# SkinSense:
# Melasma Skin Disease Detection and Advisory System using Image Processing, Machine Learning and HCI

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# Abstract

The SkinSense project is a mobile-based platform that leverages image processing and machine learning to facilitate the diagnosis and management of common skin conditions, with a particular focus on melasma. This system enables users to capture images of their skin, which are analyzed using advanced deep learning models to provide a preliminary diagnosis and treatment recommendations from healthcare professionals. By offering a remote, self-sustained diagnostic tool, SkinSense aims to reduce consultation wait times and improve dermatological care, especially for individuals with limited access to healthcare facilities. To enhance the accuracy of the diagnostic model, a comparative analysis was conducted using several pretrained deep learning architectures, including VGG16, VGG19, MobileNetV3-Large, ResNet50, DenseNet201, EfficientNet-B5, and AlexNet. These models were evaluated with various image preprocessing techniques, such as rescaling, Contrast Limited Adaptive Histogram Equalization (CLAHE), colorization using Inferno and Plasma colormaps, and histogram equalization. Among these approaches, the VGG16 model with CLAHE provided an accuracy of 82.47%, whereas VGG19 with rescalling showed a significant improvement, with an accuracy of 86.15%. But the DenseNet201 with rescalling model performed better than both, with an accuracy of 92.46%, making it the optimal choice for integration into the software platform. After successfully integrating the machine learning model, user testing was conducted to gather feedback and assess usability. This testing phase helped identify areas for further refinement, ensuring that the platform delivers an efficient, user-friendly experience. The SkinSense project thus presents a promising solution for early and accessible dermatological diagnosis, utilizing state-of-the-art machine learning techniques to bridge the gap between technology and healthcare accessibility.

# Acknowledgements

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# Publication List

[Optional] The main contributions of this research are either published or accepted or in preparation in journals and conferences as mentioned in the following list:

## Journal Articles

1.

## Conference Papers

1.

## Additional Publications

Following is the list of relevant publications published in the course of the research that is not included in the thesis:

1.

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# Chapter 1

# Introduction

SkinSense is a pioneering mobile application designed to address the challenges associated with the detection and treatment of melasma, a common dermatological condition characterized by dark, discolored patches on the skin. Leveraging advanced machine learning algorithms, SkinSense allows users to upload skin images for automated analysis and preliminary diagnosis. By facilitating early detection and providing seamless access to healthcare services, SkinSense aims to improve health outcomes, enhance healthcare accessibility, and empower users to make informed decisions about their skin health. This project endeavors to bridge gaps in dermatological care through innovative technology, ensuring timely intervention and personalized treatment recommendations.

## 1.1 Motivation

The motivation behind the SkinSense project is to address significant challenges in dermatological care, specifically the early detection and treatment of melasma. Melasma is a common skin condition that often remains undiagnosed or improperly managed due to limited access to dermatologists and delayed medical attention. By leveraging advancements in machine learning, SkinSense aims to provide a convenient and reliable mobile solution for preliminary skin assessments.

## 1.2 Project Overview

SkinSense is a mobile application developed to detect melasma, a prevalent skin condition characterized by dark, discolored patches, through user-submitted images. The app securely stores these images in a cloud database, where a trained machine-learning model analyzes them to determine the presence of melasma. Upon detection, the app suggests relevant healthcare providers, allowing users to book appointments directly through the platform. This project aims to enhance early diagnosis, increase accessibility to dermatological care, and streamline the consultation process.

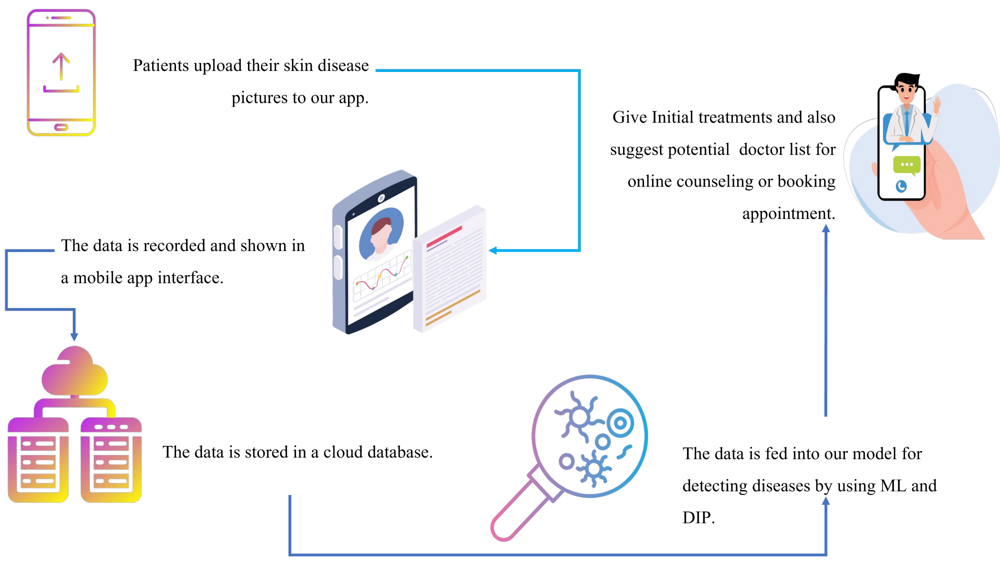


Figure 1.1: System Diagram

## 1.3 Objectives

The SkinSense project has the following key objectives:

- **Develop an Accurate Diagnostic Model:** To train and optimize a machine learning model capable of reliably detecting melasma from user-submitted skin images. This involves assembling a diverse and high-quality dataset, preprocessing images, and employing advanced ML techniques to achieve high diagnostic accuracy.

- **Ensure Data Security and Privacy:** To implement stringent security measures, including data encryption and secure cloud storage, ensuring the protection of user data. Compliance with healthcare data protection regulations is essential to maintain user trust and confidentiality.

- **Create a User-Friendly Mobile App:** To design an intuitive and accessible mobile application that allows users to easily upload their skin images, receive preliminary diagnoses, and book appointments with suggested healthcare providers. The app aims to offer a seamless user experience, accommodating individuals of varying ages and technical proficiency.

- **Integrate with Healthcare Providers:** To establish seamless communication channels with dermatologists and other healthcare professionals. This involves developing APIs for appointment scheduling and integrating the app with existing healthcare systems to facilitate smooth referrals and follow-ups.

- **Enhance User Engagement:** To incorporate features that promote consistent use of the app and adherence to medical advice. This includes reminders for regular skin checks, educational content about melasma, and easy access to support and resources.

The successful implementation of these objectives will enable SkinSense to provide a comprehensive solution for the early detection and management of melasma, ultimately improving healthcare accessibility and outcomes for users.

## 1.4 Methodology

The strategy behind the SkinSense project involves proper planning appropriate for the accurate classification of the skin condition and its further deployment on the market. First of all, a dataset of skin images, with a specific focus on melasma, was created and prepared using various computational methods, including resizing, normalization, and enhancement techniques such as rotation, flipping, and cropping to improve image quality and diversity. Throughout this preprocessing pipeline, the preprocessed images were then fed into a machine-learning algorithm. We initially used Artificial Neural Networks (ANN) for classification tasks, but the results were not satisfactory. The accuracy of this particular model was 58% and this drove the enhancement. As a result, we explored more advanced techniques to enhance the accuracy of our model. Later we conducted a comprehensive comparative analysis using several state-of-the-art pretrained deep learning architectures, including VGG16, VGG19, MobileNetV3-Large, ResNet50, DenseNet201, EfficientNet-B5, and AlexNet. These models were systematically evaluated with various advanced image preprocessing techniques to improve feature representation and overall model performance. The preprocessing techniques applied included rescaling, Contrast Limited Adaptive Histogram Equalization (CLAHE), colorization using Inferno and Plasma colormaps, and histogram equalization. Through rigorous experimentation, we observed that DenseNet201, when combined with rescaling, outperformed the other models, achieving the highest accuracy of 92.46%. Based on these findings, we identified DenseNet201 as the most optimal architecture for integration into our software platform, ensuring robust and reliable classification performance.

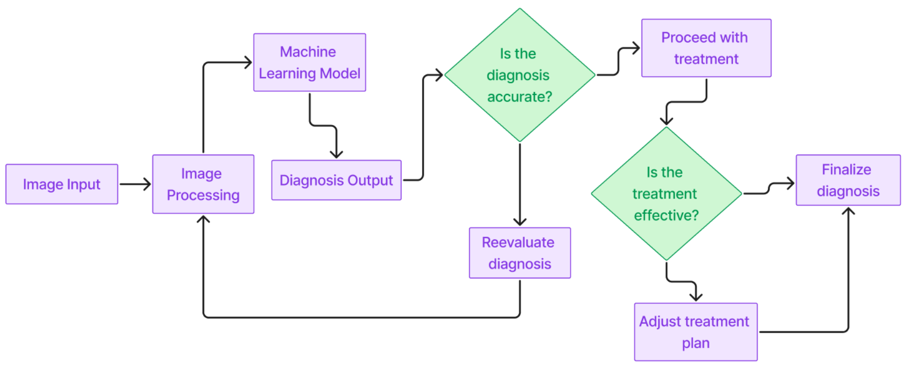


Figure 1.2: Block Diagram

## 1.5 Contributions

- **Development of a Skin Condition Detection System:** It is a mobile platform which performs skin conditions analysis with the emphasis on melasma through image processing and machine learning.
- **Development of a CNN-based classification model:** We implemented and fine-tuned VGG19 with additional dense and dropout layers, improving melasma classification accuracy.
- **Image Processing for Dataset Enhancement:** We introduced a contrast adjustment method that improves feature extraction from medical images.
- **Comparative study of deep learning models:** We evaluated VGG16, VGG19, ResNet, MobileNet, EfficientNet,Alexnet and DenseNet on the melasma dataset to identify the best-performing model.
- **Deployment of an interactive software:** We integrated our trained model into a Streamlit-based web application for real-time melasma detection.
- **Focus on Accessibility and Efficiency:** Built a solution that improves the route for access to dermatological services and reduces the time to wait for the appointment of the doctor, for patients living in remote and low serviced populations.

## 1.6 Project Outcome

The SkinSense project is expected to have the following high-level, measurable, and impactful outcomes in the field of dermatological care by making use of advanced technology:

1. **Accessible Dermatological Diagnostics**
   A SkinSense system will be developed as an accessible platform that will allow users to upload images of skin conditions and obtain preliminary diagnoses via the adoption of advanced Digital Image Processing (DIP) and Machine Learning (ML) techniques.
   SkinSense will help in empowering the people of Bangladesh, in both urban and rural areas, to work for their health without the need for instant physical consultation, providing a portable solution.
2. **Improved Healthcare Access for Underserved Communities**
   The system will act as a bridge between patients and healthcare service providers, especially in remote areas where specialists are not easily accessible. Users will be provided with nearby dermatologists based on their condition and location so that professional help can be reached in time.

3. **Reduced Healthcare Burden**
   SkinSense will ease the burden on city hospitals and dermatology clinics by filtering out non-emergency patients, enabling medical institutions to concentrate on more important cases and improve overall healthcare.
   Minor skin problems may be signposted to appropriate help or support, or users may receive advice on managing their condition until professional help is available.

4. **Empowered Patients Through Self-Awareness**
   To increase health awareness and enhance self-care practices, SkinSense will educate users about their skin conditions and provide insights into possible causes and risk factors.
   The app will allow patients to track their symptoms, leading to more prepared and smarter conversations with dermatologists.

5. **Enhanced Data-Driven Healthcare Solutions**
   The anonymized data obtained from users can be analyzed to identify trends of skin diseases in different geographical regions of Bangladesh, helping public health authorities monitor and prevent skin-related disease outbreaks.
   The system will also improve as it learns more from user feedback and as diagnostic data are accumulated with the help of interested research groups.

6. **Scalable Digital Healthcare Platform**
   The architecture of the SkinSense platform is designed to be scalable and adaptable, allowing future expansions to include other types of diseases or to integrate with other health monitoring systems, resulting in broader healthcare applications.
   As one of the first applications of AI and digital technology in medical diagnostics in Bangladesh, this will help drive innovation in the healthcare sector.

7. **Ethical and Privacy-Respecting Health Solution**
   SkinSense will ensure that users' health data are strictly maintained and processed by setting up robust data privacy measures. This will increase user trust and encourage the adoption of digital health platforms in Bangladesh.
   The anonymous diagnosis feature helps break down the stigma attached to certain skin conditions, encouraging more people to seek help before their condition worsens.

## 1.7 Organization

1. **Introduction**
   This chapter introduces the SkinSense project, discussing its motivation, project overview, objectives, methodology, contributions, and expected outcomes. It highlights the importance of addressing melasma through advanced technology and outlines the goals of the project.

2. **Background**
   This chapter covers the preliminaries of the healthcare system in Bangladesh and the challenges in dermatological care. It provides a literature review on relevant studies, existing solutions, and the gaps in current research related to skin disease detection and management.

3. **Project Design**
   In this chapter, the requirements, both functional and non-functional, for the SkinSense platform are detailed. It also discusses technical requirements, constraints, system design, and the user interface. Task allocation for the development team is also outlined.

4. **Implementation and Results**
   This chapter will provide a detailed explanation of the environment setup, testing procedures, and evaluation results of the SkinSense platform.

5. **Standards and Design Constraints**
   This chapter will explore the standards adhered to in the development of SkinSense, as well as the design constraints encountered, including economic, environmental, ethical, and health and safety concerns.

6. **Conclusion**
   The final chapter summarizes the thesis, highlights the limitations of the project, and provides recommendations for future work.

## 1.8 Summary

Here , the SkinSense application designed to monitor melasma, a common skin disorder. Responding to the necessity of easier dermatological care, especially when it comes to timely diagnosis, SkinSense allows users to upload photos of their skin so they can be examined. Next, in the chain are advanced machine learning algorithms that provide preliminary diagnosis as well as suggest healthcare providers if required. First attempts with Artificial Neural Networks (ANN) did not provide the accuracy needed, hence more sophisticated models like Convolutional Neural Networks (CNN) were investigated to enhance detection precision. The project goals are to improve the accuracy of the diagnosis, secure user data, create a user-friendly interface and integrate with healthcare services. Some of the contributions by SkinSense include developing a powerful diagnostic tool, leveraging machine learning models, applying image processing techniques to fine-tune the dataset. Ultimately, the project aims to decrease patient burden on clinical services and empower users with a greater understanding of the health of their skin.

# Chapter 2

# Background

## 2.1 Preliminaries

The healthcare industry has seen a game-changing transformation in recent years, with the use of digital technology primarily in diagnostics and tools for treatment recommendations and patient-doctor interactions. Nevertheless, ample obstacles are yet faced in ensuring fair, timely and high-quality services to all citizens of developing countries like Bangladesh especially in dermatology. Sky-high waiting times, disastrously overcrowded emergency rooms and a lack of specialist care in rural areas together add up to abysmal treatment and care. Thus, there is a paramount need for an iatrogenesis solution which can meet the requirement of patients directly from healthcare providers concerning dermatological services. Due to all these problems skin diseases are one of the most frequent health issues in Bangladesh which remain mostly untreated. All of this can be made worse by misdiagnosis, ignorance, and delayed treatment — spreading these conditions further that lead to even more serious complications. Moreover, a lot of these individuals who fail to visit a dermatologist because they cannot afford it or simply never mention their skin issues due to stigma. As a result, such a system which offers assistance in preliminary diagnosis and treatment support would have a profound beneficial effect on people suffering from skin diseases. Due to all these problems skin diseases are one of the most frequent health issues in Bangladesh which remain mostly untreated. All of this can be made worse by misdiagnosis, ignorance and delayed treatment — spreading these conditions further that lead to even more serious complications. Moreover, a lot of these individuals who fail to visit a dermatologist because they cannot afford it or simply never mention their skin issues due to stigma. As a result, such a system which offers assistance in preliminary diagnosis and treatment support would have a profound beneficial effect on people suffering from skin diseases. The essential use of skinsense is:

- Including an image upload feature that allows users to photograph their skin conditions

- Improving image quality for better detection using image enhancement techniques

- Processing images with sophisticated pattern recognition and classification techniques
- Providing an initial diagnosis using image analysis
- Referrals to local dermatologists or healthcare providers

SkinSense provides such functionality to meet the dire demand for affordable, accessible, and dependable dermatological services in Bangladesh. The app acts both as a diagnostic and educational/advisory tool, educating users about their skin condition and what to do next. With privacy in mind, the system allows users to request help in a way that is not shared. Additionally, the application works offline for core functionalities to enable its use in low internet connectivity areas. The proposed SkinSense system follows a modular structure, including the following components:

1. **User Interface (UI)** for image upload and symptom input
2. **Digital Image Processing (DIP)** to enhance image quality
3. **Machine Learning (ML)** Model for disease detection and classification
4. **Backend Services** for storing data, providing treatment suggestions, and offering doctor recommendations

The combination of these components results in a full solution that can be used for the automatic detection of skin diseases and consequently, this leads to lesser burden on already choked healthcare systems leading to better treatment outcomes and empowering individuals to manage their health. The basics of this project include altogether understanding the technology that is used in DIP for image enhancement and then using machine learning tools for better Image Classification. A large dataset of images with many types of skin diseases is also key. Lastly, developing a user-friendly interface that allows for easy use while maintaining patient privacy is necessary to ensure the application can be widely adopted, particularly among lay users in rural communities. Addressing these areas, SkinSense presents a stand-out solution to some of the prominent healthcare challenges haunting Bangladesh and simultaneously lends significant momentum in pushing the envelope for quality dermatological care through technological innovation.

### 2.1.1 Related Research

In [1], the pilot study involved ten female patients with Fitzpatrick skin types III–V and melasma, treated with four to six sessions of Fraxel laser (initially 1,535 nm, later 1,550 nm). Treatment settings ranged from 2,000 to 3,500 mctz/cm$^2$ and energy levels of 6 to 12 mJ per microthermal zone, spaced 1 to 2 weeks apart. Post-treatment care included Aquaphor and moisturizer. Evaluation methods included photo comparisons, patient-reported satisfaction (very satisfied to unsatisfied), pain scores (1 to 10), and treatment outcomes based on melasma clearance (0-100%). Results showed mild side effects, moderate pain (average 6.3/10), and 60% of patients achieving 75-100% clearance. Limitations included the absence of melasma type categorization and a small sample size, necessitating larger studies and long-term follow-up to optimize treatment efficacy and recurrence management.

In [2], the document examines melasma using databases like PubMed, Cochrane Library, MEDLINE, and Embase. It discusses symptoms and challenges in treatment, noting tools such as Mexameter for skin pigmentation assessment. Treatments like sunscreen, creams, peels, and lasers are reviewed for efficacy. It advocates a multidisciplinary approach to enhance patient quality of life, addressing medical and emotional needs. Despite progress, melasma's exact cause remains unclear, with variable treatment outcomes prompting the need for early intervention. Future research aims to understand causes better, develop new treatments, personalize care, explore prevention, and assess psychological impacts, emphasizing the importance of long-term treatment studies.

In [3], this study, approved by the Ethics Committee of the First Affiliated Hospital of Chongqing Medical University, analyzed 4005 melasma and 4005 non-melasma images from the VISIA imaging system to develop a binary classifier for melasma. Using deep learning models including MobileNetv2, Swin Transformer, ResNet50, and DenseNet121, the study evaluated ROC curves, with DenseNet121 achieving the highest AUC of 97.87%. Confusion matrices showed ResNet50 had the highest sensitivity (97.14%), while DenseNet121 balanced specificity (95.88%) and sensitivity (94.29%), yielding the highest overall accuracy of 93.68% among the models tested.

In [4], this updated review on melasma pathogenesis explores its multifaceted origins involving genetic predisposition, UV exposure, and hormonal influences. It emphasizes how UV irradiation stimulates melanogenesis through molecular pathways affecting both melanocytes and keratinocytes, although direct evidence linking UV exposure to melasma remains inconclusive. The review also discusses similarities in dermal changes between melasma and chronically sun-exposed skin, suggesting shared underlying mechanisms despite their distinct clinical presentations. Melasma's higher prevalence in females, varying by country (e.g., 21:1 in Singapore, 4:1 in India), underscores hormonal influences, with estrogen and progesterone receptors elevated in hyperpigmented areas, potentially enhancing melanogenesis through various biochemical pathways. Factors such as pregnancy and oral contraceptives exacerbate these hormonal effects, contributing to melasma development.

In [5], the study conducted at Yeouido St Mary's Hospital from 2015 to 2018 compared quality of life (QOL) in Korean adults with Riehl's melanosis, melasma, and healthy controls using DLQI and MELASQOL questionnaires. It involved 164 participants: 52 with

Riehl's melanosis, 57 with melasma, and 55 healthy individuals. Statistical analyses including Student's t-test and Spearman's rank correlation coefficients found that patients with Riehl's melanosis reported significantly higher DLQI and MELASQOL scores compared to both melasma patients and healthy controls, indicating poorer QOL across various domains.

In [6],the paper reviews non-invasive techniques for evaluating melasma treatment progress, focusing on tools like Chromameter, Mexameter, and Dermacatch for objective assessment. It explores advanced imaging methods such as UV light imaging with sCMOS CCD cameras, VISIA for complexion analysis, Antera 3D for reflectance mapping, dermoscopy, and reflectance confocal microscopy (RCM) to quantify pigmentation, melanin concentration, and vascular changes. These techniques aim to provide detailed insights into disease severity and treatment outcomes, addressing the limitations of subjective evaluation methods in melasma management.

In [7] the study uses image processing and machine learning to detect Eczema, Melanoma, and Psoriasis with 100% accuracy using a small dataset of 100 images. It standardizes image sizes, extracts features with a pretrained convolutional neural network (CNN), and employs a Support Vector Machine (SVM) for classification. Limitations include the need for a larger, more diverse dataset, deeper skin analysis, a mobile app for accessibility, severity detection capabilities, and testing with varied image conditions. Future work aims to develop a mobile app, expand disease detection capabilities, and enhance skin analysis depth.

In [8],the study utilized a methodology involving resizing images to 227x227 pixels, extracting features with AlexNet (a pretrained CNN), and classifying diseases using SVM. It achieved 100% accuracy in detecting Eczema, Melanoma, and Psoriasis, but with limitations: a small dataset of 100 images, restricted disease scope, and shallow skin analysis. Future work includes developing a mobile app for accessibility, expanding disease detection capabilities, analyzing deeper skin layers, and validating the system with larger datasets for broader application.

In [9], the study enhances the Hybrid method using a generalized distance measure and combines local and global thresholding for better segmentation in melasma assessment. It introduces the modified Melasma Area and Severity Index (mMASI), evaluating severity across facial regions based on area and darkness. Output includes MASI scores for severity assessment, compared with dermatologists' mMASI scores to measure accuracy using correlation. Challenges include noise sensitivity, addressed by the generalized distance measure. Future work aims to refine this measure, apply methods to other skin lesions, and improve preprocessing for enhanced performance. Achieving an  value of 1.2, the study shows high correlation indices (Spearman's ratio) with fewer errors compared to other methods, indicating superior accuracy in melasma severity assessment.

In [10],the study introduces a novel distance measurement method to improve the analysis of melasma in images, combining local and global techniques for enhanced processing. Using data from 29 patients evaluated by dermatologists, it develops an improved hybrid segmentation method and applies a new distance measurement technique. Output includes severity scores of melasma using different  values, with optimal results observed at  = 1.2. Previous methods were challenged by noise sensitivity and variability among assessors. Future work aims to refine image preparation, score estimation, and noise handling in segmentation methods. Accuracy is assessed by comparing the new method's results with dermatologists' scores, showing highest consistency and accuracy at  = 1.2.

## 2.2 Literature Review

**Table 2.0 – Literature Review table**

| **Ref no** | **Methodology** | **Models** | **Output** | **Gap** |
|---|---|---|---|---|
| [1] | Ten melasma female pateints received 4–6 Fraxel laser sessions spaced 1–2 weeks apart, using a 1,535 nm prototype and later a 1,550 nm laser. Post-care included Aquaphor and moisturizer. Evaluations were based on photos, patient satisfaction, and pain scores.. | • Photo comparisons<br>• Patient-reported satisfaction<br>• Pain scores (1 to 10)<br>• Melasma clearance percentage | • Moderate pain reported (average score: 6.3/10)<br>• 60% of patients achieved 75-100% melasma clearance<br>• Mild side effects observed | Lack of categorization of melasma types via biopsy or Wood's light examination. |

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**Table 2.1 – continued from previous page**

| Ref no | Methodology | Models | Output | Gap |
|---|---|---|---|---|
| [2] | Discussing pathogenesis, treatment options, and advancements in the field of melasma research and management. | • The document reviewed studies from databases such as:<br>– PubMed<br>– Cochrane Library<br>– MEDLINE<br>– Embase | • Melasma's exact causes remain unclear despite research progress | Need to enhance patient quality of life through holistic care addressing medical and psychosocial aspects. |
| [3] | Collected and analyzed 4005 melasma and 4005 non-melasma images from the VISIA imaging system. Four deep learning models (MobileNetv2, Swin Transformer, ResNet50, DenseNet121) were used. | • MobileNetv2<br>• Swin Transformer<br>• ResNet50<br>• DenseNet121 | • DenseNet121 achieved the highest Area Under the Curve (AUC) at 97.87% | No gap found. |
| [4] | Discusses the complex etiology of melasma, implicating genetic factors, UV exposure, and hormonal influences. | • No models required | • Highlights hormonal involvement and genetic factors in melasma | No gap found. |

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**Table 2.1 – continued from previous page**

| Ref no | Methodology | Models | Output | Gap |
|---|---|---|---|---|
| [5] | Cross-sectional study involving adults diagnosed with Riehl's melanosis and melasma by dermatologists, using DLQI and MELASQOL questionnaires. | • DLQI<br>• MELASQOL | • Riehl's melanosis patients had higher DLQI and MELASQOL scores, indicating poorer quality of life | Lack of specific quantitative findings or statistical data comparing QOL scores. |
| [6] | Utilized various imaging and measurement techniques to assess pigmentary skin conditions. | • sCMOS CCD<br>• VISIA<br>• Antera 3D<br>• Dermoscopy<br>• RCM | • Quantified pigmentation distribution<br>• Melanin concentration<br>• Vascular changes | Highlights the limitations of current methods and the need for objective indicators. |
| [7] | Images were resized, important features were identified, and an SVM classified skin diseases. AlexNet was used for feature extraction. | • AlexNet<br>• SVM | • Detected Eczema, Melanoma, and Psoriasis with 100% accuracy | Small dataset, limited to 3 diseases, needs expansion and deeper analysis. |

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**Table 2.1 – continued from previous page**

| Ref no | Methodology | Models | Output | Gap |
|---|---|---|---|---|
| [8] | Images were resized, AlexNet extracted features, and a SVM classified skin diseases. | • AlexNet<br>• SVM | • 100% accuracy for detecting three skin diseases | Small dataset, limited disease detection, needs mobile app and deeper analysis. |
| [9] | Improves optimal hybrid thresholding (oHybrid) by using a generalized distance measure and combining local and global thresholding methods. | • Modified Melasma Area and Severity Index (mMASI) | • $\alpha$MASI score correlates well with dermatologist-provided mMASI scores | Addresses sensitivity to noise, improving segmentation reliability. |
| [10] | Introduces a new distance measurement method for melasma analysis, validated with images from 29 patients. | • Enhanced hybrid method for image segmentation | • Optimal $\alpha = 1.2$ for measuring melasma severity | Previous methods had noise sensitivity and assessor inconsistency. |

### 2.2.1 Benchmark Applications

The following table provides a benchmark analysis of existing skin disease detection systems and research studies. It highlights key features, methodologies, and technologies that set the standard for SkinSense's development. This analysis serves as a reference point to ensure that SkinSense meets or exceeds industry standards in terms of functionality, accuracy, and user experience.

**Table 2.1 – Benchmark Analysis table**

| Feature | SkinSense | SkinVision | DermaAid | Miiskin |
|---|---|---|---|---|
| Scope of Condition | wide range(general skin disease) | Focus on skin cancer | Multiple skin conditions | focus on mole monitoring |
| Ai Diagnosis | yes(DIP and ML for detection) | yes(Melanoma/cancer) | yes (multiple Condition) | no (image monitoring only) |
| Doctor Recommendation | yes connects to dermotologies based on location and condition | yes with teledermotology | no integration | yes user can sent images to dermotologies |
| Educational Resources | planned (educating users on condition) | limited | yes provide information on conditions | no |
| Symptom tracking | yes user can track symptoms | no | yes allows tracking | yes for monitoring changes |
| Price | free(open access) | paid for premium features | free with somE paid features | free with some optional paid features |
| Market Availiability | Bangladesh Focused | Global | Global | Global |
| Multilingual support | Planned Bangla and English | English | Multilingual | English |

### 2.2.2 Gap Analysis

To evaluate the existing solutions and identify areas of improvement for SkinSense, a comprehensive gap analysis was conducted. The following table compares various skin disease detection applications and research studies, highlighting key features and methodologies. This analysis helps pinpoint the unique contributions of SkinSense and identifies gaps in current approaches, thereby guiding the enhancement of its features and functionalities.

**Table 2.2 – GAP Analysis table**

| **Paper Title** | **Fitzpatrick Skin Type Classification** | **CNN** | **ResNet 50** | **VISIA Complexion Analysis System** | **YOLO V8** | **Detecting Skin Disease** |
|---|---|---|---|---|---|---|
| SkinSense: Comprehensive Skin Disease Detection and Advisory System using Image Processing, Machine Learning and HCI | no | yes | no | no | yes | yes |
| Using Machine Learning Algorithms to Diagnose Melasma from Face Images | no | no | no | no | yes | yes |
| The Treatment of Melasma with Fractional Photothermolysis: A Pilot Study | yes | no | no | no | no | no |
| Melasma Detection Using Neural Networks | no | yes | no | no | no | yes |
| An Intelligent Diagnostic Model for Melasma Based on Deep Learning and Multimode Image Input | no | no | yes | no | no | yes |
| A Method of Skin Disease Detection Using Image Processing and Machine Learning | no | yes | yes | no | no | yes |

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**Table 2.3 – continued from previous page**

| **Paper Title** | **Fitzpatrick Skin Type Classification** | **CNN** | **ResNet50** | **VISIA Complexion Analysis System** | **YOLO V8** | **Detecting Skin Disease** |
|---|---|---|---|---|---|---|
| Pilot Study of an Automated Method to Determine Melasma Area and Severity Index | yes | no | no | yes | no | no |
| Recent Advancements and Perspectives in the Diagnosis of Skin Diseases Using Machine Learning and Deep Learning | no | yes | yes | no | no | yes |

## 2.3 Summary

The dermatological situation in developing countries like Bangladesh is rather critical, as waiting periods are long, specialist care is in shortage, and facilities are overcrowded— all these factors make access to timely and quality care prohibitive. Skin diseases are common, mostly untreated, with resultant complications because of misdiagnosis and delayed treatment, also compounded by a low financial status and social stigma that make them not seek help.

To that end, SkinSense is developing a platform for ease of preliminary diagnosis and treatment support. Its key functionalities will include uploading of the skin condition on the platform for further analysis, enhancing the quality of such images using digital image processing techniques, usage of sophisticated algorithms for disease detection and classification by machine learning, and suggesting local dermatologists or healthcare. Integration of these functionalities allows SkinSense to educate the users about their conditions for better management of health besides diagnosis. The system maintains privacy and works in Bengali, offline, to help poor people in remote areas where access to the internet is limited.

This modular approach powers dermatological care with a more effective user interface, digital image processing, machine learning, and backend services to position SkinSense for a game-changing experience in best dermatological care in the Bangladesh healthcare system.

# Chapter 3

# Project Design

This chapter outlines the design methodology, system requirements, and the project plan for SkinSense, a skin disease detection system utilizing AI/ML and Digital Image Processing (DIP).

## 3.1 Requirement Analysis

While developing the SkinSense platform, it is important to define what requirements will be necessary for guiding the system's functionality and performance. This section describes functional requirements, outlining what features and capabilities the system must supply to satisfy user needs. Additionally, the non-functional requirements will address the performance attributes and constraints that the system should adhere to, ensuring a reliable and efficient user experience.

## 3.2 System Requirements

### 3.2.1 Functional Requirements

The functional requirements articulate those specific behaviors and functionalities that the SkinSense platform must deliver. These requirements document what the system is supposed to be doing, such as features to facilitate interactions by users in support of the primary objectives of the platform. These are the core features and functionalities that the system must implement:

1. **Image Upload & Input Management**
   Users must be able to upload images of their skin conditions via mobile app or web platform. The system should allow users to input additional symptoms in text form, if applicable.

2. **Image Preprocessing (DIP - Digital Image Processing)**
   The system should automatically enhance the uploaded images (adjust brightness,

contrast, remove noise) to prepare them for disease detection. Image normalization should ensure the system handles different image sizes and qualities consistently.

3. **Skin Disease Detection (ML - Machine Learning)**
   The system must analyze the uploaded images using trained machine learning models to detect potential skin diseases.

4. **Symptom Matching**
   The system should cross-reference the image analysis with the reported symptoms to improve diagnostic accuracy.

5. **Doctor Recommendation System**
   The system should recommend dermatologists based on the detected skin condition and the user's location.

6. **Educational Resources**
   The system should provide educational information about the diagnosed skin condition, including symptoms, causes, and prevention measures.

7. **User Account Management**
   Users should have the option to create accounts to save their previous diagnoses, symptom history, and track changes over time.

### 3.2.2 Non-Functional Requirements

The non-functional requirements specify the quality attributes and constraints that the SkinSense platform must satisfy. These requirements focus on how the system performs its functions; for example, addressing issues related to usability, reliability, performance, and security. These ensure the system performs well and delivers a quality experience:

1. **Usability**
   The app has an intuitive user interface for easy navigation.

2. **Performance**
   The system processes image uploads and delivers a preliminary analysis within 10-15 seconds.

3. **Scalability**
   The software architecture has been designed to scale, allowing the system to handle more users over time.

4. **Data Security and Privacy**
   User data is encrypted and stored securely, complying with data protection laws like GDPR or HIPAA.

5. **Availability**
   The app has high availability, ensuring users can access it at all times, ideally with 99.9% uptime.

6. **Maintainability**
   The system should have a modular architecture for easy updates and feature additions.

### 3.2.3 Technical Requirements

The SkinSense platform requires a non-complex mobile application that can be versatile on different operating systems; this would mean both operating systems, Android and iOS, using a robust framework such as React Native for cross-platform. Further, it requires integration with a secure cloud-based database like firestore to store user information and uploaded images in conformation with privacy regulations. The model is capable of image processing, using libraries like OpenCV that help improve the quality of an image. Advanced machine learning algorithms like CNN were used for the detection of disease which will efficiently classify skin conditions based on uploaded images. The system work offline to cater to users where internet access may be underprivileged people. Local referral features will need access to a geolocation service to recommend nearby dermatologists or healthcare providers. In general, infrastructure should guarantee scalability, security of data, and smooth user experiences. These are the technical specifications necessary for implementing the system:

1. **Software**
   - Mobile app development using React Native.
   - Backend using Firebase
   - AI/ML frameworks like TensorFlow, Keras etc.
   - Databases like firestore

### 3.2.4 Regulatory Requirements

The legal and compliance standards that the SkinSense platform has to adhere to operate in the healthcare industry. This section throws light on the regulations, guidelines, and industrial standards that dictate the basis of data privacy, security, and care of patients. Satisfaction of such requirements is of paramount importance in building user trust in the delivery of health solutions that are effective and safe. These ensure compliance with health and safety standards:

1. **Compliance with Health Regulations**
   The application comply with Bangladesh's healthcare regulations, ensuring accurate information and certified healthcare connections.

2. **Ethical Use of AI**
   The AI models must be trained and validated to prevent bias in diagnosis, ensuring fair treatment for all users.

### 3.2.5 Constraints

These are the limitations or restrictions the project might face:

1. **Internet Access**
   Users in rural areas might face connectivity issues, so offline functionality should be considered.

2. **Medical Certification**
   The app may need medical certification before its release.

3. **Financial Constraints**
   The cost of developing and maintaining AI models may pose financial challenges.

### 3.2.6 Block Diagram

The process begins by using an image dataset containing classified pictures of melasma and clear skin. These images underwent preprocessing, where adjustments were made to contrast and saturation to improve clarity and enhance the features necessary for accurate detection and later some preprocessing techniques were used like CLAHE and colourization were used to improve the training process. Once the dataset were ready, a Convolutional Neural Network (CNN) model with pretrained models such as VGG16, VGG19 ResNet, DenseNet,MobileNet,ALexnet and EfficientNet were applied for melasma detection. These models are specifically chosen for their ability to effectively analyze and identify patterns associated with skin conditions. If the detection accuracy improves and the system reaches a satisfactory level of confidence, the diagnosis is confirmed. Upon confirmation, a list of doctors is provided to the user, offering options to schedule appointments based on availability. Additionally, if further consultation is required, users are offered online counselling services. This final step ensures that individuals can receive proper medical guidance from the comfort of their own homes, bringing the process to a complete and well-rounded conclusion.

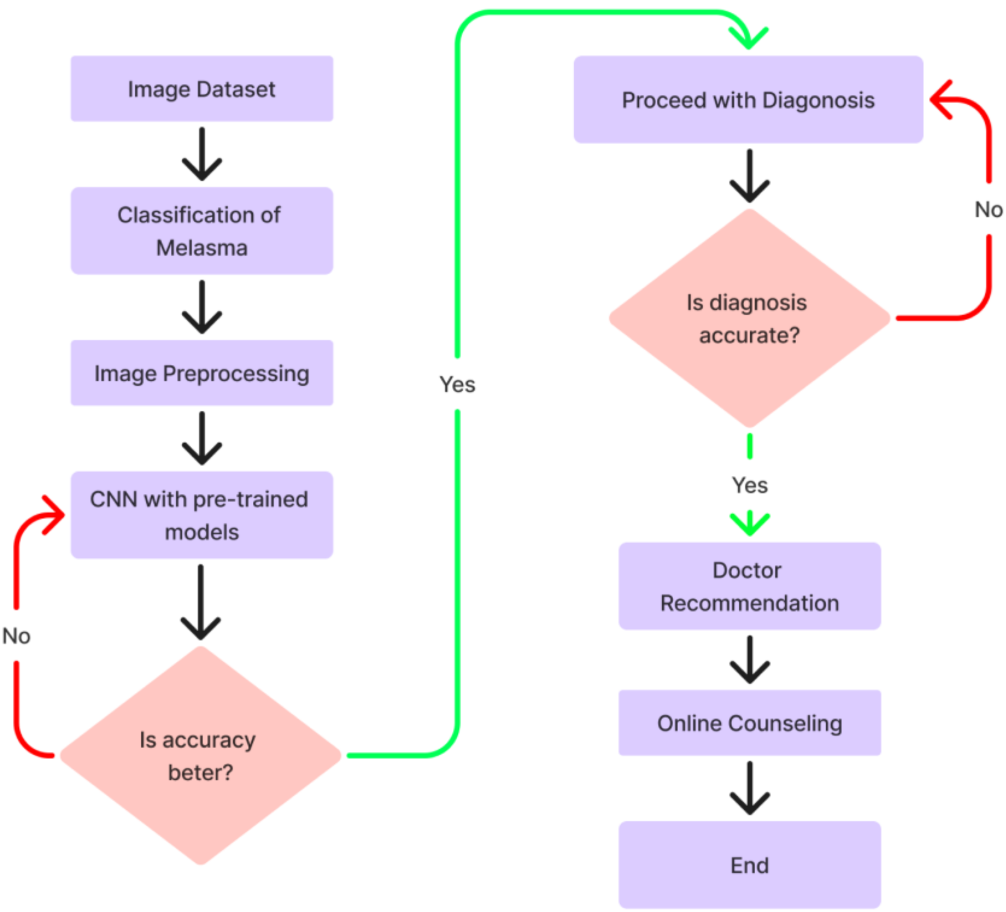


Figure 3.1: Block Diagram

### 3.2.7 Context Diagram

This diagram represents the high-level workflow of the **SkinSense** system, illustrating the interactions between various modules.

**Patient Schedule Management**: Manages the patient's scheduling information and processes their skin condition images, along with basic information such as name, age, and preliminary diagnosis. This data is forwarded to the core **SkinSense** system for analysis.

**Doctor Suggestion**: Based on the analysis, **SkinSense** generates a list of suggested doctors for consultation. It evaluates the preliminary diagnosis and patient data before recommending doctors.

**Image Processing and Analysis**: This module is responsible for processing the skin condition images received from the patient schedule management system. It adjusts images (contrast, saturation, etc.) and performs classification on the skin conditions using machine learning models.

**Diagnosis Generation**: Once image analysis is complete, this module generates a suggested preliminary diagnosis, which includes analyzed skin conditions and classification results.

Each of these modules interacts with the central **SkinSense** system to provide a cohesive diagnosis and doctor suggestion service, automating the process for patients seeking dermatological care.

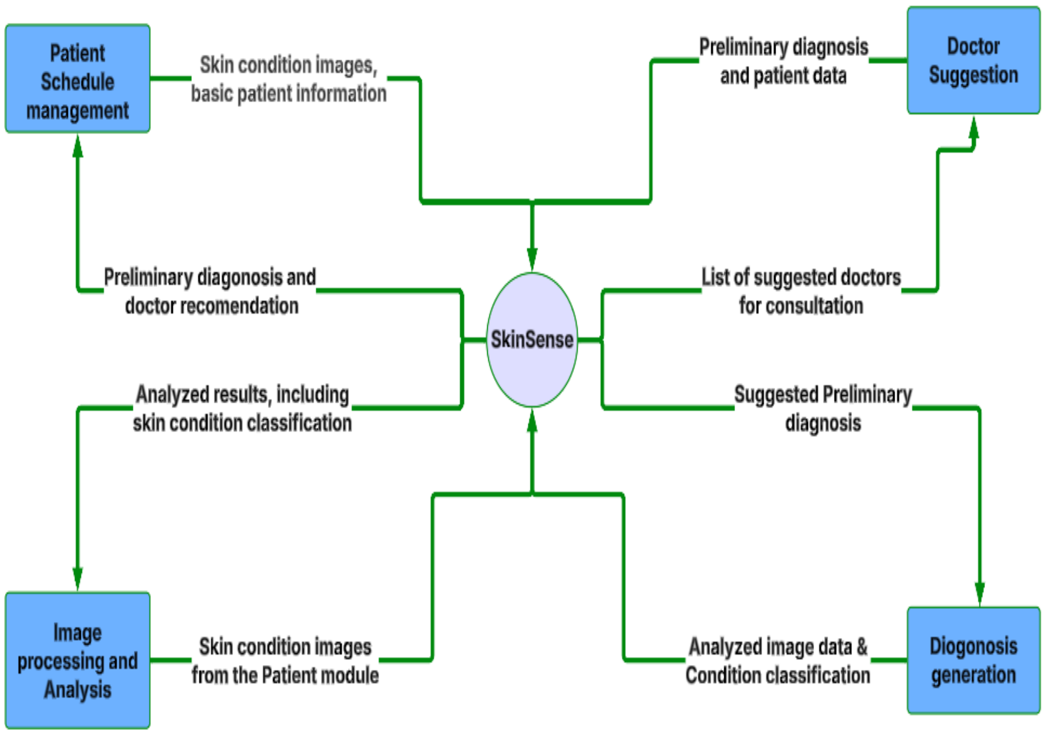


Figure 3.2: Context Diagram

### 3.2.8 Detailed Methodology and Design

This method describes the methodical process of applying machine learning for the detection and diagnosis of melasma. Prompt detection of melasma is important for early treatment and effective management, since delayed diagnosis will result in deteriorating pigmentation and psychological stress for patients. Our goal is to create a strong and efficient melasma detection system that can allow dermatologists and healthcare practitioners to make accurate diagnoses, allowing for early intervention. This is a multi-step procedure involving data gathering, preprocessing, model development, testing, and deployment. The system attempts to enhance diagnostic performance and distinguish between melasma and other dermatologic disorders using the latest deep-learning techniques. It aims to provide an easy and efficient tool for melasma identification irrespective of severity level, thereby improving patient treatment and aiding physicians in clinical decision-making.

**Dataset Collection:** For this study, we collected a diverse dataset from different

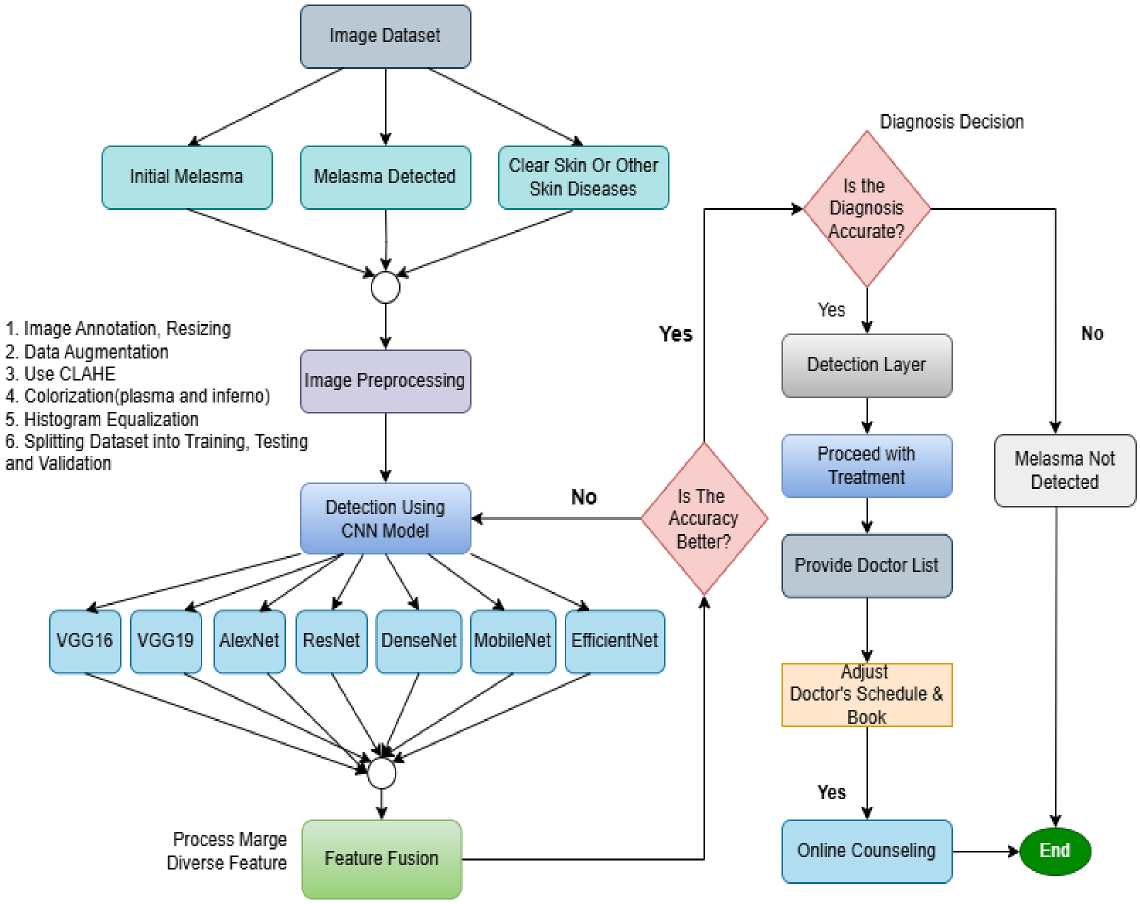


Figure 3.3: Experimental Diagram

sources, including Kaggle, Roboflow, and Google Dataset, to yield a diverse and representative set of melasma-connected images. To facilitate an appropriate classification process, we organized the dataset categorically into three varying subsets: Initial Melasma, Melasma, Null and other Diseases. This categorization helps differentiate between varying phases of melasma and distinguish it from other unrelated conditions of the skin, improving the model's ability to make reliable predictions. In addition, to enrich the quality of our dataset and standardize labelling, we labelled the images attentively using Roboflow, a powerful tool for annotation. Correct labelling is an important aspect of properly training deep learning models, as it enables the model to learn how to recognize and classify melasma properly.

**Dataset Preprocssing:** After organizing and labeling the dataset, we went further to split data to guarantee a good training process. The dataset was split into three parts: training (70%), testing (20%), and validation (10%), adopting a common approach in machine learning to maximize model performance. The training set was employed in training the model to identify melasma patterns, while the validation set facilitated the fine-tuning of hyperparameters and the test set was kept for testing the final model's performance on new data.To improve performance and avoid overfitting, we employed data augmentation methods like rescaling and resizing to ensure consistency. Additionally, we implemented preprocessing techniques like CLAHE, Inferno and Plasma colorization, and histogram equalization to improve contrast and highlight melasma features.

**Detection System Architecture:**This method utilizes several of the pretraining CNN models, such as VGG16, VGG19, MobileNetV2, AlexNet, EfficientNet, DenseNet, and ResNet, are utilized by the detection model. As a comparison, all of them were trained along with multiple preprocessing techniques such as rescaling, CLAHE, inferno colorization, plasma colorization, and histogram equalization. For the enhanced diagnostic accuracy, a CNN Feature Fusion approach is utilized for integration of heterogeneous feature representations of various models. After the model predicts, the system checks its accuracy. If the diagnosis is close enough, the system moves on to the next step. However, if precision is poor, additional refinements are made in order to make the model work better before finally making a decision.

**Diagnostic Decision System:** Upon obtaining an accurate diagnosis, the system moves to the detection layer where treatment steps are suggested. In the detection of melasma, the system moves to suggest treatment via medical means. The system also provides patients with a list of dermatologists. This allows patients to receive professional guidance from medical professionals. The system also assists in doctor scheduling and booking, thus enabling patients to book appointments based on the availability of the doctor.

**System Output Handling:** After a confirmed diagnosis, the system provides online counseling services to enable patients to learn about the condition and treatment options. This is an additional benefit of accessibility to allow users to receive counseling online. If melasma is not detected, the system notifies the user and terminates the process. Through these systematic steps, the system takes an integrated, effective, and user-friendly platform for melasma detection and diagnosis.

### 3.2.9 UI Design

The UI Design for the SkinSense cellular utility was developed with a user-centric approach, focusing on ease of navigation and accessibility. The interface provides a simple and intuitive experience for users to upload skin images for analysis. Key elements of the design include a clear homepage, a step-by-step image uploading process. The color scheme and layout are optimized for clarity, ensuring that users of various technical abilities can operate the app with ease.

## 1. Application UI Screens

### User Onboarding:

The user onboarding screen serves as the first point of interaction for new users. It provides an overview of the SkinSense app, explaining its features and guiding users through the initial setup.

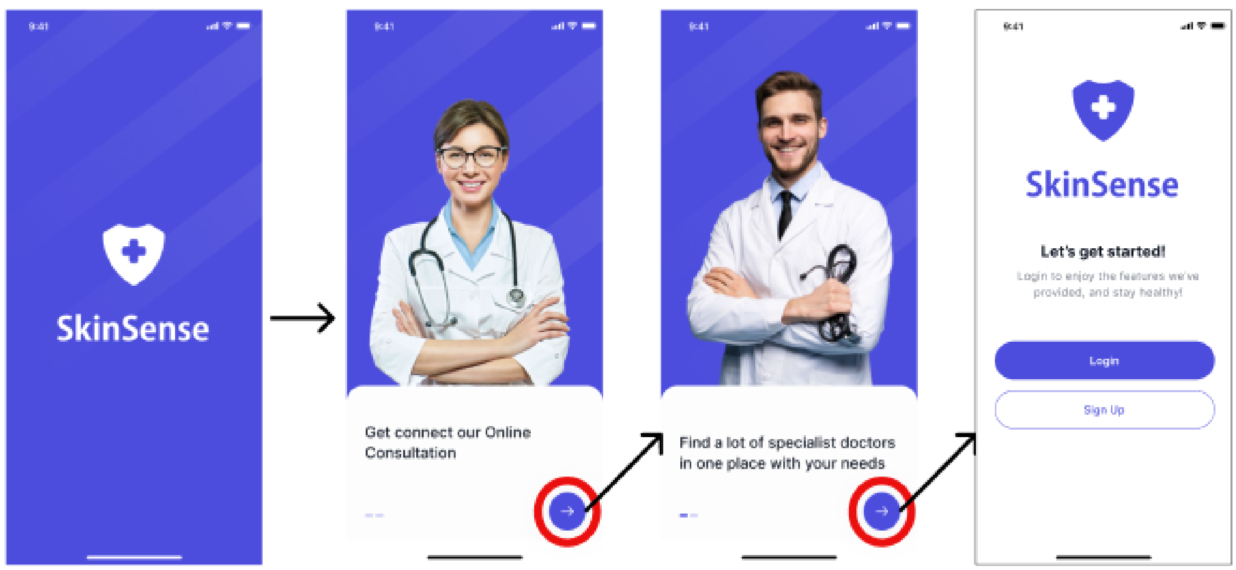


Figure 3.4: User Onboarding

### User Authentication:

Visitors will have two options here: sign up as a Doctor or Patient. If they don't have an account, they must create one. If they already have an account, they can sign in directly by providing valid credentials. If any user tries to give invalid credentials, the system won't let them enter.

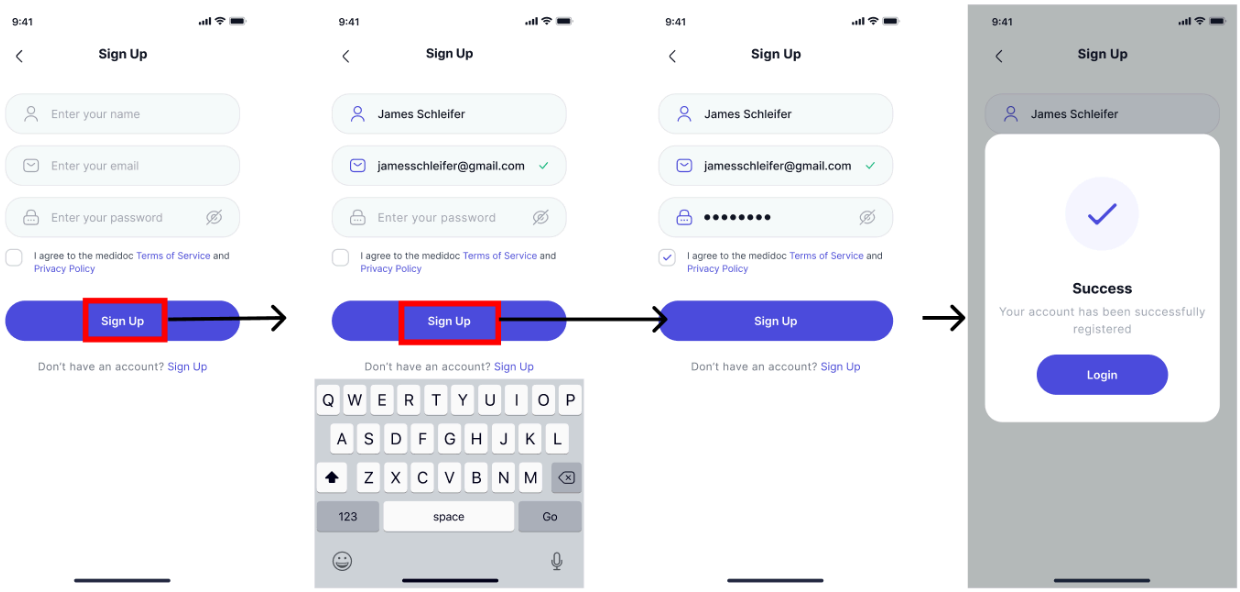


Figure 3.5: User Authentication

## User Home Screen:

Users will get many options here. They can see the doctors available in the system. They have the option of making an appointment with any doctor. They have the option to upload images to verify whether they have Melasma or not. They have the option to search for doctors for specific departments. The Blogs & Articles section in the SkinSense app offers a collection of expert-written articles. The content is regularly updated to keep users informed about the latest developments in dermatology.

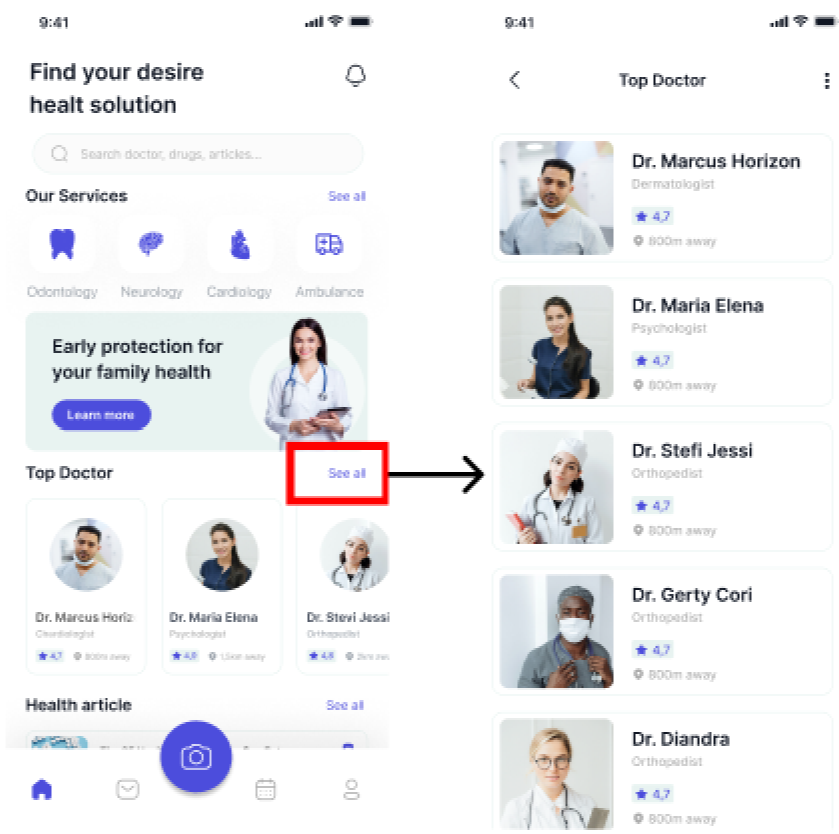


Figure 3.6: User Onboarding

## Melasma Detection:

Users can capture or upload an image of their skin through the app. The image is processed to check for melasma symptoms. The system then categorizes the result into different stages, such as:

- No Melasma (Normal Skin)
- Initial Melasma (Early-stage symptoms)
- Melasma (Visible melasma patches)

Once the detection is complete, users receive detailed insights along with recommendations for further steps, such as consulting a dermatologist through the app.

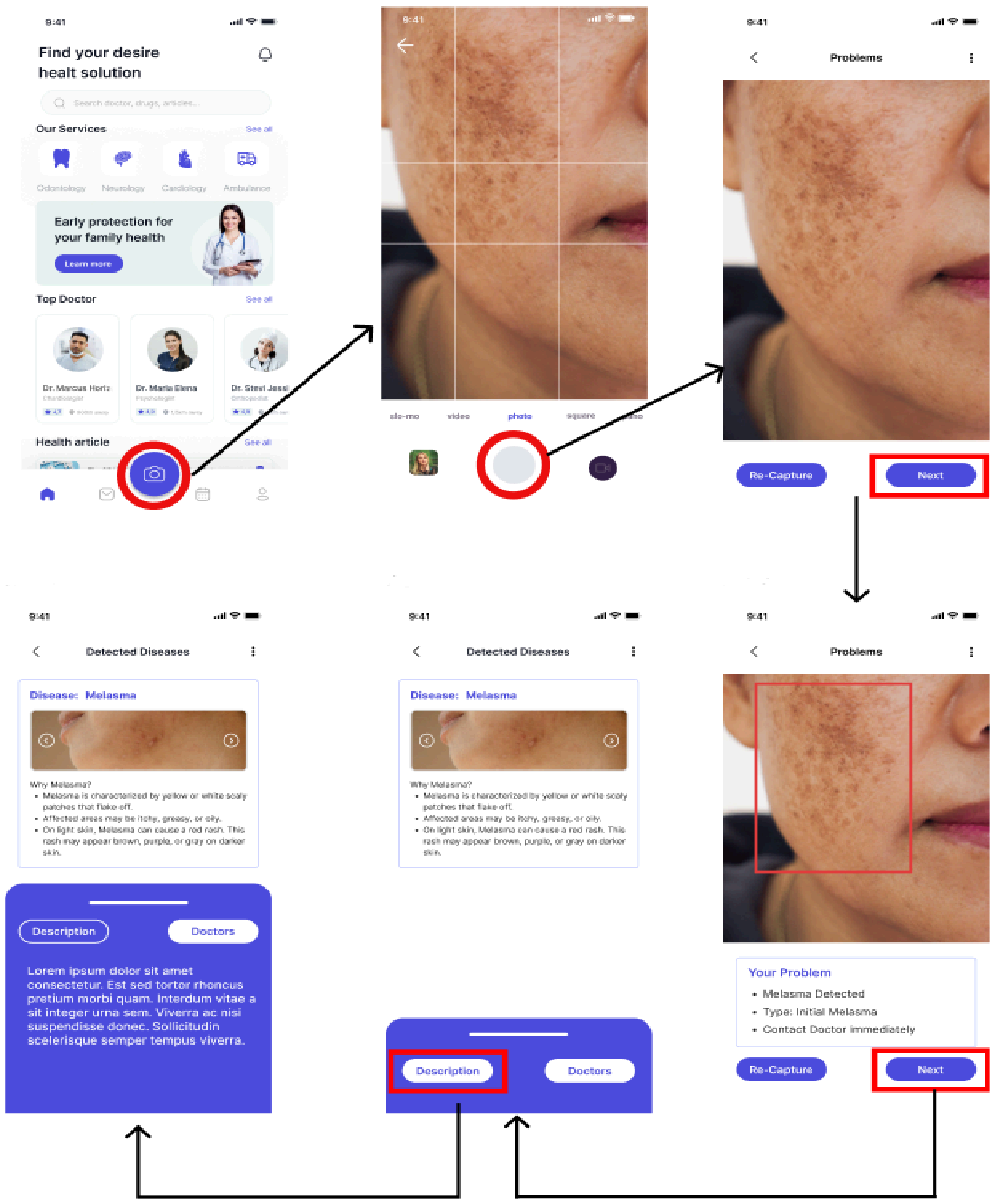


Figure 3.7: Melasma Detection

## Doctor's Portal:

This portal allows doctors to accept or reschedule appointments requested by patients. They can receive calls from patients through the app for online consultations. This makes it easy for users to refer to an expert without visiting a clinic.

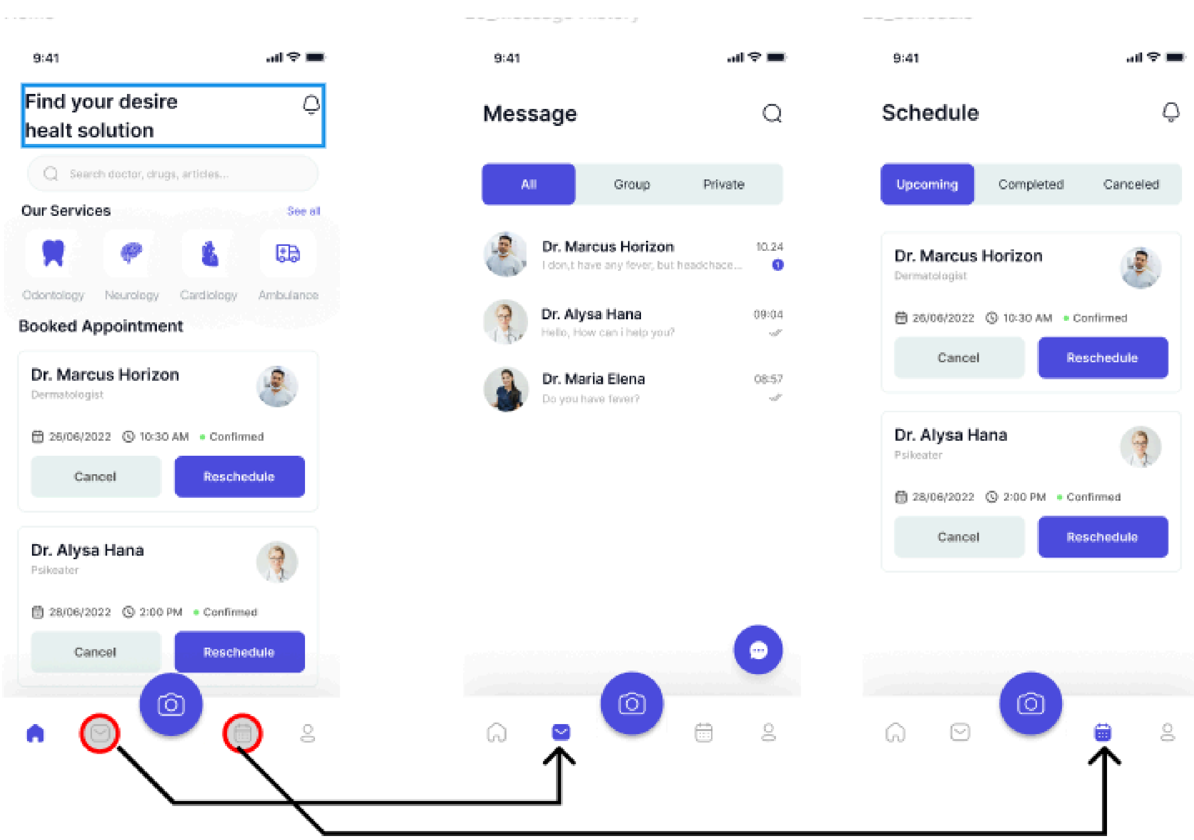


Figure 3.8: Doctor’s Portal

## Doctor's Appointment:

Patients select their physician, decide on the day and time, and request an appointment. The doctor can either accept or reschedule the appointment based on his or her availability. Users can then communicate with the physician through the app via call or message for consultation after confirmation of appointment.

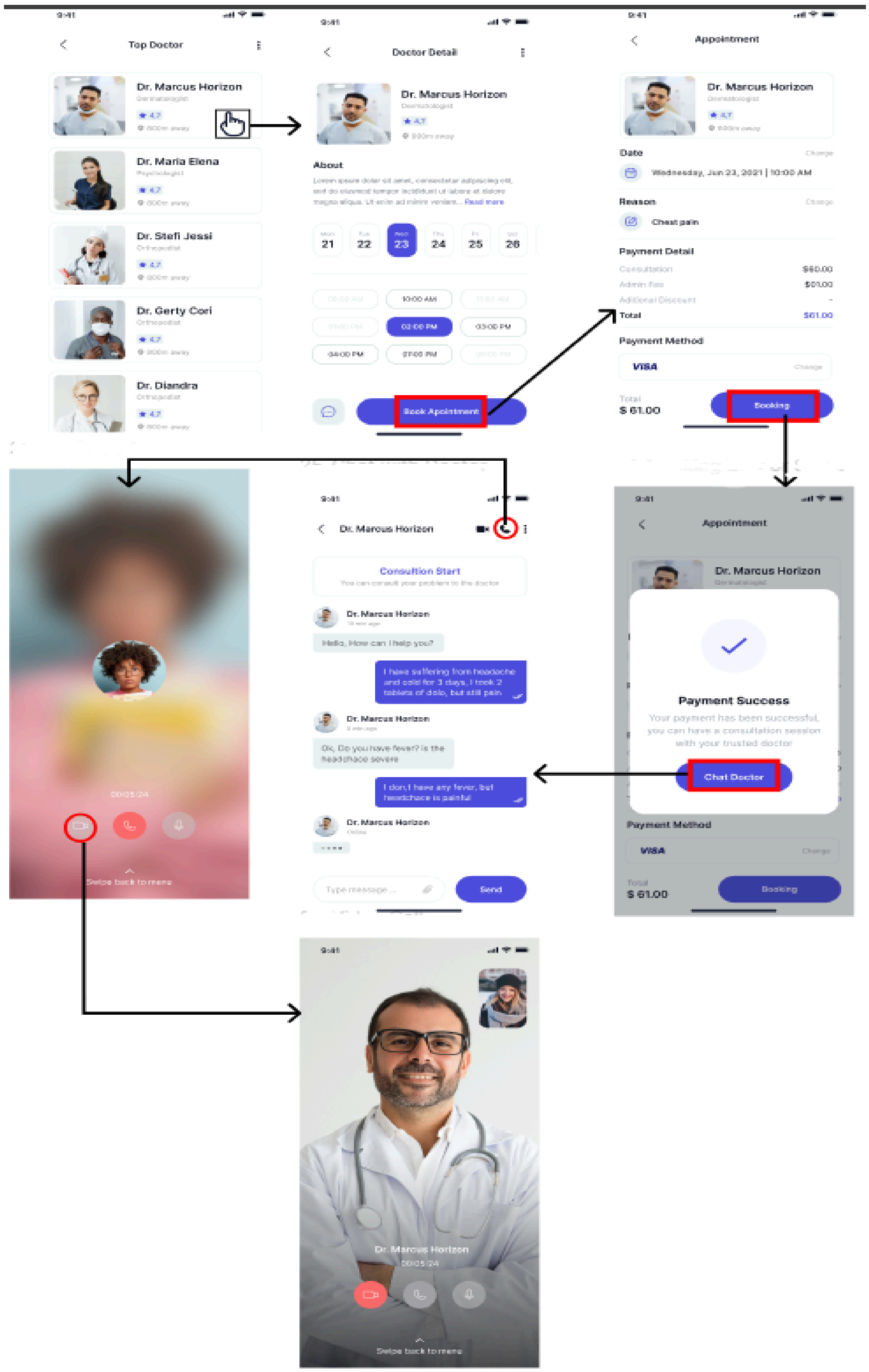


Figure 3.9: Doctor’s Portal

## 3.3 Task Allocation

### 1. Literature Review (May 2024)

**Tasks:**

- Research on skin diseases, particularly melasma.
- Study existing skin disease detection systems.
- Analyze related work on AI/ML and Digital Image Processing (DIP).

**Team Members:** All members.

### 2. Dataset Collection (June 2024)

**Tasks:**

- Identify and collect skin disease datasets.
- Validate and clean datasets for training.

**Team Members:** All members.

### 3. Model Training & Accuracy Optimization (July - September 2024)

**Tasks:**

- **Image Preprocessing:** Implement DIP techniques.
- **Model Training:** Train the machine learning model (CNN).
- **Accuracy Optimization:** Tune hyperparameters for best accuracy and validate with test data.

**Team Members:** Dhrubo, Sama (Model Training), Tazveer, Iqbal, Aungona (Accuracy Optimization).

### 4. Prototype Development (August - September 2024)

**Tasks:**

- Develop initial mobile app prototype.
- Test the prototype for usability and accuracy.

**Team Members:** Dhrubo, Iqbal, Tazveer.

## 3.4 Summary

It's a complete plan for developing the SkinSense platform. It starts through outlining the system's necessities, breaking them down into useful, non-useful, and technical categories. These necessities make sure that the platform will perform its number one feature—detecting melasma—whilst additionally addressing person enjoy, overall performance, and protection concerns.

The bankruptcy goes into detail approximately the gear and frameworks required, consisting of cell app development platforms (e.G., Flutter or React Native), backend technologies (e.G., Node.Js or Django), and machine mastering fashions (e.G., TensorFlow or PyTorch). It further explains the regulatory requirements the platform must meet, which includes compliance with healthcare laws and information safety standards.

Next, the bankruptcy gives the limitations of the assignment, including net access limitations and financial limitations. A context diagram is provided, illustrating the interactions among users, the system, and healthcare vendors. The bankruptcy additionally discusses the undertaking allocation among group contributors and the timeline for development sports.

Finally, the chapter concludes with a UI design that emphasizes simplicity and simplicity of use, catering to customers with various technical skills.

# Chapter 4

# Implementation and Results

## 4.1 Environment Setup

Setting Up the Environment A robust development environment was established for developing and rolling out the SkinSense mobile app, incorporating these configurations.

**Front-end:** React Native (Expo) for cross-platform mobile application development.
**Back-end:** Firebase with Express for API development.
**Database:** Firestore for storing user data and doctor recommendations.
**Deep Learning Model:** VGG16, VGG19, MobileNetV, Alexnet, Resnet, EffecientNet and Densenet.
**Libraries used :** Numpy, Pandas, Tensorflow, Matplotlib, OpenCv, PIL
**Deployment:** Expo Go for testing, with plans to release on the Google Play Store and Apple App Store.
**Tools:** VS Code: This is the main code editor to be used while developing the mobile application. Kaggle: Here, datasets can be gathered, preprocessed, and models can be tested. Android Emulator: This emulated Android platform allows for the mobile application to be tested. Figma: This tool is used for creating the app's UI/UX design and prototyping.
**OS:** Both Windows and macOS OS's will be used for the development, testing, and deployment of the application. This arrangement made for smooth development by merging AI-powered detection of skin diseases with an easy-to-use mobile front end.

## 4.2 Testing and Evaluation

The entire system underwent heavy testing at various levels for the sake of rendering it dependable:

#### Unit Tests

We conducted unit tests on our image preprocessing module to verify correct image resizing and normalization. The tests confirmed that all input images were resized to (224, 224, 3) and normalized within the range [0,1].
All React Native components have been tested with Jest to see whether the UI works properly.
The API endpoints have been tested with Postman to ensure that data communication between the front end and back end occurs.

#### User Testing

We conducted user testing with regular users and dermatologists to assess the usability and accuracy of our melasma detection system. Participants uploaded images of the skin, inspected classification outputs, and provided feedback on result interpretability, response time, and interface clarity. Surveys and observation feedback guided us to enhance the system for better user experience and diagnostic confidence.

## 4.3 Results and Discussion

Among the different pretrained models that were experimented with, VGG16, VGG19, and DenseNet201 provided better performance compared to other models, each with different accuracy levels. The VGG16 model with CLAHE provided an accuracy of 82.47%, whereas VGG19 with rescalling showed a significant improvement, with an accuracy of 86.15%. But the DenseNet201 with rescalling model performed better than both, with an accuracy of 92.46%. These three models provided the best results among all other pretrained models.

| **Pretrained Model** | **Rescaling** | **CLahe** | **Colorization-Inferno** | **Colorization-Plasma** | **Histogram Equalization** |
|---|---|---|---|---|---|
| VGG16 | 80.00% | 82.47% | 79.34% | 80.01% | 82.24% |
| VGG19 | 86.15% | 85.24% | 82.64% | 83.23% | 85.23% |
| ResNet50 | 43.85% | 50.01% | 47.46% | 47.25% | 49.74% |
| MobileNetV3 | 40.00% | 40.00% | 41.12% | 40.00% | 40.00% |
| AlexNet | 45.38% | 65.05% | 40.00% | 54.34% | 65.00% |
| EfficientNet-B5 | 40.00% | 40.00% | 44.23% | 41.00% | 40.00% |
| DenseNet201 | 92.46% | 83.23% | 85.43% | 88.21% | 83.12% |

Table 4.1: Comparative Table of pretrained Models and Preprocessing Techniques

As can be observed from Table 4.1, the DenseNet201 model with rescaling provided a higher accuracy rate and was the top-performing pre-trained model among the tested

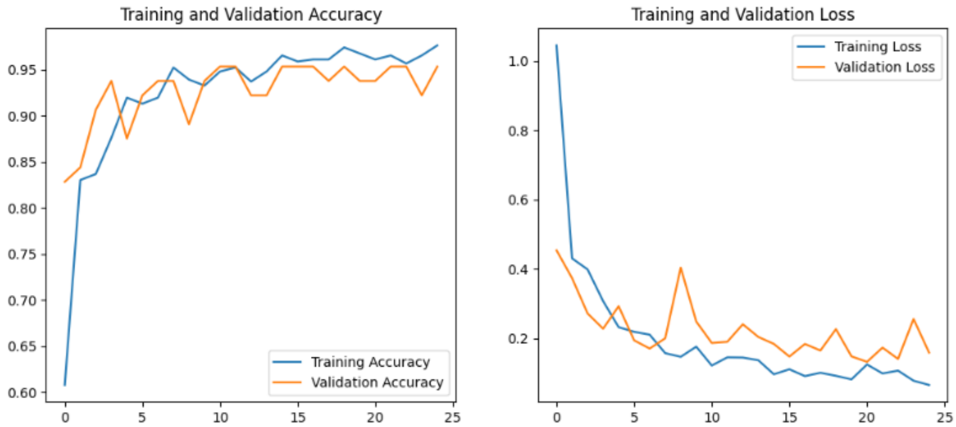


Figure 4.1: Train-validation accuracy and loss

models. Accordingly, we have chosen to implement the DenseNet201 model within our software program due to its high-performance level in accurately classifying the melasma dataset. This merge guarantees that the software delivers strong and consistent results for the purpose intended, taking advantage of DenseNet201's deep learning structure to improve overall performance and user experience.

In figure 4.1 shows that the left chart's training and validation accuracy over some epochs. The blue line, representing training accuracy, begins around 65% and rapidly rises to around 90% within the first five epochs. Similarly, the orange line, representing validation accuracy, begins at 80% and gradually increases to around 93-94%. Both accuracy rates level off after the tenth epoch, with slight fluctuations while still remaining above 90%. The training accuracy sometimes even shoots above 95%, whereas validation accuracy plots a smoother trend. The plot on the right indicates training and validation loss patterns with epochs. Blue is the training loss trace, which starts at very high around 0.8 and sharply decreases throughout the first five epochs. In the same way, the orange line, or validation loss, begins at around 0.5 and falls quite steeply at the start of the training process. At epoch ten, the two values overlap and then level off slowly. After the fifteenth epoch, the validation loss has some fluctuations, but the training loss continues to fall slightly, indicating that the model is continuing to improve.

The heatmap in figure 4.2 shows the confusion matrix of a three-class classification problem: Initial-melasma, Melasma, and Null and Other Diseases. The diagonal entries—26, 43, and 50—represent correct predictions for each class, which reflects the precision of the model. Misclassifications are shown in the off-diagonal cells, where 2 initial-melasma samples were misclassified as melasma, and 4 initial-melasma samples were misclassified as null and other diseases. Also, 1 misclassified case of melasma was classified as initial-melasma, and 2 classified as null and other diseases. Also, 2 null and other diseases were misclassified into other classes. Color intensity in the heatmap indicates the

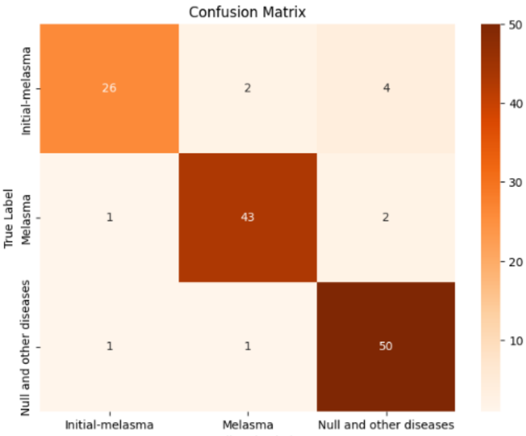


Figure 4.2: Confusion matrix

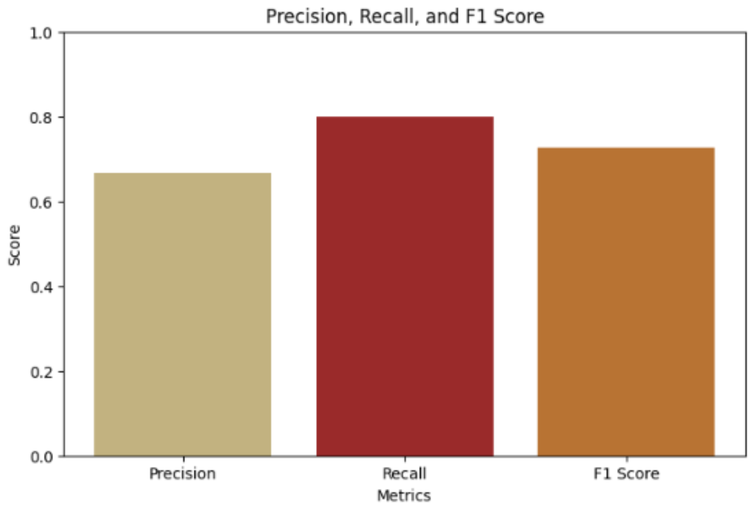


Figure 4.3: Bar chart of precision, recall, and f1-score

performance of the model: dark colors on the diagonal indicate strong classification, and light colors in the areas of misclassification indicate areas where the model can improve.

Figure 4.3 shows that the model is performing well in the three classes with an overall accuracy of 92%, meaning that 92% of the predictions are correct. The model has excellent performance in the "Melasma" class with precision of 0.93, recall of 0.93, and F1-score of 0.93, meaning that it is both accurate in predicting melasma cases and good at getting the majority of them. The "Null and other diseases" class also performs well with precision of 0.89, recall of 0.96, and F1-score of 0.93, showing that the model is very able to identify this category and does not miss a lot of instances. The "Initial-melasma" class does slightly worse with precision of 0.93, recall of 0.81, and F1-score of 0.87, which means that while it is accurate when it predicts this class, it has a tendency to overlook some examples and could be optimized. The macro average and weighted average scores provide a balanced view of the model's performance with good overall model performance of 0.92 for precision, 0.90 for recall, and 0.91 for F1-score. These scores indicate that the model is performing excellent overall but still has room to improve, especially in predicting "Initial-melasma" cases.

## 4.4 Summary

The project integrates AI-driven skin disease detection with a simple-to-use mobile application. It uses React Native (Expo) for cross-platform and Firebase with Express for backend and API development. The application uses deep learning models, including VGG16, VGG19, DenseNet201, and others, for melasma detection. After rigorous testing, DenseNet201 with rescaling proved to be the top-performing model with 92.46% accuracy. User testing was conducted between dermatologists and general users to test usability and correctness of the system, which was useful to improve the system. The model worked exceptionally well in "Melasma" and "Null and other diseases" classification, but showed a small area for improvement for "Initial-melasma" predictions. The system performance is strong with 92% precision, 90% recall, and 91% F1-score overall.

# Chapter 5

# Standards and Design Constraints

## 5.1 Compliance with the Standards

### 5.1.1 Software Standards

The software is designed to adhere to the industry's best practices to ensure it remains maintainable, scalable, and secure. There is a coding convention that is adhered to in a standard way to ensure the structure of the code, readability, and modularity. Security is the utmost priority of the software. Therefore, there are security best practices to be implemented, such as employing secure authentication mechanisms, API security, and data encryption mechanisms to prevent other forms of vulnerabilities.

The application adheres to React Native best practices in terms of state management, reusable components, and performance optimization, which is claimed to enable a better user experience. To enable quick, effective, and universally accepted communication between the front end, back end, and cloud storage, the API integrations are RESTful compliant. The app is also made accessible to adhere to accessibility standards and serve all users, including the disabled.

### 5.1.2 Hardware Standards

The application is developed for generic hardware setups of the devices with the intention of accommodating various models and brands. It is made to perform optimally on Android and iOS operating systems, but it accommodates any device that meets the minimum requirements of:

**Internet Connection:** A proper network connection is needed for uploading the photos and online processing.

**Camera:** The camera must be in good working order to take high-quality images of the skin in order to determine correct and appropriate pathogens.

**Processing Power:** Though the bulk of the computationally heavy machine learning processing is transferred to the cloud, some processing will occur on the device. It will require a minimum of 4GB RAM and a speedy processor for seamless operation. Low-end hardware system optimization promotes diversity among users on a socioeconomic level and allows for low-end hardware penetration into health solution offerings.

### 5.1.3 Communication Standards

Security and privacy are of extremely high importance to the management of private medical information. The application provides information security during transmission through the HTTPS (Hyper Text Transfer Protocol Secure) protocol; therefore, data exchanged between the client side and the server cannot be accessed by third-party interceptors. **Data Encryption:** User images and personal data are encrypted before transmission. Encryption discourages unauthorized access. **Security API:** The app adheres to the OAuth 2.0 standard for secure API calls with authenticated requests; there is no access to other users. **Cloud Integrations:** The system safely communicates with cloud-based storage systems to store and retrieve processed image data in a manner consistent with data protection laws (GDPR, HIPAA). Adherence to these security controls guarantees trust, reliability, and safeguarding of users' sensitive data.

## 5.2 Design Constraints

### 5.2.1 Economic Constraint

In order to reduce economic strain while having a maximum effect, the app is being created to adhere to an economical model with considerations for making open-source development possible by utilizing frameworks such as React Native, TensorFlow, and Firebase; thereby, substantially reducing development and infrastructure expenses.

**Cloud computing:** In contrast to expensive local servers, cloud-based AI processing lowers hardware costs and maintenance burdens.

**Services:**The application offers free use of core features, with extra premium services potentially monetized down the road to support operations. By optimizing available resources, the project offers affordability without compromising on performance or reliability.

### 5.2.2 Environmental Constraint

In general, the traditional method of diagnosing diseases includes face-to-face consultations first which increases the ecological footprint because of the traffic flow and excessive use of paper. The SkinSense app is almost zero-carbon in the following ways:

- **Telemedicine:** By allowing people to send images from home, saves staff time and money and reduces the use of fuel for the staff car.

- **e-Health Clutter-Free Environment:** By computerizing the reports and records, there will be almost no use of printed medical records making it an environment-friendly healthcare practice.

- **Energy-Optimizing Cloud Storage:** With the help of cloud services, servers have a lower energy requirement, consequently, it enables sustainability practices.

### 5.2.3 Ethical Constraint

Better moral aspects are the primary keys in the matter of artificial intelligence (AI) use in medicine. In order to ensure ethical use of the system, we have:

- **Fair Training of AI:** The data collection and analysis model have been designed in a way that eliminates the potential bias of racial and gender, hence, diagnosis in a multi-racial population will be valid and unbiased.
- **Privacy Protection:** Adherence to data protection laws like GDPR and HIPAA ensures that the information of the users is kept private.
- **Transparent AI Decisions:** The app renders its AI actions transparent, so users can observe decision-making instead of getting esoteric predictions.

Such programs aid the ethical advancement of AI technologies with the maintenance of trustworthiness and fairness in dermatological examinations.

### 5.2.4 Health and Safety Constraint

While SkinSense provides early diagnostic information, it is not intended to substitute for a medical consultation with an expert. Key safety precautions include:

- **Medical Disclaimer:** Users are explicitly informed through a message that this application only serves as an auxiliary tool instead of a primary one, thus it cannot replace a specialist dermatologist's advice.
- **Periodic Updates:** Periodic updates as well as constant assessments are witnesses for such performance.
- **User Education:** The application incorporates educational stuff. It includes such basics as: the causes, medicines, and preventive measures.

These benchmarks ensure the safe and suitable use of the device and the reduction of the chance of medical misdiagnosis.

#### Social Constraint

Discoloration of the skin is a psychological problem that affects anyone not only physically but also mentally through social discrimination. The app is structured to advocate for inclusivity and accessibility by accomplishing the following:

- **Confidential Consultations:** A feature is included where a user can ask a question without profaning their identity, which in return lowers social phobia.

- **Educational Activities:** On the one hand, intensive public information campaigns are provided to the user to get to know enough about melasma and its treatment.
- **Different Skin Shades Training:** It is trained in a multiracial way, so as not to be discriminatory against any person as he/she/they should all be detected accurately.

With the incorporation of these options, SkinSense becomes a more inviting and caring setting for health care.

### 5.2.5 Social Constraint

Certain skin conditions such as melasma may lead to social and psychiatric implications; thus, the app avails awareness and access to dermatological insights to ensure inclusivity and better access to healthcare.

### 5.2.6 Political Constraint

Health applications must be compliant with local and international legislation so as to execute legal operations. SkinSense complies with:

- **Digital Service Regulations:** Complying with Bangladesh's digital regulations for online healthcare solutions.
- **Medical Information Standards:** Meeting compliance with international health data regulations (GDPR, HIPAA).
- **Regulatory Approvals:** Collaborating with medical centers to conform to state health policies.

These legal considerations ensure that SkinSense operates within ethical and legal boundaries.

### 5.2.7 Sustainability

The application of digital healthcare solutions forms part of world sustainability efforts. SkinSense app promotes sustainability by: Reducing physical hospital visits, and easing healthcare infrastructure burdens. Encouraging remote diagnoses, and reducing carbon footprint. Through cloud computing, avoiding overuse of resources. With the integration of AI-based diagnostics, the app encourages sustainable, technology-driven healthcare solutions.

## 5.3 Cost Analysis

This project provides an inexpensive and fast solution that leverages non-COTS applications, open-source libraries, and a robust development framework primarily aimed at hosting model training and further application maintenance.

| **Category** | **Details** | **Cost (TK)** |
|---|---|---|
| **Development Team Cost** | Team Members: 5<br>Project Duration: 10 months<br>Monthly Salary per Developer: 20,000 TK | 1,000,000 |
| **Developer Device Cost** | Laptops<br>Mobile Devices for Development | 250,000 |
| **Testing & Maintenance** | Quality Assurance & Testing<br>Post-Development Maintenance | 30,000<br>40,000 |
| **Total Project Cost** | | **1,320,000 TK** |

Table 5.1: Organized Cost Breakdown of the SkinSense Project

## 5.4 Complex Engineering Problem

### 5.4.1 Complex Problem Solving

The teachings of this project will allow for problem-solving in the field of image processing and machine learning for skin disease diagnosis, providing users with accessibility, reliability, and convenience.

Table 5.2: Mapping with Complex Engineering Activities.

| P1 | P2 | P3 | P4 | P5 | P6 | P7 |
|---|---|---|---|---|---|---|
| Dept of Knowledge | Range of Conflicting Requirements | Depth of Analysis | Familiarity of Issues | Extent of Applicable Codes | Extent of Stakeholder Involvement | Interdependence |
| √ | √ | √ | √ | √ | √ | √ |

Table 5.2 presents a mapping of intricate factors of problem-solving along seven parameters (P1 to P7). It captures the extent of complexity of various factors such as Department of Knowledge, Range of Contending Requirements, Depth of Analysis, Familiarity of Issues, Extent of Applicable Codes, Extent of Stakeholder Involvement, and Interdependence. Each factor is symbolized using a tick based on the occurence in association with the respective parameters . The table highlights the varying level of complexity for each parameter and specifies how some of the factors for problem-solving affect the general evaluation of complex tasks. The organization is such that it emphasizes bringing into limelight the major dependencies and stakeholders in the context of machine learning and image processing to diagnose skin disorders.

### 5.4.2 Engineering Activities

The scope of engineering tasks will include gathering datasets for training, designing UI/UX, developing mobile applications, and implementing secure cloud services as joint efforts. (Use Table 5.3).

Table 5.3: Mapping with complex engineering activities.

| A1<br>Range of resources | A2<br>Level of Interaction | A3<br>Innovation | A4<br>Consequences for society and environment | A5<br>Familiarity |
|---|---|---|---|---|
| √ | √ | √ | √ | √ |

Table 5.3 shows the mapping tasks of advanced engineering on five core dimensions: Range of Resources, Level of Interaction, Innovation, Consequences to Society and the Environment, and Familiarity. These dimensions are the range of different elements to be determined when conducting tasks such as gathering datasets, developing user interfaces, designing mobile apps, and setting up secure cloud services. The table is a model for comparing these tasks, with blanks in every cell where information or ratings can be filled. The purpose is to provide a systematic way of comparing and analyzing the difficulty of each engineering task.

## 5.5 Summary

The two tables are utilized to evaluate and convert complex engineering tasks in various key aspects. The first table provides a template for thinking about activities such as data acquisition, UI/UX work, mobile app development, and cloud deployment of services, and quantifying them along five axes: Range of Resources, Level of Interaction, Innovation, Consequences to Society and Environment, and Familiarity. These axes are utilized to quantify the complexity, resource requirements, and potential societal impact of each activity. The second table applies the same five dimensions to individual tasks within a project with blanks for close evaluation. This allows one to quantify the personality of each task and plan for it. The two tables combined make it easy to plan projects in an orderly manner, enable effective resource management, understanding levels of innovation, and consideration of environmental and social impacts, making sure that every aspect of a project is adequately analyzed and addressed.

# Chapter 6

# Conclusion

## 6.1 Summary

The project developed a new mobile application for the detection of melasma using digital image processing and machine learning. Thus providing a user-friendly and efficient way to evaluate skin conditions and obtain prompt medical examinations; artificial intelligence is used to characterize the feature extraction process. The research and development had model training, dataset refinements, and ensured a good user experience. We will exploit this work as a channel to fast-track early detection and professional medical advice, hence, improving skin care awareness and accessibility to healthcare.

## 6.2 Limitation

The application can offer impressive accuracy for melasma detection but has its challenges. The applicability of the model is determined by the input image quality, while lighting conditions and skin tones can influence accuracy. The system does not, however, include other skin diseases; at the moment, it finds its target within melasma. Moreover, a bigger difficulty arises from the constantly changing healthcare regulations regarding patient data and confidentiality. The future will continue to offer solutions that will expand on these constraints by improving the model, broadening the dataset supply, and adding fortified security. Additionally, there was difficulty in obtaining a diverse range of melasma images, especially across various skin color tones and ethnicities. This limitation made it challenging to create a balanced dataset. Organizing the dataset between subsets of initial melasma and melasma also presented obstacles, further complicating the model's training process.

## 6.3 Future Work

Our future goal is to enhance the melasma detection application by expanding it to other diseases such as acne, eczema, and psoriasis. I plan to improve the model to handle variations in environmental conditions, such as light and skin texture, which will become a high priority. Additionally, integrating AI-recommended skin treatments and dermatologist consultations will enrich the user experience. Collaborations with medical professionals and dermatologists will ensure the application remains medically relevant and effective. Optimization of the mobile app's performance to support international scalability will be a key focus. Furthermore, I aim to increase accuracy and create a dataset that includes variations in ethnicity and skin colors to ensure inclusivity and robustness.

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# Appendix A

# Diagrams

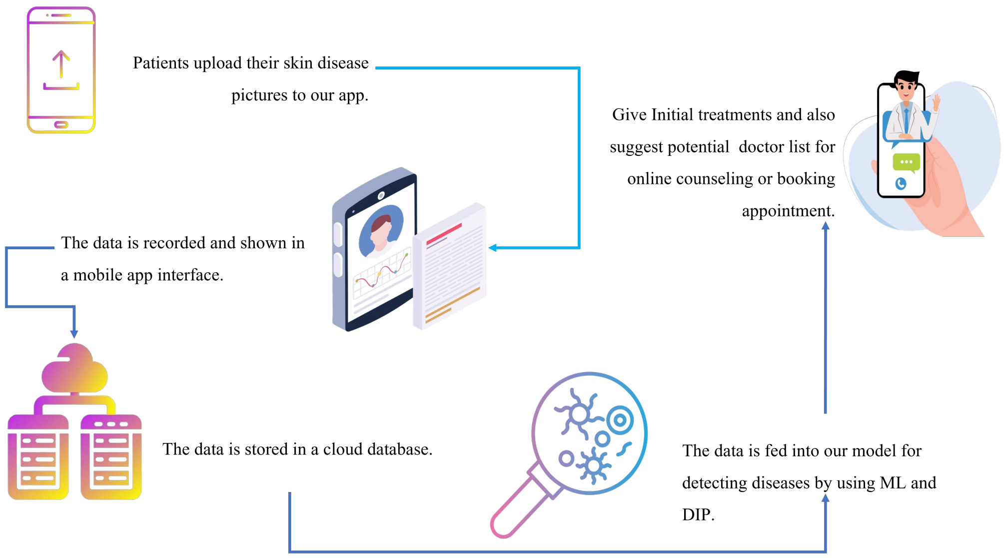


Figure A.1: System Diagram

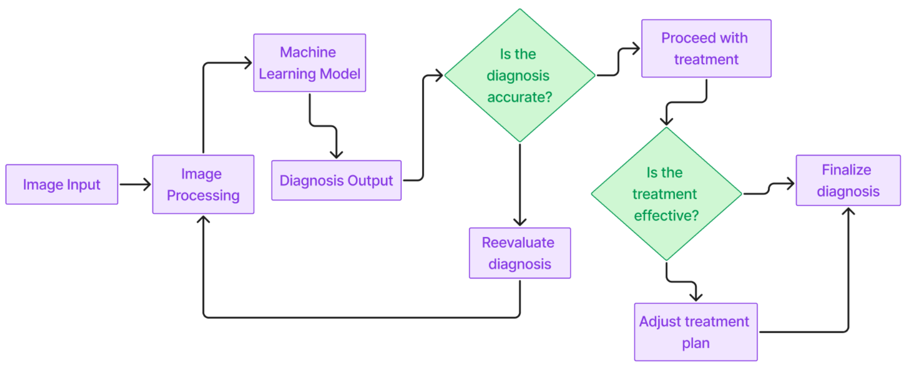


Figure A.2: Block Diagram

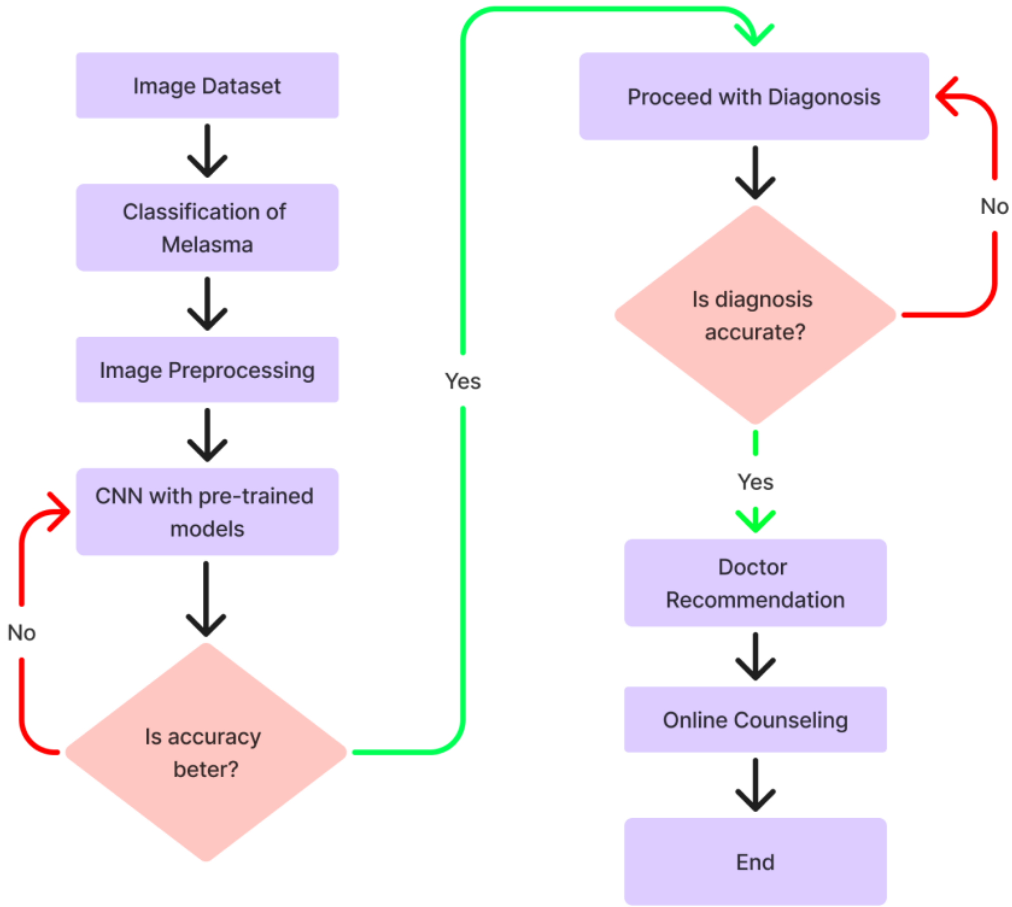


Figure A.3: Block Diagram

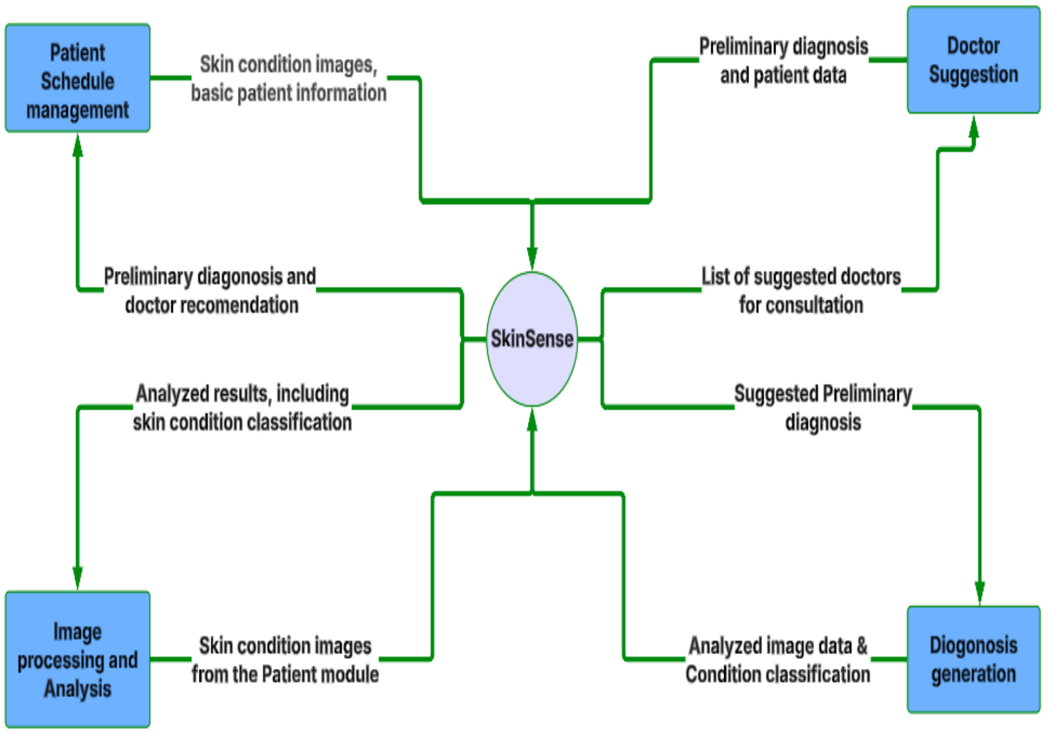


Figure A.4: Context Diagram

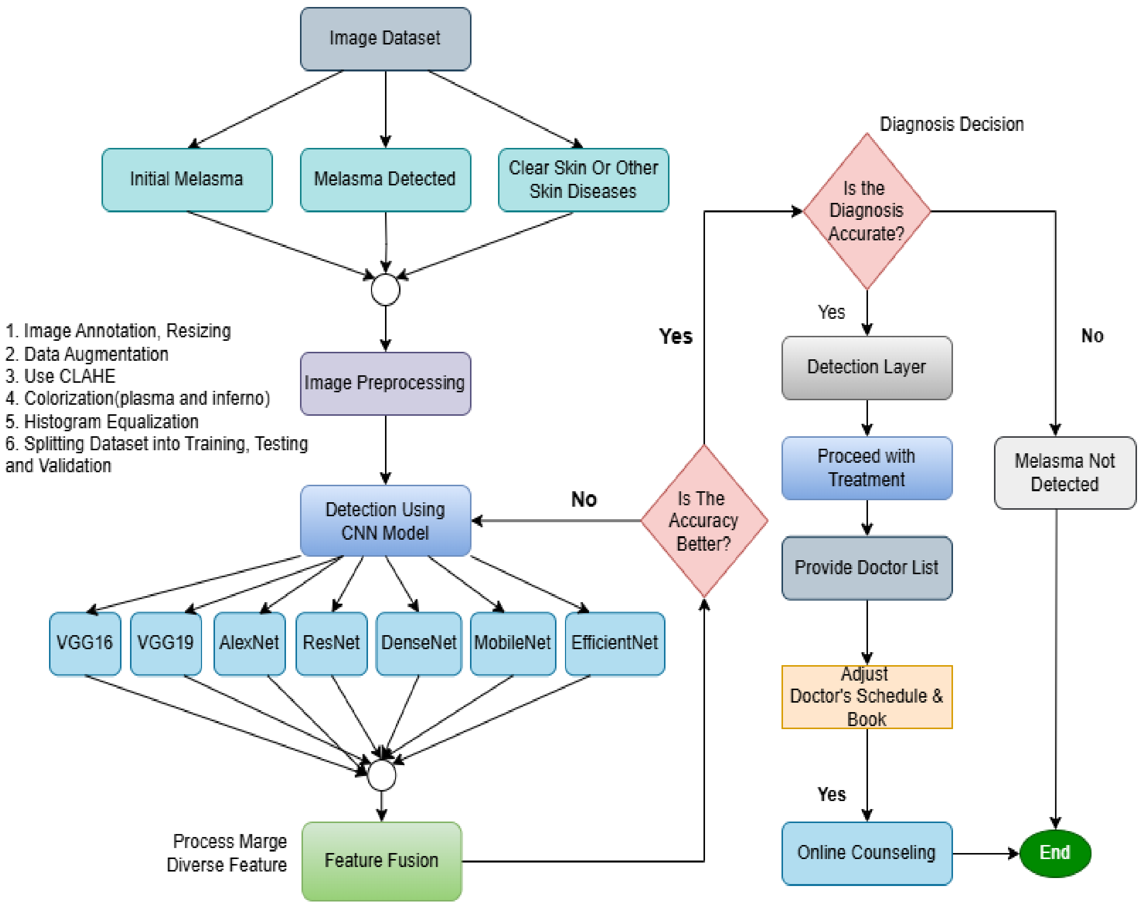


Figure A.5: Experimental Diagram

# Appendix B

# UI Design

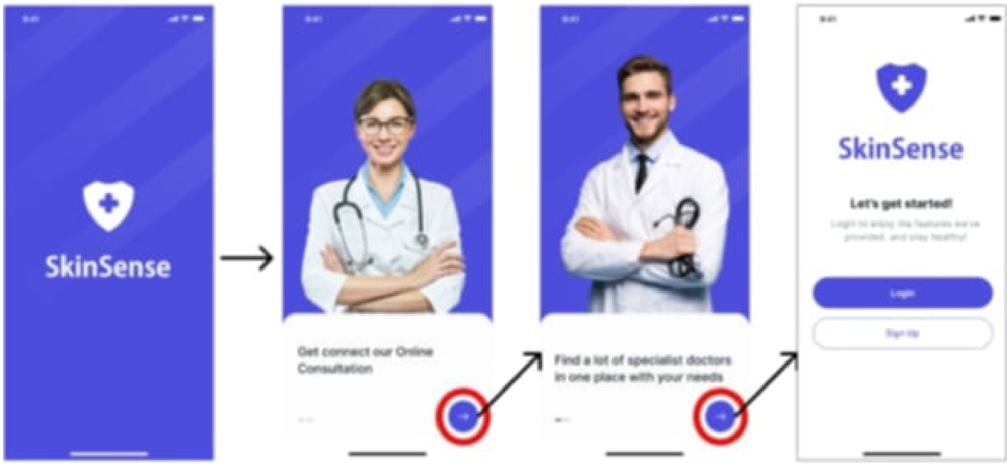


Figure B.1: User Onboarding

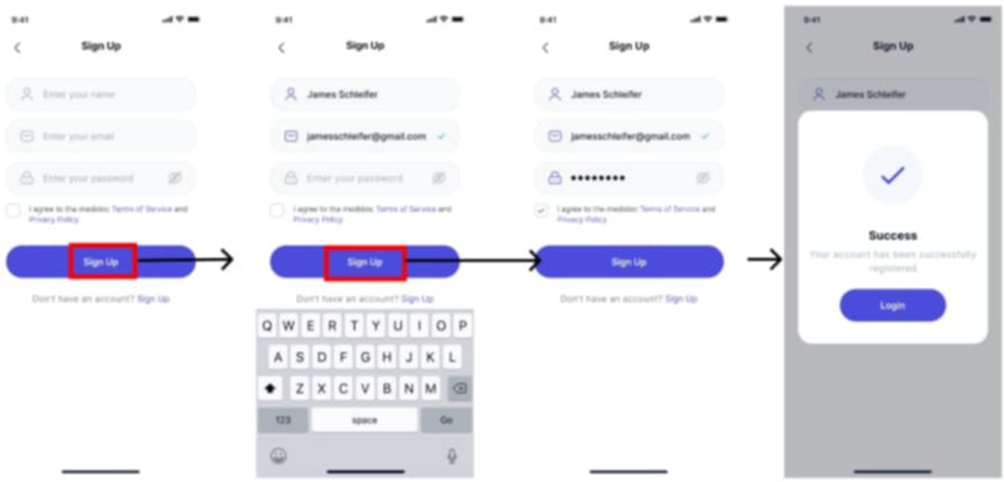


Figure B.2: User Authentication

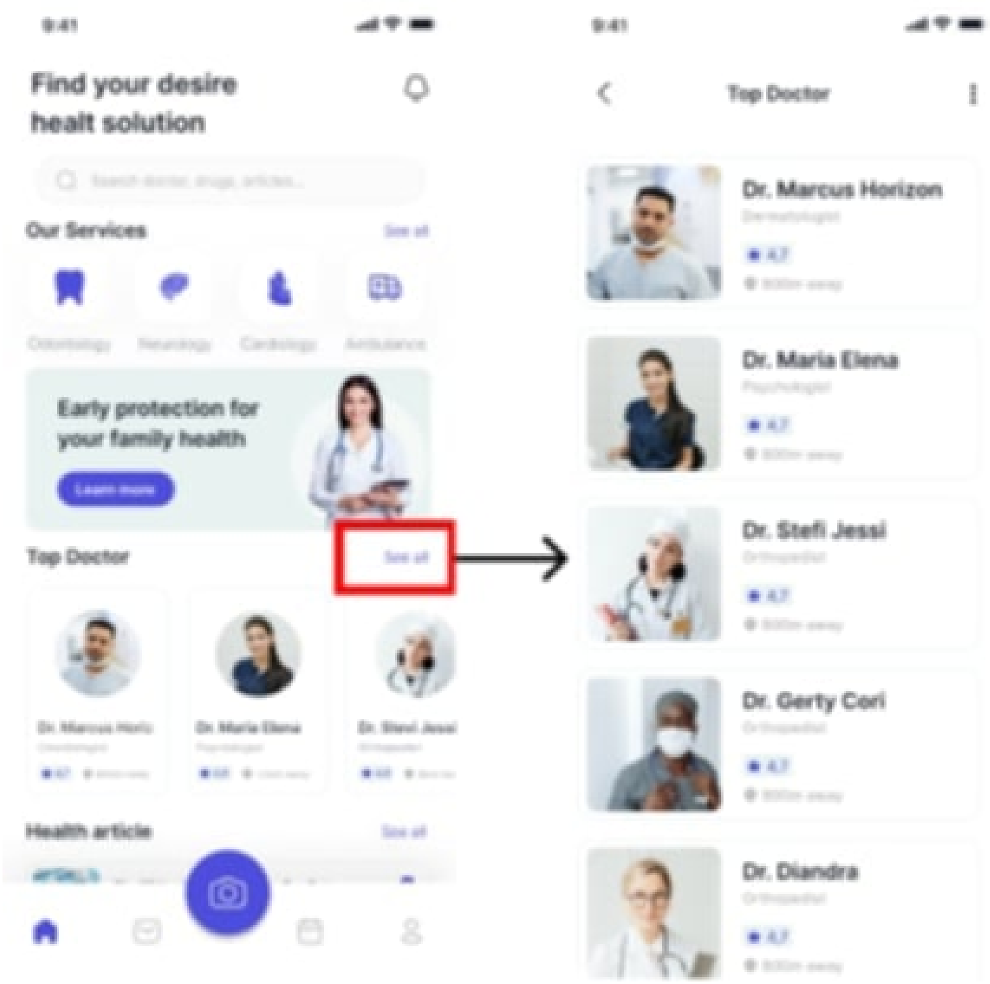


Figure B.3: User Onboarding

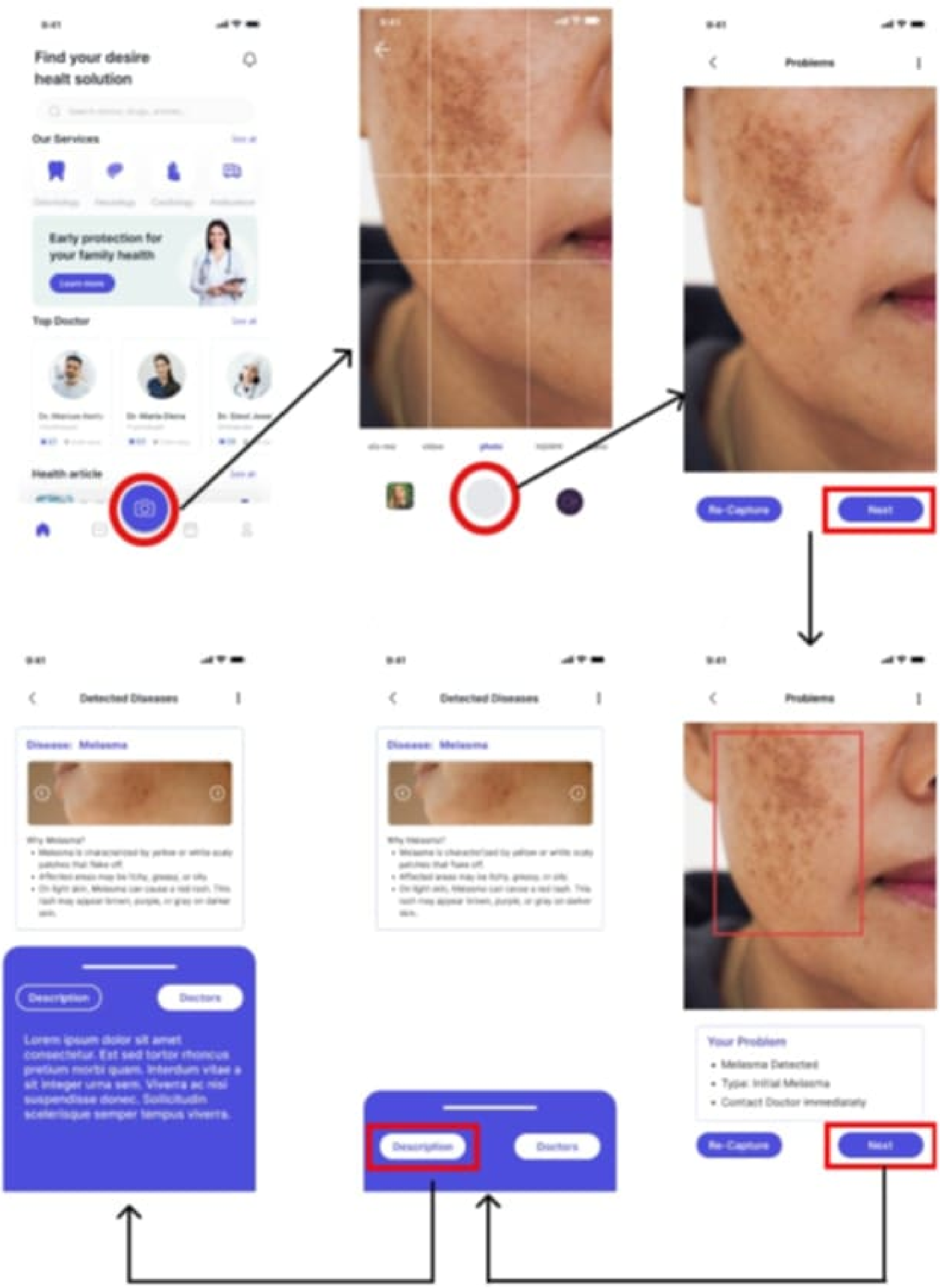


Figure B.4: Melasma Detection

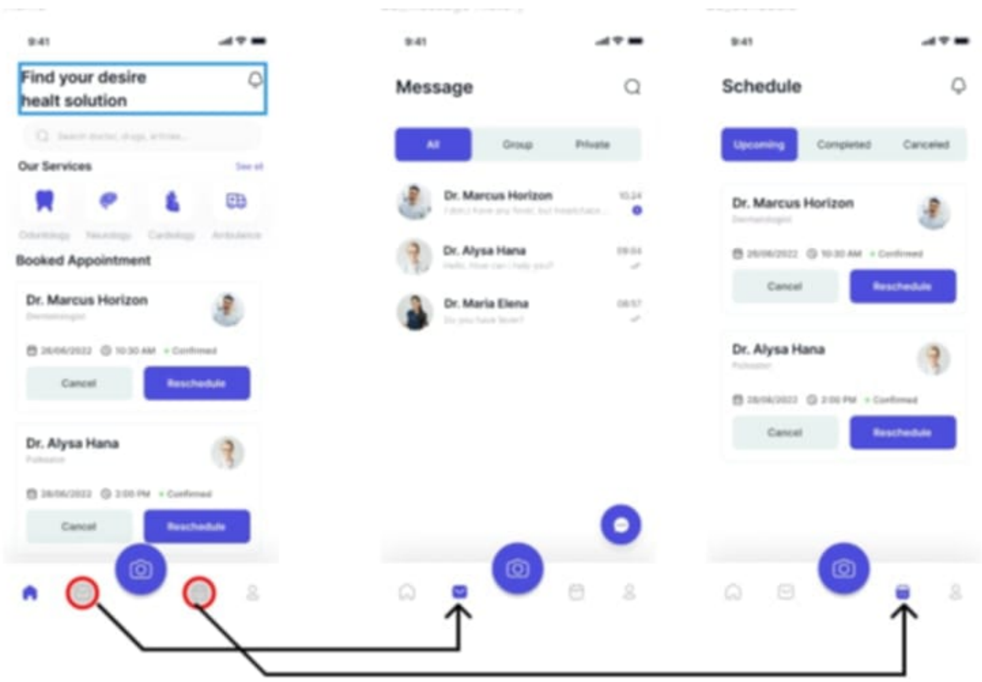


Figure B.5: Doctor's portal

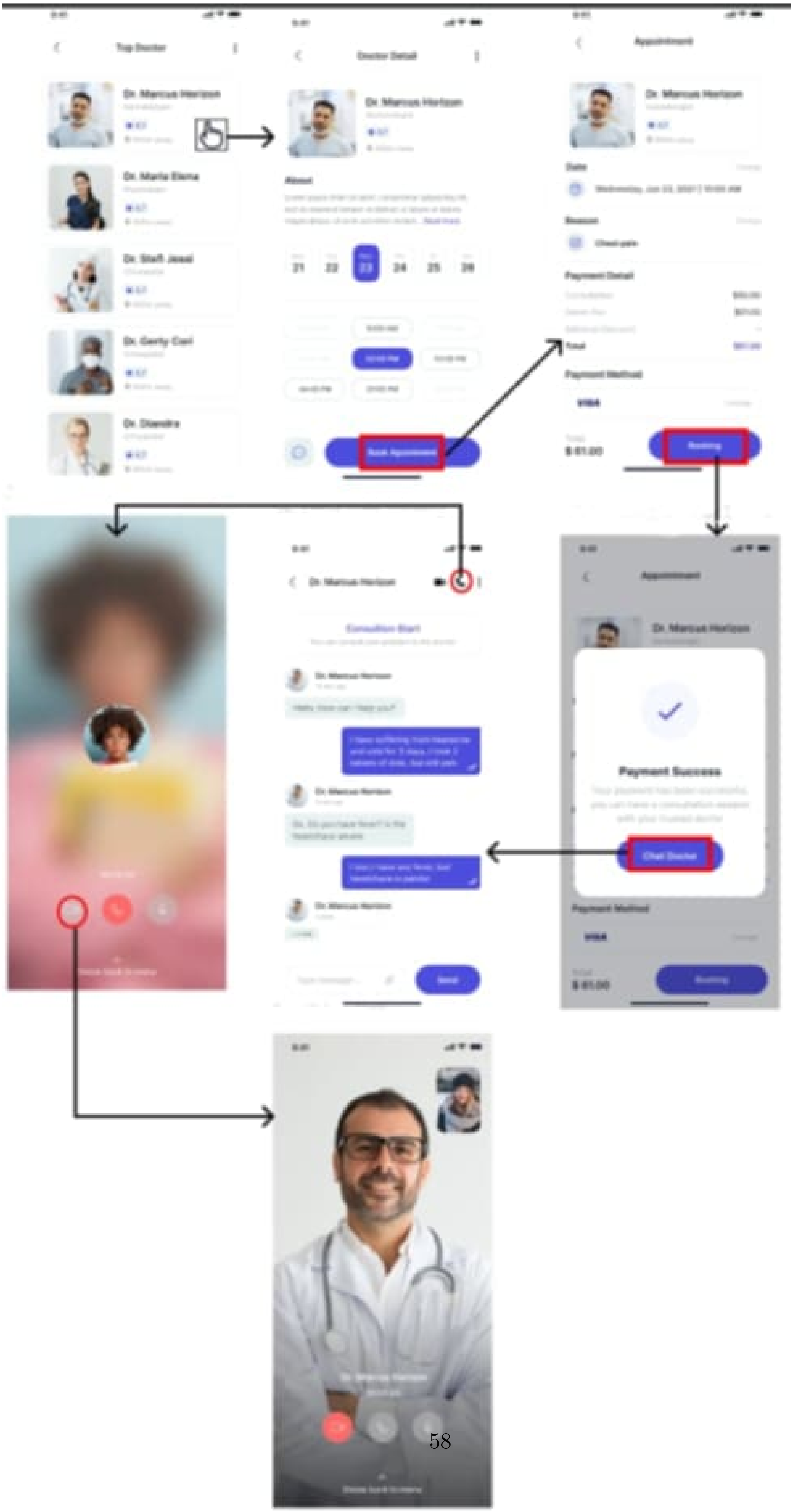


Figure B.6: Doctor's portal

# Appendix C

# Graph and charts

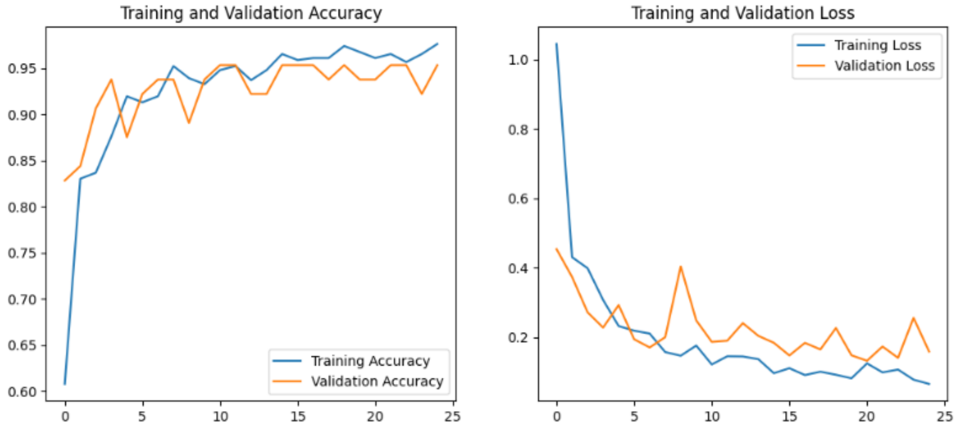


Figure C.1: Train-validation accuracy and loss