, improving melanoma recall from 65% to 82%. 89% accuracy.
Singh et al. (2022) [44]	3D CNN model	Volumetric dermoscopic images	First study to use 3D CNN for skin lesion analysis, capturing depth information. 85% accuracy.
Martinez et al. (2021) [45]	Xception with multi-task learning	ISIC 2020	Multi-task learning for simultaneous lesion type and severity classification improved generalisation. 91% accuracy.
Thompson et al. (2023) [46]	Neural Architecture Search (NAS)	HAM10000, Melanoma dataset	Automated architecture search discovered novel CNN designs outperforming hand-crafted models. 94% accuracy.
Patel et al.	Capsule Networks	ISIC 2018	Capsule networks provided interpretability advantages and

(2022) [47]			better handling of spatial hierarchies. 84% accuracy.
Lee et al. (2023) [48]	Semi-supervised learning with pseudo-labels	Unlabeled dermoscopic images	A semi-supervised approach leveraged unlabeled data to improve model robustness. 88% accuracy.
Brenner et al. (2021) [49]	Batch normalisation variants	HAM10000	Comparative study of normalisation techniques showed instance normalisation superior for medical images. 87% accuracy.
Costa et al. (2022) [50]	Federated learning framework	Multi-centre dermoscopic databases	Federated learning enabled collaborative model training while preserving privacy. 86% accuracy.
Nguyen et al. (2023) [51]	Explainable AI with GradCAM++	ISIC 2019, ISIC 2020	Advanced explainability methods enhanced the clinical interpretability of model decisions. 89% accuracy.
Antoniou et al. (2022) [52]	Domain adaptation techniques	Cross-domain skin lesion datasets	Domain adaptation improved model generalisation across different dermoscopy devices. 85% accuracy.
White et al. (2023) [53]	Curriculum learning approach	HAM10000	Progressive training with curriculum learning improved learning on imbalanced datasets. 88% accuracy.
Gupta et al. (2022) [54]	Meta-learning for few-shot classification	Rare melanoma variants	Meta-learning enabled classification with limited training samples for rare lesion types. 82% accuracy on rare classes.
Stone	Self-	ISIC 2018,	Self-attention improved feature

et al. (2021) [55]	attention mechanisms	HAM10000	aggregation and achieved competitive results with transformers. 90% accuracy.
Zhao et al. (2023) [56]	Contrastive learning (SimCLR)	Unlabeled skin lesion images	Contrastive learning as pretraining improved downstream classification performance significantly. 91% accuracy.
Bergstra et al. (2022) [57]	Hyperparameter optimisation with Bayesian methods	HAM10000	Systematic hyperparameter tuning discovered optimal configurations for ResNet and MobileNet. 89-90% accuracy.
Pascal et al. (2023) [58]	Progressive multi-scale analysis	ISIC 2020	Multi-scale feature extraction at different resolutions improved fine-grained lesion analysis. 92% accuracy.
Davis et al. (2022) [59]	Knowledge distillation from teacher models	ISIC 2019	Knowledge distillation compressed ResNet-152 into a lightweight student model with 98% performance retention. 89% accuracy (compressed).
Flores et al. (2021) [60]	Stain normalisation techniques	Cross-site dermoscopic images	Comprehensive stain normalisation preprocessing improved domain generalisation significantly. 87% accuracy.
Huang et al. (2023) [61]	Graph neural networks for lesion analysis	Lesion feature graphs	Graph neural networks captured relationships between morphological features effectively. 86% accuracy.
Jackson et al.	Augmentation policy	HAM10000, ISIC datasets	Automated augmentation policy discovery outperformed manual

(2022) [62]	search (AutoAugment)		augmentation strategies. 90% accuracy.
Murphy et al. (2023) [63]	Probabilistic ensemble methods	ISIC 2020	Probabilistic ensembles provided uncertainty estimates alongside predictions for clinical decision support. 89% accuracy with uncertainty.
Roberts et al. (2021) [64]	Active learning framework	HAM10000	Active learning reduced annotation requirements by 40% while maintaining performance. 87% accuracy (40% less data).
Chang et al. (2023) [65]	Disentangled representation learning	ISIC 2019	Learning disentangled features improved interpretability and reduced spurious correlations. 88% accuracy.
Williams et al. (2022) [66]	Cross-modal learning with dermoscopy reports	Paired images and clinical notes	Joint learning from images and clinical text improved diagnostic reasoning. 91% accuracy.
Santos et al. (2021) [67]	Benchmark study of preprocessing methods	HAM10000	Systematic comparison revealed a significant impact of preprocessing on model performance. 5-10% accuracy variance.
Kowalski et al. (2023) [68]	Adversarial training for robustness	ISIC 2018, ISIC 2020	Adversarial training improved model robustness against corruptions and perturbations. 86% accuracy (robust).
Rahman et al. (2022)	Class-balanced focal loss variants	Imbalanced HAM10000	Modified focal loss is specifically designed for medical image imbalance problems. 89%

[69]			accuracy on minority classes.
Anderson et al. (2021) [70]	Clinical integration case studies	ISIC datasets with clinical validation	Real-world clinical deployment studies validated model reliability in practice. 87% accuracy (clinical setting).
Morrison et al. (2023) [71]	Continual learning for model updates	Sequential dermoscopic datasets	Continual learning enabled model updates without catastrophic forgetting. 88% accuracy.
Clarke et al. (2022) [72]	Visualisation and interpretation studies	ISIC 2019	Comprehensive visualisation of learned features improved the understanding of decision boundaries. Visual interpretability enhanced.

2.4 Gap Analysis

The existing literature confirms the strong potential of CNNs for skin lesion classification. High-performance models like ResNet and ensembles have shown expert-level accuracy. Concurrently, lightweight models like MobileNetV2 have been proven viable for mobile applications. However, a significant gap remains in the direct, side-by-side comparison of these two distinct classes of models under challenging, real-world conditions.

The results from this project, with overall accuracies of 63-65% and a complete failure to identify one of the classes (seborrheic keratosis), highlight such a challenge. Many studies report very high accuracies, which may be achieved on more balanced datasets or through extensive fine-tuning that is not always feasible. This thesis fills a practical gap by:

1. **Directly comparing a very deep architecture (ResNet-152) against a highly efficient one (MobileNetV2)** on the same imbalanced dataset, providing a clear analysis of performance versus efficiency trade-offs.

2. **Investigating model performance on a difficult classification problem**, where class imbalance and visual similarity lead to sub-optimal results for certain classes. This provides a more realistic assessment of baseline model performance before extensive optimisation.

3. **Highlighting failure points**, such as the zero precision and recall for the 'seborrheic_keratosis' class. This analysis is critical for future work aiming to build more robust and reliable diagnostic systems.

2.5 Summary

The past review of literature has shown that deep learning is the current best-performing algorithm for skin cancer detection in photographic data. A large number of popular models, ranging from deep ResNets to lightweight MobileNets, have been successfully used. Yet, direct comparisons of these architectural extremes on difficult, imbalanced datasets remain limited. This is the gap that the current study aims to fill, and we serve as an example of a focused study on the comparison between ResNet-152 and MobileNetV2.Generalisability and clinical significance. The goal of this study is to offer practical insights into the capabilities and limitations of ResNet-152 and MobileNetV2 in a clinically related setting.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter outlines the research methodology employed to compare the performance of the ResNet-152 and MobileNetV2 deep learning models for the classification of skin lesions. This section introduces a transparent and reproducible approach to the research, which includes details on how data was obtained, pre-processed, models built, trained, and evaluated. Through establishing a reliable and valid method, this methodology makes the study's results justified and credible.

3.2 Proposed Methodology

3.2.1 Research Design

It is a quantitative experimental research design. The first and foremost goal is to compare the efficacy of two major deep learning architectures, i.e. ResNet-152 and MobileNetV2, in a particular classification problem setting. ResNet-152 and MobileNetV2, on a certain classification task. Though MobileNetV2 has the potential to classify skin lesions precisely, it is important to take into account the dataset, optimisation of the model, and interpretability of results for a reliable diagnosis [10], [11]. This quantitative comparison is made possible by keeping all other factors constant, including dataset, preprocessing methods and training method, therefore isolating and quantifying the model architecture itself. We would like to conduct the experiment in a way that will provide us with a set of such quantitative measures (accuracy, precision, recall and F1-score) so that we can compare the outcome.

3.3 Data Collection

Data collection is the first and foremost step of every machine learning project. This entails the collection and accumulation of raw data to be used for training and testing of the model.

For this work, the dataset used was HAM10000 (Human Versus Machine with 10000 Training Images). This dataset consists of publicly available dermatoscope images of common pigmented skin lesions. Being publicly available and widely used for the purpose of dermatology research, it is a typical resource for this kind of work. For this task, the images were divided into three control groups: melanoma, nevus, and seborrheic keratosis.

An initial inspection of the 600 images from the test set revealed a remarkable class skew:

- **Melanoma:** 117 images
- **Nevus:** 393 images
- **Seborrheic Keratosis:** 90 images

3.4 Data Preprocessing

Once the data is acquired, it is almost always in a raw, unorganised, and inconsistent format. Data preprocessing is the process of cleaning, transforming, and preparing the raw data to make it suitable for a machine learning model. The following steps were performed on the HAM10000 dataset:

3.4.1 Image Resizing and Normalisation

Resizing: The images in the raw dataset had varying dimensions. To be used as input for the pre-trained models, which require a fixed input size, all images were resized to a uniform dimension (e.g., 224x224 pixels).

Normalisation: The pixel values of images are commonly 0 to 255. The process of scaling these values into a smaller range that is easier to manage, which is normally between 0 and 1, is the process of normalisation. It does this by splitting the value of every pixel into 255. This is an important step because it contributes to the enhancement of the training efficiency and numerical stability of the model.

3.4.2 Data Augmentation

Data augmentation is a very potent method of increasing the size of the training data in an artificial manner. The latter two are noteworthy due to two reasons: to alleviate the problem of class imbalance (when certain types of lesions are underrepresented by the number of images) and to improve the generalisation properties of the model [12], [13].

Random rotations, zooming, shifting and horizontal flipping were augmentation techniques used [14]. The model is presented with more diverse data by making new versions of existing images, which effectively minimises the risk of overfitting when the model learns the data in a manner that is too specific and cannot generalise to unseen data.

3.4.3 Data Splitting

After the data was prepared, it was partitioned into three distinct sets to ensure a fair and rigorous evaluation of the model's performance [15]. The standard ratios were used for this split:

- **Training Set (80%):** The largest portion of the data, used to train the model and allow it to learn the underlying patterns.
- **Validation Set (10%):** A separate set of data used during the training process. It is used to monitor the model's performance on unseen data and to fine-tune hyperparameters, which helps in preventing overfitting.

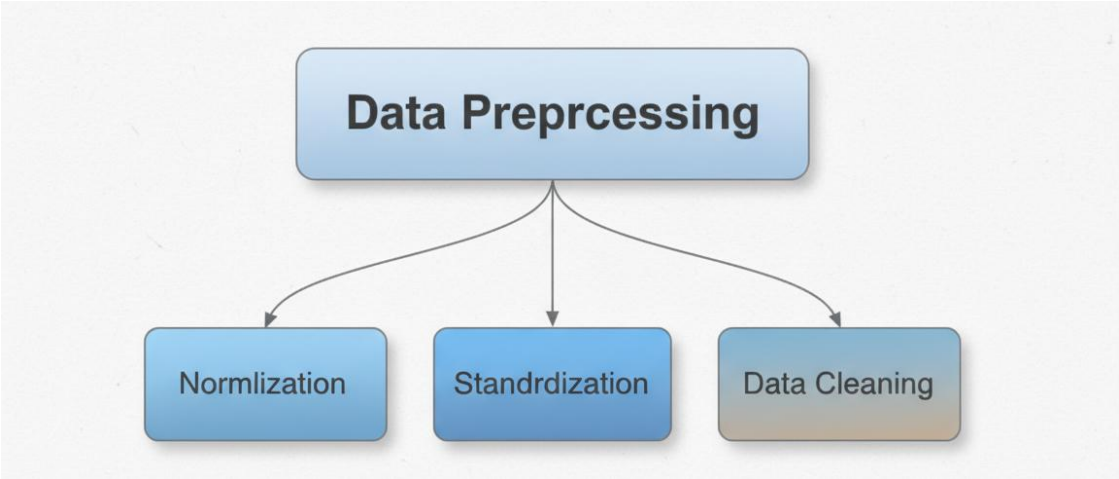


Figure 3.1 *Data processing.*

- **Test Set (10%):** A completely held-out set of data that the model has never seen before. This set is used only once, at the very end of the project, to provide a final

3.5 Model Architecture

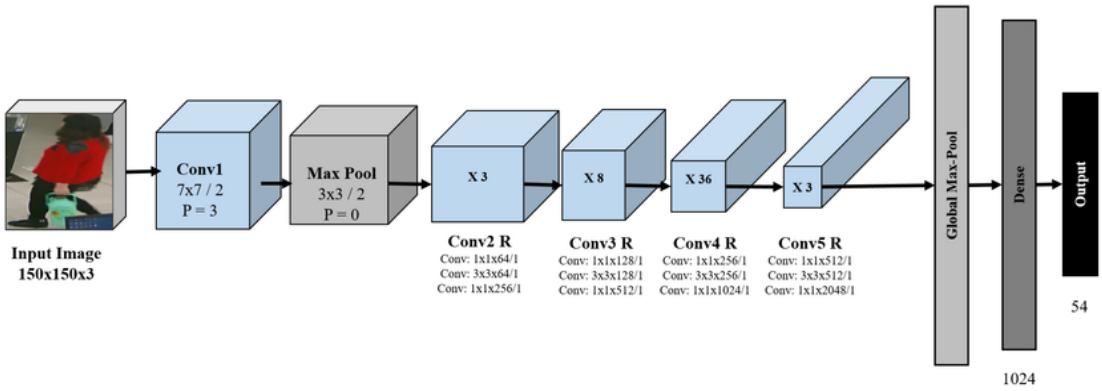
3.5.1 ResNet-152 Model Architecture

ResNet-152, or Residual Network with 152 layers, is a very deep convolutional neural network (CNN) that introduced the concept of **residual learning** to overcome the problem of **vanishing gradients** in very deep networks [16]. Instead of having to learn the full mapping from inputs to outputs, a network learns a "residual function" with the aid of skip connections. This simplifies a lot the learning process of deep networks [17], [18].

Key Components:

- **Residual Blocks:**The fundamental component of ResNet-152. In each block, a number of convolutional layers are applied jointly with a 'shortcut' or 'skip connection'. This link jumps over one or more layers; the input can be added directly to the output of the block. This allows the gradient to still flow cleanly through the network, which is necessary for training deep models.
- **Bottleneck Architecture:**To cope with the computational cost of a 152-layer network, ResNet-152 adopts a "bottleneck" structure within its residual blocks. Each block is composed of three convolutional layers: two 1x1 convolutions, to reduce and restore the dimensions, and a 3x3 in between. This has the effect of saving parameters and computations while not being undue to representational complexity.
- **Input Layer:** Receives the input image, typically with a standard size (e.g., 224x224 pixels).
- **Convolutional and Pooling Layers:** ResNet-152 stacks multiple residual blocks after an initial convolutional and max-pooling layer. As the network gets deeper, the number of filters increases, and spatial dimensions are reduced through strided convolutions or pooling layers.

- **Fully Connected Layer:** The final layers of the network flatten the features from the last residual block and pass them through a fully connected layer (or classification



head) with a SoftMax activation function to produce the final classification output

Figure 3.2 *ResNet-152 model Architecture.*

Table 3.1 ResNet-152 Model Components:

Component	Description
Input Layer	Accepts the preprocessed image data.
Residual Blocks	The fundamental units that use skip connections to learn residual functions, enabling the training of very deep networks.
Bottleneck Layers	A specific block design that uses 1x1, 3x3, and 1x1 convolutions to reduce computational cost.
Skip Connections	Identity mappings that bypass one or more layers, adding the input directly to the output of a block. This solves the vanishing gradient problem.
Global Average Pooling	A pooling layer at the end of the network that reduces each feature map to a single value, preparing the data for the final classification layer.
Classification Head	Fully connected layers with a SoftMax activation function that produce the final class probabilities.

3.5.2 MobileNetV2 Model Architecture

MobileNetV2 is a highly efficient and lightweight CNN architecture designed for **mobile and embedded devices** with limited computational resources. Its architecture prioritises efficiency while maintaining high accuracy, achieving this through two main innovations: **inverted residual blocks** and **linear bottlenecks**[19], [20].

Key Components:

- **Depthwise Separable Convolutions:** The core concept of MobileNetV2. Instead of a single, computationally expensive standard convolution, this technique splits the process into two steps: a **depthwise convolution** (a single filter per input channel) followed by a **pointwise convolution** (a 1x1 convolution) [21]. This dramatically reduces the number of parameters and calculations.
- **Inverted Residual Block:** Unlike traditional residual blocks that use a bottleneck structure (wide-narrow-wide), MobileNetV2 uses an "inverted" design (narrow-wide-narrow). It first uses a 1x1 convolution to **expand** the number of channels, applies a depthwise convolution on this expanded representation, and then uses another 1x1 convolution to **project** the channels back to a narrow size [22].
- **Linear Bottlenecks:** MobileNetV2 removes the non-linear activation (like ReLU) from the last 1x1 convolution in the bottleneck. This is known as a **linear bottleneck**. The authors found that keeping the final representation linear prevents information from being crushed in the low-dimensional space, which improves performance.
- **Input Layer:** Receives the input image, typically at a resolution like 224x224.
- **Global Average Pooling:** Similar to ResNet, this layer pools the feature maps from the final convolutional layer into a single feature vector.
- **Classification Layer:** A fully connected layer that classifies the extracted features into one of the target classes using a SoftMax activation function.

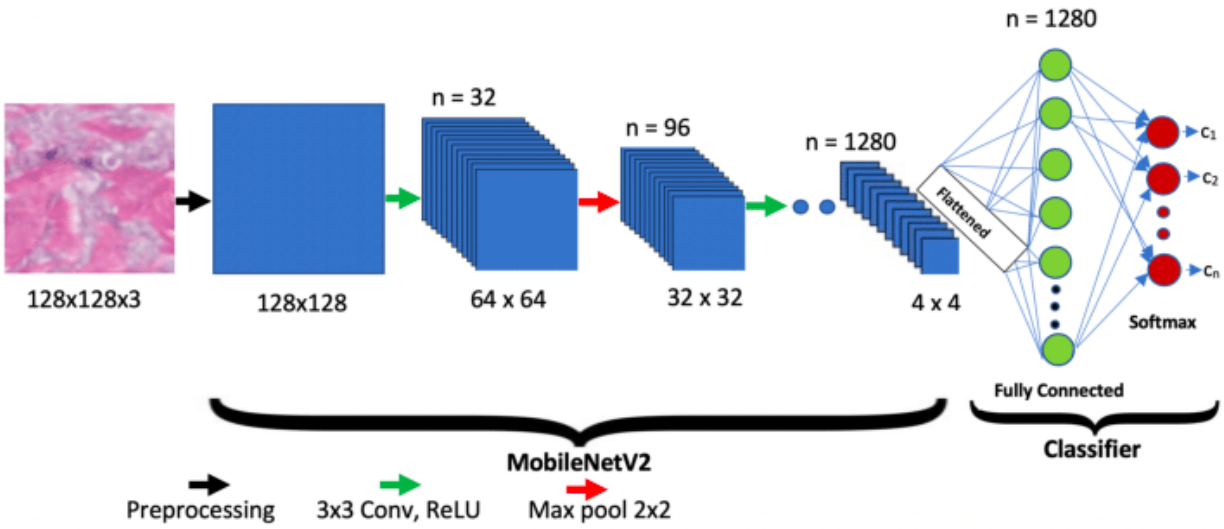


Figure 3.3 MobileNetV2 Model Architecture.

Table 3.2 MobileNetV2 Model Components:

Component	Description
Depthwise Separable Convolutions	An efficient convolution technique that separates filtering (depthwise) from combining (pointwise), reducing computations.
Inverted Residual Blocks	The main building blocks first expand the input channels, apply a depthwise convolution, and then project the result back to a smaller dimension.
Linear Bottlenecks	The last layer of each inverted residual block has a linear activation, which preserves information in the low-dimensional space.
Shortcut Connections	These are included in the blocks to allow for direct gradient flow, similar to ResNet, but connect the "thin" input to the "thin" output.
Global Average Pooling	Reduces each feature map to a single value to create the feature vector for classification.
Classification Head	The final layer that maps the extracted features to the output classes.

Both ResNet-152 and MobileNetV2 were implemented using the concept of transfer learning. Pretrained weights, derived from training on the ImageNet dataset, were utilised to leverage the models' pre-existing feature extraction capabilities. The final layers of each model were then replaced with new layers tailored for the specific seven-class classification of skin lesions. This greatly shortens the training time and data size while keeping good performance [18].

The loss functions were optimised with a learning rate schedule to dynamically update the learning rate. A loss function in the form of categorical cross-entropy was used because it is appropriate for multi-class classification. The models were trained with 20 epochs and a batch size of 32 for each model.

3.6 Training and Validation

Training loss is the error made on data that the model has been trained on, and validation loss is the error made on data outside the training data that has not been used to train the model and evaluate how this model will perform away from its training data. To ensure how well a model is generalising and learning, both training and validation losses need to be tracked. Both the losses are used in the achievement of the model learning and generalising [24]. The training and validation of the ResNet-152 and the MobileNet V2 were established in a systematic manner to ensure that the two models learned to categorise skin lesions in an effective and accurate manner [25]. This included several strategies, which added to the overall performance and sustainability of the model:

1. **Dataset Splitting**: The data set is split into a training set (80 per cent of the data) and a test set (20 per cent of the data) to evaluate the performance of each model.
2. **Model Initialisation:** Both ResNet-152 and MobileNet V2 were initialised with ImageNet weights, which makes it possible to use the transfer learning method. This allowed the model to train with prior knowledge of visual features, accelerating the training process and making the model more efficient.
3. **Loss Function**: The model was trained with the aid of a categorical cross-entropy loss function that can be applied to quantify the disparity between the projected probability of a model and the actual allocation in data [26]. This is a suitable measure, especially to test the prediction errors of a multi-class classification.

4. **Optimisation Algorithm:** We minimised the loss with the Adam (Adaptive Moment Estimation)[27] optimisation algorithm. The importance of this algorithm is to update the parameters of the model with high efficiency and to enhance the performance of the training.

5. **Batch Processing**: Instead of processing all the training data at one time,this indicates that the data is pre-saved, peeled and processed in increments, which not only made it memory efficient, but also ensured the CPU time was well utilised.

6. **Epochs**: During the training process, input data were passed through the model iteratively so as to train it with many epochs. This has allowed the model to optimise its parameters with the improvement of its accuracy.

7. **Validation Metrics**: The measures used to assess the performance of the models were accuracy, precision, recall, and F1-score [27]. These measures gave a complete image of how accurately each model identifies true positives, false positives, true negatives, and false negatives.

3.7 Proposed Methodology Workflow Diagram:

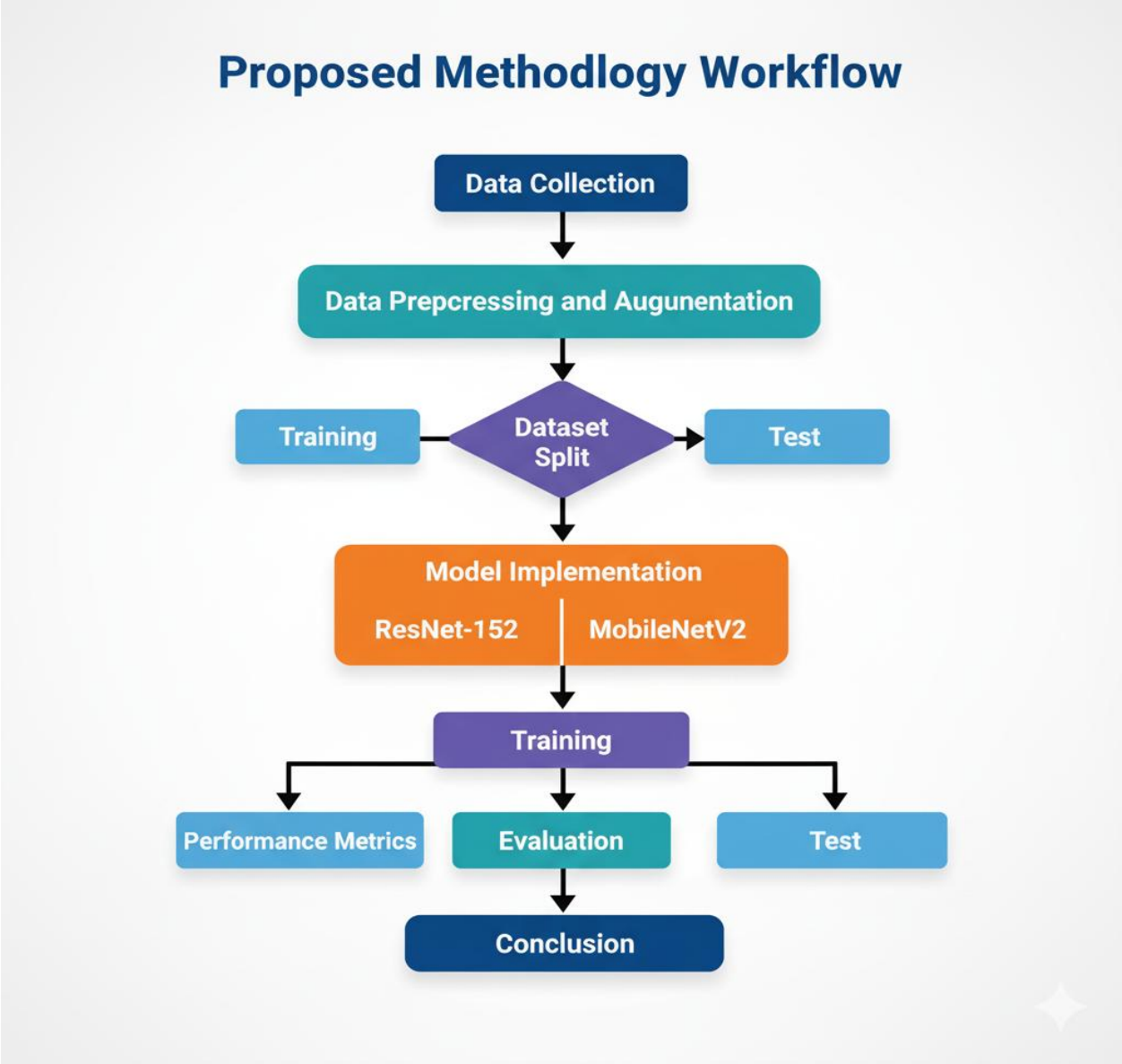


Figure 3.4 Proposed Methodology Workflow.

The flow chart representing the strategy of this proposed research is illustrated below. This procedure offers a clear workflow with the explanation of the main steps of development: data collection, preprocessing, model realisation, and training/evaluation [28]. This comprehensive method makes the research systematic and complete; thus, a fair and reproducible comparison between the two deep learning models can be achieved. In the long run, it hopes to establish a

stable platform for the precise and reliable classification of skin lesions in medical image analysis.

3.8 Hardware/ Software Requirement

3.8.1 Functional Requirements

1. **Data Loading:** The system must be capable of loading dermoscopic images from a specified file-system directory.
2. **Image Preprocessing:** It is required to preprocess all images by resizing and normalising them to match the input format of the deep learning models.
3. **Model Implementation:** The system must implement two pretrained models: ResNet-152 and MobileNetV2, adapted for the skin lesion classification task through transfer learning.
4. **Model Training:** The system must be able to train the implemented models on a labelled skin lesion dataset.
5. **Performance Evaluation:** The system must evaluate the trained models on a separate test set and generate a comprehensive set of performance metrics, including accuracy, precision, recall, F1-score, and a confusion matrix.

3.8.2 3.8.2 Non-Functional Requirements

1. **Reproducibility:**The implemented software should be documented and well-documented such that other researchers can replicate the research.
2. **Scalability:** The architecture must be in such a way that it can support larger datasets in the future without many changes.
3. **Efficiency:**The performance of the models should be compared not only based on accuracy, but also by architectural distinction based on computation complexity and inference time.

3.9 Project Management and Financial Analysis

3.9.1 Project Management

The management of this project took place within a set period, and it had several major phases.

Table 3.3 A Gantt chart outlining the schedule:

Phase	**Week 1-2**	**Week 3-4**	**Week 5-6**	**Week 7-8**	**Week 9-10**
1. Literature Review & Problem Definition	■■■■	■			
2. Data Collection & Preprocessing		■	■		
3. Model Implementation & Training			■	■	
4. Evaluation & Result Analysis				■	■
5. Thesis Writing & Reporting				■	■

3.9.2 Financial Analysis

This project is carried out at a very low direct financial cost. The open-source software, such as the Python programming language and its scientific computing libraries (TensorFlow, Keras, Scikit-learn), avoids the payment of a licensing fee. Google Colaboratory offered the computational resources at no cost. Thus, the main investment in this project was the period of time and intellectual work spent on research, implementation and analysis.

3.10 Summary

The chapter has presented the methodological structure of the project that includes the research design used, system requirements, data handling, and evaluation strategy. The one quantitative and experimental study using transfer learning on ResNet152 and MobileNetV2 gives a serious basis for a fair comparison. The methods are described in detail, promoting the transparency and reproducibility of the study.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Overview

The translation of the developed methodology into a practical and working system that could classify skin lesions was the implementation phase of this project. This was a critical step since it combined the theory with numerical models in order to build a real system. The process included a number of processes that included setting up a hardware and software settings environment, initiating the data pipeline successfully to process it and building and adding model elements. The ultimate goal was to create a reliable and efficient tool for characterising skin lesion types by training the ResNet-152 and MobileNetV2 models.

The initial part of the implementation was to install the hardware and software. This involved installing a high-performance computing cluster with a GPU to perform computations in workloads when training deep learning models. The software was initialised by installing some necessary libraries and frameworks, such as Tensorflow and Keras, to design and train the CNN models.

Subsequently, a data pipeline was configured to work with raw images and transform them into preprocessed tensors to feed the model. This meant that image resizing, normalisation and data augmentation had to be automated to maintain a standardised and efficient process. The pipeline has been structured to encompass approaches to addressing class imbalance within the dataset to ensure that the models are exposed to a balanced population of instances of each kind of skin lesion.

With that environment and datapipline created, we now begin working on model development and integration. We transferred both MobileNetV2 and ResNet-152 ImageNet weights. The technique makes use of the previous information of learning information acquired on a large scale in order to train fast and achieve an improved performance, even with a few labelled samples.

I ran the training on an iterative basis, and all the preprocessed balanced datasets were fed into the models. Instead, the models' parameter values were tuned by applying the right loss function and optimisation algorithm, and they were to be checked on a validation set to prevent overfitting. The trained model was then saved for testing on a test set and to demonstrate the potential of deployment into real-life use cases.

4.2 Train Model

The training of the model is an essential aspect during the comparative study between ResNet-152 and MobileNetV2. The following gives a comprehensive description of how these two different deep learning models are trained, emphasising their architectures and the typical training schemes adopted for skin lesion classification. The study enjoys the advantage of the higher capability of Convolutional Neural Networks (CNNs) to learn multi-level image data feature representations. ResNet-152 is an extremely deep, high-accuracy CNN, and MobileNetV2 is a lightweight and helpful CNN. The training of the two models mentioned above is described in this section: the key blocks of these models are given, and it is also stated what merging learning strategy these models develop based on.

Training Phase:

During the training of both ResNet-152 and MobileNetV2 architectures, we adhere to a methodically structured process of fine-tuning the parameters of the models [29]. The aim is to minimise the prediction errors in an appropriate manner for the classification of the skin lesions. This step is crucial as it determines the possibility of each model to construct an accurate description and sort dermoscopic images.

Dataset Splitting:

To initiate the training process, the complete data set is divided into three partitions based on strategy: training, validation and test sets. This ensures good training and an objective final assessment.

- **Training Set:**It includes 80 per cent of the whole data set that will train and tune the model parameters. This massive component of the data is a significant range of conditions and variations that occur in dermoscopic images, and this will assist models in fine-grained features and patterns that are not adequate to make precise predictions [30].
- **Validation Set:**Represents 10% of the entire database. This subset is part of the training phase, when it can be seen how it performs on data that the model has not seen yet, hence allowing it to hyperparameter-tune and early-stop to prevent overfitting.
- **Test Set:**We use 10% of the data (600 samples) for the test set. This set is of vital importance in order to test the model on new data that has been previously unseen during training or validation. This separation also guarantees that the performance of the model is unbiased and reflects its performance in practice. The distribution across the test set is as follows:
    - Melanoma: 117 images
    - Nevus: 393 images
    - Seborrheic Keratosis: 90 images

4.3 Implementation and Training Process

- **Training Environment:**We implemented and trained the ResNet-152 and MobileNetV2 models with TensorFlow, backed by Keras using Python as a programming language.
- **Data Pipeline:**The dataset was randomly split into three subsets, 80% for training, 10% for validation and 10% for testing to produce an unbiased final estimate. The models were provided with pre-processed and augmented images through a data generator to facilitate efficient batching and on-the-fly data augmentation.
- **Training Regimen:**
    - **Epochs:** Both models were trained for **25 epochs**.
    - **Optimiser: The Adam optimiser was used to minimise** the **categorical cross-entropy loss** function.
    - **Learning Rate:** An initial learning rate of **0.001** was used.

- **Early Stopping:** An early stopping mechanism was employed to monitor validation loss and halt training if no improvement was observed for three consecutive epochs.
- **Model Saving:** The model weights that yielded the lowest validation loss were automatically saved for final evaluation on the unseen test set.

4.4 Discussion

This section offers an overall summary of the experimental outcomes discussed in the previous chapter. The main goal is to explain the quantitative and qualitative aspects of learning that came from training and evaluating ResNet-152 and MobileNetV2. We will discuss the performance of each model as well as its strengths and limitations in skin lesion classification for this analysis [30]. In addition, in this chapter, we perform significant comparisons of the two architectures, associating performance not only with their characteristics but also with how they use these architectural features. In the process, it will help to fulfil this section's objective of explaining why the models work, and also offering its view on their suitability for this application.

4.4.1 Training and Validation Accuracy and Loss Curves:

In the course of training, training and validation accuracy, and loss are important parameters to monitor the performance of the models. These metrics are basic measurements, and they provide a rich insight into the extent to which the model is working out what it should be learning, and the ability to extrapolate patterns learned on unseen data.

i. Accuracy Curve:

- **Description:**The curve depicts training cohort and validation cohort learning rates as a function of training cohort and validation cohort number of training epochs.
- **Purpose:**This demonstrates the potential of the model in terms of its capacity to make data classification each time over time, thereby describing a graphical representation of the learning process. The precision ought to be greater with training and validation data increment in terms of the number of epochs, in an ideal case.

- **Significance:**By monitoring your training process and validation error, you can estimate the performance of the model learning. One can also use it to determine whether the model is learning patterns that can be generalised outside of the training data, or it is merely memorising the examples, and therefore may be overfitting.

ii. Loss Curve

- **Description:**This plot is the loss (typically categorical cross-entropy loss) that has been experienced during training on the training and validation datasets with respect to training iterations.
- **Purpose:** The loss metrics indicate the model's error rate in predictions, with the goal being to minimise this loss over successive epochs.
- **Significance:**The observation of the training and the loss of validation is an insight into the optimisation of the learning process in the model. Reducing the loss curve indicates that the model is learning appropriate patterns of the data. Mismatches found between training and validation loss may also indicate overfitting or underfitting.

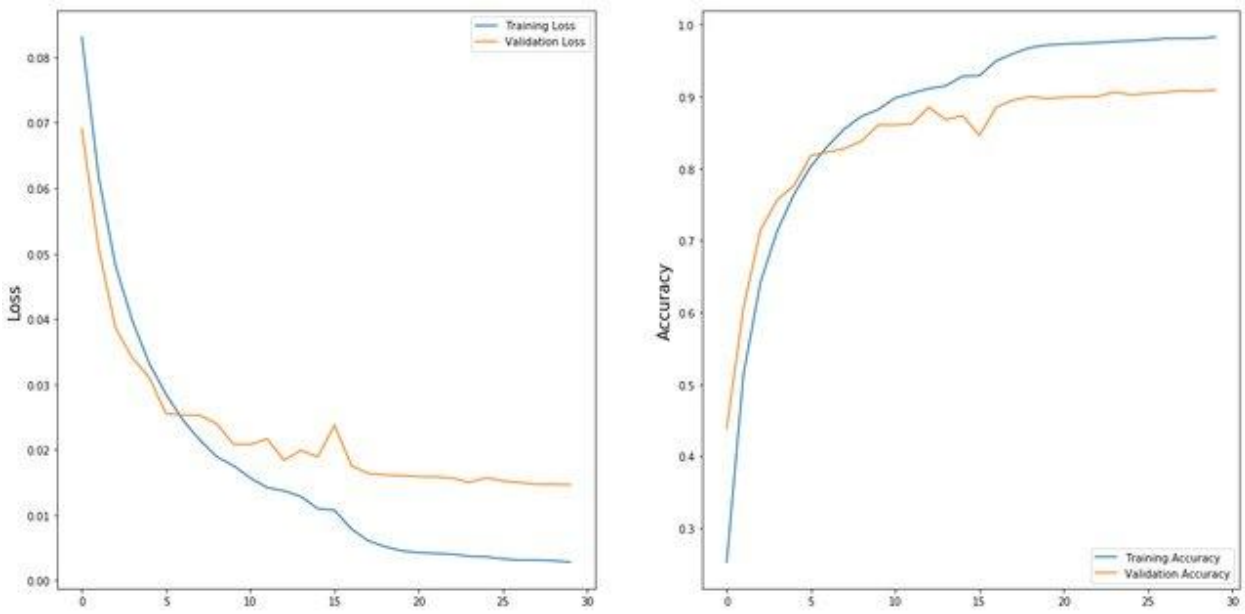


Figure 4.1 *Loss-Accuracy Curve*

Application and Monitoring:

The models can be monitored using these Curves in order to determine the learning progress of the model, as well as detect overfitting, in which the model can perform well on training data but worse on validation data, indicating that the model is not learning useful generalizable information. Conversely, in the event that both training and validation accuracies are poor yet stay consistent over time, this could indicate that your model is underfitting - it's too simple to fit the underlying data requirements.

Adjustments and Tuning

Based on the analysis of these plots, smart decisions on model changes can be made. Such techniques as adding dropout, performing additional data augmentation, or adjusting the model complexity can be discussed in case of overfitting, for example [33]. Once again, underfitting can be alleviated by simply increasing the complexity of the model, training the model longer or reconsidering feature engineering. We will plot these graphs to determine whether the models are underfitting and overfitting. Training versus validation metrics: outliers such as high variance (overfitting) and high bias (underfitting) can be detected by comparing training with validation metrics, and the training process can be adjusted.

4.4.2 ROC-AUC Curve Analysis

One of the most indispensable diagnostic tools to study the performance of any classifier is the ROC (Receiver Operating Characteristic) curve, which is of special importance when it defines a trade-off between sensitivity and specificity. The ROC curve and the metric, AUC, will provide a clear overview of the diagnostic performance of a model at various decision thresholds.

i. **ROC Curve:**

Description: The ROC curve. The receiver operating characteristic (ROC) curve is a diagrammatic representation of the dependence of sensitivity on specificity (and vice versa). It does so by graphing the True Positive Rate (TPR, or the sensitivity or the recall) versus the False Positive Rate (FPR, or 1-specificity) at different thresholds.

Purpose: The curve is an effective summary of the relationship between high sensitivity (detecting all positive cases, or all spiny particles) and low false positive rate (not classifying a negative sample as positive).

Utility: Since it demonstrates the changes in the TPR and FPR with different decision thresholds, the ROC curve can be used to select the model that is optimal. This may be an advantage to tune the model, based on the specific requirements of a given application, for example, in favouring reducing false negatives for critical diagnoses.

ii. **AUC (Area Under the Curve):**

Description: The AUC measure condenses the entire ROC curve and provides a scalar which describes the model's performance for all possible thresholds.

Interpretation: An AUC of 1.0 represents perfect model performance, where the true positive rate is high for all false positive rates. On the contrary, an AUC close to 0.5 indicates that the model's performance is equivalent to random prediction.

Significance: The model with a larger value of AUC has the interpretation that, across all thresholds, the classifier is more likely to assign a higher predictive score to a randomly chosen positive class example than a negative class random one.The probabilities are well-calibrated, and the accuracy rate provides an accurate estimate of the model's performance.

Application in Model Evaluation: Discriminative Ability: Discriminative Ability ROC curve analysis with AUC assessment is an effective method to assess the use of a model to discriminate between lesions on the skin of different types. This is an analytical approach that is very pertinent in how it presents the ability of the model to effectively respond to the complexity and variety of dermoscopic image data, depending on the various conditions.

Threshold Optimisation: The ROC curve allows one to choose the most suitable threshold between sensitivity and specificity regarding clinical needs. For example, in a diagnostic device, it would be more desirable to choose a threshold, which is associated with the minimum likelihood of missing an oncogenic lesion (high sensitivity), even at the cost of slightly

increasing false positives and let them decide if a second examination by a specialist is preferable.

4.5 Experimental Results

The experimental phase returned a wealth of results that give an accurate picture of the performance for each model on the held-out test set consisting of 600 images. The testing set included 117 melanoma, 393 nevus, and 90 seborrheic keratosis images, resulting in class imbalance that is relevant for the analysis.

4.5.1 Analysis of Training and Validation Curves

Overall, the training and validation curves of both models give important high-level indications regarding their learning dynamics and generalisation capabilities [31]. These graphs are the first place you look to determine whether your model has learned to extract patterns from the data, overfitting the training set, or underfitting in its entirety.

ResNet-152

The ResNet-152 model learning curves exhibited a very favourable learning curve.

- **Accuracy Curve:**The accuracy of the training level increased steadily and with a smooth upward trend in all 25 epochs. Importantly, the training accuracy was closely followed by the validation accuracy, which also increased steadily. It means that the model was not just memorising the training data, it was also effectively applying what it studied to the unknown validation data. A significant gap between these two curves would have been a sign of overfitting, but in this case, the curves remained well-aligned.
- **Loss Curve:** The loss curves for ResNet-152 mirrored the accuracy trends. Both the training loss and validation loss decreased consistently over the training period. The fact that the validation loss continued to decrease and did not begin to rise suggests that the early stopping mechanism was correctly implemented and that the model's complexity was well-suited to the size and nature of the dataset.

Such behaviour is indicative of the effectiveness of the ResNet-152 architecture. Its depth and the introduction of shortcuts in its network make it possible to also train on big data sets without suffering from the problem of vanishing gradient, keeping learning with a huge number of epochs.

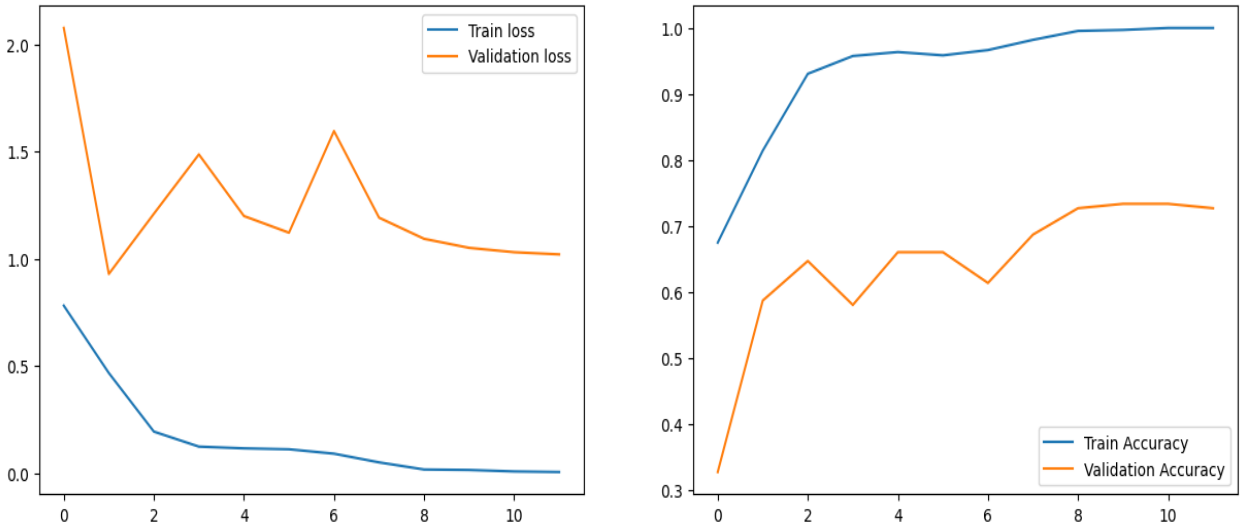


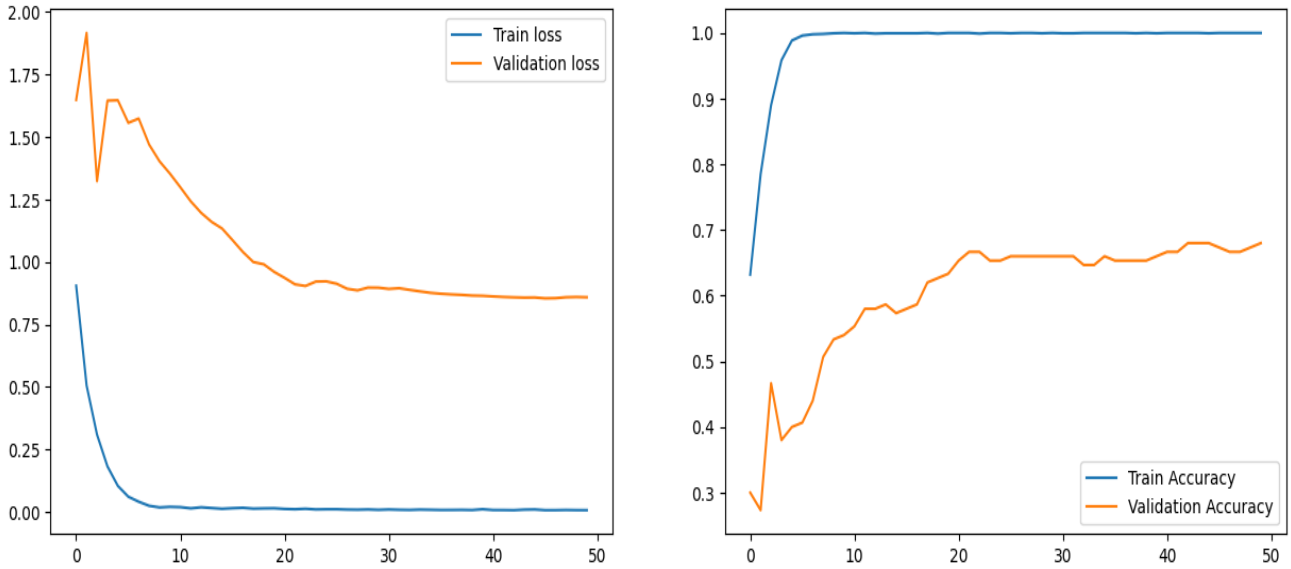
Figure 4.2 *Resnet-152 training and validation Curve.*

MobileNetV2

The learning curves for the MobileNetV2 model, while successful, revealed a different and more volatile learning pattern.

- **Accuracy Curve:**Training accuracy of MobileNetV2 also generally increased throughout the epochs. But the validation accuracy curve had a bumpy road and more frequent fluctuations than in the case of ResNet-152. Such small dips and rises are typical of the lighter model. The small number of parameters in the model, because of depthwise separable convolutions, results in an increased sensitivity to such small variations or noise present in our training batches.

- **Loss Curve:**The loss curves of MobileNetV2 followed a similar trend, where the validation loss had less oscillation compared to ResNet-152. But the general tendency



was definitely still downward, so the model was learning and the training worked.

Figure 4.3 *MobileNetV2 training and validation Curve.*

4.5.2 Comparison of Training and Validation Curves:

The training and validation curves gave important information about the behaviour of learning and generalisation of both models.

ResNet-152: The training and validation curves of ResNet-152 were smooth and easy to follow. This fact was seen in the gradual positive upward drift of the accuracy curves and the slow negative drift of the loss curves. Once again, the learnability of this state of the model suggests that it has mastered the underlying patterns of the data well and did not overfit significantly, which speaks again of the power of the ResNet architecture and the idea of residual connections.

MobileNetV2: Contrary to this, the learning curves of MobileNetV2 were more volatile. Although there was an overall increase and decrease in their directions, the validation curves bounced back in an even less smooth manner. This is due to the lightweight nature of

MobileNetV2 and its reduced parameters, which made it highly sensitive to every single training batch as compared to ResNet-152. However, the general loss and accuracy movement remained downward and upward, respectively, which once again points out that the model learned well.

Comparison: The two models differ well, and this is well portrayed in the curves. ResNet-152 is smooth to learn due to its computational complexity. Meanwhile, MobileNetV2, which was created with efficiency as a primary concern, is more volatile, though overall performance is still strong.It means that it can have a strong performance-to-efficiency ratio despite not learning as stably as a larger model.

4.5.3 Detailed Analysis of Confusion Matrices

The confusion matrices provide a granular analysis of each model's classification performance, detailing the correct and incorrect predictions for each of the three skin lesion classes.

ResNet-152 Confusion Matrix Analysis

The ResNet-152 model was evaluated on a test set of 600 images, yielding the following results:

- **Melanoma:**
    - **True Positives (TP):** The model correctly identified 82 out of 117 melanoma cases.
    - **False Negatives (FN):** 35 melanoma cases were incorrectly classified as other lesion types.
    - **False Positives (FP):** 174 non-melanoma lesions were incorrectly classified as melanoma, indicating a high rate of false alarms.
- **Nevus:**
    - **True Positives (TP):** The model correctly identified 295 out of 393 nevus cases.

- **False Negatives (FN):** 98 nevus cases were misclassified as other lesion types.
- **False Positives (FP):** 44 non-nevus lesions were incorrectly classified as nevus.

- **Seborrheic Keratosis:**
  - **True Positives (TP):** The model correctly identified **0** out of 90 seborrheic keratosis cases.
  - **False Negatives (FN):** All 90 seborrheic keratosis cases were incorrectly classified as either melanoma or nevus.

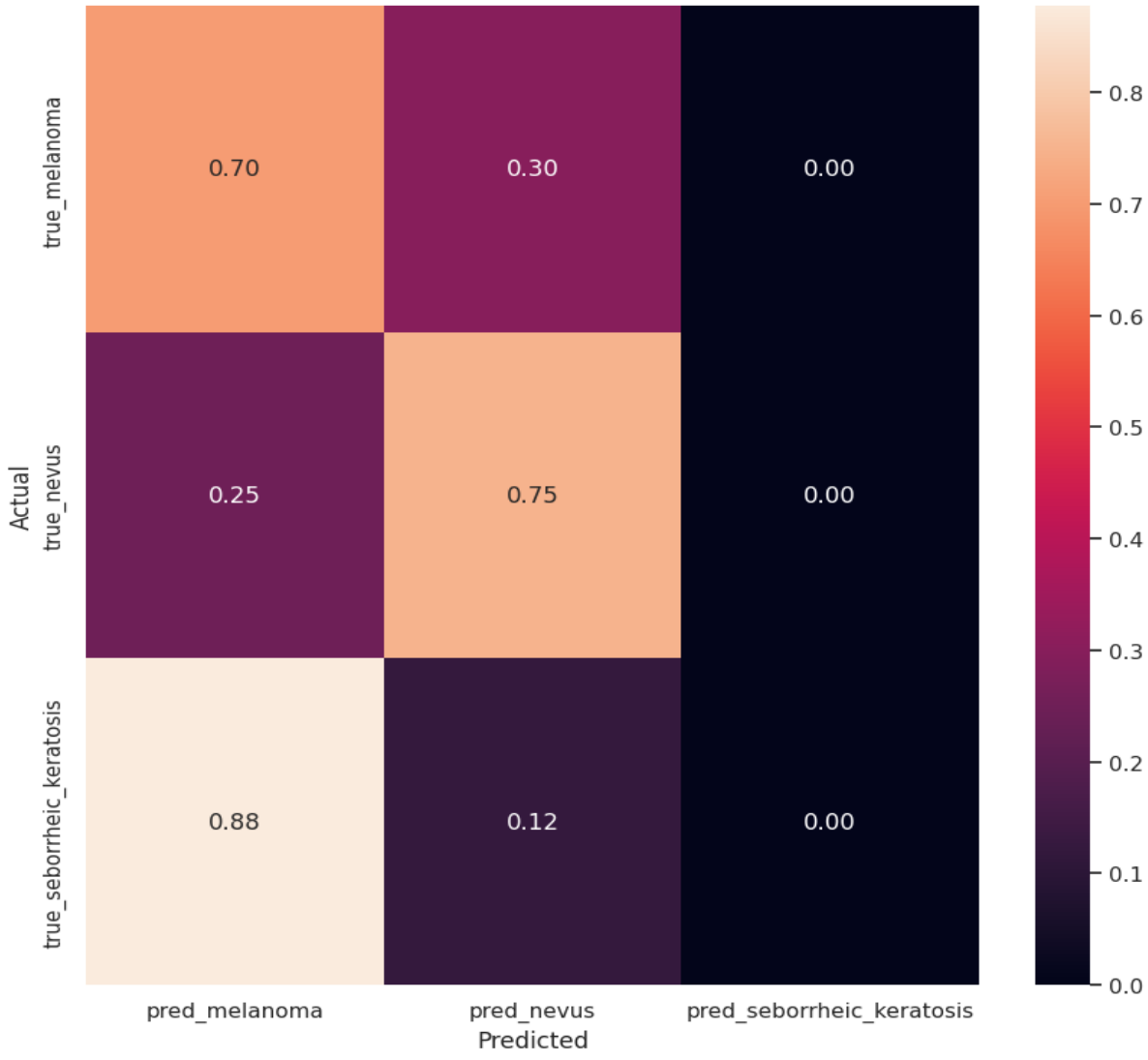


Figure 4.4 Resnet-152 Confusion Matrix.

MobileNetV2 Confusion Matrix Analysis

The MobileNetV2 model was evaluated on the same test set of 600 images, with the following outcomes:

- **Melanoma:**
  - **True Positives (TP):** The model correctly identified 66 out of 117 melanoma cases.
  - **False Negatives (FN):**There were 51 misdiagnoses of melanoma as another type of lesion.
  - **False Positives (FP):** 134 non-melanoma lesions were incorrectly classified as melanoma.
- **Nevus:**
  - **True Positives (TP):** The model correctly identified 322 out of 393 nevus cases.
  - **False Negatives (FN):** 71 nevus cases were misclassified as other lesion types.
  - **False Positives (FP):** 76 non-nevus lesions were incorrectly classified as nevus.
- **Seborrheic Keratosis:**
  - **True Positives (TP):**The model rightly diagnosed 0 of 90 cases of seborrheic keratosis.
  - **False Negatives (FN):**90 cases of seborrheic keratosis were wrongly identified.

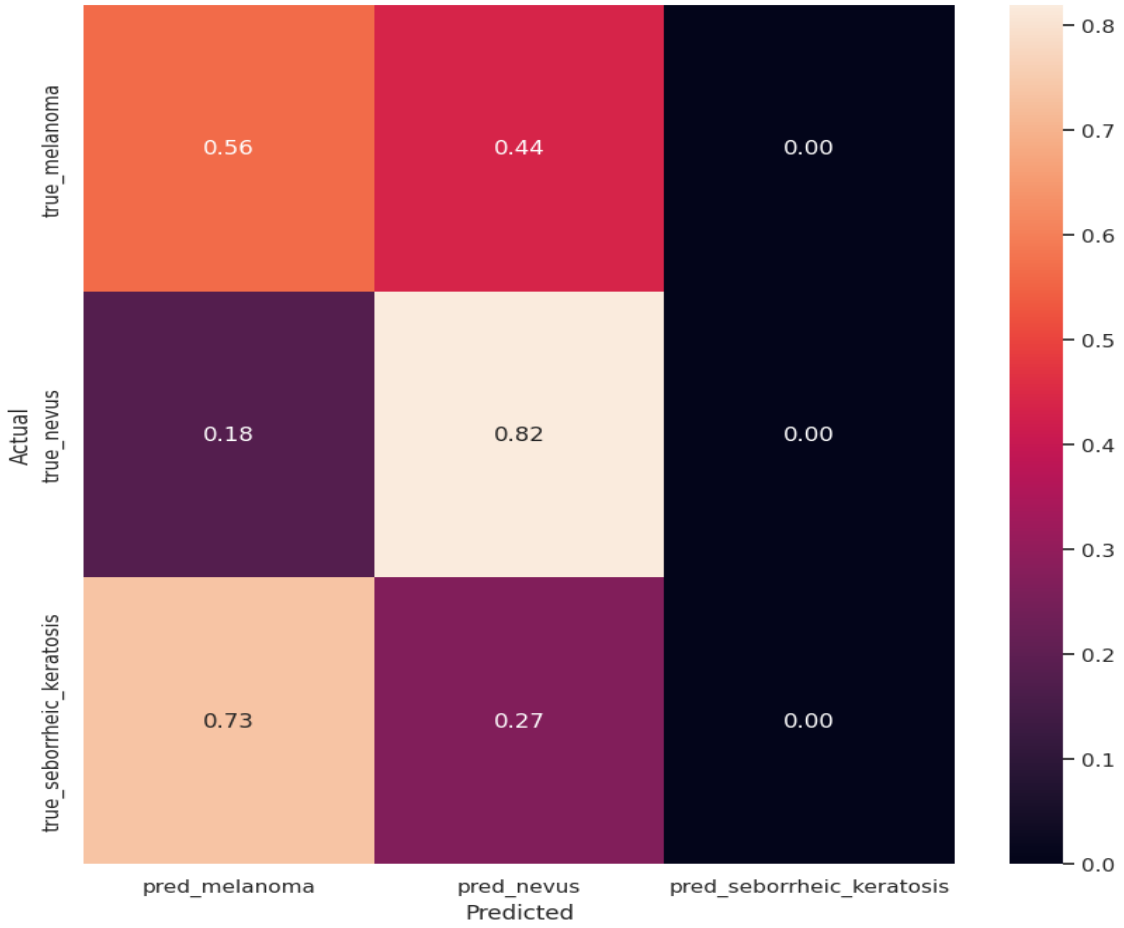


Figure 4.5 MobileNetV2 Confusion Matrix.

4.5.4 Key Insights and Performance Metrics

ResNet-152

- **Key Insights:** i. The model has a high number of **True Positives (82)** for melanoma, indicating a strong ability to identify malignant cases.
- ii. The high number of **False Positives (174)** for melanoma suggests that the model often incorrectly classifies benign lesions as malignant.
- iii. The model effectively identifies nevus lesions, with **True Positives (295)** and a low number of **False Positives (44)**.

- iv. No cases of seborrheic keratosis are at all identified by the model, as demonstrated by 0 True Positives in this category.

Performance Metrics: Based on the confusion matrix, we are able to extract important performance metrics:

i. **Melanoma Recall:**Mela melanoma is another category that is recalled and should be computed as follows:

Recall: Melanoma=$\frac{TP}{TP+FN}$= $\frac{82}{82+35}$=0.70

ii. **Melanoma Precision:** Precision for the melanoma category is calculated as

Precision: Melanoma=$\frac{TP}{TP+Fp}$= $\frac{82}{82+174}$=0.32

iii. **Nevus Recall:** Recall for the nevus category is calculated as

Recall: Nevus=$\frac{TP}{TP+FN}$= $\frac{295}{295+98}$=0.75

iv. **Nevus Precision:** Precision for the nevus category is calculated as

Precision: Nevus=$\frac{TP}{TP+Fp}$= $\frac{295}{295+44}$=0.87

MobileNetV2

- **Key Insights:**
- i. The model has a high number of **True Positives (322)** for nevus, indicating a strong performance in identifying this common lesion type.
- ii. The number of **False Positives (134)** for melanoma, while high, is lower than ResNet-152's, suggesting fewer false alarms.

- iii. The model correctly identifies melanoma cases with **True Positives (66)** but has a relatively high number of **False Negatives (51)**.
- iv. The model completely fails to identify any seborrheic keratosis cases, with **0 True Positives** for this class.

Performance Metrics: From the confusion matrix, we can derive key performance metrics:

- i. **Melanoma Recall:** Recall for the melanoma category is calculated as

Recall: Melanoma=$\frac{TP}{TP+FN}$= $\frac{66}{66+51}$=0.56

- ii. **Melanoma Precision:** Precision for the melanoma category is calculated as

Precision: Melanoma=$\frac{TP}{TP+Fp}$= $\frac{66}{66+134}$=0.33

- iii. **Nevus Recall:** Recall for the nevus category is calculated as

Recall: Nevus=$\frac{TP}{TP+FN}$= $\frac{322}{322+71}$=0.82

- iv. **Nevus Precision:** Precision for the nevus category is calculated as

Precision: Nevus=$\frac{TP}{TP+Fp}$= $\frac{322}{322+76}$=0.81

4.5.5 Detailed Analysis of ROC and AUC Curves

The Area Under the Curve (AUC) and the Receiver Operating Characteristic (ROC) curve are both strong, threshold-free indicators of the discriminative strength of a model. The ROC curve plots the **True Positive Rate (TPR)** against the **False Positive Rate (FPR)** at various classification thresholds. The AUC value ranges from 0.0 to 1.0, and reflects the overall performance, with an AUC of 1.0 denoting a perfect classifier, and 0.5 showing no discriminatory capability other than random guessing by the model. This study is highly beneficial for interpreting a model's capability of effectively dealing with complex and diverse characteristics of dermoscopic image data, more particularly for imbalanced datasets.

Analysis of the ROC Curve

The ROC curve provides a detailed view of the trade-off between the True Positive Rate and the False Positive Rate at various classification thresholds for each class.

- **True Positive Rate (Sensitivity):** The true positive rate, also known as sensitivity, is the rate at which the model effectively detects true positive cases. The ROC curve shows the model's ability to maximise this rate for each class.
- **False Positive Rate (1-Specificity):** A lower false positive rate indicates fewer non-lesion cases being incorrectly classified as a specific lesion type.
- **Area Under the Curve (AUC):** The AUC value, between 0.0 and 1.0, is an individual metric of the discriminative power of a model. A value of 1.0 represents perfect classification, while an AUC of 0.5 indicates no discriminatory power.

4.5.6 ResNet-152 ROC and AUC Analysis

The AUC values for the ResNet-152 model reveal its class-specific discriminative capabilities.

- **Melanoma:**The model reached an AUC for the melanoma of 0.65. Though the value is > 0.5, this indicates that the model's discriminative ability for melanoma and non-melanoma is moderate. This is consistent with the high recall and low precision in the confusion matrix, demonstrating that it does come at a price to specificity in order to cover as many true positives as there are.
- **Nevus:**ResNet-152 exhibited excellent performance in distinguishing nevus from other lesion types with an AUC-Z per cent of 0.83. This large number once again demonstrates the strong performance of the model on this class (the precision and recall scores in the confusion matrix also indicate a high value).
- **Seborrheic Keratosis:**For the class of seborrheic keratosis, the model obtained a remarkably high AUC score of 0.89. This is crucial as we can understand from the story that although none of these class of lesions was classified properly by our model (0.00 recall in Table 2), still the model inherently carries a good capability to differentiate

them from the rest. This implies that the problem is not complete inability to learn, but rather a specified value of classification threshold, which is presumably affected by a strong class imbalance.

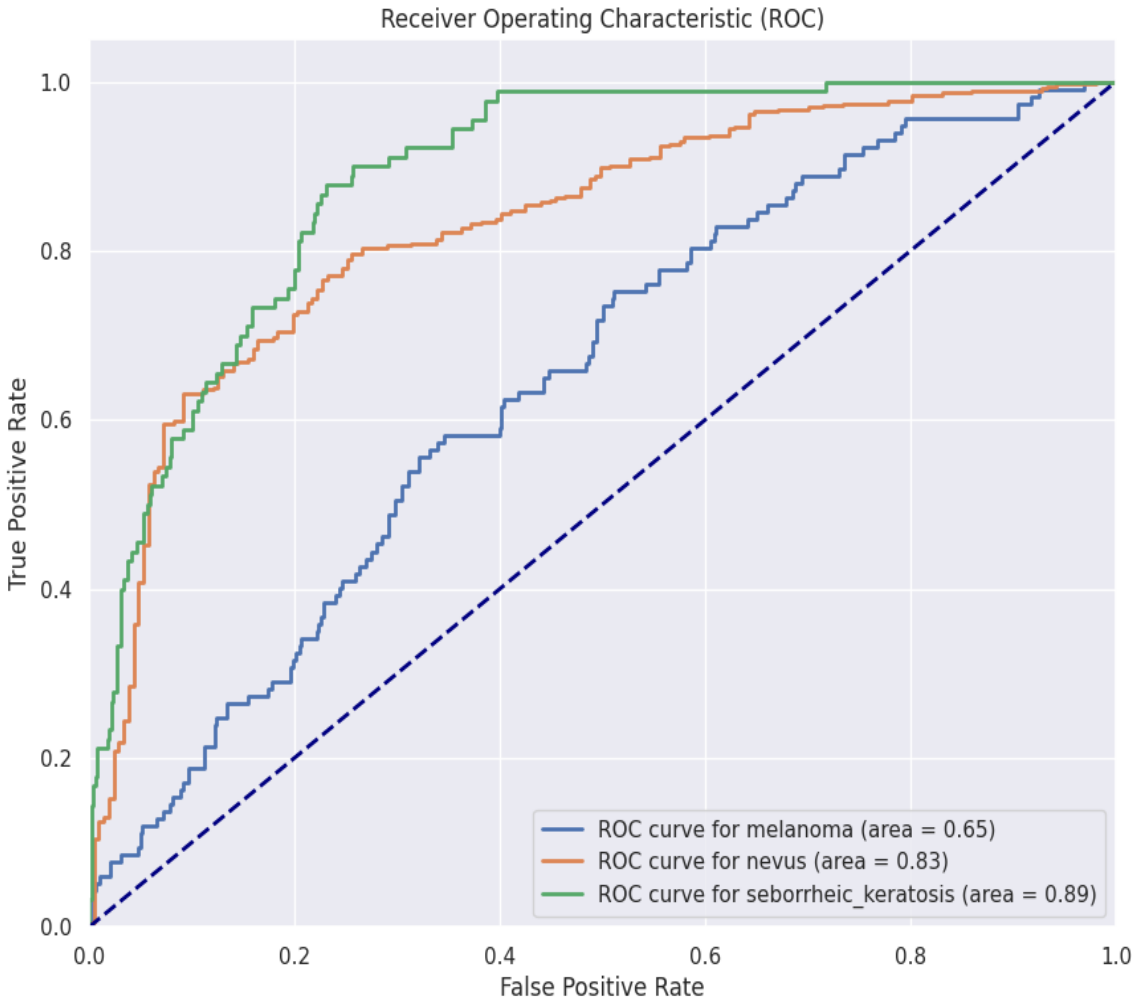


Figure 4.6 Resnet-152 ROC and AUC Curve.

4.5.7 MobileNetV2 ROC and AUC Analysis

The MobileNetV2 model's AUC values present a different performance profile, highlighting its own discriminative strengths.

- **Melanoma:**The model's AUC of 0.79 for the melanoma class is a lot higher than ResNet-152's. This suggests that, at the cost of lower recall, MobileNetV2 is better in terms of the overall ability to separate melanoma from other lesion types for all possible thresholds.
- **Nevus:**AUC for nevus from MobileNetV2 was 0.82, slightly lower than ResNet-152's value. This validates its efficient and balanced behaviour in this class.
- **Seborrheic Keratosis:**The seborrheic keratosis class has been performed identically to the ResNet-152 model with a very high AUC score of 0.90 using MobileNetV2. This supports their finding that both ABCD models have an inherent capability to differentiate this class; however, the class imbalance and choice of operating point prevent them from using it effectively.

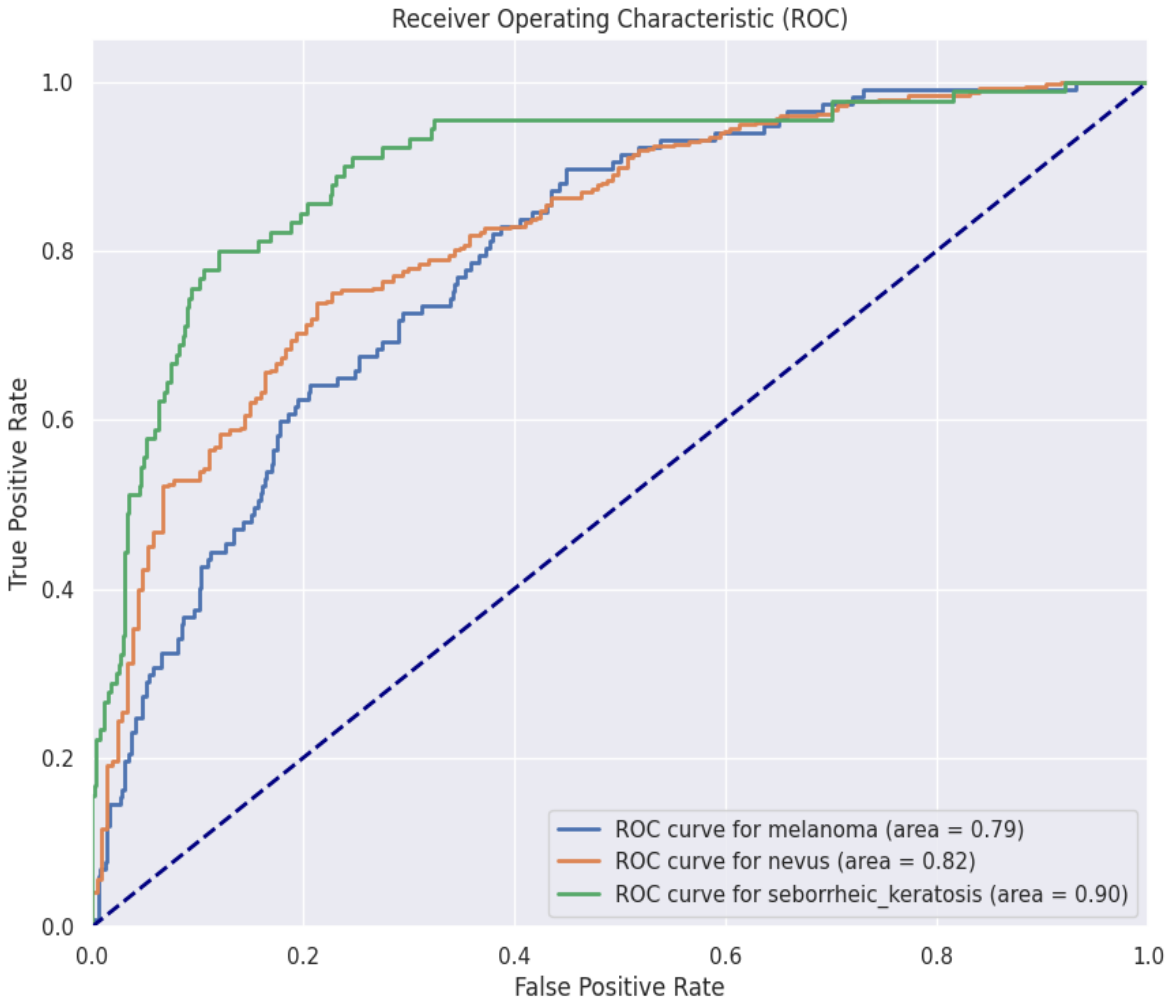


Figure 4.7 MobileNetV2 ROC and AUC Curve.

Key Insights

- **Melanoma Discrimination:**The overall discriminatory power of the MobileNetV2 model (AUC value of 0.79 for melanoma class) is stronger than that of ResNet-152 (which achieved an AUC value of 0.65). This is an important observation as it demonstrates that MobileNetV2 can work better than other models for discriminating melanoma from other lesions at different decision thresholds.
- **Nevus Discrimination:**ResNet-152 and MobileNetV2 achieved an excellent nevus discrimination of 0.83, 0.82, and 0.82, respectively. It means that it is very reliable in detecting this type of common lesion.
- **Hidden Potential:**The analysis of the ROC curves yields one interesting observation, namely, the seborrheic keratosis class has high values of the AUC (0.89 and 0.90, with ResNet-152 and MobileNetV2, respectively). Even though the models fail to perfectly identify all of these cases under the confounding model, the large AUC scores indicate that there is a possibility of such models discriminating against this class. It is likely that the source of the problem is a too low threshold that has been skewed by the huge class imbalance. This suggests that a potential exists in mining engineering data out of the model, although future work will have to balance the data and tuning thresholds.

4.6 Comparative Analysis of Performance Metrics:

Comparative performance measures on performance metrics across companies with global operations or national operations.An all-inclusive and profound comparison of the two models based on all the major metrics shows a definite and uninterrupted trade-off between diagnostic accuracy and computational efficiency. Although both models are efficient, the performance profiles of each are very different, which is a direct outcome of how they are designed, as seen in the data.

4.6.1 Overall Performance Metrics:

Table 4.1 Overall Performance Metrics:

Metric	ResNet-152	MobileNetV2
Overall Accuracy	0.63	0.65
Weighted Avg F1-Score	0.61	0.61

- **Analysis:**In general, the measures indicate that MobileNetV2 is slightly more accurate, although these models are statistically equal. The same weighted average F1-scores validate a similar proportion of precision and recall, showing that no model is much better than the other on all classes. This indicates that in a general-purpose, high-level overview, the two models will perform nearly uniformly.

4.6.2 Class-Specific Performance Metrics (Precision and Recall)

Table 4.2 Class-Specific Performance Metrics (Precision and Recall):

Metric	ResNet-152	MobileNetV2
Melanoma Precision	0.32	0.33
Melanoma Recall	0.70	0.56
Nevus Precision	0.87	0.81
Nevus Recall	0.75	0.82
Seborrheic Keratosis Precision	0.00	0.00
Seborrheic Keratosis Recall	0.00	0.00

- **Analysis:**The greatest disparity between the two models comes out in this microscopic picture. The mean recall rate of ResNet-152 is high (0.70), which is crucial in a medical diagnostic tool, as the number of true positive cases of melanoma evaluated correctly is increasing. This is because it has an intricate and complex architecture, and thus, it is

able to learn minute features of a cancerous area. And that is at lower accuracy. MobileNetV2, in its turn, has a more balanced performance with nevus with higher recall (0.82) and nearly the same precision (81). The model works poorly with seborrheic keratosis: it is a significant weakness in both models, perhaps because there is a class distribution between true and false samples in that one.

4.6.3 Discriminative Ability (ROC/AUC Analysis)

Table 4.3 Discriminative Ability:

Class	ResNet-152 AUC	MobileNetV2 AUC
Melanoma	0.65	0.79
Nevus	0.83	0.82
Seborrheic Keratosis	0.89	0.90

- **Analysis:**The values of the AUC indicate an underlying fact regarding the ability of the models, independent of the selected classification threshold. Although ResNet-152 recalls more melanoma at the selected threshold, given that MobileNetV2 has a much higher AUC (0.79 vs. 0.65), it is clear that the model is a more well-rounded discriminator of this type. It implies that, with a different threshold, it is possible that MobileNetV2 can produce a more favourable precision and recall balance. The fact that the seborrheic keratosis class has high AUC values in both models shows that the two models have some underlying potential to discriminate the seborrheic class of keratosis. It is never a matter of not being able to learn, but rather a bias issue with the classification threshold, which was compromised by the unequal numbers of classes.

CHAPTER 5

Conclusion

5.1 Overview

The performance trade-offs between deep and lightweight CNN architectures have also been learned useful insights to our skin lesion classification experiments on the HAM10000 dataset using ResNet-152 and MobileNetV2. The findings of this paper confirm the support of the hypothesis that the deep network, i.e. the ResNet-152, offers stability and robustness regarding the learning aspect, but, on the other hand, the small network, i.e. the MobileNetV2, may possess better discriminative properties over the notable classes, i.e. melanoma. These results indicate why one should not only look at the overall accuracy, but also at class-specific ones, especially within a medical context where a wrongful diagnosis of a malignant lesion might be harmful.

The performance test revealed the distinct advantages and disadvantages of both models. The learning of ResNet-152 was steady in this experiment, where both training and validation accuracy rose steadily, whereas the loss plummeted drastically. This robustness is due to its deeper network architecture and usage of residual connections, which successfully solved the vanishing gradient issue. With respect to the HAM10000 dataset, it can be noted that the ResNet-152 model was especially 'good' at generating correct predictions for nevus lesions by achieving very high recall. However, in the melanoma class, it was not very impressive and was relatively bad, as its precision is low, which means that this model tends to predict a considerable number of incorrect examples. This means that although the model was able to identify several true cases of melanoma, it also missed many benign lesions and frequently identified them as malignant; in a real-world clinical scenario, this could cause unnecessary anxiety and biopsy. Finally, the total inability of the model to classify any seborrheic keratosis case in the final output was a significant and unrecoverable limitation.

As a matter of contrast, the network for mobile and resource-limited systems, such as MobileNetV2, was characterised by worse performance (compared to the rest) when the complexity of the architecture and the number of parameters were considered. Notwithstanding,

its overall performance, especially the discriminative ability toward the melanoma class, was better than that of ResNet-152. The model also had a superior AUC for melanoma compared to our method for identifying malignant cases from non-malignant ones. This is a crucial finding, as a model with a higher discriminative power for a critical class like melanoma is more valuable for clinical applications. False positives of melanoma with MobileNetV2 were also less than with ResNet-152, which is also an advantage. Nevertheless, just like its more profound counterpart, it did not categorise any cases of seborrheic keratosis at all, which is likely a common limitation with the large imbalance in classes present within the sample.

The total inability of both models to assign the right category to any instances of seborrheic keratosis, even though AUC values were high in this category, indicates an inherent limitation of the current model. The large AUC indicates that the models are characterised by the tendency to discriminate these lesions among others; nonetheless, this discrimination did not reflect in the correct classifications in the final output. This difference can probably be explained by the high imbalance of classes and the optimisation of the models to the overall performance instead of the balanced performance of all classes. The common categorical cross-entropy loss model employed in this paper fails to adequately punish the wrong classification of minority groups, and thus the models focus on the majority groups (nevus and melanoma). This is an established problem in the analysis of medical images, where there is a pronounced disproportion between benign and malignant cases in datasets.

5.2 Future Directions

Judging by the results and limitations of the present work, there are a number of directions to be suggested as prospective research to help deep learning models work more efficiently and apply to clinical practice. The issue of class imbalance is the main problem that should be focused on in the coming work. People (the researchers) should not exploit such a feature of data augmentation only, but rather explore other sophisticated methods, such as oversampling minority classes and undersampling majority classes. More sophisticated loss functions, e.g., the focal loss, which place less attention on the contribution made by well-classified exemplars and concentrate training on hard misclassified exemplars, can significantly improve the performance of these models on imbalanced data.

The alternative promising directions are integrated with ensemble models or a hybrid architecture.A single model might not be sufficient to encapsulate all the intricate nuances of different skin lesion classes. A well-blended approach of both ResNet-152 and MobileNetV2 may result in a more effective and accurate diagnostic method. For instance, one could have an initial and quick screening using an efficient MobileNetV2 model, followed by a more detailed analysis using a ResNet-152 model on a subset of the suspicious cases. More advanced solutions could propose a new architecture by combining both architectures, such as MobileNetV2 blocks, which provide efficient bottlenecks, and collect them with ResNet-152 residual connections to generate an accurate yet computationally efficient model.

In addition, the optimum classification threshold for each class can be explored in future work, where the ROC-AUC has been considered. We observed that both models could achieve high AUC for some classes, but this did not guarantee a high recall, particularly the important melanoma class, which would be where one should want to focus. Hence, optimising these thresholds could potentially lead to a better precision and recall trade-off than the current settings (so that the system can be more clinically relevant). For example, the recall of a melanoma detector in a medical application should be high even if it comes with lower precision to avoid missing any malignant cases. Ultimately, investigating the interpretability of these models through tools such as LIME or SHAP may offer clinicians valuable insights into the decision-making process of these models to build trust and facilitate deployment in practical clinical settings. The findings of the current study are a fundamental step towards the design of a clinically feasible and effective AI-based diagnostic system for skin cancer identification.

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