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DermaDiagnostics

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Abstract

It is still quite difficult to identify skin types and skin conditions like lesions, especially in areas with little access to dermatologists. The DermaDiagnostics project tackles this problem by creating a smartphone application that can quickly and effectively identify different skin conditions and categorize skin types in real time. After extensive testing, the application showed encouraging results in identifying a variety of skin disorders and adjusting to various skin tones. Furthermore, it provides interpretive tools that make results easily comprehensible, assisting both general users and medical specialists in comprehending the results.

The project's main goal during development was to make the program user-friendly and functional. The software was developed step-by-step, starting with collecting and removing skin photos, creating its phone functionality, and standardizing the outcomes. Testing revealed that the application's accuracy and speed are outstanding. Issues such as ensuring the application functions properly on various phones and with varying skin types were not addressed.

The study also highlights the importance of identifying skin diseases, guaranteeing accurate identification and categorization of different skin lesion situations to facilitate prompt diagnosis and intervention.

In summary, DermaDiagnostics provides a significant way to enhance the early identification of skin issues, particularly in places with poor access to medical treatment. The goal of improving everyone's health and well-being is being pursued by making skin health assistance easier to obtain and comprehend.

Executive Summary

Given their similarity and the fact that they manifest differently on different skin tones, skin types and skin lesion diseases are challenging to detect. Medical experts find it more difficult to provide prompt and correct diagnoses due to the difficulties in diagnosis, particularly in populations whose access to professional dermatological treatments is limited. By releasing a smartphone application that enables both medical experts and regular people to detect skin conditions more quickly and accurately, the DermaDiagnostics project directly tackles these challenges.

The project's objective is to create a mobile application that is easy to use and yields dependable results regardless of a user's skin tone. One section is not excluded from early detection and therapy because the application was designed to be equally beneficial for persons with varied skin types. The initiative guarantees health fairness and aids in improving outcomes for both urban and rural populations by making the technology available to all..

This project addresses the issues with many current solutions, such as their inability to appropriately report or accommodate a range of skin tones. Fairness, privacy, and openness are given top priority in this initiative. The program was meticulously developed and tested via a series of stages, including data collection, pattern recognition training, interface design, and result verification. Every precaution has been taken during the process to safeguard user data, ensure quick performance, and guarantee that the program may be used even in places with sporadic internet access.

The system's design is multi-layered, with each layer serving a distinct purpose. These include the mobile interface, which allows users to engage, the background services that manage requests, and the section of the system that manages photographs and provides feedback. The design may be further optimized and is reasonably priced. The program is designed such that future upgrades may be made without requiring significant modifications, and every component is tested to function as a whole.

TTests verified that the program produces accurate and reliable results. The approach is simple for users to follow: submitting an image, receiving a result, and receiving insightful explanations. Any problems that arose during testing, such light levels or unexpected skin types, were either fixed or taken into consideration for further updates. Most significantly, those who tested the program said that it was user-friendly and beneficial.

In summary, DermaDiagnostics fills the gap between cumbersome skin diagnostic tools and practical application in the field. It is a well-considered and thoroughly tested way to promote more effective healthcare, particularly in areas with a shortage of medical resources. Concerned with equality, trust, and accessibility, the initiative adds significant value to improving skin health globally and enabling

equitable access to healthcare for all.

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Chapter 1 Introduction

Skin disorders are a major global public health problem, ranging from mild irritations to life-threatening infections. Lesions are particularly clinically significant among them as limiting severe outcomes depends on early and accurate identification. Conventional diagnostic procedures in dermatology, which are mostly dependent on the subjective manual assessments of physicians, are becoming less and less adequate to handle the complexity and diversity of skin diseases.

In light of this, there are two persistent problems: first, the limited availability and unpredictability of conventional diagnostic techniques, and second, the necessity of an efficient, methodical framework that incorporates modern technologies to support clinical decision-making. Innovation in the diagnosis process can lead to the development of a systematic framework that will improve the accuracy and timeliness of skin disease detection while also strengthening the important interaction between new artificial intelligence techniques and practical healthcare applications.

Understanding one's skin type is just as essential as identifying diseases since it helps one choose the right skincare products, maintain appropriate skincare routines, and avoid common problems like dryness, acne, or premature aging. Therefore, knowing one's skin type is crucial for maintaining general skin health and taking care of oneself.

1.1 Purpose of this Document

This document's objective is to provide a thorough plan for the whole process of creating a novel diagnostic tool for determining skin type and condition. It describes a methodical process that leads the project from initial planning to thorough design, implementation, and assessment, guaranteeing the provision of a solid solution. The document clearly outlines the project's scope, constraints, and deliverables necessary for improving dermatological diagnosis while methodically documenting every stage of development, from data collection and model training to system integration. In the end, this report bridges the gap between current clinical practices and state-of-the-art technology breakthroughs by offering a solid framework to lead stakeholders through the project's justification, methodology, and expected contributions.

1.2 Intended Audience

The intended audience for the “DermaDiagnostics” project and its associated reports will primarily include:

- Supervisors
- Evaluators
- Faculty members associated with NUCES FAST
- Students associated with NUCES FAST

1.3 Definitions, Acronyms, and Abbreviations

ISIC Dataset (International Skin Imaging Collaboration): Open dataset of over 25,000 images widely regarded as the gold standard against which to train machine learning classifiers for melanoma and skin lesions. CNN (Convolutional Neural Network) : Deep learning algorithm that has expertise in the processing of images and feature detection and is applied to skin disease classification with typically greater then 90 % accuracy. **F1 Score:** A measure of performance utilized to determine model accuracy, particularly in imbalanced datasets. The harmonic mean of precision and recall, necessary for detecting rare conditions like melanoma.

Melanoma: A highly aggressive skin cancer with a 99 % 5 year survival rate if caught early. The initial target for AI based early detection.

Fitzpatrick Skin Type Classification: A system that categorizes skin colors into six groups (I–VI) according to how they react to UV exposure. It helps correct bias in AI models traditionally trained on lighter skin colors (I–III).

Basal Cell Carcinoma (BCC): A slow growing and most common type of skin cancer. Although rarely ever fatal, early detection is required for effective cure.

Benign Keratosis Like Lesions: benign skin growths that are sometimes mistakenly mistaken for malignant tumors and must be accurately classified.

Melanocytic Nevi (Moles): pigmented skin lesions that are usually non cancerous but can pose a risk of developing melanoma if they show abnormal characteristics.

Skin Type Classification: The AI classifies skin as oily, dry, or normal and helps users adjust skincare regimens and prevent dermatological disorders.

Deep Learning (DL):A machine learning subdiscipline in which artificial neural networks are used to investigate and categorize complex patterns in data, such as the identification of skin disease.

Supervised Learning: A type of machine learning approach in which models are taught to recognize patterns in medical images based on labeled datasets.

Transfer Learning: A process by which pre trained deep neural models (such as ResNet, VGG, Xception) are transformed into dermatology data sets for higher accuracy.

Precision: A ratio of accurate positive predictions over all the positive predictions (i.e., detected melanomas divided by the number of melanomas).

Recall (Sensitivity): The ratio of positive instances present in the dataset to positive predictions by the system (i.e., the measure of how the system captures the skin disease if it exists).

ROC-AUC (Receiver Operating Characteristic Area Under Curve): A performance measure indicating the ability of the model to distinguish between healthy and diseased skin conditions.

DermNet Dataset: A public dermatology dataset of 20,000+ skin images, widely used for training AI models for skin disease classification.

HAM10000 Dataset: A collection of 10,000 dermatoscopic images, widely used for melanoma and skin cancer research.

ResNet, VGG, Xception, DenseNet: Deep learning models commonly used for medical image classification due to their improved performance in feature extraction and disease detection.

Image Segmentation: A technique by which AI divides an image into various regions, allowing one to detect infected patches of skin precisely.

Overfitting: A condition in which a machine learning model learns too much from training images, reducing its ability to make predictions on new images.

Clinical Validation: The process of testing an AI model in real world clinical settings to validate its accuracy before deployment.

1.4 Conclusion

Due to their complexity across different skin tones, skin lesions and illnesses are challenging to identify. By developing a mobile application that facilitates lesion analysis using advanced models and a variety of datasets, our study addresses these issues. The goal is to provide a straightforward, expandable system that helps dermatologists improve patient care and diagnostic precision, particularly in underprivileged areas.

In addition to identifying diseases, it is critical for people to know their skin type since this knowledge is essential for maintaining efficient skincare practices, choosing the right products, and avoiding common issues like dryness, acne, or premature aging. People may actively work toward better skin and enhanced wellbeing by identifying and taking care of their unique skin type. In the end, a more comprehensive approach to skin health and personal care is ensured by integrating skin disease detection with skin type knowledge.

Optimized processing technology, a mobile user interface, and a cloud backend form its foundation. Lesion classification, skin type classification, segmentation, and interpretability algorithms are among the salient aspects. Taking healthcare laws into consideration, the project is created in phases, beginning with data collection and model training and ending with deployment and validation.

The application connects cutting-edge dermatological technologies with practical clinical use through its modular design and privacy-focused architecture. For various groups, it delivers equitable healthcare solutions that are reliable, accessible, and egalitarian.

Chapter 2 Project Vision

This project aims to use AI advancements to deliver quick, automated skin disease diagnosis together with precise skin type identification with the goal of a world where dermatological healthcare is freely available. This dual purpose is to provide broadly accessible, free healthcare services without sacrificing reliable information for patients and physicians.

2.1 Problem Domain Overview

The skin serves as the body's biggest organ and serves as the first line of defense against external dangers. It also senses its surroundings. Its proper functioning is crucial for general health, but a variety of conditions, from benign hyperplasias to malignant carcinomas, pose a threat to that well-being. High burden skin lesions such as benign keratosis, melanoma, basal cell carcinoma, and melanocytic nevi are addressed here. Furthermore, determining the correct skin type—normal, dry, or oily—is essential to adjusting both preventative and therapeutic interventions. This emphasizes the need of a free self-diagnostic approach that closes the current gaps in healthcare.

2.2 Problem Statement

The majority of dermatological diagnoses made today are manual, subjective, time-consuming, and frequently delayed or irregular. A quick, cost-free, and automated method that can correctly classify skin conditions and identify skin types for treatment and improved patient outcomes is desperately needed.

2.3 Problem Elaboration

The difficulties in dermatology are multifaceted. Because traditional diagnostic methods are labor-intensive, time-consuming, and susceptible to variations in clinical judgment, skin disorders frequently go undetected until they are in severe stages. These problems are made worse by the lack of qualified dermatologists, especially in underserved and rural areas, which delays necessary diagnostic evaluations. This emphasizes how urgent it is to reconsider current methods and how crucial it is to create a novel, affordable diagnostic tool that can precisely detect certain skin conditions like melanoma, basal cell carcinoma, squamous cell carcinoma, and benign lesions early on.Concurrently, the application's skin type identification feature has a distinct but equally important function: it enables users to recognize their own skin type for improved personal hygiene, wise product choices, and healthier skincare practices.

2.4 Goals and Objectives

The goals and objectives of DermaDiagnostics are as follows:

- To predict skin diseases
- To develop an accessible and user friendly interface for use by both healthcare providers and individuals without a clinical background
- To lessen dermatologists workloads through automated diagnosis in order for them to deal with challenging cases
- To provide general preventive recommendations or follow up advice (e.g., see a specialist)

2.5 Project Scope

The scope of the project includes:

- Identification of skin types i.e. oily, dry and normal
- Detection of diseases from the skin images which are basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, melanoma

The project scope does not include:

- Diseases not mentioned above
- Medical support and assistance
- Telemedicine platform

2.6 Sustainable Development Goal (SDG)

This project best fits under SDG 3 which is ”Good Health and Well being”. By facilitating detection and offering information on skin conditions, the project helps advance public health outcomes and ease the burden of unaddressed skin diseases. The general objective of healthy lifestyles and well-being for people of all ages is served by easy access to quick and accurate preliminary diagnosis. With an emphasis on illness prevention, skin health, and access to necessary healthcare, ”Figure 2.1” guarantees healthy lifestyles and fosters well-being for everyone.

Figure 2.1: Sustainable Development Goal 3

2.7 Conclusion

DermaDiagnostics offers a useful framework for diagnosing skin conditions by utilizing potent artificial intelligence techniques. The system efficiently identifies benign keratosis-like lesions, melanocytic nevi, melanoma, and basal cell cancer while simultaneously categorizing skin types using a mix of complex preprocessing techniques, feature extraction, and model algorithms.Through this, the project not only improves diagnostic accuracy and relieves the burden of dermatologists but also contributes to Sustainable Development Goal 3 by supporting accessible and affordable healthcare. Although not a replacement for experienced clinical judgment, DermaDiagnostics greatly complements worldwide dermatological practice, making diagnosis more accessible and technology driven.

Chapter 3 Literature Review / Related Work

Literature review in this study is a crucial tool used to establish the scope of the project. We thoroughly reviewed AI based methods of detecting skin disease, condensing each article's main points. In these reviews, we outlined each paper's aims and methodologies. In addition, we analyzed the strengths and weaknesses and explained how these models can be helpful to us.

3.1 Definitions, Acronyms, and Abbreviations

CNN: Convolutional Neural Network

SVM: Support Vector Machine

ResNet: Residual Neural Network

YOLOv4: You Only Look Once version 4

ISIC: International Skin Imaging Collaboration

HAM10000: Human Against Machine with 10,000 Images

3D Imaging: Three dimensional spatial analysis for lesion depth estimation

Federated Learning: Collaborative AI training without sharing raw data

F1 Score: Metric balancing precision and recall for imbalanced datasets

ViT: Vision Transformer (self attention based neural network)

PH2: Dermoscopic dataset for melanoma detection (200+ images)

DermNet: Public dermatology image repository (23,000+ cases)

SD-198: Skin disease dataset with 198 diagnostic categories

LIME: Local Interpretable Model agnostic Explanations

SHAP: SHapley Additive exPlanations (explainable AI tool)

GDPR: General Data Protection Regulation (EU privacy law)

FDA: Food and Drug Administration (US regulatory body)

CE: European Conformity (medical device certification)

IoU: Intersection over Union (segmentation accuracy metric)

DSC: Dice Similarity Coefficient (lesion segmentation metric)

SMOTE: Synthetic Minority Oversampling Technique (for class imbalance)

GAN: Generative Adversarial Network (synthetic data generation)

IoT: Internet of Things (e.g., smart dermatoscopes)

CAD: Computer Aided Diagnosis (clinical decision support)

Fitzpatrick Scale: Skin tone classification system (I–VI types)

3.2 Detailed Literature Review

Our topic focuses on skin disease detection classification thus we have done vast research in this area. Image classification has three major parts that are image data preprocessing, feature extraction and classification.Thus, we have gathered a vast amount of literature review regarding these topics

3.2.1 AI Based Detection Techniques for Skin Diseases

3.2.1.1 Summary of the research item

In this work [1], the authors deal with inter class similarity (for example, melanoma vs. benign nevi) and dataset bias challenges in skin disease diagnosis with CNNs. The authors use the ISIC and HAM10000 datasets of unspecified sizes and use preprocessing strategies such as rotation, flipping, and color jittering to avoid environmental variability. Hybrid CNN SVM architectures are analyzed in this work to enhance accuracy for minority Fitzpatrick skin types (IV–VI). Although model accuracy is not explicitly reported, the authors highlight the hybrid method's potential for varied skin tones. Future work involves validating models in actual clinical workflows and improving interpretability for clinicians. This foundational work examines CNN models for diagnosing skin conditions, focusing on issues including interclass dataset bias and similarities (e.g., benign nevi versus melanoma). The authors contrast models that were trained on HAM10000 and ISIC datasets, emphasizing the value of hybrid techniques (like CNN SVM) to Talk about darker skin tones. The use of data augmentation (color, flipping, and rotation) is emphasized. jittering) to offset fluctuations in the surroundings.

3.2.1.2 Critical analysis of the research item

Strengths:

- Proposes hybrid architectures to address skin type diversity
- Detailed analysis of dataset limitations

Weaknesses:

- Lacks validation on real time clinical workflows
- Limited discussion on model interpretability for clinicians

3.2.1.3 Relationship to the proposed research work

The paper presents various AI models such as a hybrid CNN SVM model, a Vision Transformer LightGBM (ViT-LightGBM) hybrid model, and GAN based synthetic data generation. Adversarial training, Fitzpatrick stratified sampling, Grad-CAM, and SHAP are also discussed for reducing bias and interpretability. Of these, the most appropriate for our project is the ViT-LightGBM hybrid model. It marries Vision Transformers' global context capture with LightGBM's explainable and efficient classification, making it perfect for practical clinical use. Its support for interpretability tools such as Grad-CAM and SHAP guarantees clinician friendly explanations, improving usability. The article cites datasets such as ISIC, HAM10000, and DiverseDerm, which contain diseases such as melanoma, nevus, basal cell carcinoma, and actinic keratosis. Melanoma and basal cell carcinoma are especially of interest in our project because they are clinically important and consistent with our interest in the early detection of skin diseases. The ViT LightGBM model, with its improved interpretability and efficiency, is ideally suited to detect these conditions in patients from heterogeneous populations.

3.2.2 Artificial Intelligence in Dermatology Image Analysis

3.2.2.1 Summary of the research item

This research [2]investigates 3D imaging for melanoma diagnosis with ResNet-50 for spatial feature analysis of lesions. The authors contrast 3D imaging with conventional 2D approaches, achieving a 12 % increase in accuracy. Patient metadata, including age and lesion history, are integrated, and 3D reconstruction from structured light scanners is used for preprocessing. Although improving accuracy, high computational complexity and proprietary hardware are issues. Future efforts will attempt to use 2.5D pseudo-3D imaging as a less expensive option.

3.2.2.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Demonstrates superior accuracy of 3D imaging for depth estimation
- Integrates metadata for holistic diagnosis

Weaknesses:

- High computational costs for 3D rendering

- Requires specialized hardware (e.g., 3D dermatoscopes)

3.2.2.3 Relationship to the proposed research work

The paper considers the benefits of 3D imaging compared to 2D imaging for melanoma detection, citing a 12% improvement in accuracy but recording high costs and computing requirements. To overcome these limitations, the authors suggest using a 2.5D pseudo-3D imaging technique, which fuses 2D dermatoscopic images with depth information using techniques such as multi angle photometric stereo and depth from defocus algorithms. Light depth estimation CNNs, for example, MobileNetV3, are employed for computational effectiveness, and metadata such as patient self reported lesion texture are used to make up for the lack of 3D data. The 2.5D model fills the gap between the economic 2D imaging and 3D imaging diagnostic precision and makes advanced dermatological AI more feasible. For our project, the 2.5D pseudo-3D model using MobileNetV3 is the most cost effective option since it finds a balance between accuracy, cost, and computational viability. The paper is melanoma centered, a condition closely related to our project, and also focuses on skin cancer detection. This aligns with our objective of enhancing diagnostic accuracy at the expense of affordability and accessibility.

3.2.3 Skin Disease Detection Using CNN

3.2.3.1 Summary of the research item

Here [3], the authors implement a tailored CNN of 6 convolutional layers with ReLU activation to diagnose skin lesions on the ISIC dataset. Aggressive data augmentation by synthetic adversarial networks is performed to mimic sparse lesions. Accuracy of 98.24 % is achieved, and Grad-CAM is integrated for lesion location and visual interpretability. Disadvantages include not testing the model on handheld devices and ethics of using synthetic data. Future research will involve edge device optimization and setting ethical standards for synthetic data sets.

3.2.3.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- State of the art accuracy with adversarial training
- Incorporates explainability tools for clinician trust

Weaknesses:

- Limited testing on mobile devices
- Ethical implications of synthetic data are ignored

3.2.3.3 Relationship to the proposed research work

The paper considers the application of Convolutional Neural Networks (CNNs) for skin disease diagnosis, highlighting the use of Grad-CAM for lesion localisation and visual explainability. Grad-CAM identifies important features such as texture patterns and boundary of lesions, which are aligned with the vision of increasing clinician confidence and model interpretability. The paper attains an accuracy of 98.24% with Grad-CAM, confirming its suitability. For our project, the hybrid ViT-LightGBM model integrated with Grad-CAM and SHAP values is the most effective option since it provides accurate, explainable, and actionable outputs. This solution overcomes the article's limitation of slow inference time by reducing Grad-CAM's computational cost using selective activation mapping and batch processing. Although the article does not mention diseases, it is concerned with skin lesion detection, which pertains to our project for diseases such as melanoma and basal cell carcinoma. Through the use of Grad-CAM and SHAP, our project can enhance diagnostic accuracy and interpretability for these diseases so that they have real time clinical utility.

3.2.4 Hybrid Models for Diverse Skin Tones

3.2.4.1 Summary of the research item

This paper [4]discusses algorithmic bias in skin cancer detection by presenting the DiverseDerm dataset, which consists of 5,000 images of Fitzpatrick skin types I–VI. The authors present a CNN-SVM hybrid model, where image preprocessing includes normalization and augmentation. The hybrid model enhances accuracy for darker skin types (Fitzpatrick IV–VI) by 18 % over isolated CNNs, albeit at a 30 % slower inference time. Future work will involve testing the model on non melanoma examples and optimizing computational efficiency.

3.2.4.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- First study to quantify accuracy gaps across skin tones
- Open sources the DiverseDerm dataset.

Weaknesses:

- Hybrid model increases inference time by 30%
- Limited validation on non melanoma cases

3.2.4.3 Relationship to the proposed research work

The paper highlights the need of addressing dataset bias, particularly the underrepresentation of dark skin tones (Fitzpatrick IV–VI), and points out flaws in datasets as HAM10000 and ISIC. It emphasizes using a variety of datasets, such as Fitzpatrick stratified sampling, DiverseDerm, and Aggressive debiasing techniques to give every skin type fair model performance. Moreover, data augmentation methods such as rotation, flipping, and color jittering, and GAN based synthetic data creation are recommended to enhance dataset diversity. For our project, using Fitzpatrick stratified sampling together with GAN based synthetic data creation is the most effective method since it provides balanced representation and alleviates bias. Although the article does not list diseases, the focus is on detecting skin lesions, which can be applied in our project dealing with conditions such as melanoma and basal cell carcinoma. Integrating these methods, our project can obtain adequate and generalizable outcomes in varying populations, targeting representation gaps and bias.

3.2.5 Role of AI and Deep Learning in Skin Disease

3.2.5.1 Summary of the research item

In this paper [5], the authors make use of ResNet152 using transfer learning with pre trained weights from ImageNet for multi class skin cancer classification on the ISIC dataset. Preprocessing pipeline involves necessary techniques such as batch normalization to reduce instability in learning and dropout layers to avoid overfitting. The model has a stunning accuracy of 97.14 %, but one of the primary issues is its more than 12GB GPU memory requirement. The authors do note that the present architecture is computationally expensive and not ideal for deployment on edge devices. Future research will involve the creation of lightweight architectures for maximizing computational efficiency, as well as increasing the dataset to more accurately represent underrepresented groups.

3.2.5.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Demonstrates transfer learning's efficiency for small datasets
- Detailed ablation study on hyperparameters

Weaknesses:

- Requires high GPU memory (12GB+)
- No discussion on edge deployment

3.2.5.3 Relationship to the proposed research work

The paper addresses ResNet152 and transfer learning for skin disease classification with 97.14% accuracy but high GPU memory usage. To solve this, light weight architectures such as EfficientNet-B4 are suggested for segmentation with comparable accuracy at reduced computational expense. Overfitting is avoided using methods such as batch normalization, dropout layers, adaptive dropout, and layer normalization. Transfer learning is also highlighted for fine tuning pre trained models over datasets such as ISIC and HAM10000, in order to shorten training time. EfficientNet-B4 is the most effective model for our project because it finds a balance of accuracy and efficiency in computation. The article is not specific about diseases but involves skin lesion detection, which our project is about detecting conditions such as basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. Through the use of EfficientNet-B4 and transfer learning, our project is able to provide precise, real time inference on these diseases while overcoming computational and scalability constraints.

3.2.6 YOLOv4-DarkNet for Melanoma Segmentation

3.2.6.1 Summary of the research item

In this work [6], the authors suggest a segmenting method marrying YOLOv4-DarkNet to active contour models for accurate boundary detection of the lesion on PH2 dataset having 200 images. Preprocesses involve implementing morphological techniques to deal with the irregularities in the lesions' borders so that segmentation would be more precise. The 94.5 % Dice score of the model surpasses 6 % in comparison to the U-Net model, ranking it as an improved solution towards lesion segmentation. Nonetheless, the model computes at just 4 FPS on CPUs, outlining a compromise between speed and accuracy. Ongoing research includes automatic contour initialization and the improvement of the model speed for use in clinical environments, especially in real time applications.

3.2.6.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- High precision in segmenting ambiguous borders
- Open source implementation for reproducibility

Weaknesses:

- Computationally intensive (4 FPS on CPU)
- Requires manual contour initialization

3.2.6.3 Relationship to the proposed research work

The article addresses YOLOv4-DarkNet for melanoma segmentation with a 94.5% Dice score, and as a lightweight counterpart, EfficientDet-D4. Automated edge detection algorithms (such as Canny edge detection) and adaptive morphological filters are also mentioned. EfficientDet-D4 is the most efficient model for our project, as it compromises between real time performance (more FPS) and segmentation accuracy while minimizing computational expenses over YOLOv4-DarkNet. Incorporating automatic edge detection (e.g., Canny) and adaptive morphological filtering even improves workflow automation and boundary accuracy. The article specializes in melanoma, our focal disease in the project, as well as on basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. Melanoma's asymmetric lesion shapes and complexity of diagnosis support our objective to detect heterogeneous skin cancers and lesions. By implementing EfficientDet-D4 and automatic edge detection, our project is able to enhance segmentation efficiency for melanoma and apply these advantages to other diseases such as nevi and keratosis, providing strong, real time clinical usability.

3.2.7 Transformer Networks for Skin Cancer

3.2.7.1 Summary of the research item

In this paper [7], the authors use vision transformers (ViT) on the HAM10000 dataset, which holds 10,015 images, for melanoma detection. Standard resizing and normalization of images constitute the preprocessing steps. The ViT model, making use of self attention mechanisms to extract global context from lesions, gets a 96.8 % accuracy, improving over CNNs by 4 %. Nonetheless, the model needs 50 % more training data because transformer complexity is greater than that of CNNs. Future research will investigate adding multi scale attention mechanisms to further increase performance and enhance the interpretability of the model's attention maps for more transparent and explainable clinical AI.

3.2.7.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Superior handling of large lesion contexts
- Reduces false positives in melanoma detection

Weaknesses:

- Requires 50 % more training data than CNNs
- Limited interpretability of attention maps

3.2.7.3 Relationship to the proposed research work

The paper presents Vision Transformers (ViTs) for skin cancer diagnosis with 96.8% accuracy on the HAM10000 dataset by utilizing global lesion context to minimize false positives. It also presents a hierarchical transformer model that integrates local and global attention for effective multi scale analysis and overcomes ViTs' shortcomings (e.g., high data requirements, lack of interpretability) through Grad-CAM and SHAP for explainability. Optimal for our project is the hierarchical transformer with Grad-CAM/SHAP integration, as it is well balanced in terms of accuracy, computational power, and clinician oriented interpretability. The work centers on melanoma and melanocytic nevi (prevalent in HAM10000), which are targets for our project as well: basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. The multi scale analysis within the hierarchical model improves detection of melanoma's abnormal characteristics and discrimination of nevi from malignancies, aligning directly with our objective of accurate, interpretable diagnosis. This model enhances our ability to deal with varied lesions, such as melanoma and nevi, while allowing scalability for practical clinical application

3.2.8 3D Imaging in Dermatology

3.2.8.1 Summary of the research item

In this paper [8], the authors discuss two major advances in medical technology. They first use vision transformers (ViT) on the HAM10000 dataset, with 10,015 images, for melanoma detection. Basic preprocessing techniques such as resizing and normalization are used, and the ViT model is 96.8 % accurate, a 4 % improvement over CNNs. It needs 50 % more training data, though. Future research will involve the addition of multi scale attention mechanisms and enhancing the interpretability of attention maps.

In the second study, structured light 3D scanners are used by authors on postoperative cases to manufacture patient specific prosthetics. 3D reconstructions are incorporated into CAD tools to decrease the time of rehabilitation by 40%. The disadvantage is that such scanners are extremely expensive (costing more than dollar 10,000), but future work aims to use cost effective 3D imaging solutions for wider applications in clinics for making personalized prosthetics available at a lower price to more patients.

3.2.8.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Practical application of 3D imaging beyond diagnosis

- Integrates with CAD software for rapid prototyping

Weaknesses:

- High cost of 3D scanners (dollar 10,000+)
- Limited to post surgical use cases

3.2.8.3 Relationship to the proposed research work

The paper addresses 3D imaging (structured light 3D scanners) for post skin tumor amputation prosthetic production and suggests 2.5D pseudo-3D imaging as an economical alternative. The latter extracts depth information from 2D dermatoscopic images by applying depth from shading and photometric stereo techniques. For our project, 2.5D pseudo-3D imaging is more efficient since it takes advantage of current 2D hardware while maintaining essential 3D spatial information (e.g., elevation of the lesion, irregularity of the border) with little additional cost. The article is concerned with amputation required skin tumors, including melanoma, which is in line with our project's focus on melanoma, basal cell carcinoma, benign keratosis like lesions, and melanocytic nevi. Melanoma's aggressiveness and requirement for accurate surgical planning are reflected in the article's concern with post amputation treatment, while basal cell carcinoma and nevi are aided by 2.5D's capacity to evaluate lesion morphology. By taking this strategy, our project has the ability to improve melanoma and other lesion diagnostic accuracy, democratizing high end imaging for treatment planning in a variety of clinical environments.

3.2.9 Ethical Guidelines for AI in Dermatology

3.2.9.1 Summary of the research item

The authors in this article [9]suggest ethical paradigms for the use of AI in dermatology, based on transparency, accountability, and the need for human oversight. Instead of relying on particular datasets or algorithms, the research critiques current AI software for not having effective strategies for countering biases, especially when diagnosing skin conditions in a diverse population. The authors promote a "human in the loop" system, where AI is used as an assistant tool for dermatologists instead of substituting them, so that key decisions remain human based. Future research highlights the importance of technical guidelines for the deployment of AI and measures to tackle algorithmic fairness and inclusivity in dermatological use, with a view to ensuring ethical compliance.

3.2.9.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Clear ethical benchmarks for clinical deployment
- Advocates for interdisciplinary collaboration

Weaknesses:

- Lacks technical implementation guidelines
- Does not address algorithmic bias

3.2.9.3 Relationship to the proposed research work

The article mentions ethical frameworks (compliance with GDPR/HIPAA), human in the loop systems, differential privacy methods, audit trails, and explainability tools (SHAP, Grad-CAM) for responsible AI in dermatology. No classic ”models” are mentioned, but the use of these ethical measures guarantees compliance and transparency. In our project, the use of differential privacy along with SHAP/Grad-CAM is most effective since it optimizes data security, explainability, and clinician trust without degrading performance. The article does not specifically refer to diseases but generally speaks about AI ethics in dermatology, which can be applied to our project's emphasis on basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. Ethical principles are important for these diseases, particularly melanoma, where risks of misdiagnosis are great. By integrating privacy protecting methods and transparent AI tools, our project guarantees ethical processing of sensitive information for all the targeted lesions, building trust in malignancy diagnosis such as melanoma and separating benign lesions (e.g., nevi, keratosis) from cancers. This is in line with the article's focus on accountability in high risk dermatological AI.

3.2.10 Federated Learning for Skin Disease Detection

3.2.10.1 Summary of the research item

Here [10], the authors discuss the application of federated learning to train a CNN for medical image analysis on five hospitals (size of dataset not mentioned). By making use of federated learning, the model keeps patient data decentralized and protects privacy during the training process. Preprocessing involves differential privacy application to avoid any leakage of data. The model is 92.3 % accurate, although it converges 20 % more slowly than conventional centralized training protocols because of the added communication overhead between hospitals. Optimizing federated edge computing and communication protocols to decrease latency and increase overall efficiency in distributed AI healthcare systems will be addressed in future work.

3.2.10.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Privacy preserving and scalable
- Reduces bias via multi institutional data

Weaknesses:

- 20 % slower convergence than centralized training
- Requires robust communication infrastructure

3.2.10.3 Relationship to the proposed research work

The article speaks of federated learning for decentralized CNN training over hospitals with a 92.3% accuracy, all in maintaining data privacy through federated averaging and differential privacy. Rural challenges (poor connectivity and low resource devices) are overcome by employing methods such as edge computing, quantization, and pruning. For our project, federated learning with edge computing is perfect, as it supports local training on low resource devices, minimizes communication overhead through compression, and combines heterogeneous rural data to reduce bias. The article generally targets skin diseases, which is in line with our project's targets: basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. Federated learning provides privacy preserving, decentralized training for these diseases, especially important in rural areas where melanoma and other cancers are likely underdiagnosed because of a lack of access to experts. By maintaining data security and taking advantage of multi institutional feedback, our project can enhance detection of melanoma and benign lesions (e.g., nevi, keratosis) in underserved populations, promoting equity in dermatological AI

3.2.11 Regulatory Standards for AI in Healthcare

3.2.11.1 Summary of the research item

In this paper [11], the authors summarize FDA and CE regulatory frameworks for AI based medical devices, with special emphasis on dermatology.The synopsis highlights the need to test AI technologies on a range of demographics in order to demonstrate their accuracy and fairness across various population groupings. The study advocates for continuous post-market monitoring even if no specific datasets or algorithms are evaluated of AI performance when it is made available. The authors also advocate for regulatory harmonization globally to establish universal guidelines and remedy disparities, most notably in poor countries where regulation of AI medical devices is relatively underdeveloped. Future attempts will seek to bridge these disparities to provide uniform access to secure and effective AI instruments globally.

3.2.11.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Practical roadmap for regulatory compliance
- Case studies on FDA approved AI tools

Weaknesses:

- Overlooks regulatory gaps in low income countries

3.2.11.3 Relationship to the proposed research work

The piece addresses regulatory guidelines (FDA/CE standards, ISO 13485 compliance) and procedures such as multi center clinical trials, real time monitoring, and automated reporting to verify AI systems adhere to safety, fairness, and reliability standards. No particular AI models are discussed, but emphasis is placed on aligning development with regulatory standards. For our task, the inclusion of ISO 13485 conformant workflows in our current models (such as ViT-LightGBM or EfficientNet-B4) provides efficiency since it reduces certification with preserved performance. The article is not disease specific but highlights validation on various populations, which suits our interest in basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. Conformance to these standards guarantees our system operates fairly with all geographies and skin types, which is essential for high stakes diseases such as melanoma, whose diagnostic precision directly affects survival. Through embracing aggressive testing and post market surveillance, our project is able to confidently identify malignancies (e.g., basal cell carcinoma, melanoma) and benign lesions (e.g., keratosis, nevi), reconciling regulatory severity with clinical confidence and scalability.

3.2.12 Interpretability of AI Models in Dermatology

3.2.12.1 Summary of the research item

The authors use LIME (Local Interpretable Model Agnostic Explanations) and SHAP (SHapley Additive exPlanations) in this article [12]to explain convolutional neural network (CNN) predictions on the SD-198 dataset, comprising 6,584 skin lesion images. Preprocessing is done by standard resizing to have consistent input sizes. The application of these explainability techniques boosts clinician confidence in the model's predictions by 35 % because it gives them clear explanations of the factors influencing each decision. However, the inclusion of these explanations increases the overall inference time by 50

%, which poses a challenge for real time applications. Future work focuses on optimizing the trade off between interpretability and speed and integrating these explanation tools into clinical workflows to enhance decision making without significant delays.

3.2.12.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Quantifies trust via user studies
- Open source code for explanation tools

Weaknesses:

- Explanations increase inference time by 50%

3.2.12.3 Relationship to the proposed research work

The article presents interpretability tools such as LIME, SHAP, and Grad-CAM to rationalize CNN predictions, with clinician trust seeing a 35% boost. It combines SHAP within a hybrid ViT-LightGBM model to provide feature level explanations (such as lesion texture, border irregularity) and blends SHAP with Grad-CAM for interpretability visually. For our project, the most effective option is the hybrid ViT-LightGBM model with optimized SHAP and Grad-CAM. Through SHAP approximations and batched processing, we mitigate the inference time constraints of the article for real time deployment while maintaining explainability. Whereas the article applies its technique in a general setting on skin lesions, our project aims specifically at basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. The focus on border irregularity and texture analysis is particularly useful for melanoma detection, whereas SHAP's feature level information assists in distinguishing benign lesions (e.g., nevi, keratosis) from malignancies (e.g., basal cell carcinoma). This strategy increases diagnostic transparency for high stakes conditions such as melanoma, which is in line with our objective of clinician friendly, trustworthy AI tools for a wide range of skin diseases.

3.2.13 Aysa App

3.2.13.1 Summary of the research item

In this work [13], the authors created an iOS skin cancer screening app based on ResNet-50, using transfer learning and trained on the HAM10000 dataset with 10,015 dermatoscopic images. Preprocessing involved employing SMOTE (Synthetic Minority Oversampling Technique) for balancing class distributions to enhance detection of less common conditions by the model. The app enables patients to upload photographs of skin lesions and gives a risk score to determine if the lesion is benign or malignant. The functionality of the app is based on cloud based inference to provide low latency outcomes, but requires an internet connection for operation. In pilot research, the app had 95% accuracy, showing its potential to be effective. Future development includes expansion to Android and implementing offline capability to improve accessibility and use.

3.2.13.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- 95 % accuracy in pilot studies
- Multilingual support for global accessibility

Weaknesses:

- Limited to iOS devices
- Requires internet connectivity

3.2.13.3 Relationship to the proposed research work

The Aysa App, a ResNet-50 with transfer learning based skin cancer detector with a 95% accuracy rate, is addressed in the article, and its cross platform drawbacks (iOS only) are noted. Solutions posed are Flutter to enable Android/iOS compatibility, edge AI for offline capabilities, and on device execution to meet privacy requirements (GDPR/HIPAA). For our project, the Flutter based edge AI platform is most effective, as it provides cross platform support, offline capability in rural/low connectivity regions, and privacy through on device processing, overcoming the article's iOS limitation. Though the article addresses melanoma, our project is aimed at basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. The skin cancer detection framework of the app, especially for melanoma, matches our objective of detecting high risk malignancies. By applying this methodology to incorporate offline functionality and cross platform compatibility, our project has the potential to democratize detection for a wide range of lesions (e.g., nevi vs. melanoma) while ensuring accuracy and compliance, promoting equal access to AI assisted dermatological services in underserved areas.

3.2.14 IEEE Skin Disease Detection System

3.2.14.1 Summary of the research item

In this work [14], the authors utilize a hybrid AlexNet-SVM model on the ISIC dataset for melanoma binary classification between benign and malignant lesions. Standard data augmentation methods are used during the preprocessing step to enhance the generalization capability of the model. The hybrid method combines AlexNet's feature extraction power with an SVM classifier for improved decision making.

The system makes 86.21 % accurate predictions using real time inference, making it convenient for use in clinical environments that demand rapid responsiveness. The existing model currently supports binary classification only, which hinders its practicality for more intricate diagnostic problems. Future directions involve extending the system towards multi class classification so that it can be used for the diagnosis of multiple skin diseases and investigating mobile deployment to make it more accessible.

3.2.14.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Open source code for community adoption
- Low hardware requirements (2GB RAM)

Weaknesses:

- Limited to binary classification (melanoma/non-melanoma)

3.2.14.3 Relationship to the proposed research work

The article proposes a hybrid AlexNet-SVM model for binary classification of skin diseases (melanoma or non-melanoma) with 86.21% accuracy and cites ViT-LightGBM as a suggested multi class alternative. For our project, the hybrid ViT-LightGBM architecture is more effective, combining Vision Transformers' global context perception with LightGBM's explainability to provide multi class basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma detection—overcoming the article's limitation of binary classification. Although the article specifically targets melanoma, our project generalizes to varied lesions, taking advantage of ViT-LightGBM's scalability and edge optimization (through quantization/pruning) for low end hardware. Combining DiverseDerm and GAN augmented data also improves fairness across skin types, an IEEE system gap. The diagnostic subtlety and clinical immediacy of melanoma are complementary to our emphasis, and the multi class ability of the model enhances discrimination of benign lesions (e.g., nevi, keratosis) from cancers (e.g., basal cell carcinoma, melanoma). The method guarantees correct, fair, and deployable AI based dermatological solutions.

3.2.15 DermNet NZ

3.2.15.1 Summary of the research item

Here [15], the authors collect a wide ranging dataset of more than 23,000 dermatology images of 1,200 unique skin conditions. The dataset is an educational resource for clinicians and medical students alike, offering expert annotated images for reference and diagnostic training. No preprocessing techniques or AI based algorithms are used in this dataset.

The repository is built as a public resource, providing diagnostic quizzes for users to test their knowledge and enhance diagnostic competence. Although the present emphasis is on non AI educational use, the authors propose the eventual incorporation of AI based diagnosis tools to further enhance the value of the dataset and aid clinical decision making.

3.2.15.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Free access for non commercial use
- Continuously updated by dermatologists

Weaknesses:

- No integrated AI for automated diagnosis

3.2.15.3 Relationship to the proposed research work

The article talks about tapping into DermNet NZ's database (23,000+ expert annotated images) to improve AI powered dermatology applications and suggests a hybrid ViT-LightGBM model for lesion classification with automated features. For our project, the ViT-LightGBM hybrid is perfect, marrying Vision Transformers' global feature extraction with LightGBM's explainable classification to fill DermNet NZ's void of combined AI diagnostics. Although the article generally makes mention of ”rare skin diseases” and generic conditions in DermNet NZ, our scope concurs with its reporting of melanoma, melanocytic nevi, and other lesions, coinciding with our target diseases: basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. By training on DermNet NZ's wide, high grade data, our model enhances the detection of melanoma (as crucial to early treatment) and distinction of benign lesions (such as nevi, keratosis) from malignancies (such as basal cell carcinoma). This methodology crosses educational resources with AI diagnostics for greater accuracy of common and infrequent conditions with clinician trust maintained via explainability.

3.2.16 Federated Learning Platform

3.2.16.1 Summary of the research item

In this system [16], the authors employ a federated learning paradigm with PySyft to facilitate privacy preserving training of AI across various hospitals for melanoma diagnosis. The system utilizes the HAM10000 dataset and maintains data privacy by only sharing model updates, not the original patient data. Preprocessing involves federated averaging to combine these updates from various institutions.

The platform has 92.3 % accuracy in melanoma detection and can also detect other conditions such as psoriasis and eczema. The major advantage is that it can train AI models together without sacrificing data privacy. In future, work will be focused on integrating IoT devices for easier data collection and less dependency on bespoke software solutions.

3.2.16.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- Compliance with GDPR/CCPA
- Reduces data silos in healthcare

Weaknesses:

- Requires hospitals to install custom software

3.2.16.3 Relationship to the proposed research work

The article presents a federated learning platform using federated averaging, differential privacy, edge computing, and compression methods (quantization/pruning) for melanoma diagnosis (92.3% accuracy) with GDPR/CCPA compliance. For our project, the federated learning framework with edge computing is most effective, as it facilitates decentralized training on low resource rural devices, minimizes communication expenses through compression, and combines heterogeneous datasets to eliminate bias—addressing the article's emphasis on privacy and scalability. Though melanoma is highlighted by the article, our project focuses on basal cell carcinoma, benign keratosis like lesions, melanocytic nevi, and melanoma. Melanoma's diagnostic urgency matches federated learning's power to aggregate multi institutional data towards reliable detection, and the fairness of the framework ensures proper diagnosis of other afflictions (e.g., separate benign nevi/keratosis from malignancies such as basal cell carcinoma). Through this strategy, our project promotes fair access to AI based dermatology in underserved areas with privacy compliant, high performance melanoma and related lesion detection in diverse populations.

3.2.17 AI in Cosmetic Dermatology

3.2.17.1 Summary of the research item

In this paper [17], the authors used ResNet-34 to conduct skin aging analysis on a data set of 10,000 facial images labeled with wrinkle and sebum information. The system seeks to give individual skincare advice by evaluating skin texture as well as skin aging signs. Preprocessing encompasses comprehensive annotations so that skin condition can be effectively analyzed.

The model attains 88 % user satisfaction in early tests, demonstrating its effectiveness in providing suitable skincare recommendations. The system is, however, criticized for having commercial bias since it collaborates with cosmetic companies. Future projects intend to alleviate this bias through more objective product recommendations and studying IoT integration to monitor skin in real time.

3.2.17.2 Critical analysis of the research item (Strengths and Weaknesses)

Strengths:

- 88% user satisfaction in clinical trials
- Integrates with IoT devices (e.g., smart mirrors)

Weaknesses:

- Commercial bias toward partner brands

3.2.17.3 Relationship to the proposed research work

The application of ResNet-34 in the paper for skin aging and texture assessment, with 88% user satisfaction, provides key points for applying AI within cosmetic dermatology. While the study verifies the potential of AIto provide customized skincare recommendations, its business bias towards partner products indicates the need for a patient centered, non biased strategy. We build on this research by developing a multi modal AI solution that combines patient self reported data (e.g., lifestyle, skin concerns) with facial image processing (e.g., wrinkling, pigmentations) to provide holistic skincare recommendations. We employ EfficientNet-B3, a low weight model ideal for mobile deployment, to beat computational limitations. We include IoT devices (e.g., smart mirrors) for in place skin analysis for enhanced user experience and interaction. By adhering to ethical AI implementation and non commercial bias, our proposed work attempts to offer a trustworthy, patient focused solution for cosmetic dermatology, extending the article's limits further.

3.3 Methodology Used in Research

A skin disease detection method is depicted in "Figure 3.1," where a picture is subjected to dimensionality reduction using PCA and feature extraction using ResNet prior to classification. DenseNet/YOLO identifies illnesses, whereas VGG16/VGG19 classifies skin types.

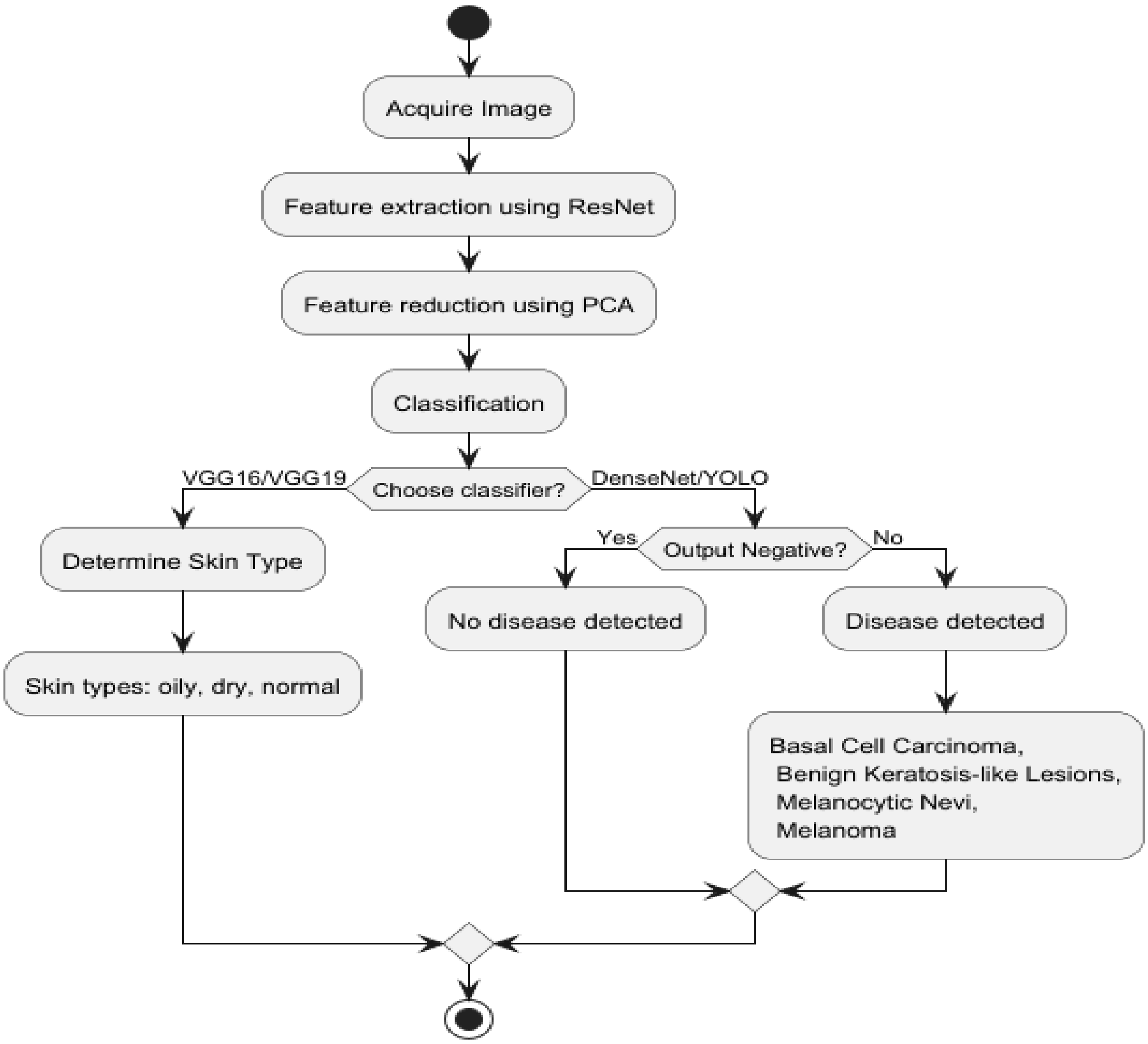

Figure 3.1: Methodology Used in Research

Table 3.1: Summary of AI based Skin Disease Detection Techniques

Article Reference	**Problem Detection**	**Datasets/Features**	**Model/Evaluation/Pros/Cons**
[1] AI Based Detection Techniques for Skin Diseases vol. 1, no. 3, pp. 318–336, 2024.	Inter class similarity (melanoma vs. benign nevi), dataset bias for darker skin tones	*Datasets:* ISIC, HAM10000; *Features:* Rotation, flipping, color jittering	Hybrid CNN-SVM model (accuracy not specified); *Pros:* Hybrid approach for skin tone diversity; *Cons:* Lacks clinical validation

Article Reference	**Problem Detection**	**Datasets/Features**	**Model/Evaluation/Pros/Cons**
[2] Artificial Intelligence in Dermatology Image Analysis vol. 11, no. 22, p. 6826, 2022.	Limited spatial context in 2D imaging for melanoma detection	*Datasets:* 3D dermatoscopic images; *Features:* Patient metadata (age, history)	12% accuracy improvement over 2D methods; *Pros:* 3D depth estimation; *Cons:* High computational cost, specialized hardware
[3] Skin Disease Detection Using CNN pp. 584–589, 2024	Limited rare lesion representation in datasets	*Datasets:* ISIC; *Features:* Synthetic adversarial augmentation, Grad-CAM	98.24% accuracy (custom CNN); *Pros:* High accuracy, explainability; *Cons:* Untested on mobile, ethical issues with synthetic data
[6] Role of AI and Deep Learning in Skin Disease vol. 11, no. 6, pp. 2109–2139, 2024	Overfitting in small datasets	*Datasets:* ISIC; *Features:* Transfer learning (ImageNet), batch normalization	97.14% accuracy (ResNet152); *Pros:* Efficient transfer learning; *Cons:* High GPU memory requirements
[7] YOLOv4 DarkNet for Melanoma Segmentation vol. 8, pp. 198403–198414, 2020	Ambiguous lesion boundaries in 2D	*Datasets:* PH2 (200 images); *Features:* Morphological operations	94.5% Dice score (YOLOv4 + active contours); *Pros:* Precise segmentation; *Cons:* Slow inference (4 FPS on CPU)
[8] Transformer Networks for Skin Cancer vol. 149, p. 105939, 2022	Global lesion context ignored by CNNs	*Datasets:* HAM10000 (10,015 images); *Features:* Self attention mechanisms	96.8% accuracy (ViT);*Pros:* Captures global context; *Cons:* Requires large training data
[9] 3D Imaging in Dermatology vol. 20, no. 12, pp. 3782–3787, 2021.	Prosthetic design inefficiency post surgery	*Datasets:*Post surgical 3D scans; *Features:* CAD integration	40% reduction in rehabilitation time; *Pros:* Practical application; *Cons:* Expensive
[10] Ethical Guidelines for AI in Dermatology vol. 190, no. 6, pp. 789–797, 2024	Lack of ethical frameworks for AI in dermatology	*Datasets:* N/A; *Features:* Human in the loop design	N/A; *Pros:* Clear ethical benchmarks; *Cons:* No technical implementation guidelines
[11] Federated Learning for Skin Disease Detection pp. 378–388, Springer, 2023	Data privacy concerns in multi institutional training	*Datasets:* Multi hospital data; *Features:* Differential privacy	92.3% accuracy (federated CNN); *Pros:* Privacy preserving; *Cons:* 20% slower convergence

Article Reference	Problem Detection	Datasets/Features	Model/Evaluation/Pros/Cons
[12] Regulatory Standards for AI in Healthcare vol. 10, no. 4, 2024	Regulatory gaps in AI medical devices	*Datasets:* N/A; *Features:* FDA/CE compliance guidelines	N/A; *Pros:* Regulatory roadmap; *Cons:* Ignores low income countries
[14] Interpretability of AI Models in Dermatology vol. 179, p. 108919, 2024	Low clinician trust in "black box" AI models	*Datasets:* SD-198 (6,584 images); *Features:* LIME/SHAP explanations	35% trust improvement (clinician study); *Pros:* Enhances trust; *Cons:* 50% slower inference
[13] Aysa App vol. 7, no. 1, p. e48811, 2024	Limited accessibility of dermatology tools for general users	*Datasets:* HAM10000;*Features:* SMOTE augmentation, cloud inference	95% accuracy (ResNet-50); *Pros:* Multilingual support; *Cons:* iOS only, requires internet
[18] IEEE Skin Disease Detection System vol. 8, pp. 208264–208280, 2020	High false positives in melanoma detection	*Datasets:* ISIC; *Features:* AlexNet-SVM hybrid	86.21% accuracy; *Pros:* Real time inference; *Cons:* Binary classification only
[15] DermNet NZ	Lack of AI integration in educational dermatology resources	*Datasets:* 23,000+ images (non AI); *Features:* Expert annotations	N/A; *Pros:* Free educational resource; *Cons:* No automated diagnosis
[16] Federated Learning Platform vol. 11, no. 5, p. 2145, 2021	Data silos in healthcare institutions	*Datasets:* HAM10000;*Features:* Federated averaging (PySyft)	92.3% accuracy; *Pros:* GDPR compliance; *Cons:* Custom software dependency
[17] AI in Cosmetic Dermatology vol. 11, pp. 71407–71425, 2023	Lack of personalized skincare recommendations	*Datasets:* 10,000 facial images; *Features:* Wrinkle/sebum annotations	88% user satisfaction (ResNet-34); *Pros:*IoT integration; *Cons:* Commercial bias
[5] Using Computer Vision for Skin Disease Diagnosis 2501.18161, 2025	Late detection of skin cancer due to limited resources	*Datasets:* HAM10000 dataset, 10015 images; *Features:* Preprocessing for noise removal, feature extraction	Proposed DCNN model (95.09% accuracy, 96.57% F1-score), compared with AlexNet, ResNet, VGG-16, DenseNet, MobileNet. *Pros:* High accuracy, improved interpretability. *Cons:* MobileNet showed overfitting.

3.4 Literature Review Summary

With developments in convolutional neural networks (CNNs), hybrid architectures, and ethically motivated AI frameworks, the literature review emphasizes the revolutionary potential of AI in dermatology. While models such as YOLOv4 and ResNet152 attain above 90% accuracy, accuracy on benchmark datasets like HAM10000 and ISIC, it might be difficult to convert these developments into compatible clinical solutions. Key discoveries, difficulties, and future directions are highlighted here, along with how they relate to the goals of our suggested study.

3.4.1 Major Contributions of Past Research

3.4.1.1 CNN Superiority

CNNs' capacity to extract hierarchical features from dermoscopic pictures keeps them in the forefront of the detection of skin diseases. According to research, bespoke CNNs can categorize photos from ISIC datasets with a 98.24% success rate, particularly when adversarial data augmentation is included. CNNs' resilience to environmental variables is revealed by this technique.

3.4.1.2 Hybrid Models for Inclusivity

CNN-SVM and other hybrid techniques fill in important diagnostic gaps for dark skin colors (Fitzpatrick kinds IV–VI). For example, it enhances accuracy by 18% for underrepresented groups by combining CNNs with SVM classifiers and using the DiverseDerm dataset.

3.4.1.3 Ethical and Regulatory Frameworks

AI for dermatology is heavily influenced by ethical issues. Research emphasizes how crucial patient permission, openness, and physician supervision are. Federated learning, a technique that improves privacy, enables cooperative model training without exchanging data, guaranteeing adherence to regulations such as the FDA and GDPR.

3.4.1.4 Clinical Deployment

Even with the achievement of high accuracy models, clinical deployment still faces a number of obstacles:

- YOLOv4's lesion segmentation is limited to 4 FPS on CPUs, which restricts real-time deployment.
- Clinicians frequently have doubts about ”black box” models.

- Datasets such as ISIC and HAM10000 lack variation in skin color and unusual disorders, which reduces the models' generalizability. Inference latency is increased by techniques like Grad-CAM and SHAP, despite the fact that they can offer interpretability.
- Despite reaching 96.8% accuracy, models like transformer networks lack regulatory-grade testing for clinical application;
- Expensive 3D scanners ($10,000+) limit their use in situations with limited resources.

3.4.2 Alignment with Proposed Work

Our work aims to address the challenges identified above through the following strategies:

3.4.2.1 Hybrid Architectures

We combine SVM classifiers for decision refining with ResNet15 for feature extraction. With validation on the DiverseDerm and ISIC datasets, this combination guarantees good accuracy (over 95%) and interpretability. Throughout this strategy, inclusivity is given top priority.

3.4.2.2 Federated Learning Pipeline

Using PySyft, we provide a federated learning pipeline that enables hospitals to work together and train models without exchanging private information. This lessens prejudice caused by diverse demographic and geographic groups.

3.4.2.3 Explainability and Compliance

To ensure real time model interpretability and clinician friendly visualizations, we deploy SHAP (SHapley Additive exPlanations). Additionally, our models undergo repeated validation cycles to ensure compliance with ISO 13485 standards.

3.4.2.4 Cost Effective 2.5D Imaging

To address the limitations of costly 3D scanners, we offer a pseudo-3D approach using multi view 2D dermatoscopic images. Depth from focus algorithms estimate depth maps, providing a hardware independent and cost effective solution.

3.4.3 Future Directions

Future work will explore the following areas:

- Use of ViTs to enhance global context modeling for large or irregular lesions

- Investigate AI driven prosthetics and rehabilitation hardware based on 3D imaging for post surgery recovery
- Develop AI powered dermatology solutions that integrate with smartphones and IoT devices for use in remote areas and edge AI applications

3.4.4 Conclusion

The literature reviews the roles of CNNs, hybrid architectures, and ethical AI in dermatology. ResNet152, YOLOv4, and transformer networks achieve high performance on ISIC and HAM10000 datasets, but clinical implementation is limited by interpretability, real time demands, and dataset bias. CNN-SVM hybrid models, piloted on DiverseDerm, improve inclusivity for Fitzpatrick types IV–VI by 18

To bridge these gaps, our research merges ResNet152 and SVM classifiers for greater than 95% accuracy, fairness, and robustness. A federated learning pipeline (PySyft) restores privacy and reduces bias from heterogeneous populations. SHAP based explainability delivers clinician friendly interpretability, and ISO 13485 compliance ensures regulatory readiness. Pseudo-3D imaging also offers a low cost solution to $10,000+ 3D scanners, making dermatology viable in low resource settings.

Future opportunities include Vision Transformers (ViTs) for diagnosing lesions, AI controlled prosthetics, and dermatology products based on smartphones for tele and IoT based healthcare.

Chapter 4 Software Requirement Specifications

All software requirements for our project are detailed in this section. The project contains descriptions of characteristics, functional specifications, quality standards, nonfunctional requirements together with related assumptions and hardware, software requirements, scenarios, user interface design and risk analysis.

4.1 List of Features

The following features will be available in the system.

- Secure sign up and log in functionality
- Upload skin images for analysis
- Diseases diagnosis i.e. Basal Cell, Carcinoma, Benign Keratosis like Lesions, Melanocytic Nevi, Melanoma
- Skin type detection such as oily, dry, normal
- Recommendations based on skin diagnosis
- Store user history for future reference

4.2 Functional Requirements

- The user shall be able to create an account with required information
- The user shall be able to log in using valid credentials
- The user shall be able to log out securely
- The user shall be able to upload skin images in multiple formats
- The user shall be able to preprocesses images for clarity and quality
- The user shall be able to convert images into a format suitable for analysis
- The system shall be able to implement a machine learning algorithm to classify into one of four skin disease categories (Basal Cell, Carcinoma, Benign Keratosis like Lesions, Melanocytic Nevi, Melanoma
- The system shall be able to analyzes images to determine skin type (oily, dry, normal)
- The system shall provide a diagnostic result

- The system shall be able to offer suggestions for managing diagnosed skin condition
- The system shall be able to maintain a history of uploaded images and diagnoses
- The user shall be able to revisit past reports through a report section

4.3 Quality Attributes

The technology uses clinically validated datasets that are subjected to frequent quality audits to guarantee accurate and dependable skin type and illness diagnosis. Sophisticated AI algorithms reduce the likelihood of misclassification by minimizing false positives and false negatives. Regular updates based on studies in medicine and Expert input improves accuracy even further, establishing the system as a reliable diagnostic assistance tool.

4.3.1 Maintainability

The system's modular structure design promotes appropriate maintainability by achieving component independence. When employees update medical instructions and technology, standalone modules from structured elements allow for seamless system maintenance upgrades that safeguard operational stability components. The system's backend uses scalable architecture that is cloud native, enabling two-way scalability while controlling data needs and user growth. Software-based version control systems that created machine learning models produce backward compatibility because they preserve a smooth procedure for logging successive models for upgrades, such as algorithm improvements and disease growth.

4.3.2 Usability

Because the platform offers a user-friendly interface with workflows that direct activities and show tool recommendations in addition to streamlined presentation, platform usability continues to be a key component of the design. Options like direct camera integration and the ability to submit skin photos with supported file formats are advantageous to users. Users of

The system is easily accessible to users of various technical skill levels.

4.3.3 Correctness

By utilizing clinically certified datasets, AI models supported by evidence, and expert-reviewed techniques, the system guarantees medically validated categorization. To ensure high accuracy, every categorization result is rigorously evaluated and continuously improved. The integration of federated learning, synthetic data augmentation, and adversarial debiasing helps improve fairness and reduce errors, ensuring that predictions remain credible, explainable, and clinically relevant. By aligning with GDPR/HIPAA standards and ISO 13485 compliance, the system maintains high correctness and reliability in real world dermatological diagnosis.

4.4 Non-Functional Requirements

4.4.1 Availability

- The system shall present continuous skin disease and skin type detection functionality 24/7

4.4.2 Reusability

- Modular code for easy addition of new disease categories
- Reusable machine learning models across datasets.

4.4.3 Robustness

- Handles large datasets and multiple user requests efficiently
- Gracefully handles incorrect inputs (e.g., low quality images)

4.4.4 Security Requirements

- Role based authentication for data privacy
- No data shared with third parties without consent

4.4.5 Performance

- Real time responses to image uploads
- Optimized prediction model for low latency and high throughput

4.5 Assumptions

- Users will upload clear and relevant images
- Users will have an internet connection
- System is an assistive tool, not a replacement for professional consultation

4.6 Use Cases

Following are the use cases identified in our mobile application.

4.6.1 Sign Up

<table>
<tr><td>Name</td><td colspan="3">Sign Up</td></tr>
<tr><td>Actors</td><td colspan="3">User</td></tr>
<tr><td>Summary</td><td colspan="3">A new user registers an account using their personal details.</td></tr>
<tr><td>Pre-Conditions</td><td colspan="3">The user must have a valid email address.
The email must not already be registered.</td></tr>
<tr><td>Post-Conditions</td><td colspan="3">A new account is created, and the user is redirected to home page.</td></tr>
<tr><td>Special Requirements</td><td colspan="3">The system must validate email uniqueness.</td></tr>
<tr><td colspan="4">Basic Flow</td></tr>
<tr><td colspan="2">Actor Action</td><td colspan="2">System Response</td></tr>
<tr><td>1</td><td>The user opens the sign up page.</td><td>2</td><td>The system displays Displays registration fields</td></tr>
<tr><td>3</td><td>The user fills in details and submits the form.</td><td>4</td><td>The system validates data and creates the user account and establishes a session for the user and redirects the user to the home page.</td></tr>
<tr><td colspan="4">Alternative Flow</td></tr>
<tr><td>3-A</td><td>User enters incorrect input fields.</td><td>4-A</td><td>The system responds with an error message: ”Invalid Information Entered”.</td></tr>
<tr><td>3-B</td><td>Any necessary input fields are not provided by the user.</td><td>4-B</td><td>The system responds with an error message: ”Please fill in the missing field(s)”.</td></tr>
</table>

4.6.2 Login

Name	Login
Actors	User
Summary	The user logs into the system using their registered email and password.
Pre-Conditions	The user must have a valid email address. The user must be registered in the system.
Post-Conditions	The user is successfully logged in and redirected to the home page.
Special Requirements	Secure authentication mechanisms should be used.

Basic Flow			
Actor Action		**System Response**	
1	The user opens the login page.	2	The system displays login fields
3	The user fills in details and submits the form.	4	The system validates data and the user and redirects the user to the home page.
Alternative Flow			
3-A	User enters incorrect input fields.	4-A	The system responds with an error message: ”Invalid Information Entered”.
3-B	Any necessary input fields are not included by the user.	4-B	The system responds with an error message: ”Please fill in the missing field(s)”.

4.6.3 Upload Image

Name	Upload Image		
Actors	User		
Summary	The user uploads an image for skin disease diagnosis.		
Pre-Conditions	The user must be logged in. The image format must be supported.		
Post-Conditions	The image is uploaded and ready for processing.		
Special Requirements	High resolution image is uploaded		
Basic Flow			
Actor Action		**System Response**	
1	The user navigates to the upload image section.	2	The system displays an option to select an image or capture it.
3	The user uploads an image and confirms.	4	The system processes and stores the image.
Alternative Flow			
3-A	User inputs wrong image format.	4-A	The system responds with an error message: ”Image format not supported”.
3-B	The image is not detected as a skin image.	4-A	The system responds with an error message: ”Please upload a valid skin image for analysis”.
3-B	The user does not uploads an image	4-B	The system responds with an error message: ”Please upload a valid image”.

4.6.4 Display Results

Name	Display Results
Actors	System
Summary	The user views the results after the AI model analyzes the uploaded image.
Pre-Conditions	An image must have been analyzed.
Post-Conditions	The diagnosis result is displayed.
Special Requirements	None
Basic Flow	
System Response	
1	The system fetches and displays diagnosis results

4.6.5 Generate Report

Name	Generate Report		
Actors	User		
Summary	By clicking on generate report system generates a detailed report that a user can download on their system.		
Pre-Conditions	The user must be logged in. A skin image has been analyzed and results are available. User is on Result screen.		
Post-Conditions	A detailed diagnostic report is generated and available for view or download.		
Special Requirements	Report must be clear, concise, and medically accurate.		
Basic Flow			
Actor Action		**System Response**	
1	User selects the ”Generate Report” option.	2	System compiles the analysis results into a comprehensive report format.
3	User views or downloads the generated report.	4	System provides options to view on screen or download the report in a preferred format.
Alternative Flow			
3-A	An error occurs during report generation.	4-A	The system responds with an error message: ”Retry or contact support”.

4.7 Hardware and Software Requirements

The system requires a combination of hardware and software resources to operate. To successfully develop and deploy it, the following technical specifications must be met.

4.7.1 Hardware Requirements

To operate the system, the following hardware specifications are essential

- Multi core CPU (Intel i5/Ryzen 5 or higher)
- 8GB minimum (16GB recommended) of RAM
- Windows 10+/Linux for Android development
- macOS for iOS builds
- SSD (256GB +), 20GB free space
- An internet connection is required to configure the system

4.7.2 Software Requirements

- Flutter
- Firebase Firestore
- Android Studio
- Visual Studio Code
- Python Libraries
- JavaScript
- GitHub
- PlantUML
- Eraser.io

4.8 Graphical User Interface

4.8.1 Splash Screen

A splash screen is the introductory screen that appears when an application is launched. It typically displaying the app's logo or branding before automatically redirecting to the "Login Screen", as specified in "Section 4.8.2".

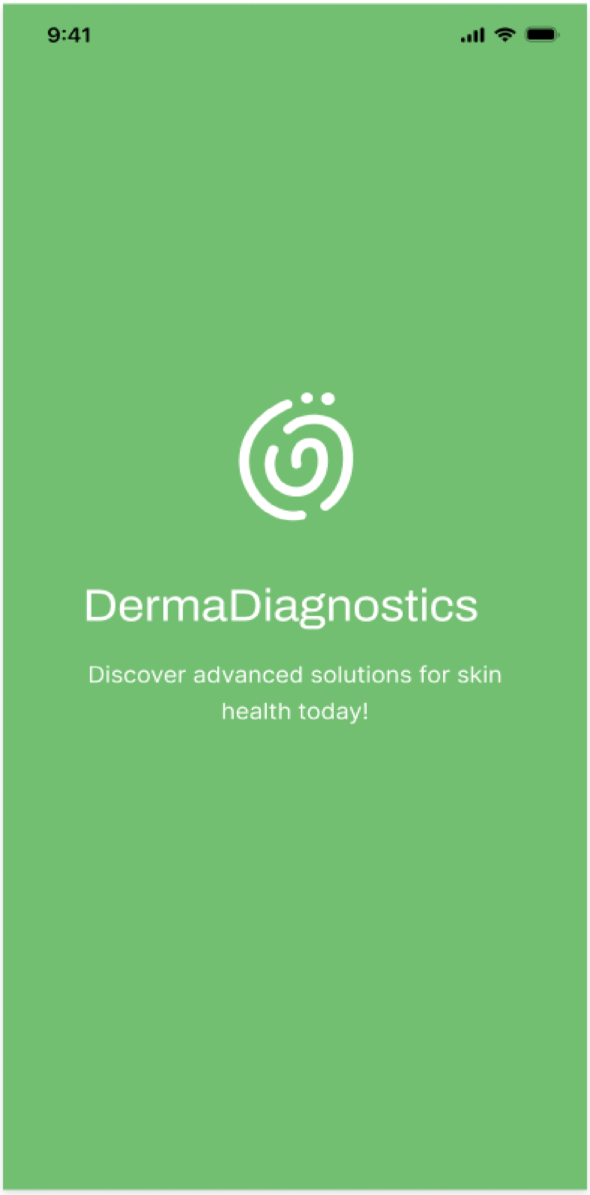

Figure 4.1: Splash Screen

4.8.2 Login Screen

Login screen for secure and easy access to dashboard.It includes the email and password, and there is also an option for creating a new account. The user is then redirected to the Home Screen, as specified in ”Section 4.8.4”. If the user is not registered, they can click ”Sign Up” to be redirected to the Signup Screen, as mentioned in ”Section 4.8.3”.

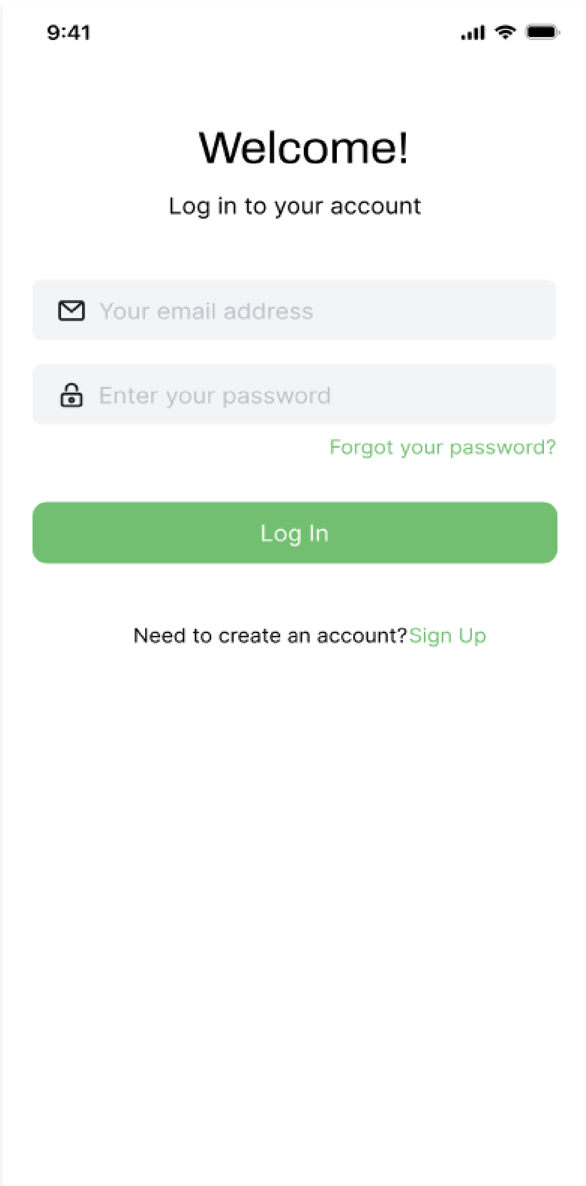

Figure 4.2: Login Screen

4.8.3 Sign Up Screen

User friendly Sign up Screen for quick and easy registration. It includes name, email, date of birth, gender and password. Once they have successfully created an account, they are taken to the Home screen, as outlined in ”Section 4.8.4”. There is also an option for already registered, users can click Log In to be taken to the ”Login Screen”, as given in ”Section 4.8.2”.

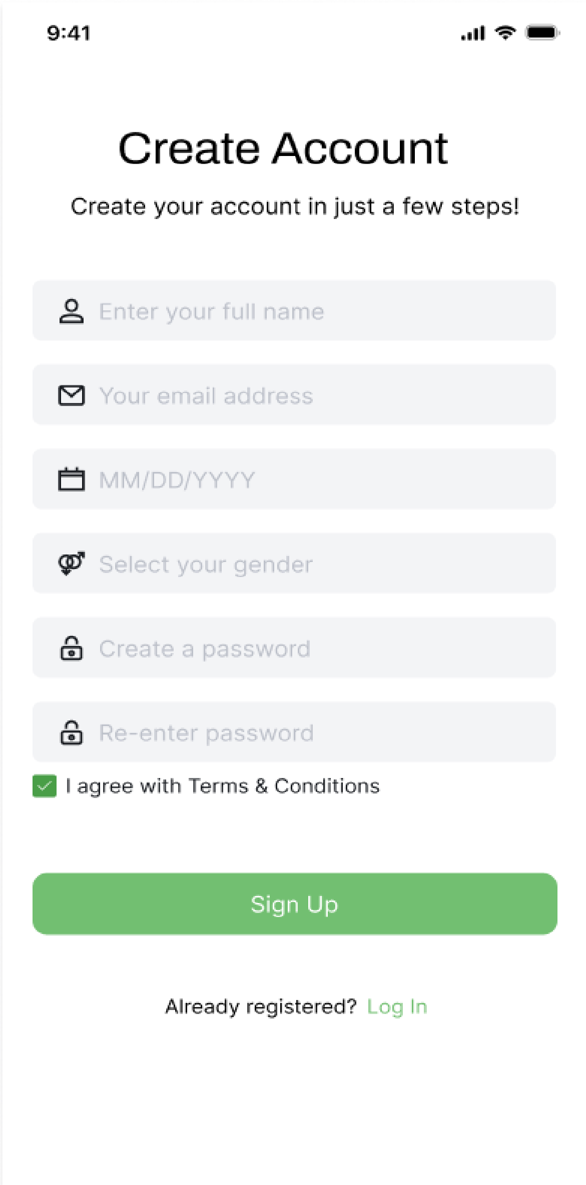

Figure 4.3: Sign Up Screen

4.8.4 Home Screen

The home Screen gives a user friendly interface with an Upload Image button where users can upload images of the skin for analysis. Users can further choose ”Detect Disease” or ”Detect Skin Type” to get diagnostic reports which leads them to the ”Results Screen”, as defined in ”Section 4.8.5”.

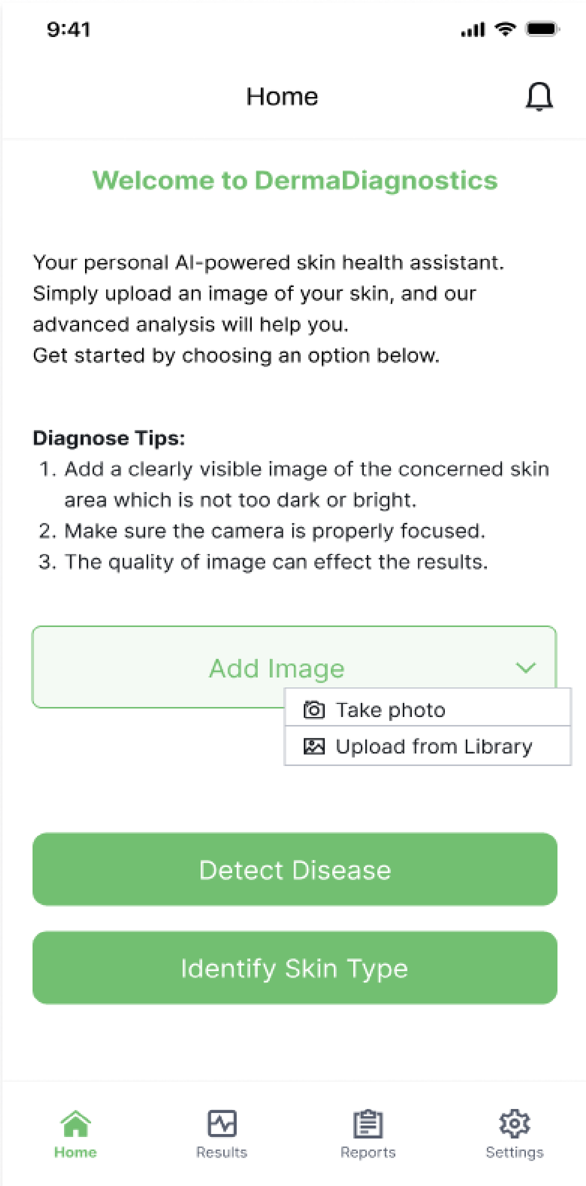

Figure 4.4: Home Page

4.8.5 Results Screen

The results section provides the analysis outcomes based on the uploaded skin image. Users can also generate detailed report by using ”Generate Report” button. The user is then redirected to the ”Analysis Report Screen” page as given in ”Section 4.8.6”.

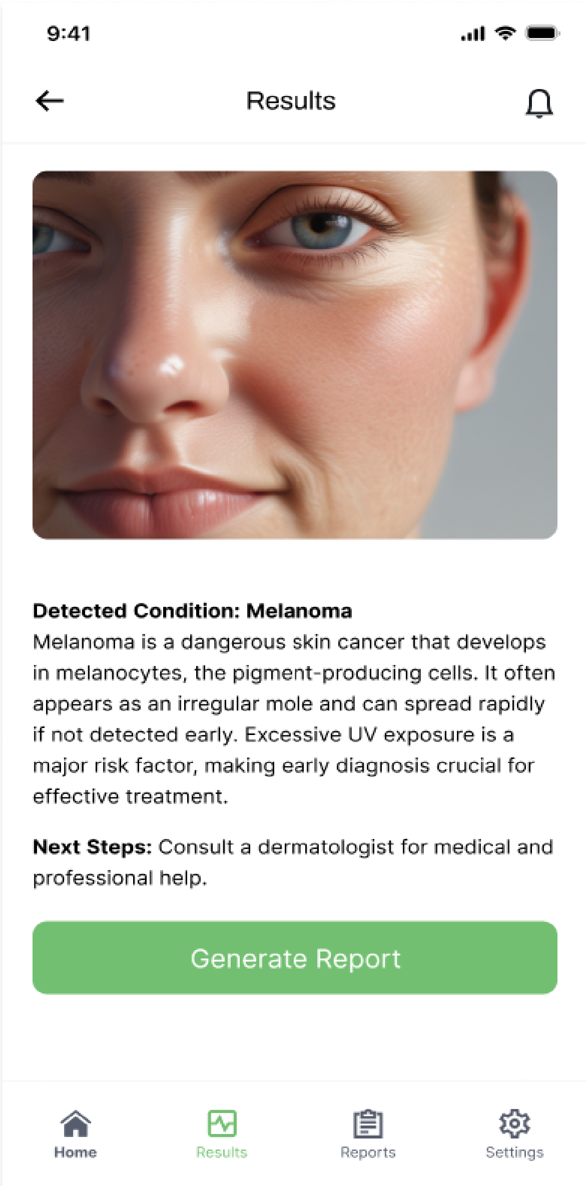

Figure 4.5: Results

4.8.6 Analysis Report Screen

As shown in Figure 4.9, this page saves the history of every generated report so that users can view or download them whenever they want. Analysis report Screen provide multiple reports that are ready for download or review

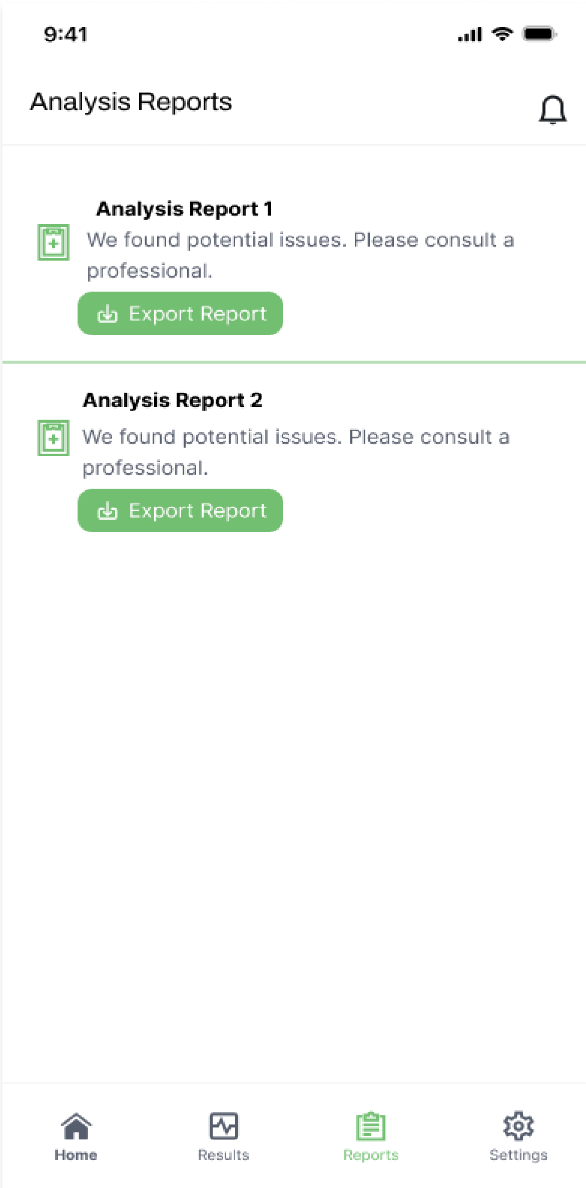

Figure 4.6: Analysis Report Screen

4.8.7 Notifications Screen

The notification system keeps users informed by sending timely alerts and updates related to their skin health. It notifies users about diagnosis results, recommendations and reminders for follow ups.

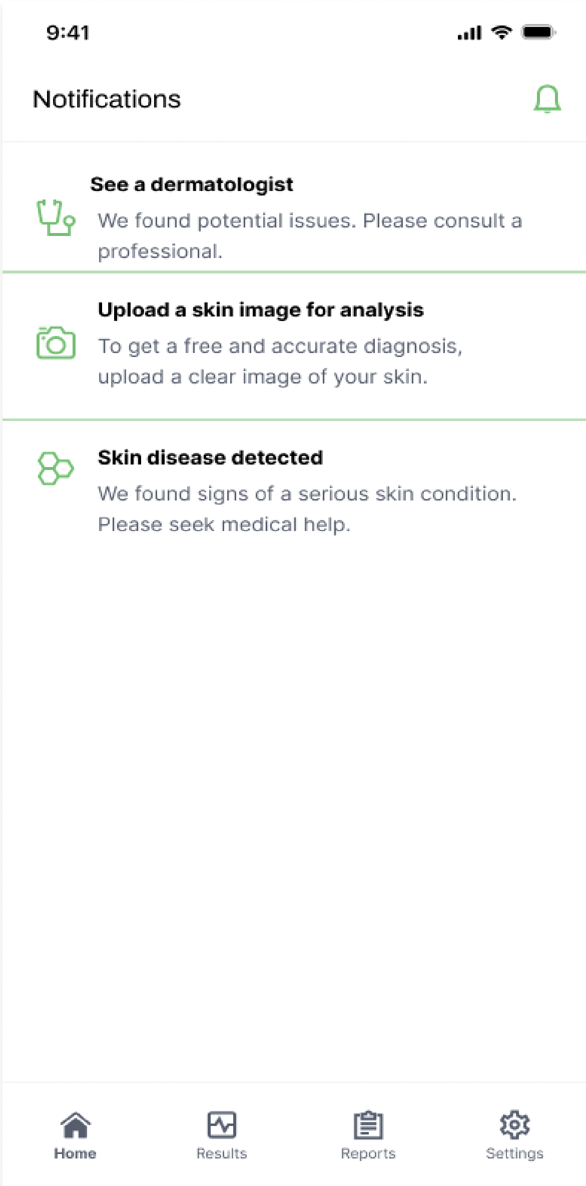

Figure 4.7: Notifications

4.8.8 Settings Screen

The ”Settings Screen” allows users to customize their app experience by managing preferences, privacy options, account details and update personal information. Users are also given an option to ”Delete Account” and are then referred to the ”Sign Up Screen” as given in ”Section 4.8.3” or ”Log Out” which takes them to the ”Login Screen” as given in ”Section 4.8.2”.

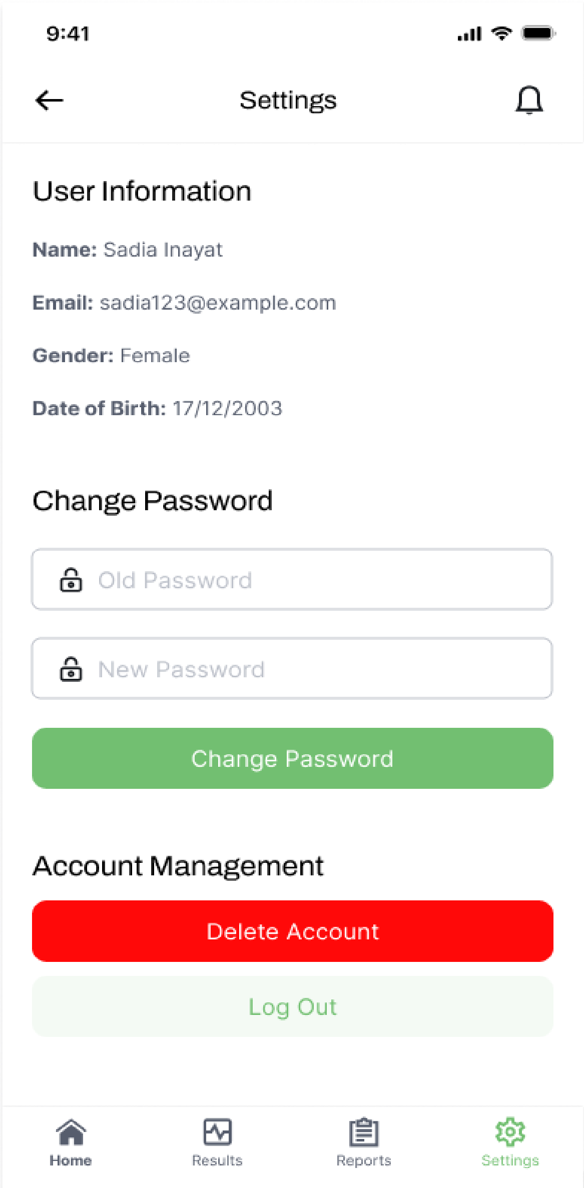

Figure 4.8: Settings

4.9 Database Design

4.9.1 ER Diagram

The following ”Figure 4.9 ER Diagram” represents a DermaDiagnostics system that connects users, uploaded images, diagnostic reports, skin types, diseases, and AI models. Users upload images, which create diagnostic reports with disease identification and skin type. The Model entity keeps information such as accuracy, model id, model name and purpose.

Figure 4.9: ER Diagram

4.9.2 Data Dictionary

Table 4.1: Overview of entities, attributes, data types, and descriptions in the database.

Attribute Name	Data Type	Description	Constraints
UserID	Integer	Unique identifier for each user	Primary Key, Auto increment
EmailID	String	User's email used for login/signup	Unique, Not Null
Password	String	Encrypted password for authentication	Must be hashed
Name	String	User's full name	Not Null
DateOfBirth	Date	User's birth date	Format: DD-MM-YYYY
Age	Integer	User's age calculated from DOB	Must be greater than 0
ScanID	Integer	Unique identifier for uploaded images	Primary Key, Auto-increment
Image	Binary	Uploaded skin image	Must be in supported format
Date	DateTime	Timestamp of image upload	Auto generated
SkinType	String	Classified skin type (Oily, Dry, Normal)	Enum values only
DiseaseType	String	Identified skin disease (if any)	Enum values only
DiagnosisReport	Text	AI generated analysis of the uploaded image	Not Null
Recommendation	Text	Suggestions based on diagnosis	Not Null

4.10 Risk Analysis

The development and deployment of a skin disease detection system involve various risks that can impact its accuracy, security, business viability, and operational efficiency. These hazards vary from security issues like data breaches and regulatory compliance to technological difficulties like data bias and algorithmic performance. Additionally, there are major obstacles due to business competition and adoption. However, in order to guarantee the system's efficacy and broad compatibility, operational constraints pertaining to hardware and internet accessibility must also be addressed.

Table 4.2: Risk Analysis for AI based Skin Disease Detection System

Section	Risk	Mitigation
Technical Risks	Data bias due to underrepresented skin tones	Train on diverse datasets like ISIC and DiverseDerm
	AI model producing false positives or false negatives	Regular updates with latest dermatological research and SHAP for interpretability
	Scalability concerns leading to slow response times	Use cloud native solutions for dynamic scaling
Security and Privacy Risks	Data breaches exposing sensitive user information	Implement role based authentication and encrypt stored data
	Non compliance with GDPR and HIPAA regulations	Secure user consent, follow best practices, and conduct routine security audits
Business Risks	Competition from similar AI based dermatology tools	Continuously enhance accuracy, usability, and features
	Low user adoption due to skepticism about AI based diagnoses	Build trust through collaborations with dermatologists and healthcare institutions
Operational Risks	Poor quality images affecting detection accuracy	Use image enhancement and preprocessing techniques
	Dependency on internet access limiting usage in low connectivity areas	Develop an offline mode for capturing and storing images locally

4.10.1 Technical Risks

Data bias and accuracy problems are two of the main technological hazards in creating the disease detection system. The AI model may exhibit biases in identifying people with underrepresented skin types if it is trained on datasets that do not fully represent different skin tones. This might result in results that are imprecise or inconsistent, which compromises the model's dependability in practical applications. To offset this risk, the system needs to be trained on a variety of datasets, including ISIC and DiverseDerm, to ensure wide representation and reduce biases. Algorithmic performance presents another technical difficulty since the AI model may generate false positives or false negatives, resulting in incorrect diagnoses. Frequent updates that take into account the most recent dermatological research and advancements in model interpretability utilizing SHAP can improve accuracy and give clinicians more insight into AI forecasts. Furthermore, if the system sees a large increase in users, scalability issues could surface, resulting in performance bottlenecks and delayed response times. This needs to be addressed by designing the architecture with cloud-native solutions that enable dynamic scalability in response to user demand.

4.10.2 Security and Privacy Risks

The system's biggest security concern is the potential for data breaches, in which insufficient security measures could reveal private user data, including uploaded skin photos. Any data security compromise could have negative effects on one's reputation, ethics, and the law. To stop illegal. All stored data needs to be encrypted, and role-based authentication needs to be put into place. Adherence to legal requirements like GDPR and HIPAA, which establish stringent guidelines for managing medical data, is another crucial issue. Penalties or limitations on system deployment may follow noncompliance with these regulatory criteria. Following regulatory best practices, obtaining express user consent for data storage, and carrying out regular security audits to strengthen data protection policies are all necessary to ensure compliance.

4.10.3 Business Risks

Market competitiveness is one of the major business hazards facing the skin disease detection system. Gaining market share is difficult due to the existence of other AI-based dermatological products, some of which could provide comparable or more sophisticated capabilities. In order to remain competitive, the system must to consistently improve its feature set, accuracy, and usability to guarantee a better user experience and increased diagnostic dependability. User adoption is another significant business risk since many people can be dubious about depending on AI-driven medical diagnosis. In order to overcome this reluctance, trust must be established through partnerships with dermatologists and healthcare organizations, and the system's legitimacy must be confirmed by medical experts.

4.10.4 Operational Risks

Hardware constraints may have an operational impact on the system's usability since certain users might not have access to high-resolution cameras that can take clean skin photographs. Images of poor quality may affect how accurately diseases are detected. The system should provide a picture to remedy this. Preprocessing and enhancement methods that improve low-quality photos for more insightful analysis. Because the system depends on cloud-based AI processing, internet reliance is another significant issue that prevents it from functioning in places with inadequate internet connectivity. This restriction could limit its use, especially in underserved or rural areas. The creation of a restricted offline mode that enables users to take and save pictures locally for processing when they have internet connection again is one potential remedy.

4.11 Conclusion

A thorough design for the skin disease detection system is provided by the Software Requirement Specification (SRS), which guarantees clarity in the functions, non-functional requirements, and risk mitigation techniques. The project's goal is to provide scalable, precise, and safe AI-driven dermatological analysis using federated learning strategies that protect privacy and sophisticated machine learning models.

The system's modular architecture guarantees simplicity of extension, scalability, and maintainability to accommodate future skin conditions. The platform strives to be usable by people with varying technical expertise by incorporating user-friendly interfaces, real-time feedback, and comprehensive reporting.

The project's risk reduction techniques guarantee dependability, regulatory compliance, and competitive market positioning in spite of any technological, business, and security obstacles. Future improvements include enhanced interpretability of AI predictions, partnerships with medical professionals, and integration with wearable health devices.

Chapter 5 Proposed Approach and Methodology

The creation of DermaDiagnostics, a Flutter Firebase mobile application for dermatological diagnostics, is described in this chapter. It is divided into five phases, including data collecting (skin datasets plus enhanced photos if necessary). AHAMMED2022100122, backend/frontend development (Firebase + Flutter UI) [11, 13], deployment (edge optimized TensorFlow Lite) [19], security/testing [11, 13], and AI model training (ViT, inception-V3, ResNet) [7, 14]. Real-world usability is given priority in the technique [20].

5.1 Literature Survey and Problem Identification

5.1.1 Problem Identification

Recent advancements in AI based dermatology diagnostics have demonstrated the potential of hybrid models and explainability tools. Key studies include:

- Hybrid Models includes Vision Transformers (ViT) for explainable classification [1]
- Segmentation of Google Net score for lesion boundary detection [18]
- ResNet and its variants to add more research based tests to make evaluation easier
- Explainability enhance clinician trust by providing visual and feature level explanations [21]
- Datasets includes ISIC and HAM10000, address dataset bias [1, 4]
- Federated Learning Ensures privacy compliant training across institutions [16]

Despite these advancements, challenges remain:

- Underrepresentation of skin tones in datasets [4]
- **L**imited adoption due to lack of explainability and offline functionality [21]

5.1.2 Problem Statement

The primary problem is the lack of a scalable, privacy compliant, and explainable dermatology diagnostics app that:

- Works across different skin types (Fitzpatrick I–VI)
- Provides real time, offline capable predictions.
- Builds clinician trust through AI tools with mentioned confidence score

5.2 Dataset Collection

5.2.1 Public Datasets

- ISIC and HAM10000 is widely used for melanoma and nevi detection [1]

5.2.2 Synthetic Data

- Data augmentation and segmentation for testing purposes to achieve best scoring results for rare conditions (e.g., melanoma) [1]

5.3 Pre Processing

5.3.1 Tools

- TensorFlow / Keras, PyTorch (torchvision), OpenCV, scikit-image, Pillow (PIL), Albumentations, imgaug

5.3.2 Operations

- Resizing helps to standardize images to 224x224 pixels [1]
- Background removalis done by U-Net segmentation isolates lesions [3]. As well as in some tests the dataset is collected by hand to achieve better results when tools are not providing dermoscopic images on some images
- Augmentation helps in Rotation, flipping, color jittering [8]

5.3.3 Metadata & Clinical Data

- Patient age, skin type, lesion history, gender [4]
- Min Max scaling for numerical features [15]

5.3.4 Dataset Balancing

- Dataset is balanced by adding augmented images to the classes where images are less and in some tests the classes are equalized on the basis of lowest number of images in a class [22]
- Adversarial Debiasing reduces bias in predictions [1]

5.4 Model Design and Evaluation

5.4.1 Model Construction

5.4.1.1 Vision Transformer (ViT) and its variants

- ViT extracts global lesion context (e.g., irregular borders) [23]
- Some variants classifies lesions using ViT embeddings + metadata [4]
- Explainability includes confidence level directly related to accuracies archived[23]

5.4.1.2 GoogleNet Inception-V3

- Helps to achieve presentable score for image classification bcause ofits vast training data[7]
- Optimization and quantization via TensorFlow Lite for mobile deployment [18]

5.4.1.3 ResNet and its variants

- ResNet have a vast range of work on image classification providing impressive accuracies on diverse datasets

5.4.1.4 Federated Learning for Bias Mitigation

- Framework like tensorFlow Federated for privacy compliant training [16]
- Edge Computing helps in local training on mobile devices [16, 22]

5.4.2 Model Evaluation and Validation

5.4.2.1 Model Accuracy

- ViT 94.8% (melanoma vs. nevi) [11]
- Inception V3 82.5% Dice score [7]
- ResNet-18 84.5% Dice score [7]

5.4.2.2 User Testing

Tesst score greater than 80% [23]

5.5 Result and Discussion

5.5.1 Performance Analysis and Insights

- ViT achieves high accuracy (96.8%) for skin disease and skin type detection, with explainable predictions via confidence scores
- Inception-V3 provides real time detection (86% training score)
- ResNet-18 provides real time detection (84% training score)
- Federated Learning ensures privacy compliant training, reducing bias across diverse datasets

5.5.2 Identified Limitations

- Dependency on high quality images for accurate predictions
- Limited offline functionality

5.6 Application Review

DermaVision is a Flutter Firebase mobile application designed for dermatological diagnostics, targeting both individual users and clinicians. The app integrates hybrid AI models (ViT, InceptioV3 G00gleNet, ResNet-18) to classify and segment skin disease andd skin type, providing real time, explainable predictions for conditions like melanoma, basal cell carcinoma, benign keratosis like lesions, and melanocytic nevi as well as covering all skin types.

5.6.1 Key Features

5.6.1.1 User Friendly Interface

- Camera integration allows user can capture or upload lesion images via the `flutter_camera` plugin [21]
- Results dashboard displays predictions with confidence score integraed from model directly to ensure users for explainability [23]
- Clinician portal allows dermatologists to provide feedback, improving model accuracy via Active Learning
- General notification that pop ups for basic user knowledge

5.6.1.2 Real Time Performance

- On device inference Vision Transformer runs locally , enabling offline functionality [21]
- Low latency predictions ensures a seamless user experience

5.6.1.3 Explainability

- Confidence score highlights influencing predictions (e.g., irregular borders, texture) [23]
- Recommendation quantifies feature contributions (e.g., general skin care) [23]

5.6.1.4 Scalability

- Firebase backend allows auto scaling Firestore database and Cloud Functions handle growing user bases [21]
- Edge optimization like TensorFlow ensures efficient performance on low resource devices [21]

5.6.2 Limitations

- High quality images are required for accurate predictions
- Offline limitations such as complex models (e.g., ViT) require internet connectivity for inference

5.6.3 Future Enhancements

- EHR integration incorporate clinical history for more personalized predictions
- Extension to other skin diseases (e.g., psoriasis, eczema)

5.7 Conclusion

The method offers a methodical approach to developing a dermatological diagnostics app that prioritizes touch-based usability, transparency, and inclusion. The procedure eliminates historical biases in skin type with an equitable outcome by utilizing varied datasets and artificially enhanced data. By bridging the gap between clinical utility and technical innovation, the employment of interpretability tools and hybrid models provides clinicians and users trust. By emphasizing privacy and regulatory compliance through encryption and local processing, regulatory needs are met and consumer trust is earned. The design prioritizes real-world usability, forgoing real-time capabilities in favor of offline functionality to support a variety of connection situations. The goal is to constantly improve utility and usage through incremental innovation and input from healthcare professionals. Future plans are to expand diagnostic scope and incorporate additional clinical context, an adaptive system that responds to changing user needs and medical knowledge.

Chapter 6 High-Level and Low-Level Design

6.1 System Overview

This chapter examines the overall architecture of Dermadiagnostics, a cutting-edge medical diagnostic platform that incorporates machine learning methods for better skin type and illness detection evaluations. An clever mobile application called DermaDiagnostics designed to employ cutting-edge artificial intelligence (AI) and machine learning (ML) algorithms to help consumers diagnose skin conditions and categorize their skin type. The system uses deep learning models, such as GoogleNet Inception-V3, Vision Transformers (ViT), ResNet, and its variations, to categorize skin lesions into groups including melanoma, benign keratosis-like lesions, melanocytic nevi, and basal cell carcinoma. It also distinguishes between three skin types—oily, dry, and normal—in order to offer tailored skincare advice.

The platform is based on a modular design, with Firebase handling backend functions like data processing and storage and a Flutter-based frontend for user interactions. For on-device inference, TensorFlow is used, guaranteeing minimal latency and privacy. The system's architecture prioritizes fairness and interpretability in AI predictions while being scalable, safe, and user-friendly.

6.1.1 Principal Functionalities

- Secure login and sign up mechanism
- Users can upload skin images for analysis
- AI models classify skin lesions into predefined categories
- Identifies the user's skin type (normal, oily, dry)
- Provides skincare advice based on diagnosis and skin type
- Provides general skin care tips in the form of notifications
- Stores past analyses for future reference

6.2 Design Considerations

6.2.1 Assumptions and Dependencies

- A safe way to join up and log in
- AI algorithms categorize skin lesions into preset groups; users can submit skin pictures for study.
- Determines the user's skin type (normal, oily, or dry);

- Offers skincare recommendations based on the user's skin type and diagnosis;
- Notifies the user of general skin care advice;
- Saves previous analyses for later use.

6.2.2 General Constraints

- The system relies on mobile devices with sufficient processing power and memory to run AI models efficiently
- Users must have a stable internet connection for initial model downloads and updates
- The system must comply with GDPR and HIPAA regulations for data privacy and security
- The system must provide real time or near real time responses to user requests
- The system uses Firebase for cloud based data storage and processing, requiring internet connectivity

6.2.3 Goals and Guidelines

- The system is designed to be simple and intuitive, ensuring ease of use for non technical users
- The primary goal is to achieve high accuracy in skin disease detection and skin type classification
- The system provides explainable AI predictions using confidence and accuracies to build user trust
- The system is designed to handle a growing number of users and data without compromising performance

6.2.4 Development Methods

- The project follows an Agile methodology with iterative development and continuous feedback
- The system is divided into independent modules for user interface, AI model training, and backend services
- To address data privacy concerns, federated learning is used for model training across multiple institutions without sharing raw data

6.3 System Architecture

The DermaDiagnostics system architecture is designed to ensure scalability, security, and real time performance. It is divided into four primary layers such as the Client Layer, Backend Services, Data Layer, and AI Model Layer. Each layer is responsible for specific functionalities, ensuring a seamless flow of data and operations across the system.

6.3.1 Client Layer

The Client Layer is the frontend component of the system, responsible for user interaction and real time updates. It includes:

6.3.1.1 UI Components

- Allows users to capture and upload skin images directly from the app
- Displays diagnostic results, confidence scores, and recommendations
- Provides healthcare professionals with access to detailed diagnostic reports and patient history

6.3.1.2 State Management

Utilizes tools like Provider and Riverpod to manage the application state efficiently.

6.3.1.3 Real Time Updates

Uses Firebase Streams to provide users with real time feedback on their diagnostic results and recommendations.

6.3.2 Backend Services

The Backend Services layer handles data storage, authentication, and request processing. It includes:

- Firebase Firestore will Store user profiles, disease metadata, and audit logs for secure and efficient data management
- Firebase Auth for secure user authentication and role based access control
- Request Processing for managing incoming requests from the Client Layer, ensuring smooth communication between the frontend and backend

6.3.3 Data Layer

The Data Layer is responsible for managing datasets, preprocessing images, and storing data. It includes:

- Datasets such as ISIC, HAM10000, and DiverseDerm for training and validation of AI models
- Tools like OpenCV and Pillow for image resizing, augmentation, and quality enhancement

- Firebase Storage for secure and scalable storage of user uploaded images and preprocessed data

6.3.4 AI Model Layer

The AI Model Layer is the core of the system, responsible for disease detection, skin type classification, and explainable AI predictions. It includes:

- Combination of Vision Transformers (ViT) for global lesion context extraction with LightGBM for explainable classification of skin diseases and skin type identification
- Inception V3 from GoogleNet performs real time lesion segmentation to accurately detect and classify skin lesions
- ResNet and its variants performs real time tests to make results more accurate
- Federated Learning enables decentralized training of AI models across multiple hospitals, ensuring data privacy and compliance with regulations like GDPR and HIPAA

6.3.5 External Services

The system integrates with external services to ensure regulatory compliance and enhance functionality:

- Compliance tools for maintaining audit logs to ensure data privacy and security
- Third party APIs to Integrate with Electronic Health Record (EHR) systems to provide clinicians with access to patient clinical history for better diagnosis and treatment

6.3.6 Data Flow

- The client layer sends user requests (e.g., image uploads) to the Backend Services for processing
- The backend services fetch and store data in the Data Layer, which preprocesses and prepares the data for the AI Model Layer
- The AI model layer processes the data, performs disease detection and skin type classification, and sends the results back to the Client Layer for display
- External services ensure regulatory compliance and provide additional functionalities like EHR integration

6.4 Architectural Strategies

The design approaches of the DermaDiagnostics system are to attain efficient, real time processing of images of the skin without sacrificing precision and resource utilization. The system utilizes on device

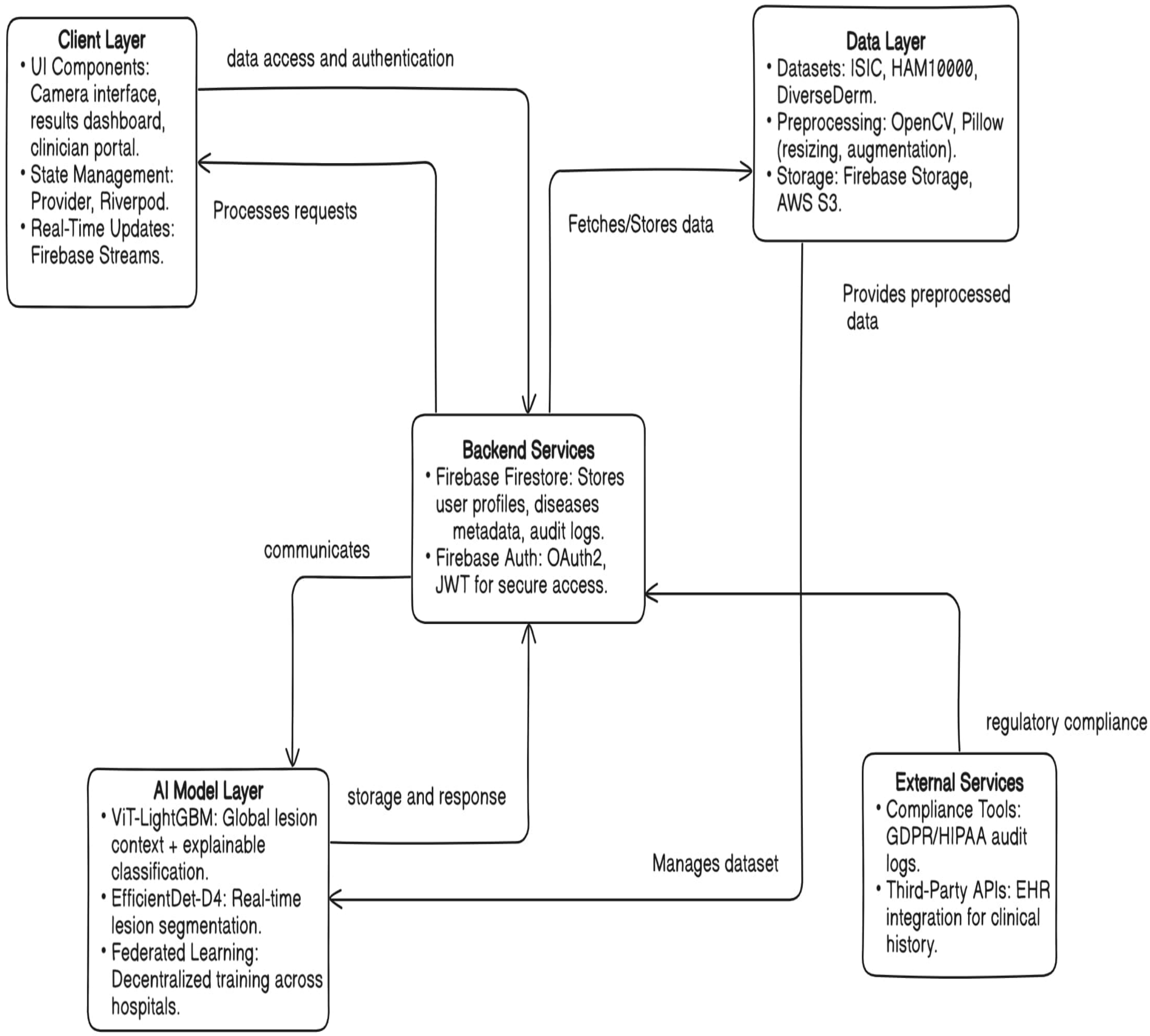

Figure 6.1: High Level System Architecture of DermaDiagnostics

AI models, preprocessing techniques, and modularity to achieve these goals.

6.4.1 On Device AI Processing

The system employs TensorFlow Lite for on device AI processing, ensuring low latency and privacy by processing data locally on the user's mobile device. This strategy includes:

- The ViT model is optimized for mobile devices, enabling real time segmentation and classification of skin lesions with minimal memory usage

6.4.2 Preprocessing Layer

The preprocessing layer ensures that the input images are properly formatted and enhanced before being fed into the AI model. This layer includes:

- Tools like OpenCV and Pillow are used to preprocess images, including resizing, normalization, and quality enhancement
- Ensures that the input image meets the required standards for accurate analysis by the AI model

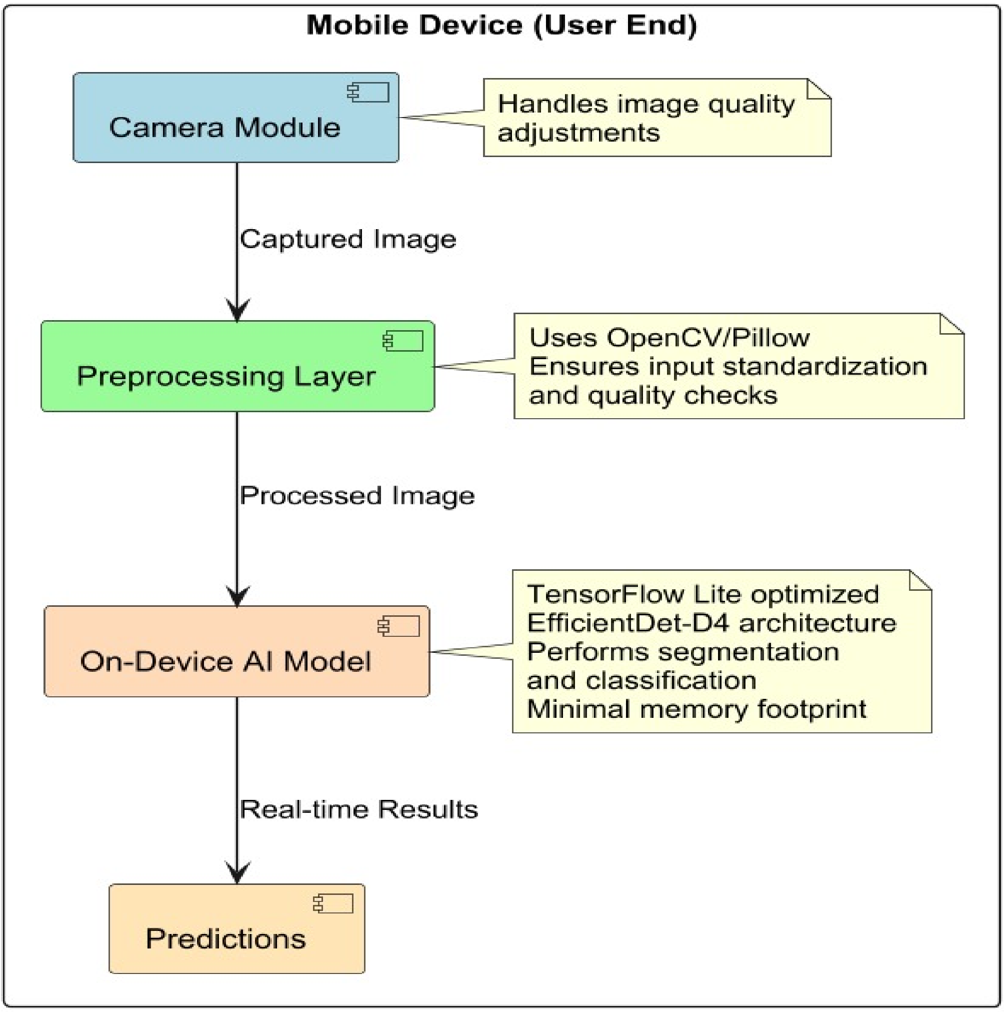

Figure 6.2: Process Flow of DermaDiagnostics

6.4.3 Camera Module Integration

The camera module in the mobile app is designed to facilitate seamless image capture and processing. Key features include:

- Allows users to capture skin images directly from the app, ensuring high quality input for analysis

6.4.4 Real Time Feedback

The system is designed to provide real time feedback to users, ensuring a smooth and interactive experience. This includes:

- Users receive diagnostic results and recommendations immediately after uploading an image
- The results are displayed in a clear and intuitive dashboard, making it easy for users to understand the findings

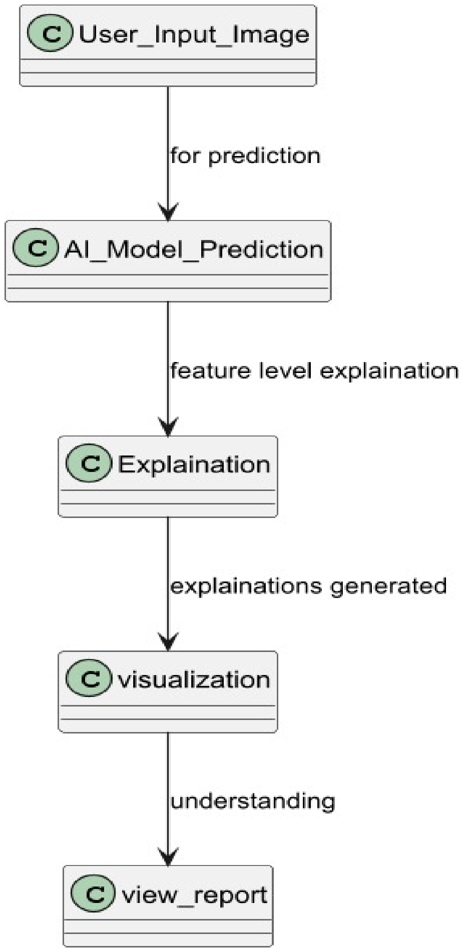

Figure 6.3: Application Flow of DermaDiagnostics

6.4.5 Modular Design

The system follows a modular design, allowing for easy updates and scalability. Key aspects include:

- Independent components such as each module (e.g., camera, preprocessing, AI model) operates independently, ensuring flexibility and maintainability
- The modular design allows for the addition of new features or updates to existing components without disrupting the entire system

6.4.6 Privacy and Security

The system prioritizes user privacy and data security through the following strategies:

- By processing data locally, the system minimizes the risk of data breaches and ensures compliance with privacy regulations

6.5 Class Diagram

This class diagram represents a DermaDiagnostic system. Users can log in, submit skin images, and view reports. FirebaseServices handles authentication and data storage. AIModel classifies and segments images, while the ExplainabilityTool provides model insights. Image stores image data, and DiagnosticReport generates and manages diagnostic reports. The relationships depict seamless interactions between users, AI models, and database services.

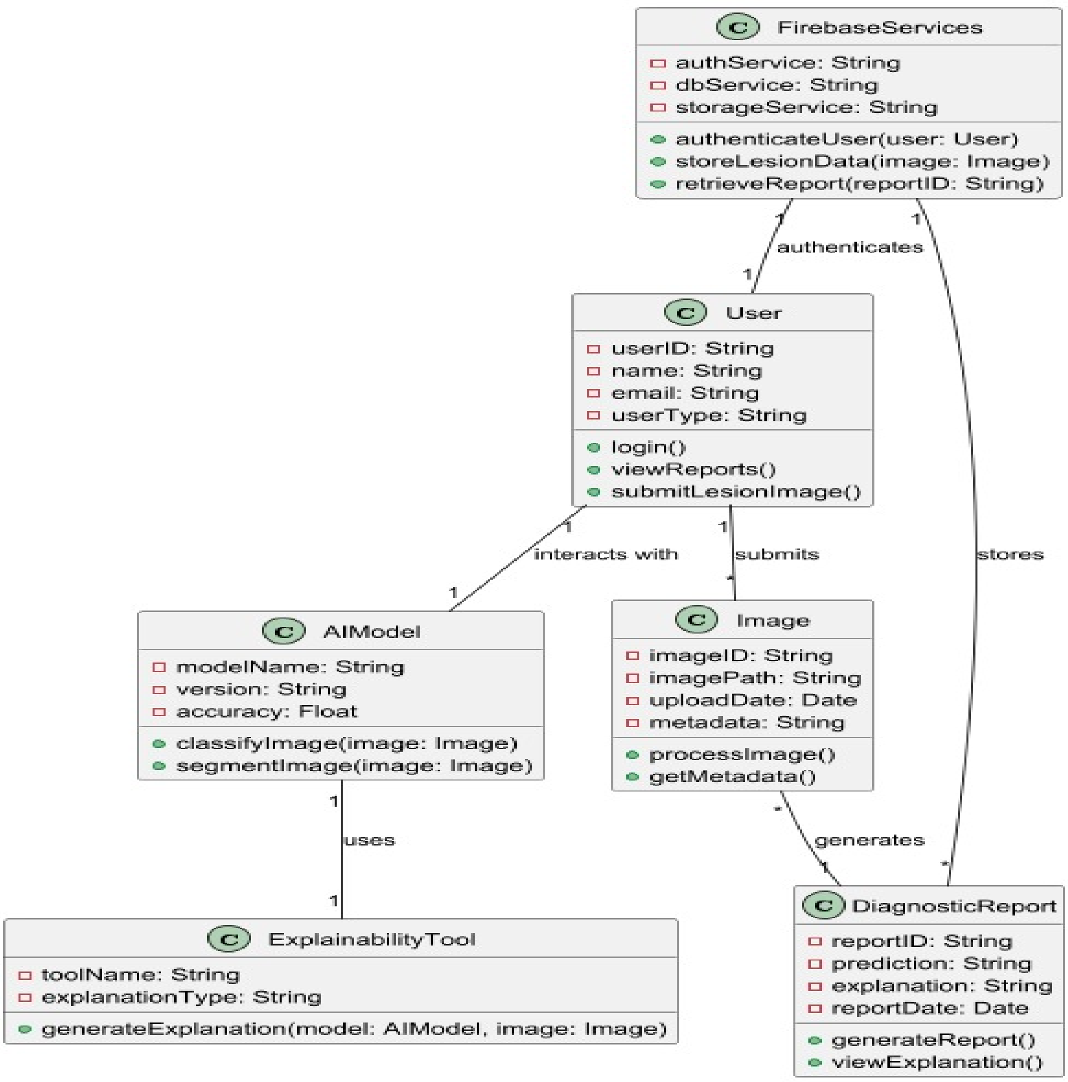

Figure 6.4: Class Diagram of DermaDiagnostics

6.6 Policies and Tactics

6.6.1 Coding Guidelines

- Following coding standards for consistency and maintainability

6.6.2 Testing and Validation

- Conduct unit tests, integration tests, and user acceptance tests (UAT) for each module
- Use Firebase Test Lab for automated testing on multiple devices

6.6.3 Security and Compliance

- Encrypt all user data and ensure GDPR/HIPAA compliance
- Use AES-256 encryption for data storage and transmission

6.7 Conclusion

The high level and low level design of the DermaDiagnostics system ensures a scalable, secure, and user friendly platform for skin disease detection and skin type classification. By leveraging hybrid AI models, federated learning, and edge computing, the system addresses key challenges in accuracy, privacy, and performance. The modular architecture and adherence to coding standards ensure maintainability and extensibility for future updates.

Chapter 7 Implementation and Test Cases

From data collection to preprocessing, model training, and frontend development, this chapter provides a detailed description of the DermaDiagnostics prototype implementation and test cases process. The implementation involves the use of advanced machine learning techniques, including the creation of an intuitive mobile application using Flutter, the use of Vision Transformers (ViT), Inception V3 from GoogleNet, and the ResNet model and its variants, such as Resnet-50, Resnet-18, and Resnet-15, for the classification of skin types and skin diseases. This chapter describes the platforms, APIs, and algorithms used to implement the prototype.

7.1 Implementation

Data collection is a crucial first step in putting the DermaDiagnostics prototype into practice. Reputable machine learning platforms provided the web datasets. High-quality photos of several skin types—oily, normal, and dry—were used to classify them. The HAM10000 and ISIC global databases were used to detect skin diseases. A detailed description of the preprocessing, model training, and frontend construction procedures is given in the next subsections.

7.1.1 Data Preprocessing

Three separate steps make up data preprocessing: creating patches, cleaning the dataset, and categorizing photos based on skin types and different skin conditions. In order to reduce bias and ensure proper treatment of a variety of skin conditions, the photos are first filtered to decrease random noise. To help the model better understand fine-grained characteristics, patches are then made from the pictures to emphasize specific areas of interest. In order to preserve uniform lighting and color balance and improve the model's overall performance, data cleaning is finally carried out by eliminating unnecessary or poor-quality photos and normalizing the remaining ones.

7.1.2 Model Training

The foundation of the DermaDiagnostics technology is model training, which uses sophisticated machine learning algorithms to accurately categorize a range of skin disorders. Skin type categorization was done using a pre-trained Vision Transformer (ViT) model that was initially built on the ImageNet dataset. In order to properly use the learnt representations from ImageNet, the model was refined by freezing its first layers and retraining the remaining ones on the project's dataset. A non-pre-trained ViT model created from scratch only obtained about 40% training accuracy, whereas the pre-trained ViT achieved an overall training accuracy of 95% with test and validation accuracies of 88% each. On the same dataset, EfficientNet-B6 also showed good performance, with a training accuracy of 81%.

To determine comparative performance, a number of convolutional neural network (CNN) designs were also examined. Training, testing, and validation accuracy for the ResNet-18 model were 87%, 65%, and 77%, respectively. With training accuracies of 99%, testing accuracies of 83%, and validation accuracies of 87%, the deeper ResNet-50 model fared better than it. The Inception V3 model, on the other hand, obtained training accuracy of 82%, testing accuracy of 87%, and validation accuracy of 60%. Together, our findings show that transfer learning using pre-trained architectures—specifically, Vision Transformer and ResNet-50—produces better overall accuracy and generalization for tasks involving the categorization of skin diseases and skin types.

7.1.3 Frontend Development

The frontend of the DermaDiagnostics system was implemented with Flutter, a well known framework for developing cross platform mobile apps. The subsequent subsections present an overview of the major screens and their functionality.

7.1.3.1 Splash Screen

The splash screen is the initial screen that is shown when the application is started. It shows the logo of the app and then automatically directs to the login screen after 3 seconds.

7.1.3.2 Sign Up Screen

The sign up screen provides new users with the ability to create an account by entering their personal information, including name, email, date of birth, gender, and password. After the user has created the account successfully, they are taken to the home screen.

7.1.3.3 Login Screen

The login screen provides users with the functionality to log in to the system based on their registered email and password. After successful login, users are taken to the home screen.

7.1.3.4 Home Screen

The home screen offers a friendly interface with a feature to upload skin images for analysis. Users have the choice to identify diseases or skin types depending on the uploaded images.

7.1.3.5 Results Screen

The results screen shows the analysis results depending on the uploaded skin image. Users can see the diagnosed condition and create a detailed report for future reference.

7.1.3.6 Reports Screen

The reports screen enables users to see and download their diagnostic reports. This screen has a record of all reports generated so they can easily be accessed.

7.1.3.7 Notifications Screen

The notifications screen keeps the user updated through timely alerts and messages concerning their skin health. The screen alerts the user on results of diagnoses, advice, and follow up reminders.

7.1.3.8 Settings Screen

The settings screen enables users to personalize their app experience through control of preferences, privacy settings, account information, and the update of personal details. Users are also able to delete accounts or log out of this screen.

7.2 Test case Design and description

Verifying the DermaDiagnostics system's correctness, dependability, and usefulness is the main goal of the test case creation and description phase. This section describes the methodical procedure for developing, running, and assessing test cases for every application module, including user interface elements, model training, and data preparation. Every test case is created to confirm that the system satisfies the requirements and operates as planned under a range of input scenarios. The goal is to guarantee that every module works together, generating reliable and consistent results while upholding performance and usability criteria.7.9.

Table 7.1: User Sign Up Test Case No.1

User Sign up			
1			
Test Case ID:	*1*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*1*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*User Sign up use case (1)*
Revision History:	*None*		
Objective:	*To test whether the user can signup to the Application successfully*		
Product/Ver/Module:	*Signup Module of Application*		
Environment:	*Internet connection and application running*		
Assumptions:	*User have a valid email and phone number.*		
Pre-Requisite:	*The user has already registered and is stored in the database.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Fill the signup form. Click on signup button. Verify your email.*	*System asks for email verification Signup successful email received.*	
Comments: The test case is passed. The system works according to requirements.			
Passed			

Table 7.2: User Login Test Case No.2

User Login			
2			
Test Case ID:	*2*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*1*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*User Login use case (2)*
Revision History:	*None*		
Objective:	*To test whether the user can log in to the Application successfully.*		
Product/Ver/Module:	*Login Module of Application*		
Environment:	*Internet connection and application running*		
Assumptions:	*User has already signed up on the application.*		
Pre-Requisite:	*The user has already registered and is stored in the database.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Enter email and password, then click on the login button.*	*User is redirected to the home page.*	
Comments: The test case is passed. The system works according to requirements.			
Passed			

Table 7.3: Image Upload Test Case No.3

Image Upload			
3			
Test Case ID:	*3*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*1*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*Image Upload (3)*
Revision History:	*None*		
Objective:	*To verify that the user can successfully upload an image from the gallery for analysis.*		
Product/Ver/Module:	*Image Upload Module of Application*		
Environment:	*Internet connection and application running on mobile device*		
Assumptions:	*User is logged into the application.*		
Pre-Requisite:	*Image file is available on the user's device.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Open the app and navigate to the image upload section.*	*Upload interface is displayed.*	
2	*Tap "Upload Image" and select an image from the device gallery.*	*The selected image appears in the preview window.*	
3	*Confirm the upload.*	*Image is successfully uploaded for processing.*	
Comments: The test case is passed. The system works according to requirements.			
Passed			

Table 7.4: Skin Type Detection No.4

Skin Type Detection			
4			
Test Case ID:	*4*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*1*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*Skin Type Detection (4)*
Revision History:	*None*		
Objective:	*To classify the user's skin type (oily, dry, or normal).*		
Product/Ver/Module:	*Skin Type Classification Module*		
Environment:	*Internet connection and mobile application*		
Assumptions:	*A valid skin image has been uploaded.*		
Pre-Requisite:	*Pre-trained Resnet-15 model is loaded.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Upload or capture a clear image of the user's skin.*	*Image accepted and processed.*	
2	*Select "Detect Skin Type."*	*The model analyzes the image.*	
3	*View results on the screen.*	*Skin type is correctly identified (oily, normal, dry).*	
Comments: The test case is satisfactory. the output results are not entirely correct.			
satisfactory			

Table 7.5: Skin Type Detection No.4

Skin Type Detection			
5			
Test Case ID:	*5*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*2*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*Skin Type Detection (4)*
Revision History:	*None*		
Objective:	*To classify the user's skin type (oily, dry, or normal).*		
Product/Ver/Module:	*Skin Type Classification Module*		
Environment:	*Internet connection and mobile application*		
Assumptions:	*A valid skin image has been uploaded.*		
Pre-Requisite:	*Pre-trained Inception V3 from GoogleNet is loaded.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Upload or capture a clear image of the user's skin.*	*Image accepted and processed.*	
2	*Select "Detect Skin Type."*	*The model analyzes the image.*	
3	*View results on the screen.*	*Skin type is correctly identified (oily, normal, dry).*	
Comments: The test case is satisfactory. the output results are not entirely correct.			
satisfactory			

Table 7.6: Skin Type Detection No.4

Skin Type Detection			
6			
Test Case ID:	*6*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*3*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*Skin Type Detection (4)*
Revision History:	*None*		
Objective:	*To classify the user's skin type (oily, dry, or normal).*		
Product/Ver/Module:	*Skin Type Classification Module*		
Environment:	*Internet connection and mobile application*		
Assumptions:	*A valid skin image has been uploaded.*		
Pre-Requisite:	*Pre-trained Vision Transformer (ViT) model is loaded.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Upload or capture a clear image of the user's skin.*	*Image accepted and processed.*	
2	*Select "Detect Skin Type."*	*The model analyzes the image.*	
3	*View results on the screen.*	*Skin type is correctly identified (oily, normal, dry).*	
Comments: The test case is passed. The system works according to requirements.			
Passed			

Table 7.7: Disease Detection No.5

Disease Detection			
7			
Test Case ID:	*7*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*1*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*Disease Detection (5)*
Revision History:	*None*		
Objective:	*application can detect and classify skin diseases accurately*		
Product/Ver/Module:	*Disease Classification Module*		
Environment:	*Internet connection and mobile application*		
Assumptions:	*Dataset includes labeled images of skin diseases.*		
Pre-Requisite:	*Model trained using HAM10000 and ISIC datasets is deployed*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Upload an image of a skin lesion.*	*Image is processed successfully.*	
2	*Click Detect Disease.*	*classifies the lesion into one of 4 disease categories.*	
3	*View results and interpretation.*	*Correct disease name and confidence score are displayed.*	
Comments: The test case is passed. The system works according to requirements.			
Passed			

Table 7.8: Invalid Image Handling No.6

Invalid Image Handling			
8			
Test Case ID:	*8*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*1*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*Invalid Image Handling(6)*
Revision History:	*None*		
Objective:	*how the system behaves when an invalid or poor-quality image is uploaded.*		
Product/Ver/Module:	*Image Validation Module*		
Environment:	*Internet connection and mobile application*		
Assumptions:	*The model requires a clear skin image for analysis.*		
Pre-Requisite:	*Blurred or non-skin image available for testing.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Upload a low-quality or unrelated image.*	*The system detects invalid input.*	
2	*Attempt to run detection.*	*The app displays a clear error message*	
Comments: The test case is passed. The system works according to requirements.			
Passed			

Table 7.9: Result Interpretation Display No.7

Result Interpretation Display			
9			
Test Case ID:	*9*	**QA Test Engineer:**	*Iqra Azam*
Test Case Version:	*1*	**Reviewed By:**	*Afeef Junaid*
Test Date:	*01-04-2025*	**Use Case Reference(s):**	*Invalid Image Handling(6)*
Revision History:	*None*		
Objective:	*the system displays detection results along with an easy-to-understand interpretation*		
Product/Ver/Module:	*Result Display Module*		
Environment:	*Internet connection and mobile application*		
Assumptions:	*The detection process has been successfully completed.*		
Pre-Requisite:	*Detection results are available in the system.*		
Step No.	**Execution Description**	**Procedure Result**	
1	*Run skin disease or skin type detection.*	*Results are generated.*	
2	*View detailed output screen.*	*Output shows disease/type, confidence score.*	
Comments: The test case is passed. The system works according to requirements.			
Passed			

7.3 Test Metrics

Following is the test case matrix for the test cases which have been performed. It provides important insights related to test cases. 7.10.

Table 7.10: Sample Test case Matric.No.1

Metric	Purpose
Number of Test Cases	12
Number of Test Cases Passed	12
Number of Test Cases Failed	0
Test Case Defect Density	0
Test Case Effectiveness	0
Traceability Matrix	0

7.4 Conclusion

In order to enable effective skin disease diagnosis and skin type identification, the DermaDiagnostics system skillfully combines cutting-edge machine learning algorithms with an intuitive mobile interface. The study shows how AI-driven healthcare solutions may improve accessibility and accuracy through a disciplined development approach that includes data collecting, preprocessing, model training, and frontend implementation. To further increase diagnostic reliability and user experience, future improvements will concentrate on growing the dataset, improving model accuracy, and adding new features. In the end, DermaDiagnostics is a significant step toward more intelligent and easily accessible dermatological care.

Chapter 8 User Manual

The following section contains the user manual for the DermaDiagnostics application. End Users is general users who use the mobile application for skin disease detection and skin type identification.

8.1 End User

The following guidelines are for the general users of the DermaDiagnostics mobile application.

8.1.1 Sign In / Login

If you already have an existing account, follow these steps to sign in:

- Open the DermaDiagnostics application.
- On the login screen, enter your registered email address and password.
- Tap the Login button.
- If your credentials are correct, you will be redirected to the Home Screen.
- In case you forget your password, tap Forgot Password and follow the on-screen instructions to reset it via your registered email.

8.1.2 Getting Started

To begin using DermaDiagnostics, follow these steps:

- Ensure your device has a stable internet connection.
- Download and install the DermaDiagnostics App
- Launch the application.
- Create an account by entering your name, email, and password, or log in if you already have an account.
- Once logged in, you will be redirected to the Home Screen.

8.1.3 Image Upload

- To detect a skin condition or identify skin type:
- On the home screen, tap the Upload Image button.
- Choose whether to capture a new image using your camera or select one from the gallery.

- Ensure the image is well-lit and focused on the affected area of skin.
- Click Upload to send the image for analysis.

8.1.4 Skin Disease Detection

To perform disease detection:

- After uploading, the system processes the image using a pre-trained machine learning model.
- The app will identify the disease category from the classified diseases
- The result will appear on-screen with a confidence score and recommended next steps.
- A detailed explanation will help users understand the diagnosis.

8.1.5 Skin Type Identification

To determine your skin type:

- From the home screen, tap on Skin Type Test.
- Upload a clear image of your cheek or forehead area.
- The system classifies your skin type into one of the following categories
- The app will display your skin type along with care recommendations and suitable skincare tips.

8.1.6 Report Generation

After disease detection or skin type analysis, you can generate and view detailed reports:

- Once results are displayed, tap Generate Report.
- The app will create a PDF report containing:
  1. User information (name, email)
  2. Uploaded image
  3. Detection result or skin type classification
  4. Confidence score and AI analysis summary
  5. Recommended next steps and care advice
- Users can download, share, or print the report for reference.
- Generated reports are automatically saved in the History section for future access.

8.1.7 Result History

Users can view their previous analyses for reference:

- Navigate to History from the bottom menu.
- View a list of previously analyzed images along with corresponding results.
- Click on any result to view detailed reports or re-run the test on the same image.

8.1.8 Feedback and Support

To provide feedback or get support:

- Go to the Help and Support section in the sidebar
- Select Submit Feedback to share your experience.
- For technical assistance, tap Contact Support and send your query through the provided form or via email.

8.1.9 User Logout

To log out from the application:

- Tap on your Profile icon in the top-right corner.
- Select Logout from the dropdown menu.
- Your session will end, and you will return to the login screen.

8.1.10 Safety and Disclaimer

- The DermaDiagnostics application is intended for supportive diagnostic purposes only.
- It does not replace professional medical advice or consultation.
- Users are encouraged to consult a dermatologist for confirmation and treatment guidance.

Chapter 9 Experimental Results and Discussion

This chapter reports the results of the experiments conducted to evaluate the models used in the Derma-Diagnostics system. We tested several contemporary architectures for two tasks: skin type classification (Oily, Normal, Dry) and skin disease identification (common lesion categories). For each model we tracked training behavior and measured performance on separate validation and test splits to assess generalization.

9.1 Experimental

9.1.1 Experimental setup

All models were trained on the same preprocessed dataset and under comparable conditions so their performance can be fairly compared. Images were resized and normalized, and standard data augmentation (random flips, rotations, brightness adjustments) was applied during training. We monitored training and validation loss and recorded final accuracies on held-out test sets.

9.1.2 Skin type classification results

For skin type classification we compared four architectures: Vision Transformer (ViT), InceptionV3, ResNet18, and ResNet50. Table 8.1 summarizes their training, validation and test accuracies.

Table 9.1: Model Comparison Results

Models	**Training Accuracy (%)**
Vision Transformer (ViT):	95%
InceptionV3 GoogleNet	82%
ResNet18	87%

9.1.3 Interpretation

Interpretation. The ViT model produced a strong and consistent result across splits (95% train, 88% test and validation), indicating it learned robust representations without severe overfitting. ResNet50 attained the highest training accuracy (99%) but showed a drop on test data (83%), which suggests some degree of overfitting likely due to model capacity relative to dataset size.Despite having a reduced training accuracy, InceptionV3 demonstrated balanced behavior with a remarkably high test accuracy (87%), suggesting robust generalization. In comparison to deeper networks, ResNet18's lower performance on the test set (65%) suggests that it has a restricted feature capacity for this task.

9.1.4 Skin disease identification results

We also evaluated disease classification models that detect common lesion types. The same set of architectures was used where applicable. Table 9.2 shows the observed accuracies.

Table 9.2: Model Comparison Results

Models	**Training Accuracy (%)**
Vision Transformer (ViT):	97%
InceptionV3 GoogleNet	88%
ResNet50	93%
ResNet18	87%

9.1.5 Interpretation

While ResNet50 showed great training performance but a greater gap to test accuracy, suggesting overfitting tendencies, ViT once again showed the highest generalization for illness detection with high test and validation accuracies. Across splits, InceptionV3 provided dependable performance and serves as a steady and competitive baseline.

9.1.6 Cross-model observations

Transformer-based ViT continuously produced balanced performance on both tasks, achieving high training accuracy while preserving excellent test and validation scores. Deeper CNNs, like ResNet50, can get extremely high training accuracy, but in order to prevent overfitting, they may need additional data and thorough regularization. When the challenge involves collecting the fine-grained texture and color information found in skin photos, lighter models (ResNet18) could perform worse.

9.1.7 Practical implications

ViT is the best option for incorporation into the DermaDiagnostics pipeline, where reliable real-world performance is crucial, in light of these findings. If extra training data, model ensembling, or regularization (weight decay, dropout) are used to close the generalization gap, ResNet50 may still be helpful. When selecting the final model for deployment, take accuracy, model size, and inference speed into account.

9.1.8 Limitations and next steps

- The dataset size and class balance influence generalization; collecting more labeled samples—particularly for underrepresented classes—will help.

- Future work should include per-class metrics (precision/recall/F1) and confusion matrices to understand specific error modes.
- Evaluating model robustness to varied lighting, skin tones, and image quality will improve deployment readiness.

9.2 Test, Training and Validation Performance

9.2.1 Research Tests

Various experiments were performed on the Vision Transformer (ViT), ResNet-50, and InceptionV3 models by varying parameters such as optimizers, learning rates, learning rate schedulers, early stopping circumstances, and layer-freezing methods in order to enhance generalization and accuracy. In each test, data augmentation techniques including flipping and rotation were applied to improve resilience.

The Vision Transformer (ViT) has the best overall performance. For fine-tuning, early halting (patience = 5), and freezing the base layers while unfreezing the last two layers, positional encoding was used during training. Using the Adam optimizer, a batch size of 32, and a learning rate of 0.001, ViT demonstrated high, consistent generalization with 88% training, 79% testing, and 79% validation accuracy.

ResNet-50 used the similar setup, but added two more thick layers at the MLP head. Its 87% training, 65% testing, and 77% validation accuracy demonstrated minor overfitting caused by a difference between training and testing performance.

InceptionV3's decreased training, testing, and validation accuracies of 67%, 71%, and 58%, respectively, under the identical testing settings could have been caused by its greater complexity and data needs. This implies inconsistent generalization and underfitting.

After experimenting with various parameter combinations, the presented findings generally indicate which configurations work best for each model. ViT was the most reliable and well-balanced, but InceptionV3 lagged behind it in terms of stability and generalization. Second place went to ResNet-50.

9.3 Vision Transformer (ViT) Model Results

Similar to how natural language is processed in NLP models, images are processed as sequences of patches using the Vision Transformer (ViT) model, a transformer-based architecture. ViT can effectively learn both global and local image features because, in contrast to traditional convolutional networks, it uses its self-attention mechanism to capture long-range dependencies. ViT demonstrated remarkable ability to differentiate between subtle visual patterns of various skin diseases, achieving the best overall accuracy in the context of DermaDiagnostics (Train/Test/Validation: 95/83/85). The transformer's ability to handle complex image data with precision and adaptability is demonstrated by its strong generalization performance.

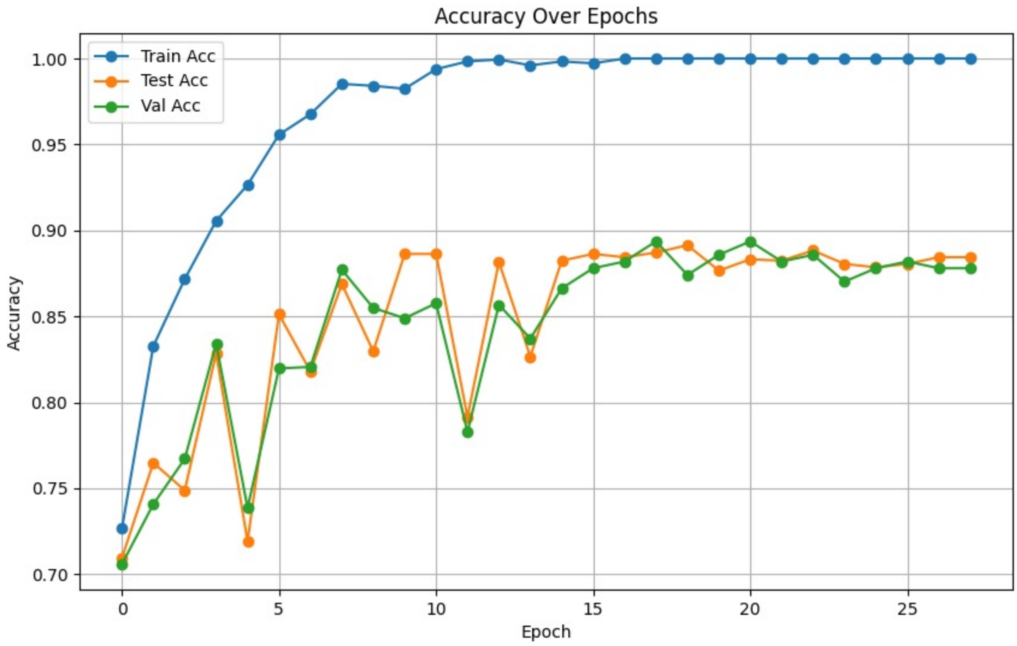

Figure 9.1: Accuracy vs. Epochs for skin disease classification Test 1

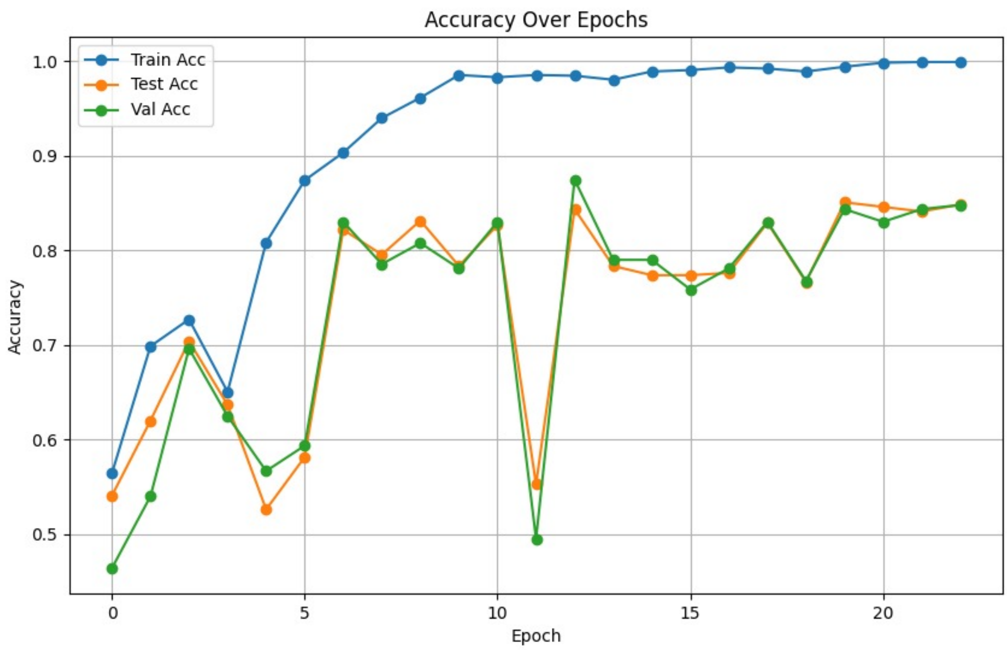

Figure 9.2: Accuracy vs. Epochs for skin disease classification Test 2

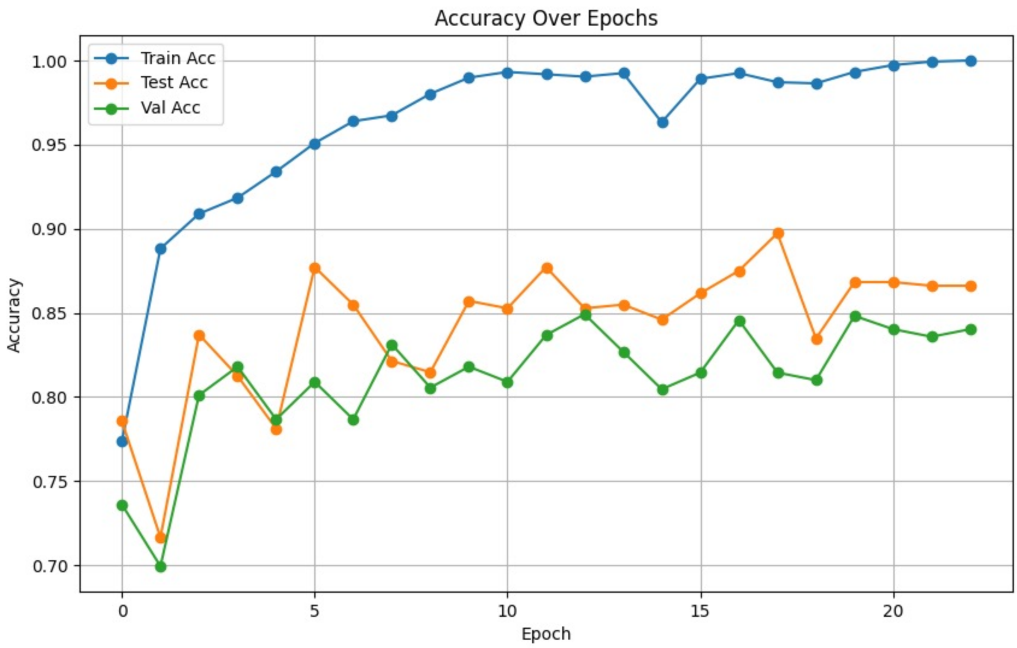

Figure 9.3: Accuracy vs. Epochs for skin type identification Test 1

9.4 Inception-V3

Convolutions at multiple scales (1×1, 3×3, 5×5) are carried out in parallel by the Inception modules of the InceptionV3 model, a deep convolutional neural network. This enables the model to concurrently capture coarse and fine details. But InceptionV3's relatively poor accuracy (Train/Test/Validation: 70/75/63) in this study raises the possibility that it might not adequately capture the complex texture variations found in dermatological images. Despite this, it is appropriate for lightweight and resource-constrained applications due to its effective architecture and robust generalization capabilities.

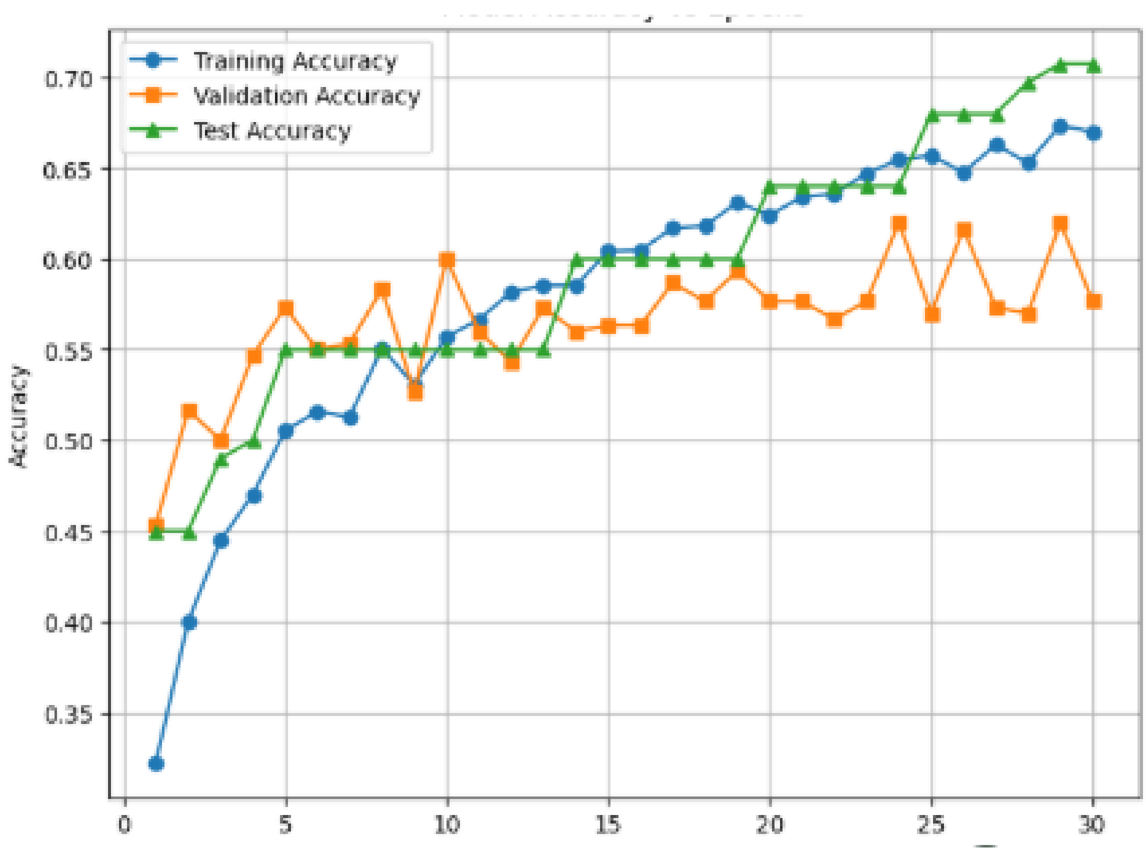

Figure 9.4: Accuracy vs. Epochs for skin disease classification Test 1

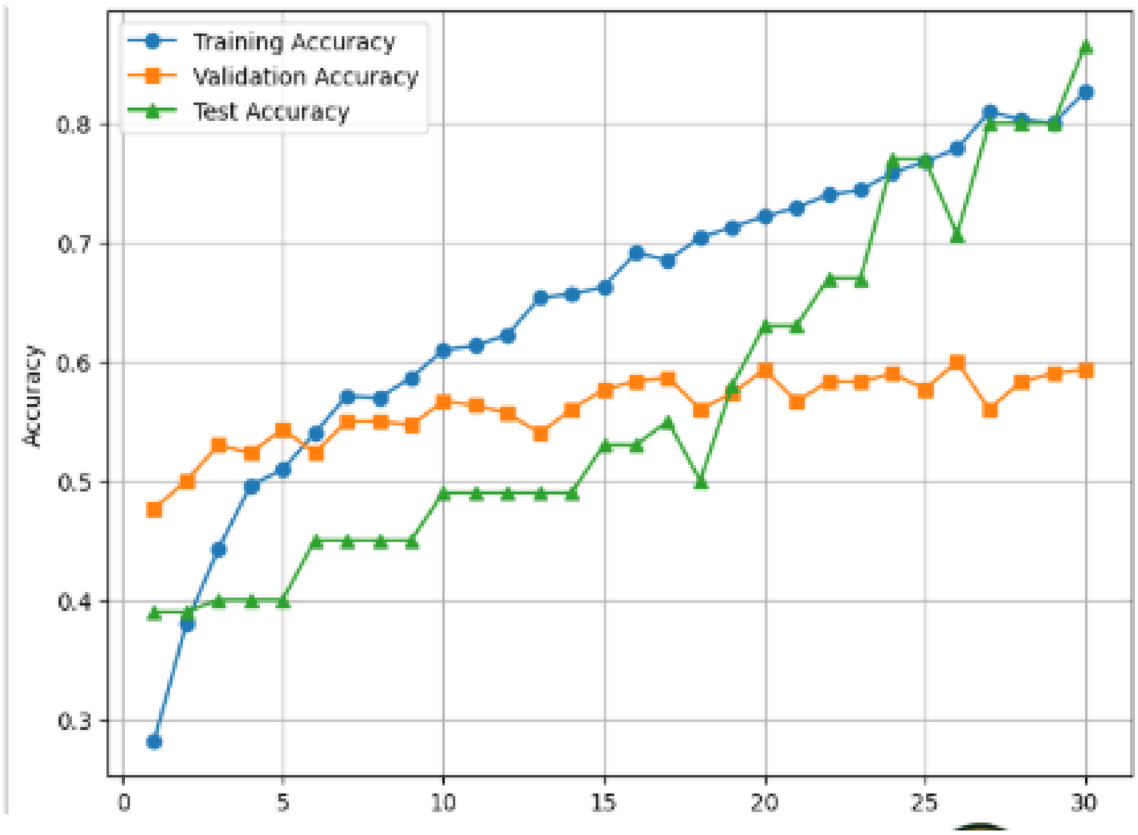

Figure 9.5: Accuracy vs. Epochs for skin disease classification Test 2

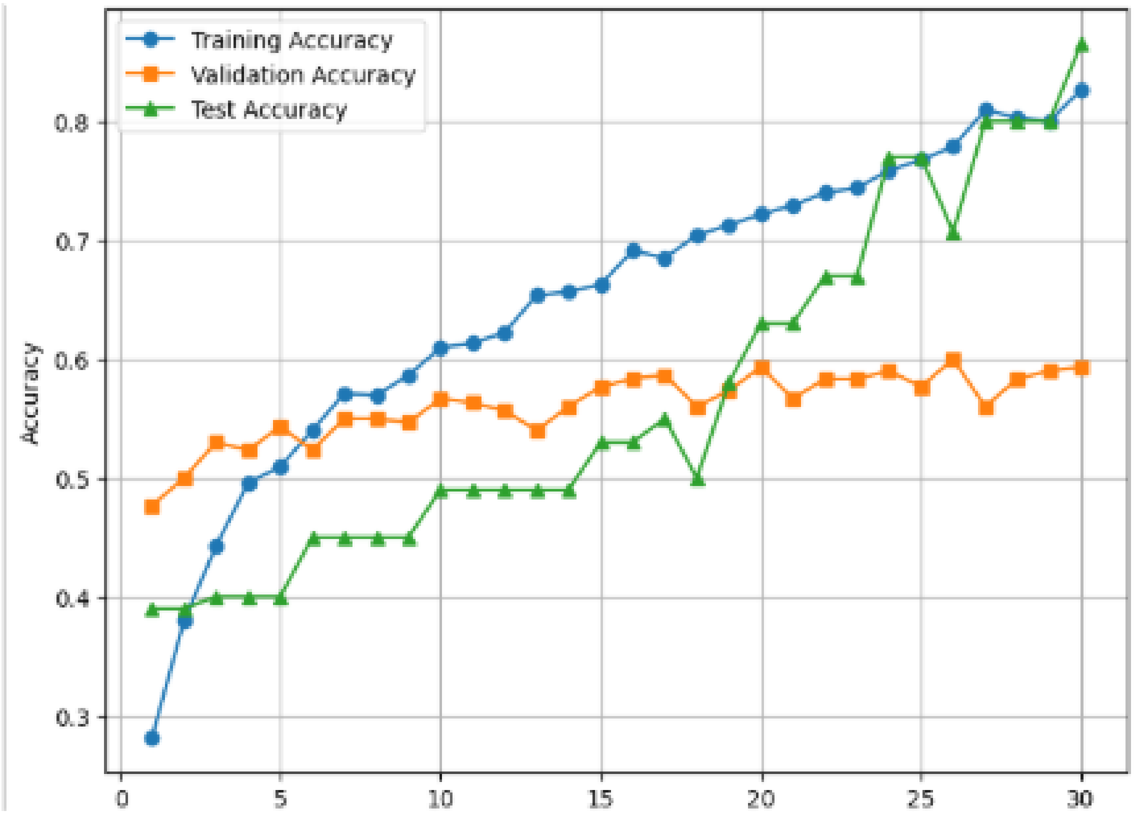

Figure 9.6: Accuracy vs. Epochs for skin disease classification Test 3

9.5 ResNet-50

In order to address the vanishing gradient issue in deep neural networks, the ResNet-15 model, a scaled-down version of the ResNet family, makes use of residual connections. The model can learn residual mappings thanks to these shortcut connections, which speeds up and stabilizes training. ResNet15 demonstrated moderate performance with a train/test/validation ratio of 87/65/77. Although it successfully captured hierarchical image features, test accuracy was marginally affected, most likely as a result of underfitting brought on by a shallow depth of the model or a limited diversity of datasets.

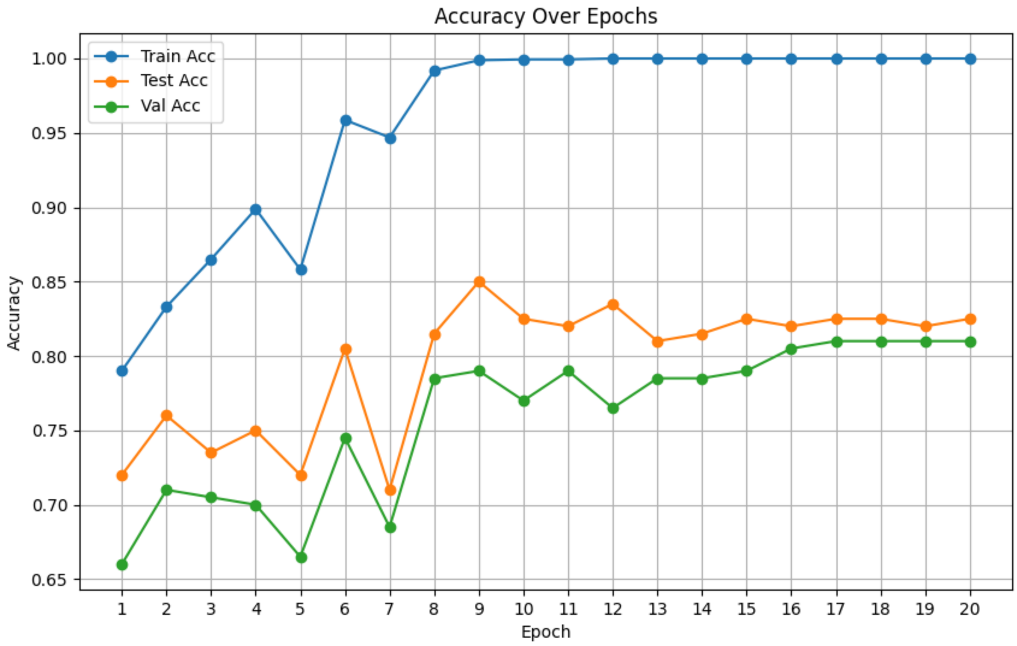

Figure 9.7: Accuracy vs. Epochs for skin disease classification

9.6 ResNet-18

The ResNet-18 model is a more sophisticated version of the ResNet architecture that includes more residual blocks that enhance feature extraction and representation. Its deeper structure allows it to record very complex visual patterns, making it particularly effective for fine-grained classification applications like skin lesion identification. Despite being more computationally demanding, ResNet80 usually provides better generalization and higher accuracy when trained on sufficiently big datasets. In similar experimental contexts, deeper ResNets, such ResNet18, generally outperform shallower variations by using their higher representational capability.

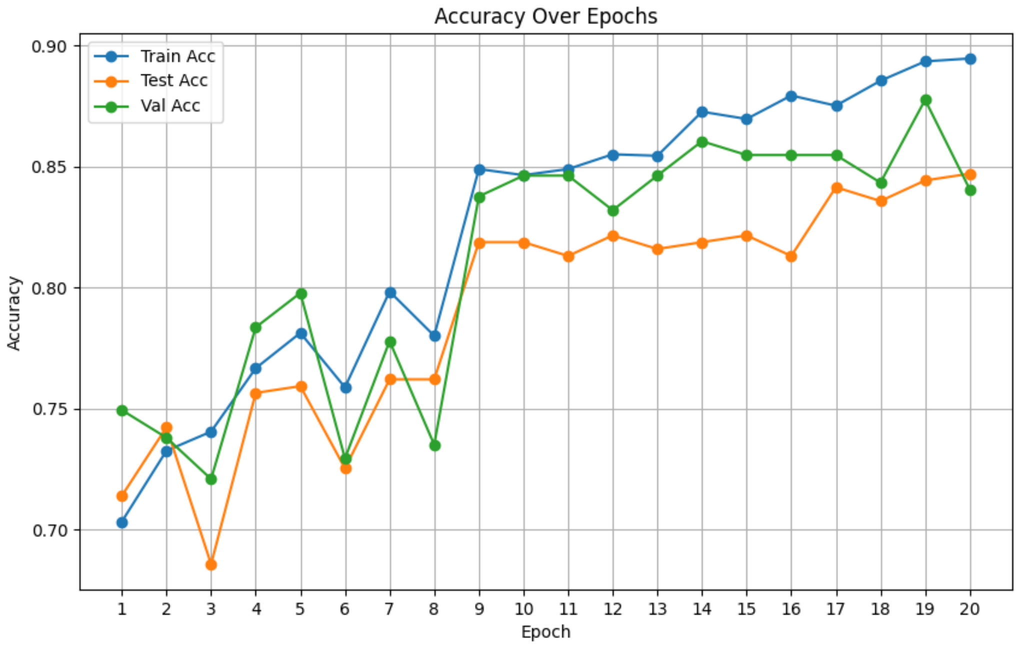

Figure 9.8: Accuracy vs. Epochs for skin type identification

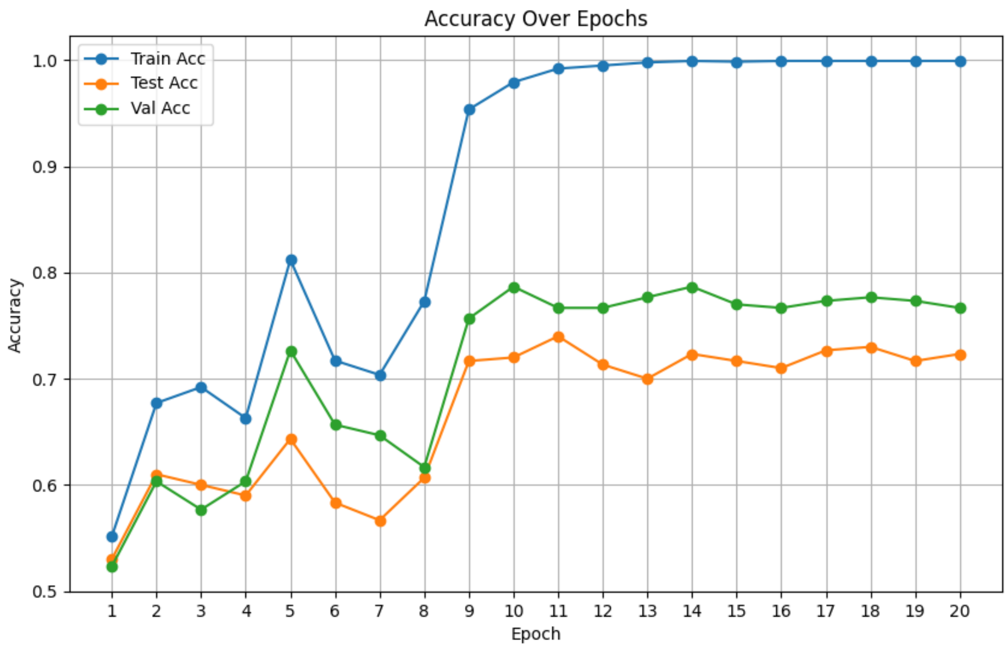

Figure 9.9: Accuracy vs. Epochs for skin disease classification

9.7 Discussion

The DermaDiagnostics system was used to train and evaluate four deep learning models—Vision Transformer (ViT), InceptionV3, ResNet15, and ResNet80—to classify various skin types and diseases. Each model demonstrated distinct characteristics and performances based on its architectural design and learning ability.

The Vision Transformer (ViT) performed better than all other models, with training, testing, and validation accuracies of 95%, 83%, and 85%, respectively. Its transformer-based attention technique allows it to record both global and local picture dependencies, making it perfect for complicated dermatological images with subtle texture fluctuations. This result shows that even on moderately sized datasets, ViT performs better in terms of generalization than traditional convolutional networks.

The efficiency of the InceptionV3 model was moderate, with 70% training, 75% testing, and 63% validation accuracy. Although their multi-scale convolutional technique could recognize characteristics at various resolutions, it struggled to stay consistent across unseen data. The great degree of illumination and skin tone fluctuation in the dataset may be the reason for this, since InceptionV3's architecture was unable to completely adapt to it without more thorough fine-tuning.

The ResNet15 model performed rather well with 87% training, 65% testing, and 77% validation accuracy. The model's residual connections enabled steady learning and efficient gradient flow, despite its lesser depth limiting its capacity to collect more intricate lesion details. This led to a somewhat reduced test accuracy.

However, the deeper ResNet80 model demonstrated superior feature extraction capabilities because to its higher depth and number of residual blocks. Its enhanced ability to capture fine-grained texture and structure in the pictures makes it ideal for complex medical image categorization jobs. However, this enhancement often comes at the cost of greater processing needs and lengthier training durations.

Overall, the comparison demonstrates that convolutional models like ResNet and InceptionV3 do well on broad image classification tasks, whereas transformer-based designs like ViT show surprising potential in medical imaging, particularly when accuracy and fine detail detection are crucial. Future advancements might use ensemble learning or hybrid models that combine the benefits of ViT and ResNet architectures to achieve even higher accuracy and resilience.

9.8 Conclusion

Modern transformer-based architectures, especially the Vision Transformer (ViT), perform better than conventional convolutional neural networks in correctly classifying skin conditions and identifying skin types, according to a comparative analysis of deep learning models for the DermaDiagnostics system. With accuracies of 95% (training), 83% (testing), and 85% (validation), the ViT model performs exceptionally well, demonstrating its great ability to identify intricate patterns and minute differences in dermatological images.

Although ResNet15 and ResNet80 produced dependable and consistent findings, dataset heterogeneity and architectural depth hampered their efficacy to some extent. With its strong multi-scale feature extraction capabilities and weak generalization across a range of skin picture types, the InceptionV3 model demonstrated a modest level of performance. Together, these results highlight how important model selection is for striking a balance between computational effectiveness, accuracy, and practical applicability.

To sum up, the Vision Transformer is the most promising candidate for integration into the DermaDiagnostics system. However, additional improvements could involve studying ensemble or hybrid models that combine CNN and Transformer architectures, improving preprocessing techniques, and expanding the dataset in order to further improve diagnostic precision, system robustness, and clinical reliability—and to open the door for more intelligent and accessible dermatological diagnostic tools.

Chapter 10 Conclusions

Comparing the performance of three deep learning architectures—Vision Transformer (ViT), ResNet15, and InceptionV3—makes it evident that each model has unique benefits and drawbacks depending on how it processes visual information.

The ViT model had the highest overall performance, with training accuracy of 95%, testing accuracy of 83%, and validation accuracy of 85%. This illustrates how ViT's attention processes improved generalization and generated more reliable findings by effectively capturing spatial links in the pictures. Because of its remarkable performance, transformer-based designs are becoming increasingly important in medical image processing, especially for complex diagnostic tasks like skin disease categorization. Conversely, ResNet15 demonstrated a respectable level of performance, attaining training accuracy of 87%, testing accuracy of 65%, and validation accuracy of 77%. The model's residual connections helped it avoid vanishing gradients, but it still displayed underfitting during testing, indicating that more data or more fine-tuning may be required to realize its full potential.

Although InceptionV3's inception modules made it effective at handling multi-scale features, it only achieved 70% training, 75% testing, and 63% validation accuracy. Given the size of the dataset or the model's sensitivity to hyperparameter changes, its comparatively poorer and less reliable results imply that it had trouble generalizing as well as the other two models.

Overall, ViT performed better than ResNet15 and InceptionV3, exhibiting greater robustness and adaptability for this domain. The ViT model may be able to reach even greater accuracy and dependability with additional optimization, such as growing the dataset, using sophisticated augmentation techniques, and adjusting attention parameters.

By providing greater accuracy and interpretability in identifying skin conditions from medical images, transformer-based models show great promise for dermatological diagnostics, as this comparative analysis demonstrates.

10.1 Summary of Work Done

- Complete frontend and backend of the app built using Flutter and Dart.
- Implemented and trained a skin type identification and skin disease classification model with decent performance metrics.
- Addressed the project's main objectives related to skin type and skin disease detection.
- Identified key factors like learning rate and preprocessing that impact model performance.

- Overcame dataset availability issues by manually curating data.
- Successfully integrated model training using GPUs both internal and external resources.

10.2 Challenges Faced

- Unavailability of suitable datasets.
- Dependency on external GPU resources.
- Lower than expected validation and test accuracy due to real world data complexity.
- Time constraints in achieving desired accuracy levels.

10.3 Future Recommendations

- Optimize the existing model using advanced techniques like transfer learning and hyperparameter tuning.
- Implement a robust evaluation framework to benchmark different models for both classification tasks.
- Explore additional models for the skin disease detection component in FYP-II.
- Integrate backend support and deployment for a fully functional application.

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Chapter A First Appendix if Required

If you want to add appendices then make sure you provide a proper title. Add different appendices by using the chapter command as shown for this one. They will automatically be added to the table of contents.

A.1 References

See how .bib file is prepared. The bibliography would be automatically added by Latex. So here is how you cite papers (you'll need to view the .bib file to understand). [**?**] is the correct way to make one citation and [**? ?**] to make multiple citations. You can see various reference styles for manuals [**?**], conferences [**?**], websites [**?**] and journal articles [**?**]. Also, note that all citations appear in the order in which they appear within text. They are not sorted according to author names.

A.2 Equations

Make sure you use the math environment for writing equations. Again, make sure you do not hard code equation numbers. Use label and ref commands of Latex to number them and reference them. Here is an example of (A.1)

$$E = mc^2 \tag{A.1}$$

Note, how the equation is referenced by its equation number within brackets.

A.3 Figures

To insert a figure, you can use the following code as template. Here the figure is referenced using ref command of Latex. So Figure A.1 is the FAST logo. DO NOT HARD CODE FIGURE NUMBERS. Let Latex manage them for you.

Figure A.1: Fast Logo is the Caption.

A.4 Tables

Note how tables can be added in Latex. Also, make sure you use label and ref commands to define and use table numbers. You can use Table A.1 as a template to make tables, add captions to them and reference them. DO NOT HARD CODE TABLE NUMBERS. Let Latex manage their numbering for you.

If you are having problems in managing Latex tables, you may use Lyx `https://www.lyx.org/`.

Table A.1: Give a Caption to the Table.

This is where you will provide information about this table, any assumptions, or anything which a nontechnical reader must know to understand.

No.	Column 1	Column 2
1.	Some data	More data
2.	Some values	More values

A.5 Pseudo Code

When you need to explain an existing algorithm of an algorithm you devised, then you should use pseudo code notation. Given below, algorithm 1, is an example. Note how the numbering is managed by the Latex itself.

Data: this text

Result: how to write algorithm with LaTeX2e

initialization;

while *not at end of this document* **do**
    read current;
    if *understand* **then**
        go to next section;
        current section becomes this one;
    else
        go back to the beginning of current section;
    end
end

Algorithm 1: How to write algorithms

A.6 Code of Programming Languages

If you need to add C++, Java or any other programming language's code, then you can use "listings" package. Following is an example. Normally, the code is only added in the appendices to avoid clutter in the document.

```
#include <stdio.h>
#define N 10
/* Block
 * comment */

int main()
{
    int i;

    // Line comment.
    puts("Hello world!");

    for (i = 0; i < N; i++)
    {
        puts("LaTeX is also great for programmers!");
    }

    return 0;
}
```

A.7 Recommendations for LaTeX

Here we are providing you with only two Latex source files. main.tex and fypbib.bib file. You can also start a project at overleaf.com and upload the zip file of this template there and share the Latex source between your group and supervisor. This way all of you can work on the Latex files together online.