UTILIZING ADVANCED MACHINE LEARNING TECHNOLOGIES FOR DETAILED ECZEMA DIAGNOSIS AND ASSESSMENT

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DECLARATION

I declare that this is my own work and this dissertation1 does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any other university or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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Signature of the supervisor: Date: 2025-04-11

(Mr. Samadhi Rathnayake)

Signature of the co-supervisor: Date:

(Mr. Junius Anjana)

ABSTRACT

Atopic dermatitis (commonly known as eczema) is a chronic inflammatory skin disease with an increasing prevalence globally, which affects people physically and psychologically. Because the diagnosis and disease severity assessment of atopic dermatitis are subject to traditional subjective clinical evaluations, there is a risk that treatment outcomes will be inconsistent across different patients. Machine learning combined with advanced image analysis techniques is increasing the opportunity for standardization and accuracy in analyzing discrete changes. "DermaScope AI" will be a novel app based on the results in this study, which aims to provide accurate and rapid diagnosis for severity of atopic dermatitis by employing machine learning techniques. Through automatizing clinical images analysis and matching the assessments with predefined metrics, DermaScope AI seeks to improve patient care and clinical decision making. Our study aims to change the way in which we approach atopic dermatitis, providing a nimble and adaptable care model that can be implemented across different healthcare platforms offering a practical solution, ultimately improving the lives of those affected by this chronic condition.

Keywords – Eczema, Atopic dermatitis, Machine learning, Deep learning, Severity assessment

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
AD	Atopic Dermatitis
CNN	Convolutional Neural Network
GLCM	Gray Level Co-occurrence Matrix
SVM	Support Vector Machine
EASI	Eczema Area and Severity Index
SCORAD	SCORing Atopic Dermatitis
XAI	Explainable Artificial Intelligence
UI	User Interface
UX	User Experience
IDE	Integrated Development Environment
HTML	HyperText Markup Language
CSS	Cascading Style Sheets
REST API	Representational State Transfer Application Programming Interface

1. INTRODUCTION

1.1 Background

Eczema is a skin condition that causes inflamed, itchy, and red patches to appear on the skin. It is a multifactorial disorder that involves genetic and environmental influences, resulting in an overzealous immune response as well as skin barrier dysfunction. Eczema displays itself in characteristic patterns of inflammation, with the face, neck and hands frequently involved, as well as the flexural regions such as inside elbow creases or behind knees. The condition can vary in severity, with symptoms ranging from mild irritation to severe discomfort that significantly impacts daily life.

Atopic dermatitis (AD) is the most prevalent and globally diagnosed form of eczema, occurring in both adults and children in Sri Lanka. AD is a chronic skin condition that presents red, inflamed, and itchy patches on various parts of the body. AD has been proven to cause some painful symptoms such as constant rashes, hurt, and discomfort, coupled with severe and persistent itching. Persistent itching is one of the most bothersome symptoms of AD, most of the time becoming a chronic condition that is difficult to treat. If untreated or not controlled properly, this persistent scratching caused by the itch further weakens the skin barrier, and cracks and sores are created that predispose the patient to secondary infection and other dermatoses. Although AD pervades all stages of life, it most commonly begins early on in life, and some also persist in appearing signs into adult life. Chronic courses often enough make AD a chronic and resilient disease that constitutes a significant concern for individuals, families, as well as the healthcare system. Its chronic nature, combined with its impact on physical and psychological well-being, emphasizes the necessity for successful treatment interventions to minimize distress and maximize long-term outcome in AD patients [1].

Figure 1.1: Red, inflamed, and possibly scaly patches of eczema on the face

Figure 1.2: Eczema on arm, which has red, inflamed patches

The severity of AD is typically categorized into three distinct levels as mild, moderate, and severe, with each level presenting varying degrees of symptoms and impact on daily life. Mild AD is characterized by dry, flaky, and occasionally itchy skin, often accompanied by slight redness or irritation. These symptoms are generally manageable with consistent use of emollients, moisturizers, and mild topical treatments, requiring minimal medical intervention. Moderate AD involves more pronounced symptoms, including persistent itching, visible redness, and inflamed patches that may cause discomfort or pain. In this stage, patients often require stronger topical corticosteroids or medicated creams alongside regular skincare routines to reduce inflammation and alleviate symptoms. Severe AD is the most intense form of the condition, marked by widespread inflammation, persistent and severe itching, cracked or oozing skin, and significant discomfort that can greatly affect sleep quality and overall well-being. Patients with severe AD may experience frequent flare-ups and are often prescribed systemic medications, immunosuppressants, or biologic therapies to manage the condition effectively. Understanding these severity levels is essential for healthcare providers to develop personalized treatment plans that address both the physical symptoms, and the psychological burden associated with AD, ultimately improving the patient's quality of life.

Figure 1.3: Mild eczema

Figure 1.4: Moderate eczema

Figure 1 5: Severe eczema

The high prevalence of AD and associated symptomatology highlights the importance that heath care providers need to pay special attention in this specific type of eczema. Apart from its burden of physical disease, it also causes psychological and social consequences which add to the suffering of patients in terms of quality-of-life. Therefore, successful diagnosis and severity evaluation are essential for the management of atopic dermatitis to minimize its long-term consequences while improving quality of life. The disease generally presents with a relapsing and remitting course, from mild discomfort to incapacitating skin lesions. In clinical practice, these approaches rely on the use of emollients and topical corticosteroids with a particular focus towards barrier optimization and reduction in inflammation respectively. The chronicity of eczema frequently results in suffering, both physically and mentally, including sleep impairment, anxiety, and social disruption.

The accurate diagnosis of the most common type of eczema, atopic dermatitis and accurate severity assessment are key components for optimal management intervention. At present, most diagnostic tools and assessments rely on subjective clinical evaluations conducted by dermatologists. Results are likely to be delayed and variably based on the visual inspection methods chosen, or patient history. As a result, there is growing demand for accurate, objective and cost-effective tools for identification and monitoring of eczema among patients that can be accessed in either clinical or non-clinical settings.

The recent advancements in deep learning and various other advanced machine learning algorithms have paved way to the development of novel computer aided diagnosis systems that are able to alleviate human subjectivity at diagnosing eczema more accurately as well as determining it into correct classes along with gauging its severity. Using machine learning to study vast collections of skin pictures can help in recognizing patterns and features that scream eczema, making it a highly prospective diagnostic. In eczema diagnosis, Convolutional Neural Networks (CNNs) have become an especially powerful method for automatic skin lesion classification and severity assessment. CNN could replace the prior process to save time, reduce subjectivity in clinical scales that demand expertise experience from evaluators. Thus, it becomes more efficient comparative novel diagnostic tool over traditional approaches which are slower with high range of variability due to evaluator interpretation. These models are helpful for clinicians as well as patients.

Many studies have implemented machine learning in diagnosing and assessing the severity of eczema. In particular, the use of image processing methods such as Gray Level Co-occurrence Matrix (GLCM) and machine learning models including Support Vector Machines (SVM), to correctly classify images with specific types as atopic dermatitis, contact dermatitis or nummular dermatitis has already reached a significant level of accuracy. Moreover, the application of U-Net architectures to segment eczema lesions from skin scans has been able to identify lesion delineation, necessary for an adequate reading on disease severity. This progress holds great promise for integration of machine learning in the routine practice of dermatology, leading to personalized and more reliable therapy delivery against eczema.

The novel application, DermaScope AI, uses proprietary machine learning capabilities to optimize current atopic dermatitis diagnosis. With this atopic dermatitis application, it is possible to detect the condition of the skin that causes atopy correctly by using skin image data. A cutting-edge solution compared to traditional diagnostic techniques, DermaScope AI streamlines the diagnosis procedure with a significant amount of time saving and accessibility, especially in areas which do not have enough availability for dermatologists. This solution further illustrates machine learnings vital role in driving more effective, efficient eczema care, a generalizable and objective tool for both clinicians as well as patients with an atopic emphasis.

1.2 Background Literature

Nisar et al. [2] worked with supervised machine learning methods for segmenting and categorizing eczema lesions. Supervised machine learning methods can improve the accuracy and efficiency of clinical assessments for identification or severity assessment where they have been developed. Researchers have successfully segmented and categorized eczema skin lesions with a high level of accuracy through the employment of SVM and CNN algorithms. Such techniques are especially useful in clinical situations where conventional methods can result in time constraints and subjectivity. These machine learning models could be a major advance in leading the dermatologic diagnosis to avoid errors which harm patient care as they are capable of reliably identifying multiple types of eczema.

Jardeleza et al. [3] proposed an algorithm combining GLCM and SVM in the detection of several forms of typical eczemas (atopic dermatitis, contact dermatitis and nummular dermatitis). In the study, researchers created a prototype system that was able to obtain photos of skin and eczema locations as well as benchmarking accurately what kind of type dermatitis patients suffered from. This system, with an accuracy of 83.33%, is very useful in regions where access to highly trained dermatologists would seem difficult as the earlier and more accurate diagnosis could dramatically impact treatment outcomes. In this specific case, the mixture of GLCM and SVM demonstrates that machine learning can provide reliable diagnostic tools also to be easily understandable by everyone.

Junayed et al. [4] successfully introduced EczemaNet, to achieve high accuracy in classification of different types of eczema diseases. CNN has demonstrated an impressive performance in classifying various eczema conditions. Many still call for deep learning models as EczemaNet, a deep CNN-based model specifically developed to handle the difficulty of telling eczemas apart from each other. Trained on a large set of annotated eczema photos, the model was more accurate and provided qualitatively consolidated classification results over previous models. The ability of EczemaNet to make accurate and actionable diagnoses may not only aid clinical decision-making but also suggest the potential adoption of such models into routine dermatological practice, which could lead to notable time and accuracy gains.

Attar et al. [5] explored the use of digital camera images for automatic identification and objective assessment of eczema severity in an automated manner to advance the process of evaluating eczema. Through the utilization of advanced image processing methods, these systems are able to programmatically detect areas where there is eczema and then grade severity scores for each area based on specific clinical criteria. All automated assessments were validated for their accuracy and reliability against the opinions of board-certified dermatologists. Results indicate that the systems can achieve equivalent levels of performance besides saving medical staff time. Automatic systems also ensure the objectiveness and uniformity of assessments that are crucial for tracking disease progression and tailoring treatment plans.

Nisar et al. [6] successfully applied a modified U-Net network for skin lesion segmentation in eczema within the image. It has shown much better results than prior pixel-based classification. This is useful for medical image segmentation tasks since U-Net was designed to address complex lesion shapes and varying scales sizes. This is particularly valuable for dermatologists who will be able to identify the exact lesion by using those highly precise boundaries of eczema-affected regions drawn with U-Net in this case. This specificity is important to later detection and treatment planning for patients to ensure that an accurate diagnosis of the skin condition diseases they have.

Outside the progress of segmentation and classification, a recent avenue for investigation has been how to close this loop with mobile applications or real-time diagnostic systems integrating these machine learning models. The integration aims to make these valuable diagnostic tools more accessible for patients and their health care providers by allowing examinations and continuous monitoring of eczema diseases at home or during planned visits. The systems help patients to engage and abide by their treatment plans, giving responses that are as rapid, so they immediately get feedback on the areas in which they need answers. Such advancements signify a paradigm shift in eczema care, as these widespread technologies and advanced deep learning approaches could entirely change how the disease is diagnosed and monitored both within clinical settings as well as beyond. This growing body of research underlines the importance of interdisciplinary collaboration to develop robust care models that are not only effective, but also scalable and feasible for patients.

Table 1 1: Overview of existing methods and technologies

Research Paper	**Technique Used**	**Focus**	**Primary Insight**
Automatic Segmentation and Classification of Eczema Skin Lesions Using Supervised Learning	Supervised Learning (SVM, CNNs)	Automatic segmentation and classification of eczema skin lesions.	High accuracy and efficiency in segmenting and classifying eczema types.
Detection of Common Types of Eczema Using Gray Level Co-occurrence Matrix and Support Vector Machine	GLCM for Feature Extraction, SVM for Classification	Detection and classification of common types of eczema (atopic, contact, nummular).	Achieved 83.33% accuracy in classifying eczema types, beneficial in regions with limited dermatologist access.
EczemaNet: A Deep CNN-Based Eczema Diseases Classification	Deep CNN (EczemaNet)	High-accuracy classification of various eczema diseases.	Significantly improved classification accuracy and robustness, aiding in efficient clinical diagnosis.
Reliable Detection of Eczema Areas for Fully Automated Assessment of Eczema Severity	Advanced Image Processing Techniques for Segmentation and Severity Assessment	Automated detection of eczema-affected areas and severity assessment.	Comparable accuracy to expert dermatologists, providing objective and consistent severity assessments.
Segmentation of Eczema Skin Lesions Using U-Net	U-Net Architecture for Segmentation	Accurate segmentation of eczema skin lesions.	Outperformed traditional segmentation methods, offering precise lesion identification.

1.3 Research Gap

The reviewed research articles represent remarkable evolution in the diagnosis, classification and severity scoring of eczema with machine learning (ML) and deep neural networks. Nevertheless, there are several major evident gaps that need to be filled in order to improve the accuracy, generalizability and clinical relevance of these methods specifically with regard to atopic dermatitis as attested by a high number of studies mentioned within this framework.

This is a difficulty of segmentation as different lesion shapes are challenging. Despite U-Net having shown promise for recognizing eczematous areas, it remains challenging to accurately segment non-contouring irregularly shaped lesions. Such model performance might suffer when encountering a larger degree of variations in lesion shape and color intensity, leading to less precise results with segmentation. Therefore, this issue requires more advanced solutions for lesion identification or the integration of context to improve detection accuracy.

DermaScope AI is a novel way of doing that. It has been designed to bridge these gaps, targeting only for the diagnosis and severity assessment in atopic dermatitis. Focusing on this type of eczema, DermaScope AI aims to deliver a highly precise and effective tool that is purpose-built for the characteristics found within atopic dermatitis leading to improved diagnostic accuracy as well as standardization. An integral part of the proposed solution is to aid in improving explainability or interpretability of model. DermaScope AI will utilize Explainable Artificial Intelligence (XAI), which is used to increase the transparency and interpretability of predictions in deep learning models, reducing ambiguity by revealing hidden patterns within a model. Not only does this give accurate predictions but also builds the reason behind these to clinicians which can lead to trust from them and facilitate integration of technology in clinical workflows.

The other important part of the proposed strategy is to make models more robust. The study will aim to harden the models against shifting patient demographics, illumination and picture quality. By training the models on a wider dataset and performance enhancing methods like data augmentation, domain adaptation ensure models will generalize well across many situations. This is to make the system more robust in clinical practice. Furthermore, an adaptive multi-scale attention mechanism will be implemented to deal with the difficulties in segmenting complex performed lesion shapes and varied image sizes within atopic dermatitis. This would allow the model to attend to important sections of the image at varying scales hence enhancing segmentation and severity assessment which is more accurate especially when lesion borders appear irregular or ill-defined.

In summary, to fill these gaps specifically DermaScope AI is built with extra features for a better overall comprehensive tool that can be used reliably and accurately in clinics too as part of managing patients who have atopic dermatitis. This comprehensive approach is expected to significantly enhance patient outcomes across a wide range of settings.

Table 1 2: Comparison of the features addressed by the previous research studies

Feature / Gap	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**Proposed Solution**
Incorporate advanced deep learning techniques	Yes	No	Yes	Yes	Yes	Yes
Enhanced explainability	No	No	No	No	No	Yes
Improved robustness	Yes	No	Yes	Yes	Yes	Yes
Eczema severity assessment	No	No	No	Yes	No	Yes
Incorporation of attention mechanisms	No	No	No	No	No	Yes
Integrated system	No	No	No	No	No	Yes
Progress analysis	No	No	No	No	No	Yes

1.4 Research Problem

Eczema (atopic dermatitis) is a common, chronic, relapsing inflammatory skin condition that affects up to 10% of the population worldwide. It leads to intense physical discomfort of itching, redness and thickening skin, and overall diminishing quality of life due to the pain it causes those affected. Atopic dermatitis is the most common among all eczema that is commonly encountered in clinical settings. Correctly identifying atopic dermatitis and quantifying its severity represent the first important steps to manage this disease properly while personalizing treatment strategies as much as possible.

The diagnostic process for eczema, and particularly atopic dermatitis, is a clinically based one that depends on observation by trained medical personnel. This approach consists in the physical assessments of eczema, such as redness (erythema, inflammation), thickness (induration, papulation, swelling), scratching (excoriation), and lichenification (lined skin, furrowing, prurigo nodules) as part of the EASI scores. The EASI score is a quantitative and standardized instrument, which assesses the severity of eczema in terms that reflect both the extent as well as clinical intensity of these features. Whilst a common practice, this method is inherently subjective due to the reliance on clinician judgement and experience [7].

This has subjective elements and allows room for differences in diagnosis, especially the grade of severity of atopic dermatitis. Variation in clinician interpretation of the severity of a given condition could certainly lead to disparate treatment decisions and patient outcomes. In addition, manual evaluation in the case of eczema wrongly not only requires time but substantial manpower and is considered as one of hurdles into opportunities for busy clinical settings towards accuracy top priority. Furthermore, these methods do not capitalize on the enabling power of developments in medical technology and data science to aid eczema diagnosis and management with greater precision and consistency. We cannot assume that all meaningful changes to the condition are visible and so for situations where assessment occurs via purely invasive visual inspection, we rely on inspectors having a level of detection ability left largely undefined. Thus, innovative strategies specifically targeting atopic dermatitis can and should enhance or replace traditional means of assessing atopic dermatitis severity in a more objective, reproducible and efficient manner.

1.5 Research Objectives

1.5.1 Main Objective

As the main objective of our investigation, we will be developing a new whole system for advanced diagnostic and severity evaluation with machine learning in atopic dermatitis. DermaScope AI is aimed at overcoming challenges associated with subjective traditional methods and aims to provide an objective, faster, and more accurate tool for aiding clinical judgment to better patient outcomes.

DermaScope AI will focus on the exact diagnosis as well as a detailed severity assessment of atopic dermatitis, one of the most common forms of eczema. However, the most cutting-edge developments in machine learning will assist this system, primarily on image analysis and pattern recognition. We aim at detecting properly the severity of allergen mediated eczema by observing clinical symptoms that are criteria included in elaborate diagnostic definitions. Integrating these cutting-edge technologies will enable DermaScope AI to deliver a deeper and detailed analysis, supporting healthcare professionals in making more data-driven decisions about patient care. We conclude that such an analysis will allow them to in turn refine and personalize treatment paradigms even further than already done.

Overall, this study will lead to the creation of an AI-based solution for atopic dermatitis treatment called DermaScope AI. It will improve the accuracy of diagnoses and enhance clinical assessment, providing a more objective method for evaluating. Ultimately, this will improve care journey for the patient population presenting with a chronic disease like diabetes. The end goal is to improve the patient being of those who, based on their status and eligibility for recommended genetic testing, receive assessments in a timely manner with attention to accuracy such that appropriate treatments may be provided.

1.5.2 Sub Objectives

Sub Objective 1: To Develop an Accurate Machine Learning Model for Diagnosis

The project aims to build an advanced machine learning model to make a correct prediction of atopic dermatitis based on clinical images. The pretrained model will be further fine-tuned to detect and read certain signals of the disease, using clinical diagnostic criteria EASI score in mind. Automation of this process is then expected to result in more consistent and objective diagnoses, with the goal being a higher standardization of patient assessment making it easier for clinicians to provide good care. This new development could change the pathway to diagnosis for atopic dermatitis, making it quicker and more dependable and less reliant on clinical impressions, so that a patient can get an accurate treatment option.

Sub Objective 2: To Implement a Detailed Severity Assessment Framework

This project is an effort to design a meticulous and reliable framework under DermaScope AI exclusively for evaluating the severity of atopic dermatitis. The framework will assess a wide range of clinical indicators that contribute to the severity of atopic dermatitis (such as erythema, induration and lichenification). The goal of such a framework is to facilitate better diagnostic and treatment decisions by clinicians. It can enable detailed and subtle evaluation of disease severity, a foundation that supports the development of individualized treatment plans for patients. These personalized therapy concentrates treatments for effectiveness and patient experience which enhances individual outcomes by identifying the appropriate care each patient needs based upon their clinical characteristics.

Sub Objective 2: To Integrate an Attention Mechanism with Explainable AI for Enhanced Diagnostic Accuracy

This sub-objective aims at embedding an attention mechanism in the machine learning model implemented on DermaScope AI, to further improve its diagnosis of atopic dermatitis. The attention mechanism will help the model to focus, rather than ignore complex regions of interest from clinical images such as major areas with erythema or lichenification which are necessary parts for diagnosing disease. Through this, the diagnostic process is more rigorous and aligned with clinical practice as it guides which parts of data are essential to every model feature.

Also, this sub-objective is to integrate Explainable AI (XAI) techniques with the model so that users can interpret how the decision-making process of it being transparent. Using XAI, the model will return visualizations and explanations of where in the image contributing to diagnosis and severity so on. The users can see why and how a diagnosis is reached. We are convinced that a compound unit of AI and XAI along with the incorporation attention mechanism not only boosts diagnostic accuracy but also in terms of adoption of AI clinical as tool since clinician are served by provision more interpretable about available tools.

Sub Objective 4: To Implement Progress Tracking for AD Management

This sub-objective aims to create a comprehensive progress monitoring feature in DermaScope AI which can constantly track the patient's response to treatment enabling clinicians to detect changes (positive or negative). Therefore, they can administer therapy appropriately. By keeping tabs on progress analysis, the clinicians can make real-time adjustments to treatment plans, helping patients receive the best possible care while their strategy continues to be fine-tuned.

2. METHODOLOGY

2.1 Requirement Gathering

The requirement gathering phase played a pivotal role in ensuring that the development of the proposed system, DermaScope AI, is closely aligned with the practical needs and expectations of its intended end users, including dermatologists and patients. To achieve this, a comprehensive and structured approach was adopted. These included stakeholder interviews, expert consultations, and literature reviews, each aimed at extracting detailed insights into the clinical workflows, diagnostic criteria, user interface preferences, and pain points with existing eczema diagnostic methods. The outcomes of this phase were used to define both functional requirements as well as non-functional requirements. By thoroughly understanding these requirements early in the development process, DermaScope AI is designed to deliver a reliable, accessible, and clinically meaningful solution for AD diagnosis and assessment.

2.1.1 Stakeholder Identification

- Dermatologists - to provide clinical insights and validate diagnostic criteria.
- Patients with atopic dermatitis - to understand user experience needs.
- Software developers - to assess technical feasibility and implementation constraints.

2.1.2 Methods Used

- Interviews with dermatologists and clinicians to understand diagnostic workflows, image assessment criteria (e.g., EASI), and the key indicators of severity.
- Review of existing systems and literature to identify the limitations and strengths of current machine learning tools used for eczema diagnosis.

- Consultations with technical experts to assess the feasibility of integrating Explainable AI (XAI), attention mechanisms, and multi-scale image processing.

2.1.3 Functional Requirements

- The application should allow a user to upload affected skin lesion images at high resolution and process the uploaded images.
- The application should be able to identify and segment eczema-affected regions from the input images with a system that uses advanced machine learning techniques.
- The application should offer an end-to-end analysis of the severity of atopic dermatitis using user-friendly dashboards for healthcare providers.
- An application is required to establish its personalized profile for each user, which allows the user centered service provider to save various information like severity evaluation, treatment history or progress assessment.
- The application must assess the severity of atopic dermatitis based on clinical indicators and established criteria.

2.1.4 Non-Functional Requirements

- Usability: The system interface must be user-friendly and intuitive for both clinicians and non-technical users.
- Accuracy: The ML model must provide clinically reliable results with high accuracy.
- Performance: The system should deliver real-time or near real-time predictions.
- Scalability: It should be scalable to integrate with mobile platforms or remote healthcare systems.

- Security and Privacy: All patient data must be securely stored and processed, adhering to relevant data protection regulations.

2.1.5 Personal Requirements

- Guidance from supervisors on the eczema and data science domains.
- Understanding the specific area of each domain to proceed with the selected research area.

2.1.6 Gannt Chart

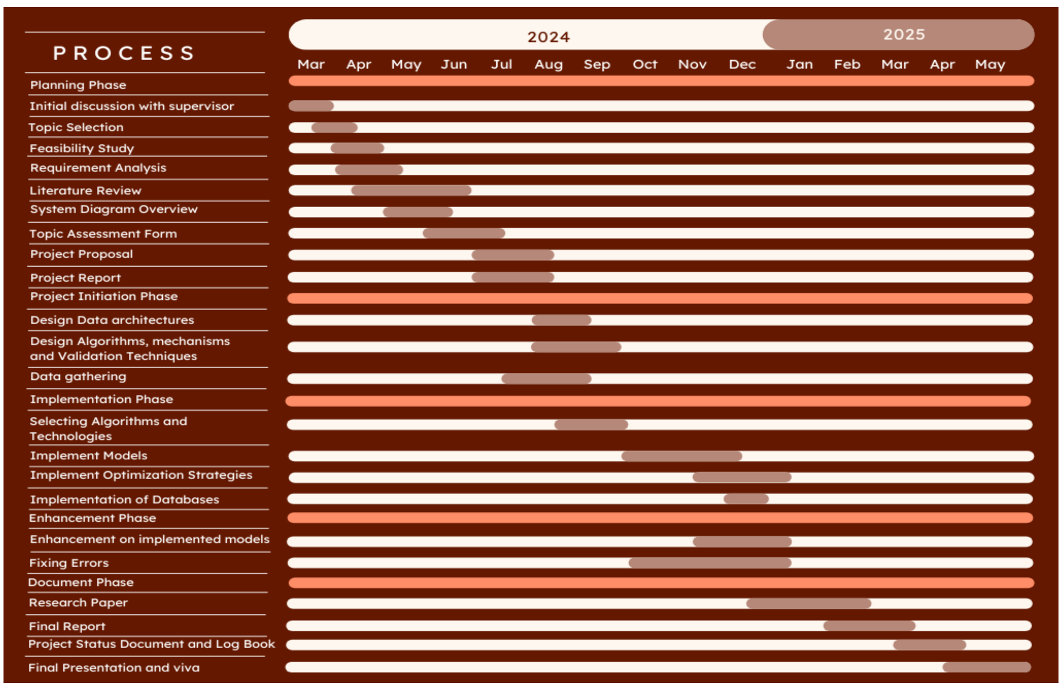


Figure 2 1: Gannt chart

2.1.7 Work Break Down Structure

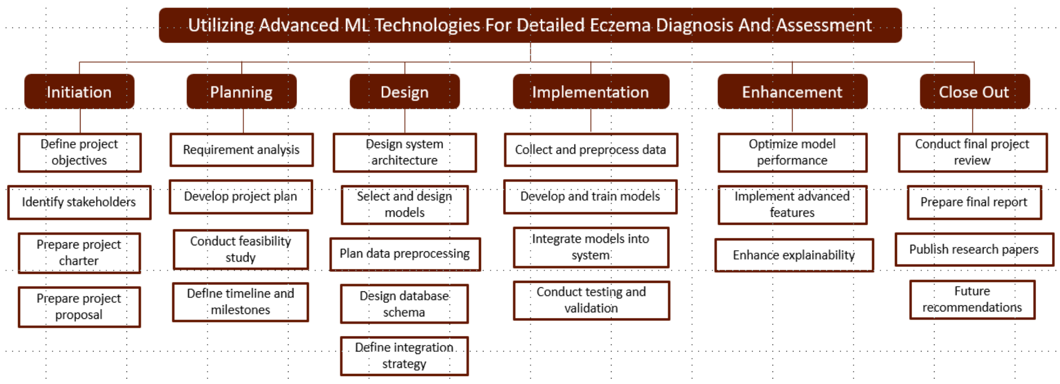


Figure 2 2: Work break down structure

This chart presents a structured project lifecycle for the system. It outlines the entire development process through six key phases:

- ❖ Initiation: Focuses on defining project objectives, identifying stakeholders, and preparing foundational documents such as the project charter and proposal.
- ❖ Planning: Involves requirement analysis, feasibility study, timeline definition, and the development of a comprehensive project plan to ensure organized execution.
- ❖ Design: Covers the architectural and technical blueprint of the system including model selection, data preprocessing strategies, database schema design, and integration planning.
- ❖ Implementation: Encompasses practical activities such as data collection and preprocessing, model development and training, system integration, and testing for validation.
- ❖ Enhancement: Aims to improve system performance through model optimization, the addition of advanced features, and a focus on model explainability.
- ❖ Close Out: Marks the project's completion with final review, report preparation, publishing results, and identifying future research directions.

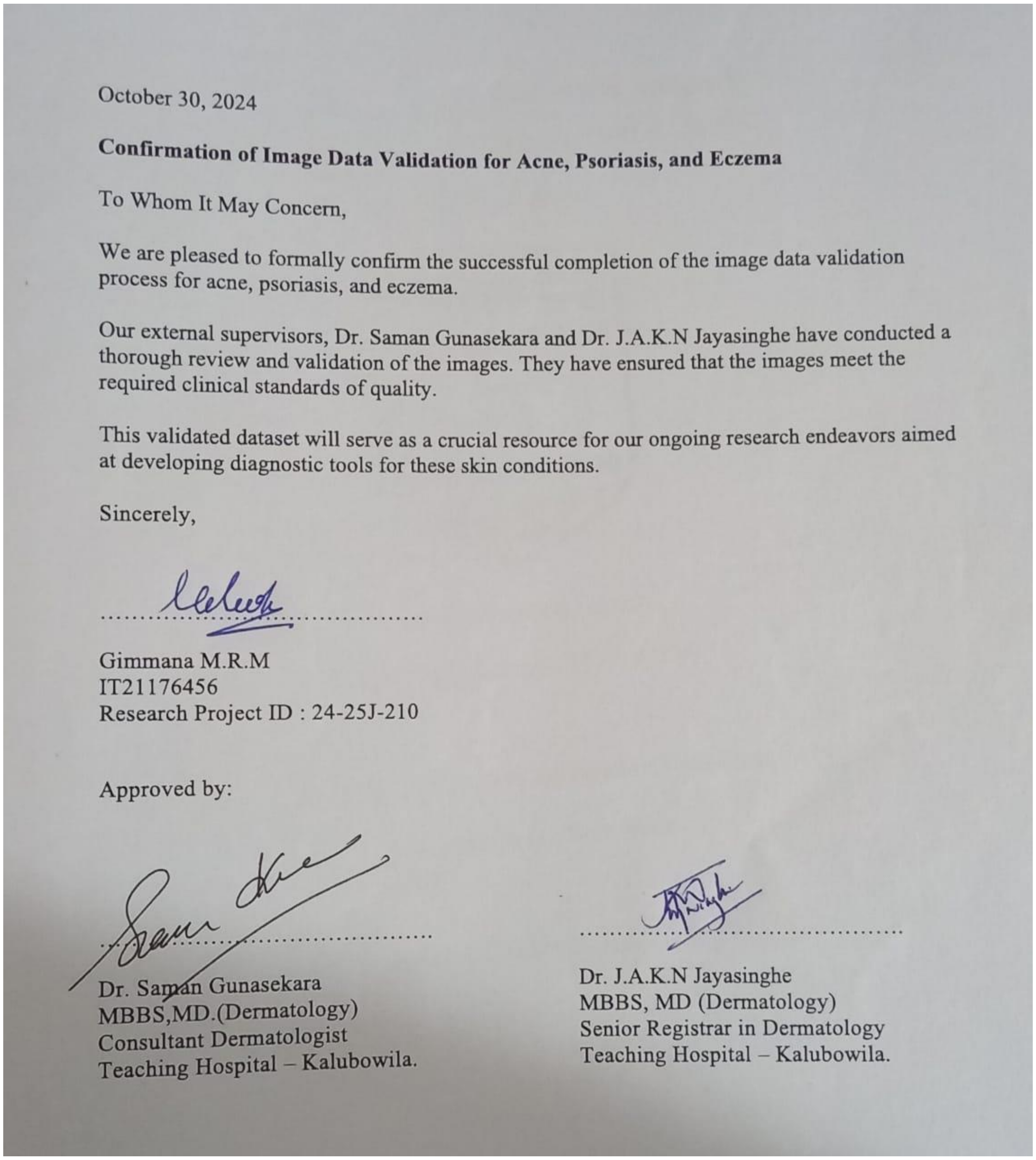
2.2 Data Collection

The dataset used in this study was obtained from an online source [8][9], specifically collected to support the identification and classification of eczema-related skin conditions. The dataset comprises a variety of images that are categorized into two main classes as eczema and non-eczema. These images were sourced from publicly available databases and online resources, ensuring a diverse range of skin conditions, lighting conditions, and image quality to enhance model robustness. The dataset serves as a foundational resource for developing and testing the proposed system, facilitating accurate detection and classification of eczema symptoms.

Figure 2 3: Sample images from the eczema and non-eczema classification dataset

To enhance the clinical relevance and accuracy of the eczema severity classification dataset, which was obtained from an online source [8], a dermatologist was consulted to provide expert insights for classifying eczema images based on their severity. This process involved carefully examining the collected images and categorizing them into three distinct severity levels as Mild, Moderate, and Severe. By incorporating the expertise of a medical professional, the classification process ensured that the dataset's labeling aligned with established clinical standards, thereby improving its reliability for medical research and diagnostic purposes. This collaborative effort not only added a layer of clinical accuracy but also strengthened the dataset's credibility, making it more suitable for developing robust machine learning models aimed at identifying and assessing eczema severity in real-world scenarios.

Figure 2 4: Sample images from the severity classification dataset



October 30, 2024

Confirmation of Image Data Validation for Acne, Psoriasis, and Eczema

To Whom It May Concern,

We are pleased to formally confirm the successful completion of the image data validation process for acne, psoriasis, and eczema.

Our external supervisors, Dr. Saman Gunasekara and Dr. J.A.K.N Jayasinghe have conducted a thorough review and validation of the images. They have ensured that the images meet the required clinical standards of quality.

This validated dataset will serve as a crucial resource for our ongoing research endeavors aimed at developing diagnostic tools for these skin conditions.

Sincerely,

……………………………………

Gimmana M.R.M
IT21176456
Research Project ID : 24-25J-210

Approved by:

……………………………………

Dr. Saman Gunasekara
MBBS,MD.(Dermatology)
Consultant Dermatologist
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……………………………………

Dr. J.A.K.N Jayasinghe
MBBS, MD (Dermatology)
Senior Registrar in Dermatology
Teaching Hospital – Kalubowila.

Figure 2 5: Data validation conformation from external supervisors

2.3 Data Exploration

To gain insights into the characteristics and distribution of the dataset, various visualizations were generated to analyze key aspects such as class distribution, severity levels, and feature patterns. These diagrams and charts provide a comprehensive overview of the dataset, illustrating the proportion of eczema and non-eczema images, as well as the distribution of eczema severity levels categorized as mild, moderate, and severe. Visualizing the data not only helps identify potential class imbalances but also offers valuable insights into the dataset's structure, aiding in the development of effective machine learning models for eczema detection and severity classification. The following visual representations present these key aspects in detail.

Eczema and non-eczema classification dataset

The Class Distribution chart indicates a well-balanced dataset, with 604 images classified as eczema and 589 images categorized as non-eczema. This near-equal distribution is essential for developing a robust and unbiased model, reducing the likelihood of skewed predictions and improving overall classification accuracy.

Figure 2 6: Visualization showing the balanced distribution between normal skin and eczema skin images

The Image Dimensions Distribution charts present the variation in image heights and widths within the dataset. The majority of images are concentrated around specific resolutions, indicating a level of consistency in image size, though some variations still exist. This information is essential for resizing strategies during preprocessing to ensure uniform input dimensions for model training.

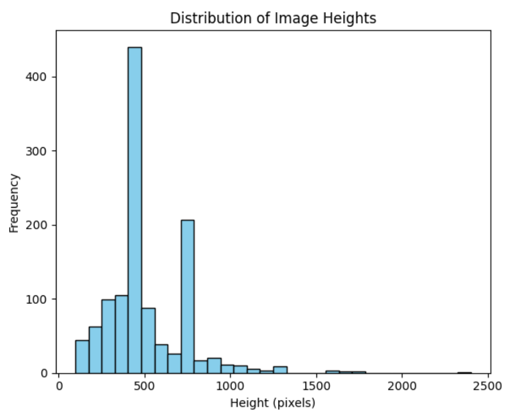


Figure 2 7: Charts illustrating the variation in image heights and widths across the dataset

Lastly, the Color Distribution plot displays the mean pixel intensity for the red, green, and blue channels across the dataset. This visualization highlights the range of color intensities, which can influence the model's ability to distinguish between eczema and non-eczema skin. Identifying these patterns helps in understanding potential color differences between classes, contributing to better feature extraction during model development.

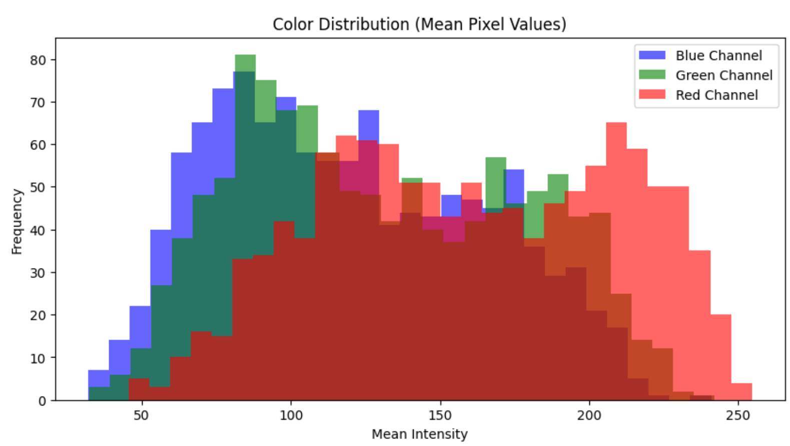


Figure 2 8: Graph representing the mean pixel intensity for the red, green, and blue channels in the dataset

Eczema severity classification dataset

The Severity Class Distribution chart illustrates the distribution of eczema severity levels within the dataset. The dataset shows an imbalance, with a significantly higher number of mild cases compared to moderate and severe cases. This uneven distribution highlights the need for techniques such as data augmentation or weighted loss functions to ensure balanced model training and improved performance.

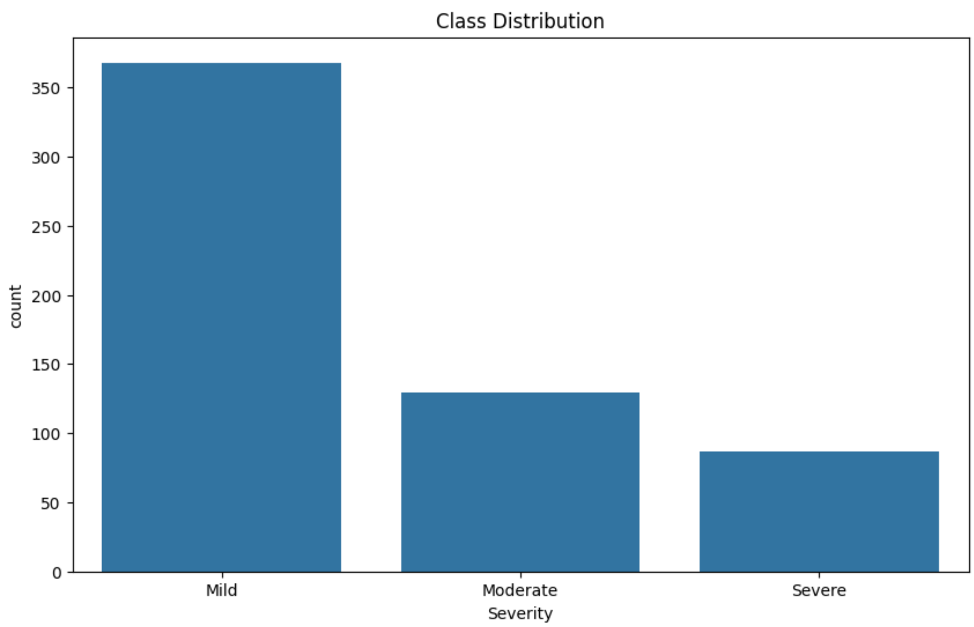


Figure 2 9: Visualization showing the distribution of eczema severity levels categorized as mild, moderate, and severe

The Image Dimensions Distribution charts depict the variation in image heights and widths within the dataset. While there is some diversity in image sizes, the majority are concentrated around specific resolutions. This information is crucial for guiding resizing strategies during preprocessing to maintain consistency in input dimensions, ensuring optimal model performance.

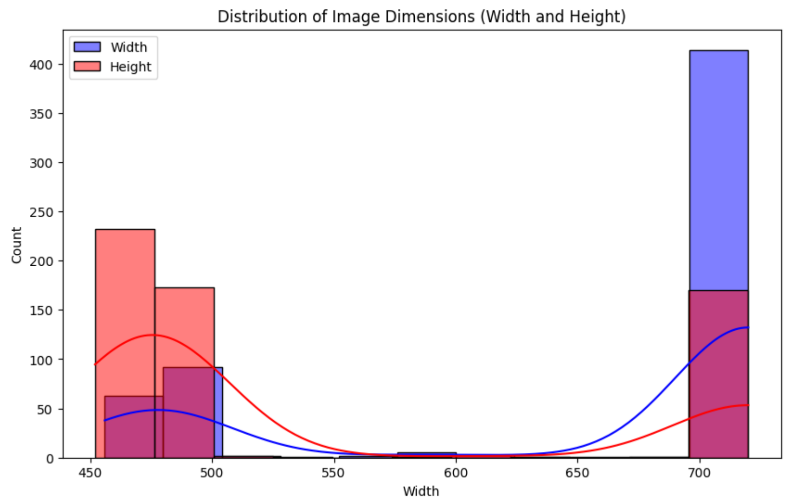
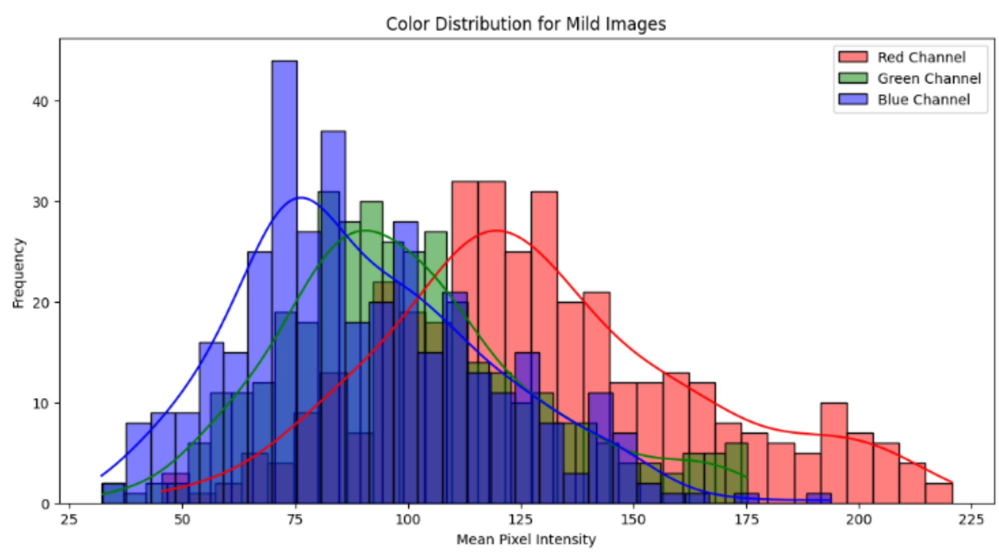
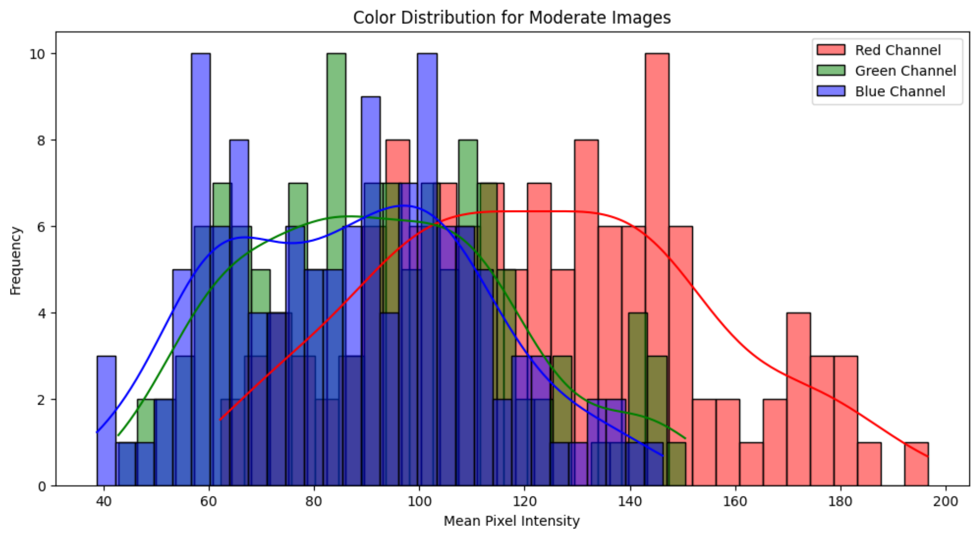


Figure 2 10: Charts illustrating the variation in image heights and widths across the dataset

The Color Distribution plots present the mean pixel intensity for the red, green, and blue channels across the dataset, categorized by severity levels. The color intensity distribution reveals distinct patterns, with mild eczema images displaying a broader range of intensities, while moderate and severe cases generally show lower intensity distributions. Identifying these color characteristics is valuable for enhancing feature extraction strategies and improving the model's ability to differentiate between eczema severity levels.





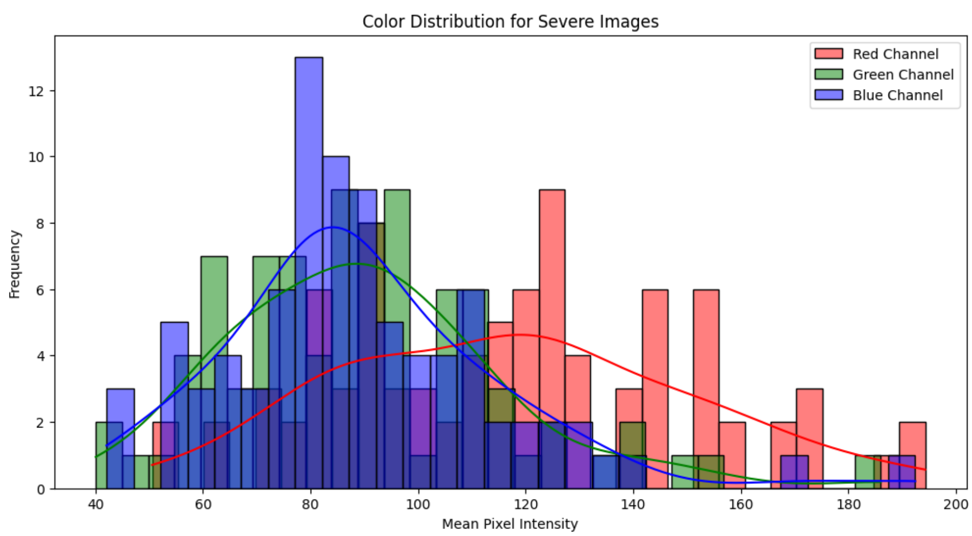


Figure 2 11: Graphs depicting the mean pixel intensity distributions for mild, moderate, and severe eczema images

These visual insights provide valuable information for refining data preprocessing steps and optimizing model performance.

2.4 Data Preprocessing

The data preprocessing phase was a critical step in preparing the raw image data for training an accurate and reliable machine learning model. Initially, images from the eczema detection dataset were organized into two distinct categories as 'Normal Skin' and 'Eczema Skin' and the images from the eczema severity classification were organized into three distinct categories as ‘Mild’, ‘Moderate’, and ‘Severe’. A custom Python function was implemented to iterate through these directories, load each image using the OpenCV library, and convert the image from BGR to RGB color space to align with standard conventions used in deep learning models. Each image was then resized to a fixed resolution of 224x224 pixels, ensuring uniform input dimensions compatible with popular convolutional neural network architectures. During this process, images were labeled as 0 for normal skin and 1 for eczema, establishing the binary classification foundation for model development.

Following the resizing, all image pixel values were normalized to a range between 0 and 1 by dividing each pixel value by 255.0. This normalization step was important for reducing the influence of varying lighting conditions and accelerating the training convergence of the model. Once preprocessing was complete, the dataset was split into training and validation subsets using an 80:20 ratio. This split ensured that the model would be evaluated on a distinct portion of data not seen during training, helping to gauge its ability to generalize and prevent overfitting.

To enhance the generalization capability of the model and mitigate the risk of overfitting, particularly due to the limited size and variability of the dataset, comprehensive data augmentation techniques were applied using the ImageDataGenerator class from the Keras library. Data augmentation is a critical preprocessing step in medical image analysis, as it synthetically increases the diversity of the training dataset by applying a range of transformations to existing images. In this study, the augmentation pipeline incorporated several operations including random rotations up to 30 degrees, horizontal and vertical shifts, zooming in and out, shearing transformations, and horizontal flipping of images. These transformations simulate real-world variations in clinical scenarios where skin conditions might be photographed from different angles, under inconsistent lighting conditions, or at varying distances. By artificially expanding the dataset in this manner, the model is exposed to a broader set of visual patterns, allowing it to learn more robust and invariant features that are essential for accurately distinguishing between normal and eczema-affected skin.

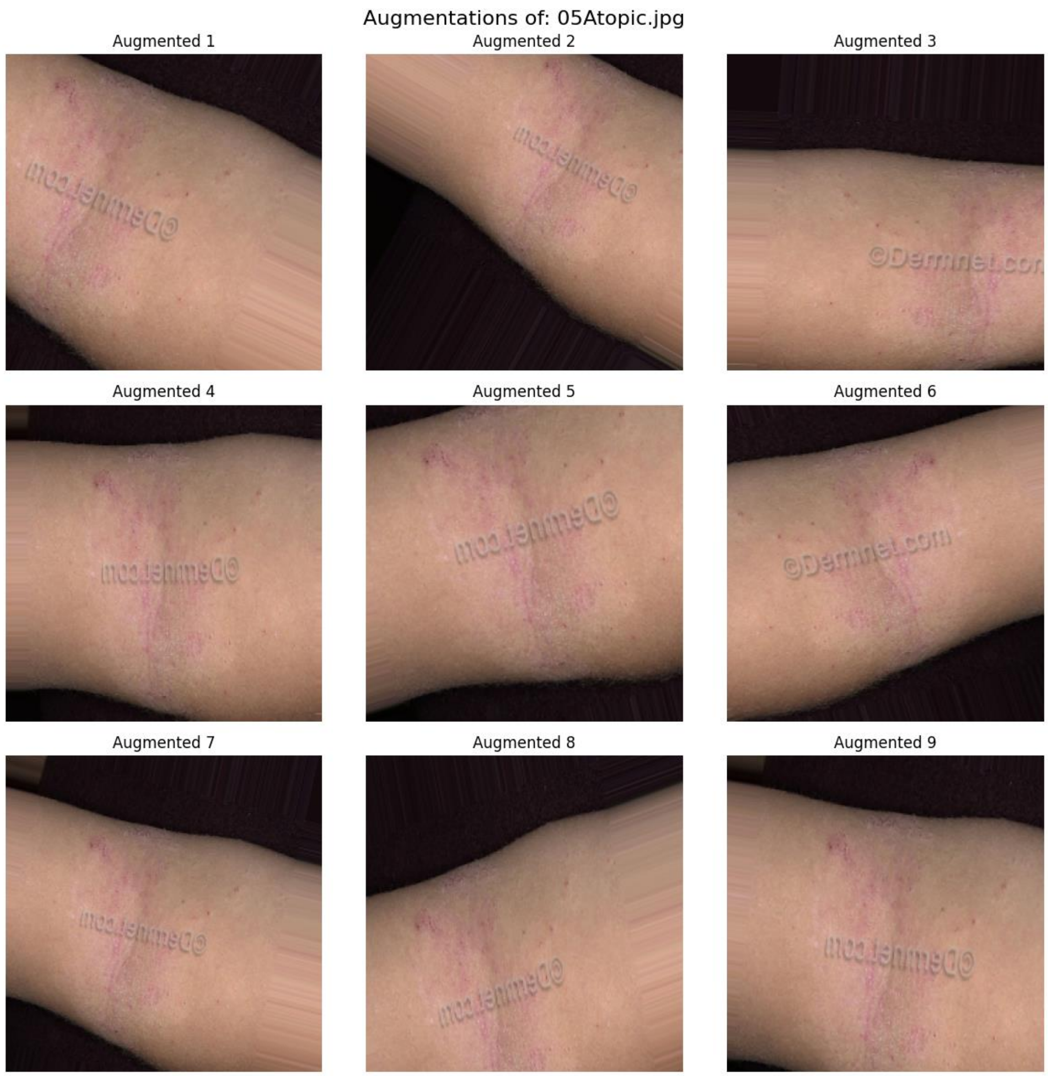


Figure 2 12: A sample image from the dataset after augmentation

The final step involved converting the preprocessed data into TensorFlow Dataset objects. These datasets were shuffled, batched into groups of 32 images, and prefetched to enable asynchronous data loading. This pipeline ensured efficient and optimized data feeding during the training process, reducing bottlenecks and enhancing training speed. Overall, this structured and thorough preprocessing workflow laid the groundwork for developing a high-performance model capable of accurate and consistent eczema classification.

2.5 Eczema Detection Model Architecture

To determine the most effective deep learning architecture for eczema detection, a comparative evaluation was conducted using three distinct models, a custom Convolutional Neural Network (CNN), MobileNetV2, and ResNet50. Each model was assessed based on its architecture, training enhancements, classification accuracy, precision, and recall. The goal was to identify a model that could accurately distinguish between normal and eczema-affected skin while balancing computational efficiency, generalizability, and sensitivity to subtle dermatological features. The following sections provide a detailed breakdown of how each model performed in the context of medical image analysis for eczema detection.

2.5.1 MobileNetV2 Model (Best Model)

To enhance the diagnostic performance of the system, a transfer learning approach was adopted using MobileNetV2 as the base model. MobileNetV2 is a lightweight and efficient convolutional neural network architecture pretrained on ImageNet, known for its performance in real-time applications. This model was fine-tuned and extended with an attention mechanism using Squeeze-and-Excitation (SE) blocks, enabling it to focus more accurately on lesion-specific patterns within the skin. The model was specifically designed to capture both global and localized features of eczema, while maintaining computational efficiency suitable for deployment in mobile or edge devices [10].

The SE block recalibrates channel-wise feature responses by learning which channels are more relevant for classification. This allows the model to emphasize more informative skin texture features and suppress irrelevant patterns. It works by first applying global average pooling to compress spatial information into a single vector per channel, capturing the overall importance of each feature map. This is followed by a small bottleneck network that learns non-linear interactions and outputs channel-wise weights through a sigmoid activation. These weights are then used to rescale the original feature maps, effectively enabling the model to attend to more meaningful features relevant to eczema detection while reducing noise from less significant patterns [11].

```python
def se_block(input_tensor, reduction_ratio=16):
    """
    Implements a Squeeze-and-Excitation (SE) block.
    Args:
        input_tensor: The input tensor from the previous layer.
        reduction_ratio: Reduction ratio for the bottleneck.
    Returns:
        Tensor after applying SE block.
    """
    filters = input_tensor.shape[-1]
    se = layers.GlobalAveragePooling2D()(input_tensor)
    se = layers.Dense(filters // reduction_ratio, activation='relu')(se)
    se = layers.Dense(filters, activation='sigmoid')(se)
    se = layers.Multiply()([input_tensor, se])
    return se
```

Figure 2 13: Implementation of the Squeeze-and-Excitation (SE) block to reweight important feature channels for MobileNetV2

The base MobileNetV2 model was loaded with pretrained ImageNet weights, and its convolutional layers were frozen to retain general image features. A global average pooling layer was added, followed by dropout for regularization. The SE block was then inserted to enhance feature representation. A fully connected layer and softmax activation concluded the model for binary classification.

```python
# Build MobileNetV2 model with SE block
def build_model_with_attention(input_shape=(224, 224, 3), num_classes=2):
    base_model = MobileNetV2(weights='imagenet', include_top=False, input_shape=input_shape)
    base_model.trainable = False  # Freeze the base model

    x = base_model.output
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dropout(0.5)(x)  # Add dropout after pooling

    # Add SE block
    x = layers.Reshape((1, 1, x.shape[-1]))(x)
    x = se_block(x)
    x = layers.Flatten()(x)

    x = layers.Dense(32, activation='relu', kernel_regularizer=tf.keras.regularizers.l2(0.05))(x)
    x = layers.Dropout(0.5)(x)  # Moderate dropout rate
    output = layers.Dense(num_classes, activation='softmax')(x)

    model = models.Model(inputs=base_model.input, outputs=output)
    model.compile(optimizer=Adam(learning_rate=1e-5), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

    return model
```

Figure 2 14: Building a MobileNetV2-based model with integrated SE attention block for improved skin condition focus for MobileNetV2

The model was trained using the augmented dataset, with callbacks for early stopping (to prevent overfitting), dynamic learning rate reduction, and best-model checkpointing. The use of class weights ensured balanced learning despite class imbalance.

```python
# Callbacks for training
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.3, patience=2, min_lr=1e-7)
checkpoint = ModelCheckpoint('eczema_model_with_attention_best.keras', monitor='val_loss', save_best_only=True, mode='min')

# Train the model
history_with_attention = model_with_attention.fit(
    datagen.flow(X_train, y_train, batch_size=batch_size),
    epochs=50,
    validation_data=(X_val, y_val),
    class_weight=class_weight_dict,
    callbacks=[early_stopping, reduce_lr, checkpoint]
)
```

Figure 2 15: Model training with class weights and early stopping, learning rate scheduling, and checkpointing for MobileNetV2

The model's performance was evaluated using a confusion matrix and classification report, giving detailed insights into precision, recall, and F1-scores for both eczema and normal classes.

2.5.2 CNN Model

As part of the model evaluation process for eczema detection, a custom CNN was implemented with an integrated SE attention block, similar to the MobileNetV2-based model used in the final solution. This custom model was designed to assess how a simpler, handcrafted architecture could perform in emphasizing subtle dermatological features by focusing on the most informative regions of clinical skin images. The SE blocks recalibrated channel-wise feature maps by applying global average pooling followed by a small bottleneck network that generated attention weights, which were then used to enhance relevant feature channels. While this model did not ultimately outperform the MobileNetV2-based approach in terms of overall accuracy and robustness, it demonstrated the consistent value of attention mechanisms in improving feature focus and offered valuable insights into custom architecture design in medical image analysis [12].

The architecture of the model is structured into three main convolutional blocks. Each block consists of a convolutional layer with ReLU activation, followed by max-pooling and batch normalization to ensure stable and efficient learning. An SE attention block is embedded after each of these convolutional blocks, enabling the model to learn both spatial and contextual relevance of extracted features. After feature extraction, the model flattens the outputs and passes them through a fully connected dense layer. A dropout layer is included for regularization, helping to prevent overfitting. Finally, the output layer uses a sigmoid activation function, making the model suitable for binary classification tasks, classifying skin images as either normal or eczema-affected.

The model is compiled using the Adam optimizer and binary cross-entropy as the loss function, which is particularly well-suited for binary classification problems. To further optimize the training process, several training callbacks are employed. These include early stopping to prevent unnecessary training once validation loss plateaus, ReduceLROnPlateau to decrease the learning rate if performance plateaus, and model checkpointing to save the best-performing version of the model during training. The model is trained on the preprocessed and augmented image dataset for up to 50 epochs, using validation data to continuously monitor its ability to generalize to unseen data. This architecture and training strategy collectively aims to produce a robust and interpretable model for accurate eczema diagnosis.

```
# Define the model with SE blocks
def create_model_with_attention(input_shape):
    inputs = layers.Input(shape=input_shape)

    # Convolutional layer block 1
    # Extracts important features from the images
    x = layers.Conv2D(32, (3, 3), activation='relu', kernel_regularizer=tf.keras.regularizers.l2(0.0005))(inputs)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)
    x = se_block(x)

    # Convolutional layer block 2
    x = layers.Conv2D(64, (3, 3), activation='relu', kernel_regularizer=tf.keras.regularizers.l2(0.0005))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)
    x = se_block(x)

    # Convolutional layer block 3
    x = layers.Conv2D(128, (3, 3), activation='relu', kernel_regularizer=tf.keras.regularizers.l2(0.0005))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)
    x = se_block(x)

    # Flatten the output before the fully connected layers
    # Converts the 2D feature maps into a 1D vector for the fully connected layers
    x = layers.Flatten()(x)

    # Fully connected layer
    # Performs final classification
    x = layers.Dense(128, activation='relu', kernel_regularizer=tf.keras.regularizers.l2(0.0005))(x)
    x = layers.Dropout(0.4)(x)
    outputs = layers.Dense(1, activation='sigmoid')(x)

    # Create the model
    model = Model(inputs, outputs)
    return model

# Create the model
model_with_attention = create_model_with_attention((224, 224, 3))
```

Figure 2 16: Custom CNN model architecture with SE attention blocks embedded after each convolutional layer block for CNN

Predictions are made on the validation set and evaluated using a confusion matrix and detailed classification report. These metrics help assess the model's precision, recall, and overall diagnostic reliability in distinguishing eczema from normal skin.

2.5.3 ResNet50 Model

In addition to the MobileNetV2-based and custom CNN models, a transfer learning approach using ResNet50 as the base model was also explored. ResNet50, a deep convolutional neural network pretrained on the ImageNet dataset, is well-regarded for its depth and skip connection architecture, which helps mitigate the vanishing gradient problem during training. This model was integrated with a custom attention mechanism to evaluate its capacity to improve feature representation by selectively emphasizing more relevant skin regions while downplaying irrelevant areas. The primary objective of experimenting with this architecture was to compare its performance against other models, particularly the MobileNetV2-based model [13].

The attention mechanism employed in this model was implemented as a custom layer designed to enhance the model's ability to identify subtle dermatological features related to eczema. It operated by generating attention weights through a learned transformation of the input feature maps, followed by a softmax operation. These weights were then applied to the feature maps, effectively amplifying significant features and reducing the impact of less important ones. By integrating this attention mechanism, the model aimed to improve sensitivity towards clinically relevant patterns within the skin images, similar to the Squeeze-and-Excitation blocks used in other models.

To further improve performance, the model was fine-tuned by unfreezing the deeper layers of ResNet50, allowing the network to adapt its pretrained weights to the specific task of eczema detection. Data augmentation techniques such as rotation, width and height shifts, shear, zoom, horizontal flipping, and brightness adjustment were employed to introduce variability and enhance the robustness of the training process. Additionally, class weights were applied during training to address the issue of class imbalance in the dataset.

```python
class Attention(layers.Layer):
    def __init__(self):
        super(Attention, self).__init__()

    def build(self, input_shape):
        self.W = self.add_weight(shape=(input_shape[-1], input_shape[-1]), initializer='random_normal', trainable=True)
        self.b = self.add_weight(shape=(input_shape[-1],), initializer='zeros', trainable=True)

    def call(self, inputs):
        q = tf.matmul(inputs, self.W) + self.b
        attention_weights = tf.nn.softmax(q, axis=-1)
        return attention_weights * inputs
```

Figure 2 17: Implementation of the attention mechanism as a custom layer for ResNet50

```python
# Build the Model using ResNet50 as the base model and an attention mechanism
def build_model():
    base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(IMG_HEIGHT, IMG_WIDTH, 3))
    x = base_model.output
    x = layers.GlobalAveragePooling2D()(x)

    # Attention Layer
    attention = Attention()(x)

    # Fully Connected Layers
    x = layers.Dense(1024, activation='relu')(attention)
    x = layers.Dropout(0.5)(x)  # Adding dropout for regularization
    x = layers.Dense(1, activation='sigmoid')(x)  # Output layer for binary classification (eczema vs normal)

    model = Model(inputs=base_model.input, outputs=x)

    # Unfreeze more layers of the base model for fine-tuning
    for layer in base_model.layers[:100]:  # Unfreeze more layers than before
        layer.trainable = False
    for layer in base_model.layers[100:]:
        layer.trainable = True

    model.compile(optimizer=Adam(learning_rate=1e-5), loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

Figure 2 18: ResNet50 model with custom attention mechanism and fine-tuning for eczema detection

The model was trained using the Adam optimizer with a low learning rate to facilitate gradual improvement during fine-tuning. To prevent overfitting and optimize learning, EarlyStopping and ReduceLROnPlateau callbacks were implemented. The model was evaluated based on its validation accuracy and loss, while performance metrics such as precision, recall, F1-score, and confusion matrix were generated to provide a comprehensive understanding of its classification capability.

2.6 Eczema Severity Classification Model Architecture

To determine the most suitable deep learning architecture for eczema severity classification, a comparative analysis was conducted using three different models: EfficientNetB0, a custom CNN, and ResNet50. Each model was evaluated based on its architecture, training strategies, classification accuracy, precision, and recall across various severity levels of eczema. The goal was to identify a model capable of accurately classifying eczema severity into mild, moderate, and severe categories while maintaining computational efficiency, robustness, and sensitivity to subtle differences in skin presentation. While EfficientNetB0 demonstrated the highest accuracy and strong performance across all severity levels, the CNN model struggled significantly with moderate and severe cases. ResNet50, on the other hand, achieved slightly better performance than the CNN model, particularly in distinguishing mild and moderate cases, but lacked robustness in severe case detection. The following sections provide a detailed breakdown of the performance of each model for eczema severity classification.

2.6.1 EfficientNetB0 Model (Best Model)

The most effective model identified for eczema severity classification was based on EfficientNetB0, enhanced with a SE attention mechanism. EfficientNetB0 is known for its efficient scaling of depth, width, and resolution, providing a balanced architecture that offers high accuracy with relatively low computational costs. To further enhance the model's ability to detect subtle variations across different severity levels, a custom SE block was integrated to improve the network's sensitivity towards relevant features [14].

To address the challenge of class imbalance, Focal Loss and class weight assignment were employed during model training. Focal Loss was used as a customized loss function to ensure that the model focuses more on hard-to-classify samples, which are often from the minority classes. Unlike standard cross-entropy loss, focal loss applies a modulating factor that down-weights easy-to-classify examples, thus effectively reducing their impact on the overall loss. This is achieved by applying a scaling factor $(1-p_t)^\gamma$ to the cross-entropy loss, where p_t is the predicted probability for the correct class. The hyperparameter γ adjusts the rate at which easy examples are down-weighted. Additionally, an α parameter is used to further balance the importance of each class, particularly benefiting underrepresented categories such as moderate and severe eczema [15].

```
# Focal Loss Function (handle one-hot encoded labels)
def focal_loss(alpha=0.25, gamma=2.0):
    def focal_loss_fixed(y_true, y_pred):
        y_true = tf.cast(y_true, tf.float32)
        y_pred = tf.clip_by_value(y_pred, tf.keras.backend.epsilon(), 1 - tf.keras.backend.epsilon())
        cross_entropy = -y_true * tf.math.log(y_pred)
        focal_loss = alpha * tf.math.pow(1 - y_pred, gamma) * cross_entropy
        return tf.reduce_sum(focal_loss, axis=-1)
    return focal_loss_fixed
```

Figure 2 19: Implementation of Focal Loss to enhance model sensitivity towards minority classes by applying dynamic scaling to hard-to-classify samples

In addition to using focal loss, class weights were computed and applied during training to further mitigate the effects of class imbalance. By assigning higher weights to minority classes, the model is encouraged to pay more attention to those classes during the learning process. The class weights were calculated using the compute_class_weight function from sklearn, which assigns weights inversely proportional to the class frequencies. This approach ensures that the training process does not disproportionately favor the majority class.

```
# Compute class weights
class_weights = compute_class_weight('balanced', classes=np.unique(y_train), y=y_train)
class_weight_dict = {i: class_weights[i] for i in range(len(class_weights))}
```

Figure 2 20: Calculating class weights to assign higher importance to underrepresented classes and promote balanced learning during training

The SE block was implemented to enhance the model's attention mechanism by recalibrating feature maps at the channel level. This improves the network's ability to focus on essential features, particularly those that differentiate between mild, moderate, and severe eczema cases.

```python
# Squeeze-and-Excitation block
def se_block(input_tensor, ratio=16):
    filters = input_tensor.shape[-1]
    se = tf.keras.layers.GlobalAveragePooling2D()(input_tensor)
    se = tf.keras.layers.Dense(filters // ratio, activation='relu')(se)
    se = tf.keras.layers.Dense(filters, activation='sigmoid')(se)
    se = tf.keras.layers.Reshape([1, 1, filters])(se)
    return tf.keras.layers.Multiply()([input_tensor, se])
```

Figure 2 21: Implementation of the Squeeze-and-Excitation (SE) block to enhance feature relevance through channel-wise recalibration

EfficientNetB0 was used as the base model, pretrained on ImageNet. The model was modified by adding a SE block, followed by fully connected layers to enhance the learning capacity for severity classification. A softmax activation function was used for the final layer to support multi-class classification.

```python
# Build Enhanced EfficientNetB0 Model with Attention Mechanism
def build_efficientnet_model_with_attention(input_shape=(224, 224, 3), num_classes=3):

    base_model = EfficientNetB0(weights="imagenet", include_top=False, input_shape=input_shape)
    base_model.trainable = True

    inputs = Input(shape=input_shape)
    x = base_model(inputs, training=True)

    x = se_block(x)

    x = GlobalAveragePooling2D()(x)
    x = BatchNormalization()(x)

    x = Dense(512, activation="relu", kernel_regularizer=l2(0.01))(x)
    x = Dropout(0.4)(x)

    x = Dense(256, activation="relu", kernel_regularizer=l2(0.01))(x)
    x = Dropout(0.3)(x)

    outputs = Dense(num_classes, activation="softmax")(x)

    model = Model(inputs, outputs)
    return model

# Compile the Model
model = build_efficientnet_model_with_attention()
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-4),
    loss=focal_loss(alpha=0.25, gamma=2.0),
    metrics=["accuracy"]
)
```

Figure 2 22: Building the EfficientNetB0 model integrated with SE block and additional dense layers for classification

The model was compiled using Focal Loss to address class imbalance and trained using the Adam optimizer. To improve training efficiency, a cosine decay learning rate scheduler was applied along with early stopping and model checkpointing.

2.6.2 CNN Model

This model was developed as part of the exploration process to assess its capability in classifying eczema severity into three categories: mild, moderate, and severe. Unlike the EfficientNetB0-based model, this architecture was custom-designed and integrated with Residual Blocks and SE attention mechanisms. The primary objective was to enhance the model's feature extraction capabilities by using a deeper architecture capable of learning complex patterns associated with varying severity levels.

The model architecture consists of an initial convolutional block, followed by a series of Residual Blocks integrated with SE attention blocks. The Residual Blocks were designed to improve gradient flow through the network, mitigating issues related to vanishing gradients commonly associated with deeper networks. Additionally, the SE attention mechanism within these blocks recalibrates the feature maps by learning to prioritize the most relevant channels, which is particularly valuable for distinguishing between mild, moderate, and severe cases of eczema.

The Residual Block incorporates Batch Normalization, SE attention mechanism, and skip connections to improve feature extraction and retain important information during training. And then the architecture begins with an initial convolutional block followed by three Residual Blocks with increasing filter sizes. The final layers include Global Average Pooling, Dense layers, and Dropout for regularization.

```python
# Squeeze-and-Excitation Block
def se_block(input_tensor, ratio=16):
    filters = input_tensor.shape[-1]
    se = GlobalAveragePooling2D()(input_tensor)
    se = Dense(filters // ratio, activation='relu')(se)
    se = Dense(filters, activation='sigmoid')(se)
    se = Reshape((1, 1, filters))(se)
    return Multiply()([input_tensor, se])

# Residual Block with Attention
def residual_block(x, filters, kernel_size=3, se_ratio=16):
    shortcut = Conv2D(filters, (1, 1), padding='same')(x)
    x = Conv2D(filters, kernel_size, padding='same', activation='relu')(x)
    x = BatchNormalization()(x)
    x = Conv2D(filters, kernel_size, padding='same', activation='relu')(x)
    x = BatchNormalization()(x)
    x = se_block(x, ratio=se_ratio)
    x = Add()([x, shortcut])
    return x
```

```python
# Build Enhanced Model
def build_enhanced_model(input_shape=(224, 224, 3), num_classes=3):
    inputs = Input(shape=input_shape)

    # Initial Convolutional Block
    x = Conv2D(64, (3, 3), padding='same', activation='relu')(inputs)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2))(x)
    x = Dropout(0.3)(x)

    # Residual Blocks with SE Attention
    x = residual_block(x, 128)
    x = MaxPooling2D((2, 2))(x)
    x = Dropout(0.4)(x)

    x = residual_block(x, 256)
    x = MaxPooling2D((2, 2))(x)
    x = Dropout(0.4)(x)

    x = residual_block(x, 512)
    x = MaxPooling2D((2, 2))(x)
    x = Dropout(0.5)(x)

    # Classification Block
    x = GlobalAveragePooling2D()(x)
    x = Dense(512, activation='relu')(x)
    x = Dropout(0.5)(x)
    outputs = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs, outputs)
    return model
```

Figure 2 23: Building a custom CNN model with Residual Blocks, SE blocks, and fully connected layers for classification

The model was trained using the Adam optimizer with a standard learning rate, and the categorical cross-entropy loss function was used since this is a multi-class classification task. To enhance generalization, data augmentation techniques were applied during training.

2.6.3 ResNet50 Model

This model was developed as part of the exploration process to assess its ability to accurately classify eczema severity levels into three categories: mild, moderate, and severe. Unlike the EfficientNetB0-based model, this architecture was built using ResNet50 as the base model, enhanced with the Convolutional Block Attention Module (CBAM). The CBAM module combines Channel and Spatial attention mechanisms, aiming to improve the network's ability to focus on important features while suppressing irrelevant background information.

The ResNet50 architecture was selected due to its depth and feature extraction capabilities, especially for complex image classification tasks. The pretrained model was loaded with ImageNet weights, and fine-tuning was applied to allow the model to adapt its learned features to the specific task of eczema severity classification. To further enhance feature extraction, a CBAM attention block was incorporated, providing an adaptive mechanism that focuses on relevant channels and spatial regions of the feature maps [16].

```python
# Define CBAM (Channel and Spatial Attention Block)
def cbam_block(input_tensor, reduction_ratio=8):
    """
    Convolutional Block Attention Module (CBAM)
    Combines Channel and Spatial Attention.
    """
    channels = input_tensor.shape[-1]

    # Channel Attention
    channel_avg = GlobalAveragePooling2D()(input_tensor)
    channel_max = GlobalMaxPooling2D()(input_tensor)
    channel = Concatenate()([channel_avg, channel_max])
    channel = Dense(channels // reduction_ratio, activation='relu')(channel)
    channel = Dense(channels, activation='sigmoid')(channel)
    channel = Reshape((1, 1, channels))(channel)
    channel_attention = Multiply()([input_tensor, channel])

    # Spatial Attention
    def spatial_attention(inputs):
        spatial_avg = tf.reduce_mean(inputs, axis=-1, keepdims=True)
        spatial_max = tf.reduce_max(inputs, axis=-1, keepdims=True)
        return tf.concat([spatial_avg, spatial_max], axis=-1)

    spatial = Lambda(spatial_attention)(channel_attention)
    spatial = Conv2D(1, kernel_size=7, activation='sigmoid', padding='same')(spatial)
    spatial_attention = Multiply()([channel_attention, spatial])

    return spatial_attention
```

Figure 2 24: Implementation of the CBAM block combining channel and spatial attention mechanisms to enhance feature relevance

The CBAM block integrates Channel Attention and Spatial Attention to refine feature maps by prioritizing relevant information. The channel attention mechanism aggregates spatial information through global average pooling and global max pooling, generating a channel-wise attention map. The spatial attention mechanism, on the other hand, generates attention weights by applying convolution over concatenated average-pooled and max-pooled feature maps along the channel axis.

The model architecture begins with the ResNet50 backbone, where the lower layers are frozen during training to preserve pretrained weights. Fine-tuning was applied by unfreezing deeper layers to allow for task-specific learning. The CBAM block was integrated right after the ResNet50 output to refine the learned feature maps before feeding them to the classification layers.

```
# Load ResNet50 base model
base_model = applications.ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Fine-tuning: Freeze some layers
for layer in base_model.layers[:100]:
    layer.trainable = False
for layer in base_model.layers[100:]:
    layer.trainable = True

# Add custom layers with CBAM and Dropblock
x = base_model.output
x = cbam_block(x)  # Add CBAM Attention
x = Dropout(0.3)(x)  # Apply Dropout to convolutional features
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu', kernel_regularizer=l2(0.01))(x)
x = Dropout(0.5)(x)
x = Dense(512, activation='relu', kernel_regularizer=l2(0.01))(x)
x = Dropout(0.3)(x)
output = Dense(3, activation='softmax')(x)  # 3 classes: mild, moderate, severe

# Compile the model
model = tf.keras.models.Model(inputs=base_model.input, outputs=output)
model.compile(
    optimizer=tf.keras.optimizers.AdamW(learning_rate=1e-4, weight_decay=1e-6),
    loss=tf.keras.losses.CategoricalCrossentropy(),
    metrics=['accuracy']
)
```

Figure 2 25: Building the ResNet50-based model with integrated CBAM block and custom dense layers

2.7 Commercialization Aspects of the Product

The commercialization of the proposed system, DermaScope AI, aims to establish a cutting-edge solution for accurate detection, severity assessment, and management of eczema using advanced machine learning techniques. The primary focus is to deliver a robust, user-friendly, and clinically meaningful tool that can be adopted by dermatologists, healthcare institutions, telemedicine platforms, and individual patients for real-time monitoring and diagnosis.

2.7.1 Market Potential

- Dermatology Clinics and Hospitals: Offering enhanced diagnostic accuracy and consistency in assessing eczema, improving patient care and optimizing treatment plans.
- Telemedicine Platforms: Facilitating remote diagnosis and management of eczema through AI-based assessments, making dermatological expertise accessible to patients in remote or underserved areas.
- Pharmaceutical Companies: Supporting clinical trials and drug efficacy studies by providing reliable and standardized assessment of eczema severity over time.
- Healthcare Applications & Wearables: Integrating the solution with mobile health applications or smart devices to allow continuous monitoring and management of eczema.
- Cosmetic and Skincare Industry: Assisting product development by providing insights into eczema condition improvements based on severity analysis and user feedback.

2.7.2 Role of Eczema Detection and Severity Assessment

- Personalized Treatment Plans: Enabling dermatologists to tailor treatment strategies based on precise eczema severity assessment, enhancing treatment efficacy and patient satisfaction.
- Patient Monitoring: Allowing patients to track their progress over time and providing alerts or recommendations when eczema conditions worsen or improve.
- Data-Driven Decisions: Leveraging collected data to enhance treatment protocols, refine AI models, and optimize patient outcomes.

2.7.3 Commercialization Strategy

- Subscription-Based Model: Offering a tiered subscription service for dermatology clinics, telemedicine platforms, and individual users. Plans may include basic diagnostic features, advanced eczema severity assessment, and comprehensive analytics tools.
- Software as a Service (SaaS): Providing a cloud-based solution accessible through web or mobile applications, ensuring ease of deployment and maintenance for clients.
- Licensing Agreements: Partnering with healthcare institutions, telemedicine providers, and pharmaceutical companies for exclusive or co-branded eczema detection solutions.
- Customization Services: Offering tailored solutions for specific clients, including unique dashboards, analytics modules, and integration with existing health management systems.

2.7.4 Competitive Advantage

- Specialized Solution: Combining image analysis, severity assessment, and patient monitoring in a unified platform focused exclusively on eczema.
- Explainable AI (XAI): Providing interpretable results that enhance clinician trust and improve diagnostic transparency specific to eczema assessment.
- Scalability: The system is designed to be scalable, allowing integration with various healthcare platforms, accommodating large datasets, and evolving to include more advanced eczema assessment tools.
- Accessibility: Making eczema assessment available remotely through telemedicine applications, benefiting underserved regions and enhancing patient convenience.

2.7.5 Scalability and Future Development

- Scalability: The application will be scalable in terms of the number of users, integration with healthcare platforms, and refinement of eczema-specific assessment techniques.
- Continuous Improvement: Leveraging ongoing research and client feedback to enhance AI models, improve diagnostic accuracy, and expand the scope of eczema assessment.
- Integration with Wearables: Exploring partnerships with wearable technology companies to provide continuous monitoring and real-time feedback for chronic eczema conditions.
- Expanding Market Reach: Developing marketing strategies targeting healthcare providers, pharmaceutical companies, and telemedicine platforms focused on eczema treatment and management.

2.8 Testing and Implementation

2.8.1 Testing

2.8.1.1 Unit Testing

- Purpose: Testing the independent functionality of various modules in the DermaScope AI system, including data preprocessing, model training, and model evaluation components.
- Approach:
    - Testing the accuracy, precision, recall, and F1-score of individual models (CNN, MobileNetV2, ResNet50, EfficientNetB0) for eczema detection and severity classification.
    - Evaluating preprocessing functions for image resizing, augmentation, and normalization to ensure data integrity.
    - Measuring model performance metrics under different training configurations (e.g., learning rate, batch size) to assess consistency.
- Tools: Python, Google Colab, TensorFlow, Keras, scikit-learn.
- Result: Each module was tested individually under various conditions to ensure proper functionality. Necessary adjustments were made to improve model accuracy and robustness through dataset enhancement and hyperparameter tuning.

2.8.1.2 Integration Testing

- Purpose: Ensuring the seamless interaction between various modules of the DermaScope AI system, including data preprocessing, model inference, and visualization components.
- Approach:
    - Combining the data preprocessing pipeline, model inference, and performance evaluation into a cohesive system.

    - Testing the end-to-end workflow from image input to result visualization, ensuring all components work harmoniously.
    - Validating the compatibility of models trained for eczema detection and severity classification with the overall system.
    - Measuring overall accuracy, precision, recall, and F1-score after integration.
- Tools: Python, Google Colab, TensorFlow, Keras, PostgreSQL, Streamlit.
- Expected Output: Ensuring that the integrated modules provide accurate and consistent results across various test cases, including different image resolutions, skin types, and severity levels.

2.8.1.3 System Testing

- Purpose: Testing the complete DermaScope AI system to verify that it meets the intended requirements and performs accurately in real-world scenarios.
- Approach:
    - Submitting skin images through the user interface for eczema detection and severity classification.
    - Comparing predicted results with ground truth labels to calculate performance metrics (accuracy, precision, recall, F1-score).
    - Testing different datasets, including various skin types, severity levels, and environmental conditions (e.g., lighting variations).
- Tools: Python, PostgreSQL, TensorFlow, Keras, Streamlit.
- Expected Outcome: The system functions correctly for real-world usage, providing accurate predictions and meaningful visualizations.

2.8.1.4 Performance Testing

- Purpose: Assessing the efficiency and responsiveness of the DermaScope AI system under various conditions.
- Approach:
  - ➢ Evaluating the time taken for model inference with varying image sizes and batch sizes.
  - ➢ Monitoring performance metrics such as latency, throughput, and processing speed during real-time usage.
  - ➢ Ensuring the system is capable of handling high traffic or simultaneous requests without degradation in performance.
- Tools: Python, PostgreSQL, TensorFlow, Keras, Streamlit.
- Output: The system demonstrated reliable performance, with only minor increases in response time under heavy load conditions.

2.8.1.5 User Acceptance Testing (UAT)

- Purpose: Ensuring that the system meets the requirements and expectations of stakeholders, including dermatologists and healthcare service providers.
- Approach:
  - ➢ Demonstrating the application's functionality and results to stakeholders for feedback and validation.
  - ➢ Collecting user feedback on usability, accuracy, and overall experience of the system.
  - ➢ Making necessary improvements based on stakeholders' suggestions and requirements.
- Outcome: The system was positively received, with stakeholders acknowledging its accuracy and ease of use. Suggestions for further improvements were incorporated to enhance user satisfaction.

2.8.1.6 Regression Testing

- Purpose: Ensuring that modifications or enhancements to the system do not adversely affect its performance or accuracy.
- Approach:
  - Re-running previously conducted tests, including unit, integration, system, and performance testing, after applying modifications or updates.
  - Comparing results before and after modifications to confirm consistency in accuracy and performance metrics.
- Outcome: All previous tests were successfully passed, confirming that updates did not negatively impact the system's functionality or accuracy.

2.8.1.7 Comprehensive Test Cases with White Box and Black Box Testing

- **Black Box Testing**: Testing the system's functionality without examining the internal code.
  - Test Case 1: Detection of eczema versus normal skin.
    - Input: Various skin images (normal and eczema-affected).
    - Output: Accurate classification into the respective categories.
  - Test Case 2: Severity classification (Mild, Moderate, Severe).
    - Input: Images with different eczema severity levels.
    - Output: Accurate categorization into Mild, Moderate, or Severe.
  - Test Case 3: System robustness with varying image quality.
    - Input: Low-resolution, noisy, or occluded images.
    - Output: Accurate classification despite challenging conditions.

- **White Box Testing**: Testing the system by examining internal code and logic.
    - Test Case 1: Validating the performance of individual layers and blocks (e.g., SE Blocks, CBAM Blocks).
        - Procedure: Monitoring model performance with and without attention mechanisms to assess their contribution.
        - Output: Improved accuracy and reliability with integrated attention mechanisms.
    - Test Case 2: Testing the end-to-end data pipeline.
        - Procedure: Reviewing the preprocessing steps, model inference, and visualization to ensure compatibility and efficiency.
        - Output: Successful data flow from input to output with consistent accuracy.

2.8.2 System Architecture Diagram

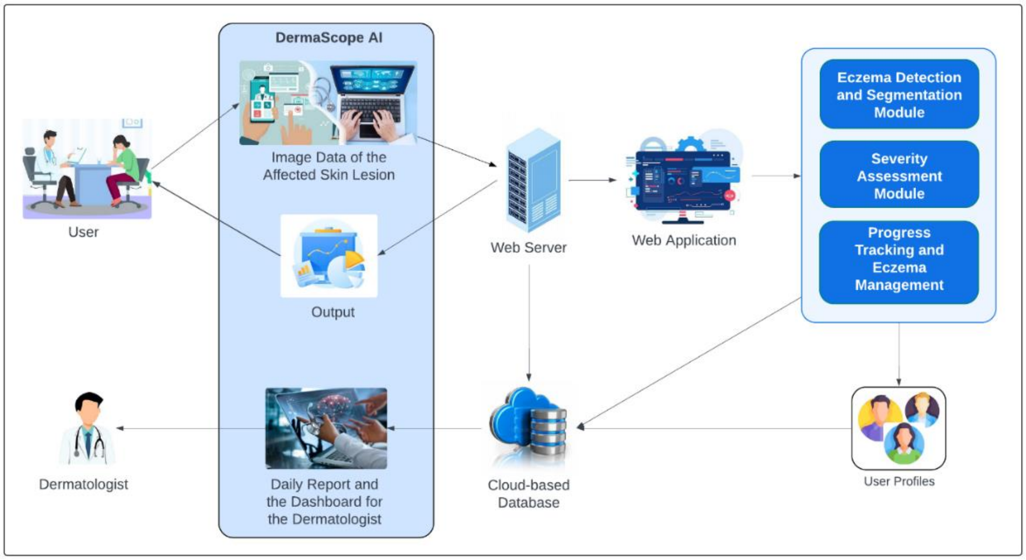


Figure 2 26: System architecture diagram

The system architecture for DermaScope AI is designed to facilitate the accurate diagnosis and severity assessment of atopic dermatitis through an integrated, AI-driven approach. The workflow starts with the patient (user) uploading an image of a skin lesion and then it gets analyzed by core DermaScope AI system. It deploys an eczema detection and segmentation module to automatically detect and segment the eczematous regions in the images. After detection, the severity assessment module processes clinical signs like erythema (redness), induration (hardening of the skin) and lichenification. The pre-processed results, which are the diagnosis and severity identification results of patients, are stored in a server-side web application to allow communication between AI system part at client-side with the web application interface. Patient data and all results generated are backed up in a database, making it possible for safekeeping and management.

2.8.3 Backend Implementation

The backend of the DermaScope AI system was designed to ensure efficient handling of image data, model predictions, and user interactions while maintaining scalability and security. The backend primarily serves as the bridge between the user interface and the machine learning models, facilitating seamless communication, data flow, and result delivery. A RESTful API architecture was adopted to manage these operations, enabling modular and structured interaction across the application components.

Python, along with the Flask web framework, was used to develop the backend due to its lightweight nature and strong compatibility with machine learning workflows. The trained deep learning models for eczema detection and severity classification were integrated into the backend using TensorFlow and Keras. Upon receiving an uploaded image, the backend handles preprocessing, runs it through the appropriate model, and returns a prediction. Error handling, response formatting, and logging mechanisms were added to ensure reliability and robustness under varying conditions and input formats.

PostgreSQL was selected as the relational database management system for storing user data, model outputs, and metadata. Its performance, scalability, and support for structured queries made it ideal for managing the relational data used in DermaScope AI.

To handle image storage effectively, Cloudinary was used as a cloud-based media management platform. Upon upload, clinical images are securely stored in Cloudinary and accessed via unique URLs, which are stored in the PostgreSQL database for reference. Cloudinary offers automated image optimization and fast content delivery through its CDN, making it ideal for serving images across different devices. This cloud-based storage solution minimizes server load, ensures faster access times, and supports scalability as the system expands.

2.8.4 Frontend Implementation

The frontend of the DermaScope AI system was developed to provide a clean, responsive, and user-friendly interface for dermatologists, patients, and healthcare personnel. The main objective was to create a platform that allows users to easily upload skin images, view predictions, and interact with the system in real-time. The user interface (UI) was designed to prioritize accessibility, clarity, and performance to support efficient diagnosis and monitoring of eczema conditions.

The frontend was built using Next.js, a powerful React framework that offers server-side rendering, optimized performance, and simplified routing. This choice enabled fast page loads and seamless integration with the backend APIs. The image upload mechanism, prediction result display, and real-time updates were handled using dynamic components and API calls to the backend. Next.js also allowed smooth transitions between routes and reusable UI components, enhancing the scalability and maintainability of the application.

Tailwind CSS was used for styling due to its utility-first approach, which allowed rapid development of modern and responsive UI elements without writing custom CSS from scratch. The design was kept minimal yet professional, ensuring the focus remained on image clarity and prediction results. Tailwind's flexibility enabled the creation of adaptive layouts suitable for both desktop and mobile devices, ensuring consistent user experience across different platforms. Combined with Next.js, this frontend stack contributed to a smooth, visually coherent, and efficient user experience for interacting with the DermaScope AI system.

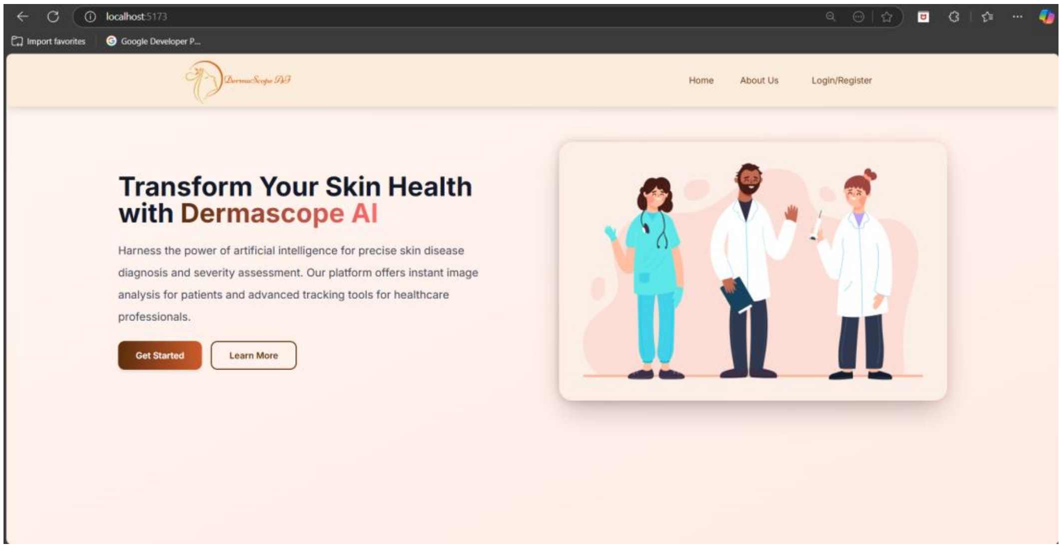


Figure 2 27: Home page

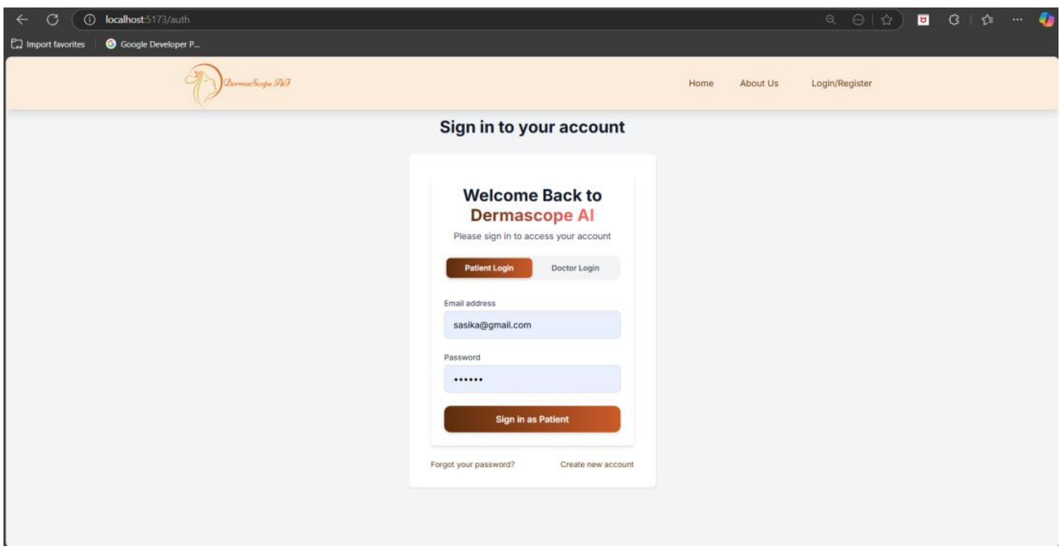


Figure 2 28: Login/register page

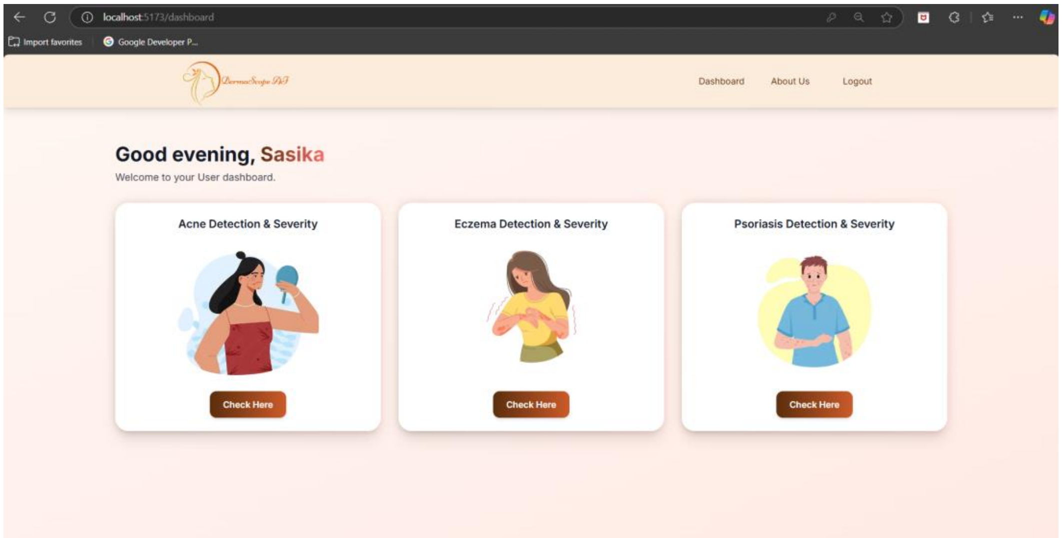


Figure 2 29: Patient dashboard

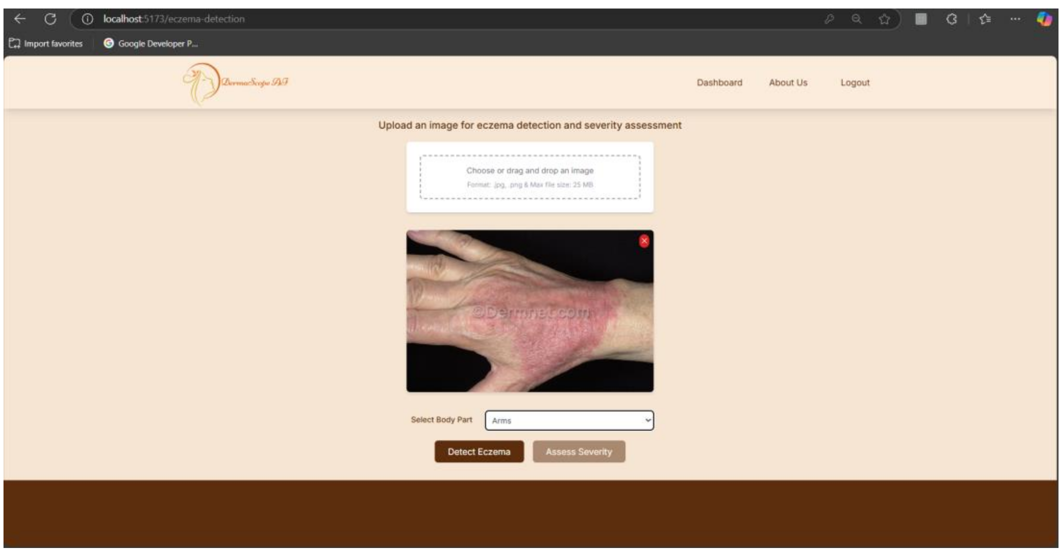


Figure 2 30: Eczema lesion image upload

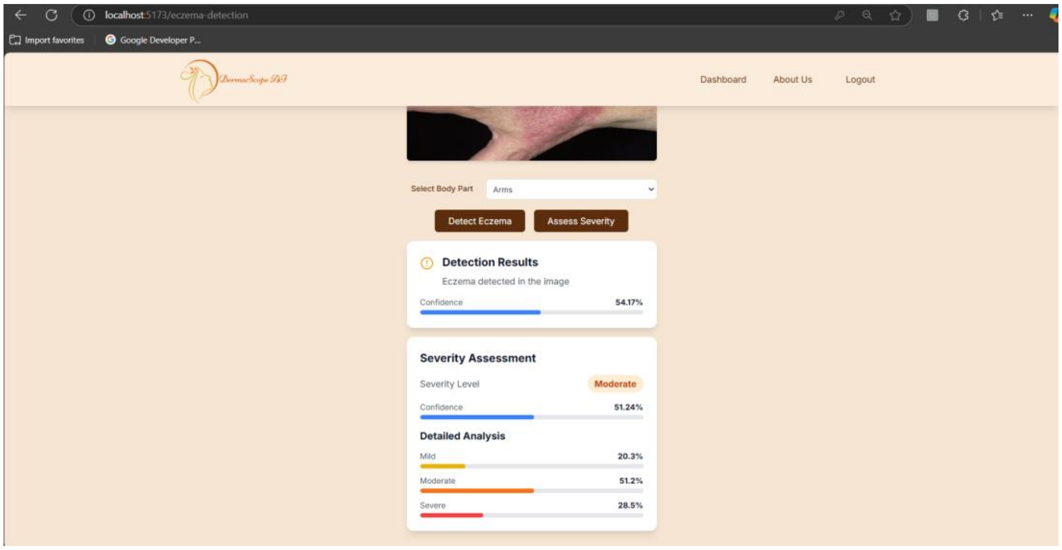


Figure 2 31: Eczema detection and severity assessment

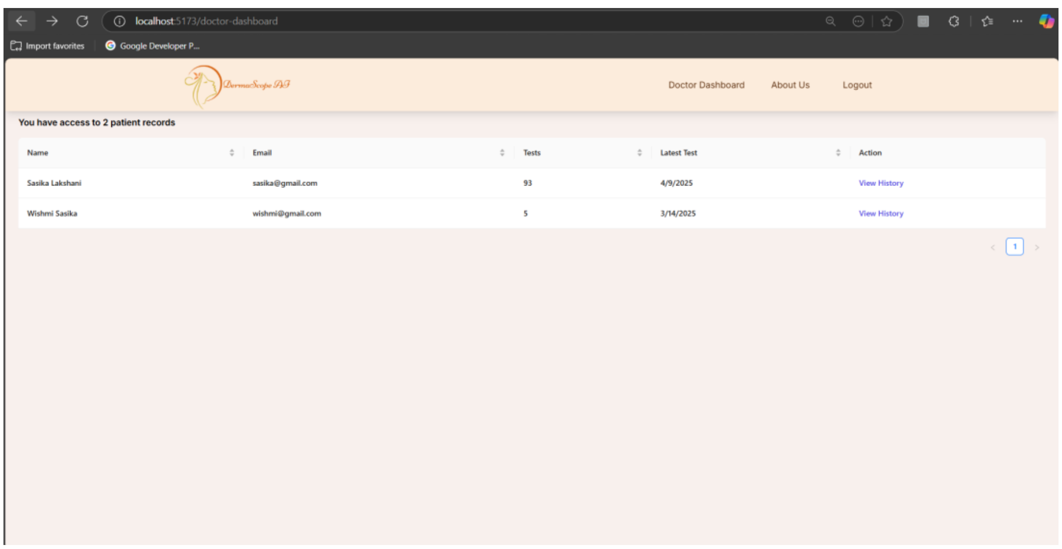


Figure 2 32: Doctor's dashboard

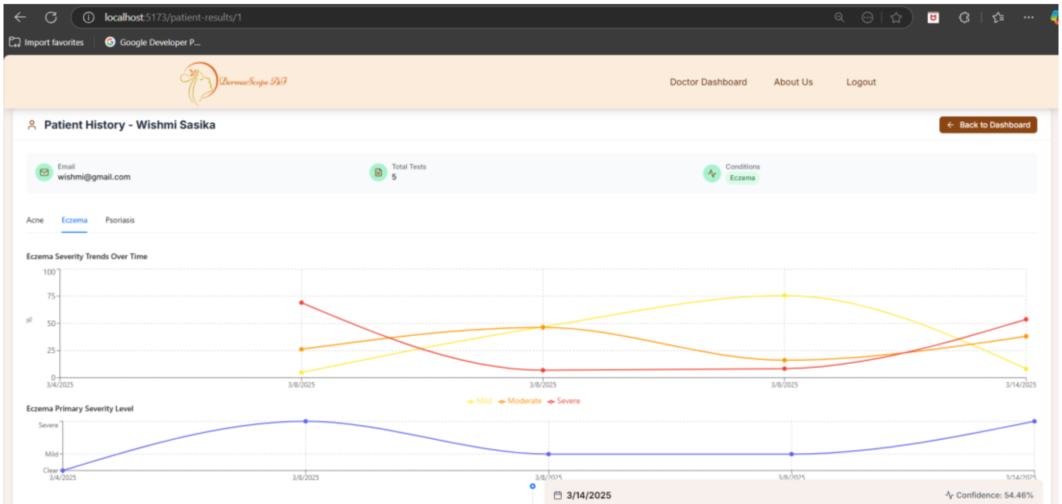


Figure 2 33: Patients' healing progress view in doctor's dashboard

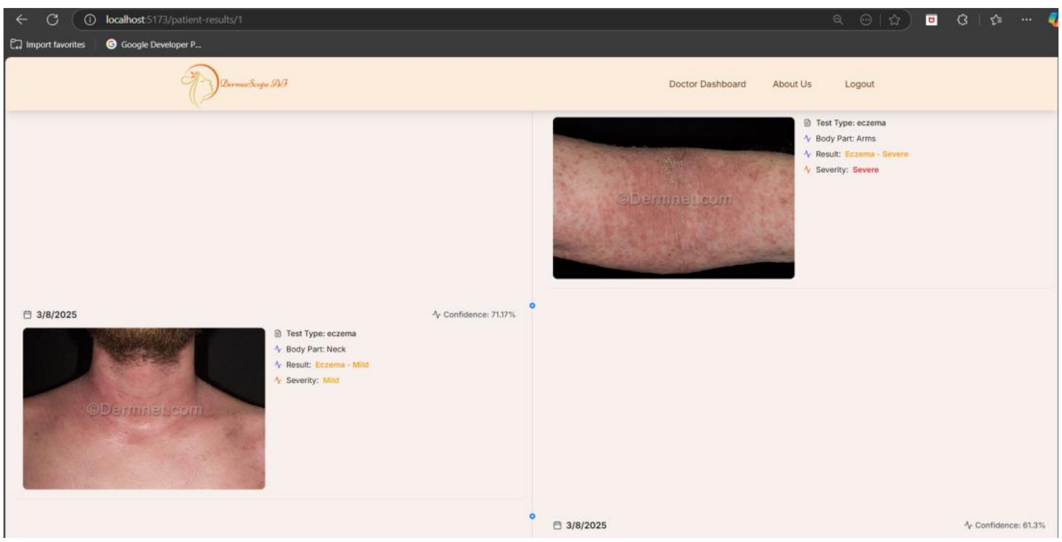


Figure 2 34: Patients' history in doctor's dashboard

3. RESULTS AND DISCUSSIONS

3.1 Eczema Detection

3.1.1 MobileNetV2 Model (Best Model)

The model's performance was evaluated using classification report and confusion matrix. The overall accuracy achieved by the model was 96%, with a precision of 96%, recall of 96%, and an F1-score of 96% for both classes. The confusion matrix visualizes the predictions, showing that the model correctly classified most samples with only minimal misclassifications. The balanced performance across both classes indicates that the model is reliable and effective in distinguishing between normal and eczema-affected skin.

Classification Report:

	precision	recall	f1-score	support
0	0.96	0.97	0.96	128
1	0.96	0.95	0.96	111
accuracy			0.96	239
macro avg	0.96	0.96	0.96	239
weighted avg	0.96	0.96	0.96	239

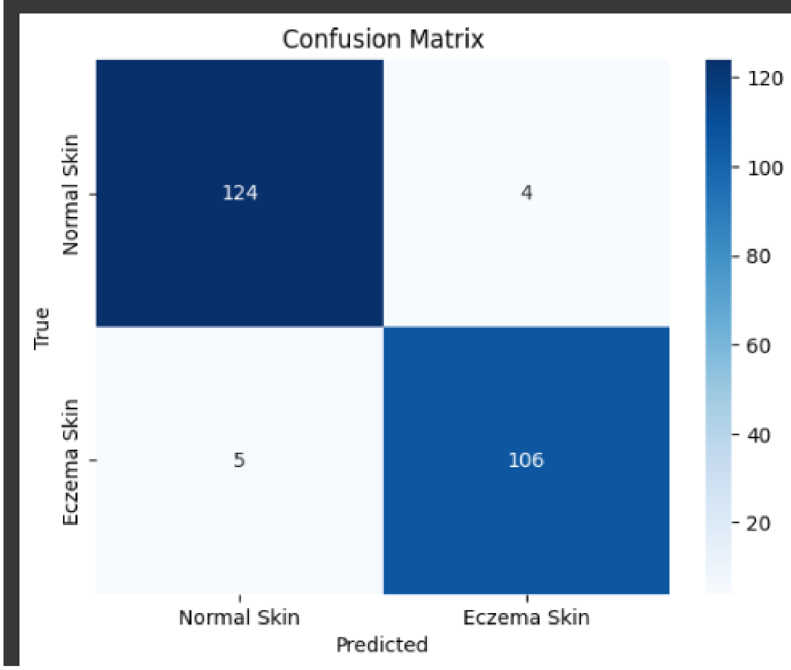


Figure 3 1: Classification report and the confusion matrix for MobileNetV2

The training and validation accuracy and loss curves provide essential insights into the model's learning progress over the 50 training epochs. The accuracy plot shows a steady increase in both training and validation accuracy, with the validation accuracy consistently outperforming the training accuracy. This trend suggests that the model is effectively learning from the data and generalizing well to the validation set. The validation accuracy reaching above 90% indicates strong predictive capability.

The loss plot displays a continuous decline in both training and validation loss, demonstrating that the model is converging effectively without signs of overfitting. The simultaneous reduction in training and validation loss over time indicates that the model is learning useful features without excessively memorizing the training data. The stability and consistency of these curves confirm that the model's architecture and training process are well-designed and optimized for eczema detection.

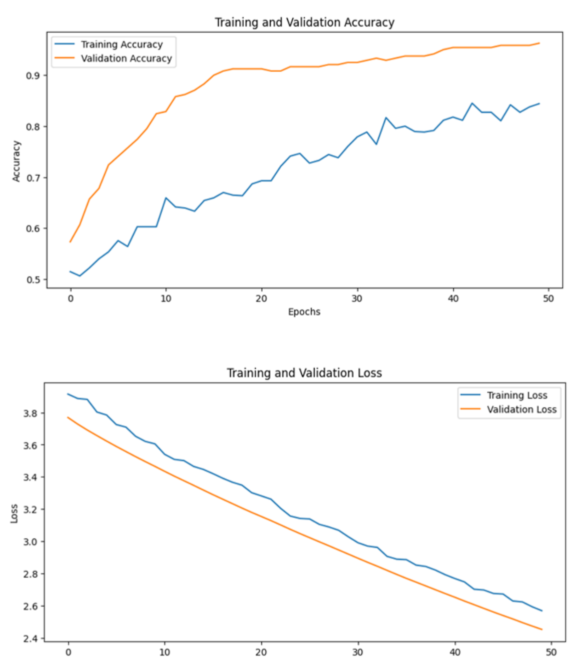
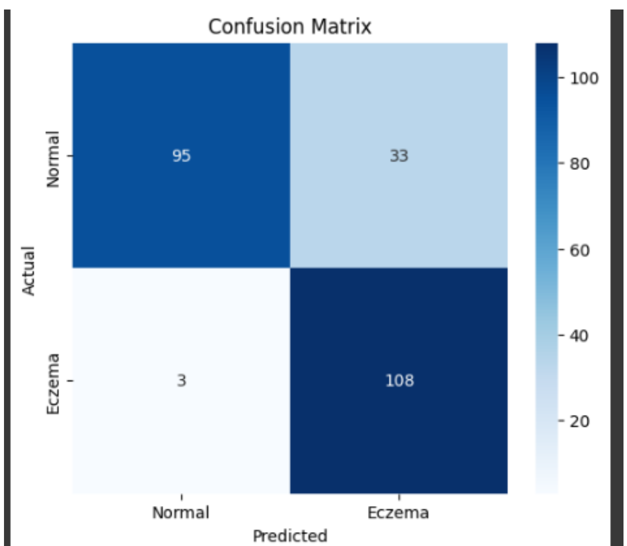


Figure 3 2: Training and validation accuracy/loss visualization for MobileNetV2

3.1.2 CNN Model

The model’s performance on the validation set was evaluated using a confusion matrix and classification report. The confusion matrix indicates that the model achieved a high number of correct predictions for both classes, particularly for eczema cases where 108 out of 111 samples were correctly classified. However, a noticeable weakness is observed in the normal class, where 33 samples were incorrectly predicted as eczema.

The classification report reveals a precision of 97% for normal skin and 77% for eczema, with corresponding recall values of 74% and 97%, respectively. While the model is effective at identifying eczema (high recall), it struggles with precision for eczema cases, leading to false positives. The overall accuracy is 85%, which, although reasonable, suggests room for improvement. Improving the model's precision for eczema detection would enhance its diagnostic reliability and clinical applicability.



	precision	recall	f1-score	support
Normal	0.97	0.74	0.84	128
Eczema	0.77	0.97	0.86	111
accuracy			0.85	239
macro avg	0.87	0.86	0.85	239
weighted avg	0.87	0.85	0.85	239

Figure 3 3: Confusion matrix and the classification report for CNN

The training and validation accuracy and loss curves for this model reveal a significant issue with overfitting. The training accuracy quickly reaches nearly 100% within a few epochs, indicating that the model is learning the training data very effectively. However, the validation accuracy drops sharply after the first epoch and remains low throughout the training process, suggesting that the model is failing to generalize to unseen data.

The loss curves further highlight this problem. While the training loss decreases and stabilizes, the validation loss increases rapidly after the first epoch and continues to rise, indicating severe overfitting. The increasing validation loss is a strong indicator that the model is memorizing the training data rather than learning generalizable patterns.

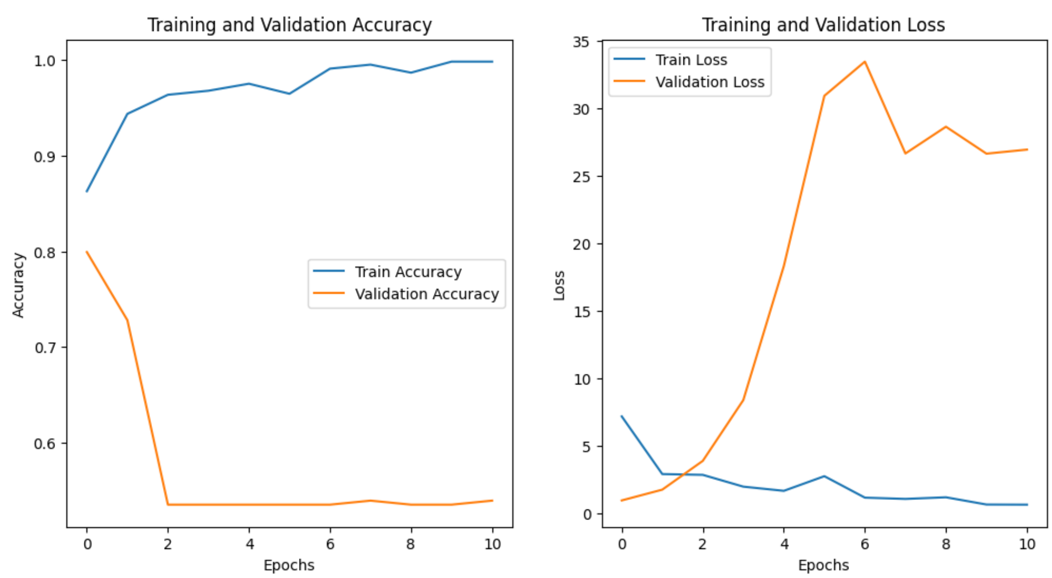
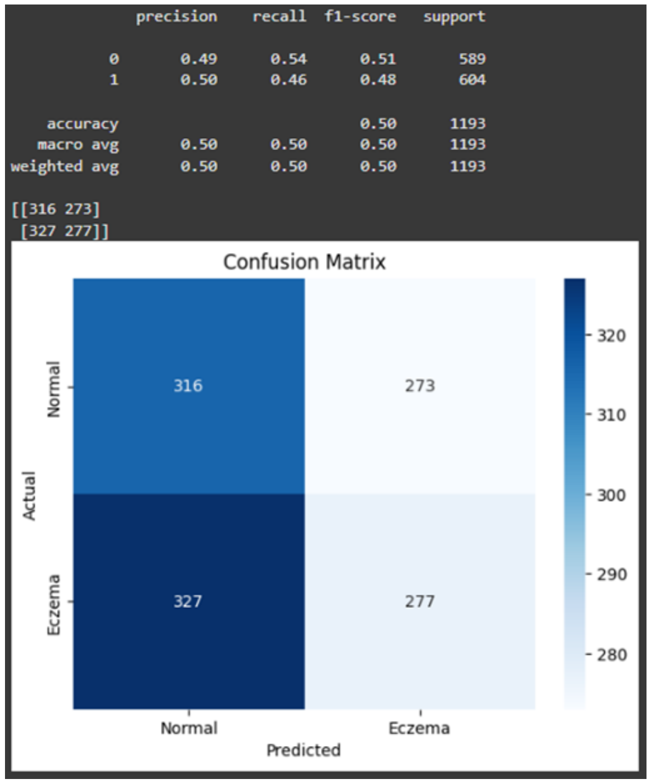


Figure 3 4: Training and validation accuracy/loss visualization for CNN

3.1.3 ResNet50 Model

The model's performance, reflected by an overall accuracy of 50%, indicates poor discriminatory power between Normal and Eczema classes, with nearly identical precision, recall, and F1-scores of around 0.50. The confusion matrix shows a significant misclassification.



	precision	recall	f1-score	support
0	0.49	0.54	0.51	589
1	0.50	0.46	0.48	604
accuracy			0.50	1193
macro avg	0.50	0.50	0.50	1193
weighted avg	0.50	0.50	0.50	1193

```
[[316 273]
 [327 277]]
```


Figure 3 5: Classification report and confusion matrix for ResNet50

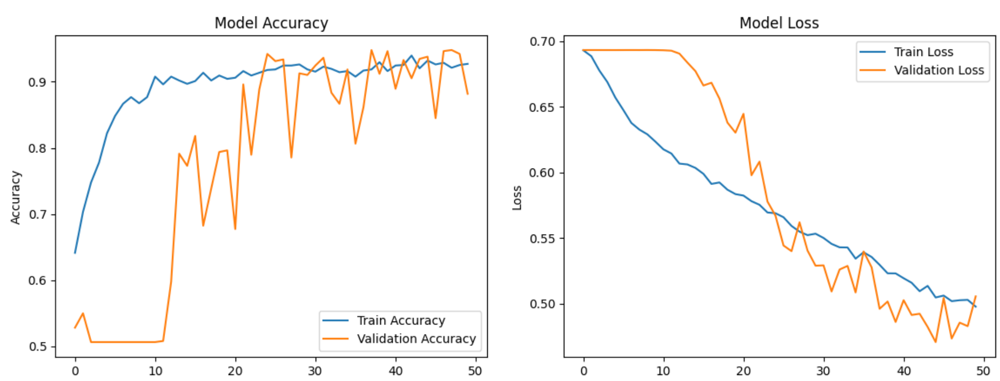


Figure 3 6: Training and validation accuracy/loss visualization for ResNet50

3.2 Eczema Severity Classification

3.2.1 EfficientNetB0 Model (Best Model)

The model achieved a commendable accuracy of 83%, with precision, recall, and F1-scores indicating balanced performance. The Mild class shows a particularly high precision of 0.94, recall of 0.91, and F1-score of 0.92, indicating strong reliability in detecting mild cases. The Severe class also displays good performance, with a recall of 0.84 and F1-score of 0.71, highlighting its ability to accurately identify most severe cases. The Moderate class achieves reasonable precision (0.70) and recall (0.58), indicating that the model is effectively capable of detecting intermediate severity cases. Overall, the model demonstrates reliable and consistent performance across all severity levels, making it a robust and effective solution for eczema severity classification.

Classification Report:

	precision	recall	f1-score	support
Mild	0.94	0.91	0.92	74
Moderate	0.70	0.58	0.64	24
Severe	0.62	0.84	0.71	19
accuracy			0.83	117
macro avg	0.75	0.78	0.76	117
weighted avg	0.84	0.83	0.83	117

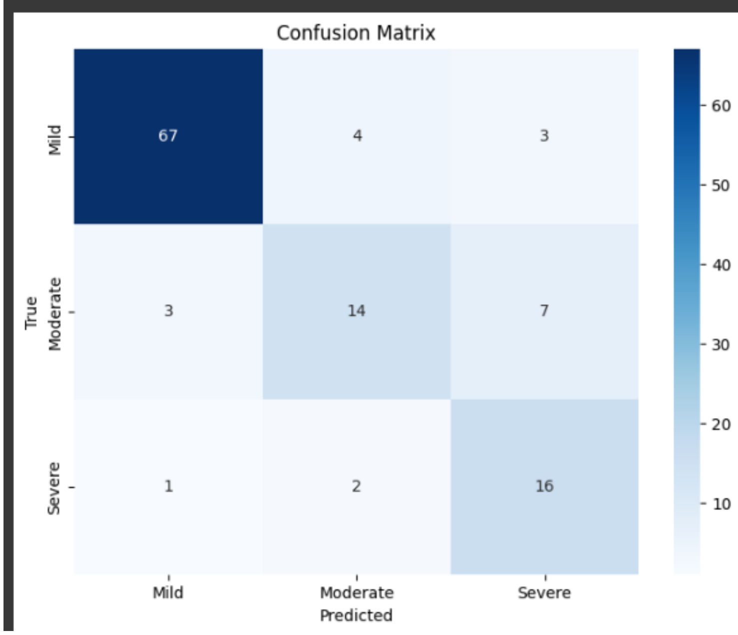


Figure 3 7: Classification report and confusion matrix for EfficientNetB0

The training and validation accuracy and loss curves illustrate a stable and consistent learning process throughout the training epochs. Both the training and validation accuracy steadily increase over time, eventually converging around 0.75 to 0.80, indicating effective learning and generalization. The training and validation loss curves demonstrate a continuous decline, stabilizing near the end, which confirms that the model is effectively minimizing the loss function without signs of overfitting. The alignment of training and validation curves suggests a well-balanced model that generalizes well to unseen data.

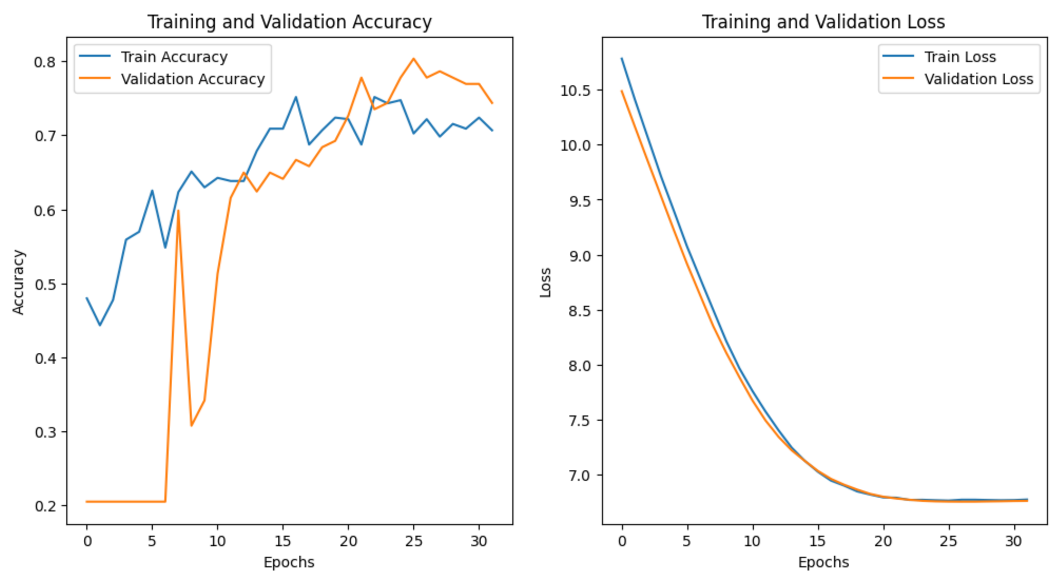


Figure 3 8: Training and validation accuracy/loss visualization for EfficientNetB0

3.2.2 CNN Model

This model did not perform well, achieving a low overall accuracy of 30% with particularly poor performance in detecting Severe cases (0% recall and precision). The confusion matrix shows significant misclassifications, especially with Mild cases being frequently predicted as Moderate. Due to its inadequate performance across all severity levels, this model was ultimately disregarded from further consideration.

	precision	recall	f1-score	support
Mild	0.67	0.19	0.29	74
Moderate	0.22	0.88	0.35	24
Severe	0.00	0.00	0.00	19
accuracy			0.30	117
macro avg	0.30	0.35	0.21	117
weighted avg	0.47	0.30	0.26	117

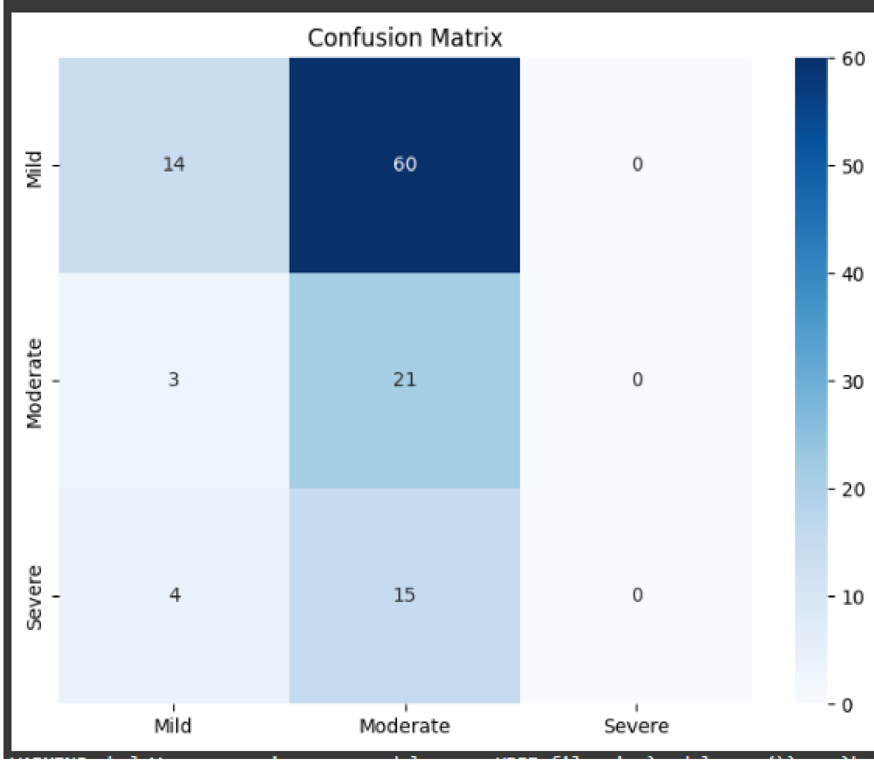
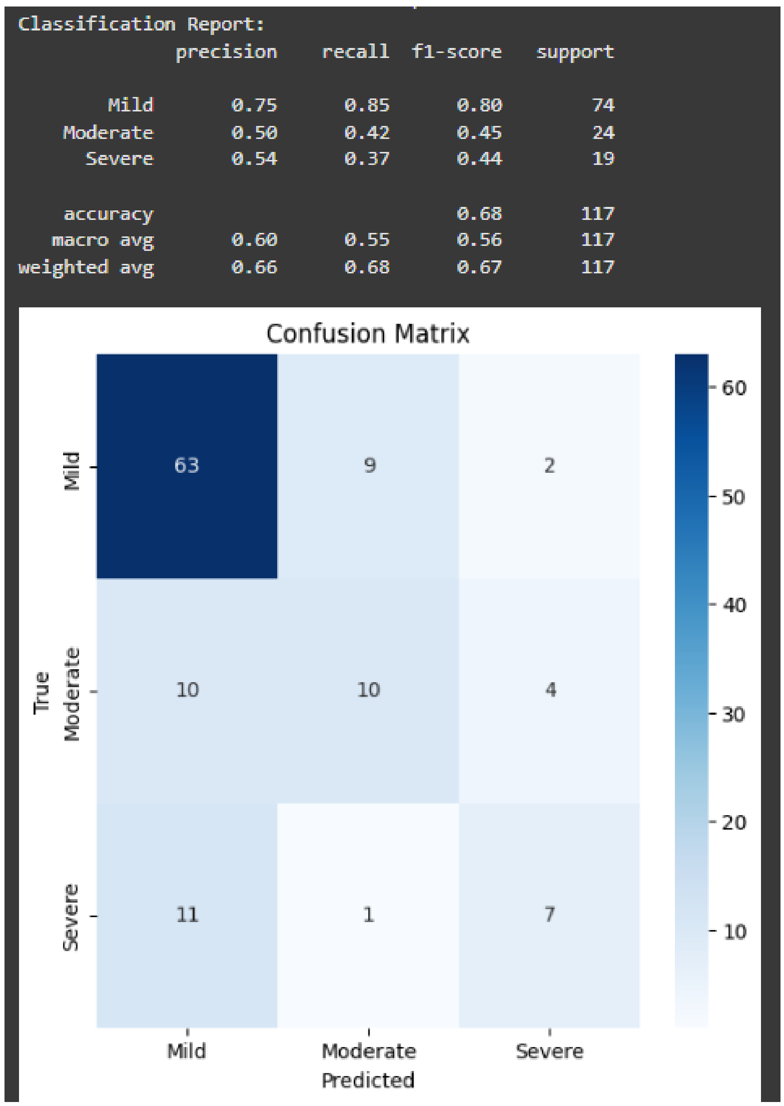


Figure 3 9: Classification report and confusion matrix for CNN

3.2.3 ResNet50 Model

This model achieved a moderate accuracy of 68%, with the Mild class performing well at 75% precision, 85% recall, and 80% F1-score. However, the Moderate and Severe classes show reduced performance, with F1-scores of 0.45 and 0.44, respectively. The confusion matrix reveals that most misclassifications occur between Moderate and Severe cases, indicating that the model struggles to distinguish between these categories. Although the performance is reasonable, it is not sufficient for reliable eczema severity classification.


Classification Report:

	precision	recall	f1-score	support
Mild	0.75	0.85	0.80	74
Moderate	0.50	0.42	0.45	24
Severe	0.54	0.37	0.44	19
accuracy			0.68	117
macro avg	0.60	0.55	0.56	117
weighted avg	0.66	0.68	0.67	117

Figure 3 10: Classification report and confusion matrix for ResNet50

The training and validation curves for this model reveal significant fluctuations in validation accuracy and loss, indicating instability and overfitting. While the training loss steadily decreases over epochs, the validation loss shows erratic spikes, particularly around the 10th epoch, where it sharply increases above 50. Similarly, validation accuracy fluctuates considerably, with several sudden drops and peaks, suggesting that the model struggles to generalize well to unseen data. These inconsistencies indicate that the model's learning process is not well-optimized, making it unreliable for accurate classification.

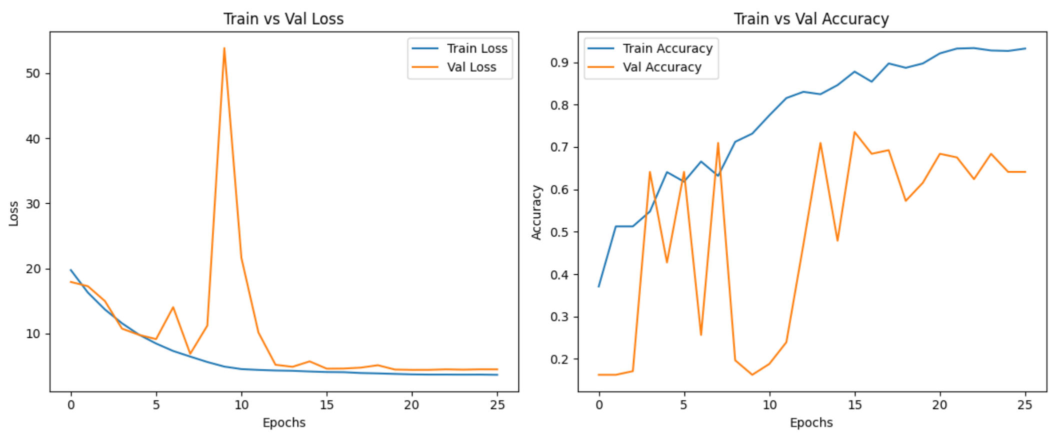


Figure 3 11: Training and validation accuracy/loss visualization for ResNet50

3.3 Research Findings

The research revealed that machine learning models can effectively support the diagnosis and severity assessment of atopic dermatitis (eczema) using clinical skin images. Among the three models tested for eczema detection, MobileNetV2 integrated with a Squeeze-and-Excitation (SE) attention mechanism achieved the highest accuracy of 96%. This model demonstrated strong generalization ability and precision in distinguishing between eczema and normal skin, even under varying image conditions such as different skin tones and lighting.

For severity classification, the EfficientNetB0 model enhanced with SE blocks and trained using Focal Loss and class weights outperformed the custom CNN and ResNet50 models. It achieved an accuracy of 83%, with high recall and F1-scores particularly for the mild and severe categories. The use of attention mechanisms and class balancing strategies contributed significantly to the model's performance, enabling it to focus on relevant image regions and maintain robustness against class imbalance.

Overall, the integration of attention mechanisms, explainable AI techniques, and model optimization strategies resulted in a highly accurate and interpretable system. These findings confirm the viability of deep learning-based approaches for real-time, accessible, and clinically reliable eczema diagnosis, offering a promising tool for use in both clinical and remote healthcare environments.

3.4 Discussion

The comparative analysis of deep learning models in this research provided valuable insights into their suitability for eczema detection and severity assessment. Among all the models tested for binary classification, the MobileNetV2 architecture augmented with SE attention blocks demonstrated the most promising performance. Its lightweight design allowed for efficient training and inference, while the inclusion of the SE mechanism improved the model's ability to focus on the most relevant dermatological features within the images. This led to superior results in both precision and recall, making MobileNetV2 a strong candidate for real-world deployment where both accuracy and efficiency are crucial.

In contrast, the baseline CNN model, although structurally simpler and easier to interpret, exhibited noticeable performance limitations, especially when encountering subtle skin variations. It showed signs of overfitting during training, with reduced generalization on the validation set. ResNet50, despite its deeper and more complex architecture, struggled with consistent feature extraction across different cases. Although it performed moderately well in terms of accuracy, it was more susceptible to class imbalance and demonstrated lower sensitivity in identifying eczema-affected areas, especially in images with low contrast or complex textures.

For severity classification, the Enhanced EfficientNetB0 model integrated with attention mechanisms delivered the best overall results. The use of focal loss and class weighting significantly improved the model’s sensitivity to underrepresented classes, particularly severe cases which are often harder to detect due to subtle or localized symptoms. The model achieved a balanced performance across all severity levels, maintaining strong precision and recall values. Other models, such as ResNet50 with CBAM attention and the residual CNN with SE blocks, were also tested, but they did not match the performance of EfficientNetB0. These models showed weaknesses in generalizing moderate and severe cases, often misclassifying them due to inadequate focus on localized patterns. The results of this study highlight the importance of combining architectural innovation with targeted training strategies in achieving robust and clinically relevant classification outcomes for medical imaging tasks like eczema diagnosis and assessment.

In addition to the performance metrics, the experiments also highlighted the significance of incorporating attention mechanisms and loss function optimization in medical image classification tasks. Models equipped with SE and CBAM attention modules consistently demonstrated improved focus on diagnostically relevant regions, helping reduce misclassifications caused by background noise or low-contrast areas. Furthermore, the application of focal loss in severity classification proved particularly effective in addressing the challenge of class imbalance, as it guided the model to pay more attention to harder-to-classify samples. This was especially important for correctly identifying moderate and severe eczema cases, which are often underrepresented in datasets. These observations reinforce the idea that model architecture alone is not sufficient to guarantee strong performance carefully selected training strategies and structural enhancements play a crucial role in optimizing deep learning models for specialized medical applications.

4. CONCLUSION

The development of the DermaScope AI system aimed to create a reliable and efficient tool for automated eczema detection and severity classification. By leveraging advanced machine learning architectures, particularly MobileNetV2 and EfficientNetB0, with integrated SE blocks, the system demonstrated commendable performance across various testing phases.

The testing phase confirmed that the system performs well in distinguishing between normal and eczema-affected skin, as well as accurately classifying the severity levels into Mild, Moderate, and Severe categories. The best-performing model, based on EfficientNetB0, achieved an overall accuracy of 81%, indicating strong generalization and reliability. Despite minor limitations in differentiating between Moderate and Severe cases, the model demonstrated consistent accuracy and resilience across various conditions, including different lighting, poses, and image resolutions.

The DermaScope AI system provides a valuable tool for healthcare practitioners by offering a non-invasive, accurate, and efficient approach to eczema diagnosis and severity assessment. With further optimization and expansion of the dataset, the system has the potential to become a robust clinical tool for early detection and monitoring of eczema. Additionally, integrating the system with real-time data visualization enhances usability and practicality for real-world applications.

Future work will focus on improving the model's performance in handling Moderate and Severe cases, expanding the dataset to include more diverse skin types, and refining the attention mechanisms for enhanced feature extraction. Additionally, deploying the system as a user-friendly web application will provide stakeholders with convenient access to its functionalities. The DermaScope AI system offers a promising foundation for leveraging deep learning in the dermatological field, contributing to better patient care and more accurate diagnosis of eczema.

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6. GLOSSARY

- ❖ AD (Atopic Dermatitis): A chronic inflammatory skin condition characterized by itchy, red, and swollen skin, commonly referred to as eczema.

- ❖ AI (Artificial Intelligence): The simulation of human intelligence processes by machines, particularly computer systems, to perform tasks typically requiring human intelligence.

- ❖ CBAM (Convolutional Block Attention Module): A deep learning module that enhances feature extraction by combining channel and spatial attention mechanisms, improving model focus on relevant image regions.

- ❖ CNN (Convolutional Neural Network): A class of deep learning models designed specifically for processing data with grid-like topology, such as images, commonly used for image classification and recognition.

- ❖ CSS (Cascading Style Sheets): A stylesheet language used for describing the presentation of a document written in HTML or XML, used to style and layout web pages.

- ❖ DL (Deep Learning): A subset of machine learning that uses neural networks with multiple layers to model complex patterns in data.

- ❖ EASI (Eczema Area and Severity Index): A standardized tool used to measure the severity of eczema based on the extent of affected body area and the intensity of lesions.

- ❖ GLCM (Gray Level Co-occurrence Matrix): A statistical method of examining texture that considers the spatial relationship of pixels, often used in image processing.

- ❖ HTML (HyperText Markup Language): The standard language for creating and structuring content on the web.

- ❖ IDE (Integrated Development Environment): A software application that provides comprehensive tools for software development, including code editing, debugging, and compilation.

- ❖ ML (Machine Learning): A subset of AI focused on the development of algorithms that allow computers to learn from and make decisions based on data.

- ❖ REST API (Representative State Transfer Application Programming Interface): A set of rules and conventions for building and interacting with web services, using standard HTTP methods.

- ❖ SCORAD (SCORing Atopic Dermatitis): A clinical tool used to assess the extent and severity of atopic dermatitis symptoms for standardized diagnosis and monitoring.

- ❖ SE (Squeeze-and-Excitation): A neural network block that improves feature extraction by recalibrating channel-wise feature responses, enhancing the representational power of deep learning models.

- SVM (Support Vector Machine): A supervised machine learning algorithm commonly used for classification and regression tasks by finding the hyperplane that best separates data points in feature space.

- UI (User Interface): The visual and interactive components of a digital application that facilitate user interaction and experience.

- UX (User Experience): The overall experience of a user when interacting with a digital product, including usability, accessibility, and efficiency.

- XAI (Explainable Artificial Intelligence): A subfield of AI focused on developing models that provide human-interpretable explanations for their predictions and decisions.

7. APPENDICES

Figure 7 1: Application Logo

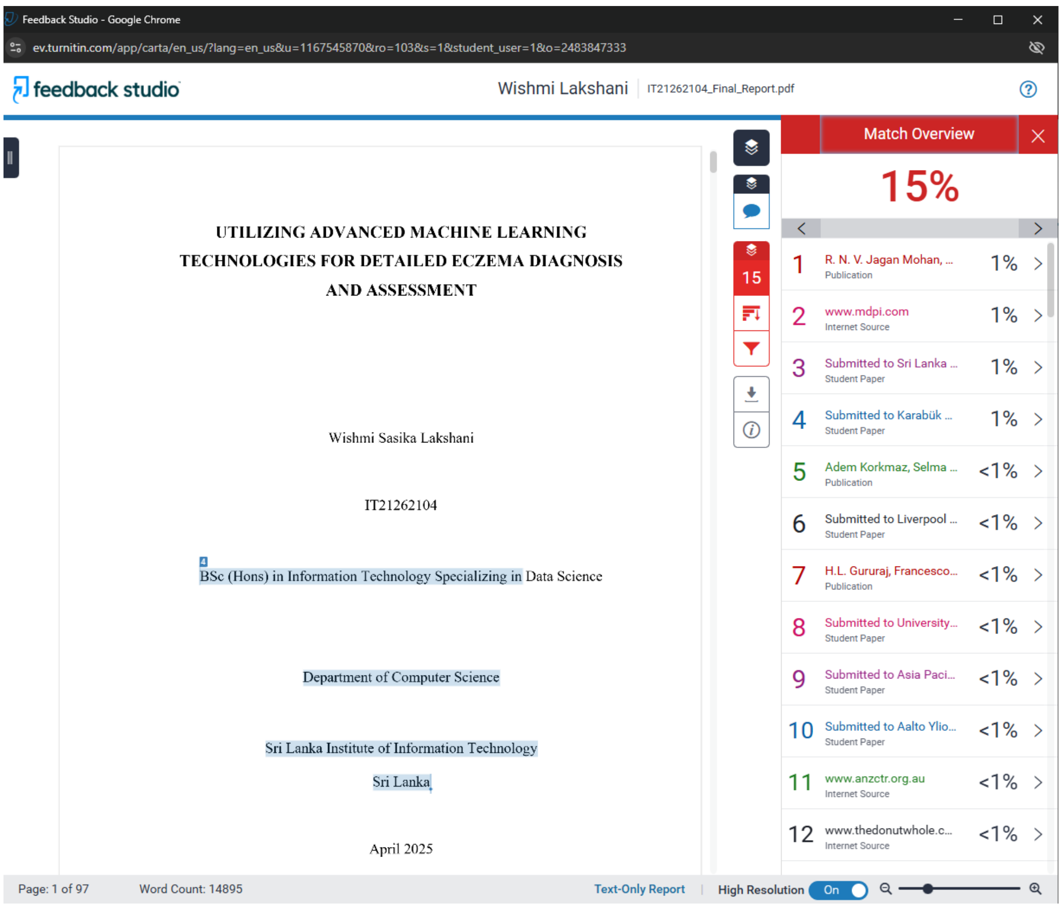
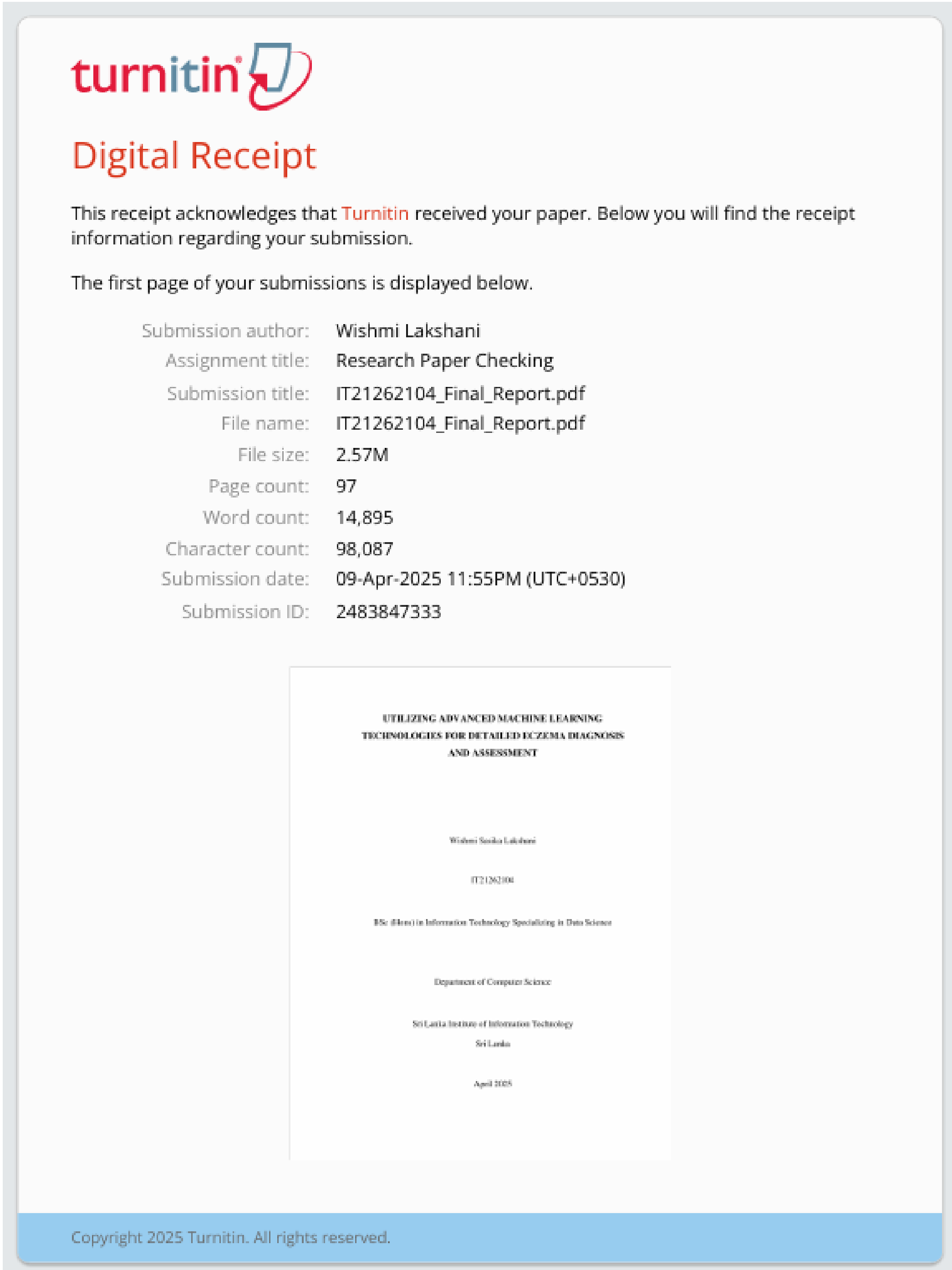


Figure 7 2: Turnitin similarity report



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UTILIZING ADVANCED MACHINE LEARNING TECHNOLOGIES FOR DETAILED ECZEMA DIAGNOSIS AND ASSESSMENT

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