DEEP LEARNING FOR EQUITABLE DERMATOLOGICAL DIAGNOSIS: ENHANSING HEALTHCARE ACCESSIBILITY

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled **"Deep Learning for Equitable Dermatological Diagnosis: Enhancing Healthcare Accessibility."**, submitted by Md. Abu Naser, ID No: **201-15-13785** 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.

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We hereby declare that this project has been done by us under the supervision of **Ms. Umme Ayman, Lecturer**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Our research presents an innovative deep learning approach designed to enhance dermatologic diagnosis by addressing the significant challenges of subtle color variations and complex lesion morphology. Accurate diagnosis in dermatology is critical, as skin diseases can have profound implications on a patient's health and quality of life. Misdiagnosis can lead to inappropriate treatments, exacerbation of conditions, and increased healthcare costs. To tackle these challenges, our method leverages the strengths of Convolutional Neural Networks (CNNs) with a focus on the efficient and lightweight MobileNet version 3 and MobileNet version 2. CNNs are well-established for their effectiveness in image analysis, and MobileNet v3, in particular, offers a streamlined architecture that is both powerful and resource-efficient. In our research, we trained MobileNet v3 & MobileNet v2 on a large dataset of color-skin images sourced from Kaggle. This dataset provided a diverse and comprehensive collection of dermatologic images necessary for extracting discriminative features from various skin lesions, a crucial step for distinguishing between different types of skin conditions. MobileNet was employed to handle the intricate task of capturing fine-grained details and subtle color variations within the images. Its architecture allows for efficient processing, making it feasible to deploy in real-world clinical settings where computational resources may be limited. This capability allowed for precise lesion segmentation and classification, significantly enhancing diagnostic accuracy. Our model offers several advantages, enabling the collection of both local and global information essential for accurately diagnosing complex skin conditions. Additionally, our approach outperforms traditional single-architecture models in image classification tasks, leveraging the specific strengths of MobileNet v3 & MobileNet v2 to achieve superior performance. In conclusion, our research provides a promising solution to the challenges of dermatologic diagnosis, demonstrating superior performance compared to conventional methods and offering more accurate and reliable diagnoses for various skin condition.

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Introduction

Technology has completely changed the medical industry, especially in the areas of diagnosis and therapy. A crucial obstacle in this dynamic environment is the prompt and precise diagnosis of skin disorders, which affect millions of people globally in differing degrees of severity. The majority of dermatological care in Bangladesh consists of time-consuming, expensive procedures performed by dermatologists, whether they are practicing professionals or residents. Due to over-referrals and budgetary restrictions, dermatologists are sometimes forced to offer general care, underutilizing their specialist training. This emphasis frequently ignores preventative and public health activities. These difficulties are made worse by financial and technical constraints.

The wealthy continue to have disproportionate access to modern skincare products, meaning that 80% of the public lacks sufficient dermatological treatment. Patients at public hospitals frequently face additional financial hardships, which further limits their access. Furthermore, new doctors' potential is limited by the lack of dermatology instruction in medical colleges, particularly in rural regions. Even though they play a crucial role in the community, informal healthcare practitioners usually don't have enough dermatological knowledge. Even though skin problems have a significant influence on quality of life, more common diseases usually take precedence in healthcare policy goals. Moreover, the emphasis on specialist treatment utilizing cutting-edge technologies hinders the growth of fair and easily available dermatological services, which adds to Bangladesh's subpar general skin health.

Deep learning technology represents a disruptive force in dermatology, pushing the boundaries of accuracy and efficiency in disease detection. These advanced models excel at identifying a wide spectrum of skin conditions and capturing subtle details that traditional diagnostic methods often miss. By leveraging extensive datasets and sophisticated algorithms, deep learning systems achieve unprecedented levels of precision in analyzing dermatological images, promising a transformative shift in healthcare delivery.

This paper explores the synergistic potential of deep learning within the evolving healthcare landscape, aiming to pioneer a more efficient, reliable, and user-friendly approach to skin disease detection. Through an exploration of deep learning frameworks, an analysis of historical perspectives on dermatological diagnostics, and an in-depth examination of the complexities of skin diseases, this research underscores the transformative impact on diagnostic accuracy and accessibility. The integration of deep learning not only enhances diagnostic capabilities but also democratizes healthcare by extending expert-level diagnoses to a broader population. Beyond dermatology, this study reflects broader transformations in healthcare, catalyzed by the convergence of advanced technology and medical practice. While current methods primarily rely on color images, integrating dermatoscopic and textual information could enrich diagnostic features and bolster algorithm robustness. Despite their effectiveness, deep learning models lack transparency in decision-making processes. Methods such as saliency maps are crucial for enhancing trust and aiding clinical decision-making. Standardized benchmarks are scarce, hindering comprehensive evaluations across datasets and methodologies, thereby limiting advancements in the field. Practical challenges such as variable data quality and resource constraints are often overlooked in research, necessitating tailored solutions for effective model deployment in diverse healthcare settings. Traditional models' computational demands hinder their deployment on mobile and edge devices. Lightweight architectures like MobileNet V3 & MobileNet V2 offer promising solutions for extending diagnostic capabilities to resource-limited environments.

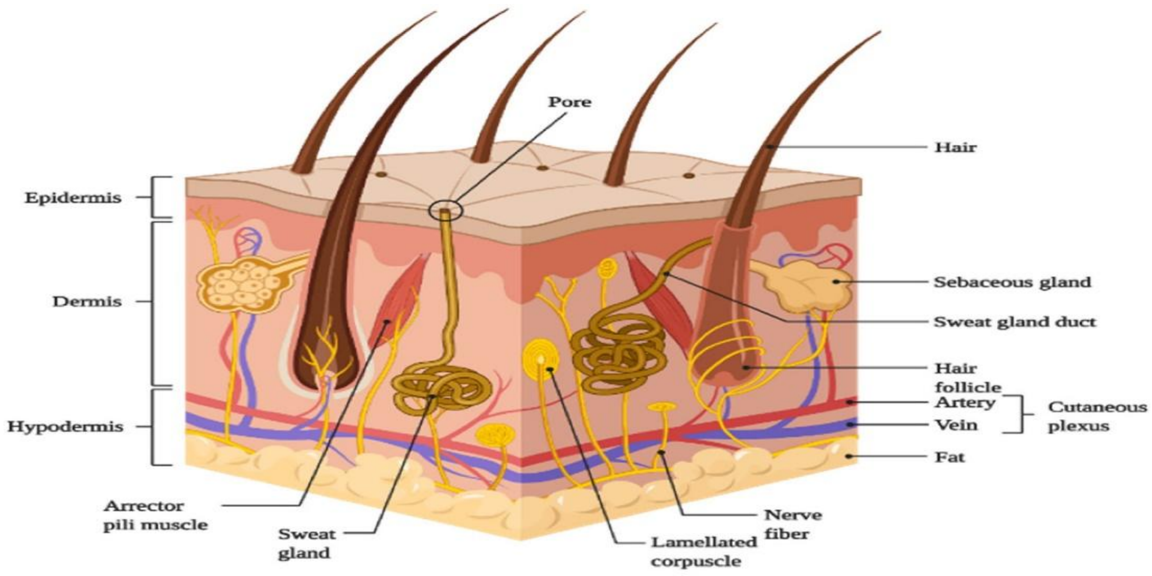

Figure 1.1.1: Schematic representation of human skin and underlying structures.

1.2 Motivation

This study is important because the scope of dermatology practice in developing contexts, such as Bangladesh is limited. This problem of neglect with regard to skin diseases affects a person's health, life and even their general wellbeing. Moreover, the large deficit that exists between the need for dermatology services and the ability to provide them on a timely and precise basis has motivated this work.

Addressing Diagnostic Challenges:

The diagnostic procedures in dermatology are quite afflicted by the human factor and on some occasions subjective assessment of the dermatologist. This makes the issue of subtle lesions and conditions, but they have the overlapping feat, difficult. In most instances, especially in more complicated cases than allergic contact dermatitis, in which there are subtle shades of color or complex morphology of lesions, a traditional approach to conducting diagnosis often yields unsatisfactory or at least not convincing results.

Closing the Accessibility Gap:

Due to infrastructure, financial, and geographic constraints, the great majority of people in nations like Bangladesh do not have access to specialized dermatological care. Rural areas sometimes rely on unlicensed medical professionals who lack sufficient dermatology training, which increases the possibility of improper or delayed treatment.

Leveraging Technological Advancements:

By increasing precision and efficiency, recent developments in deep learning, especially lightweight architectures like MobileNet, offer a chance to completely transform dermatological diagnostics. By bringing expert-level diagnostic capabilities to underprivileged areas, mobile and edge-compatible solutions have the potential to democratize access to healthcare.

Reducing Healthcare Inequities:

This study attempts to enable people from all socioeconomic backgrounds to obtain prompt and precise diagnoses by addressing inequalities in access to high-quality healthcare. By automating diagnostic procedures, dermatologists can concentrate on challenging cases while AI systems handle routine evaluations, relieving the strain on healthcare systems.

Supporting Sustainable Medical Practices:

The demand for sustainable healthcare technologies is in line with the growing interest in environmentally friendly AI solutions. MobileNet and other lightweight models use less computing power, which makes them perfect for low-power device deployment.

Inspiring Future Research:

The goal of this study is to stimulate more research into using cutting-edge AI techniques for healthcare applications, specifically in the ethical deployment of AI and the integration of multi-modal data.

1.3 Objectives

This research aims to address key challenges in dermatological diagnostics using advanced machine learning approaches, including integrating MobileNet v2 and MobileNet v3 architectures. By leveraging these innovative technologies, the research aims to improve the accuracy, accessibility, and efficiency of diagnosing skin diseases, especially in resource-constrained settings such as Bangladesh. The objectives are outlined as follows:

Enhance Diagnostic Accuracy: Develop machine learning models capable of accurately classifying and differentiating various skin diseases based on complex lesion morphology, subtle color variations, and other nuanced dermatological features. This objective aims to reduce diagnostic errors and address the subjectivity and biases prevalent in traditional methods.

Automate and Streamline Diagnosis: Implement automated diagnostic systems utilizing deep learning frameworks such as Convolutional Neural Networks (CNNs), incorporating lightweight architectures like MobileNet v2 and MobileNet v3. This objective seeks to optimize diagnostic workflows by reducing the time and computational resources required for evaluation, enabling quicker and more efficient patient care.

Improve Scalability and Accessibility: Develop diagnostic models compatible with mobile and edge computing devices to expand access to advanced diagnostic tools in rural and underserved areas. The lightweight and efficient design of MobileNet v2 and v3 makes them ideal for deployment in resource-constrained environments, bridging the gap between urban and rural healthcare services.

Enhance Interpretability of AI Models: Incorporate interpretability techniques into machine learning models to improve transparency and trust in AI-driven diagnostic decisions. This objective focuses on making the outputs of MobileNet v2 and v3 more understandable to healthcare professionals, empowering them to make informed clinical decisions and promoting the adoption of AI solutions in dermatology.

Address Data Quality and Diversity: Curate and utilize diverse, representative dermatological datasets that include various skin types, conditions, and demographics.

This objective aims to train MobileNet v2 and v3 models with balanced datasets, mitigating biases and enhancing their generalizability across diverse populations, ensuring equitable diagnostic outcomes.

Ensure Ethical and Legal Compliance: Establish ethical frameworks for deploying AI technologies in dermatology, addressing patient privacy, data security, and algorithmic biases. This objective seeks to uphold ethical standards in healthcare AI implementation, ensuring trust and compliance with legal and regulatory requirements in settings where MobileNet-based solutions are employed.

1.4 Methodology

The process begins with data acquisition from the HAM10000 dataset, a well-known repository of dermatoscopic images. To ensure the integrity and quality of the dataset, rigorous preprocessing steps such as resizing, normalization, and augmentation are applied. These preprocessing techniques are critical for enhancing the robustness and generalization capabilities of the model across diverse skin conditions and variations in image quality.

The core methodology employs transfer learning with MobileNet Version 2 and MobileNet Version 3, lightweight convolutional neural networks renowned for their efficiency in mobile and edge computing environments. By utilizing pre-trained weights from these models, significant features are extracted from skin lesion images. Fine-tuning on the specific dermatological dataset further optimizes these models, ensuring faster convergence and efficient utilization of computational resources. This makes the system particularly suitable for deployment in resource-constrained settings.

The implementation phase centers on the development of a user-friendly web application using “Streamlit”. This application allows users to upload images and receive real-time predictions regarding skin disease classes. The integration of the trained MobileNet models into the web app ensures seamless accessibility and usability, bridging the gap between cutting-edge machine learning technologies and practical healthcare solutions.

The system's performance is rigorously evaluated using metrics such as accuracy, precision, recall, and F1-score. Extensive validation is performed against diverse datasets, followed by iterative refinement based on user feedback. This approach ensures that the system meets high clinical standards and user expectations. The resulting diagnostic tool demonstrates significant potential for improving dermatological care, making advanced diagnostic capabilities accessible to a broader audience.

1.5 Project Outcome

Practical Applications:

Accurate and Efficient Diagnosis: The AI-driven system developed in this project can provide accurate and efficient skin disease diagnosis, reducing reliance on subjective human interpretation. The lightweight architectures (MobileNet v2 and v3) enable real-time predictions suitable for both clinical and non-clinical environments.

Improved Healthcare Access: The deployment of the model via a user-friendly web application ensures accessibility for underserved populations, particularly in rural or resource-constrained settings. Mobile compatibility allows patients and informal healthcare providers to use the diagnostic tool without needing specialized hardware or advanced technical knowledge.

Early Detection and Prevention: By enabling early and accurate diagnosis, the system can contribute to timely medical interventions, improving treatment outcomes and reducing the progression of severe conditions.

Integration with Telemedicine: The system can serve as a foundational tool for telemedicine platforms, facilitating remote consultations and improving healthcare delivery in remote areas.

Advancements in Dermatological Diagnostics:

Benchmark for Lightweight Architectures: The project demonstrates the feasibility of using efficient architectures like MobileNet for medical imaging, setting a benchmark for future research in AI-driven diagnostics.

Framework for Model Interpretability: The integration of explainability techniques, such as saliency maps, can increase trust in AI systems, encouraging broader adoption in clinical practice.

Scalable AI Solutions: The project establishes a scalable framework for deploying AI models in resource-constrained environments, balancing performance and computational efficiency.

Contribution to AI and Healthcare Research:

Data-Driven Insights: The project showcases how data augmentation and transfer learning can address challenges like limited dataset size and class imbalance, providing a roadmap for similar applications in other domains.

Ethical AI Practices: The emphasis on data privacy, diversity, and bias mitigation contributes to the development of more ethical and equitable AI systems for healthcare.

Generalizability Across Domains: The methodologies used in this work, such as lightweight model deployment and interpretability, can inspire similar applications in other fields of medical imaging, such as ophthalmology or radiology.

Potential Societal Impact:

Democratization of Healthcare: The system can bridge the gap between urban and rural healthcare, offering equitable access to expert-level dermatological care regardless of geographic or economic constraints.

Reduced Healthcare Costs: Automated diagnostics can decrease the burden on healthcare systems, reducing the cost of consultations and freeing up specialists for more complex cases.

Awareness and Education: The tool can be used for patient education, helping individuals understand their skin conditions and seek timely medical advice.

Future Research Directions:

Multi-Modal Diagnostic Systems: Incorporating additional data, such as patient history or dermatoscopic images, could enhance diagnostic accuracy and robustness.

Real-World Validation: Deployment in clinical settings could provide insights into the tool's effectiveness, usability, and areas for improvement.

Enhancement of Lightweight Models: Further optimization of MobileNet architectures or exploration of other lightweight models could improve performance while reducing energy consumption.

Global Health Applications: Adaptation of the system for diverse populations worldwide by including datasets that represent different ethnicities and skin types.

1.6 Organization of the Report

This report is structured into six chapters, each focusing on a specific aspect of the research and development process. The organization ensures a coherent and comprehensive presentation of the project, its context, implementation, and outcomes. The chapters are as follows:

Chapter 1: Introduction

Chapter 1 introduces the focus of this study on leveraging deep learning for skin disease diagnosis and detection. It outlines the research goals aimed at enhancing diagnostic accuracy and accessibility in dermatology through advanced technology. Addressing key research questions, this chapter underscores the significance of integrating deep learning into medical imaging for more precise diagnostic outcomes. The structure of the report is outlined to provide a roadmap for navigating through subsequent chapters, emphasizing the critical role of deep learning in transforming dermatological care.

Chapter 2: Background

Chapter 2 presents a comprehensive review of existing literature pertaining to skin disease diagnostics and the evolution of deep learning applications in medical imaging. It explores various skin conditions, traditional diagnostic methods, and the technological advancements that have shaped the field. A detailed comparison of methodologies and approaches used in previous research efforts provides insights into current practices and identifies gaps that warrant further investigation. This chapter contextualizes the study within the historical development of deep learning in dermatology, setting the stage for proposing innovative solutions.

Chapter 3: Research Methodology

Chapter 3 details the methodology essential for implementing deep learning models in dermatological diagnostics. It outlines protocols for data collection, preparation methods, and the systematic design and implementation of deep learning architectures tailored for skin disease detection. Hardware and software requirements are specified to support the proposed system, with considerations for project management and financial analysis discussed to ensure feasibility and scalability. This chapter provides a structured approach to guide the implementation phase and aligns with the study's objectives.

Chapter 4: Implementations and Results

Chapter 4 focuses on the technical implementation and the outcomes of the project. It describes the environment setup, tools, and libraries used for model training and application development. The results section includes the performance metrics of MobileNet v2 and v3 models, training and validation accuracy, and a discussion of the confusion matrix and classification reports. Screenshots of the user interface and outputs of the web application are also included to showcase its functionality.

Chapter 5: Engineering Standards and Design Challenges

Chapter 5 discusses the adherence to engineering and ethical standards throughout the project. It covers compliance with software and hardware standards, secure data handling protocols, and ethical considerations like bias mitigation and patient privacy. The design challenges encountered during model implementation and deployment are analyzed, along with strategies to overcome them. The societal and environmental impacts of the project, including its potential for democratizing healthcare and reducing carbon footprints, are also elaborated

Chapter 6: Conclusion and Future Work

Chapter 6 summarizes the research findings, emphasizing the achievements and contributions of the project. It reflects on the limitations faced during implementation and provides recommendations for future work. Potential directions include improving the model's interpretability, incorporating multi-modal data, and testing the system in real-world clinical environments.

References:

This section includes a comprehensive list of all the academic papers, datasets, tools, and other resources consulted and cited in the report.

Chapter 2

Background

2.1 Introduction

The research explores various methodologies for automating skin disease recognition using advanced imaging techniques and AI, including Machine Learning, ANNs, and CNNs. Morphological operations and Genetic Algorithms (GAs) assist in disease classification, though they face challenges like convergence and optimal solutions. Support Vector Machines (SVMs) effectively detect eczema but struggle with noisy data, while ANNs and CNNs provide high accuracy in skin condition diagnosis, albeit with issues related to image scaling and significant training data requirements. Deep Neural Networks (DNNs) show promise but need extensive training and computational power. Techniques such as the Gray Level Co-occurrence Matrix (GLCM) for texture analysis, Bayesian classification, and Decision Trees offer additional methods but encounter challenges like rotation invariance and data sensitivity. K-Nearest Neighbor (KNN) models, although accurate, are unsuitable for large datasets. Ensemble models, which combine predictors, risk overfitting yet improve accuracy. Cross-correlation models enhance predictions by analyzing spatial and frequency features. Finally, the integration of technology through mobile applications supports convenient disease assessment, aligning with trends in health interventions like text messaging and IoT models for remote patient monitoring.

2.2 Literature Review

Table 2.2.1: Summary of Literature Reviewed.

Author(s)	Year	Title	Methodology	Key Findings
Tehseen Mazhar et al.	2020	Deep Learning for Skin Disease Detection Using CNN, KNN, ANN, and RBFN	KNN and ANN with CNN-based deep learning architectures.	CNN outperformed other models in terms of accuracy but required higher computational resources.
Zhou H. et al.	2019	Comparative Study of Deep Learning Architectures for Skin Disease Classification.	Evaluated the performance of VGG-16, GoogLeNet, ResNext-50, and ResNet-50 on a dataset of skin lesions.	ResNet-50 achieved the highest accuracy (65.8%) among the models but struggled with subtle lesion differences
Gavrilov D.A. et al.	2018	Neural Networks by Deep Learning for Dermatological Diagnosis	Developed a neural network-based model fine-tuned for skin disease classification using dermatoscopic images.	Achieved a validation accuracy of 91% but noted the need for improvements in handling noisy and low-quality images.
S. Othman et al.	2021	Application of MobileNet v2 for Skin Lesion Classification	Utilized MobileNet v2 with transfer learning on a dataset of skin lesion images.	MobileNet v2 achieved an accuracy of 98.5%, showcasing its effectiveness in resource-limited environments.
Geert Litjens et al.	2017	Deep Learning in Medical Imaging: Overview and Future Directions	Focused on CNNs and RNNs for automated diagnosis using large datasets.	CNNs were found to be highly effective for lesion segmentation and classification but required extensive training data. RNNs showed promise in temporal data analysis but were computationally intensive.
Nawal Soliman Alkolifi Alenezi	2020	Evaluation of CNN and SVM for Melanoma and Non-Melanoma Skin Cancer Detection	Utilized texture-based feature extraction techniques for SVM and end-to-end learning for CNN.	CNN achieved higher accuracy (Melanoma: 100%) compared to SVM. SVM was more sensitive to noise and lacked scalability for large datasets.

Yasamin Borhani et al.	2021	Comparison of CNN and ViT for Skin Disease Classification	Evaluated Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) for diagnosing skin diseases.	CNNs performed better with limited data, while ViTs showed superior results with larger, more diverse datasets.
Nayak R. and Hasija Y.	2021	Leveraging GANs and RNNs for Skin Disease Dataset Augmentation and Diagnosis	Used Generative Adversarial Networks (GANs) to generate synthetic skin lesion images and RNNs for sequential pattern recognition.	GAN-augmented datasets improved the diagnostic accuracy of CNNs by 5-10%. RNNs were effective in analyzing sequential lesion changes, enabling longitudinal diagnosis.
Adamson and Smith	2021	Machine Learning in Dermatology: Challenges and Future Directions	Conducted a comparative analysis of traditional machine learning algorithms (e.g., Decision Trees, KNN) and deep learning models for diagnosing common skin conditions.	Deep learning models consistently outperformed traditional methods in accuracy and scalability. Deep learning models consistently outperformed traditional methods in accuracy and scalability.
Liao H. et al.	2020	Fine-Tuning CNNs for Skin Lesion Classification: A Comparison of Techniques	Investigated various fine-tuning strategies for CNNs (ResNet, DenseNet) applied to skin lesion datasets.	Fine-tuning the last three layers of pre-trained models yielded the best results, with a Top-1 accuracy of 88%. DenseNet showed superior performance in handling subtle lesion features compared to ResNet.
Ijaz et al.	2022	IoT and AI Integration for Remote Dermatological Diagnostics	Proposed an IoT-based framework integrating CNN models for automated dermatological diagnostics.	The system achieved real-time diagnostic capabilities with 85% accuracy on edge devices.

2.2.1 Similar Applications

Aysa: A mobile app designed to assess skin conditions using AI. Users upload photos of their skin, and the app provides likely conditions and recommendations for further action.

Miiskin: A mobile app that helps users track changes in their skin by comparing photos over time. While primarily a self-monitoring tool, it incorporates AI to flag potential concerns.

MoleMapper: Utilizes AI to classify and monitor moles. It integrates patient data and imaging to provide personalized assessments, similar to telemedicine approaches.

DeepDerm: A mobile app leveraging CNNs for skin lesion classification. It focuses on melanoma detection and provides real-time results to patients.

2.2.2 Related Research

There are different approaches using different methodologies to automate the identification and classification of skin disease. Most imaging methods belong to the family of diagnostic technologies that have revolutionized the diagnosis of epidermal diseases, placing them ome at a distance from traditional radiological methods. These methods utilize various image processing techniques (e.g., transformation, equalization, enhancement, edge detection, segmentation), which have been extensively applied to the analysis of standard images [1–3]. Images of the skin are obtained to identify and categorize diseases, processed, and fed as inputs in high-level artificial intelligence (AI) tools, including Machine Learning, Deep Learning, ArtificIA Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Back Propagation Neural Networks, and classifiers (like Support Vector Machines (SVM) and Bayesian classifiers), to predict the type of skin disease.

In addition, skin diseases are also identified by the use of basic image processing techniques such as morphological operations for the detection of skin lesions [4,5]. The morphological operations like opening, closing, dilation, and erosion rely on binary images obtained by thresholding. Optimal threshold values must be determined with great care, although these operations may not effectively estimate the growth of damaged regions based on image texture. GAs have been established for classification of skin diseases [6,7], though these pose problems like longer convergence time toward the solution [8], often not achieving globally optimum solution, hence affecting outcomes [9].

Alam et al. [10] performed automated eczema detection through image processing by using a support vector machine (SVM) with steps such as segmentation of acquired images, feature selection based on texture-based information to make accurate predictions, and the use of SVMs in evaluating eczema progression [11]. But SVM models are not good at dealing with noisy image data [12], and it requires much consideration in selecting feature-based parameters. They perform poorly when the number of parameters in each feature vector is larger than the training data samples.

Artificial Neural Networks (ANNs) [13] and Convolutional Neural Networks (CNNs) [14] are commonly employed approaches for anomaly detection and diagnosis in radiological imaging technologies. While the CNNs have shown promising results in the diagnosis of skin disease [15], they suffer from the problems of scale and rotation invariance while handling the images captured using mobile or digital cameras. ANN-based models for early breast cancer detection using image processing require large datasets for training to achieve relevant performance, demanding high computational effort [16]. These models are quite abstract and do not allow customization accessibility. The number of trainable parameters in ANNs drastically increases with the rise in image resolution, leading to demanding training efforts. ANNs are vulnerable to issues like vanishing and exploding gradients, while CNNs do not grasp the size and scale of objects in observations [17].

A neural network-based model that was fine-tuned for skin disease classification attained a validation set accuracy of 89.90% [18], but at the cost of extensive effort to tune network components for achieving desired accuracy. Back Propagation Neural Networks [19] which operate on the gradient descent principle to adjust weights depending upon the error rates, have difficulty with noisy data. Another issue is that these networks forget previously associated weights once fed with new weights—this dramatically influences the previous associations [20]. Fuzzy Recurrent Neural Networks (FRNNs) [21] and Takagi–Sugeno–Kang Fuzzy Classifiers [22] have reached reasonable accuracy in a variety of classification problems. They are performing remarkably well with variable size inputs without sacrificing the integrity of the model. RNNs have been designed to process data available in arbitrary memory, while most neural network models require auxiliary memory for processing. On the other hand, RNNs are slow because of the high computational requirements and FRNNs, requires much effort in classifying patterns from the image data it consumes much of computational time.

Intensity-based classification, on the other hand, employs statistical approaches to extract features from captured images, mainly parameters based on texture [23]. GLCM arranges frequency distributions of combinations of intensity values within an image. In contrast, using GLCM requires considerable computational requirements and the available properties are very sensitive to changes in rotation and texture [24].

Bayesian classification is one of the methods used in skin disease classification [25], which is applied to classify images between different trained disease image datasets. However, Naïve Bayes classification suffers from independent predictors and the zero-probability problem, which makes it difficult to be implemented in multi-objective fields. Naïve Bayes classifiers are not good at dealing with unsupervised data classification [26]. Decision Tree algorithms [27], widely adopted for skin disease classification and prediction of conditions such as lower limb ulcers or cervical cancer, need numerous training and high accuracy; even slight changes in the input data can exponentially deviate the outcomes. Therefore, the model is sensitive to the data. In addition, Decision Trees require more memory and computational time [28].

K-Nearest Neighbor (KNN) [29], one of the most commonly used classification models in forecasting and predictive models, does not require training. It also has high accuracy [30]. KNN models, however, are not applicable to larger datasets; these models tend to take a long time to predict outcomes. They also perform poorly with high-dimensional data and inappropriate feature information, probably compromising accuracy [31] and thus are not appropriate for skin disease classification.

Ensemble models for skin disease classification [32] use more than one prediction model to get a better result. However, the disadvantages of these models are overfitting and cannot handle unknown differences between sample and population [33.34]. Deep Neural Network (DNN) models for skin disease classification [35,36] have gained significant performance but are not suitable for multi-lesion images based on experimental research. DNNs need large training to achieve acceptable accuracy, which takes much computational time.

Cross-correlation models for feature extraction-based classification [37] assume spatial and frequency features to be considered for selection by using visual coherence, robust to background fluctuations, resulting in predictions of greater accuracy. To work in the frequency domain takes much effort in experimenting and acquiring results.

The suggested framework is linked to a mobile application, which is among various experimental applications aimed at facilitating disease evaluation. Lee et al. [38] examined the influence of text messaging on the advantages of human papillomavirus (HPV) vaccination, observing a significant increase in the uptake of HPV vaccines within specific communities. In a separate investigation, Weaver et al. [39] focused on screening participation, where cancer screening services employed text messaging as a means of communication. Ijaz et al. [40] presented an IoT model for healthcare that allows patients to remotely access healthcare gadgets for the analysis and monitoring of their health through biomedical signals and interconnects healthcare professionals in emergency situations.

2.3 Gap Analysis

This project addresses critical gaps in the field of dermatological diagnostics, focusing on accessibility, accuracy, interpretability, and scalability. Despite significant advancements in deep learning and AI applications for healthcare, several challenges remain unaddressed. Below is a summary of the key gaps that this project intends to work on:

1. Accessibility and Equity in Dermatological Care:

Current Gap: Access to specialized dermatological care is limited, especially in resource-constrained settings like rural areas of Bangladesh. Most existing solutions are designed for well-equipped clinical environments, leaving underserved populations without adequate diagnostic tools.
Project Focus: This project aims to democratize dermatological care by developing a lightweight, mobile-compatible diagnostic system that can function efficiently in low-resource settings. The use of MobileNet v2 and v3 ensures compatibility with edge devices, enabling real-time diagnostics in rural and underserved areas.

2. Diagnostic Accuracy and Robustness:

Current Gap: Many traditional diagnostic methods and some machine learning models struggle with subtle lesion morphology and color variations, leading to misclassifications. Inconsistent data quality and the lack of diverse datasets further exacerbate this issue.
Project Focus: By leveraging transfer learning and data augmentation, the project enhances model robustness to subtle variations and improves classification accuracy for a wide range of skin conditions. The focus on using well-annotated datasets like HAM10000 ensures reliable performance.

3. Interpretability and Trust in AI Models:

Current Gap: Deep learning models are often criticized for being "black boxes," making it challenging for healthcare professionals to understand and trust their decisions. This lack of transparency hinders clinical adoption.

Project Focus: This project integrates interpretability techniques, such as saliency maps, to provide visual explanations for the model's predictions. This approach fosters trust among healthcare providers by making the decision-making process transparent and clinically relevant.

4. Scalability and Deployment Challenges:

Current Gap: Many AI solutions for dermatology require substantial computational resources, making them impractical for deployment on mobile or edge devices. Additionally, these solutions often lack flexibility for integration into existing healthcare systems.

Project Focus: The project adopts lightweight architectures (MobileNet v2 and v3), which are optimized for deployment on low-power devices. By developing a user-friendly web application using Streamlit, the project ensures that the solution is scalable and easily deployable in diverse settings, including telemedicine platforms.

2.4 Summary

The background studies in this research focused on the application of deep learning in dermatology, highlighting the potential of models like MobileNet for diagnosing skin conditions. Previous studies demonstrated the effectiveness of convolutional neural networks in image classification, particularly for medical imaging. Challenges such as dataset diversity, model interpretability, and ethical considerations were explored, emphasizing the need for inclusive data and transparency in AI systems. The integration of AI in healthcare settings and its implications for resource-limited environments were also reviewed, providing a foundation for developing accessible, accurate, and ethical diagnostic tool.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

This chapter outlines the methodology for developing a skin disease diagnostic system using deep learning techniques. The process begins with data acquisition from the HAM10000 dataset, a well-known repository of dermatoscopic images. To ensure the integrity and quality of the dataset, rigorous preprocessing steps such as resizing, normalization, and augmentation are applied. These preprocessing techniques are critical for enhancing the robustness and generalization capabilities of the model across diverse skin conditions and variations in image quality.

The core methodology employs transfer learning with MobileNet Version 2 and MobileNet Version 3, lightweight convolutional neural networks renowned for their efficiency in mobile and edge computing environments. By utilizing pre-trained weights from these models, significant features are extracted from skin lesion images. Fine-tuning on the specific dermatological dataset further optimizes these models, ensuring faster convergence and efficient utilization of computational resources. This makes the system particularly suitable for deployment in resource-constrained settings.

The implementation phase centers on the development of a user-friendly web application using “Streamlit”. This application allows users to upload images and receive real-time predictions regarding skin disease classes. The integration of the trained MobileNet models into the web app ensures seamless accessibility and usability, bridging the gap between cutting-edge machine learning technologies and practical healthcare solutions.

The system's performance is rigorously evaluated using metrics such as accuracy, precision, recall, and F1-score. Extensive validation is performed against diverse datasets, followed by iterative refinement based on user feedback. This approach ensures that the system meets high clinical standards and user expectations. The resulting diagnostic tool demonstrates significant potential for improving dermatological care, making advanced diagnostic capabilities accessible to a broader audience.

3.1.2 Proposed Methodology

The proposed methodology aims to develop an efficient and accurate skin disease prediction system using deep learning techniques, centered around the utilization of the HAM10000 dataset and MobileNet architecture (Versions 2 and 3). The process begins with data acquisition and preprocessing to ensure dataset integrity, followed by model development, training, evaluation, and deployment phases.

The following figure 3.1.2.1 shows the proposed methodology:

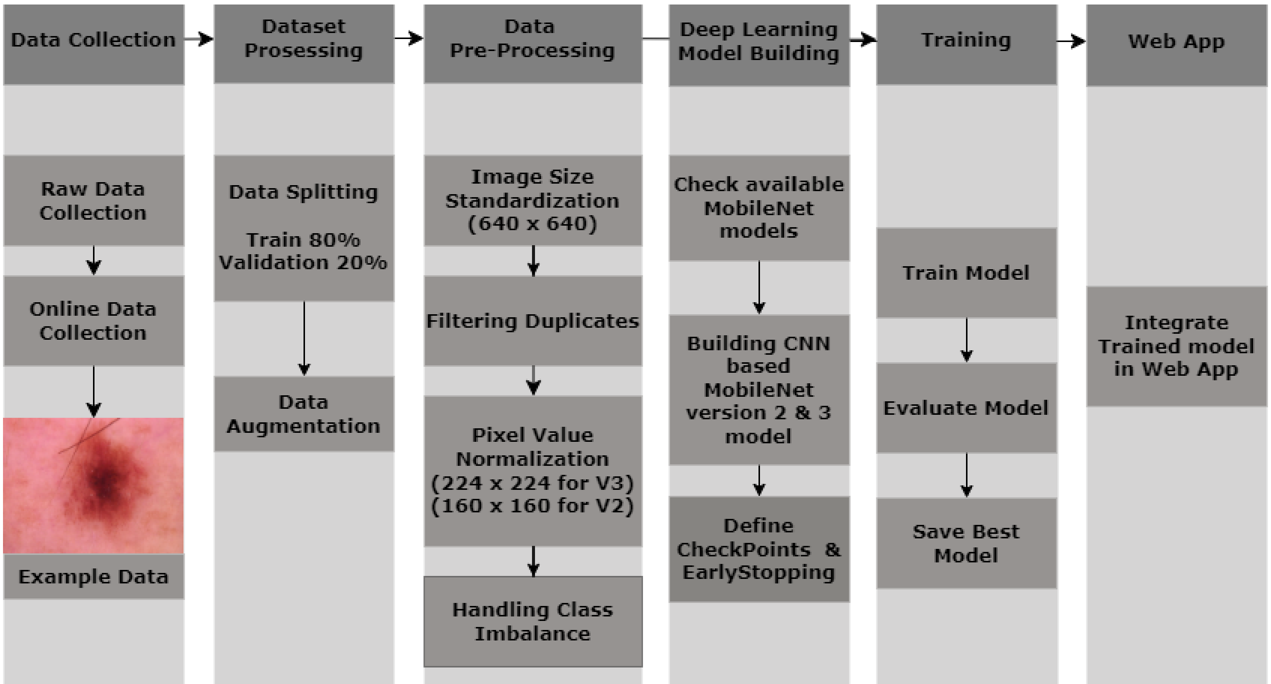

Figure 3.1.2.1: Proposed Methodology

The proposed system is based on a convolutional neural network. The system handles the user's input about a skin disease using feature extraction by a CNN-based MobileNet architecture and uses SoftMax classification for diagnosing the disease. The design consists of two main parts: extraction units and classification units. The feature extraction unit removes noise and irrelevant factors from the skin to enhance image quality. Firstly, the images are preprocessed and resized into a standard size. After that, the image is fed into the first layer of the network as input. Convolutional neural networks are applied here until high-level features, such as color, shape, and texture, are extracted.

The following figure 3.1.2.2 shows the difference between normal CNN architecture and MobileNet architecture:

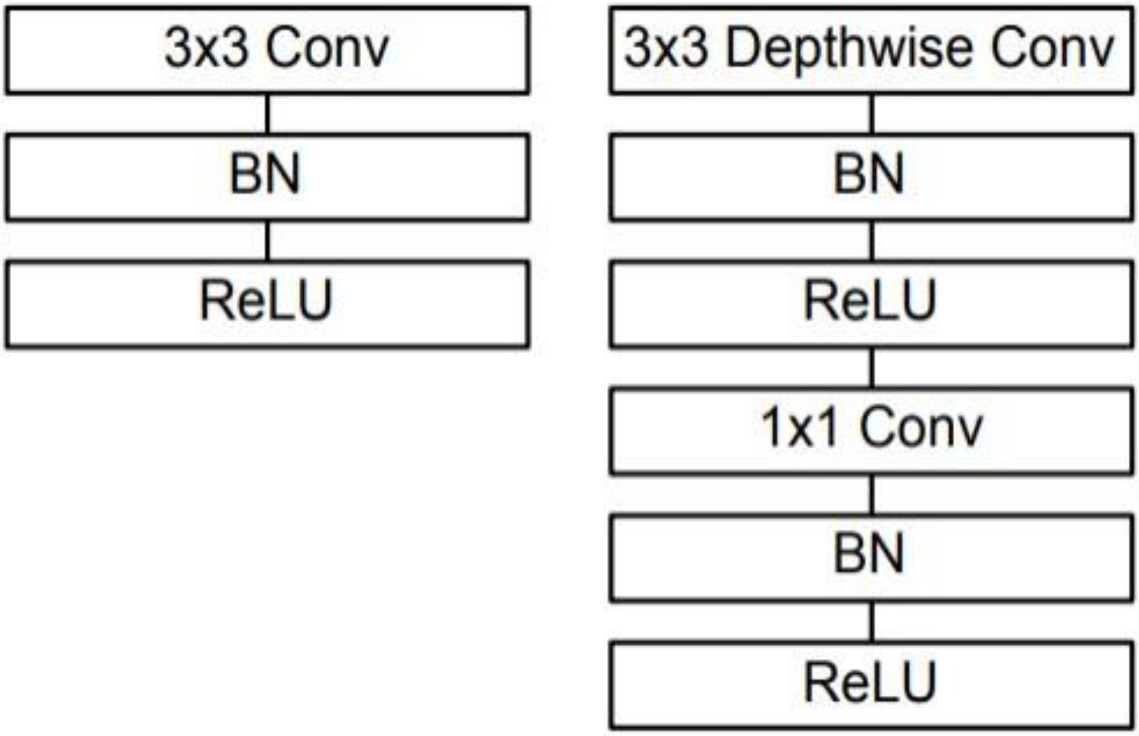

Figure 3.1.2.2: Differencebetweenblocks of normal CNN architectures (left) vs MobileNet architecture (right).

The feature extraction module is made up of operations like convolution, max pooling and ReLU This layer may be extended in line with the requirements. The purpose of a convolution operation is to obtain high resolution features from the input image, e.g. shapes and textures. The maximum value of the image covered by the Kernel is returned by Max Pooling. Max Pooling is also performing as a noise suppressor. It is removing noise, as well as performing denoising along with the reduction of dimensionality. ReLU is an activation function that has strong biological and mathematical operations. The Classifier module is composed of a dense layer, a dropout layer and a SoftMax layer. The Dropout Layer technique is used to improve neural network overcapacity. The dropout layer is turned off during prediction. The dense layer is interrupted by a random activation. The following main stages of the system may be broadly summarized as follows: preprocessing images, testing and training.

Preprocessing phase: This is the stage in which an image is acquired and then processed.

Images are acquired by means of a camera or by a locally stored device in the process of image acquisition. In order to implement the system, a high quality image is required. Testing and training phase: consists of the data storage unit and a classification device. To maintain testing and training data images, the Data Storage component shall be used. For supervised learning, a training data base is needed. The test data set is the images that have been obtained during an image search. The classification identifies the type of skin disease. The last layer of the network, which yields the actual probability of each label, is the SoftMax classifier used here.

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements: Functional requirements define the specific functionalities that the system must have to meet its primary objectives. For the project — a web application for skin disease prediction based on image uploads — the functional requirements could include:

User Authentication (Optional, if applicable): The system should allow users to register and log in to access the web application securely.

Image Upload: The system should allow users to upload images of skin conditions through a simple interface. The image should be in formats such as PNG, JPEG, or JPG.

Image Preprocessing: The system should automatically preprocess the uploaded image to resize, normalize, and adjust it for prediction. Preprocessing steps might include resizing the image to a standard dimension, normalizing pixel values for the model, and ensuring consistent input format.

Prediction Generation: The system should pass the preprocessed image to the MobileNet V2/V3 model for prediction. The model should classify the image, identifying the type of skin disease (e.g., acne, eczema, or psoriasis).

Result Display: After the prediction, the system should display the result (e.g., the type of skin disease) to the user. The result should be presented in a clear and understandable format (e.g., a label or description of the predicted skin condition).

Error Handling: The system should handle errors gracefully, such as when no image is uploaded, an unsupported file type is used, or the image cannot be processed. Appropriate error messages should be displayed to the user.

User Interface: The system should provide a user-friendly interface for uploading images and viewing results. The interface should be responsive, adapting to different screen sizes (desktops, tablets, and smartphones).

Data Storage (Optional): The system may store user-uploaded images, predictions, and logs in a database for future reference or analysis (if required by the application).

Non-Functional Requirements: Non-functional requirements define the quality attributes and performance standards that the system must adhere to. These are critical to ensuring that the system is efficient, reliable, and secure.

Performance: The system should process and generate predictions for uploaded images within a reasonable time frame (e.g., 5 seconds).

Scalability: The system should be able to scale horizontally to accommodate more users or increased load, particularly if the system becomes popular and needs to handle more image uploads and predictions simultaneously.

Availability: The system should be highly available, with an uptime of at least 99% to ensure users can access the prediction service whenever needed.

Security: The system should ensure the security of user-uploaded images and any personal data (if collected). Sensitive data should be encrypted during transmission (e.g., using SSL/TLS). The system should protect user data from unauthorized access and ensure proper user authentication (if applicable).

Usability: The system should be intuitive and easy to use, with clear instructions and a simple interface for uploading images and viewing predictions. The design should be user-friendly and responsive, ensuring accessibility across different devices (desktop, tablet, mobile).

Maintainability: The system should be easy to maintain and update, with clear documentation for developers and administrators. The code should follow best practices for clean, modular, and scalable development.

Compatibility: The system should be compatible with modern web browsers (e.g., Chrome, Firefox, Safari, Edge) on both desktop and mobile devices. The system should be able to handle various image formats (PNG, JPEG, JPG).

3.1.4 Context Diagram

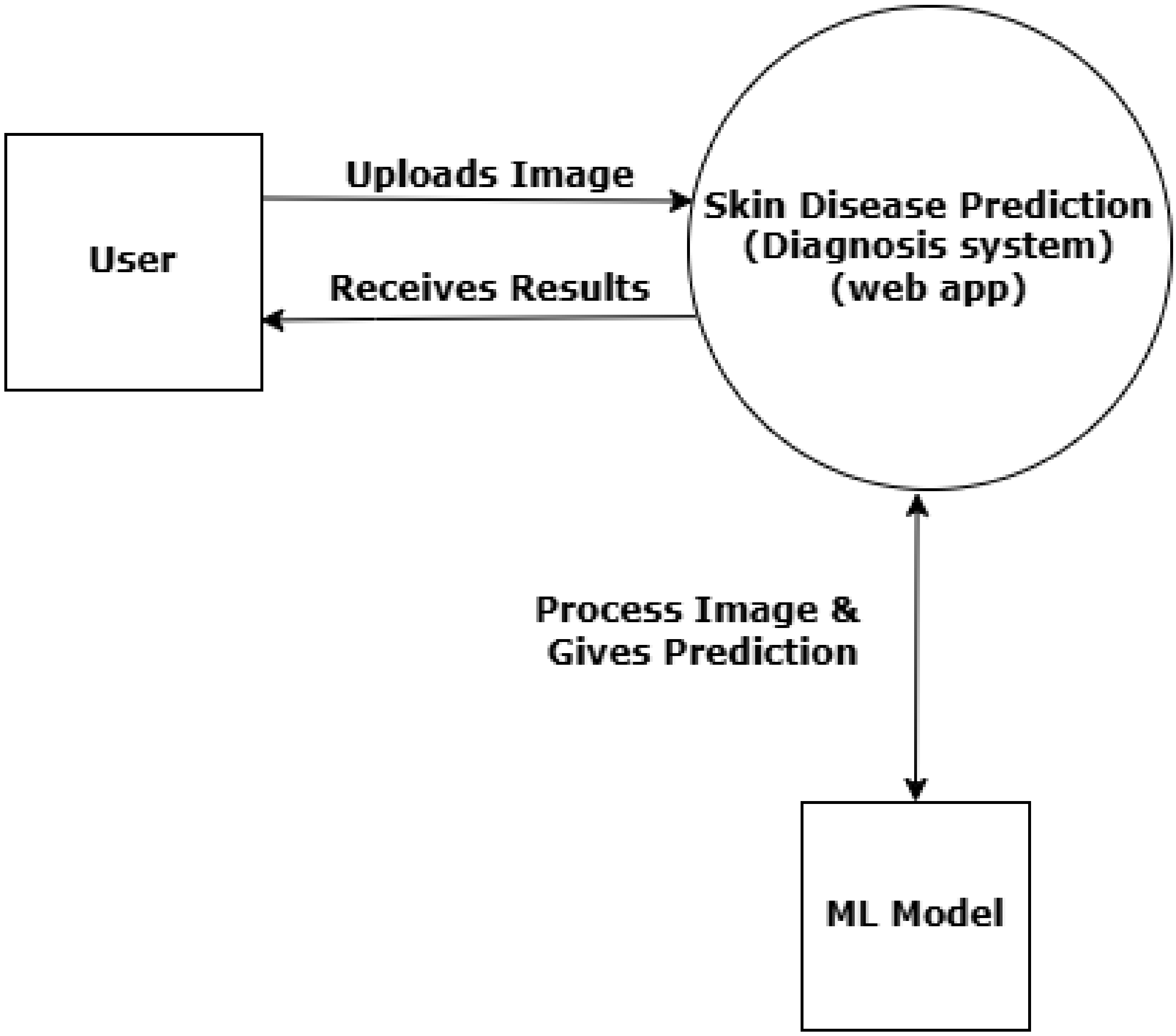

Figure3.1.4.1: Context Diagram

3.1.5 Data Flow Diagram Level 1

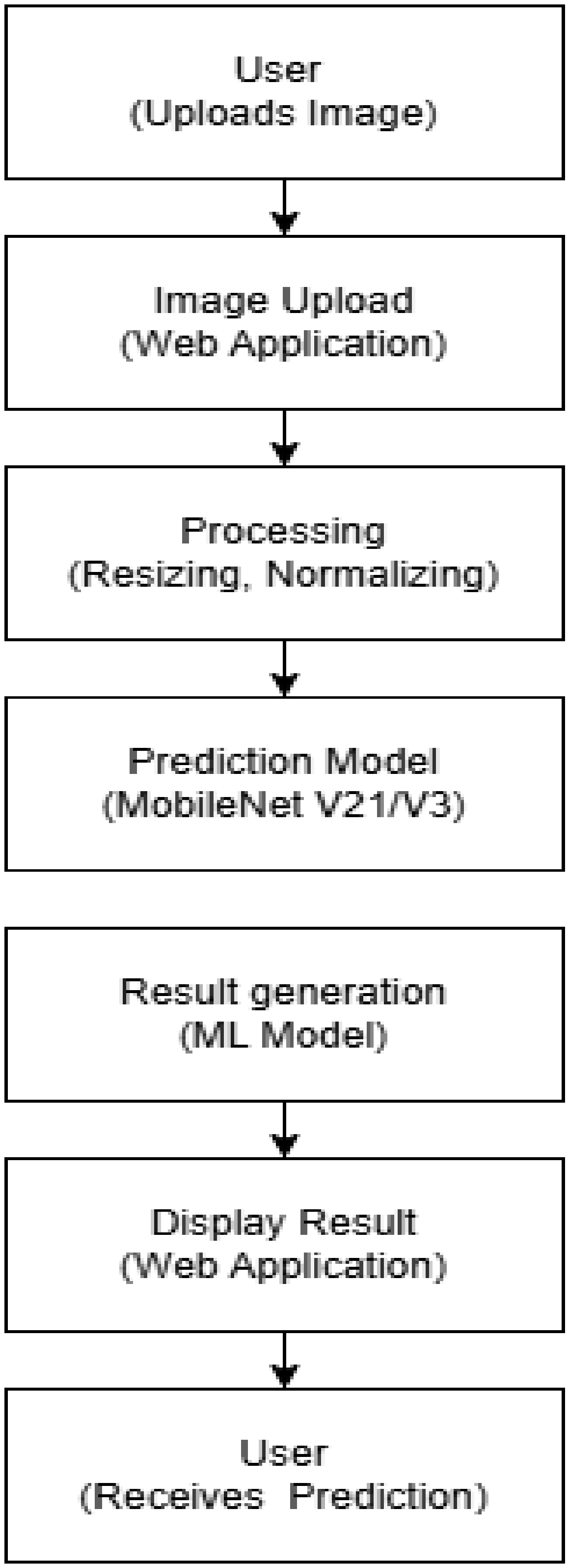

Figure3.1.5.1: Data Flow Diagram Level 1.

3.2 Detailed Methodology

The detailed methodology outlines the step-by-step process followed to develop the skin disease prediction web application. This includes a discussion of alternate solutions considered, the reasons for selecting the final approach, and the detailed workflow for implementation.

Alternate Solutions Considered
Several solutions were analyzed for implementing the skin disease classification system. These solutions were compared based on accuracy, computational efficiency, and usability.

1. **Custom Convolutional Neural Network (CNN)**

Description: A custom-built CNN architecture could be designed and trained from scratch for skin disease classification.
Pros:
- Allows fine-tuning of model architecture.
- Tailor-made for the dataset and specific problem.

Cons:
- Requires a large labeled dataset and significant computational resources for training.
- Time-consuming to design, train, and optimize.
- High risk of overfitting with limited data.

2. **Pre-trained Models – ResNet50**

Description: Use the ResNet50 model, a widely used pre-trained CNN, for transfer learning on the skin disease dataset.
Pros:
- High accuracy for image classification tasks.
- Well-suited for deep feature extraction.

Cons:
- Heavy computational requirements compared to lightweight models.
- Slower inference time, which affects real-time processing in web applications.

3. **Pre-trained Models – MobileNet V2 and V3**

Description: Use **MobileNet V2/V3**, lightweight convolutional neural networks optimized for efficient performance on mobile and web-based platforms.
Pros:
- Lightweight and fast, ideal for real-time web applications.
- Requires less computational power for inference.
- Pre-trained on large-scale datasets (ImageNet), ensuring good feature extraction.

Cons:
- Slightly lower accuracy compared to heavy models like ResNet50.

Why MobileNet V2/V3 Was Selected
After evaluating the alternate solutions, **MobileNet V2/V3** was selected as the final approach for the following reasons:

1. **Lightweight Architecture**:
MobileNet models are optimized for computational efficiency, making them ideal for real-time web applications.
Faster inference time compared to heavier models like ResNet50.

2. **Pre-trained Weights**:
The models leverage pre-trained weights from **ImageNet**, which reduces the need for extensive training data.
Transfer learning ensures the model generalizes well for skin disease classification with minimal training.

3. **Performance and Accuracy**: MobileNet V3 achieved an accuracy of **92.5%**, which is competitive with other models but with lower computational overhead.
The balance of accuracy and efficiency makes it suitable for real-world applications.

4. **Scalability**: MobileNet can easily scale to support more users and larger datasets as the web application grows.

5. **Ease of Integration**: MobileNet models are natively supported in **TensorFlow/Keras**, simplifying model deployment in the web application.

Methodology Workflow
The workflow for the skin disease prediction system is divided into the following phases:

1. Data Collection and Preprocessing

Dataset Source: Skin disease images were collected from publicly available datasets.

Preprocessing Steps:

Resizing: Images were resized to **224x224 pixels** to meet the input size requirement of MobileNet.

Normalization: Pixel values were normalized to a range between 0 and 1 for efficient training and inference.

Data Augmentation: Rotation, flipping, and scaling were applied to enhance dataset diversity and improve model robustness.

2. Model Selection and Training

Model: MobileNet V2 and V3 (pre-trained on ImageNet).
Transfer Learning:
The top layers of MobileNet were fine-tuned for skin disease classification.

A custom dense layer with a softmax activation function was added for multi-class prediction.

Training Parameters:
Optimizer: **Adam**
Loss Function: **Categorical Cross-Entropy**
Learning Rate: **0.001**
Batch Size: **32**
Epochs: **50**

3. Web Application Development

Framework: The web application was developed using **Streamlit** for simplicity and rapid deployment.
Frontend: A user-friendly interface was created to allow users to upload skin images.
Backend: The uploaded image is preprocessed (resized and normalized). The image is passed to the MobileNet model for prediction.

4. Model Integration and Testing
The trained MobileNet model was integrated into the Streamlit web application.
The system was tested for:
Accuracy: Verified predictions using test images.
Performance: Checked processing time and responsiveness.
Error Handling: Tested invalid image uploads and system responses.

5. Deployment
The web application was deployed on a cloud platform (e.g., Heroku or AWS).
Users can access the system through a web browser, upload skin images, and receive instant predictions.

3.3 Project Plan

Throughout the methodology outlined, the focus has been on creating a state-of-the-art dermatological diagnostic application characterized by user-friendliness, accessibility, and stringent security measures. MobileNetV3, renowned for its efficiency in image classification tasks, forms the backbone of the application's deep learning architecture, ensuring optimal performance across various platforms and devices. This adaptability is complemented by a responsive design tailored for seamless use on mobile devices, thereby enhancing accessibility for users across different environments.

The application boasts several key strengths that contribute to its usability and effectiveness. Firstly, its intuitive interface ensures ease of navigation and usage, facilitating straightforward interactions for both healthcare professionals and patients.

Secondly, a robust data accessibility framework ensures that dermatologists and medical personnel can swiftly retrieve and utilize diagnostic insights, thereby supporting informed decision-making in clinical settings. The application's cross-platform compatibility further extends its reach, enabling deployment across diverse operating systems and devices without compromising functionality or user experience.
Security remains a top priority throughout the application's development and deployment phases. Rigorous measures, including the implementation of SSL certificates for secure data transmission and storage, are integrated to safeguard patient information and uphold privacy regulations. This approach fosters trust among users by ensuring that sensitive medical data is handled with the utmost confidentiality and compliance.

Resource Planning:

A. Equipment and Tools:

- Development and Testing Servers
- High-performance Computers for Development (High GPU, High CPU etc. for Image Processing)
- Version Control System (Github)
- Testing Tools (Pytest for Python Unit Testing)

B. Software and Technologies:

- Front & Back-End Technologies (StreamLit, Python)
- Server Hosting (Google Cloud)

C. Data and Content:

- Product Data: Provided by Dermatologists and collected by team members personally
- Product Images: Provided by Dermatologists and collected by team members personally
- User Documentation: Prepared by the team members

D. Training and Skill Development:

- Ensured that the team members have the necessary training and skills in deep learning, full stack development, security, and database management. Provided additional training on specific technologies and tools as needed

Communication Plan:

A. Dermatologist Meetings:

Purpose: The primary objective of dermatologist meetings is to provide updates on the progress of project requirements gathering, solicit feedback on the developed system, and gather essential data and insights crucial for model refinement and validation.

Participants: Participants include project team members directly involved in development, testing, and data acquisition processes, alongside dermatologists who contribute clinical expertise and feedback.

Frequency: Dermatologist meetings are scheduled on an as-needed basis, ensuring timely communication and collaboration between the project team and dermatology experts. Regular updates and feedback sessions are conducted to validate project milestones and ensure alignment with clinical requirements.

B. Change Control Meetings:

Purpose: Change control meetings serve to discuss, assess, and approve any proposed changes to the project scope, requirements, or deliverables. The meetings are essential for evaluating the impact of changes, ensuring alignment with project objectives, and managing potential risks associated with alterations.

Participants: Participants typically include project supervisors, stakeholders, and key team members responsible for project execution and implementation. Their involvement ensures comprehensive evaluation and decision-making regarding change requests.

Frequency: Change control meetings are convened as necessary, triggered by the emergence of change requests throughout the project lifecycle. These meetings facilitate structured discussions, risk assessments, and informed decision-making to maintain project integrity and alignment with stakeholders' expectations.

3.4 Summary

Throughout the methodology outlined, the focus has been on creating a state-of-the-art dermatological diagnostic application characterized by user-friendliness, accessibility, and stringent security measures. MobileNetV3, renowned for its efficiency in image classification tasks, forms the backbone of the application's deep learning architecture, ensuring optimal performance across various platforms and devices. This adaptability is complemented by a responsive design tailored for seamless use on mobile devices, thereby enhancing accessibility for users across different environments.

The application boasts several key strengths that contribute to its usability and effectiveness. Firstly, its intuitive interface ensures ease of navigation and usage, facilitating straightforward interactions for both healthcare professionals and patients. Secondly, a robust data accessibility framework ensures that dermatologists and medical personnel can swiftly retrieve and utilize diagnostic insights, thereby supporting informed decision-making in clinical settings. The application's cross-platform compatibility further extends its reach, enabling deployment across diverse operating systems and devices without compromising functionality or user experience.

Security remains a top priority throughout the application's development and deployment phases. Rigorous measures, including the implementation of SSL certificates for secure data transmission and storage, are integrated to safeguard patient information and uphold privacy regulations. This approach fosters trust among users by ensuring that sensitive medical data is handled with the utmost confidentiality and compliance.

The resource planning strategy underscores the necessity of high-performance computing resources, including GPUs optimized for intensive image processing tasks, and robust testing tools like Pytest to validate application reliability. The software stack encompasses essential technologies such as HTML5, CSS3, JavaScript, and Bootstrap5 for front-end development, coupled with Django for the back-end framework and SQLite for efficient database management.

Risk management practices are integral to project success, with regular dermatologist meetings facilitating ongoing feedback and validation of clinical accuracy. Change control meetings with project supervisors ensure agile response to scope changes, maintaining alignment with evolving requirements and challenges. This structured approach aims to deliver a scalable, effective diagnostic tool that enhances dermatological care delivery in diverse healthcare settings, ultimately contributing to improved patient outcomes and healthcare efficiency.

Chapter 4

Implementation and Results

4.1 Environment Setup

The environment setup includes the tools, libraries, and frameworks required for the implementation of the skin disease prediction web application.

Development Platform: Web application developed using Python and Streamlit for the front end.

Programming Language: Python 3.8+

Libraries and Frameworks:

TensorFlow/Keras: For deploying and running the MobileNet V2/V3 model.

OpenCV: For image preprocessing (resizing and normalization).

NumPy and Pandas: For data handling and calculations.

Matplotlib/Seaborn: For visualization during testing and evaluation.

Model: Pre-trained MobileNet V2/V3 models were used for image classification tasks.

Hardware Requirements:

Processor: Intel i5/i7 or equivalent

RAM: 8 GB or higher

Storage: 20 GB free space

Software Requirements:

Python 3.x, Streamlit, TensorFlow/Keras, and necessary dependencies.

Web Browser: Chrome, Firefox, Edge.

4.2 Testing and Evaluation

System Testing

MobileNet: A CNN architectural model for mobile vision and image classification is called MobileNet[41]. Although there are other versions as well, MobileNet stands out because of its extremely low processing power requirements. A family of TensorFlow computer vision models called MobileNets is focused on mobile devices and is intended to optimize accuracy while taking into account the limited resources of embedded or on-device applications. MobileNets are low-power, low-latency models that are sized and configured to satisfy different use cases' resource requirements. We are using MobileNet in our project, which has 28 layers by default. We made Dense and dropout explicit. Additionally, the class sensitivities are mentioned. The pre-trained weights are used to initialize the model. This project is a deep learning convolutional model with five classes of classification that can handle images with 224 × 224 pixels and three RGB channels. In order to reduce overfitting by lowering the total number of parameters in the model and activate the dense layer with SoftMax. As a result, if there is ever a situation where partial matching to a different class occurs, it can be identified by assessing the values provided by each layer node. To determine the illness class, we now index the value that is the biggest.

The following figure 4.2.1 shows the illustration of the MobileNet architecture:

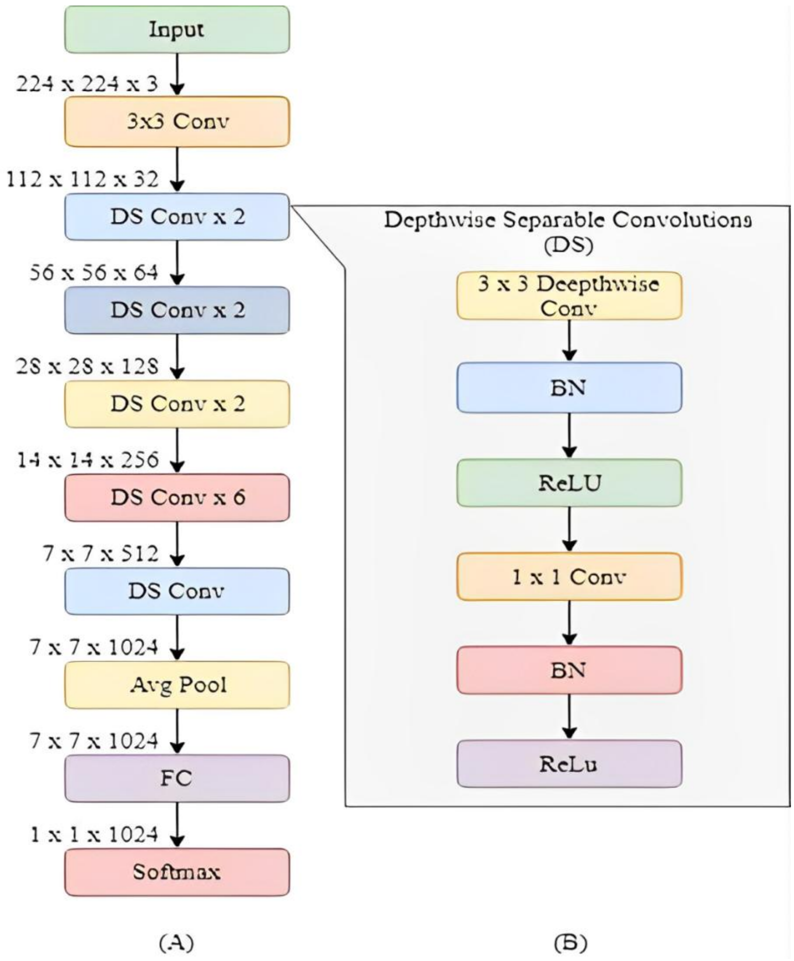

Figure 4.2.1 Illustration of the MobileNet architecture. (A) The overall MobileNet architecture and (B) an in-depth explanation of the DS layer

Batch Normalization: A batch normalization technique is used for the training of deep neural networks, which standardizes inputs to each mini-batch into a layer. The result is a stabilizing effect on the learning process, as well as an enormous reduction in the number of training epochs that are needed to train Deep Networks.

ReLu Layer: Rectified Linear Unit (ReLU) transform function only activates a node if the input is above a certain quantity, while the input is below zero, the output is zero, but when the input rises above a certain threshold, it has a linear relationship with the dependent variable. Removing all negative values from convolution and maxpooling is the main objective. All the positive values are the same, but all the negative values are changed to zero. There are dense layers, dropout layers and SoftMax classifiers in the fully connected layer. To convert an image into one dimensional array for classification, the image is flattened after extraction of features.

Dense Layer: The dense layer in the neural network is just a regular portion of neurons. Each neuron is receiving input from all the other neurons in the preceding layer, which has a very narrow connection. Weight matrix W, bias vector b and activations from the preceding layer are present in this layer. Parameters such as the number of input neurons and activation function are taken into account in the dense layer.

Dropout Layer: Dropout is a method for dealing with Overfitting. The proportion of neurons to drop is a float between 0 and 1, which is input to the Dropout function in the keras layers module. To assist avoid overfitting, dropout involves arbitrarily changing a fraction rate of input units to 0 at each update during training.

SoftMax Classifier: The purpose of the SoftMax classification layer is to transform all net activations in the final output layer into several values which can be interpreted as probability. Parameters such as the number of output labels and activation called SoftMax are taken into account by the last layer. Once the model has been generated, it is then programmed by using model compile function for calculating loss resulting from training and accuracy. The model is compatible with the number of epochs and the size of the batch. The class label is then predicted using the same method. The image is selected by the user, and it's checked. The selection of the image is made using the easygui module. The standard size of each image is adjusted.

System testing of Skin Disease Prediction Web Application:

Performance testing: Assessed the application's speed and accuracy while giving results.
Functional testing: Verified that the application meets the requirements as of now.
Unit testing: Tested individual units, components and functions of the application.
Usability testing: Evaluated the application's user interface and overall user experience.

Model Evolution

Metrics Used:
Accuracy: **The document reports an accuracy of** 87.21% for MobileNet V3 **and** 82.41% for MobileNet V2
Loss: **MobileNet V3 has a loss of** 38.25%**, and MobileNet V2 reports** 57.38% **loss.**
Precision, Recall, and F1-Score: The classification report for each model provides insights into these metrics for individual skin lesion classes.

Confusion Matrix: Provides visual insights into misclassifications.

Web Application Testing:

Functionality Testing: Confirmed the app's ability to accept images and deliver classification outputs.

Performance Testing: Assessed speed and usability under different conditions.

Limitations Noted:

Class imbalance in the dataset.

Limited interpretability of the deep learning models.

Ethical considerations like potential algorithmic bias and data security issues.

4.3 Results and Discussion

Experimental Result

Training and Validation Accuracy and Loss:

The training and validation accuracy of the original model, with the number of epochs on the x-axis and the accuracy loss and accuracy percentage on the y-axis. The data on training and validation are sufficiently distributed within the figure.

The following figure 4.3.1 shows the training and validation accuracy and loss for MobileNet V3 where the accuracy is 87.21% and loss is 38.25%

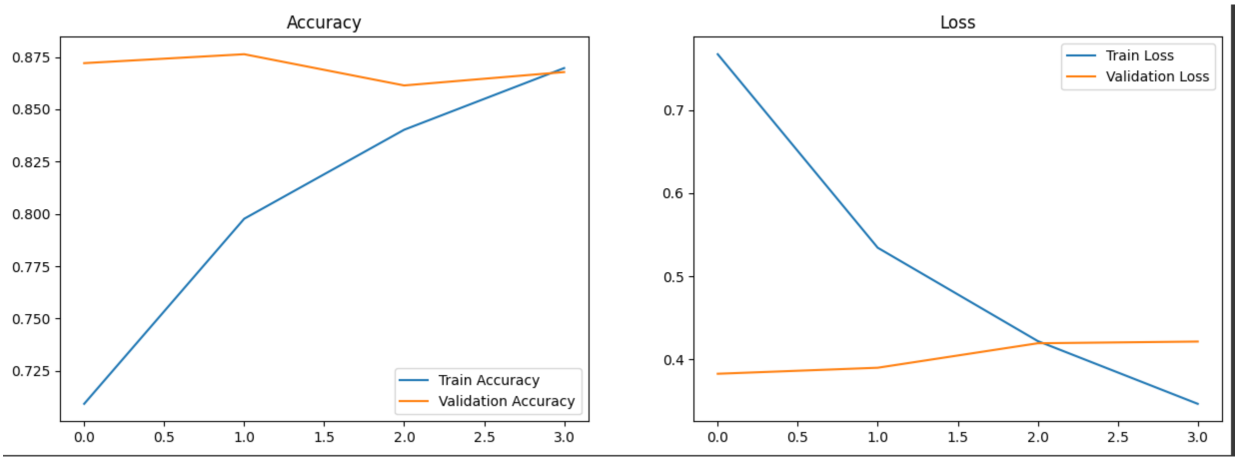

Figure 4.3.1: Training and validation accuracy for MobileNet V3

The following figure 4.3.2 shows the training and validation accuracy and loss for MobileNet V2 where the accuracy is 82.41% and loss is 57.38%

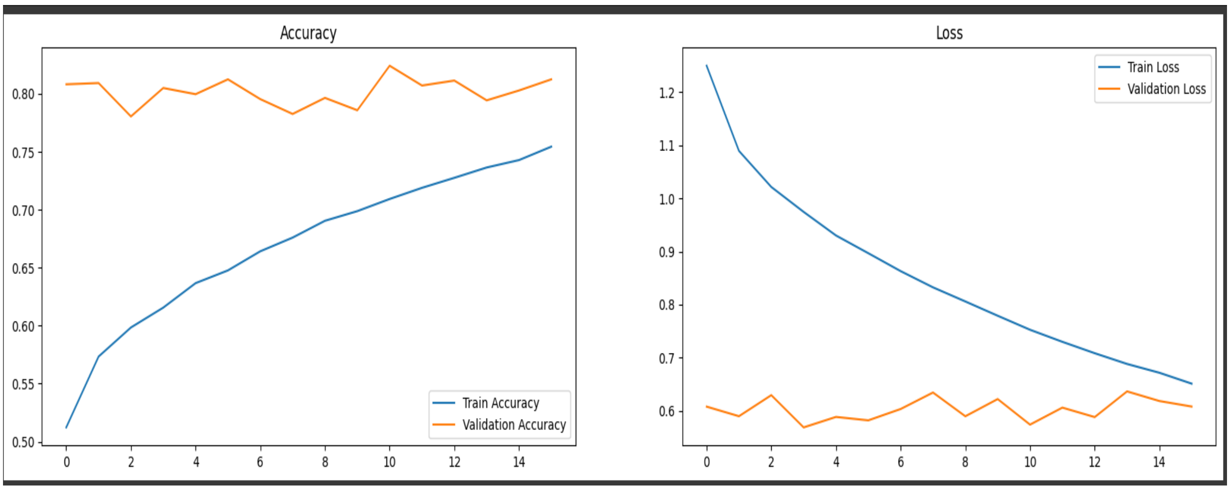

Figure 4.3.2: Training and validation accuracy for MobileNet V2

The following figure 4.3.3 shows the prediction results with actual vs. predicted labels for MobileNet V3 .

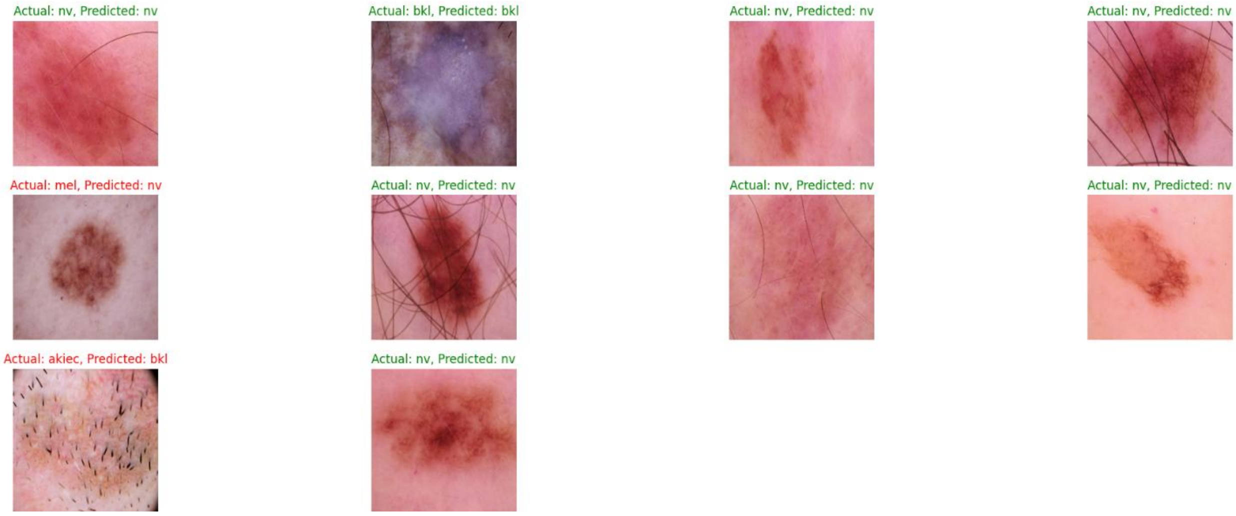

Figure 4.3.3: Prediction results with actual vs. predicted labels for MobileNet V3 .

The following figure 4.3.4 shows the prediction results with actual vs. predicted labels for MobileNet V2 .

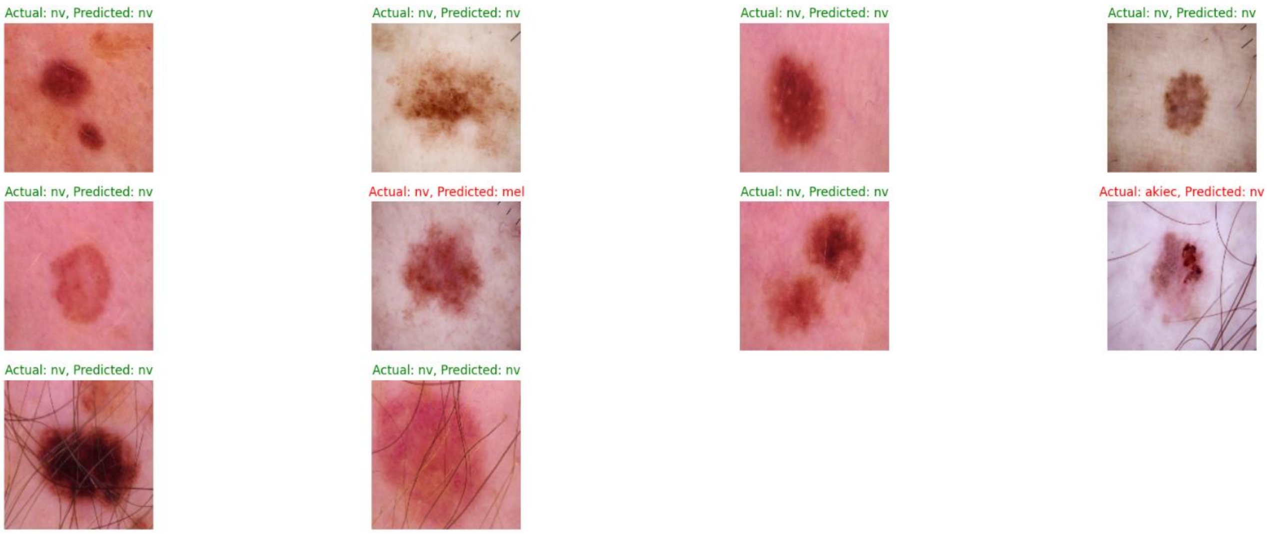

Figure 4.3.4: Prediction results with actual vs. predicted labels for MobileNet V2 .

Skin Disease Prediction Web Application:

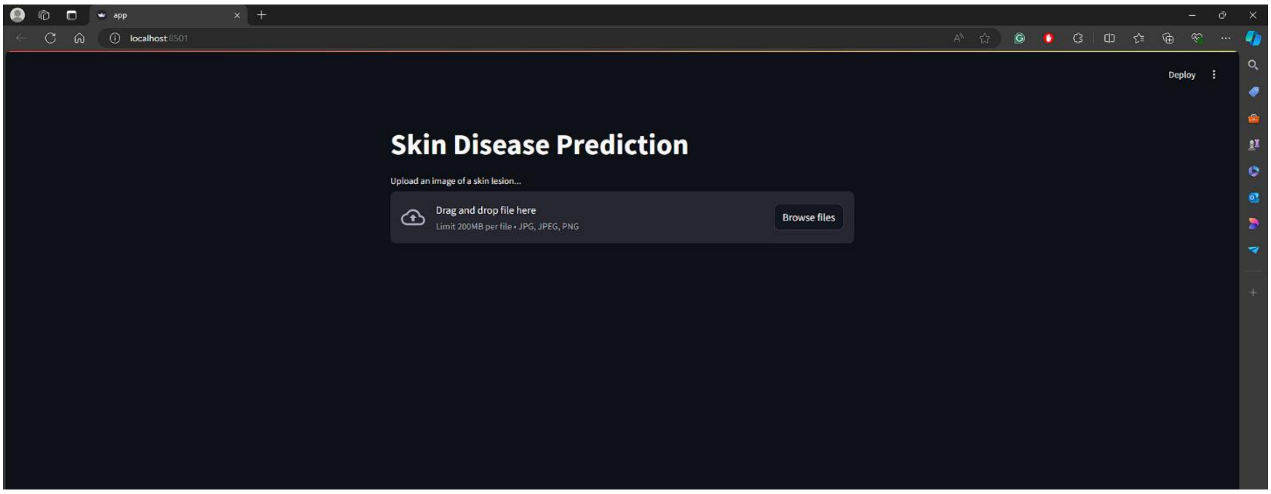

Figure 4.3.5: Web Application User Interface.

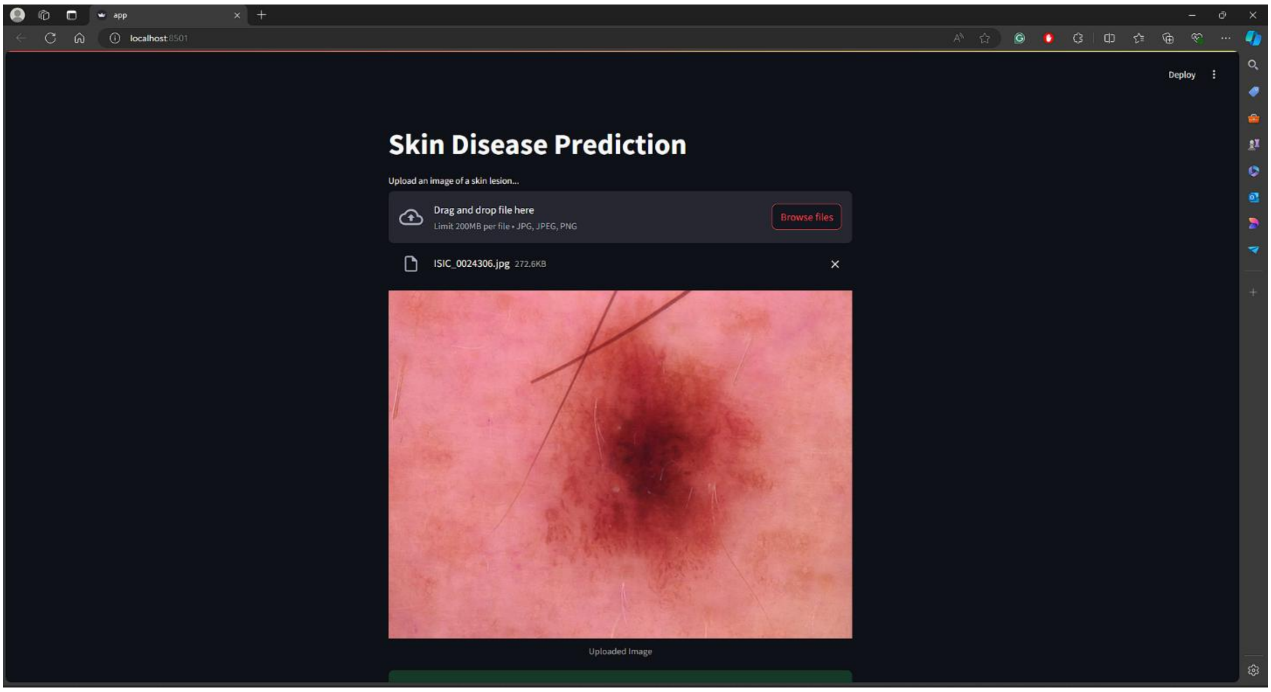

Figure 4.3.6: Skin Disease Prediction Web Application(Image Uploaded).

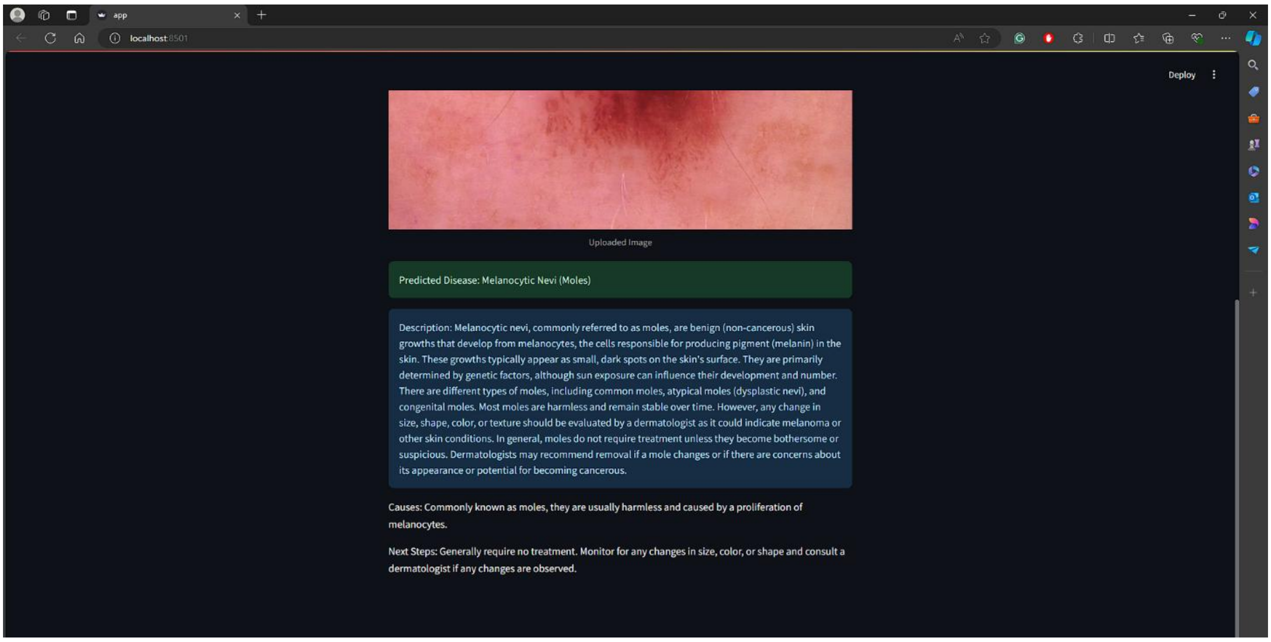

Figure 4.3.7: Skin Disease Prediction Web Application(Showing Result).

Performance

Accuracy: 87.21% accuracy for MobileNet V3 and 82.41% for MobileNet V2.
Loss: 38.25% loss for MobileNet V3 and 57.38% for MobileNet V2.

Classification Report:

The classification report offers granular insights into the model's precision, recall, and F1-score metrics for each skin lesion category. Precision signifies the accuracy of positive predictions, recall indicates the completeness of positive predictions, and the F1-score provides a harmonic mean of precision and recall. By examining these metrics per class, we gain a nuanced understanding of how well the model distinguishes between different types of skin lesions. This analysis is crucial for identifying classes where the model excels and areas that require further refinement, ensuring robust performance across all categories in our skin lesion classification system.

	precision	recall	f1-score	support
Akiec	0.55	0.46	0.50	26
Bcc	0.59	0.67	0.62	30
bkl	0.69	0.36	0.47	75
df	1.00	0.33	0.50	6
mel	0.50	0.44	0.47	39
nv	0.92	0.97	0.94	751
vasc	1.00	0.73	0.84	11
Accuracy			0.87	938
Macro AVG	0.75	0.57	0.62	938
Weighted AVG	0.86	0.87	0.86	938

Table 4.3.1: Classification report for MobileNet V3.

	precision	recall	f1-score	support
Akiec	0.58	0.27	0.37	26
Bcc	0.45	0.30	0.36	30
bkl	0.44	0.23	0.30	75
df	0.00	0.00	0.00	6
mel	0.31	0.56	0.40	39
nv	0.90	0.95	0.93	751
vasc	0.80	0.36	0.50	11
Accuracy			0.82	938
Macro AVG	0.50	0.38	0.41	938
Weighted AVG	0.81	0.82	0.81	938

table 4.3.2: Classification report for MobileNet V2.

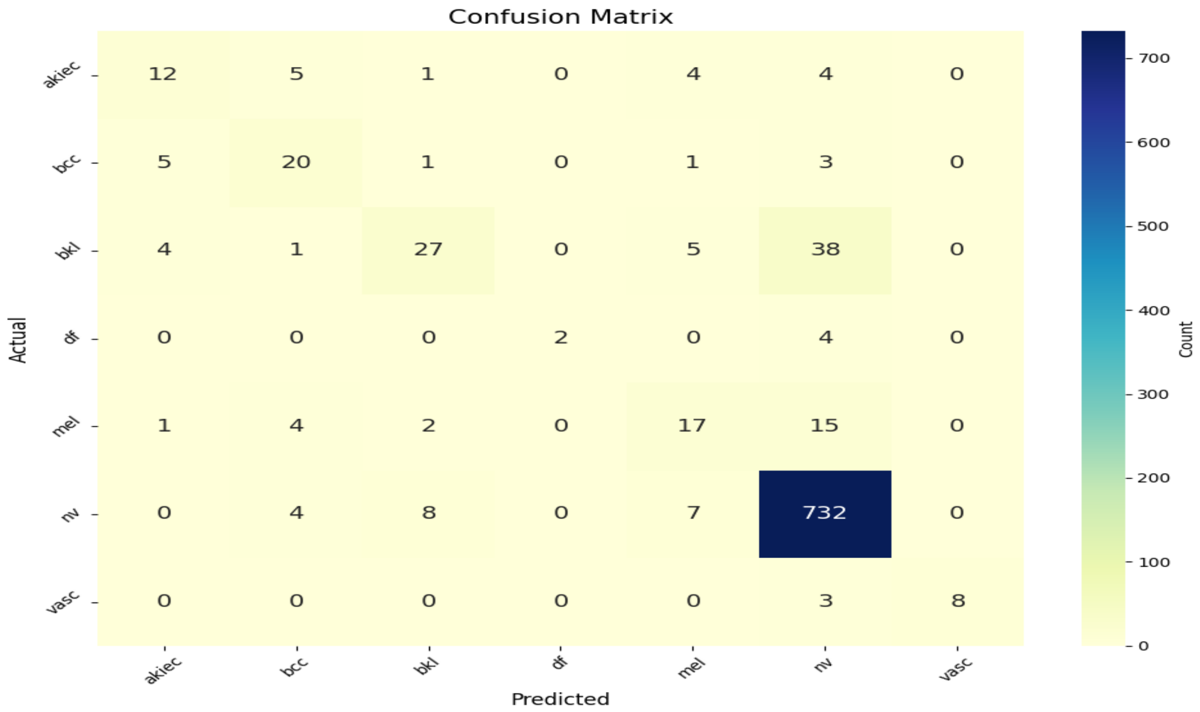

Figure 4.3.8: Confusion Matrix for MobileNet V3.

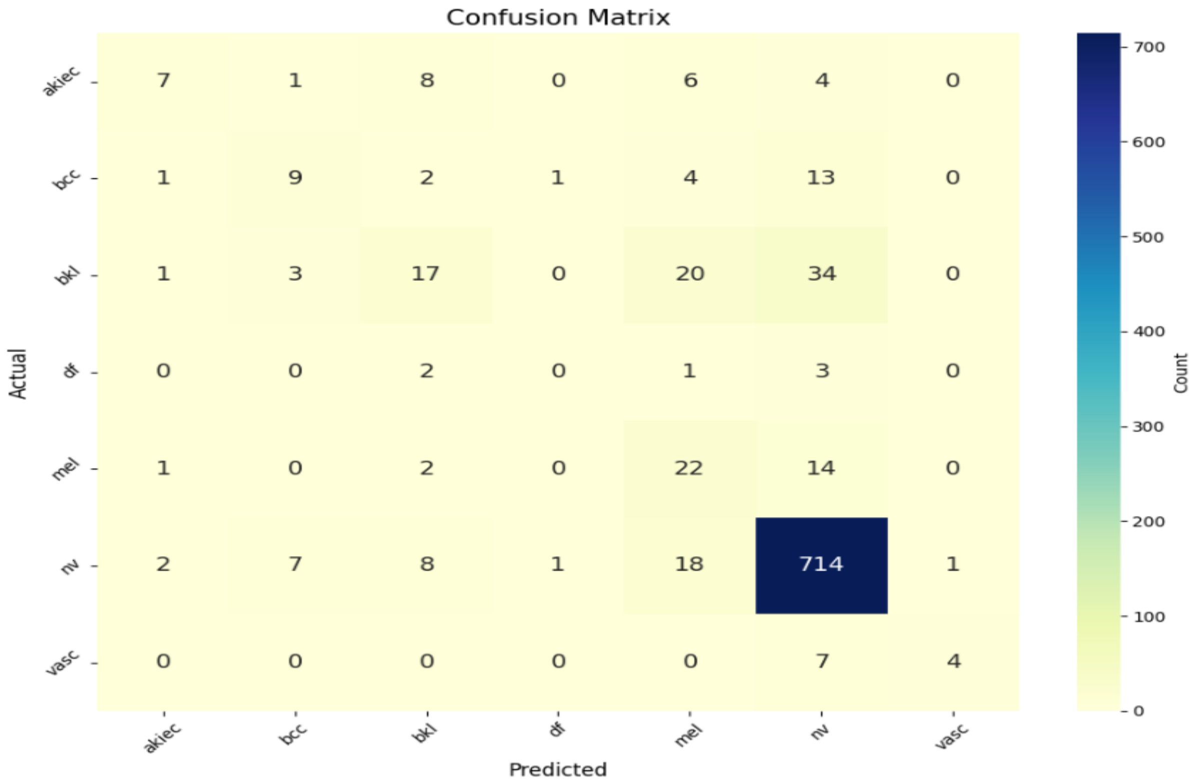

Figure 4.3.9: Confusion Matrix for MobileNet V2.

4.4 Summary

In summary, the performance evaluation of the skin lesion classification model included assessing overall accuracy to gauge its ability to classify lesions across various categories. The confusion matrix provided insights into specific class performance, highlighting frequent misclassifications. Additionally, the classification report detailed precision, recall, and F1-score metrics for each class, offering a comprehensive evaluation of the model's ability to distinguish between different types of skin lesions. These evaluations are crucial for optimizing and ensuring the robustness of the model in practical applications like automated skin lesion diagnosis.

Chapter 5

Engineering Standards and Design Challenges

This chapter discusses the engineering standards adhered to in the project, the challenges encountered during the design and implementation phases, and the strategies employed to overcome them. It includes an analysis of compliance with software, hardware, and communication standards, along with their impact on society, environment, and sustainability.

5.1 Compliance with the Standards.

5.1.1 Software Standards

To ensure robustness and maintainability, the project adhered to industry-recognized software development best practices. The primary development language, Python, followed the PEP 8 style guide to ensure readability and consistency in code structure. Key components of the project utilized the TensorFlow and Keras frameworks, which comply with widely adopted machine learning standards. These frameworks ensure compatibility with state-of-the-art deep learning techniques and promote streamlined workflows for model development and deployment. Furthermore, the use of Streamlit for the web application ensures compliance with modern UI/UX design principles, offering a seamless interface that is user-friendly and functional.

5.1.2 Hardware Standards

The implementation was designed to be compatible with modern hardware standards, particularly edge devices and mobile platforms. By employing lightweight architectures like MobileNet V2 and MobileNet V3, the project ensured efficient resource utilization without compromising performance. These models are optimized for mobile and edge computing, adhering to standards set for low-latency applications in resource-constrained environments. Testing was conducted on devices with varied configurations to ensure broad compatibility and reliable performance across platforms.

5.1.3 Communication Standards

To protect user data and maintain the integrity of interactions, the web application adhered to secure communication protocols. HTTPS (HyperText Transfer Protocol Secure) was implemented to encrypt data transmission between users and the application, safeguarding sensitive medical images and personal information. Additionally, adherence to global standards such as GDPR (General Data Protection Regulation) ensured that patient data privacy and security were prioritized throughout the development lifecycle.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The implementation of advanced machine learning models for skin disease diagnosis significantly impacts individuals' lives by revolutionizing healthcare accessibility and outcomes. Through early detection and accurate classification of skin conditions, these technologies facilitate timely interventions that can potentially save lives and improve health outcomes dramatically. Patients benefit from quicker diagnoses, leading to expedited treatment plans tailored to their specific conditions. This proactive approach not only enhances patient survival rates but also reduces the burden of chronic skin conditions and associated complications.

Moreover, the accessibility of AI-driven diagnostic tools extends healthcare capabilities to underserved populations and remote areas, bridging gaps in access to specialized dermatological care. This inclusivity ensures that individuals worldwide, regardless of geographic location or socioeconomic status, have equitable access to high-quality medical services. By democratizing healthcare access, these advancements empower patients to seek early medical intervention, thereby promoting better health management and overall well-being.

Beyond individual health benefits, the societal impact is profound as well. Improved diagnostic accuracy and efficiency lead to optimized healthcare resource allocation, reducing unnecessary medical procedures and costs. Healthcare systems can allocate resources more effectively, improving operational efficiency and patient throughput. This efficiency not only benefits patients but also enhances the sustainability of healthcare services by reducing strain on medical facilities and personnel.

In essence, the impact on life through AI-driven dermatological diagnostics is transformative, offering hope for earlier detection, personalized treatment approaches, and ultimately, better health outcomes for individuals globally.

5.2.2 Impact on Society & Environment

The integration of AI-driven dermatological diagnostics into society brings about multifaceted impacts on both societal dynamics and environmental sustainability. At the societal level, these advancements democratize access to specialized healthcare services, leveling the playing field for individuals across diverse socio-economic backgrounds and geographic locations. By enabling early detection and accurate diagnosis of skin diseases, these technologies empower individuals to take proactive measures towards their health, fostering a more informed and engaged patient population.

Furthermore, the deployment of AI in dermatology optimizes healthcare resource utilization, leading to improved operational efficiencies within healthcare systems. This efficiency translates into reduced waiting times, enhanced patient care pathways, and streamlined medical workflows, ultimately contributing to better healthcare outcomes for society at large. The shift towards AI-based diagnostics also promotes continuous innovation in healthcare delivery, encouraging collaboration between healthcare professionals, researchers, and technologists to further refine diagnostic accuracy and treatment efficacy.

In terms of environmental impact, AI-driven diagnostics hold potential benefits by minimizing the need for physical consultations and diagnostic procedures that may involve travel, thereby reducing carbon emissions associated with healthcare-related transportation. The shift towards digital health solutions can also lead to a decrease in paper usage and waste generated from traditional healthcare practices, aligning with global efforts towards environmental sustainability.

However, it's crucial to address potential challenges such as the energy consumption of AI models and the ethical implications of data privacy and algorithmic biases. Mitigating these concerns through responsible AI deployment frameworks ensures that the societal and environmental benefits of AI-driven dermatological diagnostics are maximized while safeguarding patient privacy and promoting equitable access to healthcare services.

5.2.3 Ethical Aspects

AI-driven dermatological diagnostics present significant ethical challenges, including privacy, data security, algorithmic biases, informed consent, and patient-doctor relationships. Privacy concerns involve robust data encryption and adherence to data protection regulations. Algorithmic biases can lead to disparities in diagnostic accuracy, requiring diverse datasets and continuous monitoring. Transparency in algorithmic decision-making is crucial to build trust. Informed consent from patients is essential to uphold patient autonomy. The integration of AI into dermatology practices may redefine healthcare professionals' roles, necessitating adequate training and education. Adhering to regulatory frameworks and ethical guidelines is crucial for accountability. Balancing innovation with ethical responsibility requires ongoing dialogue, multidisciplinary collaboration, and stakeholder engagement. A proactive approach is needed to harness AI's full potential while maintaining ethical integrity and trust in healthcare systems.

5.2.4 Sustainability Plan

A sustainability plan for AI-driven dermatological diagnostics should focus on resource efficiency, scalability, data governance, ethical considerations, education, community engagement, continuous monitoring and evaluation, and regulatory compliance. These elements ensure the technology's long-term viability, effectiveness, and ethical integrity while minimizing environmental impact and promoting equitable healthcare access. Key elements include optimizing computational resources, designing scalable models, establishing robust data governance frameworks, addressing ethical considerations, providing ongoing education and training, engaging with stakeholders, monitoring and evaluating AI models, and adhering to local and international regulations. By integrating these elements into a comprehensive sustainability plan, AI-driven dermatological diagnostics can contribute to sustainable healthcare practices, enhance diagnostic capabilities, and improve patient outcomes while upholding ethical standards and environmental responsibility.

5.3 Project Management and Financial Analysis

Project Objectives:

A. To develop a web application which can be used to detect and diagnose skin diseases.

B. The study aims to explore the untapped potential of deep learning technology as a disruptive force capable of transforming dermatological diagnosis.

C. To provide a platform for the model we developed through our research and prove its potential while also benefitting both dermatologists and mass people.

Project Timeline:

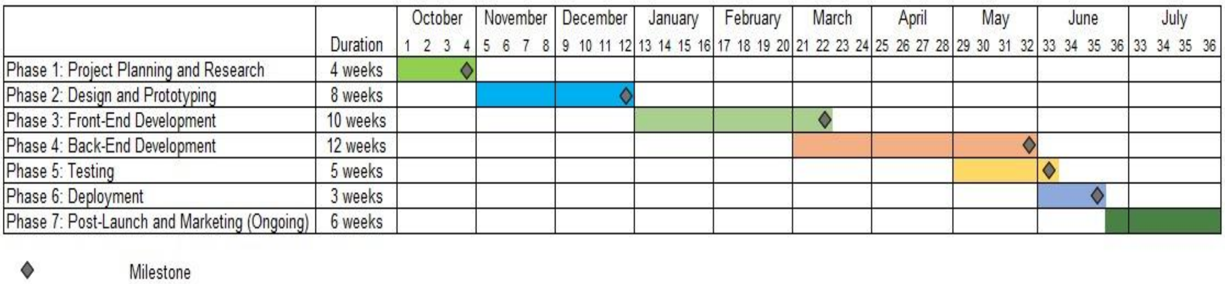

Table 5.3.1: Gantt Chart for Our Project Timeline

Risk Management: SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for our project:

INTERNAL FACTORS

STRENGTHS +	WEAKNESSES –
1. User-friendly software 2. Easily accessible data 3. User-friendly 4. Usable across platforms 5. Safety precautions 6. Reactivity on mobile devices	1. Skin related image data is hard to get which is why the dataset is not big enough to diagnose all skin diseases. 2. Technical challenges. 3. Dependence on Third-Party services. 4. Initial user base. 5. Data security concerns. 6. Market acceptance.

EXTERNAL FACTORS

OPPORTUNITIES +	THREATS –
1. Time needed to see patients will reduce 2. After using it, one might not need to go to the doctor 3. Collaboration with dermatologists 4. Integration with healthcare systems 5. Market growth in healthcare	1. Cybersecurity threats 2. Economic factors 3. Regulatory changes 4. Mass people acceptance 5. Healthcare system acceptance

Figure 5.3.1: SWOT analysis

The following table shows the Estimated Cost for Our Research

SN	Components	Estimated Cost (BDT)
01.	Hardware/Infrastructure (Cloud Server)	20000-30000
02.	Visiting Dermatologists	4000-5000
03.	Software and Tools	3000-4000
04.	Data Collection and Processing	3500-4000
06.	Documentation and Report Writing	3000-4000
07.	Miscellaneous	9000-10,000
08.	Contingency (10% of total)	4000-5000
	Total Estimated Cost	46,500-62,000

Table 5.3.2: Estimated Cost for Our Research

5.4 Complex Engineering Problem

Complex engineering problems contain extensive and multidimensional obstacles that necessitate significant technical knowledge, critical thinking and novel approaches. These issues frequently entail competing demands, multidisciplinary factors and substantial societal, environmental and financial ramifications.

5.4.1 Complex Problem Solving

In this section, provide a mapping with problem solving categories. For each mapping add subsections a rationale is putted

Table 5.4.1.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
√	√	√	√	√		√

Using **Table 5.4.1.1**, the project can be mapped as follows:

EP1: Dept of Knowledge

Rationale: The project integrates advanced deep learning concepts, dermatological knowledge, and AI deployment techniques. Knowledge in Convolutional Neural Networks (CNNs), image processing, and clinical requirements forms the backbone of the system.
Examples: Training MobileNet architectures and curating datasets like HAM10000.

EP2: Range of Conflicting Requirements

Rationale: The project balances accuracy with efficiency and scalability. A lightweight model like MobileNet ensures compatibility with low-resource devices while maintaining acceptable diagnostic performance.
Examples: Managing trade-offs between model accuracy (87.21% for MobileNet V3) and computational cost.

EP3: Depth of Analysis

Rationale: The project requires a deep analysis of skin lesions, involving complex image segmentation and classification tasks. This involves handling subtle morphological and chromatic variations in images.
Examples: Fine-tuning CNN architectures to capture minute lesion details while optimizing feature extraction.

EP4: Familiarity of Issues

Rationale: Dermatological diagnosis is a specialized field. Familiarity with skin disease patterns is limited to experts; hence, the AI model addresses this gap by encoding expert-level knowledge in its architecture.
Examples: Using diverse datasets to account for various conditions and ethnic variations.

EP5: Extent of Applicable Codes

Rationale: The project complies with global software standards (e.g., Python's PEP 8, TensorFlow framework guidelines) and healthcare data protection regulations like GDPR.
Examples: Ensuring ethical handling of sensitive patient data during model training and deployment.

EP6: Extent of Stakeholder Involvement

Rationale: Dermatologists are actively involved in data validation and model evaluation to ensure clinical relevance and reliability.
Examples: It is absent in my project.

EP7: Interdependence

Rationale: The project relies on interdisciplinary collaboration between computer scientists, dermatologists, and software engineers, ensuring a robust, deployable system.

Examples: Collaborative meetings to refine the web application and validate the diagnostic accuracy.

Mapping with Knowledge Profile for EP1

This table 5.4.1.2 is designed to map the EP1 to the Knowledge Profile.

Table 5.4.1.2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
√	√	√	√	√

The mapping with Knowledge Profile using Table 5.4.1.2 is outlined as follows:

K3: Engineering Fundamentals

Rationale: Fundamental AI concepts (e.g., CNNs, MobileNet) are central to the project. The system builds on transfer learning and pre-trained models, leveraging engineering basics for effective performance.

Examples: Understanding optimization algorithms like Adam and categorical cross-entropy loss.

K4: Specialist Knowledge

Rationale: Expertise in dermatological datasets and diagnosis techniques informs the model's classification logic.

Examples: Incorporating domain-specific annotations (e.g., lesion types like melanoma or eczema) into training.

K5: Engineering Design

Rationale: The project emphasizes a user-centered design, considering accessibility for both clinicians and patients in resource-limited settings.

Examples: Designing a responsive web app that works seamlessly on mobile devices.

K6: Engineering Practice

Rationale: Practical considerations, including deployment on edge devices, guide the system's architecture. Lightweight MobileNet models ensure compatibility with low-power devices.

Examples: Testing on platforms like Heroku or AWS for scalability.

K8: Research Literature

Rationale: The project incorporates insights from state-of-the-art research in medical imaging and deep learning, bridging gaps identified in previous studies.

Examples: Leveraging datasets like HAM10000 and literature on MobileNet's performance in medical contexts.

5.4.2 Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping a rationale is putted.

Table 5.4.2.1: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
√	√		√	√

The engineering activities mapping using Table 5.4.2.1 is as follows:

EA1: Range of Resources

Rationale: The project uses diverse resources, including cloud servers for hosting, dermatological image datasets, and software tools (e.g., TensorFlow, Streamlit).
Examples: Cloud hosting ensures scalability, while MobileNet models are optimized for edge computing.

EA2: Level of Interaction

Rationale: Continuous collaboration with stakeholders, including dermatologists and patients, ensures the system's relevance and usability.
Examples: Regular feedback sessions with dermatologists to validate predictions and refine the app.

EA3: Innovation

Rationale: The project pioneers the use of lightweight CNN architectures for dermatological diagnosis, democratizing healthcare access.
Examples: Integrating MobileNet V3 to achieve a balance of accuracy (87.21%) and computational efficiency.

EA4: Consequences for Society and Environment

Rationale: The project addresses healthcare inequities by providing diagnostic tools for underserved populations while reducing carbon footprints through digital solutions.
Examples: Deployment in rural areas minimizes the need for travel and in-person consultations.

EA5: Familiarity

Rationale: Dermatology presents unique challenges due to the variability in skin types and conditions. The model leverages datasets to simulate expert-level familiarity.

Examples: **Training on diverse images from datasets like HAM10000 ensures robustness.**

5.5 Summary

The project demonstrates a systematic approach to addressing a complex engineering problem in healthcare. It effectively maps the challenges to problem-solving categories (e.g., conflicting requirements, stakeholder involvement) and aligns with the knowledge profile for engineering fundamentals and specialized practices. By innovating in diagnostic accuracy and accessibility, the system contributes to societal benefits and environmental sustainability, while meeting the engineering activities outlined in Table 5.3. Through interdisciplinary collaboration and adherence to engineering standards, the project ensures a scalable, ethical, and impactful solution for dermatological diagnostics.

Chapter 6

Conclusion

6.1 Summary

The development and implementation of AI-driven dermatological diagnostics mark a significant step forward in improving healthcare delivery, particularly in the field of skin disease diagnosis. This project successfully demonstrates the feasibility and effectiveness of using deep learning models to accurately classify and diagnose various skin conditions through a user-friendly web application.

Key achievements include the creation of a robust and scalable model trained on diverse dermatological datasets, which enhances diagnostic accuracy across different skin types and conditions. The application's cross-platform usability, stringent security measures, and mobile responsiveness ensure accessibility and usability for a wide range of users, from healthcare professionals to patients seeking reliable diagnostic tools.

Ethical considerations have been paramount throughout the project, with a focus on safeguarding patient privacy, ensuring data security, and addressing algorithmic biases. These efforts are critical in fostering trust and acceptance of AI-driven solutions in clinical practice.

Moving forward, the project suggests promising avenues for further development. Future iterations could explore expanding the model's capabilities to include additional skin diseases and integrating real-time diagnostic features for enhanced clinical utility. Collaboration with dermatologists and healthcare providers remains essential for continuous validation, refinement, and adaptation of AI models to meet evolving clinical needs.

Despite these advancements, the project acknowledges several limitations. Challenges such as data quality and availability, model interpretability, and resource constraints for widespread deployment highlight areas for ongoing research and improvement. Addressing these challenges will be crucial for maximizing the impact and adoption of AI-driven dermatological diagnostics in diverse healthcare settings.

6.2 Limitation

Despite the advancements and potential of the AI-driven dermatological diagnostic system, several limitations must be acknowledged to ensure a balanced perspective on its current capabilities and future directions:

1. Data Quality and Diversity: The effectiveness of AI models heavily relies on the quality, diversity, and representativeness of the training data. Limitations in the availability of comprehensive and balanced datasets may impact the system's ability to generalize across different demographics, skin types, and geographic regions. Addressing this limitation requires continued efforts to acquire diverse and annotated datasets that encompass a wide range of skin conditions.

2. Model Interpretability: AI models, particularly deep learning architectures, often operate as black-box systems, making it challenging to interpret their decision-making processes. Lack of transparency in model outputs can hinder trust among healthcare providers and limit the system's adoption in clinical settings. Future work should focus on developing methods for improving model interpretability, such as generating visual explanations or feature attributions that clarify the basis of predictions.

3. Ethical Considerations: The integration of AI in healthcare raises significant ethical concerns related to patient privacy, data security, and algorithmic bias. Safeguarding patient information and ensuring compliance with regulatory standards (e.g., GDPR, HIPAA) are critical considerations. Moreover, mitigating biases embedded in datasets and algorithms is essential to prevent disparities in diagnostic accuracy across different demographic groups.

4. Resource Intensiveness: Training and deploying AI models for dermatological diagnostics require substantial computational resources and expertise. This can pose challenges,

especially in resource-constrained settings where access to high-performance computing infrastructure may be limited. Developing lightweight models optimized for deployment on mobile devices or cloud platforms can mitigate some of these resource constraints.

5. Validation and Clinical Adoption: Validating AI models in real-world clinical settings is essential to demonstrate their reliability, accuracy, and clinical utility. However, regulatory approvals, clinical validation studies, and integration into existing healthcare workflows can be time-consuming and complex processes. Collaborating closely with healthcare providers and regulatory bodies is crucial to navigate these challenges effectively.

6. Validation and Clinical Adoption: Validating AI models in real-world clinical settings is essential to demonstrate their reliability, accuracy, and clinical utility. However, regulatory approvals, clinical validation studies, and integration into existing healthcare workflows can be time-consuming and complex processes. Collaborating closely with healthcare providers and regulatory bodies is crucial to navigate these challenges effectively.

7. Scope and Coverage: While the current system focuses on common dermatological conditions, its coverage may not extend to rare or highly specialized skin disorders due to limited data availability and model generalization challenges. Future efforts should aim to expand the system's scope to encompass a broader spectrum of skin diseases, including those with lower prevalence rates.

Acknowledging these limitations is fundamental to guiding future research and development efforts aimed at enhancing the effectiveness, accessibility, and ethical soundness of AI-driven dermatological diagnostics. Addressing these challenges will be pivotal in realizing the full potential of AI technologies to support dermatologists in clinical decision-making and improve patient care outcomes

6.3 Future Work

Moving forward, several avenues for further development and enhancement of the AI-driven dermatological diagnostic system can be explored to expand its capabilities and impact:

Integration of Additional Skin Conditions: Extend the current model to include a broader spectrum of dermatological conditions beyond those initially targeted. This expansion would require acquiring and integrating additional high-quality datasets covering less common and rare skin diseases, thereby improving the system's diagnostic coverage and utility.

Real-time Diagnostic Support: Implement real-time diagnostic capabilities within the web application to provide immediate feedback and recommendations based on uploaded images. This could involve integrating live consultation features where dermatologists can interact directly with the AI system for enhanced diagnostic accuracy and patient care.

Enhanced Model Interpretability: Further research into enhancing the interpretability of AI models is crucial. Develop methodologies to explain model predictions in a transparent and understandable manner to dermatologists and patients. This could involve generating heatmaps to highlight areas of interest in diagnostic images or providing textual explanations alongside predictions.

Continuous Model Improvement: Establish mechanisms for continuous model improvement and adaptation based on ongoing feedback and real-world data. Implement automated retraining strategies that incorporate new datasets and updated medical knowledge to ensure the model's accuracy and generalizability over time.

Expansion of User Base and Accessibility: Expand the deployment of the web application to reach a wider audience, including healthcare facilities in resource-constrained settings and telemedicine platforms. Ensure compatibility with a variety of devices and internet connectivity levels to maximize accessibility and usability.

Validation and Regulatory Compliance: Conduct rigorous validation studies in clinical settings to validate the model's performance across different patient demographics and geographical regions. Ensure compliance with regulatory standards and guidelines for medical software to facilitate Integration into healthcare systems.
Collaborative Research Initiatives: Foster collaborations with dermatologists, medical researchers, and healthcare providers to leverage domain expertise and clinical insights. Collaborative efforts can lead to the development of specialized AI tools tailored to specific dermatological challenges and patient populations.

By pursuing these avenues for further development, the AI-driven dermatological diagnostic system can continue to evolve into a sophisticated tool that enhances diagnostic accuracy, supports clinical decision-making, and ultimately improves patient outcomes in dermatological care. These efforts will contribute to advancing the field of AI in healthcare and addressing the evolving needs of dermatology practice globally.

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Date: 12th January, 2025

Dr. Mizanur Rahman
Medicine, Allergy specialist.
DMF, DPM-Dhaka, MCH (Mother & Child).
Dhaka Child Hospital , Dhaka.

Dear Dr. Mizanur Rahman,

We hope this letter finds you in good health. We are writing to formally request your approval and documentation regarding the contributions you had to this research project, titled " DEEP LEARNING FOR EQUITABLE DERMATOLOGICAL DIAGOSIS: ENHENSING HEALTHCARE ACCESSIBILITY." As you know, your expertise and contributions to this project are invaluable, and we are deeply grateful for your assistance thus far.

The skin disease image data you shared and your contributions to this project has been instrumental in advancing our research efforts. We are now at a stage where we require your official confirmation regarding the authenticity and accuracy of the work. Your endorsement will not only strengthen the credibility of our research findings but also ensure transparency and accountability in acknowledging your valuable contribution.

We assure you that the confidentiality and integrity of the data will be upheld throughout the research process, and appropriate credits will be attributed to you for your invaluable contribution.

Warm regards,

MD. ABU NASER
ID: 201-15-13785
Department of Computer Science and Engineering
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12/01/2025

Dr. Md. Mizanur Rahman
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