DermDiag

- **Abdelrahman Sayed Shaaban**
- **Amir Rabiee Abdelmeniem**
- **Doaa Nady Gaber Ali**
- **Rana Mahmoud Ahmed**
- **Alaa Mohammed Abdelghaffar**
- **Ahmed Ramadan Ahmed**
- **Nourhan Ebrahim Rabea**
- **Ibtsam Ali Mohamed**

Supervised by:

Dr. Esraa El-Hariri **Dr. Asmaa Hashem**

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Sincerely,
DermDiag Team

Abstract

The field of dermatology faces multifaceted challenges, encompassing a myriad of skin conditions, diagnostic complexities, and patient diversity. **DermDiag** emerges as a beacon of innovation, aiming to alleviate the burdens faced by dermatologists, patients, and healthcare systems alike. With an overarching goal to enhance diagnostic accuracy, streamline clinical workflows, and empower patients, **DermDiag** stands as a testament to the fusion of advanced technology and medical expertise.

DermDiag is an automated diagnostic tool designed to revolutionize dermatological care, catering to the needs of dermatologists, healthcare providers, and patients. Leveraging state-of-the-art machine learning algorithms, **DermDiag** offers unparalleled capabilities in skin condition identification, lesion analysis, and treatment recommendations. By harnessing the power of deep learning, **DermDiag** excels in recognizing a diverse range of dermatological conditions, from common ailments to rare disorders, with exceptional accuracy and efficiency.

Moreover, **DermDiag** serves as a comprehensive resource for dermatological education and awareness, providing insights into skin health, preventive measures, and treatment options. With its user-friendly interface and intuitive design, **DermDiag** bridges the gap between medical expertise and patient empowerment, fostering informed decision-making and proactive skin care practices.

Through rigorous validation and testing, **DermDiag** has demonstrated remarkable performance, achieving accuracy rates exceeding 80% across various skin conditions and lesion types. Furthermore, **DermDiag** continues to evolve and adapt, with ongoing enhancements and updates driven by feedback from dermatologists, researchers, and users worldwide.

In conclusion, **DermDiag** epitomizes the transformative potential of technology in dermatology, offering a paradigm shift in diagnostic precision, clinical efficiency, and patient-centric care. As we embark on this journey towards a brighter future for dermatological health, **DermDiag** stands as a beacon of hope, innovation, and excellence.

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List of Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
NLP	Natural Language Processing

Chapter 1

Introduction

1.1 Overview

In modern health care, the intersection between dermatology and artificial intelligence stands ready to revolutionize the diagnosis and treatment of various skin diseases, with particular emphasis on skin cancer and its countless complexities. With almost 10% of the world's population suffering from skin-related diseases, the importance of dermatology cannot be overstated in the face of these challenges. The integration of artificial intelligence, a rapidly expanding market expected to reach $45.2 billion by 2026, represents an unprecedented opportunity to enhance patient care and outcomes.

At the heart of this paradigm shift lies the project's dedication to the classification of skin diseases based on artificial intelligence, especially in the critical area of skin cancer diagnosis. With high rates of skin cancer, where more than 5.4 million cases are treated annually in the United States alone, the importance of early detection cannot be overstated.

By utilizing artificial intelligence capabilities, the project aims to improve the accuracy of diagnosis and the design of treatment methods commensurate with the unique needs of each patient. This cooperative endeavor between dermatology and artificial intelligence reflects the transformative potential of technological innovation in healthcare, which promises to significantly improve patient health and quality of life. As artificial intelligence continues to reshape health-care delivery models, this initiative emphasizes the deep synergy between these disciplines and their collective ability to bring about positive change.

In this rapidly evolving landscape, the integration of leather expertise with the analytical ingenuity of artificial intelligence represents an unprecedented opportunity to promote the diagnosis and management of skin diseases, particularly in the context of skin cancer and related situations. As these synergies emerge, the likelihood of improved patient care and outcomes is increasingly felt, reflecting the essence of healthcare innovation.

1.2 Problem Definition

Skin diseases encompass a diverse array of conditions, varying in severity from mild irritations to life-threatening disorders. Traditional diagnostic processes often rely on manual examination and human expertise, which can be time-consuming and subject to variations in interpretation. The integration of AI offers the promise of improved accuracy, consistency, and efficiency in diagnosing and classifying these diseases. This project aims to contribute to the growing body of knowledge that explores the potential of AI-driven solutions in dermatology by harnessing the power of machine learning algorithms and large-scale dermatological datasets.

1.3 Problem Motivation

Traditional diagnostic methods for skin diseases, and skin cancer often face challenges stemming from subjectivity, variations in clinician experience, and the wide spectrum of disease presentations. Human visual assessment can be subjective, leading to discrepancies in interpretation and potential misdiagnosis. Moreover, the complexity of distinguishing between various skin conditions, accurately assessing burn severity, and identifying early signs of skin cancer can pose hurdles for even experienced dermatologists. The integration of AI into dermatological diagnostics presents a compelling solution. By harnessing machine learning algorithms and large-scale datasets, AI offers the potential to significantly enhance accuracy, streamline diagnostic processes, and provide rapid insights. AI-driven systems can identify subtle patterns and features that human eyes might miss, leading to more precise diagnoses. However, this integration raises important ethical considerations. Patient data privacy, informed consent, and potential biases in algorithmic outcomes must be carefully addressed to ensure that AI-powered diagnoses maintain the highest standards of patient care, trust, and fairness in healthcare practices.

1.4 Project Objectives

- **Accurate Classification:** Develop AI models capable of accurately identifying a range of skin diseases, including common conditions, and skin cancer types.
- **Early Cancer Detection:** Implement an AI tool for early detection of skin cancer by analyzing lesion images and providing risk assessments for timely intervention.
- **Medical Advancement:** Contribute to improved dermatological diagnosis and management through innovative AI solutions.
- **Holistic Data Integration:** Incorporate diverse patient data into AI algorithms to improve diagnostic accuracy and treatment recommendations.
- **Promotion of Patient-Doctor Communication:** Provide direct communication channels between patients and doctors, enabling patients to ask questions, exchange information about their health status, receive counseling, and solve problems related to their treatment.

Chapter 2

Literature Review

2.1 Overview

In recent years, significant progress has been made in integrating artificial intelligence into dermatology, significantly enhancing the accuracy and efficiency of diagnosis and treatment of skin diseases. These studies include the development of convolutional neural network (CNN) models for classifying skin lesions and diagnosing skin cancer at an early stage. Artificial intelligence algorithms were also used to segment skin images and accurately identify areas of interest, achieving high accuracy rates of up to 98.64%. Other efforts include using deep learning to improve classification of skin tumors. This chapter highlights the great potential of AI to enhance diagnostic accuracy and simplify medical processes, thus significantly improving patient care.

As discussed in the previous chapter, this project offers the following:

- A deep learning-based approach to predict early diagnosis of skin diseases.
- Employing traditional algorithms to distinguish between different types of skin diseases and skin cancer.

2.2 Deep Learning Approaches for Skin Disease Classification

Lidia Talavera-Martínez and Pedro Bibiloni, along with their collaborators, have introduced an innovative and robust deep learning Convolutional Neural Network (CNN) model for the classification of skin lesion images based on their symmetry. The primary objective of their work is to address the inconsistency in the interpretation of physicians when evaluating lesion symmetry. Their approach involves developing a Computer-Assisted Diagnostic (CAD) tool that can quantitatively assess lesion malignancy by analyzing their visual attributes. To evaluate the effectiveness of their proposed method, the researchers curated a novel dataset known as SymDerm. This dataset comprises 615 publicly accessible images of skin lesions, meticulously annotated by three expert dermatologists. As part of their study, the authors also conducted a transfer learning investigation to compare their CNN model's performance against conventional methodologies. The results of their study are indeed promising. The CNN-based approach they devised surpasses the performance of traditional methods. Notably, it demonstrates a Balanced Accuracy (B.Acc) of 61.5% in a three-class classification scenario and a B.Acc of 71.9% in a binary classification setting. These outcomes underscore the method's potential utility in a computerized skin lesion diagnosis system. By accurately assessing the symmetry of skin lesions, this method could significantly aid specialists in their diagnostic tasks.[1].

Viswanatha Reddy Allugunti developed a deep learning technique aimed at diagnosing the type of melanoma in the preliminary stages of the disease. The study's goal was to create a screening method for skin cancer that is both prompt and straightforward, facilitating early diagnosis and timely treatment. To achieve this, the author employed a convolutional neural network (CNN), a deep learning algorithm, to assess the effectiveness of a CNN classifier in classifying skin diseases. The training data for the CNN classifier were sourced from the website dermnetnz.org. The study's final results demonstrated that the proposed method outperformed existing state-of-the-art methodologies in terms of diagnostic accuracy for classifying various types of melanoma, including lesion maligna, superficial spreading, and nodular melanoma. The CNN classifier achieved an accuracy of 91.07%, accompanied by recall, F1 score, and overall accuracy scores of 87.68%, 89.32%, and 88.83%, respectively.[2].

Puneet Thapar, Manik Rakhra, et al, presented a reliable approach for diagnosing skin cancer utilizing dermoscopy images in order to improve healthcare professionals' visual perception and diagnostic abilities to discriminate benign from malignant lesions, The swarm intelligence (SI) algorithms were used for skin lesion region of interest (RoI) segmentation from dermoscopy images and the speeded-up robust features (SURF) was used for feature extraction of the RoI marked as the best segmentation result was obtained using the Grasshopper Optimization Algorithm (GOA), ISIC-2017, ISIC-2018, and PH-2 data sets, with an average classification accuracy of 98.42%, precision of 97.73%, and MCC of 0.9704%.[3].

Anurag Kumar Verma and colleagues showcased the effective use of ensemble data mining methods to categorize skin conditions. Their primary goal was to categorize six specific types of skin disorders: Psoriasis, Seborrheic dermatitis, Lichen planus, Pityriasis rosea, Chronic dermatitis, and Pityriasis rubra. To achieve this, they employed a combination of five distinct data mining techniques: CART, SVM, DT, RF, and GBDT. They also developed an integrated approach that combined all five techniques into a single unit. The dataset used for this study was obtained from the UCI machine repository. Among these various techniques, the highest achieved accuracy was 95.90% using GBDT. Through the fusion of these five techniques, they further elevated the accuracy to an impressive 98.64%.[4].

Long Hoang and colleagues introduce an innovative technique for skin image segmentation, utilizing entropy-based weighting (EW) and first-order cumulative moment (FCM) of the skin image. Following the application of EW-FCM, a two-dimensional wide-ShuffleNet network is employed to classify the resultant segmented image. Notably, at the time of their research, both EW-FCM and wide-ShuffleNet represent pioneering methodologies. The experimentation employed HAM10000 and ISIC2019 datasets. The study is structured around three distinct experiments, each varying in the proportion of data allocated to training and testing. They obtained an average accuracy of 97.57%.[5].

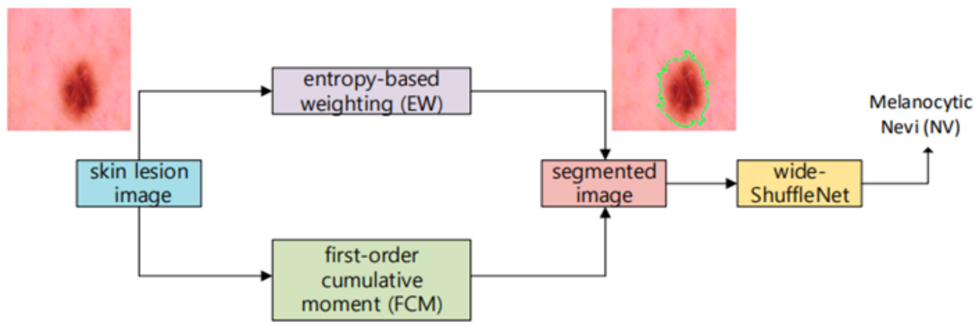

Figure 2.1: Structures of the proposed method

Walaa Gouda, Najm Us Sama, et al, The deep learning method convolution neural network (CNN) was used to detect the two primary types of tumours, malignant and benign, Using ES-RGAN, the photos were first retouched and improved. The photos were augmented, normalized, and resized during the preprocessing step. Skin lesion photos could be classified using a CNN method based on an aggregate of results obtained after many repetitions, Then, multiple transfer learning models, such as Resnet50, InceptionV3, and Inception Resnet, Using the ISIC2018 dataset, An 83.2% accuracy rate was achieved by the CNN, in comparison to the Resnet50 (83.7%), InceptionV3(85.8%), and Inception Resnet (84%) models.[6].

Parvathaneni Naga Srinivasu, Jalluri Gnana SivaSai, Muhammad Fazal Ijaz, Akash Kumar Bhoi, Wonjoon Kim, and James Jin Kang, propose a computerized process using deep learning models, specifically MobileNet V2 and LSTM, to classify skin diseases. Their objective is to develop an efficient and accurate model that can assist general practitioners in diagnosing skin conditions, leading to a reduction in complications and morbidity. And to accomplish this goal, They utilize the HAM10000 dataset, which consists of images representing various skin diseases. The dataset includes melanocytic nevi, benign keratosis-like lesions, dermatofibroma, vascular lesions, actinic keratoses and intraepithelial carcinoma, basal cell carcinoma, melanoma, and normal skin. By implementing their model using the PyTorch Deep Learning framework, they train it to classify and diagnose these different skin conditions. Their proposed model surpasses other state-of-the-art models, achieving an accuracy rate of over 85.34%. They attribute the efficiency and accuracy of their model to the combination of deep learning models, MobileNet V2 and LSTM. Additionally, they mention the use of a grey-level co-occurrence matrix to evaluate the progression of diseased growth. Their ultimate aim is to provide instant and appropriate action through a mobile application they have designed, making the model suitable for use on lightweight computational devices.[7].

Weihong Huang , Xiang Chen and Yi Li,Authors performed studies using an independent dateset of the same disease types, but from other body parts, to perform transfer learning on our models an to Distinguish between 6 diseases (skin Seborrheic keratosis (SK) – Actinic keratosis (AK) – Rosacea (ROS) Lupus erythematosus (LE) – Basal cell carcinoma (BCC) – Squamous cell carcinoma (SCC)) . authors do this to solve the problem of face skin diseases (classification problem).The test dataset which included total 4,394 images from Xiangya-Derm databases The best model achieved recalls mean 88.8%. Accuracy for cnn algorithm 87.25%,7.25%.[8].

2.3 Summary of Presented Exhaustive Survey

Table 3.1 summarizes the presented exhaustive survey of state-of-the-art studies related to Deep Learning Approaches for Skin Disease Classification.

Author	Objectives	Model	Dataset	Performance Accuracy
Lidia Talavera et al.2022[1]	Classification of skin lesion images based on their symmetry	CNN	SymDerm	61.5% in three-class classification, 71.9% in binary classification
Viswanatha Reddy.2021[2]	Skin Cancer Diagnosis in the preliminary stages	CNN	dermnetnz.org	91.07%
Puneet Thapar et al.2022[3]	Diagnosis of skin cancer using dermoscopy images to abilities in discriminating benign from malignant lesions.	-Pre-processing: (Hair Removal using the HR-IQE algorithm) -Segmentation: Kmeans with GOA -Feature Extraction: SURF using CNN	ISIC 2017, ISIC 2018, PH-2	98.42%
Anurag Kumar.2019[4]	Categorizing six specific types of skin disorders	Ensemble data mining techniques	UCI machine repository	Highest accuracy: 98.64%
Long Hoang.2022[5]	Skin image segmentation	EW, FCM, followed by classification with wide-ShuffleNet	HAM10000, ISIC2019	Average accuracy: 97.57%
Walaa Gouda et al.2022[6]	Detecting malignant and benign skin tumors	CNN	ISIC 2018	83.2% (CNN), 83.7% (ResNet50), 85.8% (InceptionV3), 84% (Inception Resnet)
Parvathaneni et al.2021[7]	Classifying various skin diseases	MobileNet V2 and LSTM	HAM10000	85.34%
Weihong Huang et al.2019[8]	Distinguishing between six face skin diseases	CNN	Xiangya_Derm database	87.25%

Table 3.1: Summarizes the Presented Exhaustive

Chapter 3

Proposed System

3.1 Overview

In this chapter, we will explore the methodology used in the development of the DermDiag application. We will also review its functional and non-functional requirements. Additionally, we will discuss the system analysis throughout its life cycle and highlight the key requirements. We will present visual representations such as the USE-CASE Diagram and Activity diagram to help with the understanding of the system.

3.2 Proposed Framework

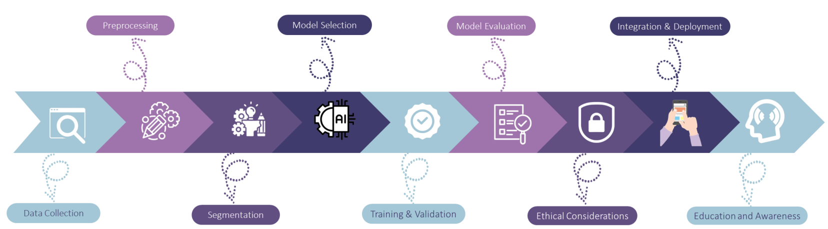

Figure 3.1: Framework

As you can see in Figure 3.1, the function grows near the origin. This example is on page 15.

3.3 System Analysis

Throughout this chapter, we will cover the essential project requirements that are necessary for the successful implementation of the DermDiag application. These requirements can be classified into two main categories: functional and non-functional requirements. Functional requirements define the specific functions and features that the software must perform, while non-functional requirements specify the criteria used to assess the system's performance and behavior. Let's explore both types of requirements in the context of the proposed DermDiag system.

3.3.1 Process Modeling

Chapter 4

System Development

4.1 Overview

DermDiag stands at the forefront of dermatological care, revolutionizing the industry with its seamless interface and advanced capabilities. Developed using Flutter and .NET, it caters to both healthcare professionals and patients with precision-tailored interfaces. For professionals, DermDiag harnesses a sophisticated machine learning model, empowering them to diagnose and manage skin conditions with unparalleled accuracy. By simply uploading patient data and images, the platform provides personalized treatment recommendations, streamlining the diagnostic process and enhancing patient care.

Meanwhile, on the patient front, DermDiag offers an intuitive platform for individuals to take control of their skin health journey. Through easy-to-navigate features such as questionnaires and image uploads, users can identify diseases and assess severity levels, all while receiving guidance on daily routines and early diagnosis. With multilingual support for English and Arabic, DermDiag ensures inclusivity and accessibility on a global scale, reshaping the landscape of dermatological care delivery and fostering informed decision-making for all users.

4.2 App's architecture & design patterns

DermDiag's architecture reflects a meticulous consideration of factors crucial for seamless operation and user satisfaction. Throughout this chapter and beyond, our development team has prioritized efficiency, security, and user experience. By leveraging the Flutter framework for the client-side application, DermDiag ensures cross-platform compatibility, enabling users to access the app seamlessly across various devices and operating systems. Additionally, the utilization of a .NET-based backend API underscores our commitment to robustness and scalability, empowering DermDiag to handle large volumes of data and user interactions effectively. Furthermore, adherence to industry-standard design patterns like MVC not only enhances code organization but also facilitates collaboration among developers, streamlining the development process and ensuring rapid iteration and deployment of new features. With a RESTful API design, DermDiag facilitates seamless communication between the client and server, ensuring that data exchange is efficient, secure, and compliant with industry standards. Overall, DermDiag's architectural choices reflect a dedication to excellence, innovation, and user-centric design, laying the groundwork for a transformative experience in dermatological care.

4.3 Methodological Assumptions

To activate the DermDiag system, certain user and system requirements must be met to ensure optimal functionality and usability.

4.3.1 User Requirements

- Users should have basic computer skills in operating systems and internet browsers, enabling them to navigate the DermDiag application effectively.
- A stable internet connection is essential for users to access DermDiag's features and services seamlessly.
- Eligible users are limited to university students or staff members (Advisors, Administrators), ensuring that access to DermDiag is aligned with its intended user base and scope of application.

4.3.2 System Requirements

- The system requires basic computer hardware specifications, including a minimum of a core i3 processor and 4 GB RAM, to ensure smooth performance and responsiveness.
- DermDiag is compatible with various operating systems, including Microsoft Windows, providing flexibility and accessibility to a wide range of users.
- Supported internet browsers such as Internet Explorer, Mozilla Firefox, and Google Chrome are required for optimal functionality, allowing users to interact with DermDiag's web-based components effectively.

4.4 Used Technologies

The DermDiag application utilizes a combination of cutting-edge technologies to deliver its robust functionality and user experience.

4.4.1 Dart

Dart serves as the primary programming language for DermDiag, optimized for building fast and reliable applications across various platforms. With its flexible execution runtime and productivity-focused approach, Dart facilitates multi-platform development, offering a versatile toolkit for creating high-quality applications.

4.4.2 Flutter

Flutter, an open-source UI framework developed by Google, forms the backbone of DermDiag's cross-platform compatibility. By enabling developers to write code once and deploy it across multiple platforms including Android, iOS, Windows, Mac, and Linux, Flutter streamlines the development process. Its native performance, hot reload feature, and extensive widget library empower developers to build responsive and visually appealing applications effortlessly.

4.4.3 MVP Architecture

DermDiag utilizes the MVP (Model-View-Presenter) architecture by Feature pattern to maintain a clear separation between data, user interface, and presentation logic. This approach enhances code organization, scalability, and maintainability by structuring the application into distinct layers. The Model represents the data and business logic, the View encompasses user interface elements, and the Presenter acts as an intermediary, handling user interactions and updating the UI. By adopting MVP, DermDiag ensures efficient development, easier collaboration among developers, and a more structured development process overall.

4.4.4 ASP.NET Core

ASP.NET Core serves as the backend framework for DermDiag, providing a robust and scalable foundation for server-side development. Leveraging the power of .NET, ASP.NET Core enables seamless integration with the Flutter frontend, ensuring smooth communication and data management within the application.

4.4.5 Google Cloud Platform (GCP)

Google Cloud Platform offers a comprehensive suite of cloud-based services and tools that DermDiag utilizes for various purposes. From hosting the application's backend services to accessing Google Products APIs such as Google Drive for retrieving patient data, GCP provides the scalability, reliability, and security required for modern healthcare applications.

4.4.6 Mobile Development

- The DermDiag onboarding screen provides a seamless introduction to the app's features, guiding users through its functionalities. With clear steps and engaging visuals, users can quickly familiarize themselves with DermDiag's capabilities, setting the stage for a personalized and user-friendly experience.

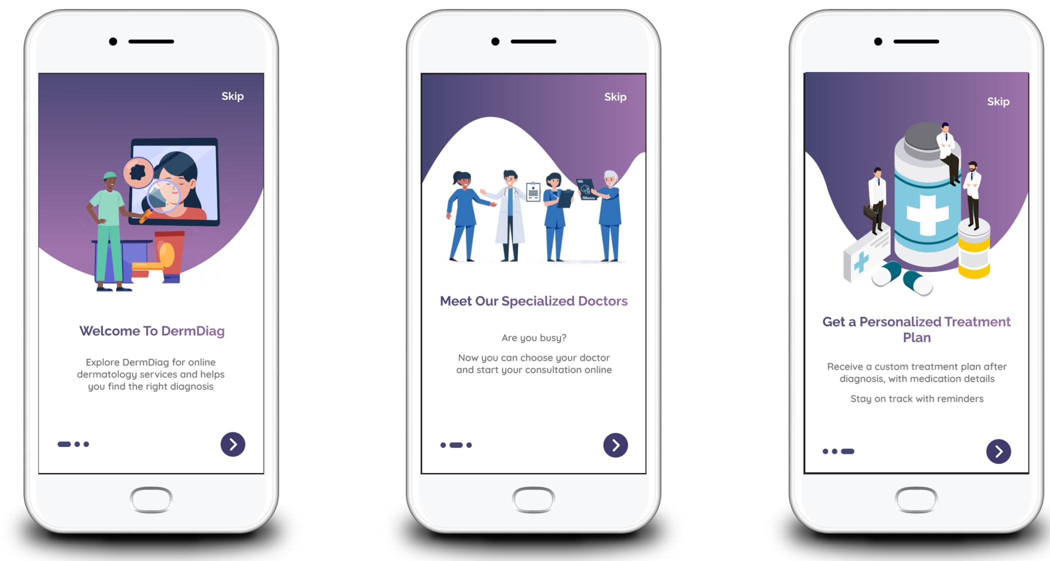

Figure 4.1: Onboarding Screens - DermDiag Interface Overview

- In DermDiag, users can easily select their preferred language and specify their user type, whether they are a patient or a doctor, enhancing accessibility, customization, and user experience.

Figure 4.2: Select Language Screen

- First, You have to choose which interface you will sign up with.

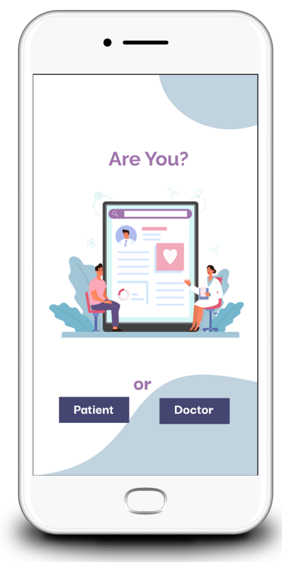

Figure 4.3: Role Selection in DermDiag: 'Doctor' or 'Patient'