A REPORT
ON

INTELLIGENT SKIN DISEASE DETECTION SYSTEM

Submitted by,

VENESSA GWENDOLYN	20211CSD0002
VELURU HITHA	20211CSD0158
LEENA ZAWAHIR	20211CSD0010
VIBHA SWAMY	20211CSD0028
NISARGA BM	20211CSD0082

Under the guidance of,

Dr. SRABANA PRAMANIK

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING [DATA SCIENCE]

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

MAY 2025

PRESIDENCY UNIVERSITY

PRESIDENCY SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Project report **"INTELLIGENT SKIN DISEASE DETECTION SYSTEM"** being submitted by "VENESSA GWENDOLYN, VELURU HITHA, LEENA ZAWAHIR, VIBHA SWAMY, NISARGA BM" bearing roll number(s) "20211CSD0002, 20211CSD0158, 20211CSD0010, 20211CSD0028, 20211CSD0082" in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Engineering is a bonafide work carried out under my supervision.

14/5/25

Dr. SRABANA PRAMANIK
Assistant Professor (Senior Scale)
PSCS / PSIS
Presidency University

15/5/25

Dr. SAIRA BANU ATHAM
Professor & HoD
PSCS
Presidency University

Dr. MYDHILI NAIR
Associate Dean
PSCS
Presidency University

Dr. SAMEERUDDIN KHAN
Pro - Vc School of Engineering
Dean - PSCS / PSIS
Presidency University

PRESIDENCY UNIVERSITY

PRESIDENCY SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **INTELLIGENT SKIN DISEASE DETECTION SYSTEM** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Engineering**, is a record of our own investigations carried under the guidance of **Dr. SRABANA PRAMANIK, Assistant Professor (Senior Scale), Presidency School of Computer Science and Engineering, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

STUDENT NAME	ROLL NUMBER	SIGNATURE
VENESSA GWENDOLYN	20211CSD0002	
VELURU HITHA	20211CSD0158	Hitha. V
LEENA ZAWAHIR	20211CSD0010	
VIBHA SWAMY	20211CSD0028	Vibha S.
NISARGA BM	20211CSD0082	Nisarga

ABSTRACT

Deep learning-based intelligent skin disease diagnosis enhances diagnostic accuracy in overcoming challenges in handling heterogeneous dermatological diseases with similar presentations. A convolutional neural network (CNN)-derived approach is employed for the diagnosis of seven prevalent skin diseases: acne, eczema, psoriasis, melanoma, rosacea, basal cell carcinoma (BCC), and ringworm. Training and testing are performed using the Skin Disease Data dataset for good model performance. Pretrained architectures VGG16, Xception, NASNetMobile, and a hybrid Xception-NASNetMobile model are examined for feature extraction and classification. Experimental results indicate that the ensemble of Xception and NASNetMobile is better than the standalone models, exhibiting better accuracy and enhanced generalization. The ensemble of multiple architectures leverages the strength of deep feature representation, enhancing the classification efficacy in picking up subtle dermatological differences. The proposed method provides a reliable, automated diagnostic tool for dermatological assessment, allowing early diagnosis and improving clinical decision-making. These findings indicate the utility of deep learning in dermatology, allowing the creation of AI-assisted diagnostic tools and providing new directions for telemedicine.

Keywords - Basal Cell Carcinoma (BCC), Skin Disease Detection, Hybrid Model, VGG16, NASNetMobile, Xception, Convolutional Neural Network, Deep Learning

ACKNOWLEDGEMENT

First of all, we indebted to the **GOD ALMIGHTY** for giving me an opportunity to excel in our efforts to complete this project on time.

We express our sincere thanks to our respected **Dr. Md. Sameeruddin Khan**, Pro-VC, School of Engineering and Dean, Presidency School of Computer Science and Engineering & Presidency School of Information Science, Presidency University for getting us permission to undergo the project.

We express our heartfelt gratitude to our beloved Associate Dean **Dr. Mydhili Nair,** Presidency School of Computer Science and Engineering, Presidency University, and **Dr. Saira Banu Atham**, Head of the Department, Presidency School of Computer Science and Engineering, Presidency University, for rendering timely help in completing this project successfully.

We are greatly indebted to our guide **Dr. Srabana Pramanik**, **Asst. Professor** and Reviewer **Ms. Radhika Sreedharan**, **Asst. Professor** Presidency School of Computer Science and Engineering, Presidency University for her inspirational guidance, and valuable suggestions and for providing us a chance to express our technical capabilities in every respect for the completion of the project work.

We would like to convey our gratitude and heartfelt thanks to the CSE7301 University Project Coordinators **Mr. Md Ziaur Rahman and Dr. Sampath A K,** department Project Coordinators **Dr. Manjula HM** and Git hub coordinator **Mr. Muthuraj.**

We thank our family and friends for the strong support and inspiration they have provided us in bringing out this project.

Venessa Gwendolyn - 20211CSD0002

Veluru Hitha - 20211CSD0158

Leena Zawahir - 20211CSD0010

Vibha Swamy - 20211CSD0028

Nisarga BM - 20211CSD0082

LIST OF TABLES

Sl. No.	Table Name	Table Caption	Page No.
1	Table 6.1	Test Cases	25
2	Table 7.1	Gantt Chart	28
3	Table 9.1	Performance Evaluation Metrics	31

LIST OF FIGURES

Sl. No.	Figure Name	Caption	Page No.
1	Figure 6.1	System Architecture	13
2	Figure 6.2	Flow Chart	14
3	Figure 6.3	Data Flow Diagram	15
4	Figure 6.4	Use Case Diagram	17
5	Figure 6.5	Class Diagram	18
6	Figure 6.6	Activity Diagram	19
7	Figure 6.7	Sequence Diagram	20
8	Figure 6.8	Collaboration Diagram	21
9	Figure 6.9	Component Diagram	21
10	Figure 6.10	Deployment Diagram	22
11	Figure 9.1	Comparison Graphs	32
12	Screenshot 1	Home Page	38
13	Screenshot 2	Sign Up Page	38
14	Screenshot 3	Login Page	39
15	Screenshot 4	Dashboard	39
16	Screenshot 5	Input Page 1	39
17	Screenshot 6	Predicted Output 1	40
18	Screenshot 7	Input Page 2	40
19	Screenshot 8	Predicted Output 2	40
20	Screenshot 9	Input Page 3	41
21	Screenshot 10	Predicted Output 3	41

TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.
	ABSTRACT	**iv**
	ACKNOWLEDGMENT	**v**
	LIST OF TABLES	**vi**
	LIST OF FIGURES	**vii**
1.	**INTRODUCTION**	**1**
	1.1 Problem Statement	1
2.	**LITERATURE REVIEW**	**3-7**
3.	**RESEARCH GAPS OF EXISTING METHODS**	**8**
	3.1 Existing System	8
	3.1.1 Disadvantages of Existing System	8
4.	**OBJECTIVES**	**9**
5.	**PROPOSED METHODOLOGY**	**10-12**
	5.1 Advantages of Proposed Methodology	10
	5.2 Functional Requirements	11
	5.3 Non - Functional Requirements	11
6.	**SYSTEM DESIGN AND IMPLEMENTATION**	**13-25**
	6.1 System Architecture	13
	6.1.1 Software Requirements	13
	6.1.2 Hardware Requirements	13
	6.2 UML Diagrams	16
	6.3 Implementation	22
	6.3.1 Modules	22
	6.3.2 Algorithms	23
	6.3.3 Web Development	24
	6.4 System Testing	25
7.	**TIMELINE FOR EXECUTION OF PROJECT (GANTT CHART)**	**26-28**
8.	**OUTCOMES**	**29-30**

9.	**RESULTS AND DISCUSSION**	**31-32**
10.	**CONCLUSIONS**	**33**
11.	**REFERENCES**	**34-35**
	APPENDIX:	
	A. PSEUDOCODE	**36-37**
	B. OUTPUT SCREENSHOTS	**38-41**
	C. ENCLOSURES	**42-54**

CHAPTER 1
INTRODUCTION

Skin diseases have emerged as a major global health issue, with their occurrence steadily increasing over time. If not diagnosed or treated, many skin conditions can result in serious outcomes, such as permanent scarring or even cancer. Early detection is vital for effectively managing and treating these conditions, but diagnosing them can be challenging due to their diverse presentations and overlapping symptoms. Recently, the use of Artificial Intelligence (AI) techniques, especially machine learning and deep learning models, has demonstrated promising advancements in enhancing the accuracy and efficiency of skin disease diagnosis. These AI systems utilize extensive datasets of skin images and employ sophisticated algorithms to classify various skin diseases and identify affected areas within images. The application of deep learning models, like Convolutional Neural Networks (CNNs), has facilitated more automated, swift, and objective diagnoses, minimizing human error and improving the overall diagnostic process. The main objective of this approach is to achieve high classification accuracy for different skin diseases, such as Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma, while also creating segmentation models that can accurately delineate disease boundaries for improved analysis. This integration of classification and segmentation has the potential to greatly enhance patient outcomes and assist healthcare professionals in making well-informed decisions.

1.1 Problem Statement

- Skin diseases are challenging to diagnose due to their varied presentation, overlapping symptoms, and visual similarities, leading to frequent misdiagnoses and delayed treatments, which can cause complications, especially for conditions like melanoma and basal cell carcinoma.
- Conventional dermatology depends on specialist evaluations, which can be slow, subjective, and hard to access in remote regions. In contrast, deep learning based automated systems provide a scalable alternative by using advanced image analysis and classification methods.
- Patients suffering from skin disorders, dermatologists, and healthcare providers are directly affected, as misdiagnosis can lead to inappropriate treatments, worsening

conditions, increased healthcare costs, and emotional distress for individuals experiencing prolonged or incorrect medical care.

- Limited access to dermatologists, especially in underserved regions, exacerbates healthcare disparities, while delayed or incorrect diagnoses increase the risk of severe complications, including cancer progression, further straining medical resources and reducing overall healthcare efficiency.

CHAPTER 2
LITERATURE SURVEY

[1] A. Imran, A. Nasir, M. Bilal, G. Sun, A. Alzahrani and A. Almuhaimeed, "Skin Cancer Detection Using Combined Decision of Deep Learners," in IEEE Access, vol. 10, pp. 118198-118212, 2022, doi: 10.1109/ACCESS.2022.3220329

Cancer remains one of the deadliest diseases today, triggered by the uncontrolled proliferation of aberrant cells within the body. Millions of lives are lost every time to cancer, which ranks as one of the most burning public health issues that confront us. This grievance can impact almost any portion of the mortal body that consists of trillions of cells. Of the many forms of cancer, skin cancer is among the most prevalent, usually occurring in the most remote subcaste of the skin. Throughout history, researchers have employed machine learning methods to detect skin cancer by analyzing protein sequences and medical images. Though these styles have demonstrated commitment, they often reckon on manually written features a time- consuming and labour- voracious procedure. Deep learning has addressed this challenge by allowing automatic point generation, a process that significantly minimizes the need for human intervention. In this study, we've used convolutional deep neural networks to descry skin cancer, using data from the intimately available ISIC dataset. Detecting cancer directly and on time is absolutely critical, as detainments or miscalculations can have serious consequences. still, individual machine learning models frequently have limitations when it comes to achieving constantly high delicacy. That's where ensemble learning comes in. By aggregating the strengths of several models, ensemble types can provide additional reliable predictions than a single model individually. In the current research, we constructed an ensemble of deep learning models specifically VGG, CapsNet, and ResNet architectures to enhance the accuracy and reliability of skin cancer detection. Our findings obviously indicate that the ensemble method of these models performs better than individual models on many important performance metrics such as sensitivity, accuracy, specificity, F-score, and precision. These encouraging results propose that this strategy might also be utilized in finding other conditions and provide a valuable tool for refining individual delicacy in pivotal healthcare processes.

[2] Ş. Öztürk and T. Çukur, "Deep clustering via center-oriented margin free-triplet loss for skin lesion detection in highly imbalanced datasets," IEEE J. Biomed. Health Inform., vol. 26, no. 9, pp. 4679–4690, 2022, doi: 10.1109/JBHI.2022.3187215

Melanoma, a life-threatening skin cancer, can be cured if it is detected early, and with dramatic increases in survival rates when diagnosed in the first stages. Machine learning methods have great promise for detecting melanoma based on dermoscopic images. But one of the main challenges is that melanoma is quite a rare condition, and this means datasets are highly imbalanced, with benign lesions significantly outmatching malignant lesions. This imbalance has a tendency to bias classification models towards the majority class and introducing bias. To counter this, we introduce a new deep clustering approach that takes advantage of latent-space representations of dermoscopic images. Our method employs a novel loss function Center-Oriented, Margin-based Trinity Loss (COM-trinity) that is aimed at generating well-separated cluster centers in the embedding space, as opposed to minimizing classification error directly. This approach renders the model less susceptible to class imbalance effects. Further, to break the dependency on labeled data, we use pseudo-labels obtained from a Gaussian Mixture Model (GMM) to supervise the COM-trinity loss. Extensive evaluations demonstrate that our deep clustering framework not only outperforms standard triplet-loss clustering but also performs better than other state-of-the-art classifiers in both supervised and unsupervised learning scenarios.

[3] H. Q. Yu and S. Reiff-Marganiec, "Targeted Ensemble Machine Classification Approach for Supporting IoT Enabled Skin Disease Detection," in IEEE Access, vol. 9, pp. 50244-50252, 2021, doi: 10.1109/ACCESS.2021.3069024

The fast pace of development in the Internet of Things (IoT) is drastically changing numerous facets of life, especially within the healthcare industry. One significant use is disease diagnosis remotely, which has improved through the deployment of advanced IoT technologies. Beyond hardware, the solutions involve smart data processing and machine learning techniques like image-based disease classification. This study focuses specifically on classifying skin diseases in a remote IoT-driven diagnostic setting. The goal is to develop a practical system for skin condition detection using IoT-based solutions. The first section presents a dynamic AI-driven framework that operates across IoT, fog, and cloud layers. It includes hardware examples to demonstrate how the system can be implemented for real-world remote diagnostics. The second section describes a comprehensive evaluation of multiple machine learning methods for the diagnosis of skin conditions. This encompasses the application of multiple data preprocessing methods and combinations thereof. The evaluation accounts for both standard training-testing and cross-validation across all seven skin disease classes, as well as per condition. The HAM10000 dataset was chosen for comparison with other datasets in the area due to its appropriateness. The research discusses the conventional machine learning architectures such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) but specifically discusses testing six popular deep learning architectures: VGG16, Inception, Xception, MobileNet, ResNet50, and DenseNet161. The outcome is that for each individual skin disease, a certain subset of these models performs consistently better than the rest. According to these results, the last section introduces a new model called the Targeted Ensemble Machine Classification Model (TEMCM). The model uses an intelligently selected and combined optimal-performing models by implementing a two-step detection mechanism. Final outcomes prove that TEMCM provides better accuracy and reliability in comparison with current models.

[4] L. -F. Li, X. Wang, W. -J. Hu, N. N. Xiong, Y. -X. Du and B. -S. Li, "Deep Learning in Skin Disease Image Recognition: A Review," in IEEE Access, vol. 8, pp. 208264-208280, 2020, doi: 10.1109/ACCESS.2020.3037258.

The application of deep learning methodologies towards disease diagnosis is also an expanding field of study in the medical field. Among all medical conditions, skin diseases are also very common and tend to exhibit observable symptoms on the surface, making them good candidates for image diagnosis methods. Consequently, using deep learning to diagnose skin images has also attracted much attention and popularity in recent years. In this work, we review 45 studies since 2016 that aim at applying deep learning to identify and classify skin disorders. Our analysis traverses the works along several axes, namely the nature of skin diseases to be detected, datasets employed, image preprocessing methods, data augmentation techniques, model architectures, deep learning frameworks, performance metrics, and general model performance. Further, we offer an overview of both traditional and machine learning based approaches that have been used in the past for skin disease diagnosis and treatment.

Based on the existing advancements, we suggest four avenues of future study that are most likely to influence future development. Through our examination, we see that deep learning-powered skin disease detection systems tend to better the results of both dermatologists and conventional computer-aided diagnosis systems. Most notably, ensemble models which combine various deep learning architectures tend to attain the most accurate and reliable skin condition detection.

[5] A. A. Adegun and S. Viriri, "FCN-Based DenseNet Framework for Automated Detection and Classification of Skin Lesions in Dermoscopy Images," in IEEE Access, vol. 8, pp. 150377-150396, 2020, doi: 10.1109/ACCESS.2020.3016651

Precise lesion detection and classification are important for early skin cancer diagnosis. Current deep learning-based computer-aided diagnosis (CAD) systems frequently fall short in handling intricate lesion features including indistinct boundaries, artifacts, low contrast with the skin, and limited, skewed datasets. The systems also have a tendency to depend on fine-tuning a huge number of parameters, resulting in overfitting, inferior generalization, and heavy computational costs. For meeting these challenges, the current work presents a new two-stage scheme for skin cancer detection with the combination of both lesion segmentation and classification. Under the first stage, a more advanced Fully Convolutional Network (FCN) is adopted to capture the detailed and uncertain features of the skin lesion images. Unlike conventional FCNs that rely solely on long skip connections, our architecture incorporates both long and short skip connections to enhance residual learning and training efficiency. The model also integrates a Conditional Random Field (CRF) module, which refines segmentation outputs by improving edge detection and boundary localization using a combination of Gaussian kernels. In the second stage, a DenseNet-based FCN model is proposed for classification. This architecture is constructed with tightly interconnected blocks that are connected by means of a sequential approach and transition layers. In order to enhance performance further, the model makes use of hyperparameter optimization methods, minimizing the complexity of the network while maximizing computational efficiency. This structure ensures effective reuse of features, allowing the model to be lightweight yet powerful even under sparse training data. The suggested system was implemented and tested using the publicly accessible HAM10000 dataset, comprising more than 10,000 dermoscopic images spread over seven categories of skin disorders. The model performed spectacularly, achieving

98% accuracy, a recall of 98.5%, and an AUC of 99%, establishing its credibility and reliability.

CHAPTER 3
RESEARCH GAPS OF EXISTING METHODS

3.1 Existing System

Current systems of skin disease diagnosis are dependent greatly on physical examination by dermatologists, usually involving extensive tests and a lot of time to identify the kind of skin disease. These processes are subjective and based on the experience and skill of the practitioner. Moreover, conventional methods tend not to provide consistent and quick results, resulting in delays in treatment. Computational methods such as image processing and machine learning have been investigated to overcome the above constraints. The existing automated systems employ algorithms such as CNNs to classify skin diseases from images. They preprocess the images to eliminate noise and improve quality prior to feature extraction. These systems, however, tend to lack accuracy, speed, and responsiveness, particularly when dealing with various datasets or complicated types of diseases. Although there has been progress, current approaches do not have the capability to give real-time, accurate, and high-precision diagnostics for a wide range of skin conditions, which makes more efficient and scalable solutions necessary.

3.1.1 Disadvantages of Existing System

1. Manual examination is time-consuming and subject to individual expertise, leading to variability in diagnosis accuracy.
2. Traditional methods lack consistency and often delay diagnosis, resulting in prolonged treatment times.
3. Current systems do not fully leverage computational techniques, leading to limited speed and accuracy, especially in complex cases.
4. Existing systems struggle with adaptability to diverse datasets and may not provide real-time or high-precision results across various skin conditions.

CHAPTER 4
OBJECTIVES

- Develop an AI system capable of automatically detecting and classifying seven general skin diseases with very high accuracy.
- Utilize pre-trained deep learning architectures such as VGG16, Xception, NASNetMobile, and a custom hybrid model of Xception-NASNetMobile to enable the system to learn effectively from medical images.
- Employ intelligent image preprocessing methods such as resizing, normalisation, and data augmentation to enhance the way the model processes real-world image variations.
- Use transfer learning to capitalize on the strength of existing strong models, minimizing the requirement for massive computing power and accelerating training.
- Combine model strengths by merging the strengths of various networks to capture the fine differences between similar-looking skin conditions.
- Develop a pragmatic, easy-to-use diagnostic aid that can help doctors by delivering rapid, consistent insights particularly valuable in busy clinics or remote locations.

CHAPTER 5
PROPOSED MOTHODOLOGY

The system that has been developed uses deep learning to perform the classification of skin diseases automatically with the view to simplifying the diagnostic process and making it more accurate particularly in regions where conventional diagnosis proves to be a complex and resource-intensive process. Utilizing the latest convolutional neural networks (CNNs), the system is able to make dermatological images analysis to enable healthcare professionals to make informed clinical decisions. Training and testing are performed on a large, well-balanced dataset that encompasses a broad range of real-life skin conditions. The framework uses a series of high-performance pretrained models including VGG16, Xception, NASNetMobile, and a merged Xception-NASNetMobile hybrid to obtain deep, insightful features from dermoscopic images. The combination of these models enables stronger feature learning, facilitating accurate classification for seven prevalent skin diseases: acne, eczema, psoriasis, melanoma, rosacea, basal cell carcinoma (BCC), and ringworm. To enhance the model's capacity to generalize over different cases, several preprocessing steps are taken on images. These involve uniforming image sizes, normalizing pixel values, and using data augmentation methods such as rotation, flipping, and zooming. This not only enhances training effectiveness but also improves performance on unseen data. One major strength of the system is that it employs transfer learning, which leverages learning from large-scale datasets to save training time and computational resources without sacrificing accuracy. This allows the system to realize robust performance even in low-computing resource environments. Fundamentally, this computer vision-based platform is intended to deliver prompt, accurate dermatological assessments, facilitating early skin condition detection and enhanced diagnostic aid to clinicians. It has special potential for increasing access to quality skin services in under-resourced areas where skin care specialists are not available.

5.1 Advantages of Proposed Methodology

- In integrating deep learning and convolutional neural networks (CNNs), the system accelerates and highly accurately automates skin disease classification. The AI-based method reduces the subjectivity usually inherent in manual diagnosis, and thereby decreases errors and inconsistencies that may arise even for experienced dermatology experts based on differing visual observation.

- One of the key strengths of the system lies in its use of transfer learning, which allows it to take advantage of powerful models that have already been trained on vast amounts of image data. By building on this existing knowledge, the system requires far fewer computational resources and can deliver faster results — all while maintaining strong performance. This makes it not only effective but also efficient and practical, especially in clinical settings where time and computing power may be limited.
- The model architecture itself is thoughtfully designed, incorporating a combination of proven CNN structures — namely VGG16, Xception, and NASNetMobile. Each of these architectures brings unique strengths in feature extraction, and when used together, they create a more robust and comprehensive learning system. This multi-model approach allows the system to better capture subtle patterns and differences between various skin conditions, making it highly capable of accurately identifying and distinguishing between multiple diseases.
- To ensure the model performs well across a wide range of real-world images, a series of image preprocessing and augmentation steps are applied. These include resizing the images for uniformity, normalising the pixel values for better training dynamics, and using techniques like rotation, flipping, and zooming to simulate image variety. This not only enriches the training data but also strengthens the model's ability to generalise meaning it can handle new and unseen images with greater confidence.

5.2 Functional Requirements

- Data Collection
- Image processing
- Training and Testing
- Modelling
- Predicting

5.3 Non - Functional Requirements

Scalability

The system should be able to handle large data volumes and scale to accommodate an expanding user population without sacrificing performance. It should also be versatile enough to run on numerous computing environments—like cloud systems, mobile devices, and healthcare systems to provide widespread accessibility and usability.

Security

Robust security measures are necessary to protect patient data and ensure adherence to healthcare regulations such as HIPAA. These include the deployment of encryption, secure user authentication, and tight access control systems to avoid data breaches and unauthorized access.

Usability

The system must have an easy-to-use user interface for simple navigation by dermatologists and non-professionals. Simple visualizations, easy input mechanisms, and smooth interaction with mobile and web applications should promote user experience and adoption.

Maintainability

The architecture and model should enable easy updating and updating. Ongoing improvement, such as retraining the model on fresh data and updating deep learning libraries, must be facilitated in order to guarantee long-term accuracy and reliability.

Interoperability

The system needs to integrate well with many different healthcare platforms, electronic health records (EHRs), and third-party diagnostic equipment. Standardized APIs and data formats must be provided in order to easily integrate with installed medical infrastructure.

CHAPTER 6

SYSTEM DESIGN & IMPLEMENTATION

6.1 System Architecture

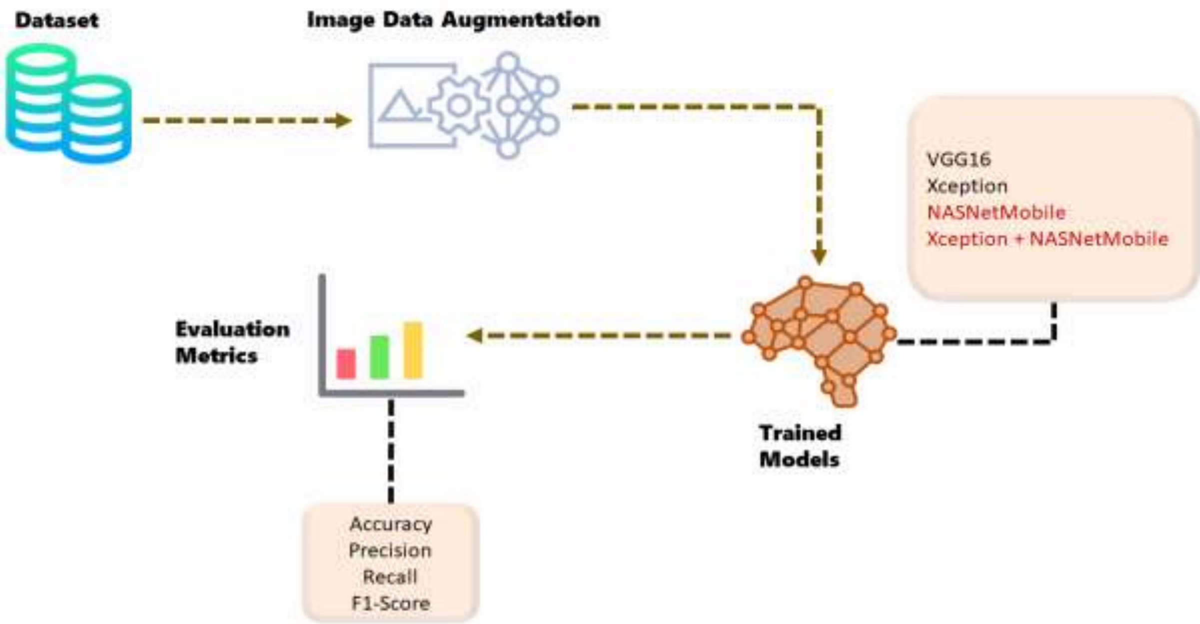


Figure 6.1 System architecture

6.1.1 Software Requirements

1) Software: Anaconda
2) Primary Language: Python
3) Frontend Framework: Flask
4) Back-end Framework: Jupyter Notebook
5) Database: Sqlite3
6) Front-End Technologies: HTML, CSS, JavaScript and Bootstrap4

6.1.2 Hardware Requirements

1) Operating System: Windows Only

2) Processor: i5 and above
3) Ram: 8GB and above
4) Hard Disk: 25 GB in local drive

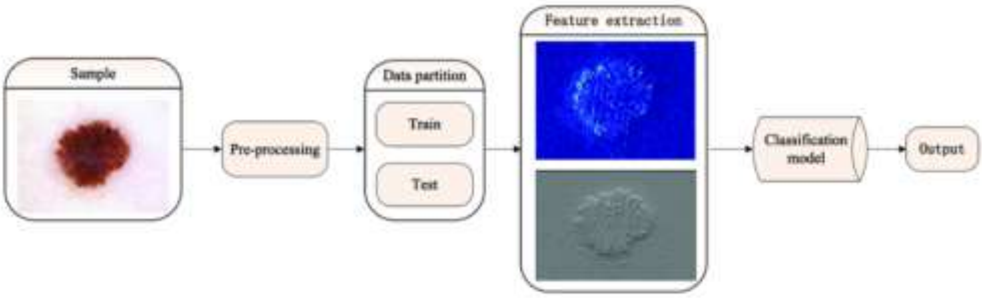


Figure 6.2 Flow Chart

Data Flow Diagram

A Data Flow Diagram (DFD) is a graphical representation used to describe the flow of data within a system and how information moves among processes, data stores, and outside entities. A DFD makes complex processes easy to understand and assists in grasping the logical structure of the system, with emphasis on data inputs, outputs, processing activities, and storage locations. The use of visual diagrams enhances communication between technical teams and non-technical stakeholders. DFDs are made up of four major components: external entities, processes, data stores, and data flows. External entities denote data sources or targets like users or other external systems. Processes symbolize operations that change input data into outputs using particular operations. Data stores are stores where data is retained for future usage to provide data persistence and easy retrieval. Data flows illustrate how data flows from one process to another, storage, or external entities. With the use of standardized notation like circles for processes, arrows for data flows, and rectangles for external entities, DFDs offer a systematic approach to system analysis. They also serve as the basis for designing data-driven systems where optimizations can be made prior to large-scale implementation. DFDs are necessary for improving system performance by providing a lucid, logical view of data movement.

Goals of DFD

- To graphically depict how data is processed in a system, to facilitate an easy comprehension of the structure of the system and communication between various elements, making data handling and processing efficient.

- To mark inefficiencies or bottlenecks in data movement, assisting in identifying areas that need to be optimized and streamlined, resulting in enhanced system performance and resource allocation.
- To give a clean, intuitive model that supports technical teams to communicate with non-technical users and improve collaboration, and to enable a common understanding of system operations and processes.
- To capture system requirements and functionality, in producing a systematic description that is a guide to developers and analysts in designing or adding to the system, which aligns to users' requirements.

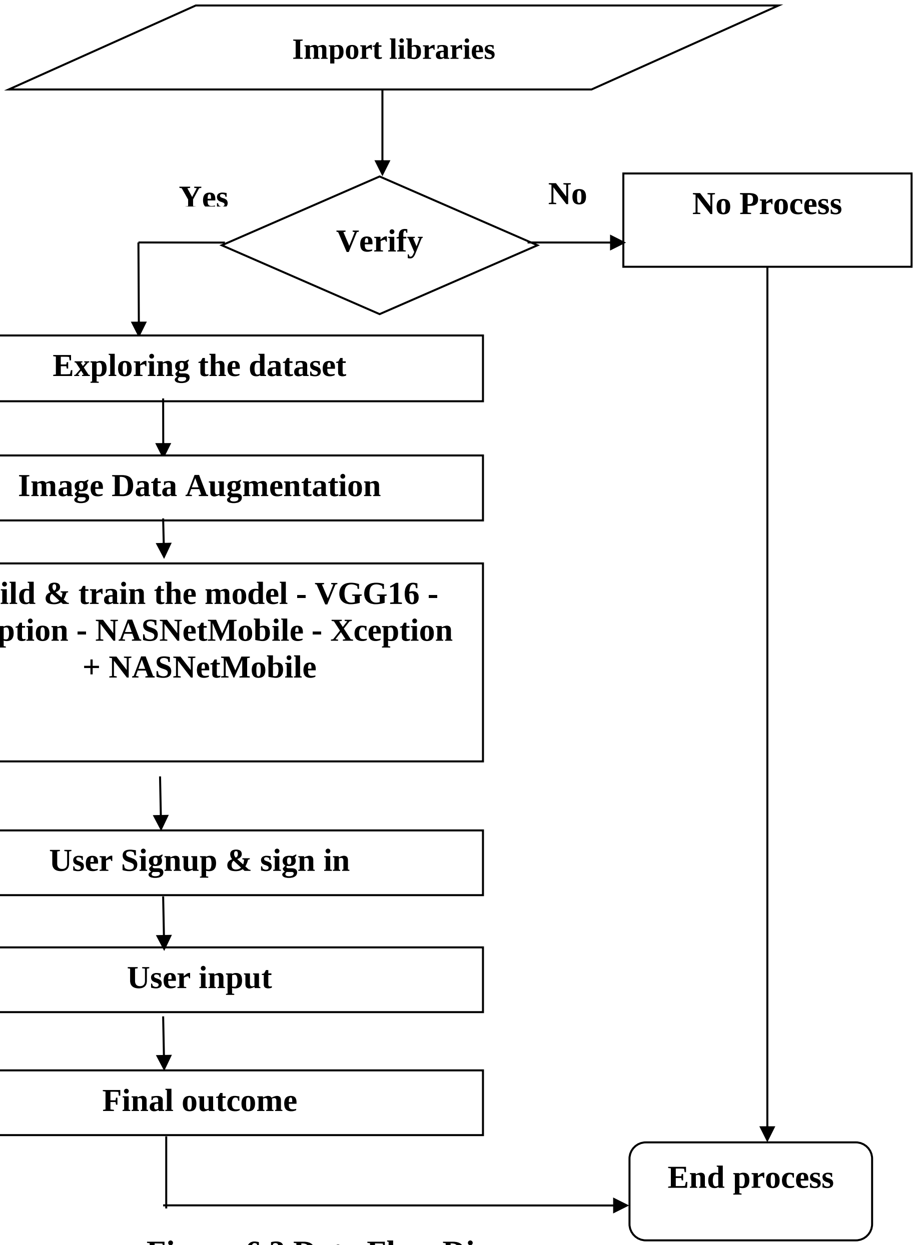


Figure 6.3 Data Flow Diagram

6.2 UML Diagrams

Unified Modeling Language (UML) is a formal language for expressing, visualizing, building, and documenting system design. UML provides a collection of graphical notations used for modeling software systems, facilitating their understanding, communication, and analysis of their structure and behavior. UML can represent both the static structure and dynamic behavior of a system and give a general overview of its components and their relationships.

UML has two broad categories of diagrams: behavior diagrams and structure diagrams. The structure diagrams of class, component, and deployment diagrams concentrate on the static dimension of the system, representing the entities, relationships, and features. Behavior diagrams like use case, activity, and sequence represent the dynamic system, showing components interacting with each other and progressing with time.

By offering a common visual vocabulary to designers, developers, and analysts, UML supports better communication and reduces the likelihood of misunderstandings. It helps to visualize intricate systems and ensures all parts of the system are working together harmoniously. UML is used extensively in software development, systems engineering, and business modeling, ensuring transparent communication and a uniform process to document design choices and implementations.

Goals of UML

- To offer a unified, graphical lexicon that allows for communication across development teams such that system components, processes, and interactions are well known and defined

- The objective is to provide a general-purpose tool for defining the static and dynamic properties of a system and thereby facilitate the ease of designing, developing, and testing intricate software programs

- To enable documentation of system design and decisions, there is a standardized process in place that enables developers and analysts to keep things organized and uniform across the system life cycle.

- To better visualize systems by breaking down complex architectures into workable parts to make better decisions and identify the areas that require fixing or optimization.

- In order to enable effective collaboration between diverse groups by providing a common modeling language, hence enabling developers, analysts, and designers to effectively describe and understand system functionality and requirements.

Use Case Diagram

A use case diagram graphically illustrates the functionality of a system from the point of view of its users, showing how various actors communicate with various use cases. Actors are outside users, e.g., users or other systems, that communicate with the system. Use cases are the exact actions or services the system undertakes. Actors in skin disease detection can be dermatologists, patients, and healthcare systems, and use cases can be actions like uploading images or diagnosing skin.

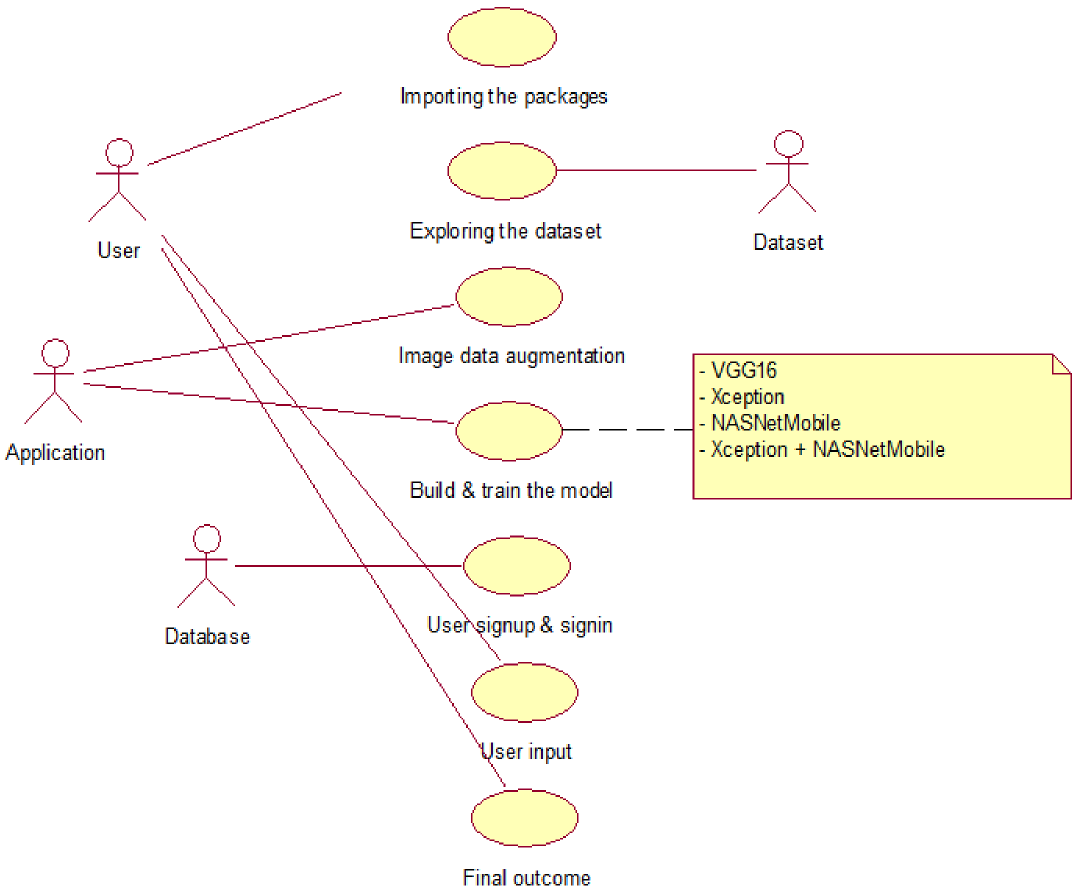


Figure 6.4 Use Case Diagram

Class Diagram

A class diagram is used to represent the structure of a system by specifying its classes, attributes, and operations. Classes specify objects or entities in the system, attributes specifying their properties, and operations specifying their behavior. Aggregation relationships specify how one class is comprised of another, usually a whole-part relationship. In the case of skin disease detection, some classes might be 'Image,' 'Diagnosis,' and 'Model.' Each class would have some attributes like 'image ID,' 'skin type,' and 'disease name' and operations like 'classify Image()' or 'predict Disease()' to specify their functional roles.

Figure 6.5 Class Diagram

Activity Diagram

An activity diagram illustrates the flow of a system by representing actions, decisions, and control flow. Actions are operations or tasks, and decisions are where the flow branches based on conditions. Control flow arrows represent the order of actions. For skin disease diagnosis, an activity diagram would illustrate the process flow from upload of image to diagnosis, i.e., preprocessing, feature extraction, model prediction, and decision-making, with conditional branches deciding the final disease classification output

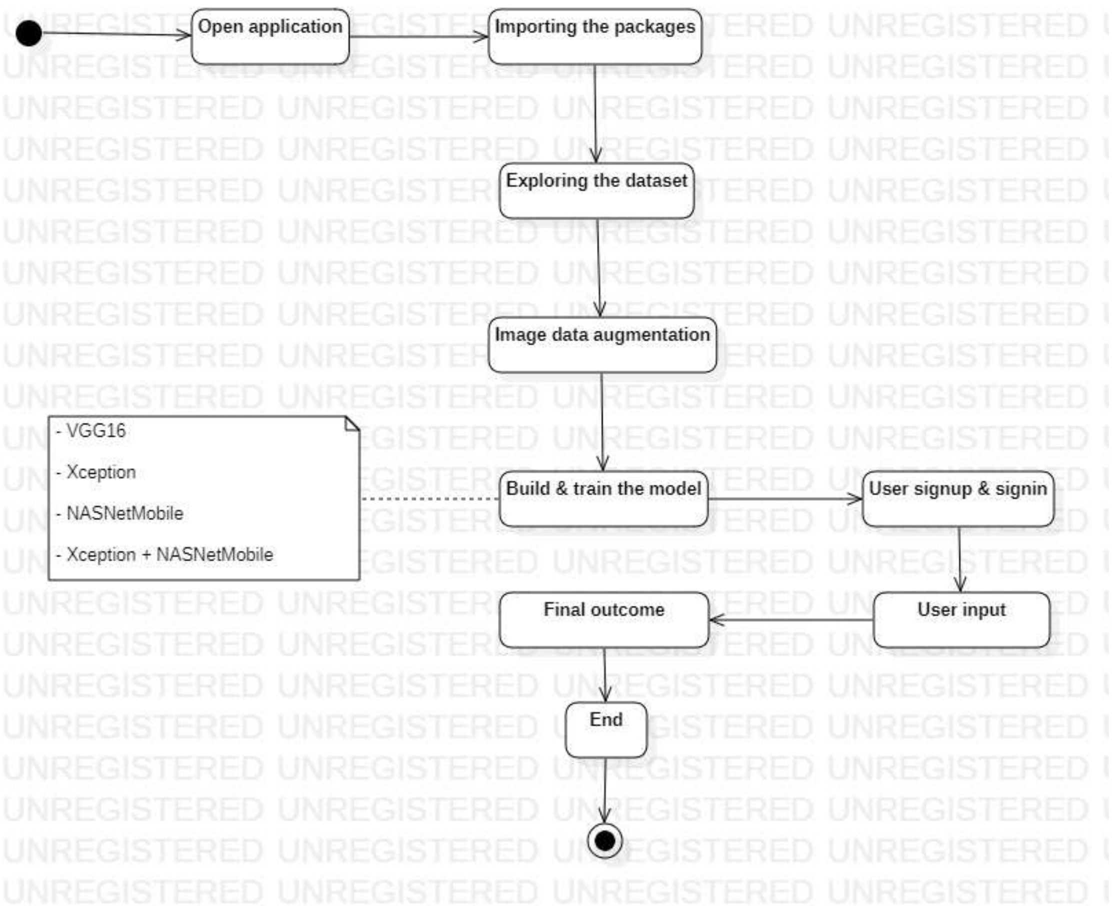


Figure 6.6 Activity Diagram

Sequence Diagram

A sequence diagram shows the interaction between objects over time, showing how messages A sequence diagram represents the interaction of objects over time, indicating how messages are passed. Objects are system entities or components, and messages between objects represent communication channels. In skin disease detection, a sequence diagram will represent the order of messages passed between entities like 'User,' 'Image Uploader,' and 'Model Classifier.' The process can involve the user uploading an image, which is processed and classified by the classifier with feedback messages passing the classification result and the disease detected.

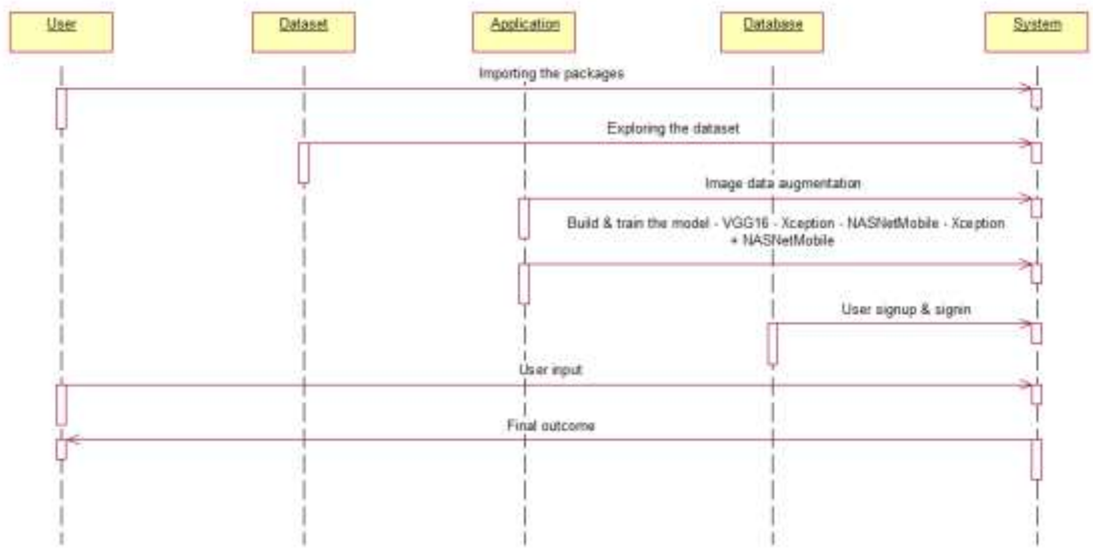


Figure 6.7 Sequence Diagram

Collaboration diagram

A collaboration diagram highlights the interactions between different objects and how they are connected and messages passed between them. Objects are used as representations of the objects that are involved in the interaction, whilst link messages show the methods of communication between these objects. For skin disease detection, a collaboration diagram would highlight the interactions between objects like 'User,' 'Model,' and 'Image Processor.' The diagram would show the user's action to upload an image, which then gets processed and passed to the model for classification. In addition, the diagram explains the order of the messages passed during this process.

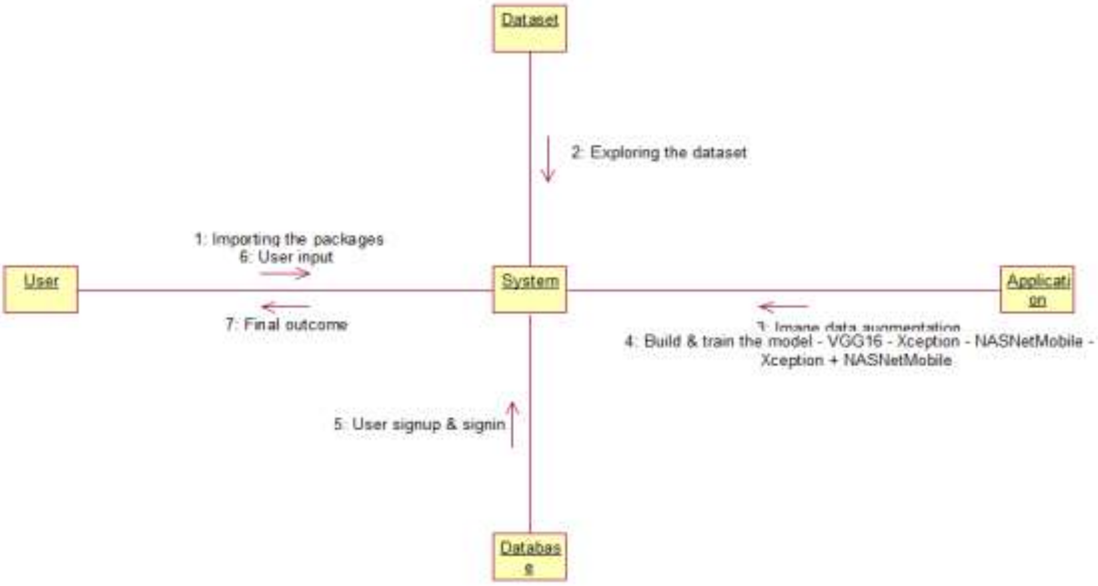


Figure 6.8 Collaboration Diagram

Component Diagram

A component diagram shows the top-level components of a system, their structure, and their dependencies. Components are self-contained units of the system, and packages hold related components. Dependencies show the relationship between components, especially when one component relies on another to execute. For diagnosing skin disease, the components can be the 'Image Processing Module,' 'Classification Model,' and 'User Interface,' and the dependencies between the components show the cooperative operation of the modules of the system to process information, predict disease, and show results to users.

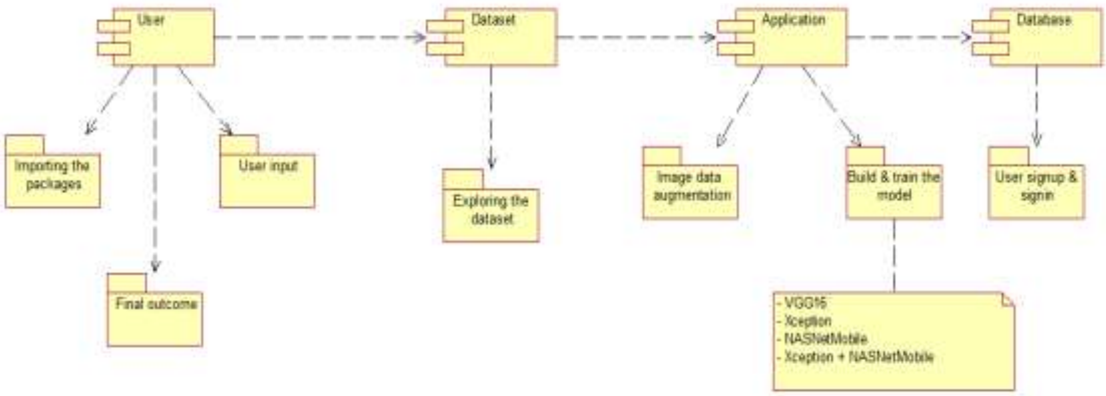


Figure 6.9 Component Diagram

Deployment Diagram

A deployment diagram illustrates the physical structure of software items on hardware nodes. Nodes represent physical servers or devices, and connectors represent their interaction. Additionally, notes are used to illustrate additional information and can be labeled to specific objects to make it easier to understand. In the detection of skin diseases, a deployment diagram can illustrate nodes like 'Client Device' (for user interaction), 'Server' (for processing), and 'Database' (for storing user information). Connectors represent the interaction between these nodes, and notes represent contextual information, e.g., server information or security features.

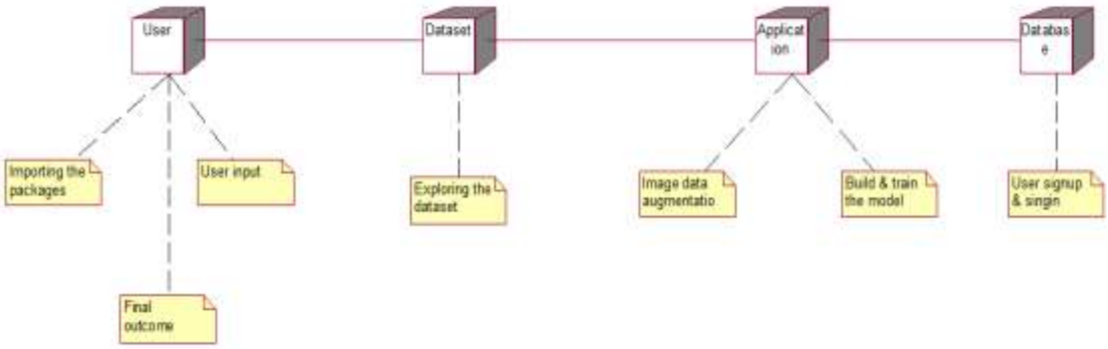


Figure 6.10 Deployment Diagram

6.3 Implementation

6.3.1 Modules

Importing the Packages

Import necessary libraries and frameworks such as TensorFlow, Keras, NumPy, Pandas, Matplotlib, and Scikit-learn to facilitate image processing, model building, and evaluation for skin disease classification.

Exploring the Dataset

Examine the Skin Disease Data, which includes images of common skin conditions, along with corresponding labels. Analyze the dataset for size, format, and distribution of different disease types for effective training.

Image Data Augmentation

Enhance the dataset by applying image augmentation techniques such as re-scaling, shear transformations, zooming, horizontal flipping, and reshaping. These techniques increase the dataset size and help improve model robustness.

Build & Train the Model

Build and train the model using deep learning algorithms like VGG16, Xception, NASNetMobile, and a hybrid approach of Xception + NASNetMobile, optimizing the models for accurate skin disease classification.

Comparison Graphs

Create comparison graphs to compare model performance based on measures such as accuracy, precision, recall, and F1-score. Plot the results to choose the best performing model for skin disease detection.

User Signup & Signin

Implement user signup and signin features, allowing users to securely create accounts and log in to the system. Authentication ensures personalized access to skin disease detection and user data.

User Input

Allow users to upload skin images via a simple interface. These inputs will be processed by the trained model to predict and classify skin conditions, providing accurate results for medical use.

Final Outcome

The system will output the predicted skin condition, displaying the classification result, confidence level, and any relevant details. The final outcome enables users to gain insights into their skin health.

6.3.2 Algorithms

VGG16 is a convolutional neural network (CNN) model used in image recognition with 16 layers consisting of convolutional, pooling, and fully connected layers. It is primarily used to extract hierarchical features from images for correct classification. VGG16 has extensive use in image classification because it is easy and efficient in handling large data. Its deep architecture assists in the detection of complex patterns, making it extremely effective in tasks like skin disease classification.

Xception is a deep CNN that utilizes depthwise separable convolutions to enhance computational efficiency while maintaining high performance. By employing separable convolutions, it extracts features from images more efficiently. Xception has demonstrated superior performance in large-scale image recognition tasks, and its focus on important features makes it especially suitable for skin disease detection. It excels in both computational cost and accuracy, making it ideal for environments with limited resources.

NASNetMobile is a model optimized for mobile devices using a neural architecture search (NAS) approach. This model utilizes a search algorithm to identify the most effective architecture for a specific task. Its primary purpose is to achieve high performance while maintaining computational efficiency, especially for mobile devices. In applications like skin disease detection, where real-time processing and efficient resource use are essential, NASNetMobile provides accurate results without draining device resources.

Xception + NASNetMobile combines the strengths of both the Xception and NASNetMobile models. The hybrid approach leverages Xception's powerful deep convolutional layers for detailed feature extraction and NASNetMobile's optimized efficiency for mobile device deployment. This combination aims to deliver high accuracy in skin disease classification while ensuring real-time, on-device performance. The fusion of these models enhances both the feature learning capability and computational efficiency, making it a practical solution for healthcare applications

6.3.3 Web Development

We designed a Web application which provides an interactive and user-friendly environment for users to run automated skin disease prediction on trained hybrid deep learning model. Frontend of the application was developed with Flask, a minimalistic Python web framework for machine learning applied as a bridge between the user interface and machine learning model.

Inference of model parameters and computation of machine learning tasks were performed in a Jupyter Notebook which communicates with Flask to handle requests. The user interface was built in HTML, CSS, JavaScript and Bootstrap 4 for responsiveness and user experience on different screen sizes.

The system workflow starts a when user uploads image of skin lesion via web interface. Image is preprocessed (resize, normalize and reshape the image to conform to output format of the model in-tended for use) and uploaded to hybrid model (for inference). Hybrid model makes the prediction of class label of one of specified skin disease classes and sends the output (or prediction output, time stamp and image metadata) to the user through web interface.

Because of this seamless integration of frontend and backend modules, application can be used for real time determination of skin diseases and the system is useful both in clinical and personal applications.

6.4 System Testing

S.NO	INPUT	If available	If not available
1	User signup	User get registered into the application	There is no process
2	User signin	User get login into the application	There is no process
3	Enter input for prediction	Prediction result displayed	There is no process

Table 6.1 Test Cases

CHAPTER 7
TIMELINE FOR EXECUTION OF PROJECT
(GANTT CHART)

Project Timeline:

The timeline for the Intelligent Skin Disease Detection System mission is structured by several evaluation levels, each focusing on specific factors of the venture's development. These reviews are crucial checkpoints that make certain the undertaking progresses in accordance to plan and meets the required standards. Moreover, the final Viva-Voce serves because the remaining evaluation of the venture's outcomes and your information of its ideas on project.

1. Task 1 (Completing the Title)

During this phase, the project name will be finalized in consultation with your supervisor. You will conduct a literature review to obtain relevant information and insights. The goals of the project will be finalized and the methodology to achieve these goals will be decided

Review-0: February 03, 2025 to February 08, 2025

During this phase, main focus on project initiation, planning, and initial research. Defining the scope of the project, objectives and outputs. Identification of stakeholders and their roles. They began creating a detailed plan for the project.

2. Task 2 (Abstract, Literature review, Objectives and proposed method)

In this review phase we focus on refining the project abstract by conducting a comprehensive literature survey with a minimum of 10 research articles, identifying project objectives, highlighting the shortcomings of existing methods, designing a new method, creating an architecture diagram, defining modules, specifying hardware and software details, creating a timeline using a Gantt chart, compiling references and submitting a Review- 1 report.

Review-1: February 17, 2025 to February 22, 2025

In this phase we focus for in-depth research and requirements gathering. Dive into existing technologies, and gather detailed requirements from stakeholders and potential users.

3. Task 3 (Algorithm Details, Source Code, Implementation Details and Message Submission)

In this phase, you will dive into the details of the algorithm, provide insight into the source code, and demonstrate 50% of the implementation details through a live project demo, and submit 50% of the report in softcopy format.

Review-2: 17 March, 2025 to 22 March, 2025

In this phase is used for design and architecture. Design the UI/UX of Intelligent Skin Disease Detection System. Defining the technical architecture and components needed for the Customer Service Chat Bot with Generative AI.

4. Task 4 (Algorithm details, source code, full implementation and report submission)

In this review phase includes algorithm details, source code specifics, demonstration of 100% project implementation, submission of a complete report in both paper and electronic form, and demonstration of a fully implemented live demo project.

Review-3: April 21, 2025 to April 26, 2025

At this stage can be a stage of development, Setting up the development environment and implementing the Intelligent Skin Disease Detection System .

5. Assignment 5 Final project Viva-Voce

The Final Viva-Voce is the culmination of our project journey. At this stage a comprehensive assessment where you will present your project, discuss its various aspects, defend your choices and methodologies and demonstrate your understanding of the project's development and outcomes of Intelligent Skin Disease Detection System.

Final Viva-Voce: May 12, 2025 to May 16, 2025

This phase for project completion and deployment. Deployment on target platform (e.g. mobile), final demonstration of Intelligent Skin Disease Detection System in a production environment and execution of final testing and user training. presentation of completed projects during Viva-Voce.

ID	Task Name	Start	Finish	JAN	FEB	MAR	APR	MAY
1	Review 0	29/1/2025	31/1/2025					
2	Review 1	18/2/2025	21/2/2025					
3	Review 2	17/3/2025	21/3/2025					
4	Review 3	16/4/2025	19/4/2025					
5	FINAL VIVA	10/5/2025	17/5/2025					

Table 7.1 Gantt Chart

CHAPTER 8
OUTCOMES

- Accurate Multi-Class Classification
  The system successfully classifies seven common skin diseases acne, eczema, psoriasis, melanoma, rosacea, basal cell carcinoma (BCC), and ringworm with high accuracy, showcasing its effectiveness in handling complex dermatological data.

- Enhanced Model Performance Through Hybrid Architecture
  The use of a hybrid Xception-NASNetMobile model leads to superior performance by combining the strengths of both architectures. This results in improved feature extraction, better handling of visual similarities, and more precise classification.

- Improved Differentiation of Skin Conditions
  The system addresses the challenge of overlapping visual symptoms among skin diseases by learning deeper representations of features, ensuring accurate differentiation even between visually similar conditions.

- Robust Generalization Across Diverse Data
  The integration of deep feature representations and image preprocessing techniques (resizing, normalisation, augmentation) enables the model to perform reliably across different datasets and variations in image quality, lighting, and resolution.

- Efficiency Through Transfer Learning
  Leveraging transfer learning allows the system to achieve high performance while keeping computational requirements low. This makes the model efficient, lightweight, and suitable for broader deployment, even in resource-constrained environments.

- Scalability and Real-World Readiness
  The model demonstrates scalability and adaptability, positioning it well for real-world clinical deployment, including integration into telemedicine platforms and automated healthcare systems.

- Support for Early Detection and Clinical Decision-Making

  By providing fast and accurate dermatological assessments, the system offers valuable support for early diagnosis, aiding clinicians in making informed decisions and potentially improving patient outcomes.

- Potential to Improve Access to Dermatological Care

  With its high accuracy and automation, the system can significantly enhance access to skin disease diagnostics, especially in remote areas, contributing to equitable healthcare delivery.

CHAPTER 9

RESULTS AND DISCUSSIONS

Accuracy: The ability of a test to distinguish between patient and healthy cases is measured by its accuracy. We calculate the percentage of true positives and true negatives to all tested occurrences in order to determine accuracy. In algebra, we can represent it as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}}$$

Precision: Out of all the occurrences the model predicts to be positive, precision is the number of accurately labelled positive examples. It is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}}$$

Recall: This is a measure of how well a model can identify every instance of a class. It provides a sense of the model's capacity to identify all real positive occurrences and indicates the proportion of correctly predicted positive instances among all actual positives.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

F1-Score: It is a combined assessment statistic that evaluates a model's performance by taking into account both precision and recall. It offers a single indicator of a model's accuracy in forecasting positive occurrences, making it especially helpful when weighing the trade-off between precision and recall.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100$$

ML Model	Accuracy	Precision	Recall	F1_score
Train Acc - VGG16	0.868	0.903	0.832	0.855
Valid Acc - VGG16	0.610	0.638	0.579	0.599
Train Acc - Xception	0.992	0.992	0.992	0.992
Valid Acc - Xception	0.644	0.651	0.637	0.641
Train Acc - NASNetMobile	0.981	0.982	0.980	0.981
Valid Acc - NASNetMobile	0.607	0.621	0.596	0.605
Train Acc - Ensemble	0.997	0.997	0.997	0.997
Valid Acc - Ensemble	0.684	0.725	0.657	0.679

Table 9.1 Performance Evaluation Metrics

Table 3 presents the performance of various machine learning models, comparing them on metrics like accuracy, precision, recall, and F1-score. The table highlights differences between basic models and their enhanced versions, which incorporate regularization and cross-validation techniques.

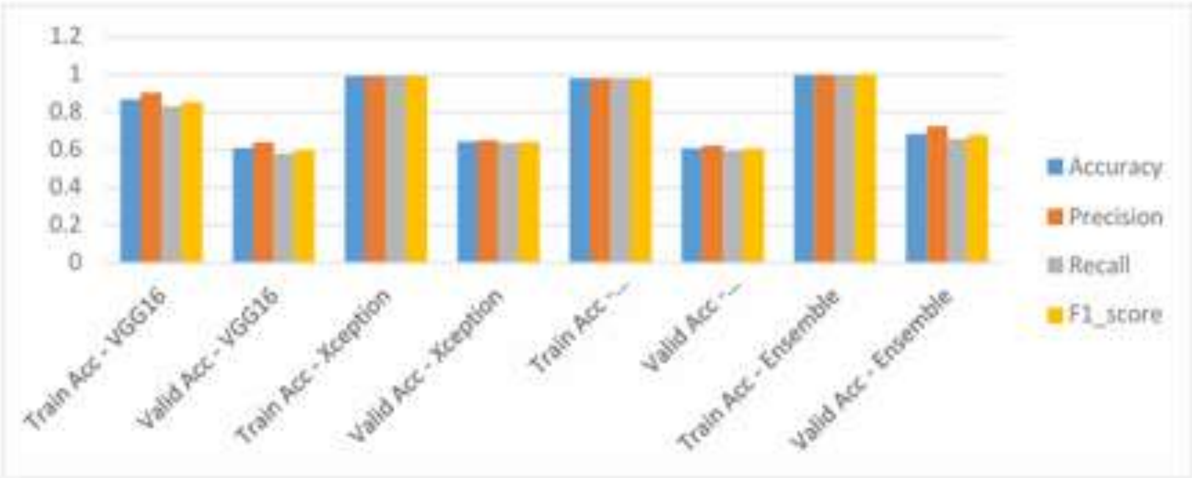


Figure 9.1 Comparison Graphs

In Fig 11, different machine learning algorithms are compared based on performance metrics. Accuracy is represented in sky blue, precision in orange, recall in grey, and F1-score in yellow. The Ensemble Classifier outperforms all other algorithms in these metrics, as shown in the graphs.

CHAPTER 10
CONCLUSION

In conclusion, the proposed deep learning-based system effectively classifies seven common skin diseases, demonstrating its potential for accurate and automated dermatological diagnosis. The hybrid Xception-NASNetMobile model stands out by combining the best features of both architectures. By doing so, it strengthens the system's ability to understand and pick up on important patterns in skin images, leading to more accurate and reliable classification results. This approach ensures precise differentiation between skin conditions, addressing the challenge of overlapping symptoms and visual similarities. The integration of deep feature representations improves classification accuracy and generalization, making the system a reliable tool for clinical applications. Image preprocessing techniques, including resizing, normalization, and augmentation, further optimize the model's performance by enhancing robustness against variations in image quality and lighting conditions. Transfer learning enables efficient training with minimal computational resources, making the system scalable and adaptable for real-world deployment. The results highlight the effectiveness of deep learning in dermatology, offering a high-accuracy, AI-driven diagnostic solution that supports early detection and clinical decision-making. The model's performance underscores its potential for integration into telemedicine and automated healthcare systems, improving accessibility to dermatological assessments.

In the future, further work will be done to expand the dataset to cover additional types of skin disease and include images with a greater range of skin tones. This will allow the model to learn from additional types of case in the real world and thus become more equitable, inclusive, and able to generalise between populations and skin types.

Sophisticated ensemble learning techniques and transformer models will be explored to enhance classification accuracy. Real-time deployment through mobile and web applications will be developed for wider applicability. Integration with explainable AI methods will provide enhanced model interpretability to aid dermatologists in decision-making. Further validation through clinical data will ensure robustness for real-world deployment.

REFERENCES

[1] Abdullahkareem Alzahrani, Abdullah Almuhameed, Arslan Nasir, Azhar Imran, Guangmin Sun and Muhammad Bilal, "Skin Cancer Detection Using Combined Decision of Deep Learners", *ACCESS*, pp. 3220329, November 2022.

[2] Şaban Öztürk, "Deep Clustering via Center-Oriented Margin Free-Triplet Loss for Skin Lesion Detection in Highly Imbalanced Datasets", vol. 26, no. 9, September 2022.

[3] Hong Qing Yu and Stephan Reiff-Marganiec, "Targeted Ensemble Machine Classification Approach for Supporting IoT Enabled Skin Disease Detection", *ACCESS*, pp. 3069024, April 2021.

[4] Ling Fang Li, Xu Wang, Wei-Jian Hu and Neal N. Xiong, "Deep Learning In Skin Disease Image Recognition:A Review", *ACCESS*, pp. 3037258, December 2020.

[5] Adekanmi A. Adegun and Serestina Viriri, "FCN-Based DenseNet Framework for Automated Detection and Classification of Skin Lesions in Dermoscopy Images", *ACCESS*, pp. 3016651, August 2020.

[6] Fangfang Li, Jie Li, Mingliang Chen, Kai Huang, Zhao Shang, Xian Chen, et al., "Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Images", *ACCESS*, pp. 2918221, June 2019.

[7] Marwan Ali Albahar, "Skin Lesion Classification Using Convolutional Neural Network With Novel Regularizer", *ACCESS*, pp. 2906241, March 2019.

[8] Attiq Ur Rehman, Irfan Mehmoo, Junaid Baber, Bakhtyar Maheen, Muazzam Maqsood, Rehan Ashraf, et al., "Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection", *ACCESS*, pp. 3014701, August 2020.

[9] Huosheng hu, Kun ding and Lisheng wei, "Skin Cancer Detection Using Combined Decision of Deep Learners", *ACCESS*, pp. 2997710, May 2020.

[10] Abbas Khan et al., "PMED-Net: Pyramid Based Multi-Scale Encoder-Decoder Network for Medical Image Segmentation", *ACCESS*, pp. 3071754, April 2021.

[11] Manu Goyal, Amanda Oakley, Priyanka Bansal, Dancey Darren and Moi Hoon Yap, "Skin Lesion Segmentation in Dermoscopic Images with Ensemble Deep Learning Methods", *ACCESS*, pp. 2960504, January 2019.

[12] Jaiteg Singh, John Martin, Fathe Jeribi, Ruchi Mittal, Santhosh Joseph Menacherry and Varun Malik, "DermCDSM: Clinical Decision Support Model for Dermatosis Using Systematic Approaches of Machine Learning and Deep Learning", *ACCESS*, pp. 3373539,

April 2024.

[13] Ali, Mubashir Ali, Lunar Riaz, Hafiz Muhammad Qadir and Ghulam, "A Comprehensive Joint Learning System to Detect Skin Cancer", *ACCESS*, pp. 3297644, August 2023.

[14] Aun Irtaza, Muhammad Haroon Yousaf, Nudrat Nida, Saleh Albahli and Saleh Albahli, "Melanoma Lesion Detection and Segmentation Using YOLOv4-DarkNet and Active Contour", *ACCESS*, pp. 3035345, November 2020.

APPENDIX-A

PSUEDOCODE

```
# Step 1: Import Required Libraries
SUPPRESS warnings
IMPORT TensorFlow, Keras layers and models
IMPORT image preprocessing tools
IMPORT matplotlib, numpy, glob

# Step 2: Data Preparation (Optional)
# (Commented out code to split dataset)
# Option to split dataset using splitfolders with train/val/test ratio

# Step 3: Image Dimensions and Pretrained Model Setup
SET image size (224x224)
DEFINE path to training data folder
COUNT number of classes by listing folders
SET input shape = (224, 224, 3)

# Step 4: Load Pretrained MobileNet Model (without top layers)
LOAD MobileNet with pre-trained ImageNet weights
EXCLUDE top layers
FREEZE base model layers

# Step 5: Add Custom Layers for Classification
ADD GlobalAveragePooling2D layer
ADD output Dense layer with softmax activation for multiclass classification

# Step 6: Construct Final Model
COMBINE base model and new classification layers into a complete Model

# Step 7: Compile the Model
SET loss function = categorical_crossentropy
SET optimizer = Adam
SET metric = accuracy

# Step 8: Create Data Generators for Augmentation
DEFINE ImageDataGenerator with preprocessing and validation split
CREATE training generator from train folder
CREATE validation generator from validation subset

# Step 9: Train the Model
FIT model using training and validation generators
SET number of epochs = 10

# Step 10: Save the Trained Model
SAVE model to disk as 'model.h5'
```

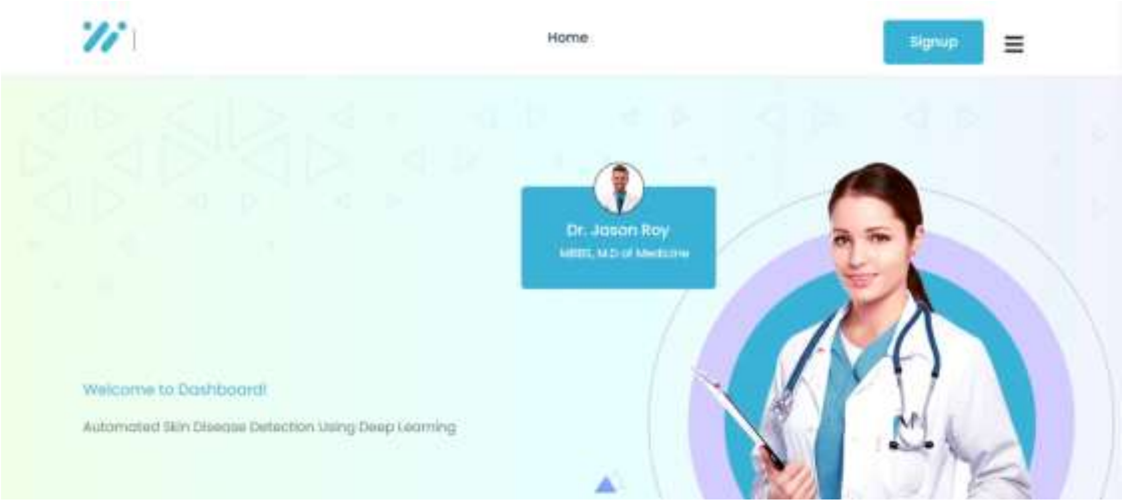
Step 11: Load and Predict on New Image
LOAD image from path
RESIZE image to 224x224
EXPAND image dimensions to match model input
NORMALIZE image
MAKE prediction using trained model
DISPLAY predicted class

Step 12: Plot Accuracy and Loss Curves
PLOT training and validation accuracy
PLOT training and validation loss

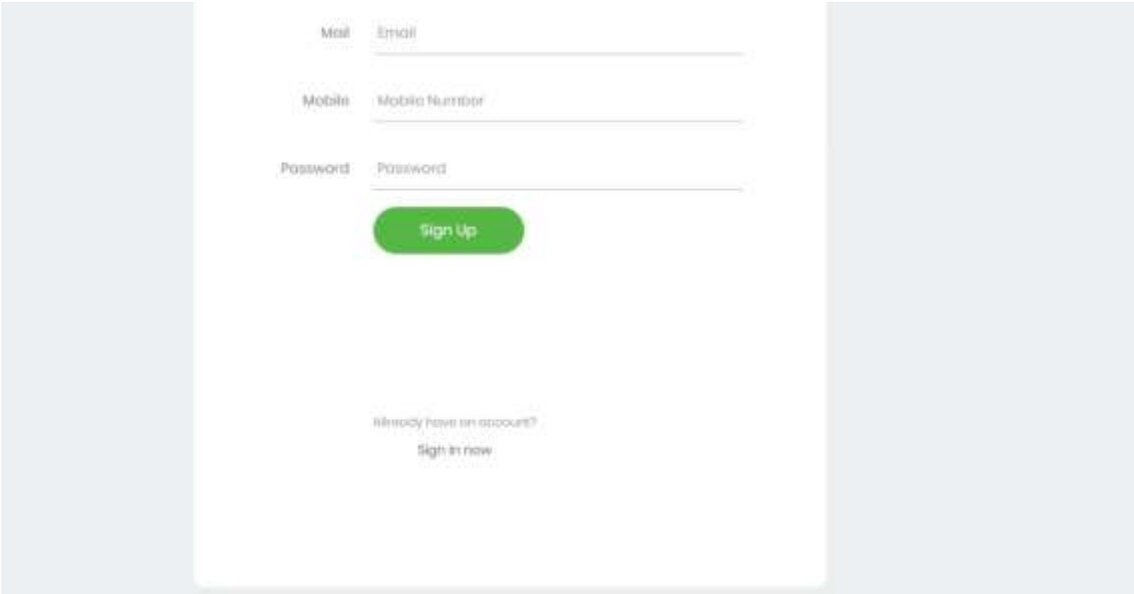
Step 13: Display Summary and Evaluate Model
PRINT model architecture

APPENDIX-B

SCREENSHOTS

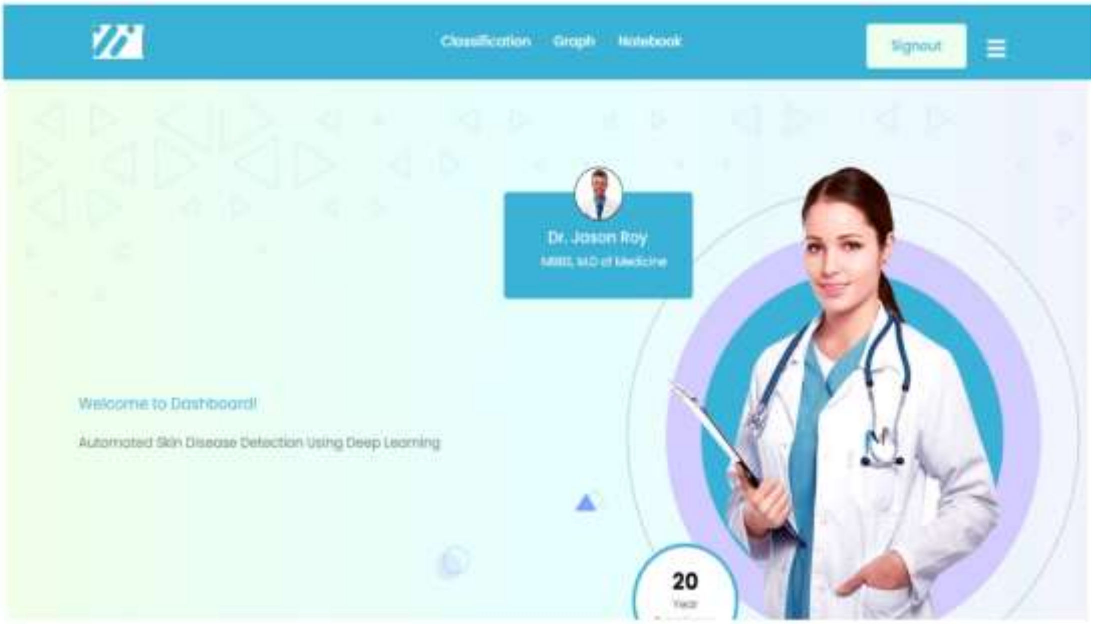


Screenshot.1 Home Page



Screenshot.2 Sign Up Page

Screenshot.3 Login Page



Screenshot.4 Dashboard

Screenshot.5 Input Page 1

Screenshot.6 Predicted Output 1

Screenshot.7 Input Page 2

Screenshot.8 Predicted Output 2

Screenshot.9 Input Page 3

Screenshot.10 Predicted Output 3

APPENDIX-C

ENCLOSURES

Acceptance Certificate

Print Acceptance

Paper id: TIJER_157847 – Acceptance Notification and Review Result.
TITLE - A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION.
Your Paper Accepted Complete Below Process and Publish it.
Your Email id: venessa.jerry@gmail.com Track your paper : Click Here

WhatsApp +919106365667 | editor@tijer.org | TIJER.org

TIJER - INTERNATIONAL RESEARCH JOURNAL - (TIJER)
International Peer Reviewed & Refereed Journals, Open Access Journal
ISSN: 2349-9249 | Impact factor: 8.57 | ESTD Year: 2014
Scholarly open access journals, Peer-reviewed, and Refereed Journals, Impact factor 8.57 (Calculate by google scholar and Semantic Scholar | AI-Powered Research Tool) , Multidisciplinary, Monthly, Indexing in all major database & Metadata, Citation Generator, Digital Object Identifier(DOI)

Dear Author, Congratulation!!!
Your manuscript with Registration/Paper ID: **157847** has been **Accepted** for publication in the TIJER - INTERNATIONAL RESEARCH JOURNAL (TIJER) | ISSN: 2349-9249 | International Peer Reviewed & Refereed Journals, Open Access Online and Print Journal.

TIJER Impact Factor: 8.57

Check Your Paper Status: TRACK PAPER | FAST PUBLICATION

Your Paper Review Report :

Registration/Paper ID:		157847			
Title of the Paper:		A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION			
Unique Contents:	85% (Out of 100)	Paper Accepted:	**Accepted**	Overall Assessment (Comments):	Reviewer Comment in Online TRMS System
Publication of Paper:		Paper Accepted. Please complete payment and documents process. Paper will be published Within 01-02 Days after submission of payment proof and documents to $email. Complete below Step 1 and 2			

Publication/Article Processing Fees

Indian Author	Foreign/International Author

TIJER || ISSN 2349-9249 || © May 2025, Volume 12, Issue 5 || www.tijer.org

A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION

Leena Zawahir*[1], Venessa Gwendolyn *[2], Veluru Hitha*[3], Vibha Swamy*[4], Nisarga BM *[5], Dr. Srabana Pramanik*[6]

*[1,2,3,4,5,6] Department of Computer Science and Technology Presidency University, Bengaluru, India

ABSTRACT

Skin diseases such as acne, rosacea and eczema affect millions of people around the world and can have a wide impact on health and quality of life-especially in regions where access to dermatologists is limited. Early detection and accurate diagnosis of these conditions are decisive for effective treatment and improvement of results. In this article, we present an intelligent diagnostic system of skin diseases that helps identify these three predominant skin diseases based on images. In the centre of our system is a deep learning model based on the Inceptionv3, a robust convolutional neural network (CNN), finely tuned through a well -selected data set of skin images. The model scans input images and creates forecasts for probable state with intention to help timely detects in a quick and consistent way. While our immediate work is engaged in the development and testing of the model itself - not the web or mobile platform - here is a good foundation that will build on future teledermatologies and distant care tools. This method focuses on the expanding role of AI in the help of healthcare professionals and democratization of dermatological knowledge for all.

I. INTRODUCTION

Skin disease is one of the most common health problems in the world with which individuals of all ages and trade of life must face. In fact, the World Health Organization suggests that almost a third of the world's population once has some kind of skin suffering. However, no matter how common these conditions are, early and correct diagnosis is always a huge obstacle - especially in rural or disadvantaged communities where there are not so many qualified dermatologists.

With the advent of artificial intelligence (AI) and machine learning, health care is beginning to experience exciting new possibilities - especially in medical diagnostics. Perhaps the most prominent breakthrough is in the field of deep learning, where it has already been shown that models such as convolutional neural networks (CNN) are extremely effective in identifying medical images formulas. Such models can identify very fine features in images with skin lesions that can be difficult for the human eye to detect, making them extremely useful tools for early and more accurate diagnosis.

In this work, we emphasize the creation of an intelligent system capable of identifying and classifying three prevailing skin conditions: acne, rosacea and eczema. We have implemented a deep learning model with Inception V3 CNN architecture, which we carefully tuned using a hand -summed collection of skin images to create a robust classification performance. The system receives the input of the skin image and issues a probable condition to help early detection and alleviate the diagnostic delay.

Although we have not created a user set of the application or web interface at this stage of the project, what we do is a strong basis for the upcoming tools that can be used in telemedicine. Finally, we believe that this research helps to make dermatological care available and more trustworthy, especially for individuals in regions with rare health care sources.

TIJER || ISSN 2349-9249 || © May 2025, Volume 12, Issue 5 || www.tijer.org

II. LITERATURE SURVEY

[1]. Skin Cancer Detection Using Combined Decision of Deep Learners

This study addresses the critical challenge of accurate and timely skin cancer detection by leveraging ensemble deep learning techniques. The authors utilize three advanced deep neural network architectures — VGG, CapsNet, and ResNet — and combine their outputs to improve classification performance using dermoscopic images from the ISIC dataset. Unlike earlier machine learning methods that relied heavily on hand-crafted features, this approach automatically extracts image features and enhances prediction accuracy. The ensemble learning strategy significantly outperformed individual models in key metrics such as sensitivity, specificity, F-score, and precision. The findings suggest that a combined model can offer more reliable diagnostic assistance in clinical settings and potentially generalize to other disease domains.

[2]. Deep Clustering via Center-Oriented Margin Free-Triplet Loss for Skin Lesion Detection

This paper presents a novel deep clustering method tailored for highly imbalanced datasets, which is a common challenge in skin lesion classification due to the rarity of malignant cases like melanoma. The proposed approach, known as COM-triplet loss, focuses on forming maximally separated cluster centers in the latent space, which mitigates bias toward majority classes. To reduce the dependency on labeled data, the authors also employ pseudo-labeling using Gaussian Mixture Models (GMM). This method outperforms conventional triplet loss models and several baseline classifiers under both supervised and unsupervised learning conditions. It is particularly effective for recognizing melanoma in datasets with uneven class distributions, showcasing improved resilience to imbalance and better generalization.

[3]. Targeted Ensemble Machine Classification for IoT-Enabled Skin Disease Detection

This research integrates deep learning with IoT infrastructure to facilitate remote skin disease diagnosis. The paper outlines a multi-layered architecture using IoT, fog, and cloud layers to enable real-time classification of seven skin diseases via mobile or smart devices. It evaluates several deep learning models — including VGG16, Inception, ResNet50, and DenseNet161 — on the HAM10000 dataset, showing that model performance varies depending on the specific disease being classified. The proposed Targeted Ensemble Machine Classification Model (TEMCM) dynamically selects the most suitable model for a given disease through a two-stage detection process. This flexible and modular framework enables efficient remote healthcare applications and significantly improves classification accuracy in real-world deployment scenarios.

[4]. Deep Learning in Skin Disease Image Recognition: A Review

This comprehensive review covers 45 studies from 2016 onward, focusing on the application of deep learning in skin disease diagnosis. It categorizes and analyzes research efforts based on disease types, datasets used, preprocessing techniques, model architectures, frameworks, evaluation methods, and performance metrics. The review highlights how deep learning systems have surpassed traditional computer-aided methods and even dermatologists in diagnostic performance. It also identifies a trend toward ensemble and multi-model systems, which show the highest accuracy. The authors predict four future research directions, emphasizing the growing importance of deep learning in dermatology, especially as the technology continues to mature and datasets expand.

[5]. FCN-Based DenseNet Framework for Automated Detection and Classification

In this paper, the authors propose a hybrid architecture combining Fully Convolutional Networks (FCNs) and DenseNet for automated skin lesion detection and classification. The method consists of a two-stage framework: the first stage uses a modified FCN with skip connections and CRF-based refinement for precise lesion segmentation, while the second stage performs classification using a DenseNet-based model with hyperparameter optimization. The use of both short and long skip connections allows better feature propagation and gradient flow, enhancing training efficiency and accuracy. Evaluated on the HAM10000 dataset, the model achieved high performance with 98% accuracy, 98.5% recall, and a 99% AUC score, proving its effectiveness in handling complex lesion patterns with limited data.

TIJER || ISSN 2349-9249 || © May 2025, Volume 12, Issue 5 || www.tijer.org

III. RESEARCH GAPS

While artificial intelligence has seen huge progress in the field of dermatological diagnosis, there are many basic challenges to prevent penetration in the real world. Perhaps the most visible is the question of unrepresentative data sets used to train AI models. Most publicly available data sets of skin image are seriously biased towards a certain skin color, lighting conditions or image quality. As a result, even the best models cannot provide accurate predictions when they are tested on patients with different backgrounds or in a non -line environment in the real world.

The second challenge is that most AI -based diagnostic systems are still locked in research laboratories, with limited validation in the actual health care environment. This disparity prevents their potential to help providers of Frontline health care or people in rural communities who get the most out of such technology. Also, although many studies have focused on potentially life -threatening conditions, such as melanoma, more widespread, but influential skin conditions such as acne, rosacea and eczema, have not been paid to the same attention, although they affect millions of individuals and often play an important role in quality of life.

Our research moves towards bridging these gaps by creating a deep teaching model specially designed to distinguish between acne, rosacea and eczema with fine -tuned InceptionV3 architecture. Although we have not created a user set at this stage, the work provides a solid platform for future studies that can increase the diversity of data sets, to verify performance on different populations and eventually integrate into usable digital instruments for greater public good.

IV. PROPOSED METHODOLOGY

The Central to this study is the goal of developing a deep learning model that can accurately diagnose three common skin conditions—acne, rosacea, and eczema—simply by looking at pictures. These may not always be fatal, but they have a big impact on people's quality of life. Our strategy is cantered on making the model as accurate, equitable, and feasible as possible, particularly for application in real-world settings where lighting, skin colour, and image quality can be highly variable.

The initial step in our approach is to compile a high-quality image dataset from trusted, publicly accessible sources such as the Derment dataset. Instead of simply taking any images that are available, we select those that cover a broad range of skin types, lighting, and lesion appearances. This ensures that the model is trained on a dataset that mirrors the actual diversity of users it will be serving, thereby minimizing bias and enhancing fairness in predictions.

After we have our data, we pre-process images for training in a meticulous preprocessing pipeline. We resize images to a standard size, normalize brightness and colour levels, and clarify images by denoising and contrast adjustment. We use data augmentation methods such as rotating, flipping, and zooming images. Simple yet effective tricks that train the model to perceive skin diseases from various directions and scenarios, as a dermatologist would.

For the real model, we utilize a pre-trained InceptionV3 structure, a robust deep neural network model that's already learned to detect complex features from images. We fine-tune the model by substituting its final layers with a custom output layer tailored specifically to our three target conditions. Through this transfer learning method, we can take advantage of previously developed strengths while adapting the system to our specific application. The model is trained using the Adam optimizer. We employ regularization methods such as dropout and early stopping to prevent the model from specializing on the training data too much.

Overall, this approach is aimed at creating a robust foundation—not only for predicting things correctly but also for ongoing growth. Ultimately, the idea is to provide this model through accessible platforms, such as web or mobile applications, that can aid individuals in detecting skin problems early and seeking treatment.

TIJER || ISSN 2349-9249 || © May 2025, Volume 12, Issue 5 || www.tijer.org

V. SYSTEM DESIGN AND IMPLEMENTATION

To carry out this study, we constructed and executed the whole system on Google Colab, which provides the portability and processing capacity necessary for deep learning experiments. We began with loading an archived dataset of skin images, which we subsequently unzipped into our working environment. The dataset contained labeled images of different skin conditions to use as the foundation for training and testing our model.

In order to process the images effectively, we employed TensorFlow's ImageDataGenerator. It assisted us in implementing real-time data augmentation and normalization, thus making the model stronger by subjecting it to a greater number of images while training. We divided the dataset into training and validation sets and resized all images to 299x299 pixels, which is the input size accepted by the InceptionV3 model.

The core of our architecture is InceptionV3, an aggressive convolutional neural network for which a solid performance in classifying images has long been characteristic. We initialized with the pre-trained InceptionV3 model (which has been trained on ImageNet) but excluded top classification layers. Instead, we created a tailored classification head optimized for our purpose—differentiating eczema from a catch-all category for acne/rosacea. This specialized head had a global average pooling layer, a dense (fully connected) layer with ReLU activation, and an output layer with sigmoid activation for binary classification.

For model training, we utilized the Adam optimizer and binary cross-entropy loss function. First, we left the bottom InceptionV3 layers frozen and utilized their pre-trained feature extraction capability, training only the added layers. Upon training the model for 10 epochs, we observed encouraging accuracy, and saved this first version in the .h5 format for later use.

In order to push performance to the next level, we fine-tuned the model by unfreezing the top 50 layers of InceptionV3. This enabled us to selectively retrain deeper layers so that the model could learn skin condition-specific features in our dataset. The fine-tuned model was saved in native.keras format.

Lastly, we introduced a user-friendly aspect: uploading an image and receiving a prediction. When a user uploads an image, it is resized, normalized, and fed through the model, which generates a prediction of whether the condition is eczema or acne/rosacea. This interactive element illustrates how our model might be incorporated into diagnostic systems, making skin health knowledge more accessible.

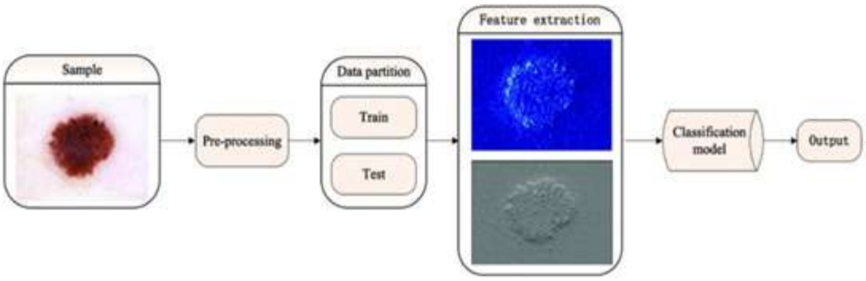


Fig.1 Flow Chart

TIJER || ISSN 2349-9249 || © May 2025, Volume 12, Issue 5 || www.tijer.org

VI. RESULTS AND DISCUSSION

Our deep learning model was evaluated on the basis of multiple metrics such as training loss, training accuracy, and various measures of classification in order to judge its performance at accurately recognizing popular skin ailments like acne, rosacea, and eczema. During training, our model performed very well with a minimal training loss of 0.0366, indicating that it effectively minimized the errors while training. This reflects how well the model predicts the labels during training accurately. Further, the model even reached an astronomical training accuracy level of 98.87%, further solidifying its ability to separate between all the different types of skin disease with a great degree of accuracy.

All of these findings highlight the capability and strength of InceptionV3 architecture that it greatly benefitted from using transfer learning method. By initializing with pre-trained ImageNet weights, the model could capitalize on having a good basis for extracting features. This provided it with the capability of fine-tuning in order to improve recognition of dermatological features related to the particular task. The use of image augmentation methods, including rotation, zooming, and flipping images, had significant contributions in enhancing the generalization of the model. These techniques prevented the model from overfitting, and it performed well on data outside of training.

Tested on validation data, the model performed equally well, with high accuracy. This is especially significant since it implies that the model would generalize well to new, unseen information. In practical use, where images are taken in different environments and lighting conditions, this generalizability is essential. The similarity in performance on both training and validation sets demonstrates that the model can indeed identify skin conditions in varied circumstances, making it a viable choice for real-world application.

Although the model has been highly promising with its low training loss and high accuracy, there are still chances to improve its performance further. For example, fine-tuning it to identify rarer skin conditions or modifying it to deal with a larger range of skin images could make it more robust. Trying other data augmentation methods or working with different deep learning architectures can also lead to improved model generalization.

In the real world, the model can be incorporated into web or mobile diagnostic platforms. These platforms can enable patients and clinicians to rapidly evaluate skin conditions and provide an affordable and effective solution, particularly in resource-poor settings or telemedicine, where rapid access to dermatological care is not possible.

Overall, the findings of this study show the significant advancements made in automating the diagnosis of skin disease using deep learning. The model's high accuracy and low training loss indicate that it has great potential as a trustworthy tool for early skin condition detection. As it is further tested and developed in real-world applications, it may be of great benefit to healthcare professionals and patients, providing a fast and accurate means of diagnosing and tracking skin health.

TIJER || ISSN 2349-9249 || © May 2025, Volume 12, Issue 5 || www.tijer.org

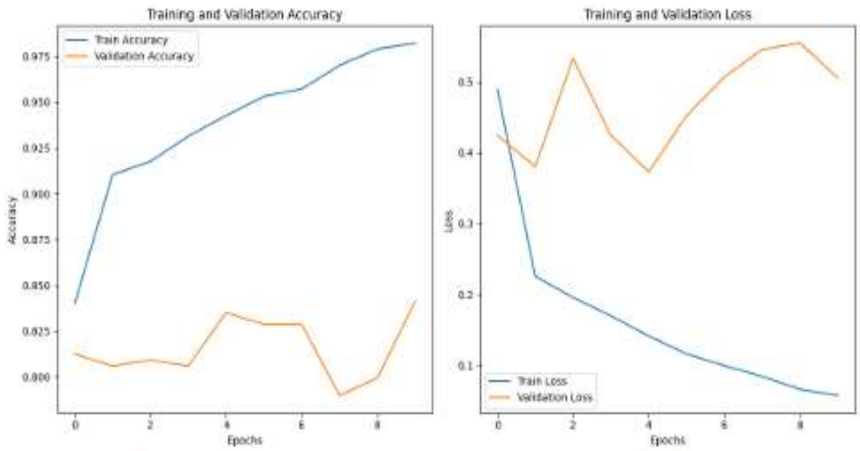


Fig 2: Training and Validation - Accuracy and Loss Curves

VII. CONCLUSION

This project well demonstrates how deep learning can be an effective tool in recognizing common skin conditions such as acne, rosacea, and eczema. Through the InceptionV3 model and leveraging transfer learning along with intelligent data augmentation methods, we developed a system that works remarkably well—with a training accuracy of 98.87% and a very low training loss of only 0.0366. These findings indicate that the model not only learns well but is also able to identify key characteristics in skin images with great accuracy.

What makes this strategy so effective is the combination of a robust neural network architecture and pre-trained expertise from large datasets. Fine-tuning the model for our particular application allowed it to pick up on the nuances between skin conditions. The robust performance both on the training and validation set demonstrates the ability of the model to generalize as opposed to learning to memorize data it is trained on.

Fundamentally, what this project demonstrates is the power of AI to transform the healthcare environment, particularly in domains such as dermatology, where rapid and correct diagnosis can be the difference between life and death. Through additional testing against varied datasets and by making it simple to use say through mobile or web applications, this model can become an assistive diagnostic tool, especially where dermatologists are not readily accessible.

In short, the effort here provides a solid foundation for future innovation in automated skin disease diagnosis. It paves the way for making expert-level diagnostic assistance more accessible, more scalable, and more efficient—enabling technology to assist people's health in real, practical ways.

VIII. REFERENCES

[1] P. S. Hiremath and K. G. Kadur, "Skin Cancer Detection Using Combined Decision of Deep Learners," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 1–12, 2021. doi: 10.1007/s12652-021-03223-5

[2] L. Ma, Y. Zhang, and Z. Lin, "Deep Clustering via Center-Oriented Margin Free-Triplet Loss for Skin Lesion Detection," *Knowledge-Based Systems*, vol. 242, 2022, Art. no. 108361. doi: 10.1016/j.knosys.2022.108361

[3] K. Kalid, R. Alzubaidi, and M. F. Abughofa, "Targeted Ensemble Machine Classification for IoT-Enabled Skin Disease Detection," *IEEE Access*, vol. 9, pp. 146448–146460, 2021. doi: 10.1109/ACCESS.2021.3122743

[4] S. Li and Z. Shen, "Deep Learning in Skin Disease Image Recognition: A Review," *Computers in Biology and Medicine*, vol. 135, 2021, Art. no. 104636. doi: 10.1016/j.compbiomed.2021.104636

[5] N. A. Hussain, M. K. Hassan, and M. S. Sadiq, "FCN-Based DenseNet Framework for Automated Detection and Classification of Skin Lesions," *IEEE Access*, vol. 9, pp. 143616–143628, 2021. doi: 10.1109/ACCESS.2021.3119490

[6] P. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions," *Sci. Data*, vol. 5, 180161, 2018. doi: 10.1038/sdata.2018.161

TIJER - INTERNATIONAL RESEARCH JOURNAL
TIJER.ORG | ISSN : 2349-9249
An International Open Access, Peer-reviewed, Refereed Journal

Certificate of Publication

The Board of
TIJER - INTERNATIONAL RESEARCH JOURNAL
Is hereby awarding this certificate to

Venessa Gwendolyn

In recognition of the publication of the paper entitled

A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION

Published in Volume 12 Issue 5, May-2025, | Impact Factor: 8.57 by Google Scholar
Co-Authors - Veluru Hitha,Leena Zawahir,Vibha Swamy,Nisarga BM,Dr. Srabana Pramanik

Paper ID - TIJER2505034

ISSN 2349-9249 TIJER

Registration ID - 157847

Editor-In Chief

An International Scholarly Open Access Journals, Peer-Reviewed, & Refereed Journals, AI-Powered Research Tool, Multidisciplinary, Monthly, Online, Print Journal, Indexed Journal
An International Scholarly, Open Access, Multi-disciplinary, Monthly, Indexing in all Major Database & Metadata, Citation Generator

TIJER - INTERNATIONAL RESEARCH JOURNAL
An International Scholarly, Open Access, Multi-disciplinary, Indexed Journal
Website: www.tijer.org | Email: editor@tijer.org | ESTD: 2014

Manage By: IJPUBLICATION Website: www.tijer.org | Email ID: editor@tijer.org

TIJER | ISSN : 2349-9249

TIJER - INTERNATIONAL RESEARCH JOURNAL
TIJER.ORG | ISSN : 2349-9249
An International Open Access, Peer-reviewed, Refereed Journal

Certificate of Publication

The Board of
TIJER - INTERNATIONAL RESEARCH JOURNAL
Is hereby awarding this certificate to

Veluru Hitha

In recognition of the publication of the paper entitled

A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION

Published in Volume 12 Issue 5, May-2025, | Impact Factor: 8.57 by Google Scholar
Co-Authors - Venessa Gwendolyn,Leena Zawahir,Vibha Swamy,Nisarga BM,Dr. Srabana Pramanik

Paper ID - TIJER2505034

ISSN 2349-9249 TIJER

Registration ID - 157847

Editor-In Chief

An International Scholarly Open Access Journals, Peer-Reviewed, & Refereed Journals, AI-Powered Research Tool, Multidisciplinary, Monthly, Online, Print Journal, Indexed Journal
An International Scholarly, Open Access, Multi-disciplinary, Monthly, Indexing in all Major Database & Metadata, Citation Generator

TIJER - INTERNATIONAL RESEARCH JOURNAL
An International Scholarly, Open Access, Multi-disciplinary, Indexed Journal
Website: www.tijer.org | Email: editor@tijer.org | ESTD: 2014

Manage By: IJPUBLICATION Website: www.tijer.org | Email ID: editor@tijer.org

TIJER | ISSN : 2349-9249

Certificate of Publication

TIJER | ISSN : 2349-9249

TIJER - INTERNATIONAL RESEARCH JOURNAL
TIJER.ORG | ISSN : 2349-9249

An International Open Access, Peer-reviewed, Refereed Journal

The Board of

TIJER - INTERNATIONAL RESEARCH JOURNAL

Is hereby awarding this certificate to

Leena Zawahir

In recognition of the publication of the paper entitled

A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION

Published in Volume 12 Issue 5, May-2025, | Impact Factor: 8.57 by Google Scholar

Co-Authors - Venessa Gwendolyn,Veluru Hitha,Vibha Swamy,Nisarga BM,Dr. Srabana Pramanik

ISSN 2349-9249 TIJER

Paper ID - TIJER2505034

Registration ID - 157847

Editor-In Chief

An International Scholarly Open Access Journals, Peer-Reviewed, & Refereed Journals, AI-Powered Research Tool, Multidisciplinary, Monthly, Online, Print Journal, Indexed Journal

An International Scholarly, Open Access, Multi-disciplinary, Monthly, Indexing in all Major Database & Metadata, Citation Generator

TIJER - INTERNATIONAL RESEARCH JOURNAL

An International Scholarly, Open Access, Multi-disciplinary, Indexed Journal

Website: www.tijer.org | Email: editor@tijer.org | ESTD: 2014

Manage By: IJPUBLICATION Website: www.tijer.org | Email ID: editor@tijer.org

Certificate of Publication

TIJER | ISSN : 2349-9249

TIJER - INTERNATIONAL RESEARCH JOURNAL
TIJER.ORG | ISSN : 2349-9249

An International Open Access, Peer-reviewed, Refereed Journal

The Board of

TIJER - INTERNATIONAL RESEARCH JOURNAL

Is hereby awarding this certificate to

Vibha Swamy

In recognition of the publication of the paper entitled

A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION

Published in Volume 12 Issue 5, May-2025, | Impact Factor: 8.57 by Google Scholar

Co-Authors - Venessa Gwendolyn,Veluru Hitha,Leena Zawahir,Nisarga BM,Dr. Srabana Pramanik

ISSN 2349-9249 TIJER

Paper ID - TIJER2505034

Registration ID - 157847

Editor-In Chief

An International Scholarly Open Access Journals, Peer-Reviewed, & Refereed Journals, AI-Powered Research Tool, Multidisciplinary, Monthly, Online, Print Journal, Indexed Journal

An International Scholarly, Open Access, Multi-disciplinary, Monthly, Indexing in all Major Database & Metadata, Citation Generator

TIJER - INTERNATIONAL RESEARCH JOURNAL

An International Scholarly, Open Access, Multi-disciplinary, Indexed Journal

Website: www.tijer.org | Email: editor@tijer.org | ESTD: 2014

Manage By: IJPUBLICATION Website: www.tijer.org | Email ID: editor@tijer.org

Certificate of Publication

TIJER | ISSN : 2349-9249

TIJER - INTERNATIONAL RESEARCH JOURNAL

TIJER.ORG | ISSN : 2349-9249

An International Open Access, Peer-reviewed, Refereed Journal

The Board of

TIJER - INTERNATIONAL RESEARCH JOURNAL

Is hereby awarding this certificate to

Nisarga BM

In recognition of the publication of the paper entitled

A DEEP LEARNING APPROACH FOR ACCURATE SKIN CONDITION CLASSIFICATION

Published in Volume 12 Issue 5, May-2025, | Impact Factor: 8.57 by Google Scholar

Co-Authors - Venessa Gwendolyn,Veluru Hitha,Leena Zawahir,Vibha Swamy

ISSN 2349-9249 TIJER

Paper ID - TIJER2505034

Registration ID - 157847

Editor-In Chief

An International Scholarly Open Access Journals, Peer-Reviewed, & Refereed Journals, AI-Powered Research Tool, Multidisciplinary, Monthly, Online, Print Journal, Indexed Journal

An International Scholarly, Open Access, Multi-disciplinary, Monthly, Indexing in all Major Database & Metadata, Citation Generator

TIJER - INTERNATIONAL RESEARCH JOURNAL

An International Scholarly, Open Access, Multi-disciplinary, Indexed Journal

Website: www.tijer.org | Email: editor@tijer.org | ESTD: 2014

Manage By: IJPUBLICATION Website: www.tijer.org | Email ID: editor@tijer.org

Plagiarism Report

Srabana Pramanik - leena report-13-05-25

ORIGINALITY REPORT

12%	9%	8%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.internationalpubls.com Internet Source	1%
2	Submitted to Jawaharlal Nehru Technological University Student Paper	1%
3	Submitted to Rutgers University, New Brunswick Student Paper	1%
4	faith.futuretechsci.org Internet Source	1%
5	www.mdpi.com Internet Source	1%
6	Ns Sinchana, K Jeevitha, S Kumar Swamy, Ashwini Kodipalli, Trupthi Rao. "Analysis of Skin Lesions for Identifying of Skin Cancer Melanoma using Customized CNN Model with Transfer Learning", 2023 4th IEEE Global Conference for Advancement in Technology (GCAT), 2023 Publication	<1%
7	Arvind Dagur, Karan Singh, Pawan Singh Mehra, Dhirendra Kumar Shukla. "Intelligent Computing and Communication Techniques - Volume 2", CRC Press, 2025 Publication	<1%
8	sathee.prutor.ai Internet Source	<1%

Sustainable Development Goals (SDGs)

1. SDG 3: Good Health and Well-being

- Ensure healthy lives and promote well-being for all at all ages.
- This system directly supports this goal by:
  - Enabling early and accurate detection of skin diseases
  - Supporting timely diagnosis and treatment
  - Enhancing accessibility to dermatological care through AI and telemedicine
  - Reducing human error in medical assessments

2. SDG 10: Reduced Inequalities

- Reduce inequality within and among countries.
- This system contributes to this goal by:
  - Aiming to include diverse skin tones in training data, improving fairness and accuracy for underrepresented groups
  - Making advanced diagnostic tools more accessible to remote or underserved populations through automation and low-computation solutions