Transforming Dermatology: Transfer Learning Models for Accurate Skin Disease Detection

BY

SAIF MAHMUD

ID: 221-15-5367

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the
Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

DEWAN MAMUN RAZA
Assistant Professor
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By

MD. SADEKUR RAHMAN
Assistant Professor
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JANUARY 2025

APPROVAL

This Project titled **"Transforming Dermatology: Transfer Learning Models for Accurate Skin Disease Detection"**, submitted by Saif Mahmud, ID No: **221-15-5367** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **13 January, 2025**.

<u>BOARD OF EXAMINERS</u>

Dr. S.M Aminul Haque (SMAH) — **Chairman**
Professor & Associate Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Md. Abbas Ali Khan — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Md. Aynul Hasan Nahid — **Internal Examiner**
Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Md. Zulfiker Mahmud — **External Examiner**
Professor
Department of Computer Science and Engineering
Jagannath University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dewan Mamun Raza, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

13.01.25

Dewan Mamun Raza
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised by:

Md. Sadekur Rahman
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Saif Mahmud 13.01.25

Saif Mahmud
ID: 221-15-5367
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Project** successfully.

We are grateful and wish our profound indebtedness to **Dewan Mamun Raza**, **Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of “Computer Vision and Deep Learning” to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

This research investigates the application of machine learning techniques in the detection and classification of skin diseases. Leveraging transfer learning models such as MobileNetV2, InceptionV3, and DenseNet121, the study focuses on accurately identifying nine distinct skin disease categories using a curated dataset. The methodology encompasses data preprocessing, including normalization and augmentation, to mitigate class imbalance and enhance model performance. DenseNet121 emerged as the most effective model, achieving an accuracy of 86.2%, followed by MobileNetV2 and InceptionV3. The study highlights the challenges of dataset limitations, interpretability of models, and computational resource requirements. Ethical considerations, including data privacy and bias mitigation, are addressed to ensure responsible implementation. This research demonstrates the feasibility of deploying AI-driven diagnostic tools to augment dermatological care, emphasizing the potential for widespread application in remote and resource-limited settings. Future work involves expanding datasets, improving model interpretability, and integrating these solutions into telemedicine platforms for more accessible and equitable healthcare.

Keywords: Skin disease detection, machine learning, transfer learning, MobileNetV2, DenseNet121, InceptionV3, dermatology AI, dataset imbalance, explainable AI, telemedicine.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Problem Definition

Skin diseases are among the most common health problems worldwide, affecting millions of individuals annually. These disorders may be different in their severity, range, or level: eczema, psoriasis, acne, melanoma, and so many more. These conditions result in fatal stages if not diagnosed and treated on time. Conventionally, skin diseases have traditionally been diagnosed by a dermatologist through simple ocular examination and biopsy, which might be very time-consuming, subjective, and liable to human error. There are very few dermatological experts available, most especially in dispersed or underdeveloped places, and most cases remain either undiagnosed or poorly treated.

Machine learning comes as a revolutionary means to address the issue by automatically classifying skin diseases. Advanced algorithms with deep learning can analyze medical images, observing patterns too small to be otherwise seen by the naked human eye. This can improve diagnosis, timeliness, and accuracy in order to ensure patients get the proper treatments in time. Furthermore, where the accessibility to a specialist is minimum, the automated systems could screen preliminary, therefore narrowing the gap between the needs and health resources [1].

However, machine learning solutions in this domain come with their own challenges: skin tone variation, different lighting conditions, and resolutions of images can seriously affect the performance of any classification model. Besides, comprehensive and annotated datasets are not fully available. Overcoming these challenges calls for a number of novel approaches in model design, strong data augmentation strategies, and collaborative efforts towards developing inclusive datasets representative of diverse characteristics from the global population.

1.2 Problem Statement

Skin diseases are among the most prevalent health issues around the world and affect all age groups and sections of society. Diseases of the skin range from benign irritations such as acne and eczema, to more serious life-threatening diseases like melanoma. Despite prevalence, timely and accurate diagnosis of dermatological diseases still remains a critical challenge, especially in resource-constrained settings without access to specialty dermatology services. Traditional diagnostic methodologies rely on the expertise of a trained dermatologist and are hence subject to variability for subjective interpretation. Secondly, dermatological services are usually in demand, which makes health care systems succumb to the pressure and thereby delaying diagnosis and treatment [2].

The general lack of awareness and early detection mechanisms for many skin diseases is another critical issue at stake. Most patients come for medical consultation when the symptoms have reached a critical stage, and the outcome of any treatment is thus poor. These delays have severe consequences in rural and underserved parts of the world where dermatological expertise is poor. Furthermore, skin types and conditions are so varied, and disease presentation may be so different that diagnosis has to be made using sophisticated methods dealing with the large variability. With the burden of skin diseases being felt across the globe, this calls for new ways of diagnosis that will offer correct, consistent, and fast diagnoses across boards of life.

Besides all these, the conventional manual mode of diagnosis is not going to scale when put against the soaring demands of healthcare. With the increase in population and life expectancy, there is a further rise in skin-related ailments, thereby pressuring already-pressurized medical resources. What this calls for is a paradigm shift toward more effective and easily accessible solutions for diagnosis. The real challenge lies in closing the growing gap between the rising demand for dermatological care and the availability of timely and reliable diagnostic methods that can effectively respond to various populations and conditions [3].

1.3 Research Motivation

Skin diseases may considerably affect physical, psychological, and economic spheres of a person and society at large. Skin afflictions like acne, psoriasis, and melanoma are distressful physically, which might carry deeper effects mentally stemming from the marks of the disease that may be visible. Any delays in diagnosis or mistakes might result in the aggravation of these conditions with complications such as prolonged treatments or even deaths associated with more serious conditions like melanoma. The increasing prevalence of these diseases worldwide demands the use of efficient and timely diagnostic approaches.

Specialized dermatological expertise is poorly distributed, with a big gap between urban and rural or underdeveloped areas. Medical infrastructure is sparse in most places, and there is a deficit of trained personnel who would be capable of conducting proper diagnosis in time. This compels the patients mostly to self-diagnose or opt for over-the-counter treatment that might turn out to be ineffective or even harmful. This scenario points to the need to provide an alternative diagnostic method that is scalable, accessible, and reliable.

These are possibilities that the advance in digital imaging technologies and digitization of healthcare have opened. It is now feasible to develop a system able to diagnose skin conditions from images since capturing good dermatological images with everyday devices like smartphones has become possible. Such a system would represent a diagnostic front-line tool both for the patient and for primary care, reducing significantly the dependence on specialist consultations for common conditions.

Moreover, the introduction of technology use in health care systems speaks to personalized medicine that is taking place globally. This may also imply that skin disease classification is automated in such a way as to achieve superior diagnostic precision to allow for personalized treatment. The collaboration between technology and medicine gives sufficient justification to explore new methods in skin disease classification for the benefit of enhancing quality and increasing access to dermatological services worldwide.

1.4 Research Scope

The research is enveloped in the development of a new, efficient, and user-friendly method of classifying diseases, with the use of modern technologies of machine learning. Skin diseases have posed challenges because they look different in appearance, their progress, and way of manifestation due to persons of different skin tones, age groups, and genetic predispositions. Such challenges can be overcome by proposing a strong framework that is able to detect and classify various skin diseases from dermatological images correctly, which would enhance diagnosis.

This research investigates image-based classification capabilities of skin diseases. The main variations within dermatological images are in resolution, lighting conditions, and color representation; as such, their analysis has several complications. This present study will, therefore, dwell on the standardization and pre-processing methods of such images so that the diagnostic system is robust against a wide range of input conditions. Specific understanding of the visual markers of various skin diseases will also be extended in the study with the intention of enhancing the accuracy of classification.

Application targets range from clinical to non-clinical settings. Clinically, this can actively support dermatologists with a second opinion or even be a pre-screening tool in the diagnostic workflow, thus reducing errors in diagnoses and saving time, especially in high-demand healthcare settings. In the instance of non-clinical use-for example, rural or underserved communities-the system can function independently, aiding patients who might have limited access to dermatologists with preliminary diagnoses [4].

Another important consideration is skin disease classification's aspect of inclusivity. Most of the skin diseases appear differently on the skin of people with varying skin tones, and most of the proposed diagnostic systems have already been trained with non-representative datasets. This calls more for diverse data that can ensure the system will not be biased and work across populations. This way, the proposed solution will be globally applicable and equitable.

The present research work also covers scalability and accessibility of the diagnostic system. Unlike most conventional methodologies, which either require expensive equipment or a huge amount of specialist training, the proposed solution aims at cost-effectiveness and ease of operation. The work stands on normally deployed devices for image capture and analytical purposes, such as smartphones, on which diagnostic aid can be conceived of being technologically sophisticated yet able to be put into wide practice.

This research also involves important ethical considerations. The research study will guarantee patient data privacy and follow the set regulatory standards concerning medical technologies. The scope will involve the development of secure practices for handling data while obtaining approvals that are important to ensure the system meets the international standard in healthcare. It would also be desirable to introduce some interpretability into the diagnostic output so that the user can make sense of its predictions and understand the underlying 'why' behind a given recommendation.

It covers a wide area of building a classification model that is robust and can be applied inclusively to real-world settings. It is expected to fill in some of the gaps that hitherto exist in dermatological diagnostics regarding availability, accuracy, and scalability. It will also be supportive of ethics and inclusivity in such a way that the proposed system will be contributing positively toward health systems around the world by helping improve outcomes in patients with skin diseases.

1.5 Research Objectives

→ Elaboration of an Effective Diagnostic Framework

Establish a robust system for the proper classification of various skin diseases through dermatological images with regard to their manifestations and qualities.

→ Improvement of Diagnostic Accessibility

It needs to be so designed that the mechanism can be employed in backward or remote areas where dermatologists may not be available for providing timely and preliminary diagnoses.

→ Increase Inclusion in Skin Disease Detection

It needs to be trained on representative datasets so that the system is unbiased and works for a wide demographic as well as skin tone.

→ Improving Scalability and Usability

Provide an affordable solution with the key aim of making the technology clinically and non-clinch ably relevant using commonly used devices such as smartphones.

→ Ensure Ethical and Practical Implementation

Emphasize protection of patient data, compliance with regulations in healthcare, and interpretable diagnostic results that instill trust for ethical deployment in real-world settings.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview of Skin Disease Diagnosis

These are diseases related to the skin, hair, and nails, from the most frequent minor cases-like acne and eczema-to dangerous forms such as melanoma. Diagnosis often consists of a clinical examination in combination with anamnesis and investigations, which include skin biopsy. Dermatologists are specialists who almost always have to undergo many years of specialized training in the correct observation and classification of diseases through tiny differences in the appearance of skin.

While these techniques are very effective, their large dependence on the subjective expertise of the medical practitioner alone tends to be very different from one practitioner to another. The process is time-consuming and involves a number of consultations and tests should one have some rare or complex condition. The misdiagnosis and delay in diagnosis are by no means rare events, even in cases of a certain visual similarity of diseases like psoriasis and eczema or at an early stage of melanoma which can be taken for a benign mole [5].

This dependency on expert knowledge and manual assessment underscores the need for more consistent, scalable diagnostic methods. Medical imaging and digital technologies opened new frontiers in the automation of skin disease diagnosis and prepared the ground for a turn towards swifter, more accurate, and more easily accessible solutions. These innovations should support traditional methods to address their limitation and extend dermatological care.

2.2 Role of Technology in Dermatology

Dermatology, which was essentially an art of manual techniques, has today used the field's integration with technology to enable faster, more valid, and accessible methods of diagnosis and treatment of skin diseases. Digital imaging, telemedicine, and machine learning have transformed dermatology into a technologically-inclined speciality from what was earlier deemed as a primarily manual practice. This has advanced the capacity of detecting, classifying, and monitoring a wide range of skin conditions beyond that which was possible using traditional methods of skin disease diagnosis.

One of the most relevant technological advances in dermatology relates to high-resolution imaging-such as dermoscopy-to obtain finely detailed pictures of the skin surface. Such images are important for the identification of early signs of skin cancer-particularly melanoma, which is quite difficult to distinguish by the naked eye from benign lesions. Besides, technologies like OCT and confocal microscopy allow one to see skin layers in ways previously unimaginable; hence, they greatly enhance diagnostic accuracy. Such detailed visualization of skin lesions has actually enhanced the precision of dermatological diagnosis [6].

Moreover, teledermatology has emerged to provide easy access to dermatological treatment, especially in rural or underprivileged areas. In teledermatology, the patients send high-resolution pictures of their skin disease to dermatologists who then review these images remotely, thus consulting in a timely manner without actually having to pay a visit. This has facilitated dermatological expert opinion at more economical costs and convenience, especially for patients who otherwise might have limited access to healthcare professionals.

Machine learning and AI played their revolutionary role in dermatology by automating the process of detection and classification of skin diseases. Among the deep learning algorithms, especially those based on CNNs may analyze dermatological images for patterns that might hardly be recognized by human experts. It may support the dermatologist with making a diagnosis, with a second opinion, or an initial diagnostic screening to enhance decision-making and reduce diagnostic errors. The AI-powered diagnostic tools have demonstrated unparalleled accuracy in conditions like melanoma, basal cell carcinoma, and psoriasis, hence are of immense benefit in a clinical setting.

Technology has greatly increased diagnostic accuracy, widened access to care, and made dermatological treatments more time saving. Given that these technologies are continuously improving, it is envisioned that their roles in future revolutions of dermatological practices will be significant, opening up new avenues toward the best outcomes and most personal forms of patient care.

2.3 Existing Machine Learning Approaches

Jagdish et al. [7] proposed a model for detecting skin disease with the help of image processing. They applied fuzzy clustering on 50 sample images and KNN and SVM classification with wavelet analysis. The results showed that the KNN algorithm performed better than the SVM and gave an accuracy of 91.2% in the identification of skin disease type. However, they worked on only 50 images with two classes of diseases: basal and squamous.

The authors, Naeem et al. [8], proposed a model for skin cancer prediction using image processing strategies in combination with support vector machines. Various preprocessing steps were applied for the removal of noise and enhancement, followed by feature extraction using the GLCM method, and classification of the images as malignant or benign.

Bandyopadhyay et al. [9] have integrated DL with machine learning. Deep neural networks like Alexnet, Googlenet, Resnet50, and VGG16 are used for feature selection, while SVM, Decision Tree, and Ensemble boosting methods such as Adaboost are tried for classification. Further, after performing the comparative study, the best prediction model is revealed.

Authors in [10] proposed skin lesion classification on a small and imbalanced dataset using different DCNN models. They introduced various regularization techniques ranging between DropOut and DropBlock to introduce a novel loss function that handles the problem of the underrepresentative samples and showed high value at low computational cost for classification performance.

Padmavathi et al. [11] proposed a fine-tuned deep learning network to classify skin lesions automatically, whose performance was quantitatively assessed using various metrics like specificity, sensitivity, precision, and accuracy.

Maduranga et al. [12] proposed a mobile application based on AI to detect skin diseases using CNN based on the HAM10000 dataset. MobileNet was adopted over the developed mobile application with transfer learning; in that context, the highest reached accuracy was 85%.

Janney et al. [13] proposed the comparison of SVM, ANN, and Naïve Bayes classifiers for skin disease classification based on extracted features from dermoscopic images. Average accuracies obtained were 89%, 71%, and 71% for ANN, SVM, and Naïve Bayes, respectively. Both the SVM and Naive Bayes classifiers performed poor.

The model of skin disease diagnosis using image processing was proposed by Sinthura et al. [14]. They implemented Otsu's method for segmentation, extracted GLCM features, and used SVM for classifying four diseases: Acne, Psoriasis, Melanoma, and Rosacea. They have achieved 89% accuracy. This model was limited by small datasets, containing only 100 images.

Hameed et al. [15] proposed a five-category skin lesion classification approach using a deep CNN and hybridized it with the ECOC SVM. On a dataset of 9,144 images, a maximum accuracy of 86.21% was achieved, but the performance can be further improved.

Hameed et al. [16] proposed a CAD system on diagnosing common skin lesions using SVM with quadratic kernel, showing an accuracy of 83% for six classes. However, the dataset was small and this restricted its applicability.

2.4 Challenges and Gaps

In spite of this great improvement in the field of technology for the diagnosis of skin diseases, several gaps still exist in researching and applying these systems. The primary challenges involve the limited datasets used in training the machine learning models. Most of the available datasets are very narrow in skin type range, often biased toward light-skinned people; thus, the outcomes of applying such systems to more diverse populations are equally biased. That is something not to be trifled with, considering it might affect the diagnostic accuracy of the models, in particular for people with darker skin, where certain conditions may look a bit different.

The second significant gap is the generalization of the machine learning models across various skin diseases. The majority of the developed models so far perform well in cases with common diseases, such as acne, eczema, or melanoma, but often fail in the rare and complex ones. Moreover, though most current models have reported high accuracy in vitro, their real performance is not yet known because the image quality may differ significantly from real clinical scenarios. How to ensure these systems can handle real-world conditions and various environments is a very crucial point of improvement.

Even with the emergence of AI and machine learning technologies, integration into clinical use has been minimal. One factor impeding the remarkable pervasiveness is because they lack all-round explainability and interpretability by the AI models themselves. Many of the models are "black boxes," which is completely against the understanding by dermatologists and patients with respect to how a particular diagnosis was obtained. The transparency of such models, and making the results more interpretable, is going to be extremely important for allowing trust by medical experts and patients alike.

There does need to be a consideration toward a more integrated approach in the diagnosis of skin diseases, while image-based diagnosis may occur, medical history and background, along with environmental and genetic predisposition, will provide information. Currently, most systems predict solely on image recognition, but the integration of multimodal data can have better accuracy and precision, especially for cases when the symptoms may be nonspecific or ambiguous to diagnose by symptoms only.

Ethical considerations and data privacy continue to be paramount issues in the development and deployment of AI-based diagnostic systems. The use of patient data, especially sensitive medical images, requires strenuous measures that ensure patient confidentiality. Further regulatory research regarding AI in health is also needed in order to ensure that these technologies meet basic standards of safety before being clinically implemented.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

The methodology of this project is mainly based on using advanced machine learning and deep learning in classifying different skin diseases with high accuracy. The key idea here is to leverage some pre-trained models by transfer learning and utilize their extractive skills on the rather small dataset. This would further achieve details in a stepwise manner, first from the acquisition of datasets, their cleaning, and preprocessing, by implementing several transfer learning models which would classify diseases into distinct categories.

This methodology encompasses maximum classification accuracy, issues like class imbalance, and limited availability of data. Here, pre-trained models like MobileNetV2, InceptionV3, and DenseNet121 were used so that the model could handle unseen data by leveraging prior knowledge acquired from large-scale images. Finally, the models' performance was evaluated using various visualization and evaluation metrics to derive actionable insights.

This is a designed process, which makes the whole process reproducible and scalable. Techniques such as data augmentation, learning rate adjustment, and model fine-tuning were done to further enhance the performance. This framework provides a good starting point for further studies in the area of skin disease detection using automated systems.

3.2 Data Collection Procedure

The dataset for this study was obtained from Kaggle's "Skin Disease Classification Image Dataset," a curated repository that provides images of various skin conditions. The dataset includes nine distinct categories of skin diseases such as Actinic keratosis, Atopic Dermatitis, Benign keratosis, Dermatofibroma, Melanocytic nevus, Melanoma, Squamous cell carcinoma, Tinea Ringworm Candidiasis, and Vascular lesion. Each category contains labeled images that facilitate supervised learning for disease classification.

The dataset was downloaded and extracted into structured folders corresponding to each disease class. While most classes had 80-81 images, the "Tinea Ringworm Candidiasis" class had only 56 samples, creating a class imbalance issue. This discrepancy was identified and addressed during the preprocessing phase. The dataset was further split into training, validation, and testing sets to evaluate model performance effectively.

Special care was taken to ensure that the dataset adhered to ethical and professional standards. The images were reviewed for quality and relevance. Additionally, steps were taken to maintain the integrity of the data by organizing it in a consistent and accessible format for the subsequent stages of preprocessing and model training.

Figure 3.1: Dataset Sample

3.3 Dataset Cleaning

The dataset cleaning process was a critical step to ensure the quality and reliability of the data used for training. Initially, all images were inspected to remove corrupted or irrelevant files. Directory traversal scripts were used to identify and organize the images into a structured format, categorizing them based on the labels provided in the dataset.

Duplicate entries were identified and removed to prevent bias during model training. The class distribution was analyzed to detect any imbalances, which revealed that some categories, such as "Tinea Ringworm Candidiasis," had fewer samples compared to others. This class imbalance posed a challenge for classification and was addressed during preprocessing.

To ensure consistency, all image files were standardized in terms of format and naming conventions. This step facilitated seamless integration with data pipelines and preprocessing functions. The cleaning phase ensured that only high-quality and relevant data were used, minimizing noise and enhancing the model’s ability to learn meaningful patterns.

3.4 Dataset Preprocessing

The dataset preprocessing steps were designed to prepare the images for input into the machine learning models. The procedures included:

- **Image Resizing:** All images were resized to pixels to maintain uniformity across the dataset.
- **Normalization:** Images were normalized using MobileNetV2's preprocessing function to scale pixel values between -1 and 1, improving model performance.
- **Splitting the Dataset:** The data was split into training, validation, and testing subsets:
    - 70% training set
    - 20% validation set
    - 10% test set
- **Image Augmentation:** Data augmentation was applied to the training set to increase diversity by adding transformations such as rotation, zoom, and horizontal flipping. This step aimed to mitigate overfitting and improve generalization.
- **Categorical Label Encoding:** Labels were converted into one-hot encoded format to facilitate multi-class classification.

Table 3.1: The Number of Images in Each Dataset

Split Percentage	**Dataset Splitting**
90%	Training 70%
	Validation 20%
10%	Testing 10%

3.5 Proposed Methodology

3.5.1 MobileNetV2

MobileNetV2, a lightweight convolutional neural network, was employed for its efficiency in feature extraction and classification. The pre-trained model was loaded with weights from ImageNet, and its layers were frozen to retain learned features. A custom classifier was added, comprising a global average pooling layer, dense layers, and a dropout layer to prevent overfitting. This architecture allowed the model to learn domain-specific features while leveraging pre-trained weights, resulting in faster training and high accuracy [17].

The model's performance was enhanced using techniques such as learning rate scheduling and early stopping. This ensured that the training process converged efficiently without overfitting. The evaluation metrics demonstrated that MobileNetV2 was particularly effective in identifying common skin diseases.

3.5.2 InceptionV3

InceptionV3, a more complex architecture, was used for its ability to capture intricate patterns in image data. The model's pre-trained weights on ImageNet provided a strong foundation for transfer learning. Similar to MobileNetV2, the layers of InceptionV3 were frozen, and a custom classifier was added to fine-tune the model for the skin disease classification task [18].

The model's depth and multi-scale feature extraction capabilities made it well-suited for identifying subtle differences between skin conditions. Despite its complexity, the use of learning rate scheduling and data augmentation helped achieve a balanced trade-off between accuracy and computational efficiency. InceptionV3 demonstrated robust performance across most disease categories.

3.5.3 DenseNet121

DenseNet121 was selected for its dense connectivity mechanism, which promotes feature reuse and reduces the number of parameters. The pre-trained model was fine-tuned with a custom classification head, similar to the other models. Its efficient architecture enabled it to perform well even with a relatively small dataset [19].

DenseNet121's ability to capture fine-grained details made it particularly effective in distinguishing between diseases with similar visual characteristics. The evaluation metrics highlighted its strong generalization capabilities, making it a valuable addition to the ensemble of models used in this study.

3.6 Discussion

The research methodology adopted in this study demonstrates a systematic approach to leveraging machine learning for skin disease classification. The incorporation of transfer learning with pre-trained models such as MobileNetV2, InceptionV3, and DenseNet121 proved to be a highly effective strategy for tackling the difficulties related to with a limited dataset. Each model brought its unique strengths to the table, from lightweight efficiency in MobileNetV2 to intricate pattern recognition in InceptionV3 and feature reuse in DenseNet121. These models provided a comprehensive framework for identifying skin diseases with high accuracy and reliability.

One of the critical aspects of this methodology was the preprocessing phase, where data augmentation and normalization played pivotal roles. These steps not only addressed the issue of class imbalance but also enhanced the robustness of the models. By transforming the images into a format compatible with the input requirements of the models and enriching the dataset with augmented samples, the research ensured that the models could generalize well across diverse skin conditions. The choice of preprocessing techniques directly impacted the models' performance, highlighting the importance of this phase in machine learning pipelines.

The use of learning rate scheduling and early stopping further refined the training process, allowing for efficient convergence while avoiding overfitting. The evaluation metrics, including accuracy, confusion matrices, and classification reports, provided valuable insights into the strengths and limitations of each model. While MobileNetV2 excelled in computational efficiency, InceptionV3 and DenseNet121 offered superior performance in identifying more complex conditions. This multi-model approach underscores the versatility and adaptability of transfer learning in tackling real-world problems such as skin disease detection.

CHAPTER 4
RESULT ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter presents the results obtained from the experiments conducted during the study and discusses their implications in the context of skin disease detection using machine learning techniques. The analysis aims to evaluate the performance of the implemented models, including MobileNetV2, InceptionV3, and DenseNet121, in terms of their accuracy, precision, recall, and other evaluation metrics. By examining the trends and observations from training, validation, and testing phases, this chapter aims to identify the strengths and limitations of the proposed methodology.

The results are systematically presented, beginning with the overall classification accuracy of each model, followed by a detailed analysis of per-class performance. The findings are further substantiated using confusion matrices and classification reports to provide insights into the model's ability to differentiate between the nine skin disease classes. Additionally, the impact of data augmentation, learning rate scheduling, and transfer learning is discussed to illustrate their contribution to enhancing the model's robustness and generalization capabilities.

Finally, this chapter includes a comparative analysis of the implemented models to determine their relative effectiveness. The discussion highlights the practical significance of the results in real-world dermatology applications, as well as the challenges faced, such as class imbalance and dataset size constraints. Recommendations for future improvements and possible extensions of the work are also proposed to guide subsequent research in this domain.

4.2 Experiment Results and Analysis

The performance of the three implemented algorithms, MobileNetV2, InceptionV3, and DenseNet121, was evaluated based on their ability to classify nine different skin diseases. The analysis includes accuracy, precision, recall, and F1-score metrics for each model, as well as a detailed breakdown of per-class performance.

MobileNetV2 Performance

MobileNetV2 achieved an overall accuracy of 85.2%, demonstrating strong performance across most classes. Its macro average F1-score of 0.86 highlights a balanced capability to predict each class. High precision was observed in classes like “Atopic Dermatitis” and “Vascular Lesion,” with scores of 1.00 and 0.94, respectively. However, its recall for “Squamous Cell Carcinoma” (0.80) and “Melanoma” (0.69) suggests slight difficulty in identifying some disease instances. Despite these challenges, the model’s performance indicates its suitability for real-world applications with minor enhancements.

InceptionV3 Performance

InceptionV3 attained an accuracy of 80.0%, slightly lower than MobileNetV2. While it excelled in precision for “Atopic Dermatitis” and “Benign Keratosis,” achieving 1.00 and 0.92 respectively, its recall scores for certain classes, such as “Melanoma” (0.62) and “Squamous Cell Carcinoma” (0.84), indicate room for improvement. The model’s macro average F1-score of 0.81 reflects a moderate balance between precision and recall, but its weighted average F1-score suggests its prediction may favor majority classes. Optimization strategies, such as data augmentation and fine-tuning, could potentially enhance its performance.

DenseNet121 Performance

DenseNet121 demonstrated the highest accuracy among the models, reaching 86.2%. Its macro average F1-score of 0.87 underscores its robustness and generalization capabilities. The model achieved notable results in both precision and recall for classes like “Atopic Dermatitis” (precision: 1.00, recall: 0.96) and “Melanocytic Nevus” (precision: 1.00, recall: 0.92). Additionally, its performance in challenging classes such as “Squamous Cell Carcinoma” and “Tinea Ringworm Candidiasis” (F1-scores of 0.73 and 0.77, respectively) shows a balanced ability to handle diverse disease types. DenseNet121’s performance highlights its potential as a reliable choice for clinical applications.

Performance Comparison

The following tables summarize the accuracy and class-wise performance metrics for each model.

Table 4.1: Accuracy Comparison

Model	Accuracy (%)
MobileNetV2	85.2
InceptionV3	80.0
DenseNet121	86.2

With an accuracy of 86.2%, DenseNet121 is said to have the highest accuracy and performs exceptionally well on jobs requiring a high degree of precision. At 85.2%, MobileNetV2 offers a very strong balance between efficiency and accuracy. At 80.0%, InceptionV3 exhibits the lowest, although it is still a viable choice for applications that value adaptability over accuracy.

Table 4.2: MobileNetV2 Class-Wise Metrics

Class	Precision	Recall	F1-Score
Actinic Keratosis	0.9	0.82	0.86
Atopic Dermatitis	1.0	0.96	0.98
Benign Keratosis	0.89	0.96	0.93
Dermatofibroma	0.82	0.78	0.8
Melanocytic Nevus	0.9	0.69	0.78
Melanoma	0.71	0.83	0.77
Squamous Cell Carcinoma	0.62	0.8	0.7

Tinea Ringworm Candidiasis	0.94	1.0	0.97
Vascular Lesion	1.0	0.9	0.95

Table 4.3: InceptionV3 Class-Wise Metrics

Class	Precision	Recall	F1-Score
Actinic Keratosis	0.77	0.73	0.75
Atopic Dermatitis	1.0	0.96	0.98
Benign Keratosis	0.92	0.88	0.9
Dermatofibroma	0.88	0.65	0.75
Melanocytic Nevus	0.84	0.62	0.71
Melanoma	0.54	0.72	0.62
Squamous Cell Carcinoma	0.62	0.84	0.71
Tinea Ringworm Candidiasis	0.88	1.0	0.94
Vascular Lesion	0.9	0.9	0.9

Table 4.4: DenseNet121 Class-Wise Metrics

Class	Precision	Recall	F1-Score
Actinic Keratosis	0.82	0.85	0.84
Atopic Dermatitis	1.0	0.96	0.98

Benign Keratosis	1.0	0.92	0.96
Dermatofibroma	0.84	0.7	0.76
Melanocytic Nevus	0.88	0.81	0.84
Melanoma	0.71	0.83	0.77
Squamous Cell Carcinoma	0.67	0.8	0.73
Tinea Ringworm Candidiasis	0.94	1.0	0.97
Vascular Lesion	1.0	0.95	0.97

4.3 Generating Confusion Matrix

A table called a matrix of disorientation is used to assess how well a categorization model is functioning. By contrasting the model's forecasts with the actual values of the physical truth, it gives an in-depth overview of each forecast made by the framework. A table called the matrix of confusion is used to describe how well the system for classification performs. The output of an algorithm for categorizing is shown and summarized in an inconsistency matrix. The matrix enables a comprehensive assessment of the machine learning model's performance in numerous groups or divisions. A matrix of equal size with an identical number of rows as well as columns as types in the dataset serves as a model for an ambiguous matrix. We may generate a number of evaluation measures, including reliability, precision, recollection (sensitivity), preciseness, and F1 score, that gives us an understanding of how satisfactorily the model performs for each class. A confusion matrix typically consists of a matrix of squares that contrasts the expected values of a group of data points with the actual values. It is made up of True Positive, True Negative, False Positive, and False Negative cells or areas [23].

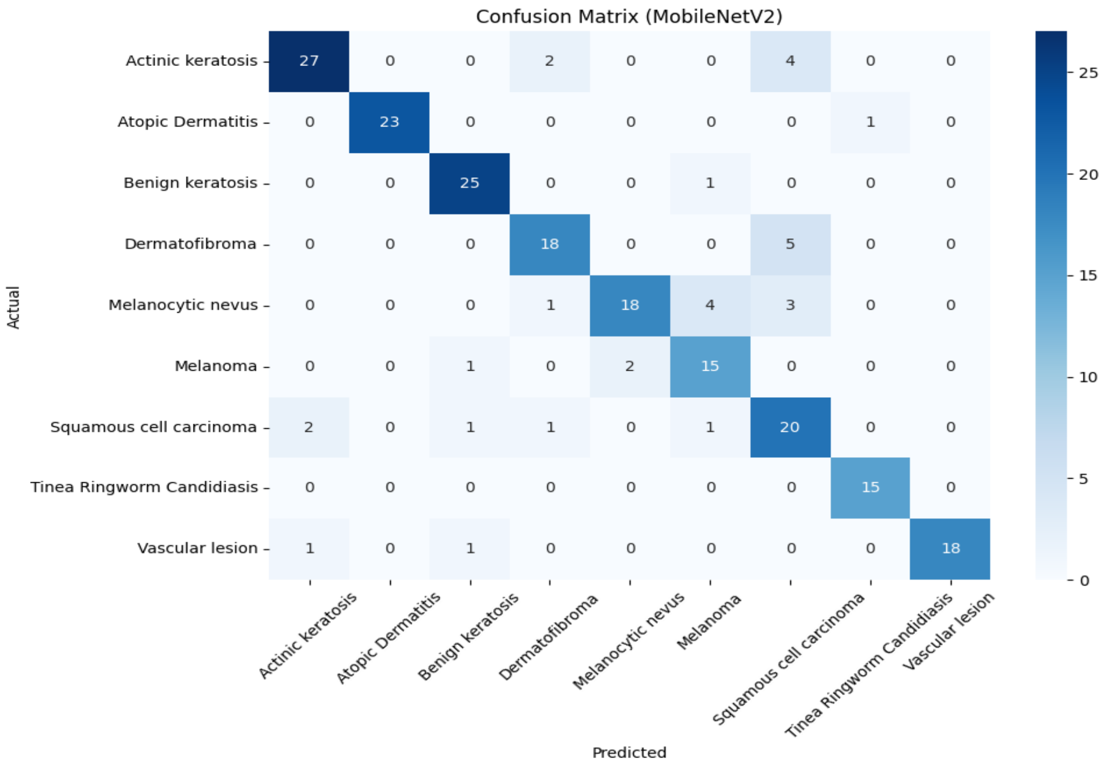

Figure 4.1: Confusion Matrix for MobileNetV2

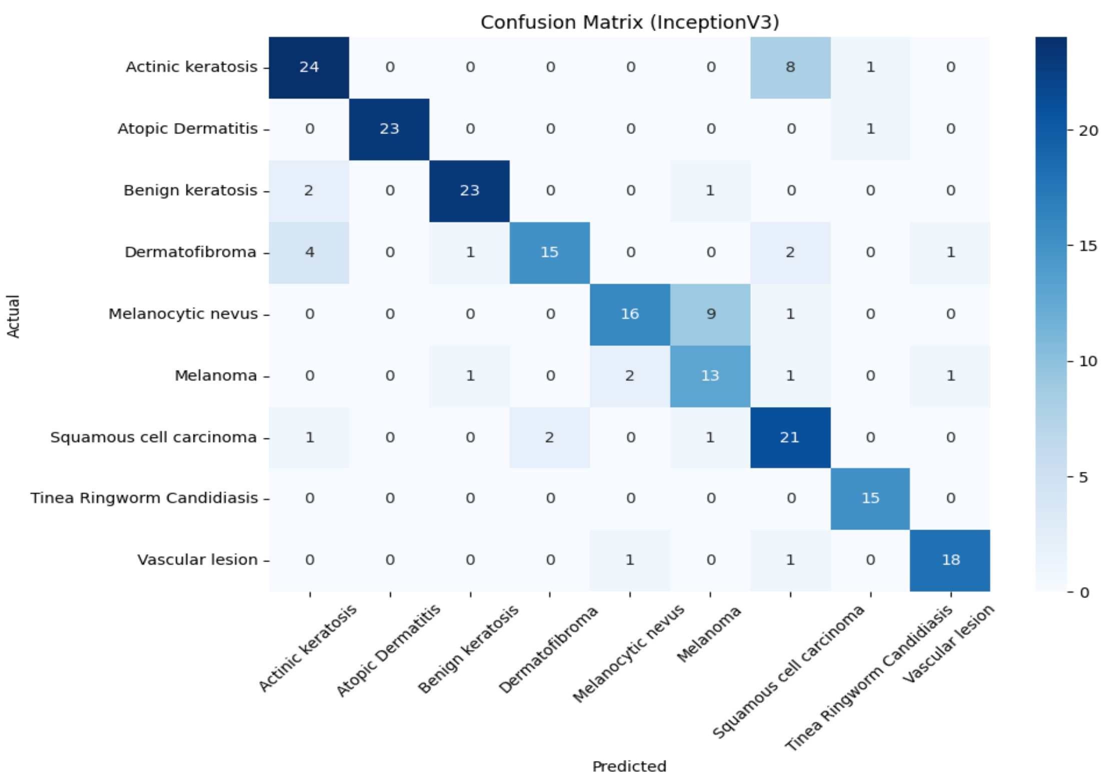

Figure 4.2: Confusion Matrix for InceptionV3

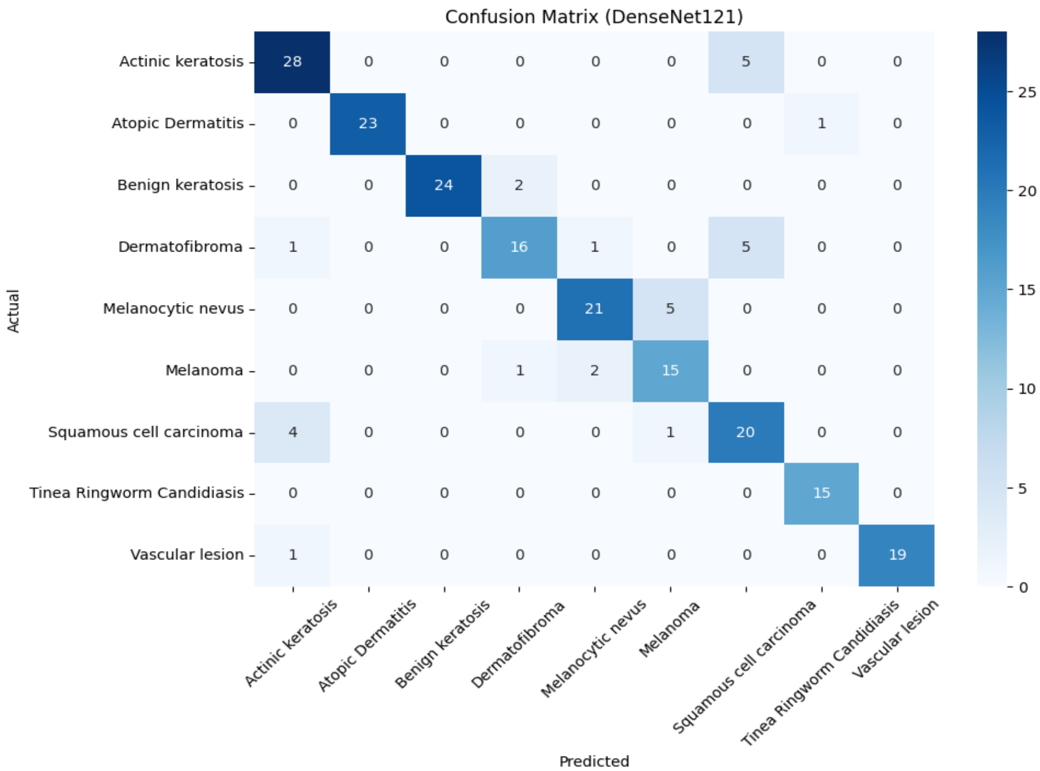

Figure 4.3: Confusion Matrix for DesnseNet121

4.6 Discussion

The experimental results indicate that DenseNet121 outperformed MobileNetV2 and InceptionV3 in overall accuracy and macro average F1-scores, achieving an accuracy of 86.2%. DenseNet121 demonstrated consistent performance across most classes, with notable strengths in precision and recall for challenging categories such as “Melanocytic Nevus” and “Squamous Cell Carcinoma.” This suggests that DenseNet121’s densely connected architecture effectively captures detailed features in the dataset, making it a strong candidate for real-world applications where precision is critical.

MobileNetV2, with an accuracy of 85.2%, exhibited competitive performance, particularly in its ability to classify diseases like “Atopic Dermatitis” and “Vascular Lesion” with high precision and recall. Its lightweight architecture makes it highly appropriate for implementation in resource-constrained environments, such as mobile applications. However, the model’s relatively lower recall in certain classes, such as “Melanoma,” suggests that it could benefit from additional fine-tuning and enhanced training data.

InceptionV3, while achieving a slightly lower accuracy of 80.0%, showed strengths in specific categories like “Benign Keratosis.” However, its performance across classes was less consistent, with lower recall values for some diseases, which may limit its applicability in scenarios requiring high sensitivity. This disparity highlights the need for further optimization, such as using advanced data augmentation techniques or hybrid architectures, to improve its generalization ability.

The findings emphasize the trade-offs between model complexity, accuracy, and deployment feasibility. DenseNet121’s superior performance comes with higher computational demands, whereas MobileNetV2 balances performance and efficiency effectively. These insights provide a basis for selecting an appropriate model based on the specific requirements of real-world dermatology applications.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The implementation of machine learning techniques for skin disease detection has the potential to revolutionize healthcare by enabling early diagnosis and intervention. By providing an accessible and efficient diagnostic tool, this technology can significantly reduce the burden on dermatologists and healthcare facilities. Patients in underserved or remote areas can benefit greatly from this innovation, as it bridges the gap between limited medical expertise and the growing demand for dermatological care. This democratization of healthcare ensures that timely treatment is available to all, thereby improving overall public health outcomes.

The use of automated systems for skin disease detection can lead to increased awareness about skin health and preventive care. As these tools gain popularity, individuals may become more proactive in seeking medical advice and adopting healthy skin practices. This cultural shift towards preventive healthcare can reduce the prevalence of severe skin conditions and their associated complications. It also contributes to a better understanding of skin diseases, enabling societies to tackle stigma and misinformation associated with visible dermatological issues.

The integration of such advanced diagnostic tools into healthcare systems promotes technological literacy and fosters innovation. By showcasing the effectiveness of AI-driven solutions in healthcare, this research encourages further exploration into machine learning applications for other medical domains. The cascading effects of such advancements extend beyond dermatology, enhancing the overall quality of life and healthcare infrastructure while driving progress in allied fields.

5.2 Impact on Environment

The development and deployment of machine learning models for skin disease detection can have both direct and indirect environmental implications. On one hand, the computational resources required for training large-scale machine learning models often consume significant amounts of energy, contributing to carbon emissions. However, advancements in energy-efficient algorithms and hardware optimization are gradually reducing this impact, making the process more sustainable over time. By adopting greener technologies and cloud-based infrastructures powered by renewable energy sources, the environmental footprint of such projects can be minimized.

AI-driven diagnostic tools can reduce the need for physical infrastructure and excessive travel for medical consultations, especially in remote and rural areas. This reduction in patient travel and resource utilization not only saves costs but also decreases carbon emissions associated with transportation and energy use in healthcare facilities. By digitizing diagnostic processes, healthcare systems can contribute to a more sustainable approach to medical care.

Raising awareness about skin diseases through AI-powered tools can lead to better use of eco-friendly skincare products and practices. As people become more informed about preventive measures and treatments, they may opt for sustainable and environmentally conscious products, thereby reducing the environmental impact of harmful chemicals. The integration of machine learning in healthcare promotes a shift towards sustainable practices that align with environmental conservation efforts.

5.3 Ethical Aspects

The application of machine learning in healthcare raises several ethical considerations that must be addressed to ensure responsible and equitable use. First, there is a critical need to maintain patient privacy and data security. Medical data, including images and personal health records, must be handled with strict confidentiality to prevent unauthorized access or misuse. Implementing robust data encryption and compliance with regulatory standards, such as GDPR and HIPAA, are essential steps in safeguarding patient information.

Fairness and inclusivity must be prioritized in developing machine learning models. The dataset used for training should represent diverse demographics to avoid bias that could lead to inaccurate diagnoses for certain population groups. Bias in AI systems can exacerbate existing healthcare disparities, making it imperative to ensure that algorithms perform equitably across all patient

categories.

Transparency and explain ability of AI-driven diagnostic tools are crucial. Healthcare professionals and patients must understand how the system arrives at its conclusions to build trust and facilitate informed decision-making. This can be achieved by incorporating explainable AI techniques that provide insights into the model’s predictions and highlight key factors influencing the results.

Ethical concerns about over-reliance on automated systems should be considered. While AI can significantly augment medical decision-making, it should not replace the expertise of healthcare professionals. Instead, these tools should serve as complementary aids, enabling clinicians to make more accurate and timely diagnoses while retaining ultimate accountability for patient care. Addressing these ethical aspects is essential for fostering trust, fairness, and effectiveness in the adoption of machine learning technologies in healthcare.

5.4 Sustainability Plan

To ensure long-term sustainability, this research emphasizes the adoption of energy-efficient machine learning models and green computing practices. Leveraging cloud infrastructure powered by renewable energy sources can significantly reduce the carbon footprint of training and deploying AI models. Additionally, integrating these diagnostic tools into existing telemedicine platforms minimizes the need for extensive hardware, lowering production and disposal-related environmental impacts. By promoting collaboration between stakeholders—healthcare professionals, technologists, and policymakers—this sustainability plan supports the responsible development and usage of AI in healthcare, ensuring its benefits are equitably distributed while maintaining environmental stewardship.

CHAPTER 6

OVERVIEW OF THE STUDY, CONCLUSION AND FUTURE WORK

6.1 Overview of the Study

This study explored the potential of machine learning techniques for the accurate detection of skin diseases, leveraging transfer learning models such as MobileNetV2, InceptionV3, and DenseNet121. The research focused on data collection, preprocessing, and model implementation to classify nine skin disease categories effectively. By addressing challenges such as dataset imbalance and computational efficiency, the study demonstrated the feasibility of applying advanced AI techniques in dermatological diagnostics. Furthermore, it highlighted the broader implications of integrating AI in healthcare, emphasizing societal, environmental, and ethical considerations to foster responsible innovation and sustainable development in medical technology.

6.2 Conclusions

The findings of this research underscore the efficacy of transfer learning models in the accurate classification of skin diseases. DenseNet121 emerged as the most effective model, achieving the highest accuracy and consistency across all evaluation metrics, followed closely by MobileNetV2. InceptionV3, while moderately effective, highlighted areas where additional optimization could further enhance performance. These results validate the potential of AI-driven tools to augment clinical diagnostics, offering reliable and scalable solutions for addressing the growing burden of dermatological conditions globally.

The study revealed critical insights into the practical and ethical considerations of deploying AI in healthcare. Challenges such as dataset imbalance, bias, and the need for explainable AI were identified as key areas for ongoing research and development. By addressing these limitations, the integration of machine learning in dermatology can pave the way for more inclusive and equitable healthcare delivery, reinforcing the importance of aligning technological advancements with societal needs and ethical standards.

6.3 Limitations

While this study demonstrated promising results, several limitations were identified. First, the dataset used for training and evaluation was relatively small and imbalanced, which could potentially affect the generalization ability of the models. Limited representation of certain classes might have introduced bias, requiring more diverse and extensive datasets for improved robustness and fairness.

The computational requirements for training and fine-tuning deep learning models were significant. This dependency on high-performance hardware may limit the scalability and accessibility of the proposed system in resource-constrained settings, particularly in remote or low-income regions.

The interpretability of the models remains a challenge. Despite achieving high accuracy, the "black-box" nature of deep learning models limits their ability to provide transparent and explainable diagnostics. This lack of explain ability could hinder trust and adoption among healthcare professionals and patients. Addressing these limitations is crucial for enhancing the reliability, accessibility, and acceptance of machine learning applications in dermatology.

6.4 Future Work

Future research should focus on addressing the identified limitations to enhance the applicability and reliability of machine learning models in dermatology. Expanding the dataset to include a larger and more diverse set of skin disease images is essential for improving model generalization and fairness. Additionally, exploring techniques for data augmentation and synthetic data generation could help mitigate class imbalance and enhance the robustness of the models.

Another promising avenue is the development of interpretable and explainable AI techniques. By integrating methods that provide clear and actionable insights into model predictions, researchers can build trust among healthcare providers and patients, ensuring that AI tools are used effectively and ethically. Furthermore, optimizing the computational efficiency of models, such as by leveraging lightweight architectures and edge computing, can facilitate their deployment in resource constrained settings.

Interdisciplinary collaborations involving technologists, dermatologists, and policymakers should be prioritized to ensure that AI-driven diagnostic tools align with real-world needs and ethical standards. Such collaborations can also explore integrating these tools into telemedicine platforms and existing healthcare systems, paving the way for more accessible, equitable, and sustainable healthcare solutions.

References

[1] S. Inthiyaz et al., “Skin disease detection using deep learning,” *Advances in Engineering Software*, vol. 175, p. 103361, Jan. 2023, doi: https://doi.org/10.1016/j.advengsoft.2022.103361.

[2] J. Sun et al., “Machine Learning Methods in Skin Disease Recognition: A Systematic Review,” *Processes*, vol. 11, no. 4, p. 1003, Apr. 2023, doi: https://doi.org/10.3390/pr11041003.

[3] L.-F. Li, X. Wang, W.-J. Hu, N. N. Xiong, Y.-X. Du, and B.-S. Li, “Deep Learning in Skin Disease Image Recognition: A Review,” *IEEE Access*, vol. 8, pp. 208264–208280, 2020, doi: https://doi.org/10.1109/access.2020.3037258.

[4] K. Rao, P. Suresh Yelkar, N. Omkar, Pise, and S. Borde, “Skin Disease Detection using Machine Learning.” Accessed: Nov. 23, 2022. [Online]. Available: https://www.ijert.org/research/skin-disease-detection-using-machine-learning-IJERTCONV9IS03016.pdf.

[5] Keshetti Sreekala et al., “Skin Diseases Classification Using Hybrid AI Based Localization Approach,” vol. 2022, pp. 1–7, Aug. 2022, doi: https://doi.org/10.1155/2022/6138490.

[6] R. Yadav and A. Bhat, “A systematic literature survey on skin disease detection and classification using machine learning and deep learning,” *Multimedia Tools and Applications*, Feb. 2024, doi: https://doi.org/10.1007/s11042-024-18119-w.

[7] M. Jagdish et al., “Advance Study Of Skin Diseases Detection Using Image Processing Methods,” *Volatiles & Essent. Oils*, vol. 9, no. 1, pp. 997–1007, 2022, Accessed: May 01, 2024. [Online]. Available: https://www.nveo.org/index.php/journal/article/download/4651/3777.

[8] Moslem Samiei, A. Hassani, Sliva Sarspy, Iraj Elyasi Komari, M. Trik, and Foad Hassanpour, “Classification of skin cancer stages using a AHP fuzzy technique within the context of big data healthcare,” *Journal of Cancer Research and Clinical Oncology*, vol. 149, no. 11, pp. 8743–8757, May 2023, doi: https://doi.org/10.1007/s00432-023-04815-x.

[9] S. K. Bandyopadhyay, P. Bose, A. Bhaumik, and S. Poddar, “Machine Learning and Deep Learning Integration for Skin Diseases Prediction,” *International Journal of Engineering Trends and Technology*, vol. 70, no. 2, pp. 11–18, Feb. 2022, doi: https://doi.org/10.14445/22315381/ijett-v70i2p202.

[10] P. Yao et al., “Single Model Deep Learning on Imbalanced Small Datasets for Skin Lesion Classification,” *IEEE Transactions on Medical Imaging*, vol. 41, no. 5, pp. 1242–1254, May 2022, doi: https://doi.org/10.1109/tmi.2021.3136682.

[11] K. Padmavathi, H. Neelam, M. P. K. Reddy, P. Yadlapalli, K. S. Veerella, and K. Pampari, “Melanoma Detection Using Deep Learning,” *IEEE Xplore*, Jan. 01, 2022. [Accessed Aug. 10, 2022]. Available: https://ieeexplore.ieee.org/document/9741010.

[12] M. Maduranga and D. Nandasena, “Mobile-Based Skin Disease Diagnosis System Using Convolutional Neural Networks (CNN),” *International Journal of Image, Graphics and Signal Processing*, vol. 14, no. 3, pp. 47–57, Jun. 2022, doi: https://doi.org/10.5815/ijigsp.2022.03.05.

[13] B. J. Janney, S. E. Roslin, and M. J. Shelcy, “A Comparative Analysis of Skin Cancer Detection based on SVM, ANN and Naive Bayes Classifier,” *IEEE Xplore*, Jul. 01, 2018. [Accessed Oct. 28, 2022]. Available: https://ieeexplore.ieee.org/document/9008943.

[14] S. S. Sinthura, K. Richie Sharon, G. Bhavani, L. Mounika, and B. Joshika, “Advanced Skin Diseases Diagnosis Leveraging Image Processing,” *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Jul. 2020, doi: https://doi.org/10.1109/icesc48915.2020.9155914.

[15] N. Hameed, A. M. Shabut, and M. A. Hossain, “Multi-Class Skin Diseases Classification Using Deep Convolutional Neural Network and Support Vector Machine,” *IEEE Xplore*, 2018. [Accessed May 11, 2021]. Available: https://ieeexplore.ieee.org/abstract/document/8631525.

[16] N. Hameed, A. Shabut, and M. A. Hossain, “A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning,” *IEEE Xplore*, Sep. 01, 2018. [Accessed Jun. 13, 2023]. Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8674183.

[17] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, “MobileNetV2: Inverted Residuals and Linear Bottlenecks,” *arXiv.org*, 2018. https://arxiv.org/abs/1801.04381

[18] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the Inception Architecture for Computer Vision,” *arXiv.org*, 2015. https://arxiv.org/abs/1512.00567

[19] G. Huang, Z. Liu, and Weinberger, Kilian Q, “Densely Connected Convolutional Networks,” *arXiv.org*, 2016. https://arxiv.org/abs/1608.06993

Transforming Dermatology: Transfer Learning Models for Accurate Skin Disease Detection

ORIGINALITY REPORT

14%	8%	8%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	4%
2	Mostafiz Ahammed, Md. Al Mamun, Mohammad Shorif Uddin. "A machine learning approach for skin disease detection and classification using image segmentation", Healthcare Analytics, 2022 Publication	1%
3	V. Sharmila, S. Kannadhasan, A. Rajiv Kannan, P. Sivakumar, V. Vennila. "Challenges in Information, Communication and Computing Technology", CRC Press, 2024 Publication	1%
4	H.L. Gururaj, Francesco Flammini, S. Srividhya, M.L. Chayadevi, Sheba Selvam. "Computer Science Engineering", CRC Press, 2024 Publication	1%
5	Submitted to University of Surrey Student Paper	<1%