PRESIDENCY UNIVERSITY
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Itgalpura, Rajankunte, Yelahanka, Bengaluru – 560064

AI-BASED TOOL FOR PRELIMINARY DIAGNOSIS OF DERMATOLOGICAL MANIFESTATIONS

A PROJECT REPORT

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PRESIDENCY SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

Certified that this report "**AI-based tool for preliminary diagnosis of Dermatological manifestations**" is a bonafide work of "Vinod (20221CIT0085), Nallin Kumar AB (20221CIT0077), Deeksha D (20221CIT0077)", who have successfully carried out the project work and submitted the report for partial fulfilment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE ENGINEERING, INTERNET OF THINGS during 2025-26.

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DECLARATION

We the students of final year B. Tech in COMPUTER SCIENCE ENGINEERING, INTERNET OF THINGS at Presidency University, Bengaluru, named VINOD, NALLIN KUMAR AB, DEEKSHA D hereby declare that the project work titled **"AI-based tool for preliminary diagnosis of Dermatological manifestations"** has been independently carried out by us and submitted in partial fulfilment for the award of the degree of B.Tech in COMPUTER SCIENCE ENGINEERING, INTERNET OF THINGS during the academic year of 2025-26. Further, the matter embodied in the project has not been submitted previously by anybody for the award of any Degree or Diploma to any other institution.

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Abstract

Over 1.8 billion people worldwide suffer from skin disorders such as eczema, psoriasis, and acne, making them one of the top five causes of non-fatal disease burden (WHO). In India, 20–25% of outpatient visits are related to dermatological issues, yet only 12,000 dermatologists are available for 1.4 billion people, creating a ratio of 1 dermatologist per 100,000 people, with less than 10% serving rural regions.

Since 65% of India's population lives in villages, many individuals lack access to trained specialists and depend on home remedies or unqualified advice, leading to delayed diagnosis, complications, and social stigma.

Due to limited access to trained dermatologists (particularly in semi-rural regions) and the large number of patients who experience some form of skin condition, many people consult a General Practitioner (GP) and receive incorrect or missed consultations, or self-treat their conditions. This leads to prolonged periods of untreated skin diseases and/or continued progression of more serious conditions than if the patient had seen a dermatology trained provider at the very beginning. In order to help meet this urgency and need, this project proposes an Artificial Intelligence (AI) based solution for assisting with the initial diagnosis of skin conditions based on images taken by patients.

A Predefined ResNet-50 Convolutional Neural Network (CNN) has been trained by taking thousands of examples of variations of skin lesions, classifying and grouping them according to their likely diseases they can develop (and thus the type of diseases). Once an AI prediction has been made, a conversational interface for the end-user to interact with the system will provide users with probable reasons for the lesions, a list of what to look for as symptoms and warning signs, and provide recommendations for treatment options. This dual approach will allow users to get an accurate and probable diagnosis for a skin condition as well as stay informed about their condition in an easy and reliable way.

Ultimately, the goal of the proposed healthcare resource is to increase knowledge about skin conditions prior to developing or finding out about them through their doctor and improve access to this resource by reducing unnecessary clinic visits, and creating avenues for general instruction and "leadership" when medical assistance is not available.

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Abbreviations

AMD	**A**dvanced Micro Devices
API	Application Programming Interface
AWS	Amazon Web Services
CPU	Central Processing Unit
CNN / CNNs	Convolutional Neural Network(s)
CUDA	Compute Unified Device Architecture
CSS	Cascading Style Sheets
DL	Deep Learning
DPDPA	Digital Personal Data Protection Act
EHR	Electronic Health Record
EMR	Electronic Medical Record
EC2	Elastic Compute Cloud
F1 / F1 Score	Harmonic mean of precision and recall
GDPR	General Data Protection Regulation
GPT	Generative Pre-trained Transformer
GPU	Graphics Processing Unit
GUI	Graphical User Interface
Grad-CAM	Gradient-weighted Class Activation Mapping
HAM10000	Human Against Machine dataset
HCI	Human–Computer Interaction
HIPAA	Health Insurance Portability and Accountability Act**.**
HTTPS	Hypertext Transfer Protocol Secure
HTML	Hypertext Markup Language
IEEE	Institute of Electrical and Electronics Engineers
IDE	Integrated Development Environment
IoT	Internet of Things
ISIC	International Skin Imaging Collaboration
MDPI	Multidisciplinary Digital Publishing Institute
ML	Machine Learning
mHealth	Mobile Health
NLP	Natural Language Processing

OpenCV	Open Computer Vision
PESTLE	Political, Economic, Social, Technological, Legal, Environmental
PHP/ phpMyAdmin	Personal Home Page / administration tool
RESTful API	Representational State Transfer Application Programming Interface
RAM	Random Access Memory
ResNet-50	Residual Network-50
SaMD	Sustainable Development Goals
SQL	Structured Query Language
SSD	Solid-State Drive
UI	User Interface
UX	User Experience
UN	United Nations
USN	University Seat Number
VS Code	Visual Studio Code
Wi-Fi	Wireless Fidelity
WHO	World Health Organization
XAI	Explainable Artificial Intelligence

CHAPTER 1

INTRODUCTION

1.1 Background

People of all ages experience skin illnesses frequently, as one of the most prevalent complaints. Skin ailments comprise an extensive range of ailments, including common conditions such as acne, eczema, and infections caused by fungi to chronic diseases such as vitiligo and psoriasis. Many skin diseases are manageable if they are diagnosed early; however, if a patient delay having a diagnosis made, they may experience emotional distress, discomfort, scarring, and/or an increase in the severity of the skin disease due to this delay.

Furthermore, not all regions of the country have the same availability of dermatological specialists, with many rural and semi-urban areas lacking adequate numbers of qualified dermatologists. Therefore, most patients have no other options than to consult a general practitioner (GP), and in many instances, GPs do not have adequate training to provide accurate diagnoses for skin problems; consequently, the GP may misdiagnose and/or inadequately treat the skin problem. At present, diagnostic techniques are primarily reliant on visual inspection, using either a dermatoscope or by conducting a tissue sample, which can only take place in an office setting that has the necessary medical infrastructure.

In recent years, Artificial Intelligence (AI) and other Deep Learning systems have evolved to perform exceedingly well in regards to Medical Imaging Technologies and in assisting in the development of access and early screening for Dermatological Conditions. Convolutional Neural Networks (CNNs) have achieved a very high percentage of accuracy in classifying images of skin lesions using CNN-based techniques and the potential for using AI for dermatological diagnosis has created excitement in the medical industry and could be an answer to improving access and early screening for dermatological conditions.

1.2 Statistics of the Project

This this research is part of the ongoing development of AI for dermatological diagnosis, and will present an AI diagnostic support tool that is intended to assist in the decision-making process for the primary diagnosis of skin lesions by unauthorised users and select healthcare providers.

In India, there are very few dermatologists, only about twelve thousand in 2023 with the population being 65 percent rural and having very limited access to specialty care for their healthcare needs, many people self-diagnose or attempted to self-treat their skin conditions using over-the-counter creams, home remedies and consulting with non-medical healthcare professionals. This can provide temporary relief for some of the symptoms with the potential of contributing to the worsening of the underlying skin condition.

In addition, delays in diagnosis cause an increase in the likelihood of experiencing chronic inflammation, visible scaring and impact mental health, particularly among younger patients. The statistics alone are alarming enough to warrant a case for the establishment of an early, simple, and low-cost method of diagnosing and identifying patients who need to start therapy using timely treatment to visualize their treatment options, and prevent negatively impacting the patient by burdening them with a stigma that they required family members to be treated by dermatology specialists.

1.3 Prior Existing Technologies

Dermatological evaluation has become an integral part of modern healthcare and patient care. There are currently many types of technologies that can provide a dermatological evaluation. Each technology evaluates the patient's skin using different diagnostic characteristics to assist the patient in receiving the needed care. The most widely adopted forms of dermatological evaluation today are clinical dermatology and dermoscopy, where the dermatologist evaluates the superficial dermal layer of the skin by visually examining it under a magnified device or light source. The traditional standards for clinical dermatology, when utilized as an assessment method, require that the patient attend an in-person visit and be evaluated by a trained dermatologist. However, due to geographical limitations or other reasons, many patients are unable to travel to consult with a dermatologist in person, creating a demand for teledermatology, which is when patients can upload photos of their skin conditions and receive a medical consultation through an internet or mobile phone-based platform.

Teledermatology platforms, such as DermAssist and SkinVision, offer similar types of consultation for those with limited or no access to traditional dermatology services. As with many teledermatology platforms, both platforms require that dermatologists review the submissions of patients who upload images of their problematic skin areas for review. Therefore, patients will have additional wait time before their teledermatology consult, will incur additional costs for their online consultation, and most likely, will need to follow up with an in-person visit if the cosmetic or medical concern indicates possible issues.

Across various disciplines, most notably Artificial Intelligence, the research and discovery of new information and treatment options have continued to flourish. Some of the most prominent new methods for identifying lesions include machine learning classifications, notably Convolutional Neural Networks (CNN), and the ResNet design. These technologies provide a means to automatically assess the risk levels associated with particular skin lesions and have enabled a more precise classification of these lesions according to disease categories.

One shortcoming of these methodologies is that the CNNs and ResNet approaches are advancing the automation of the classification of skin diseases into categories as defined by the clinician's educational experience (as opposed to patient-oriented systemic thinking and clinical judgement). There are also general medical chatbots (e.g., Ada), which provide patients with health advice based on their symptom inquiry or referral via evidence-based symptom questioning, using a similar methodology to the CNN and ResNet approaches. While these chatbots can help patients develop general questions for health care providers, they are not capable of performing image analyses of lesion submissions, and any recommendations they may provide are usually vague and do not constitute an accurate, individualized recommendation for the patient.

Thus, while each of the above solutions has strengths, none of the above provides an integrated solution that combines both the automated classification of skin disease with an individualized education and guidance system. As such, this highlights the significant need for an integrated solution that will not only allow for the automated classification of skin disease, but will also effectively communicate relevant information about dermatological conditions to the patient to facilitate informed decision-making.

1.4 Proposed Approach

1.4.1 Aim of the Project

The primary purpose of the project is to develop an Artificial Intelligence (AI)-based diagnostic system that can evaluate images of skin and provide users with relevant and accurate medical advice. It is designed to be an easy way for users to detect skin conditions and have access to accurate medical information, as well as to encourage users to seek medical attention for potential skin problems as soon as possible. By combining computer-based automatic image classification and an explanation model for users, it is our goal to switch to easier and more convenient ways for users to receive medical assessments for potential dermatological problems.

1.4.2 Motivation

The project came about due to the large disparity between how many people are affected by skin care problems and how few people have access to healthcare providers focused on dermatology. This is particularly true for rural and semi-urban areas. There are many barriers that prevent people from seeking medical assistance regarding their skin concerns such as: living a long distance away from the nearest healthcare provider; worrying about the cost of treatment; or not knowing when to go to the doctor. As a result of these barriers, many people self-treat their skin problems or seek the advice of someone other than a medical professional and that leads to misdiagnosing and providing inappropriate treatment for their skin issues.

The increasing availability of AI and vision analytics has provided us with an opportunity to develop a user-friendly, accessible assessment tool that will give people access to timely care for their skin conditions prior to worsening. The overarching goal of this project is to provide a feasible method for early detection of skin disease, as well as to serve as a low-cost and credible source of information about these diseases. By doing so, we hope to encourage people to recognize skin diseases as soon as possible when there are no other options available.

1.4.3 Proposed Approach

The proposed framework provides a combined approach of image-based analysis in conjunction with interactive, conversational support, to help provide an initial diagnosis of dermatological conditions based on image uploads from users. A ResNet-50 Convolutional Neural Network will perform classification of skin images using visual features (e.g., lesion morphology, colour patterns, texture, etc.). Once a user has received a preliminary prediction, that prediction will be input into a chatbot utilizing GPT. Within this chatbot, users will find organized, clear, and concise explanations of their preliminary prediction, as well as summaries of potential causes and symptoms of the potential diagnosis, available treatments for that condition, and preventative measures. By utilizing a two-phase approach to deliver initial indications of diagnosis, our end-users will be able to place their results in context.

The framework is accessible as a web app interface in which users can upload images of their skin, receive the classification results, and interact with the chatbot to guide their understanding of the condition further. By using an automated classifier with a human-like explanation, we hope to support early action in supporting awareness of dermatological issues, and encourage timely forward action with a professional when needed.

1.4.4 Applications of the Project

The system we are developing could be used in many different types of health care settings. Within telehealth applications, the screening software can be a separate module to enable virtual consultations with practitioners and reduce unnecessary visits to the emergency department for many patients. When used in combination with community health programs, our screening tool can be an effective educational resource to help educate and inform public awareness about maintenance of healthy skin and early detection of skin conditions. In addition, personal self-screenings are feasible with our tool and allow individuals to self-monitor and document their skin health status and to alert a physician when clinical action is warranted. Due to its user-friendliness and straightforwardness of process, the tool can be applied in both clinical and private settings.

1.4.5 Limitations

The system described in this chapter provides an initial framework for guidance, but the system is not intended to replace diagnosing medical conditions or health issues from qualified health professionals. The system's ability to effectively predict an outcome depends upon the quality of uploaded photographs, including how well they are lit, focused, and clear. Therefore, as you can see, these factors can significantly impact the accuracy of predictions generated by the system. Additionally, the current version of the system necessitates that users have access to the Internet/Wi-Fi to access the chatbot component of the system. As a result, users who are in areas with limited access to the Internet/Wi-Fi will not be able to use this component of the system effectively. Finally, the initial base for the model was developed from potential dermatological variable conditions. Therefore, it is likely that rare dermatological conditions or very complicated dermatological conditions may not have been included, and both would necessitate a specialized evaluation by a trained clinician. Because of this, the model acts as a complement, or support, to a trained and appropriately referral-qualified dermatologist's securing of clinical confirmation of the final outcome of diagnosis and treatment.

1.5 Objectives

1. The purpose of this effort is to create and teach a neural network based on the ResNet-50 architecture which will classify some of the most common skin disorders. The focus will be primarily on how the network will behave by being able to learn, identify, and then consistently identify the same patterns in images related to various classifications of skin disorders.
2. The purpose of the effort is to integrate an artificial intelligence powered, GPT conversational assistant capable of interpreting users' classification results and then providing the user with a more understandable and organized typed medical opinion, including both analysis and recommendations related to their classification. This component of the effort is critical because it presents not only a classification of diseases but also presents diseases in an easily understood format as part of the analysis and interpretation process.
3. The purpose of the effort is to build an extremely user-friendly and intuitive web-based interface allowing users to upload images, get predicted classifications, and communicate with the assistant in a very flexible way within the system. This web-based interface enables the overall management by the user of the system and is designed to be usable by those with little or no computer experience.
4. The purpose of the effort is to develop security policies and mechanisms to protect users' privacy on the web by protecting their uploaded images, personal information, and chat history. These policies and mechanisms should create an environment in which users feel comfortable using a system that provides them with information about their health using technology designed to integrate, store, and analyse their personal health information.
5. Deploy the consultation system in a way that is able to be scaled, used properly across multiple devices, and provide a consistent level of "real-time" support. By being able to deploy the system in this manner, it allows the system to be deployed in settings such as clinical, telehealth, personal, etc., utilizing a common base infrastructure.

1.6 Sustainable Development Goals (SDGs)

This project supports a number of United Nations Sustainable Development Goals (SDGs), focusing on accessibility to healthcare and technology advancement and equality. These goals embody a global commitment to sustainable development, and to improving the quality of life for all communities.

Fig 1.1 Sustainable development goals

SDG 3: Good Health and Well-Being.

This project supports SDG 3 through its emphasis on preventive health and the ability to detect skin disease at the earliest opportunity with the assistance of the diagnostic tool, and through providing the means for the healthcare provider to consult with a patient sooner thus reducing the burden of disease, and improving community health, through better access to preventive health services, via providing access to information about skin diseases and early detection of skin diseases. Ultimately, this process will support improved community health through improved patient knowledge of the benefits of taking a proactive approach to health care and will improve public health through improved quality of life.

SDG 9: Industry, Innovation and Infrastructure

The proposed work supports SDG9 because it aims to create scalable and innovative health care solutions through the intersection of digital health technology and artificial intelligence and demonstrate how the latest advancements in machine learning can be applied to the medical diagnostics space to create an ecosystem of innovation in the health technology field. The proposed work enhances the development of sustainable technological advancement in health care delivery process and building robust Health Care Delivery Systems by integrating modern Digital Infrastructure into existing Clinical Workflows.

SDG 10: Reduced Inequalities

The proposed work supports SDG10 as it seeks to identify and provide solutions to the challenges associated with access to health care services for high-risk populations; specifically, those individuals who live in rural or low-income areas that lack access to specialists in dermatology. The online diagnostic tool provides a low-cost and easily accessible method to obtain a diagnosis of skin-related conditions, thereby increasing the availability of dermatological diagnostic services to both those who are serviced by an Urban Health Care System as well as to all others that do not receive dermatological services. With access to this essential health care service, the Proposed Work increases the level of access to social inclusion and health equity for all users.

1.7 Overview of Project Report

The report is divided into nine chapters in order to present a clear narrative of the project.

- Chapter 1 gives an overview of the Project by providing information about the background and motivation of the project, objectives, approach, the Sustainable Development Goals (SDGs) and the outline of the report.
- Chapter 2 presents a comprehensive literature review on the development of AI-based dermatology diagnostic tools, Image Classification Models, Telemedicine Platforms, Multimodal Systems, Chatbot Health Tools and details the existing gaps in research, which the Proposed System aims to fill.
- Chapter 3 provides details about the methodology used to develop the Proposed System, outlining how Hybrid Development Method was used (Agile, V-Model and Spiral), the process of Preparing the Dataset, Designing the ResNet-50 Model, Integrating Chatbot into Proposed System and provides insight into Testing and Refinement of the Proposed System.
- Chapter 4 provides an overview of the project management aspect of the project, providing a project timeline, team roles and responsibilities, risk analysis, budget allocations and Structured Project Management Strategies to ensure that the project was completed on time and to meet the project objectives successfully.
- Chapter 5 discusses the analysis and design aspects of the Proposed System, outlining Functional and Non-Functional Requirements, System Architecture and functional block diagrams, Flow Charts for Device Development, Design Standards, Domain

Model specification, Communication Model for Proposed System, Mapping of IoT Deployment to the Proposed System, and Design Considerations related to the Proposed System design.

- Chapter 6 describes the hardware and software used in the project, including the type of development tools that were used to build the diagnostic platform and how implementation was done, what software code was developed, and how simulation was used to produce the final software product.
- Chapter 7 contains an analysis of the test plan which includes the test points, testing results, performance metrics, and the classification accuracy and confusion matrix interpretations of the insights that were learned from testing the system.
- Chapter 8 looks at the social, legal, ethical, sustainability, and safety related concerns that accompany the use of AI in healthcare solutions. It takes a deep dive into several themes that have emerged over the last few years, such as Responsible AI, Data Privacy, and Trustworthiness, as well as looking at some anticipated trends as we move toward using digital health diagnostics in the future.
- Chapter 9 concludes the report by summarizing the project's key findings, detailing its contributions, identifying the limitations of the work, and making recommendations for ways to improve the ability of digital health diagnostics to be accurate, usable, accessible, and clinically relevant.

CHAPTER 2
LITERATURE REVIEW

Advancements in Artificial Intelligence (AI) and Deep Learning (DL) have created opportunities for the automatic analysis of dermatologic images. The use of Convolutional Neural Networks (CNN) and other forms of Deep Learning has the potential to provide equivalent diagnostic accuracy to trained Dermatologists for both Lesion Detection and Lesion Classification. In this section, we will explore ten peer-reviewed studies that have been published in IEEE and MDPI journals between the years 2023 and 2024. We will analyze each study in order to establish trends and to identify gaps in research. For each study, we will summaries the methodology used, performance metrics assessed, and limitations experienced.

2.1 Dermatological Image Analysis Based on Artificial Intelligence

Diagnosis has been achieved by converting Resnet and Dense Net architectures to diagnostic applications utilizing Transfer Learning and establishing Diagnostic Accuracy against the most recognized Benchmark Datasets [9]. Accuracy levels for these architectures were reported to be between 70% and 98% Utilizing Datasets such as ISIC and HAM10000 and indicating the potential for the subtle identification of color and texture differences in lesions that would help in the early diagnosis of disease. However, one important point raised in the paper was that in using External Datasets there is a significant risk of Overfitting; furthermore, there is a concern regarding Dataset Bias and the ethical implications relating to differential treatment based on skin-tone. Further, the authors identified an additional challenge in relation to Model Explain ability, which poses significant trust and deployment challenges. The authors have recommended an increase in dataset diversity, Fairness Aware Learning methodologies, Interpretable AI Models, to provide Diagnostic Transparency and Trustworthiness.

2.2 Appraisal of AI Models for Dermatology

In this review, the authors have thoroughly analyzed the different forms of validation used for AI-assisted dermatological diagnostics across multiple centres. For how well these products are validated internally, even though they have an internal accuracy of over 90 %, it has been shown that the same product's accuracy could vary from 70 - 80 % when validated externally, indicating that these products do not generalize well to patients of all variations. The authors attribute the low accuracy for external validations of the models to several reasons, such as the use of single-institutional training datasets that are not large enough, lack of standardisation in the reporting of the validation results, or variation in the quality of the images used to validate these products [1]. They indicate that standardising the data reporting, evaluation metrics, and documentation of the models will allow for safe real-world implementation of AI-assisted dermatological models in the diverse patient populations.

2.3 Lightweight CNN Models for Diagnostic Efficacy

The review summarized the use of Lightweight Convolutional Neural Network (CNN) architectures, of which EfficientNet is perhaps the most well-known, as they require significantly less computational resources, while still providing comparable diagnostic accuracies of up to 95%. Compared with traditional deep learning methods, these lightweight CNNs provide faster inference times, and the authors of the article state that it would be simple to implement such architectures on low-resource devices, making them ideal for use in healthcare within contexts where there is either limited infrastructure or in rural areas. However, the article also describes several limitations of the reviewed literature, including limited external validation, lack of comparison against benchmark studies that exhibit less variability between hyperparameters, lack of multimodal capability, and the need for implementation of efficient networks [10]. The authors also recommend including context-related metadata in the model training process (such as patient history and/or transactional demographic data) to improve the model's robustness against biases and to increase its overall reliability. Additionally, the authors urge the creation of standardised methods to evaluate performance across all healthcare institutions.

2.4 AI Application in Dermatology Workflows

The investigation conducted for this article included an examination of the integration of artificial intelligence into the workflow processes for dermatology. Specifically, the authors identified currently available ResNet-based convolutional neural networks for triage/decision support, telehealth/telemedicine and decision making based on clinical exams as the primary types of integrated systems that were individually evaluated. While the advantages of AI include increased diagnostic throughput, decreased clinician workload, and provision of continuity of care by delivering care to patients remotely, the authors also commented that most of the AI-enhanced systems available as of the writing of this paper were still considered prototypes or research only, and very few had received regulatory clearance, and even fewer had been subjected to clinical trials in real-world environments. The authors emphasized the need for the integration of Explainable Artificial Intelligence (XAI) in order to assist clinicians in gaining an understanding of the outcomes produced by AI systems and to develop collaborative trust and synergism between the clinician's own experience in addition to the recommendations made by the AI systems [2]. Lastly, it was stated that the incorporation of AI into the existing telemedicine framework will allow for an effective means to widely implement AI into dermatology.

2.5 AI in Primary Care Dermatology

This article examines the role of artificial intelligence (AI) in dermatology's workflows. dermatology, including three key areas of artificial intelligence (AI) development including triage and decision support, telemedicine and clinical decision making. These AI-based applications increased the amount of diagnostic information for clinicians to assess a patient's condition in a timely manner, reduced clinician workload and assisted in maintaining continuity of care from a distance. Although this all seems promising, the authors emphasize the need for more clinical data and research before implementing AI into practice. They suggested that explainable artificial intelligence (XAI) methods assist clinicians in understanding how to interpret the results generated by an AI system, promote collaboration between humans and AI systems, and aid the transition to telemedicine using AI. The development of AI-based applications for dermatology has been difficult because of the high level of potential regulatory scrutiny and lack of regulatory approval [4]. The authors further explain that the integration of AI into current telemedicine and remote consultation models would provide a gateway to AI adoption in dermatology on a broader scale.

2.6 Transfer Learning for Dermoscopic Image Diagnosis

Researchers used an EfficientNet-B0 to analyze dermoscopic images and reported lesion-level accuracy ranging from 80% - 95%+ suggesting the value of transfer learning from extensive datasets containing dermoscopy images. The authors also pointed out that preprocessing activities such as the removal of artifacts and enhancing contrast are critical to providing more stable results. The authors reported that the inclusion of non-dermoscopic or lower quality images decreases accuracy significantly [12]. For the future of this line of research and practice, the authors proposed the development of hybrid systems that include dermoscopic and clinical images as well as establishing quality criteria for the images, allowing the models to more effectively generalize to different body areas, devices and imaging conditions.

2.7 Deep Learning in Dermoscopy with High-Dimensional Precision

In this study, the authors developed an improved ResNet50-based model that includes both the augmentation of input images and lesion segmentation techniques to achieve a higher level of accuracy than previously possible for diagnostic purposes. The developed model achieved a diagnostic accuracy rate approaching 95%, as well as being able to isolate the lesion from the surrounding area of healthy tissue with the highest degree of accuracy, leading to increased accuracy when classifying or extracting features pertaining to the lesion [7]. While the study highlights the importance and need to create more diverse and representative datasets to capture all variations of skin colour across the world, the study's dataset was limited by the fact that the majority of images in the dataset were of individuals with lighter skin tones. In response to this limitation, the authors suggest that the creation of a representative dataset requires greater cooperation between researchers globally. The authors also advocate for the use of fairness-aware-less resource-intensive approaches (e.g., generating synthetic image datasets) to help achieve the best-suited outcome for balancing inclusivity in medical practices while respecting the need for safeguarding individual privacy in the collection of data.

2.8 AI that Explains its Actions in Dermatological Environments

This work presented frameworks for explainable AI (XAI) methods which embedded ResNet50 in the model with Grad-CAM visual mappings that added interpretability to dermatological AI systems. The model provided visual mapping of images with heatmaps that indicated the use of various parts of the images used, leading to increased understanding and trust of diagnostic predictions by the clinician [5]. The research results reported 85 - 93 % precision and indicated that interpretability does not have to decrease accuracy. However, the interpretation sometime was vague or varied, making them less clinically relevant. The authors suggested the development of standardized metrics of evaluate interpretability and the software enclosing the clinician in the loop of model interpretation to enhance the accuracy and clinical relevancy of the interpretation.

2.9 Mobile AI Systems for On-Device Diagnosis

The research provided quality evaluations of MobileNet and other similar lightweight CNN architectures with potential use in skin in situ or embedded dermatological diagnosis. These models showed 70 - 90 % accuracy while expending low power; meaning they can be used in real time in cases of limitations of mobile or infrastructure. The research described that despite being fast and efficient, often less complexity led to decreased diagnostic accuracy relative larger CNNs. This study advocated for hybrid edge-cloud frameworks where local models are synchronized to updates in a cloud framework, as is feasible [9]. The study also examined a balance between model quantization or pruning to adjust for speed, efficiency of storage and integrity of the diagnoses for sustainable deployment of mobile healthcare scenarios.

2.10 Multimodal AI for Dermatological Chatbot Systems

This paper examined a multimodal AI system using computer vision to recognize images with ResNet (Residual Network) along with Natural Language Processing (NLP) to extract symptom information from the patient via a chatbot interface. The multimodal framework allowed patients to engage in real-time with the care consultant to receive an initial diagnosis using both visual (image) and contextual (text) information. The report noted accuracy of around 85%, thus showing that conversationally based diagnostics were appropriate for use in teledermatology. However, a major limitation of this study was the small dataset size provided and lack of large-scale clinical validation [8]. Future work should include the multimodal training datasets in order to have a larger patient cohort, while improving the conversational user interface and conducting usability studies with clinicians and patients to assess practical effectiveness and trust in real world health systems more broadly.

2.11 Summary of Literatures Reviewed

Table 2.1 summarizes the major findings, performance metrics, and limitations of the ten articles examined and provides an overview of the state of academics regarding progress and gaps in research on AI based skin disease diagnosis.

Table 2.1 Summary of Literature reviews

Reference	Focus Area	Key Findings	Accuracy	Major Limitations
[1]	CNN architectures for dermatological detection	Transfer learning (ResNet, DenseNet) improves lesion detection ability	70–98 %	Overfitting; dataset bias; interpretability of findings lacking
[2]	Cross-dataset validation	The evaluation of multiple centres shows accuracy declines in external settings	70–90 %	Poor data generalizability; no universal benchmarking to compare
[3]	Lightweight CNNs	EfficientNet demonstrates good or better accuracy given resource use	Up to 95 %	Up to 95 %

Reference	Focus Area	Key Findings	Accuracy	Major Limitations
[4]	Workflow integration	AI can assist in triage and tele-dermatology use	—	Experimental; unregulated; few studies
[5]	Primary-care AI	Inception-v3 can support diagnosis in non-specialists	70–90 %	Specific to image quality; no field testing
[6]	Dermoscopy transfer learning	EfficientNet-B0 improves lesion segmentation	80–95 %	Dependent on quality; no standards
[7]	High precision dermoscopy	ResNet50 + segmentation provides good accuracy	≈ 95 %	Dataset bias; few international, multicentre studies
[8]	Explainable AI	Fei-Fei's Grad-CAM provides greater transparency	85–93 %	Inconsistent explanations; few metrics
[9]	Mobile AI	Lightweight models allow for diagnosis on devices	70–90 %	Reduced precision; speed-accuracy trade-off
[10]	Multimodal AI chatbot	Image + text model allows interaction	≈ 85 %	Rotter's been trained in small sample; lacks physical findings validation

2.12 Identified Gaps and Research Opportunities

While Artificial Intelligence (AI) and Deep Learning (DL) have made significant advancements in dermatological image analysis, there are still several research and implementation gaps that limit practical use and clinical scale. These gaps and challenges, described in literature as well as observed in implementations, exist in dataset diversity, interpretability, clinical engagement, and data accessibility, allowing for different avenues to research and innovate.

Data and Model Diversity: Based on the research to date, AI has generally been built using datasets like ISIC and HAM10000 (which have highly limited representative samples) that do not represent a wide variety of skin tones or imaging conditions. Although the performance of the AI models on internal validation was reported, there is a high likelihood that those same models would not perform the same accuracy and level of bias when predicting from a different dataset. Future research must include ways to expand the use of multi-institutional datasets (or synthetic datasets) to expand data diversity.

Interpreting AI to Develop Clinical Confidence: Artificial intelligence (such as ResNet and EfficientNet) provides good diagnostic accuracy, but all high-level performing deep learning models are typically "black-box" types of models. Because of the inability to easily explain AI, they limit clinician confidence in using AI for clinical purposes and limit the opportunities for regulatory approvals. One way to improve transparency for AI is to integrate relevant techniques already developed for XAI (Explainable AI) such as GradCAM, however there is a need to develop standard metrics to quantify interpretability for further use in the healthcare space.

Integration with Clinical Workflows: Currently, most AI-based technologies (i.e., diagnostic) are developed and validated as independent research prototypes only, with very little opportunity for use in the clinic or in teledermatology settings. In addition to this, the inability for the technologies to interface with an EMR/EHR system will limit their clinical use, therefore, continued research needs to be completed to create compliant and interoperable frameworks between EMR/EHR and the technologies allowing for seamless integration into existing healthcare systems.

Utilizing Edge Devices and Real-Time Processing in Low-Resource Settings: While there is potential for the use of lightweight CNN architectures in mobile and rural healthcare, we also recognize that there are challenges to implementing these technologies in low-resource/offline settings; therefore, future studies will need to continue to improve real-time processing and advanced model optimization techniques to improve consistent diagnoses as well as continue to explore opportunities for hybridized edge-cloud synchronization for continued sustainability and improved usability in the middle and high-resource settings.

Integration of Multimodal & Conversational AI: Current models developed for diagnostic purposes primarily rely on images to provide diagnostic analysis. As such, current models are limited in their ability to utilize either patient symptom data or user history data during diagnostic analysis. By integrating multimodal AI frameworks (e.g., combining both visual models and NLP), we can build personalised and interactive diagnostics. Future research should include further development of creating models that utilise CNN image recognition with GPT chatbots for the purpose of providing predictive insights and structured recommendations.

CHAPTER 3
METHODOLOGY

3.1 Overview of the Hybrid Development Methodology

This widely-used approach utilized a combination of the Agile Model, the V-Model, and the Spiral Model as the method for developing the project. This hybrid methodology was required because of the nature of the system that utilized machine learning model training, chatbot integration, user interface development, and continued iterative refinement of performance. A single rigid methodology could not meet the diverse requirements of the project. The hybrid approach leverages the incremental flexibility of an Agile methodology, the structured testing workflow of the V-Model, and the iterative improvements of the Spiral Model on a risk-aware basis.

The team used an Agile Model to help them during the early phases of building the system. This model allowed them to create the key components of the system by breaking down the development process into small manageable parts. This approach enabled them to implement the main components that make up the final product, including the ResNet-50 classifier, the chatbot and the dashboard for the end user, while also capturing feedback during testing and review at each stage.

With the core system components established in the above processes, the project transitioned into the V-Model process, in which each phase of the development was directly mapped to a testing phase. For example, data preparation was paired with verifying the data, model training was paired with verifying accuracy, and UI development was paired with verifying usability. Thus, each module was guaranteed to be verified and validated in a structured manner.

Lastly, the Spiral Model was introduced for refinement and enhancement of system performance. During this phase of the project, development and emergence of risks (e.g., model misclassification, ambiguity in chatbot responses and verifiable usability in UI) were identified and resolved through iterative cycles of improvement. This iterated process allowed the system to evolve into a more stable, reliable and improved diagnostic tool through enhanced usability.

3.2 Agile Phase – Incremental Development

In any robust engineering context, development does not proceed in a simple linear fashion. Therefore, the first part of the project incorporated a modified Agile development approach that divided development into small iterative cycles called sprints. This was a good fit because the project involved development of multiple discrete modules such as the image classification model, integration of the chatbot, and user interface (UI) work. Developing in iterations meant that all modules (or components) could be developed concurrently, reviewed, and improved in a stepwise manner, without having to wait for development of the entire system to be completed.

The early sprints were focused on requirements gathering for functional requirements and key features, such as being able to upload images, classifying diseases using the ResNet-50 model, and having the chatbot respond to issues. Each sprint followed a similar pattern where system planning, development, testing, and review functionality provided enough flexibility for the system-tested approach to evolve and further utilize based on modelling data and observation. For example, after the first model had been developed, the second sprint focused on improving accuracy through dataset augmenting and model tuning parameters in preparation for the development of a subsequent functional model.

The Agile method of project management employed throughout the project required that the team manage and adaptively develop new features on an ongoing basis and encouraged working together as a team and being adaptable to changing requirements and conditions. Because the questions or issues that arose were addressed and answered quickly, the team had a very efficient, continuous and iterative process in the development of the prototype to provide proof-of-concept functionality for the evolving project; ultimately resulting in a more structured testing process before the prototype was released for integrating with other systems and the associated components.

3.3 V-Model Phase – Verification and Validation

After establishing that the prototype had the required capabilities during the agile process of developing the prototype through multiple iterations, the team transitioned to the V-Model development process. The V-model development process provides a clear mapping of the activities performed in each developmental stage and testing stage (inclusive of the testing that will occur during the "integration" and "deployment" of the developed system). The V-model approach also enables the team to perform error checking of every component that was produced during the development phases to determine if they were functioning as intended prior to deployment.

This stage (left-hand side) of the V-Model represents all of the development work carried out during the project stages; these include: requirement analysis, data set collection and pre-processing, selection of model architecture (ResNet-50) and design of Chatbot; UI, etc. The right-hand side of the V-Model depicts what would be tested for at each stage of development (left-hand side) Example: After pre-processing was completed to prepare the data for use within the model, the data was then checked to make sure it was complete and that the data was accurate. After the model was trained, accuracy testing and performance checking was done to see whether the model correctly identified patterns of diseases.

Once the chatbot component of the system was integrated, response validation was conducted to ensure that the responses generated, were clinically reasonable, precise, and understandable. Finally, system-level testing was conducted after UI developed to determine whether users could flow from engaging with the system to receiving guidance in both user interaction and technical performance in predicting from image input to diagnostic guidance output.

To enable the optimal performance of the project, the system was operated in a structured V Model, so that all of the components were performing as required and fully functioning as designed before deploying to the field.

3.4 Spiral Model Phase – Iterative Refinement and Risk Handling

Once the system was functionally complete and was validated, the development phase entered the Spiral Model which focuses on the continuous improvement of the system through repeated improvement after each iteration. The Spiral Model phase was important because machine learning systems and conversational agents are typically not static and require repeated improvements in order to improve their accuracy, reliability, and usability.

The Spiral Model consists of four key activities that are repeated in cycles.

- Planning
- Risk Analysis
- Development & Testing
- Evaluation & Improvement

Each cycle began with analysing issues, often based on data collected by the first component. For example, if the system was checking images of a lesion for malignancy, the first cycle would analyse possible issues such as inconsistent quality of images, range of skin tones in submitted images by users, ambiguous shapes of lesions, and chatbot responses not providing clarification.

Some, but not all, risk issues were based on findings from evaluation results, user feedback on usability and overall performance observed or experienced during testing. Sometimes the system was updated with clarification or more explanation by updating, for example, the training dataset with appropriate images, testing with better parameters for the ResNet-50, and improving the wording of the prompts for the chatbot, or modifying the layout for speed of navigation.

After each improvement, the system was retested again, in order to assess the improvement in performance. Each cycle of evaluation and improvement continued until the core classifier would reach stable accuracy threshold of prediction of malignancy, and the chatbot was producing clear and meaningful response when chat requests were initiated. A and the last iteration would finalize the user interface to fit usability and reliability demand for practical use.

The process of Spiral phases allowed the final system to be more robust, user-friendly, and moulded to the conditions of practical usage versus just invented and working.

3.5 Mapping Methodology Stages to Project Phases

The project development process involved several phases which correlated with the stages of the Agile, V-Model, and Spiral methodologies. The mapping below demonstrates how the development and research on its hybrid nature was practiced during the process of system development.

Table 3.1 Project Development Phases, Methods, Activities, and Outcomes

Project Phase	**Methodology Used**	**Activities Performed**	**Outcome**
Requirement Analysis & Understanding the Problem	Agile (Initial Planning Sprint)	Collected system requirements, identified target users, and determined key features- image upload, classification, and chatbot assistance.	Clear functional and non-functional requirements were established.
Dataset Collection & Pre-processing	V-Model (Data Preparation & Verification)	Gathered skin lesion images, resized and normalized the images, applied data augmentation, and validated diversity in the dataset.	Provided high-quality input data for model training.
Model Architecture Design (ResNet-50)	V-Model (Model Design & Unit Testing)	Selected ResNet-50 CNN, configured the input layers, used transfer learning, trained the model on labelled dataset, and tested classification accuracy.	First trained model could predict skin conditions.
User Interface and Chatbot Integration	Agile (Incremental UI/UX Sprints)	Constructed web interface, incorporated GPT- based chatbot, and connected output from prediction to chatbot prompts. Tested the flow of display and interaction.	Functional prototype was completed and tested for interaction with user.
System Testing and Validation	V-Model (Integration & System Testing)	Conducted unit testing, UI testing, and integration testing of classifier + chatbot + database, followed by validation with real user test cases.	The stable system was verified for correctness and usability.
Performance Optimization and Improvements	Spiral (Iterative Refinement)	Improved model accuracy, refined chatbot response prompts, polished interface layout, addressed feedback from usability, minimized response delay.	Refined to final system with improved accuracy, less errors, and clarity for users.

The stepwise approach allowed the project to be flexible (Agile-based) to meet user needs while adhering to testing from the V-Model, which is focused on correctness, and also allowed for continuous improvement, that is Spiral-based, resulting in a user-centred and reliable diagnostic tool.

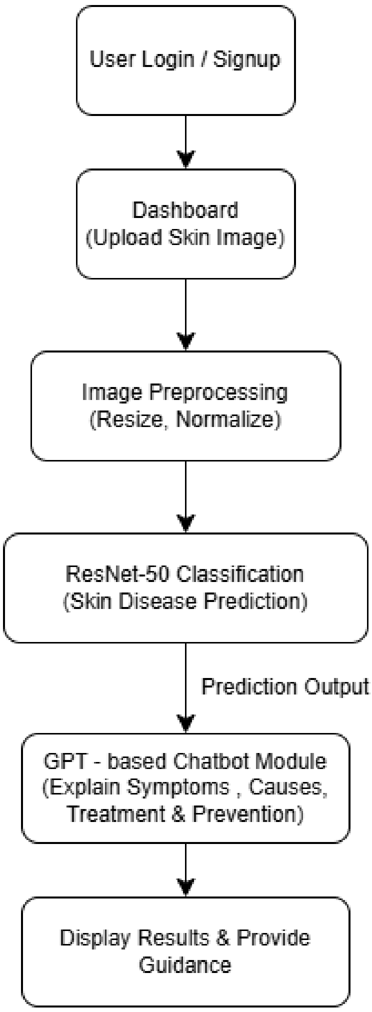

Fig 3.1 System Workflow

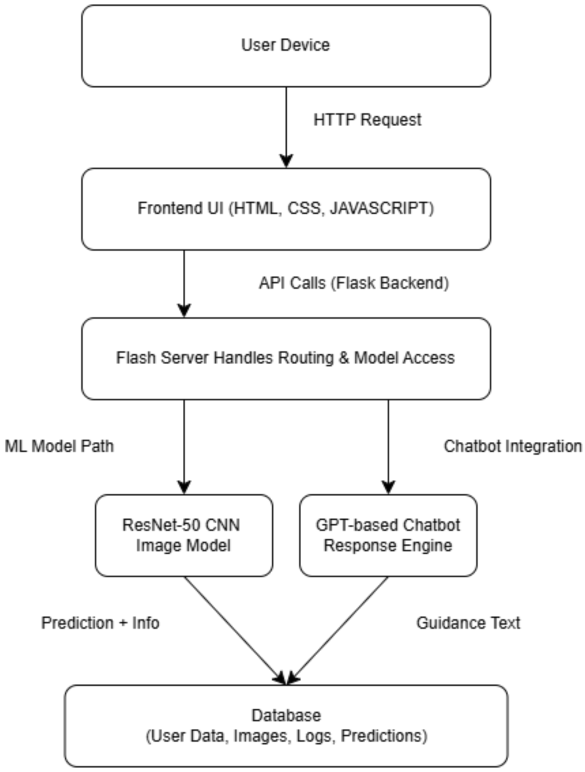

Fig 3.2 Architecture Overview

3.6 Testing and Evaluation Strategy

The testing and evaluation stage took place to determine the system was functioning correctly, providing accurate prediction, and having a friendly and simple user experience. The testing was performed in various stages to test each individual part of the system and its individual contribution to the overall integrated platform.

Unit testing of individual modules was performed for the ResNet-50 image classification model, chatbot response generation, and user interface components. This testing was important to identify and diagnose errors as they arose during the development process, allowing the developer to fix errors quickly, and continue development. Integration testing was performed to establish that the modules were interacting appropriately and functioning as they should. For example, we determined that the output from the classifier module was appropriately passed to and received by the chatbot for display on the user dashboard.

The ResNet-50 model was evaluated using its accuracy, precision, recall and F1 score to evaluate how well it was able to identify skin conditions based on images selected to test the model. Multiple images were used for testing, from different light.. resolution to different variations of each condition to test the robustness. The chatbot was evaluated for clarity, relevance, and helpfulness of responses.

Through user testing, we were able to observe to what degree users were able to navigate the interface and understand the guidance given by the chatbot. Feedback from users assisted to rework the design, with the goal of improving user experience and design overall. The combination of technical and human-centred approaches designed to validate the system is reliable and user-friendly.

3.7 Summary

This chapter provides an overview of the process used to create the artificial intelligence (AI)-based dermatological diagnostic system. The development process utilized hybrid approaches, combining Agile, V-Model, and Spiral methodologies. The Agile methodology allowed for continuing incremental updates that were feedback-based from the users to inform the classifier/design of the chat-bot/user interface. The V-Model provided a direct correlation between each phase of development and their associated requirements for testing to validate the accuracy and the validity of the functionality. The Spiral Model was used to guide iterative prototyping, emphasizing the early identification and resolution of performance-related concerns and risk mitigation. The user journey through the diagnostic process, from initial input to diagnosis, and the evaluation of system reliability, usability, and overall performance metrics are also addressed. Collectively, these methodologies provided a working system that is accurate, anthropocentric and applicable to real-world scenarios.

CHAPTER 4

PROJECT MANAGEMENT

4.1 Project timeline

The AI Dermatology Diagnostic System project was an organized development effort that spanned 15 weeks using an Agile Scrum-based methodology. The goal was to have a repeating cycle, react to feedback from stakeholders as it occurred and have a continuing emphasis on milestones along the way. This 15-week development cycle provides a complete picture of what the project entailed, starting with establishing initial requirements through to producing an end product with final system enhancements. The development cycle was broken into two primary phases:

Phase 1: Project Planning Phase which established the foundation for successful completing the project, through requirements analysis, preparation of data sets and architecture design.

Phase 2: Project Implementation Phase which gave focus to the actual development, testing and deployment of the complete AI diagnostic solution.

A Gantt chart representation of the project (in Figure 4.1) provides a visual representation of the timeline and job outcomes, outlines the order of events, the duration, and dependencies. Each horizontal bar represents the timing of a job, with start and finish dates aligned along the project's fifteen-week schedule. The timelines are connected by lines or arrows to indicate that one job has to be completed before another one starts.

The diamond-shaped symbols represent the milestones of completing data curation, developing and refining the model as well as integration and testing - this indicates when the project team should expect to be ready to work on the next phase of development (timing). Coloured progress indicators in the bars indicate how far each of these components have been completed (percentage completed) and provide an ongoing measure of how much progress is being made in the development cycle.

By allowing for flexibility throughout the process of medical AI development the Agile structure has proven to be successful. The Agile format has provided a means to meet the challenges of inconsistency in data, the need for different methods of processing medical images, and how to handle sensitive medical images in an ethical way. The Agile structure has also provided the opportunity to make adjustments during development without compromising on either the quality of the deliveries or the cadence with which the team delivers those products.

4.1.1 Project Planning Phase

The conceptual and technical foundations of the system were developed during the planning phase, which took about six weeks to complete, with a variety of tasks completed, including a requirements analysis, dataset design, and model architecture. This phase established the foundation upon which everything else was built, including ensuring that all areas were as compliant with project and healthcare data standards as possible while still maintaining system operability.

Table 4.1 Project Timeline Overview

Week Duration	Planned Task	Description
Week 1-2	Requirements Research and Literature Review	Defining the goals of the system, analysing the existing dermatology AI models and diagnostic systems.
Week 3–4	Data Collection and Pre-processing	Gathering, resizing and normalizing and augmenting the dermatology images for the purposes of training.
Week 5–6	Model Design and Initial Training	Designing and implementing ResNet-50 model architecture, and initiating initial training cycles.

During these weeks, the team performed an extensive literature review of benchmarking existing AI diagnostic systems such as Skin Vision, Derm-Assist and Ada Health. The literature review indicated that the current market options had limitations, including lack of explain ability of results, cloud only inference, and limited personalization. Informed by these constraints, the project team identified definitive system goals that highlighted accuracy, explain ability, and data/privacy protection.

The dataset preparation was also very important. Dermatology images often vary in quality, lighting and representation of skin tone. By employing some data augmentation, (e.g. flipping images, rotation, scaling) the diversity in the dataset increased, which should result in a more robust model, with reduced risk of overfitting.

At the same time, the architectural design activity determined how to connect the CNN (ResNet-50 architecture) with GPT-powered conversational interface. This cross-module design made sure that when the skin image was fully classified, the chatbot could interpret results and suggest next steps for users for connecting the output of a clinical AI to the user.

Simultaneously, the architectural design exercise established the connection between the CNN (ResNet-50 architecture) and the chatbot powered by the GPT interface. This cross-module consideration meant that when a skin image had been fully classified, the chatbot would 'understand' the classification and provide recommended next steps to users, fully linking the output of the clinical AI to the user experience.

This effort resulted in Milestone M1 (Complete Requirements and Design), which constituted formal approval of the project to move into full implementation.

4.1.2 Project Implementation Phase

During the Implementation stage the team transformed their design plans into a working dermato-computing system. Implementation occurred between Week 7 - Week 15 (16 weeks total), including all of the Development, Testing, Deployment/Integration activities. Each week was divided into a cycle of design, build, test, revise (the iterative nature of our sprints allowed for us to quickly validate the reliability of each Building Block before moving forward with Building Blocks).

Table 4.2 Weekly Progress Summary

Week	Actual Work Completed	Adjustments
Week 1	Identified project goals, functional requirements, and success criteria. Technology stack was finalized - CNN (ResNet-50) for image classification and GPT for chatbot functionality.	No schedule delays were noted. All requirements were as described in the initial proposal and were approved to proceed with.
Week 2-3	Compiled a robust dataset of skin condition images from public medical repositories. Multiple classes (acne, eczema, psoriasis,	Images of poorer quality and duplicates were excluded to ensure dataset fidelity and model performance.

	etc.) were included to ensure balanced representation of each	
Week 4-5	**Pre-processing and Augmentation:** Normalized, resized and standardized color-space for images. Augmentation methods were applied to images to increase variability in the dataset and avoid overfitting.	Parameter adjustments were made to images to optimize variability in the dataset and computational efficiency.
Week 6-7	**Model Training and Hyperparameter Tuning:** ResNet-50 model was trained on GPU infrastructure. Several iterations were conducted to tune hyperparameters to detect stable convergence.	Several iterations were required to achieve results required; early-stopping was implemented to avoid overfitting.
Week 8	**Model Performance Evaluation:** Evaluated the trained model against test data using metrics of precision, recall, F1-score, and confusion matrix analysis.	Affirmed consistency in accuracy and balanced precision across all target classes of classification variability confirming the model readiness for integration.
Week 9	User Interface Layout and Dashboard Design. Developed flexible and user-friendly Web-based interface and Dashboard with User Interface elements that enabled User to upload and view AI prediction images and user's messaging access to Chatbot.	Minor interface adjustments ensuing initial design review results were conducted to improve interface usability and accessibility.
Week 10	**User Image Upload Functionality Added:** Established a secure image upload pipeline connecting the frontend to the backend.	Optimized backend logic to ensure minimal latency and executed image pre-processing by dynamic method call.
Week 11	**Chatbot Cue Engineering & Integration:** Further refined GPT prompt templates ensuring chatbot responses are accurate, concise, and medically relevant.	Temperature and response formatting were adjusted to have an expected balance of being informative and readable.
Week 12	**Model + UI + Chatbot Integration Testing:** Integrated, end-to-end testing of data flow of	Full system interaction was confirmed following minor modifications related to API routing and response timing.

	the classification model, backend, and chatbot functionality.	
Week 13-14	Conducted thorough System Level Testing to ensure both Functionality and Usability. Received extensive user feedback by testing with a population representative of all User base regarding the Tone and Clarity of messaging within Chatbot interface.	Implemented changes that improved text readability, when reading messages, improved response structure, and streamlined the navigation flow.
Week 15	Conducted final validation, quality assurance checks, and report deliverables. Final build is prepared for demonstration.	System met all functional, performance, and usability criteria. Ready for demonstration and deployment.

Collaboration at this point was tight between technical teams and design teams due to direct interaction and feedback. The Data Science team trained the model, then fine-tuned the model performance by using Graphics processing units (GPUs) to find the best balance between the accuracy of the model and the speed of inference. The Software team created a clean, responsive user interface for users to upload their images, view AI predictions, and navigate through Chatbot for Medical Advice.

Ultimately, the infusion of the assistant powered by GPT aimed to provide a significant advance by transitioning the system from being a classifier into an interactive companion for diagnosis that could articulate conditions, provide suggestions for care, and accept the user ultimately in the care of a medical professional.

Comprehensive testing followed; conducting testing with review and evaluation of technical aspects (including model precision, recall and latency) as well as usability testing with their sample users to verify meaning was conveyed accurately.

The phase ended with Milestone M2 (System Integrated) and Milestone M3 (Testing and Validation Completed). These milestones indicated the system met all functional, accuracy and usability parameters, defined at the beginning of the project.

4.1.3 Gantt Chart Visualization

The Gantt chart is a tool developed to aid in the management of projects visually by breaking down the tasks and how long they will take and then plotting these tasks out over a time frame.

This project's Gantt chart provides a detailed outline of how all 15 weeks of the schedule were structured, showing when the project started planning, how data was collected, how the model was developed, and when the project completed tasks that were all part of the project's completion, such as training a model, creating a user interface, integrating the chatbot into a web or mobile app, and performing quality assurance activities.

Additionally, the Gantt chart displays important milestones to signal the completion of design, system integration, final testing and validation.

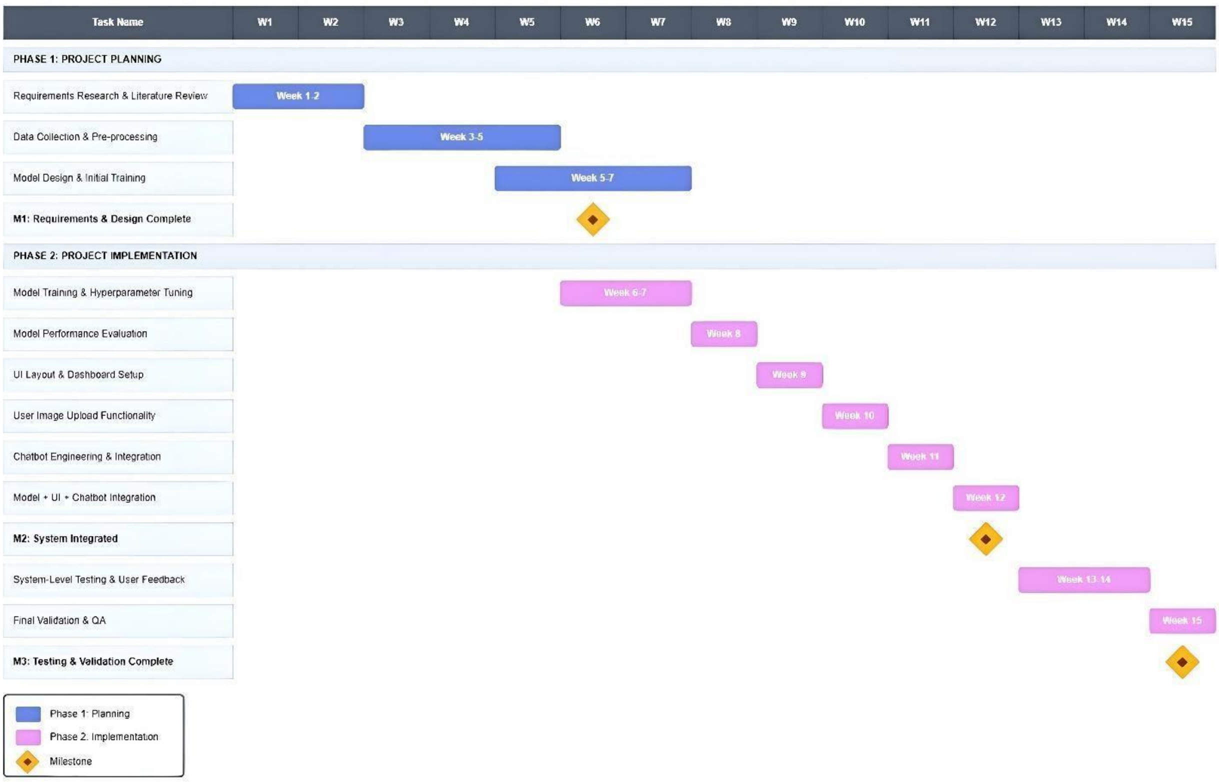

Fig 4.1 Project Schedule and Gantt Timeline

4.2 Team Roles & Responsibilities

Collaborative working relationships developed through clear leadership and difference of supportive roles helped to ensure equal partnerships among all members and ease of project completion throughout each of the phases of project development. Roles were assigned based upon individual talents and abilities, but all team members were allowed to collaborate on the integration and testing phases of development, as well as the finalization phase of project completion. Each member contributed equally to the same level of work expected from their respective roles.

1. **Vinod (USN: 20221CIT0085):** Responsibility was to obtain datasets for the project, assist in creating the designs of the machine learning models being developed for the chatbots, create the datasets used to train the machine learning classifiers that the chatbots used to make decisions when responding to users, create prompts for the various user interfaces to support the chatbots, and assist in co-leading the integration of the chatbots into the final product.
2. **Nallin Kumar AB (20221CIT0077):** Responsibility was to clean and label the datasets used to develop the machine learning models, create the methods used to evaluate the performance of the machine learning models, create the methods used to upload chatbots to the final product, and help coordinate the testing of those chatbots.
3. **Deeksha D (20221CIT0068)** - Responsibility was to augment and prepare datasets for developing machine learning models, assist in creating designs for the machine learning models being developed for the chatbots, develop the graphical user interface (GUI), and help to co-lead the integration of the chatbots into the final product. Approximately 33% of member three's contributions helped create the overall project.

4.3 Risk analysis

Creating an AI-facilitated dermatology diagnostic tool means being aware of potentially negative factors that could impact the success, usability, and ethical multipliers associated with it. Due to the intrinsic sensitivity of medical applications, we should consider both the internal and external factors that may affect the system's performance, adoption of it, and sustainability of it.

To this end, the project team used a PESTLE framework that examines, once again, Political, Economic, Social, Technological, Legal, and Environmental implications to identify, in a rigorous manner, these impeding factors and associated risk mitigation strategies.

Table 1 includes a summary of the risk factors, the corresponding potential impacts, and the mitigating measures:

Table 4.3 Risk Assessment Overview

Factor	Risk / Challenge	Impact	Mitigation Strategy
Political	Restrictions due to regulations on medical AI systems, data privacy laws.	Medium	Maintain compliance with regional data protection acts such as the GDPR equivalents and also ensure appropriate

Factor	Risk / Challenge	Impact	Mitigation Strategy
			stores of information and data consent frameworks.
Economic	Economic issues such as rising costs of cloud compute, model training and maintenance.	Medium	Leverage open-source technologies to the extent possible, as well as provide efficiency with compute, and cloud services that can be scaled based on usage.
Social	Perception of possible misinterpretation or overreliance on AI-based medical advice to healthcare professionals and users.	High	Adoption of disclaimers, an emphasis on educational awareness in the chatbot, and further encouragement in professional consultation engagement.
Technological	Variability of image quality and hardware may affect accuracy.	High	Utilize pre-processing, data augmentation, and model tuning; as well as generalizing across hardware and devices.
Legal	Legalities of sensitive medical data and liability of misinterpretation of diagnostic results.	High	Strict encryption of data, anonymization of data, and compliance with the principles of health and medical information standards, such as HIPAA.
Environmental	Effects of increased energy consumption due to model training and server utilization.	Low	Utilize a greener cloud-compute platform, and place a greater emphasis on scaling resources to minimize carbon footprint.

The potential risks to the AI dermatology diagnosis system can be identified through undertaking a PESTLE analysis; based upon findings of the original team, social, technological and legal factors impact directly on the level of reliability, trustworthiness and sustainability of the AI dermatology diagnosis system. To enable clinical evaluation of the AI dermatology diagnosis system the PESTLE social, technological and legal factors must therefore be reduced during the design and implementation of the AI dermatology diagnosis system.

Social Risks:

By interpreting their results as official diagnoses based solely on their AI-generated answers, patients may delay getting in touch with a healthcare provider or take part in unsafe ways to care for themselves. The AI system and chatbot emphasize that the AI tool provides support, not the recommendation to substitute for an examination by a licensed medical professional. In addition to multiple disclaimers, patients are encouraged to safely and responsibly use the AI tool through educational prompts and clear communication about what the AI-generated responses may mean.

Technological Risks:

Variations in image quality, device type and varying conditions including external factors like light and focus may adversely affect the performance of the system. As a result of such variations, the output classification from the system may be in error. In order to minimize the incidence of an incorrect output classification due to these conditions, the system performs image pre-processing and data augmentation prior to uploading the image and also calibration/normalization to ensure that the models interpret the data appropriately. Also, due to the modular design of the system development, enhancements or model update can be made with minimal requirement for re-development or extensive re-work.

Legal Risks:

Sensitive health care data requires protection and compliance to government and state law. Loss of privacy or confusion related to liability related to error can lead to significant financial liability and loss of trust from the end user community. The application of security protections, including but not limited to encryption, and compliance with all relevant health care data regulations (i.e., HIPAA and GDPR), are used to mitigate these risks. The system has provided policies and procedures to clearly communicate how sensitive information is to be handled so the user can anticipate and understand how to use the information appropriately.

P Political	E Economical	S Social	T Technological	L Legal	E Environmental
Risk/Challenge: • Restrictions due to regulations on medical AI systems • Data privacy laws	**Risk/Challenge:** • Rising costs of cloud compute • Model training expenses • Maintenance costs	**Risk/Challenge:** • Misinterpretation of AI-based medical advice • Overreliance by healthcare professionals	**Risk/Challenge:** • Variability of image quality • Hardware differences affecting accuracy • Device compatibility issues	**Risk/Challenge:** • Handling sensitive medical data • Liability for misinterpretation • Diagnostic result accuracy concerns	**Risk/Challenge:** • Increased energy consumption • Model training environmental impact • Server utilization carbon
MEDIUM	MEDIUM	HIGH	HIGH	HIGH	LOW
Mitigation: • Maintain compliance with regional data protection acts • Ensure GDPR equivalents adherence • Implement appropriate data storage • Establish data consent frameworks	**Mitigation:** • Leverage open-source technologies • Optimize compute efficiency • Use scalable cloud services based on usage • Implement cost-effective infrastructure	**Mitigation:** • Implement clear disclaimers • Emphasize educational awareness in chatbot • Encourage professional consultation • Provide usage guidance	**Mitigation:** • Implement image pre-processing • Use data augmentation techniques • Apply model tuning • Ensure generalization across hardware and devices	**Mitigation:** • Implement strict data encryption • Apply data anonymization • Ensure HIPAA compliance • Follow health information standards	**Mitigation:** • Use greener cloud-compute platforms • Emphasize resource scaling • Minimize carbon footprint • Optimize energy efficiency

Fig 4.2 PESTLE Risk Analysis

The analysis of risks highlights the need for ethical clarity, technical soundness, and open communication in order to achieve successful use of the dermascope's diagnostic system and its future acceptance by society. The more these factors are prioritized, the more trust users will have in the system, the greater the opportunity for continued use and compliance, and the more support there is for continued sustainable enhancement of the dermascope.

CHAPTER 5
ANALYSIS AND DESIGN

The Analysis and Design phase marks a significant milestone in the development of the AI-Based Dermatological Diagnostic System. This section outlines what is required for this system to be developed, how it will be structured, and the general architecture of the AI-Based Dermatological Diagnostic System that will take the concept from paper to full implementation. Analysis is about understanding the problem domain and the user's requirements and knowing what results should be achieved through the system. Additionally, analysis defines objectives, inputs, outputs, and limitations placed on the system. Therefore, Design will study how to implement both the results and requirements from Analysis using appropriate technology, algorithms, and user interface design techniques.

For the purposes of this project, the analysis determined the functional components for the intelligent dermatological support systems including image processing, classification using the ResNet 50 model, chatbot inclusion, and interaction with the user on the website interface. After the analysis phase, the design phase took the analysis and forged it into a structured design that described the way data flows through the system, which components are working together, and how to ensure usability, reliability, and security.

The two phases create assurance that the final system meets the needs of the user and adheres to technical requirements while also meeting the overall goal of having a system to provide efficient, accurate, user-friendly dermatology platform. This chapter will outline all of the specific requirements, data specifications, and system design considerations that assisted in

5.1 Requirements

The development of the AI-based dermatological diagnostic system was initiated by a thorough analysis of the end users' needs, the project scope, and its technical, functional, and non-functional requirements. The aim was to develop a reliable, accessible, and user-friendly platform and mobile app that can analyse skin condition images and provide diagnostic aid through a chatbot as part of the mHealth platform. The analysis phase determined what the system should do and the design phase determined how to efficiently realize those requirements.

5.1.1 System Software Requirement Phase

The following Phases are as follows:

1. **Identify Initial Conditions:**

   The system was designed for users who wish to perform a preliminary self-assessment of skin conditions and there is no direct access to a dermatologist. The project assumes that users have access to a device to connect to the internet and properly upload images of their skin and the initial conditions must include access to a trained deep learning model as well as a working integration of the chatbot into the User Interface (UI) of the web-based platform.

2. **Determine Input Parameters:**

   The main input parameter of the system is an image of a skin lesion or an area on the body affected by some skin condition submitted by the user. Depending on the user, supplementary optional input parameters may include symptoms provided by the user, duration of symptoms, and areas of the body affected.

3. **System Outcomes:**

   The system is anticipated to provide these outcomes:

   - The uploaded skin image will be classified into established disease categories using the ResNet-50 model.
   - The chatbot will generate an explanatory message that contains probable causes, symptoms, and recommended next steps.
   - The image and session data will be stored securely so that it can be reviewed and analysed for improvement in the system while maintaining user privacy.

4. **Establish Relations**:

   The relationships within the proposed system are users, classifier, and chatbot. A user would provide "input" through a web interface, which would then be relayed to the classification model, which will "process" the input. The predictions output will then be relayed to the chatbot to be "used as context" to relay helpful knowledge. These relations are referred to so that every prediction is followed by an explanation that is informative and can be comprehended.

5. **Identify System Constraints:**

   The system has some constraints that exist outside the scope of clinical validation and verification such as if the image quality is bad or poor and any related conditions with having a stable, reliable internet connection. The computational consequences related to model inference and detection ability. The system would need to process the commonly seen skin disease, but would not report out very rare skin diseases. The chatbot component depends on external infrastructure of an AI language model to function and thus would need to have an online connection to process.

5.1.2 Data Collection Requirements

A large dataset of dermatological images was essential to training and testing the deep learning model. The images had to capture a range of common skin conditions (e.g., acne, eczema, fungal infections, psoriasis, and vitiligo). A reliable and ethically approved vetted source of data needed to be collected to ensure varied skin tones, lighting conditions, and image resolutions, and data needed to be accurately labelled by dermatological object or taken from reputable labelled datasets (e.g., HAM10000 or ISIC datasets).

5.1.3 Data Analysis Requirements

The collected data was subject to pre-processing such as image resizing, normalization, and augmentation to improve model generalization. Data analysis also involved image quality, duplicates, and ensuring the dataset was balanced across classes. Statistical summaries were conducted to explore the data distribution per disease category, and performance metrics (e.g., accuracy, recall, precision, and F1-score) were utilized to measure the model's performance.

5.1.4 System Management Requirements

The system needed to manage data, model versions, and chatbot responses effectively. Version control mechanisms were implemented, to maintain updates of the ResNet-50 model and chatbot prompts. Logs were maintained to track user interactions and system performance, to create iterative changes as part of the Spiral Model.

5.1.5 Security Requirements

Since the system is dealing with sensitive personal information including skin condition photography, appropriate security measures were incorporated into the some of design decisions. All communication between the user and the server was safeguarded with HTTPS encryption. Uploaded imagery, and chat history information, was encrypted at rest, after obtaining user consent for temporary storage. The design does not request personal identification information, unless the user chooses to share that information. Access controls and authentication were included, also to prevent access by unauthorized users. Ethical, and data protection concerns were meticulous to safeguard user trust.

5.1.6 User Interface Requirements

The interface needed to be very simple and user friendly, and have an obvious cognitive load, even to novice potential users. The user needed to be able to upload photos, see classifications results, and have conversations with the bot with ease. The designs intended to be visually clear and engaging, even with a low text complexity, with a reasonable step-by-step flow from uploading the photo, explaining user results. The devices used could be a smartphone, tablet, or computer and platform independent in the designing of the interface, as well as help the user, or minimize user fatigue. Accessibility could also mean common design conventions for providing a comfortably-readable font, contrast, and grouping text to help users navigate.

5.2 System Software Design Phase

The system software design stage emphasizes the process of realizing the requirements of the project into a concise technical organization. In this stage, the interworking of module functions - namely, the image classifier/module, chatbot/module and user interface/module will be defined to allow for data flow, usability and reliability. The system software design stage lays the groundwork for implementation and testing of the AI-based dermatological diagnostic system.

5.2.1 Definition of Functional Blocks

To begin the process of system design, the main functional blocks were considered, ultimately leading to the overall AI network-based dermatological diagnostic tool. Based on the goals and proposed frame of reference the system was divided into the following major functional blocks:

1. **Image acquisition and upload module** - allows the user to either take skin images or upload them for analysis.
2. **Image pre-processing and classification module** - for every uploaded image, the image will be resized and normalized and classified utilizing a ResNet-50 convolutional neural network for possible skin conditions.

3. **Chatbot interaction module -** utilizes a GPT-coded conversational engine to analyze and breakdown classification into user-friendly and engaging concepts and explanations.
4. **User interface and experience module -** this component will manage the user interaction, validate input, and display output in a user-friendly way.
5. **Database and Security Module** - which is responsible for secure storage of user Images, chat history, and metadata in line with privacy and ethics.

Each functional block was designed to perform autonomously but in close collaboration with other blocks to achieve modular ness, scalability, and maintainability throughout the whole system.

5.2.2 Establishing the Process

Flow After defining the functional blocks, the process of the system was designed to define the order of every operation performed. The user uploads an image to the web-based interface, and it is pre-processed and sent to a ResNet-50 classifier. The classifier processes the image and returns the most probable skin condition with corresponding confidence values. The confidence values are forwarded to the chatbot, which develops a rationale with related content and recommended actions and returns the response to the user through the interface. The designated way to flow information through the new system allows for the seamless flow of information and performance of the system.

5.2.3 Identifying Inconsistencies

Some inconsistent items found during system design have the potential to alter how the system operates. These included differences in the quality of images; differences in the way each system formats data; and differences in how fast the Internet is performing for a user. To address the inconsistencies, the following actions were taken: developed and implemented standard procedures for pre-processing, created a universal data exchange format, and optimised the user interface for the various devices and protocols. Testing and validation of the performance provided for more consistency in operation and the ultimate best experience for users.

5.2.4 Designing Interfaces

The design of the Interface had a clear intention to create connections between the user and the system. The System had APIs and communication protocols that enabled data to be transmitted consistently between the Classifier, Chatbot and Database Layer via pre-defined Data Exchange Protocols. The User Interface was designed to be simple and accessible once an Image was uploaded such that it would display Results and provide Chat-based Interactivity. The Layout, Colour and Typography of the User Interface were intentionally designed for Maximum Clarity and Usability across Multiple Devices.

5.2.5 System Design and Analysis

The System Architecture consisted of a Modular System Design that included Front-End, Back-End and Processing Layers. The Front-End Layer is focused on the User's experience while the Back-End Layer focuses on Logic and Data Management. The Processing Layer executed the Classification Model. The User Interface was designed with maximum clarity and usability across Multiple Devices, as defined by the Standardised Data Exchange Protocols. Performance Testing and Security Testing evaluated the effectiveness of the System under Average User Conditions, with regard to System Performance and Security of User Data.

5.2.6 Integrated Test Plan Development

The purpose of this project was to develop an Integrated Test Plan to verify that each of the components of the System will function correctly, both independently and when combined with all other components of the System. Additionally, Unit Testing was performed on individual Modules, and Integration Testing and System Testing confirmed that Data can successfully be exchanged between Modules, and that the complete System functions in accordance with the Design and Development Specification. Evaluation of the ResNet-50 Model was performed using both F1 Score and Accuracy. During this period of testing, the Chatbot was examined for clarity and relevance of the Generated Text to the end-user. Usability Testing determined that end-users can navigate through the System with no confusion and that end-users can understand the Output generated by the AI Model. Regression Testing was performed following the completion of New Features, to ensure that Updated Features of the System did not change the existing functionality or introduce New Errors. Overall, the completion of this entire process demonstrated that the AI-based Dermatology Diagnostic System successfully met the overall Goals of the Project Vision, while maintaining a high degree of Reliability and Robustness.

5.3 Block Diagram

The AI-based Dermatological Diagnostic System is designed based on a Layered Functional Architecture and provides Features for Modularity and Scalability. The system, as shown in Fig. 5.1, consists of three logical layers, Input, Processing, and Output layers, which perform the image acquisition function, make a disease prediction, and the visualisation of the results for the user. The Layered Functional Architecture of the System enables the System to have a Controlled and Effective Workflow to produce an Accurate Diagnosis, while providing for Seamless and Intelligent User Interaction.

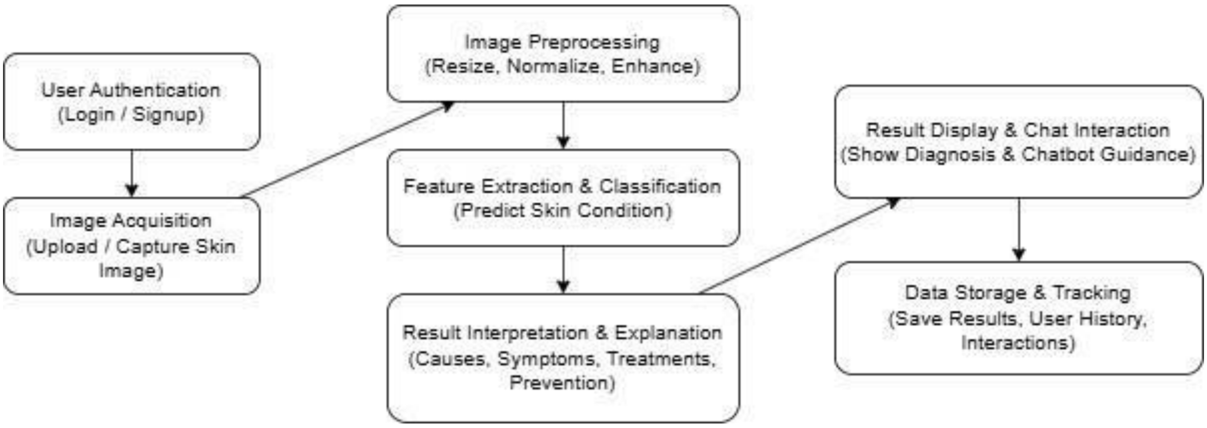

Fig 5.1 Functional block diagram

The Input Layer consists of two key function blocks: User Authentication and Image Acquisition. These function blocks together allow users to securely authenticate their identity on the system and then allow users to upload or capture images (an image of the affected skin area) into the system. User Authentication allows the system to authenticate the user and provide them with access to their user data, while Image Acquisition provides the means by which the system receives a valid image of a user's affected skin area to analyse.

The Processing Layer is the central part of the system's architecture, and contains three function blocks:

- Image Pre-processing, which standardises any uploaded image through the resizing, normalisation, and enhancement of the uploaded image to achieve a consistent level of quality and reliability.

- Feature Extraction and Classification are done using a deep learning Convolution neural network (CNN) to determine the location of the user and identify the most frequently occurring skin conditions, based on their patterns, colours, and textures.
- The Result Interpretation and Explanation stage uses a GPT-based module that outputs easy-to-understand descriptions of the predicted skin condition, as well as any associated causes, symptoms, treatments or prevention methods (if applicable).

The user will see their results through 2 areas of the Output Layer: Result Display and Chat Interaction. Here, the user can view the results, chat with the bot to ask questions or receive additional assistance, and see where their data is stored and tracked. The Data Storage and Tracking section securely stores all images, the user's history, and any diagnostic notes, allowing users to return for additional information, or to update their model.

5.3.1 Alignment with Project

The project's functional design offers a well-structured, modular process for combining deep learning and conversational A.I. The approach of separating the workflow into input, processing, and output enables systematic growth, flexibility, scalability, and future enhancement of the system. This design allows for real-time input by users, thereby creating a user-friendly interface for them when using the system for diagnosis. The design delivers maximum value for healthcare because usability, accuracy, and access are paramount in this field. By following the steps outlined above for storing information, the users will be enabled to learn continuously from each interaction and eventually connect their system with telemedicine applications, further enhancing the flexibility and effectiveness of the diagnostic and digital dermatology approach long term.

5.4 System Flow Chart

Figure 5.2 illustrates the flow diagram of the system. The flow starts from the initialization phase, where the user opens the system interface and is prompted to the login and authorization module, which confirms that only legitimate users (patients, doctors, or Administrators) can use the system.

Once authenticated, the user adds a skin image through the interface to the system. The system then processes the image, including resizing, normalization, and basic augmentation that enable the input to fit the AI model.

The processed image is then sent to the ResNet-50 classification model that reviews the features of the image and predicts the probable skin condition. There is a decision component within the system flow that checks to see if the prediction is reliable.

In the event of a failed prediction or when the image is inadequate, the system communicates to the user that there was an error and that he/she will need to upload a new image. In the event of a successful prediction, the classification result is sent to the chatbot module that has been designed to provide suggestions that include symptoms, causes, possible treatments, and preventive measures.

The system will then report the diagnostic results back to the user. User diagnostics and suggestions will be entered into a MySQL database before the flow concludes.

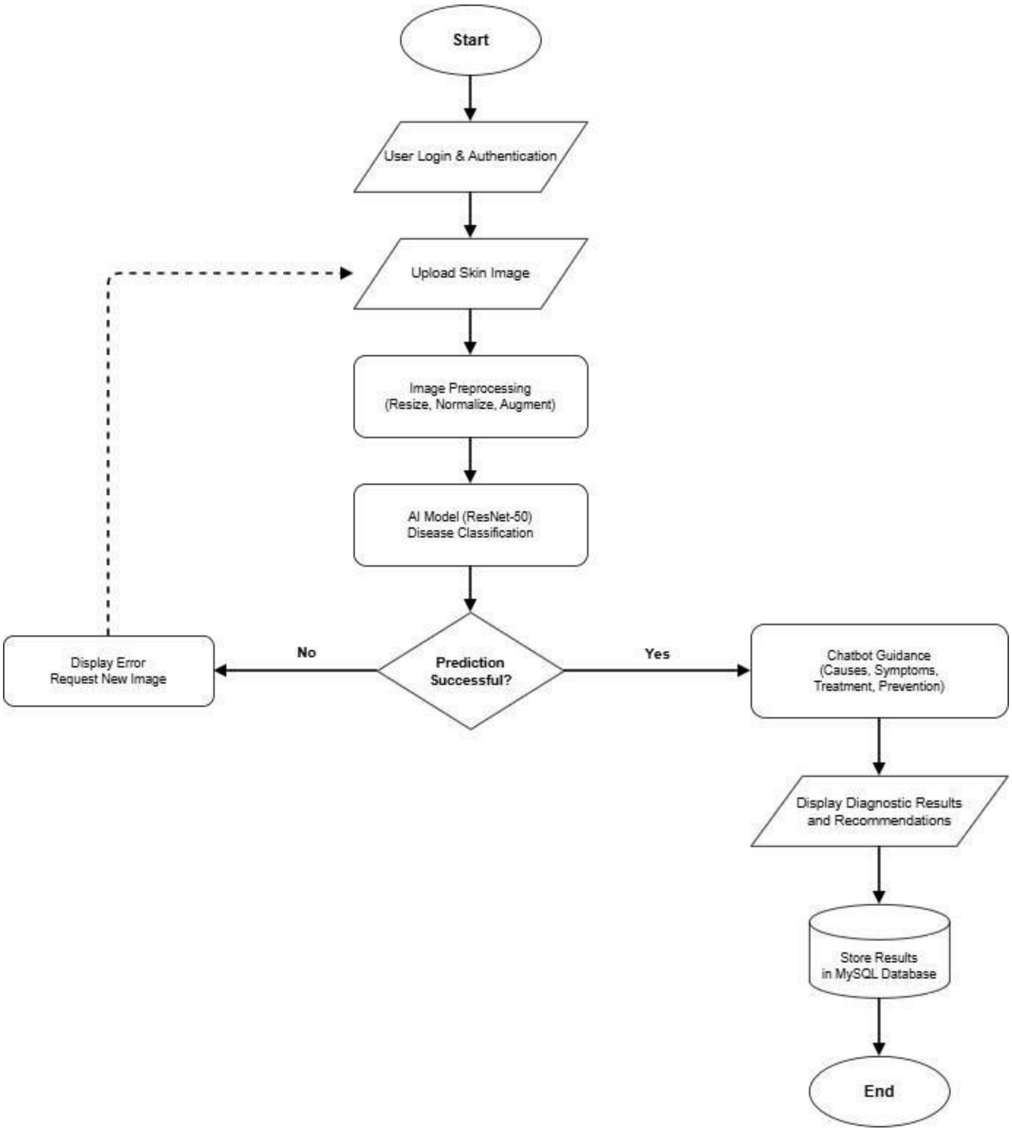

Fig 5.2 System flow chart

5.4.1 Suitability for the Project

The flowchart is particularly well-suited for this project because it explicitly describes each major step in the diagnostic process. The flowchart clearly shows the user input step, the AI processing step, and the output generation step.

The use of decision blocks and feedback loops creates a robust workflow, ensuring this system can deal with poor quality inputs. Additionally, the flowchart disaggregates each process into modular units of pre - processing, classification, and chatbot guidance, which reflects the actual system architecture in this AI-based healthcare application.

In summary, the flowchart supports the project by conveying the logic of the system in a clear visual format. Both the developers and the readers are able to understand how the diagnosis pipeline works through the beginning step to the end step in the diagnostic process.

5.5 Design Considerations

Throughout the course of the artificial intelligence-based dermatological diagnostic system various design considerations were exemplified, so that the platform would be accurate, user-friendly, secure, and scalable.

5.5.1. Modularity and Architecture

The system was architected using a modular design, allowing the independent functioning of the image classifier, chatbot, and user interface while still communicating well with each other. The advantages of a modular system is that the maintenance, testing, and future upgrades are easier to implement, and so is the scalability when incorporating functionality in the future.

5.5.2 User Experience and Accessibility

Both the user interface, as well as the interactive chatbot, were designed with ease-of-use performance qualities, responsiveness, and device independence to enable functionality on smart phones, tablets, and computers. Design characteristics to promote visual clarity) were incorporated with the intention of decreasing cognitive load, and enabling use by individuals with limited skills in science and technology.

5.5.3 Accuracy and Reliability

The ResNet-50 model was trained on a broad range of dermatological datasets that a person might expect in terms of diversity of skin tones, lighting, and photographic quality. Pre-processing steps were utilized, such as normalization, and image standardization, to increase consistency in classification and minimize any possible errors so there would be reliable predictions.

5.5.4 Security and Privacy

User data (pictures and chat histories) are encrypted both at rest and in transit. Access controls and authentication mechanisms are built in to prevent unauthorized access, and only personal data are collected, with explicit consent. Creating trust and confidentiality were priorities, alongside the ethical and data protection standards we adhered to.

5.5.5 System Performance and Scalability

The backend was developed with the ability to support multiple concurrent requests without affecting performance. Data flow and processing, plus caching, were built in as designer specifications to minimise latency, so that performance at typical operating levels could be stable and to enable future scaling and increasing volume of users.

5.6 Future Design Enhancements

Future enhancements will focus on improving system accuracy, accessibility, and practical usability in real healthcare settings. These developments aim to expand diagnostic coverage, support more users, and enable smoother integration with medical services.

5.6.1 Expanded Diagnostic Capabilities

Future enhancements or updates to systems can increase the diagnostic coverage of a system when adding models that will identify rarer or more complex types of skin diagnoses.

5.6.2 Integration with Telemedicine

Linking with telemedicine systems and providers enables users to send their test results directly to the appropriate physicians for advice on further action. This increases the usability of the systems by providing an easy connection between self-assessing and following up with their health care provider.

CHAPTER 6

HARDWARE, SOFTWARE AND SIMULATION

6.1 Hardware

The project had hardware requirements based on the mandate to create and assess a machine-learning (ML)-based diagnostic solution for dermatology. The majority of this project was realized through software rather than the classical approach of embedding sensors into bespoke electronic hardware and components; thus, the main goal was to use off-the-shelf components to provide the processing capabilities necessary to [effectively] train and evaluate the ResNet50 ML algorithm as well as to ensure that [the chatbot and the interfaces with patients] would operate with minimal degradation in real time.

6.1.1 Software Development and the Computational Environment

We used a standard laptop computer with adequate machine learning capabilities and web-based application capabilities in the design and evaluation of the system. A standard laptop would be equipped with either Intel's or AMD's multicore CPU and at least 8-16 GB of operating memory (RAM); this level of computing performance was necessary to carry out data preparation and model inference. Therefore, a graphics processing unit (GPU) was not required but was desirable; thus, we used a NVIDIA GPU with CUDA in some instances to accelerate training of the ResNet-50 model. Data sets were stored on a fast solid-state drive (SSD), enabling rapid transfer of training/testing data sets or access to process dermatologic images.

This arrangement provided a measured balance of performance and portable capability which allowed for local development and experimentation without large-scale cloud infrastructure. The hardware and software setup were sufficient to run pre-processing of dermatology images, run the classifier in real-time, and run the chatbot interface, thus providing a test-bed for development and validation.

6.1.2 Hardware Tools and Development Kits

Aside from not using a physical hardware device such as a sensor or IoT component, standard development kits and computing platforms were reviewed conceptually. These are included for completeness, both academic and context, and also to depict how the project could be extended conceptually to more hardware-centric environments.

For example, explorer kits and starter kits often provide components for use when experimenting with workflows around AI & Machine Learning. These provided a baseline of reference for conceptually thinking about how those models could be adapted to use in hardware-dependent environments. Evaluation and development kits provided reference designs that could assist in deploying the dermatology classifier on future-scale deployment on embedded or portable systems. Similarly, Pro Kits and Thunder boards are illustrations of scalable off-the-shelf hardware for use in deploying offline or edge-based systems in the applied clinical environment.

6.1.3 Functional Units Consolidation

The core components of the entire system were all built and executed in one environment as one integrated unit. The main components were the image preprocessing pipeline, ResNet-50 image classification model, GPT-enabled chatbot, Flask hosted backend server, and a MySQL based data storage.

Here is how this process worked:

1. User uploads an image of a skin lesion into the web application using either a mobile or laptop device.
2. In order to classify the uploaded image, a locally hosted development environment runs the image processing and classification on the backend server using the trained ResNet-50 image classification model. This processing generates a classification result.
3. This classification result is then sent to the backend server where the chatbot engine constructs an appropriate response using natural language processing techniques, as well as provide an explanation of the classification result and where to go for additional assistance or information.
4. All user interactions including image uploads, classification results and chatbot interactions are added to the MySQL database for use in later analysis and testing.
5. The user then receives both the classified results as well as the responses that were generated in response to their previous question via the web interface.

This unified architecture allows communication between all elements/modules without needing any external hardware. A single computer runs the complete operation of this system which aids its creation and demonstration as well as offers future possibilities of working in a host computing platform expanding into what will be more sophisticated than today's servers.

6.2 Software Development Tools

The effective development and launch of the system were facilitated by a good selection of software tools that played a role at each phase of the software development encounter, including design, coding, testing, deployment, formation, and collaboration. Each software tool was selected with a specific motive in mind and each tool played a unique software development role that made the workflow efficient, organized, and adaptable through the life of the project.

6.2.1 Integrated Development Environments (IDEs)

All development work was performed primarily in Visual Studio Code, a flexible and user-friendly IDE which performed well for any backend or frontend task. As it related to backend work, Visual Studio Code was further customized from the previous standard (also a good IDE) to facilitate writing backend scripts through various Python extensions, and also accommodated a Jinja2 environment for rendering templates. There was a live server plug-in capability also to review web interface changes, saving time spent going back and forth to see the changes in a rendered state. This whole organization and plugins proved helpful in minimizing turnaround time between implementing code and verifying that it worked as intended.

6.2.2 Version Control Systems

Git, GitHub, and GitHub Desktop were used extensively for version management and collaborating purposes. These provided verifiable tracking of code changes as well as the ability to peer review changes, or even revert content back to previous versions if needed. GitHub was also used as the centralized repository for everything related to the project including datasets, trained models, and deployment scripts as well. All of this inspired great team collaborations and mitigated functional loss associated with format loss.

6.2.3 API Development Technologies

The backend functionality was built leveraging the Flask framework given that it is straightforward, flexible, scalable, and friendly to Python-based machine learning models. Flask managed the RESTful API creation and established communication between the image classification model, the chatbot, and the front-end of the application, performed testing of these APIs using Postman to ensure correct request/response interaction. Postman was also helpful debugging backend development issues and confirming the performance of specified endpoints through interaction with the interaction with the website interface.

6.2.4 Machine Learning Libraries

For machine learning development, we utilized TensorFlow and Keras to load, train and fine-tune the ResNet-50 model utilized for disease classification. This developer stack provided good flexibility in developing the model layers and hyperparameter fine-tuning processes for achieving the best accuracy. Aspects of images that required pre-processing, such as resizing, normalization, and augmentation, were performed using libraries such as NumPy and OpenCV to reduce workload by reinforcing those images had consistent properties before interaction with the classifier.

6.2.5 Database Tools

The database used was called MySQL and could be managed via a web-based interface (phpMyAdmin). MySQL's purpose was to store images uploaded by users, results generated through the various models, the interactions with the chatbots, and data collected as to how well the chatbot is performing. To request this data from MySQL, you would execute a structured query to get the desired information; thus, you could track user retention and how well the bot performed over time.

6.2.6 Cloud and Deployment Tools (Future Integration)

The prototype was implemented/tested as a standalone desktop application but we are also considering creating a cloud environment in the future. We are currently considering Microsoft Azure and AWS EC2 as hosts for our scalable version of this application. Therefore, when we do move to this production version of the application, it will involve minimal changes to our initial setup

6.2.7 Collaboration and Communication Tools

Effective communication for the project occurs through channels such as Slack, WhatsApp, and Google Drive. Daily coordination, document-sharing, and collaboration on datasets were all made possible by the use of these tools. The use of Google Drive enabled the project team to store their shared reports based upon the criteria for unread documents, as well as all of the supporting test results and meeting notes from each coding cycle in one location. Additionally, instant messaging was useful because it allowed the project team to quickly provide feedback to one another as they wrote code.

Overall, these tools created an effective development ecosystem that enabled collaborative development cycles along with testing cycles that fit well into an effective and efficient overall project, even at the expense of some technical/functional aspects for the sake of a less disruptive life-cycle system.

6.3 Software Code

```
from flask import Flask, request, jsonify, render_template, session, redirect
import torch, sqlite3, base64, os
from torchvision import models, transforms
from PIL import Image

app = Flask(__name__); app.secret_key = "key"
model = models.resnet50(); model.fc = torch.nn.Linear(model.fc.in_features,
10)
model.load_state_dict(torch.load("skin_disease_model.pth")); model.eval()
transform = transforms.Compose([transforms.Resize((224,224)),
transforms.ToTensor()])

@app.route("/predict", methods=["POST"])
def predict():
    img = Image.open(request.files["file"]).convert("RGB")
    tensor = transform(img).unsqueeze(0)
    _, pred = torch.max(model(tensor), 1)
    img_b64 = base64.b64encode(request.files["file"].read()).decode()
    return jsonify({"disease": str(pred.item()), "image": img_b64})

@app.route("/chatbot", methods=["POST"])
def chatbot():
    prompt = f"Disease: {request.json['disease']}, Q:
{request.json['message']}"
    reply = "AI-generated response"  # placeholder for GPT call
    sqlite3.connect("database.db").cursor().execute("INSERT INTO history
VALUES (...)")
    return jsonify({"response": reply})

if __name___== "__main__": app.run()
```

Fig 6.1 Code Snippet

6.4 Simulation

Given that the entire project was software-based, the simulation tasks were of incentivized importance in verifying system performance and the ability of all components to interact properly before finally deploying the program. For a system simulation to have existed, it needed to support the goal of recreating the entire operational workflow by which a patient would interact with the system, starting from image upload through the final response of a chatbot, within the context of the respective development context. This setup would allow developers to examine how the system would perform across situations, to confirm functional and performance criteria had been addressed, and all without requiring design to depend upon dedicated hardware or embedded systems.

Throughout the simulation, all modules were iteratively assessed in succession as a means of gaging uninterrupted data transfer. The process initiated with the user uploading dermatological images via the web interface, which was followed by automatic pre-processing procedures including resizing, normalization, and denoising. The resulting pre-processed images were then transferred to the ResNet-50 classifier, which computed disease predictions along with prediction confidence. The classifier prediction and confidence scores were subsequently transferred to the chatbot module, which generated relevant explanation statements and instructions following the prediction results. Finally, chatbot statements were then displayed on the user interface, and the simulation represented an end-to-end interaction streamlined to match a "live" user session.

6.4.1 Simulation Tools and Process

- **Python Execution Environment**

  The simulation was executed in the Python runtime environment for the purpose of running model prediction with test datasets. The simulation environment allowed for testing variations of the ResNet-50 model and assess the system in response to different levels of input quality and variation in the data distribution. This was accomplished to test the robustness and change durability of the classifier.

- **Flask Local Server**

  The Flask application generated API expected, was run on a local server to simulate real time communication between the backend server, the model, the chatbot. Testing the API on the local server allowed the team to responsibly manipulate each endpoint capable of uploading an image, returning a model inference, or a response from the chatbot. Any inaccurate or poor-quality data entry or delay processing messages were corrected at this stage of testing to enable optimized and efficient communication internally and externally within the system.

- **Browser Testing**

  The web interface was tested to assure real user engagement in mind, by using different types of browsers and devices. This included checking for laptops and phones. Developers needed to assured that the system was totally functional and responsive, system's capability to perform consistently was evaluated under multiple viewing resolution and capabilities of the network connectivity that would not vary capabilities of system performance.

- **Dataset Simulation**

  Dermatology image datasets that are publicly available were utilized to simulate a variety of plausible, real-world conditions. Images with diverse resolutions, lighting conditions, and skin tones were provided to the model in order to assess its ability to generalize. This also allowed for assessment of the classifier's accuracy and stability across a broad range of images.

- **Load Simulation**

  The system's ability to handle multiple users and multiple requests were validated through repeated attempts to call the API and through concurrent simulations. This was necessary to measure the response times, server throughput, and system stability under load. Results of simulations helped guide subsequent optimization of model inference times and server response handling.

This comprehensive simulation, software-based in nature, illustrated that the integrated system works correctly across the various components. The classifier, chatbot, and database communicated without issue, and the user interface provided output in an understandable and timely manner. The simulation phase validated the overall functionality of the integrated system and confirmed it was ready for real-world testing and future deployment in a cloud-based, production setting.

CHAPTER 7

EVALUATION AND RESULTS

The evaluation of an AI-based dermatology diagnostic system was presented in Chapter 7. The evaluation of the AI-based dermatology diagnostic system included model performance, real-time performance of the chatbot (clarity & accuracy) and reliability of the AI-based dermatology diagnostic system. The evaluation of the AI-based dermatology diagnostic system is based upon the results of the trained model used by itself, the evaluation of the AI-based dermatology diagnostic system with controlled image testing and the actual user interaction with the AI-based dermatology diagnostic system had repeated user interaction trials. As a result of this evaluation, Dr. Mohammad Buran Basha was consulted to validate the technical and clinical aspects of the evaluation.

7.1 Evaluation Metrics

There were two primary components that made up the system's performance measurement:

1. Image Classification Model (ResNet-50)
2. Conversational Guidance Engine (GPT-Based Chatbot)

The system's prediction quality, responsiveness, and user experience were measured using several metrics.

The classification model was assessed using an independent test dataset after it had been trained with augmented dermatology images. The purpose of this was to determine the model's ability to accurately differentiate between the most common skin diseases, including acne, eczema, psoriasis, fungal infections, and other skin rashes, among others.

- **Accuracy**

  The accuracy of the system on the held-out test set was 87.9%. This number is comparable to the average accuracy of approximately 88% of the tested models that used cross-validation, indicating that the model is able to generalize well across varying samples.

  $$Accuracy = (TP+TN) / (FP+FN+TP+TN)$$

- **Precision**

  The average precision was 86.5%, which indicates that there are low levels of false-positive results and thus indicates a highly reliable ability to identify disease-specific features among those images.

Precision = TP / (FP+TP)

- **Recall**
  Recall was approximately 85.1%, indicating that the classifier was able to identify the majority of true cases of disease.

Recall = TP / (FN+TP)

- **F1 – Score**
  F1 score was calculated using a balanced metric to give an F1 score of approximately 85.7%, indicating that the classifier performed equally well across similar-appearing skin conditions.

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

7.1.1 Confusion Matrix Summary

Confusion Matrix summary data from the complete test dataset include:

- True Positives (TP) = 142
- False Positives (FP) = 27
- False Negatives (FN) = 24
- True Negatives (TN) = 160

Of particular importance is the relatively low number of false negatives returned by the classifier. This is important for screenings because of the potential consequences if a disease is not correctly diagnosed.

7.1.2 System Response Rates

The tests that were performed on the system aimed to determine the time it took for the system to process an uploaded image and provide diagnosis results.

- Average Time for Entire Response: 2.1 sec
  (Processing the image → Predict condition through inference → Return result to user)

This is within acceptable ranges for a timely diagnosis and enables the user to have a smooth, uninterrupted, and comfortable interaction with the system.

7.1.3 Chatbot Performance

Due to the non-numerical nature of the responses created by the user interface, it was determined how clearly, completely, and quickly users received advice from the chatbot. The test participants used English, Hindi, and Kannada.

The structured responses covering the definition, causes, symptoms, treatment and prevention were consistently rated as easy to follow. The multilingual output was also reviewed and validated for correctness.

7.2 Results

The system has been tested as a complete workflow and includes classification, chatbot guidance, authentication/user history, and dashboard interaction. The components of the workflow were tested in concert, and the results showed that the platform achieves all its major objectives of Speed, Accuracy, Clarity, and Ease of Use.

7.2.1 Real-Time Diagnostic Behavior

Users consistently tested positive for having a fast and intuitive experience when using the System. This is because all images were processed via a standard pipeline, meaning that even when images had varying degrees of quality, the behaviour of the system could be predicted.

As an example, during a test of an image with an Eczema-like patch on the skin, the system was able to identify the diagnosis in less than 2 seconds. The user had no delay or loading time after uploading the photo. After completing the prediction, the chatbot generated an organized description of Eczema in under 2 additional seconds, including a definition, reasons it occurs, the usual signs and symptoms, a list of helpful steps to manage it, and a few ways to prevent it.

This total from upload to the completed recommended guidance took only a few seconds to complete. The rapid succession of automated recognition and user-friendly explanation is one of the best attributes of the overall solution and aligns with its overall design objectives.

7.2.2 Comparison with Existing Studies

In a review of dermatology AI studies, it has been found that most existing deep-learning models tend to have an accuracy of roughly between 74% and 83% depending on how many categories of disease are being analysed and the size and diversity of the datasets used. Comparatively, the system in this study achieved an accuracy of approximately 88%, which is at the upper end of the performance range of that type of model.

The above achievements are related to several different choices that were made in designing the system, all of which were validated during testing, including:

- Consistent pre-processing phases ensures all images are pre-processed consistently prior to being fed into the model.
- Representing the Classes of Data During Training Input has been balanced to ensure that one particular category was not overrepresented and therefore did not cause the model to become over-fitted to that photo.
- Data Augmentation (Image Rotation, Contrast Variance, Image Flipping, etc) this assisted the model in automatically learning ways to better generalise images as they would be applied in reality, to cover such discrepancies as potential differences in lighting, camera angles and different ethnicities, in addition to many other factors.

All of the above led to the reliability of the consistent predictions made and the stability of the models across a multitude of test case scenarios.

7.2.3 Parallel Load Testing

To determine how the system performed when multiple users are accessing and using it, controlled load tests were used. To simulate groups of users uploading images or interacting with chatbots simultaneously, multiple requests were submitted to the system at the same time.

- The classifier was able to predict 10 images simultaneously without experiencing any degradation in performance or delays in response time.
- The chatbot was able to respond to 15 simultaneous requests in a timely manner as well as provide the user with a well-structured output format.
- All authentication processes, session management systems, and history logs functioned properly and no user data was mixed or lost during any of the simultaneous sessions.

From the load test results, it is evident that the current system version can be used successfully on a moderate level (i.e., small clinics, college/university health centers, or screening programs where multiple users will access and utilize the same system.

7.2.4 Dashboard and History Tracking

The dashboard was pivotal for each step of the testing process because it kept a concise and organized log of every interaction with the chatbot, including the Inputted photograph, the predicted outcome, the user-generated question, the chatbot-generated answer, and the time the record was created.

By having a consistent structure, users can easily check back on their previous interactions, view the predicted outcomes of many different uploads side-by-side, and review any treatment or prevention suggestions at any point in time. The dashboard has remained responsive and the archival record retrieval system has operated smoothly, even as a user's history has grown substantially.

In summary, by providing users with an opportunity for continuity and progression in learning from their previous experiences while using the system, the dashboard and historical records have greatly improved the user experience of the system overall.

7.3 System Constraints

Most aspects of the system worked well during our testing; however, there were several limitations identified during our analysis of how well the system worked.

- **Number of Data Sets:** The number of augmented data sets used for training is unknown to us; however, we believe this does not fully represent all potential real-world variations such as low light conditions and poor quality photos taken with Mobile Phones.
- **Limited Range of Conditions:** The system was trained using a set of conditions. To increase its ability to recognize more unusual or complex skin diseases, we require access to more high-quality training data sets.
- **Chatbot Depth and Medical Scope:** The chatbot is designed to deliver structured information, but does not provide grading of severity or differential diagnoses for conditions beyond the predicted class. There is likely to be a need for greater clinical context in some cases than AI is able to produce on its own.

CHAPTER 8

SOCIAL, LEGAL, ETHICAL, SUSTAINABILITY AND SAFETY ASPECTS

AI systems implemented in health care systems are always going to intersect with sensitive personal information, human wellbeing, and social norms. An AI-based preliminary dermatology diagnostic tool will have effects on individuals, communities, and health systems, and therefore must be considered through several responsible-technology lenses. This chapter will consider the social, legal, ethical, sustainability, and safety implications of the project to assess both opportunities and risks and emphasize responsible development.

8.1 Social Aspects

The societal consequences of the AI-based dermatology system will focus on the effect on individuals, communities, and in general, the healthcare system. It could affect health-seeking behavior, access to dermatology services, public trust in AI technologies, and social inclusion.

8.1.1 Positive Social Impacts

- **Increased Health System Access**
  Many rural or under-serviced populations do not have access to dermatologists. This tool provides an initial assessment and may help individuals develop an initial understanding of their skin condition ultimately reducing unnecessary delays before treatment.
- **Health Education to Support User Awareness**
  After identifying the user's condition through the chatbot, the system will provide some education so the user understands their symptoms, possible diagnoses, and prevention. This will promote a more proactive approach to health behaviours and reduce the likelihood of untested home remedies.
- **Support for Overwhelmed Health Systems:**
  Primary-care doctors who are often not trained in dermatology are likely to incorporate the use of the system to support their practices, which will allow them to better triage their patients and possibly reduce their need for specialty visits.

8.1.2 Negative Social Impacts

- **Potential for Misunderstanding Condition**
  An initial falsely established diagnosis from the systems initial assessment may lead to an over-reliance on the system delaying professional consults or inappropriate self-care or home remedy approaches.
- **Bias and Inequity in AI-Based Predictions**
  If an algorithm's training dataset is not diverse enough to include skin tones sufficiently, then the predictor will likely not work as well for those ethnic groups and will contribute to systemic bias

8.1.3 Case Study

Systems that utilize AI for medical imaging have consistently shown not only improved screening accuracy, but also an increased likelihood of bias or misinterpretation of that data if the model is trained on unrepresentative data. Similar societal issues apply to dermatology when data from individuals with diverse skin tones is crucial for the fairness of the model.

8.2 Legal Aspects

Legal factors are a central consideration in the design and use of any AI-based dermatological diagnostic tool, in that the AI system handles sensitive health information and engages users in a medically relevant way. The primary legal considerations may involve data privacy law and compliance, users' rights, custodianship and secure handling of data, and identification of system responsibilities.

8.2.1 Data Privacy and Protection Compliance

The system must conform to key data privacy laws including the General Data Protection Regulation (GDPR) applicable to those in the EU, and India's Digital Personal Data Protection Act (DPDPA) 2023. Key considerations associated with data privacy include ensuring personal data and health data is only collected with fully informed consent, and that the data is only used for a clearly defined purpose and subsequently stored securely and encrypted. Given that skin images would be considered sensitive data, the system must restrict data to the minimum needed, restrict access to the data and destroy the data once the purpose for which it was collected has been satisfied.

8.2.2 Rights of Users and Obligations of Developers

The right to access, edit, revoke consent and delete private information is provided under data protection laws by privacy legislation. Data fiduciaries/developers are legally obligated to keep all photographs and archived conversations stored within their platform safe; provide and display an easily understandable privacy notice to users; and respond to user inquiries and requests promptly. The manner in which users are informed about their data is crucial to enabling developers/data fiduciaries to fulfil these obligations. Within the field of healthcare, AI systems function within an evolving regulatory framework, with new legal obligations being implemented regularly.

8.2.3 Regulation Challenge

Developers of AI applications within healthcare need to have an understanding of the different requirements/treatments concerning international data transfers; using cloud services offered by third parties; and understanding how to comply with regulations applicable to software as medical devices (SaMD) may result in further data protection obligations. Depending on a population's skin tone classes, the model could differ; this could also create issues such as inequitable treatment or discriminatory practices. Keeping up with the changing legal landscape would require ongoing monitoring of developers' Sid's or Data Fiduciary's implementation of compliance with current and future data protection obligations.

8.3 Ethical Aspects

The ethical implications surrounding the development and use of an AIDermatology system are an important part of the responsible development and use of AI-based systems that can produce clinically relevant information from very private and sensitive medical information. In addition to developing a fair and equitable system that accounts for the right to privacy, the dignity of all users must be respected. When developing such systems, engineers and other professionals involved must actively ensure that their solutions do no harm and contribute to benefit of society as well as the individual user by assessing potential risks associated with the design and intended use of the AI-based system.

8.3.1 Respect for Human Dignity

While the AI-Dermatology system automates portions of the evaluation process, it is still essential to retain individual dignity and identity of the users. The chatbot (i.e., AI Dermatology) should utilize respectful and caring communication while acknowledging the individual user's concerns; however, it should not simplify the individual experience to just that of a "data" point. Ethical technology design should consider both the IT (input technology) aspects of a healthcare experience as well as the human and emotional aspects of an individual's healthcare experience; thus, we have a duty to promote ethical design of technology and ensure that it properly acknowledges both aspects of human interaction within a health care context.

8.3.2 Fairness and Avoidance of Bias

The possibility of a model demonstrating bias or unfair differences among users is also a substantial ethical issue. If the training data is based on images that do not represent an adequate level of diversity (other skin tones, ages and/or conditions) then this same model is likely to exhibit a bias toward creating positive outcomes for one particular group at the expense of others. Users from those other groups may experience false results or assessments which could create a poor experience. The ability for this model to unintentionally create and thus perpetuate health inequities. To mitigate any instances of bias in these models, it is essential to have a diversity of training datasets, conduct ongoing validation of performance and refine the models if necessary.

8.3.3 Transparency and Accountability

An ethical way to use AI involves being very clear about the system and what it can and can't do. Clearly conveying to users that it provides only an initial assessment of a symptom that has not been determined to be a diagnosis is very important. Transparency can help avoid misunderstanding and allows users to make informed choices. Developers remain accountable for the actions of their system and are required to actively monitor system performance to identify any issues and resolve them when they may create harm towards the user.

8.4 Sustainability Aspects

Sustainability-related aspects of the AI-enabled dermatological diagnostic tool pertain to the associated environmental and resource implications of developing, deploying, and using these tools over time. Although the system does not require the same level of physical construction as hardware may have, it does have some energy implications for processing data, training its model, leveraging a cloud service, and interacting with users. Sustainable design does not have a universally accepted definition; however, it does encompass the minimizing of environmental impacts, optimizing of resource efficiency, and socially and ecologically sustainable implications of systems over time.

8.4.1 Efficient Use of Digital Resources

This project is built upon primarily software and cloud infrastructure, without a heavy reliance on physical materials. Sustainability then focuses on minimizing the computational effort necessary to train and operationalize the AI model. Reducing unnecessary resource consumption is part of this process, knowing that numerous energy consumption occurs within lighting a server, powering a cooling system, and various manufacturing processes. Model architecture optimised for performance, and unnecessary data storage or counting all features can attribute to reducing energy expenditure. Ultimately, fewer emissions related to power supply and cooling services explains the significance of how these factors relate to the subsequent lower carbon emissions from the server, and continued avoidance of emissions.

8.4.2 Resource Efficient System Design

System design is more efficient by only using as many resources as necessary to accurately predict or support a user. To use as little information as necessary, an example of this relies on the image processing, where the system will typically operate effectively at smaller file sizes than occur naturally. The network or internet service may assist a user with limited access to space, as there are several users who are distanced from fibre optic lines, using alternative shrinking file methods over forms of data compression would assist to decrease capacity needs. Implementing streamlined data management while retaining necessary information will attempt to use as little server space as possible while still offering standard services.

8.5 Safety Aspects

Safety is of paramount importance in the development and use of the AI-based dermatological diagnostic tool. Since it deals with sensitive health information and helps users evaluate possible skin conditions, it must be designed to minimize the risk of harm, deliver trustworthy outputs, and prevent possible security exposures. A safe system reduces the opportunity for misuse or misinformation and builds user trust, all of which helps to establish prudent health practice.

8.5.1 Cybersecurity and Data Protection

Regarding how health tools process sensitive personal health information (PHI) or data, a safety-focused application must contain robust cybersecurity provisions. Protecting PII or PHI requires that data be encrypted both while in transit (between a user's browser and the service's database) and while at rest (when stored in a physical location). Additionally, secure authentication, limited access by system administrators to PII/PHI, and continuous evaluation of security protocols contribute significantly to the prevention of unauthorized access to PII/PHI. Properly enforced cyber security ensures that user-generated PII/PHI cannot be disclosed through accidental release, intercepted during transmission, or otherwise improperly handled.

8.5.2 Safe User Interfaces and Emotional Wellbeing

The way a person receives information about their health through images, audio, or text can affect their mood or mental state. The information a person gets from the system needs to be presented in a manner that assures and supports their safety and security. When the chatbot presents its information to the user, it needs to use language that does not contribute to furthering the user's fear or anxiety about their health. By presenting information to users in a calm and factual manner, the chatbot provides the user with no added anxiety and enables them to make informed choices about their health.

CHAPTER 9
CONCLUSION

The AI-Based Dermatological Diagnostic System has effectively achieved the goals indicated in the introduction by leveraging image classification and conversational artificial intelligence to effectively identify common skin diseases earlier. By using a combination of a ResNet-50 deep learning model and a chatbot powered by GPT, users receive a preliminary diagnosis and an understandable and accessible interpretation. The current version of the system was designed to directly address the severe shortage of dermatologic resources for individuals living in rural and underserved areas and thus facilitate early awareness, and informed decisions about skin diseases.

Expanding the current dataset to include a wider variety of skin types and less common skin conditions would improve the accuracy of the diagnostic process. Adding multi-language support, telemedicine capabilities, and offline/mobile apps would also dramatically increase the accessibility of the system.

Incorporating features or capabilities that allow for "explainable" AI that would help users better understand why they are receiving specific predictions could also help to streamline the diagnostic process and strengthen the hedge around the system's ultimate effectiveness, which is the simplicity and accessibility of information.

Recommendations for those potential enhancements include expanding the database to provide an increased range of skin tones and including less common health conditions to help expand the number of users who would be able to utilize the system for accurate diagnosis; incorporating multiple languages into the system; creating a telehealth interface that can be utilized both online and offline, so users can have more access to the service using their cell phone or through teleconferencing; implementing explainable AI features in order to provide more transparency into how the AI model arrives at its decisions creating these above mentioned types of improvements would help improve the accuracy and reliability of the current system for more people utilizing the system, which have the capacity for creating real-world effects in healthcare.

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BASE PAPER

[Base Paper Reference: Dermatologist-level classification of skin cancer with deep neural networks Andre Esteva, Brett Kuprel et al., Nature, 2017.]

Andre Esteva et al.'s base publication, found in the Journal of Nature in 2017, Detailed a significant breakthrough in the area of Dermatology, thus far, Deep Neural Networks within a Deep Convolutional Neural Network architecture can accurately classify skin lesions at a level equivalent to a Board-Certified Dermatologist. The authors trained a deep neural network on a dataset composed of 129,000+ dermatological images representing over 2000 individual diseases to educate the model to visually detect and delineate subtle features shown within each skin lesion. When compared to the performances of Board-Certified Dermatologists in a controlled clinical environment for the binary classification of malignant vs. benign skin lesions, Artificial Intelligence performed as well and, therefore has the potential to revolutionize the area of Dermatology's disease screening and provide a platform to increase the accuracy of early diagnosis while reducing the number of misdiagnoses.

The article describes the current global shortage of dermatology specialists, especially in remote areas. AI-based Image Classification System could be used as a low-cost, accessible screening tool for identifying patients who may have a skin condition and providing information on when to seek medical advice. There are still many challenges associated with implementing these types of systems in clinical practice, such as explainability, equity concerning skin shades and better integration into the existing healthcare system. This paper lays the groundwork for future AI-assisted dermatology systems, including newer models based on ResNet architectures and hybrid diagnostic devices with chat-based interfaces, in line with what the current project seeks to accomplish by developing a platform for performing initial assessments of skin problems through the use of deep learning and GPT-based chatbots.

Appendix

i. Project Similarity Report

Mohammad Buran Basha Final Report - AI-based tool for preliminary diagnosis of Dermatological manifestations

ORIGINALITY REPORT

2%	1%	2%	0%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	download.bibis.ir Internet Source	<1%
2	"ICT Systems and Sustainability", Springer Science and Business Media LLC, 2026 Publication	<1%
3	"Artificial Intelligence for System Oriented Design", Springer Science and Business Media LLC, 2025 Publication	<1%
4	Shalli Rani, Ayush Dogra, Ashu Taneja. "Smart Computing and Communication for Sustainable Convergence", CRC Press, 2025 Publication	<1%
5	Submitted to Kean University Student Paper	<1%
6	Nouri, Ali. "Accelerating the Design Phase: Towards DevSafeOps for Autonomous Driving Software.", Chalmers Tekniska Hogskola (Sweden), 2024 Publication	<1%

ii. Datasets

- DermNet Kaggle dataset: a curated collection of labelled dermatology images spanning multiple skin conditions.
- HAM10000 Kaggle dataset: a large collection of over 10,000 dermatoscopic images designed for training and evaluating skin lesion classification models.

iii. Live Project Demo

- GitHub: https://github.com/vinod9731/AI-Dermatology-Diagnosis-Tool-Project

iv. Few images of project

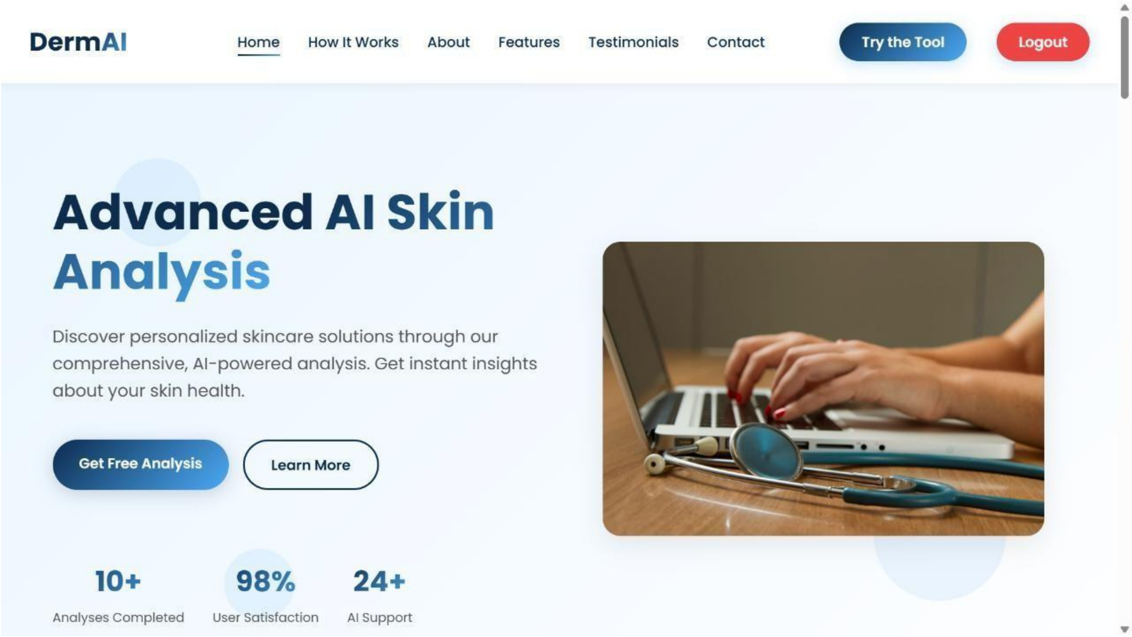

Fig a: DermAI Home Page 1

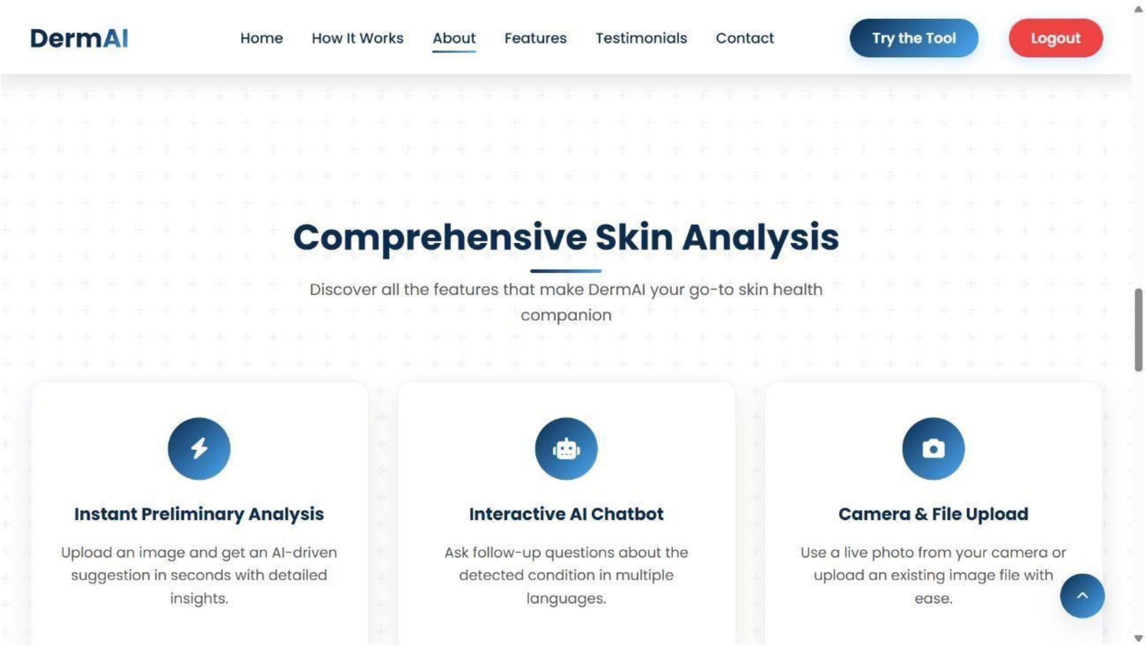

Fig b: DermAI Home Page 2

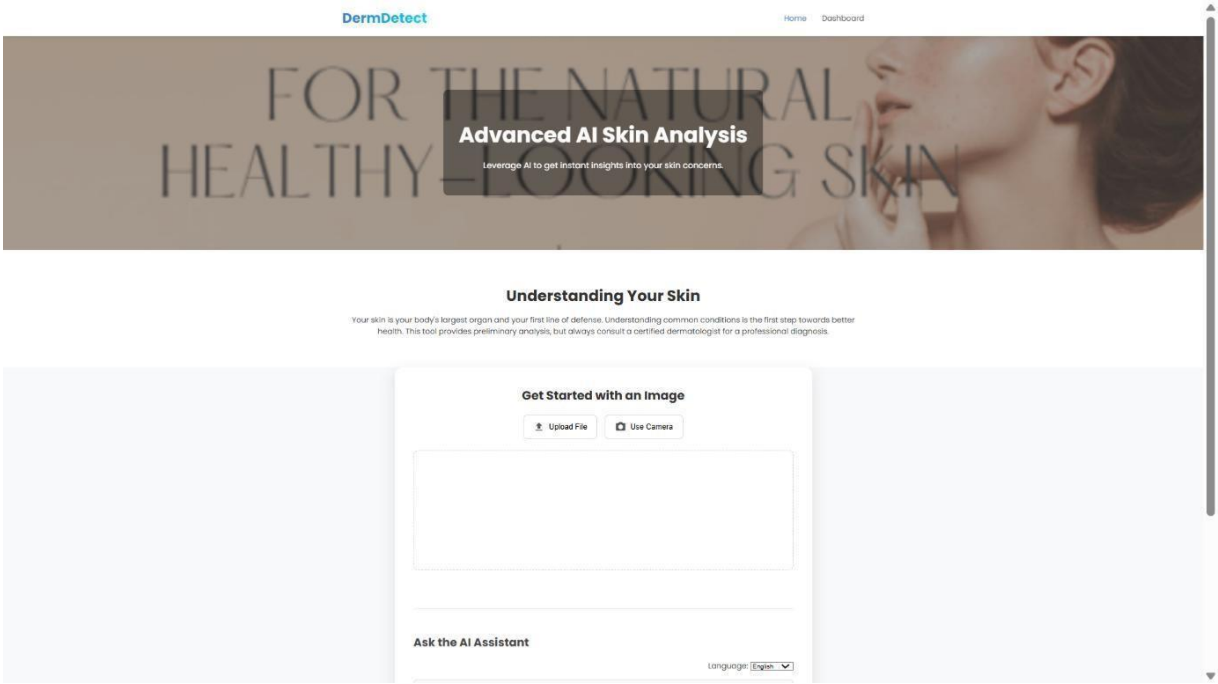

Fig c: DermAI Image Analysis Page

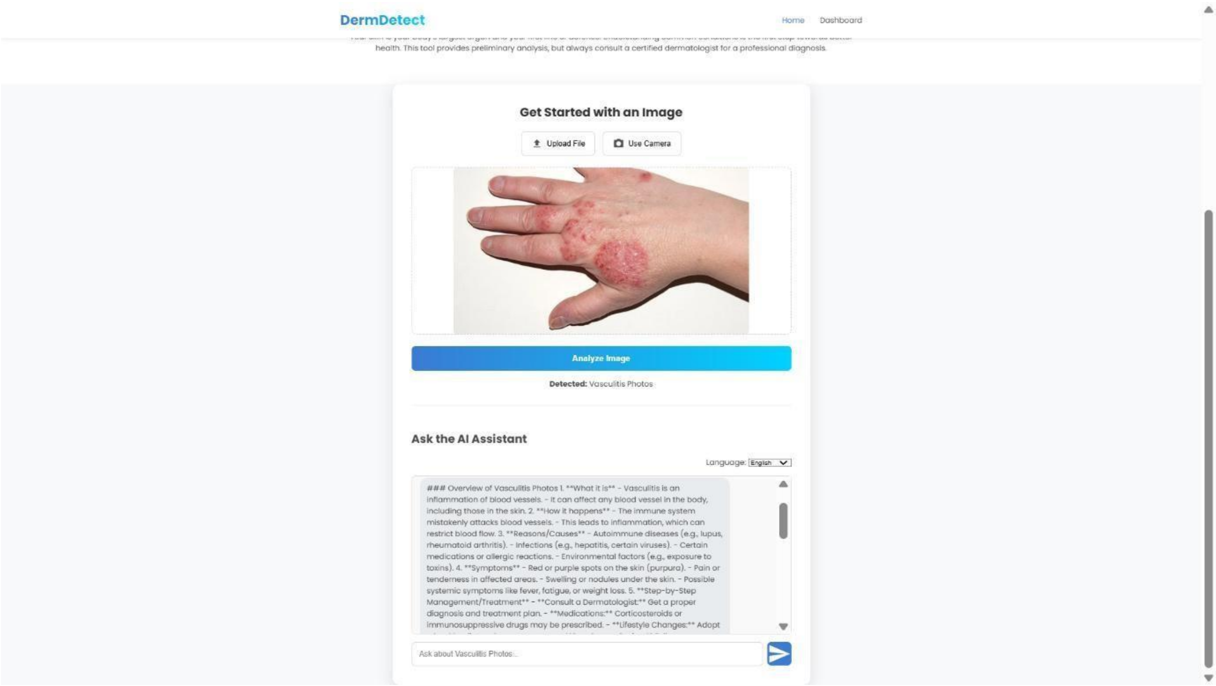

Fig d: DermAI Image Analysis Result