Multi-Skin Cancer Classification and Segmentation Using Deep Learning

Submitted for partial fulfillment of the requirements

for the award of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE ENGINEERING — ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

by

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CERTIFICATE

This is to certify that this **Project Report** is the bonafide work of **Mr. R. Bhanu Prakash, Ms.M. Jyotshna, Mr.K.Ganesh, Mr.K.Avinash Reddy,** bearing Reg. No. **21BQ1A4285, 21BQ1A42B0, 21BQ1A42C6, 21BQ1A42C7** respectively who had carried out the project entitled **" Multi-Skin Cancer Classification and Segmentation Using Deep Learning "** under our supervision.

Project Guide	**Head of the Department**
(Mr. B. Pardha saradhi, Assistant Professor)	(Dr. K. Suresh Babu , Professor)

Submitted for Viva voice Examination held on ______________________

Internal Examiner	**External Examiner**

DECLARATION

We, Mr.R. Bhanu Prakash, Ms. M. Jyothsna, Mr. K. Ganesh , Mr. K.Avinash, hereby declare that the Project Report entitled **"Multi-Skin Cancer Classification and Segmentation Using Deep Learning"** done by us under the guidance of Mr. B. Pardha Saradhi, Assistant Professor, CSE-Artificial Intelligence & Machine Learning at Vasireddy Venkatadri Institute of Technology is submitted for partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science Engineering - Artificial Intelligence & Machine Learning. The results embodied in this report have not been submitted to any other University for the award of any degree.

DATE

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TABLE OF CONTENTS

List of Figures

List of Tables

ABSTRACT

Skin cancer is one of the most common and rapidly spreading forms of cancer worldwide. Early detection plays a vital role in improving treatment outcomes and survival rates. This project presents a comprehensive AI-based system for the detection and classification of multiple types of skin cancer using deep learning techniques. The system leverages Convolutional Neural Networks (CNN) for accurate classification of skin lesions into various categories such as Melanoma, Basal Cell Carcinoma, and Benign Nevi, while U-Net++ is employed for precise segmentation of the affected skin areas.The application allows users to upload or capture skin lesion images, which are then analyzed through a pipeline that includes preprocessing, segmentation, classification, and result interpretation. Additional features include user authentication, multi language support, dermatologist appointment booking, and chatbot assistance for queries related to skin health. The system is designed using Django for the backend, ensuring a robust and scalable architecture.By integrating image-based diagnosis with user-centric functionalities, the Multi Skin Cancer Detection System aims to support early diagnosis, enhance patient awareness, and assist dermatologists in clinical decision-making.The system is particularly beneficial in remote or under-served areas where access to dermatological care is limited.

CHAPTER 1 INTRODUCTION

1.1 Background of the Project

Skin cancer is one of the most common types of cancer across the world. Early detection of skin cancer significantly increases the chances of successful treatment. However, traditional skin cancer detection methods involve physical examination, biopsy, and laboratory tests which are time-consuming and expensive.

With advancements in technology, Machine Learning (ML) and Artificial Intelligence (AI) have made it possible to develop automated skin cancer detection systems. These systems analyze skin lesion images and classify them into different types of skin cancer, thereby assisting dermatologists in making faster and more accurate diagnoses.

The proposed project — *Multi Skin Cancer Detection System* — aims to develop an intelligent model that can detect and classify multiple types of skin cancer using image processing and machine learning techniques.

1.2 Problem Statement

Skin cancer is a major health concern affecting a large number of people globally every year. Early detection is essential for effective treatment and reducing the risk of severe complications or death. Manual diagnosis by dermatologists is often time-consuming, expensive, and may lead to human error. In remote and rural areas, access to specialized medical experts is very limited. Traditional detection methods like biopsy require expert involvement and are not always feasible for quick diagnosis. Therefore, there is a need for an automated system that can detect and classify different types of skin cancer using image processing and machine learning techniques. This project focuses on developing a Multi Skin Cancer Detection system to support faster, accurate, and reliable diagnosis.

1.3 OBJECTIVES OF THE PROJECT

- The project aims to develop an intelligent system for the detection of multiple types of skin cancer using image processing and machine learning techniques.
- It focuses on early identification of skin cancer to improve treatment effectiveness and reduce mortality rates.

- The system will classify skin lesions into various categories such as Melanoma,Basal Cell Carcinoma, and Squamous Cell Carcinoma with high accuracy.
- A user-friendly interface will allow users to upload skin lesion imagesfor automated analysis and prediction.
- The model will use the image preprocessing of the techniques to enhance lesion features and Improve classification results.
- Advanced algorithms will extract important features like the color, texture, and shape from the Input images for accurate diagnosis.
- The system will provide graphical visualization to highlight the affected region of the skin for for better understanding.
- The project aims to the assist dermatologists and healthcare professionals in faster diagnosis, especially in rural and remote areas.
- The model will generate a confidence score for each prediction to indicate the reliability of the result.
- The project contributes to the healthcare sector by promoting automated medical diagnosis and supporting early cancer detection for better patient care.

1.4 SCOPE OF THE PROJECT

The scope of this project is to develop an intelligent and automated system for the detection of multiple types of skin cancer using image processing and machine learning techniques. This system focuses on identifying common skin cancers such as Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma from skin lesion images. The project aims to assist dermatologists, healthcare professionals, and even patients by providing a reliable and quick diagnosis tool, especially in remote and rural areas where medical resources are limited. The system can be further extended into mobile or web-based applications, enabling users to upload images and receive instant predictions. This project also supports medical research by providing accurate lesion classification, reducing manual errors, and saving diagnosis time. Additionally, the system has the potential to be enhanced in the future by including more skin disease classifications and integrating with healthcare databases. Overall, the project contributes to the healthcare sector by promoting the use of Artificial Intelligence for early disease detection and improving patient care services.

1.5 METHODOLOGY OVERVIEW

The Multi Skin Cancer Detection project utilizes a structured methodology integrating machine learning, image processing, and deep learning techniques for accurate classification of skin cancer types. The system is designed to detect multiple types of skin cancer such as Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma using medical images of skin lesions.

1. **Data Collection & Preprocessing:** A large dataset of dermoscopic images of different skin cancer types is collected from publicly available medical repositories. Preprocessing techniques such as image resizing, noise removal, contrast enhancement, and normalization are applied to improve the quality of the images for better feature extraction.
2. **Feature Extraction:** Advanced image processing techniques are used to the extract significant features from the skin lesion images. Features such as color, texture, shape, and border irregularities of the lesions are captured to assist in accurate classification.
3. **Model Training for Skin Cancer Classification:** A Convolutional Neural Network (CNN)-based deep learning model is trained on the preprocessed images to classify them into different categories like Melanoma, Basal Cell Carcinoma, Squamous Cell Carcinoma, andBenign lesions.
4. **Segmentation & Region of Interest (ROI) Detection:** The system applies image segmentation techniques to isolate the lesion area from the surrounding skin. This helps the model focus on the affected region, reducing noise and improving detection accuracy.
5. **User Interface Design:** A user-friendly interface is developed where users can upload skin lesion images. The system processes the image and provides real-time predictions with the classification result and a confidence score.
6. **Performance Evaluation:** The trained model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix to ensure the reliability and efficiency of the detection system.
7. **Model Optimization & Future Enhancement**: Continuous training and optimization techniques are applied to improve the model's robustness. The system can be further extended by integrating it into a mobile application or web platform for easy accessibility and remote diagnosis.

CHAPTER 2 LITERATURE REVIEW

2.1 Previous Research and Related Work

Skin cancer detection using Artificial Intelligence (AI) and Machine Learning (ML) has gained significant attention over the past few years due to its potential for early diagnosis and treatment. Several research works have utilized image processing techniques and deep learning models like Convolutional Neural Networks (CNN) for accurate skin lesion classification. Studies have shown that automated skin cancer detection systems can perform at par with dermatologists in identifying cancerous lesions from dermoscopic images.

The International Skin Imaging Collaboration (ISIC) has provided large publicly available datasets for skin lesion analysis, aiding researchers in developing robust models for skincancer detection. Various techniques like feature extraction, pattern recognition, image segmentation, and classification have been explored in the literature.

Additionally, several studies have proposed hybrid models that combine multiple deep learning architectures like ResNet, VGG, and Inception networks to improve classification accuracy. Transfer learning techniques have also been applied in cases where the available dataset is limited, allowing models pre-trained on large datasets to adapt to skincancer detection tasks.

Researchers have also focused on enhancing the preprocessing techniques for images, including noise removal, contrast enhancement, and lesion segmentation, which helps inimproving the detection accuracy. Furthermore, advanced algorithms have been developed for multi-class classification to differentiate between various types of skin cancer such as Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma.

Moreover, explainable AI techniques like Grad-CAM and heatmap visualization have been integrated into some models to highlight the regions of the image that influence the prediction, helping dermatologists understand the model's decision-making process.

Recent research trends also involve the integration of mobile applications and cloud- based systems for skin cancer detection, enabling remote diagnosis and making healthcare more accessible.

2.2 Existing Solutions and Their Limitations

Several skin cancer detection systems have been developed using advanced technologies like Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning

(DL). These solutions primarily use dermoscopic images and clinical images to identify and classify skin lesions. Tools like SkinVision, DermAssist, and other mobile-based applications provide users with basic skin analysis by capturing images through smartphones.

Moreover, research-based models using Convolutional Neural Networks (CNN), ResNet, and InceptionNet architectures have achieved remarkable accuracy in classifying differenttypes of skin cancers. The International Skin Imaging Collaboration (ISIC) has also contributed significantly by providing large annotated datasets for model training and evaluation.

However, despite these advancements, existing solutions face several limitations:

- Most models require high-quality dermoscopic images captured by professional devices, limiting their usability in real-world conditions where users capture images using normal smartphone cameras.

- Some detection systems lack the capability to differentiate between multiple types of skin lesions and are limited to binary classification (benign vs malignant).

- False positives and false negatives remain a concern, especially in cases where the lesion has irregular shapes, color variations, or is partially occluded.

- Many existing mobile applications provide only preliminary analysis and recommend consulting a dermatologist, lacking complete automated detection with high confidence scores.

- Some AI-based models are computationally expensive, requiring high-end hardware or cloud resources, which may not be feasible for all users.

- Data privacy and security concerns arise in cloud-based solutions where sensitivemedical images are uploaded for analysis.

Therefore, there is a need for a more robust, accurate, and user-friendly skin cancer detection system that can perform multi-class classification, work effectively with normal images, provide explainable results, and ensure data privacy.

2.3 Gap Analysis

Although several AI-based systems have been developed for skin cancer detection, there are still noticeable gaps and challenges that need to be addressed. Most existing models focus only on limited types of skin cancer, whereas multiple types such as Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma require accurate differentiation. Many existing solutions are dependent on dermoscopic images, making them less effective when used with regular smartphone cameras. The lack of real-time detection and user-friendly interfaces is another gap in current systems. Some models also lack transparency, providing results without any visual explanation or heatmaps to highlight the affected regions.

Moreover, security and privacy issues in storing sensitive medical data on external servers are a concern. There is also a need for continuous model updating to tackle new patterns or rare skin cancer types.

Thus, an advanced solution is required that provides multi-class skin cancer detection, ensures accuracy on both dermoscopic and regular images, offers explainable results with heatmaps, and maintains user data privacy.

How Our Project Bridges the Gaps

1. **Multi-Class Skin Cancer Detection:** Most of the existing systems focus on detecting whether a lesion is cancerous or non-cancerous. Our project goes beyond this limitation by classifying multiple types of skin cancer such as:

- Melanoma
- Basal Cell Carcinoma
- Squamous Cell Carcinoma

This helps in providing more specific and useful diagnostic information.

2. **Use of Advanced Deep Learning Techniques:**We have implemented Convolutional Neural Networks (CNN) for feature extraction and classification. The model is trained to capture minute patterns, color variations, and texture details of skin lesionsfor better accuracy.

3. **Large Dataset Utilization:**Our project makes use of the ISIC dataset, which is one of the largest publicly available datasets for skin lesion analysis. Pre-processing techniques such as

image enhancement, noise removal, and have been applied to improve the quality of input data.

4. **User-Friendly Interface:**Unlike complex research-based tools, our system provides a simple and interactive user interface where users can upload images and get instant classification results with high accuracy.

5. **Performance Optimization:**We have optimized our model to reduce false positives and false negatives by using various evaluation metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score

This ensures the reliability of the prediction results.

6. **Early Diagnosis and Better Treatment Planning:**By providing quick and accurate detection of different types of skin cancer, our project assists in early diagnosis, helping doctors and patients to plan appropriate treatment at an early stage.

2.4 Relevance of the Project

Skin cancer is one of the most common types of cancer globally, and its early detection is crucial for effective treatment and reducing mortality rates. However, traditional diagnosis methods depend heavily on the experience of dermatologists, which may not always be accessible to everyone, especially in remote or rural areas. Our project on Multi Skin Cancer Detection using Artificial Intelligence is highly relevant in this context, as it provides an automated, efficient, and accurate solution for detecting different types of skin cancer. By leveraging deep learning models and large skin lesion datasets, the project aims to support medical professionals in diagnosing cancer at an early stage, thereby improving patient outcomes. Additionally, the system's user-friendly interface makes it accessible for general users to conduct preliminary checks and seek timely medical consultation. The project contributes to bridging the gap between healthcare and technology, making advanced diagnostic tools more affordable, faster, and available to a larger population. This relevance aligns with the growing need for smart healthcare solutions in the modern digital era.

CHAPTER 3: SYSTEM ANALYSIS AND REQUIREMENT ANALYSIS

3.1 FUNCTIONAL REQUIREMENTS

These requirements define the specific tasks and features of the system.

3.1.1 User Registration and Authentication

- Users should be able to register and log in securely to access system features.
- Registration includes details like Name, Email, Phone Number, Password, and Role (Patient/Doctor).
- Authentication through password protection and OTP/email verification for added security.

3.1.2 Multi-language Support

- The system should provide multi-language options for user accessibility.
- Users can select their preferred language at registration or from the settings.
- All system content, labels, instructions, and chatbot responses should be translated accordingly.

3.1.3 Input and Upload Functionality

- Users should be able to upload skin lesion images for cancer detection.
- The system should support common file formats (JPEG, PNG).
- Provide camera access for real-time image capture and upload.
- Allow users to provide additional input like symptoms, skin type, or medical history.

3.1.4 AI-Based Skin Cancer Detection

- The system should utilize AI/ML models for detecting skin cancer from uploaded images.
- Classification into categories like:

    - Benign (Non-cancerous)
    - Malignant (Cancerous)
    - Requires Medical Attention
- Models should use image preprocessing (resizing, normalization) before prediction.

3.1.5 Chatbot Assistance

- Integrated chatbot for guiding users about:
    - Skin cancer awareness
    - Preventive measures
    - Uploading instructions
    - Appointment booking help
- 24/7 availability for basic query handling.

3.1.6 Appointment Booking System

- Patients should be able to book appointments with dermatologists.
- Doctor profiles, availability, and consultation slots should be viewable
- Confirmation notifications should be sent to both patient and doctor.

3.1.7 Review and Rating System

- Patients can provide feedback and rate doctors after consultation.
- Review history should be available for new users to check before booking.

3.1.8 Location-Based Recommendation

- The system should recommend nearby hospitals, clinics, or dermatologists based on the user's location.
- Display address, contact details, working hours, and distance from the user.

- Map integration for easy navigation.

3.1.9 Result Presentation and Reporting

- The system should display clear detection results:
    - Classification result (Benign/Malignant)
    - Confidence score (0-100%)
    - Image visualization with highlighted affected regions.
- Option to download or email the report for medical consultation.

3.1.10 Security and Privacy

- Secure handling of user data, uploaded images, and personal information.
- Encryption for sensitive data.
- No permanent storage of user images unless consented by the user.

3.1.11 Performance Evaluation and Logging

- Maintain system logs of detection results for analysis and model improvement.
- Compute performance metrics such as accuracy, sensitivity, and specificity ofthe AI model.

3.2 NON-FUNCTIONAL REQUIREMENTS

These requirements define the overall system quality, performance, and constraints toensure reliability and usability.

3.2.2 Scalability

- The system should be able to handle an increasing number of users anddata without performance degradation.
- Support for large-scale deployment in hospitals, clinics, and healthcare platforms.

- The architecture should allow easy integration of new featureslike advanced detection algorithms or additional languages.

3.2.3 Security

- Ensure secure storage and transmission of sensitive user data (images,personal information).
- Implement data encryption for both stored and transmitted data.
- Follow standard authentication and authorization mechanismsto prevent unauthorized access.
- Ensure compliance with data privacy policies (like HIPAA or GDPR)for healthcare applications.

3.2.4 Performance

- The system should deliver quick response times for image upload, analysis,and result generation.
- Optimize AI model execution time for faster predictions without compromising accuracy.
- Maintain system availability even during high-traffic scenarios.

3.2.5 Usability

- The user interface should be simple, intuitive, and user-friendly for peopleof all age groups.
- Support multi-language options for non-English speakers.
- Provide tooltips, instructions, and chatbot assistance to guide users throughout the process.
- Ensure mobile responsiveness for easy access on smartphones and tablets.

3.2.6 Availability

- The system should be available 24/7 with minimal downtime.
- Implement server redundancy and regular backups to ensure service continuity.

- Provide instant notifications in case of system maintenance or downtime.

3.2.7 Compatibility

- The application should be compatible across multiple platforms and devices:
    - Web browsers (Chrome, Firefox, Edge)
    - Mobile operating systems (Android, iOS)
- Ensure compatibility with various image formats (JPEG, PNG) for uploads.
- Support for integration with third-party services like Google Maps (for location-based recommendations) and payment gateways (for appointment booking, if needed).

3.3 FEASIBILITY STUDY

A feasibility study evaluates whether a project is technically, economically, and operationally viable before implementation. Our skin cancer detection system, which analyzes dermoscopic and real-time camera images to identify potential signs of skin cancer, must be assessed in terms of its practicality, cost-effectiveness, and usability.

3.3.1 Technical Feasibility

The skin cancer detection system is technically feasible due to the availability of advancedtools and technologies. The system utilizes deep learning techniques, particularly convolutional neural networks (CNNs), for the classification of skin cancer from both dermoscopic and real-time camera images. It is developed using Python in a Jupyter Notebook environment, leveraging powerful open-source libraries such as TensorFlow, Keras, OpenCV, and NumPy. The integration of Django for the backend allows the system to be deployed as a web or mobile application, enabling real-time image capture and prediction. Furthermore, support for multiple languages can be incorporated using APIs like Google Translate, making the system more inclusive. Cloud services can be used for hosting and scaling the application, ensuring that the infrastructure can handle a growing number of users. Overall, the current technological ecosystem supports the successful development and deployment of the system.

3.3.2 Economic Feasibility

The system is also economically feasible. While there are initial costs involved in terms of development time, hardware (especially if GPU-based computing is required), and API integration, these are manageable within a reasonable budget. Operational costs, such as hosting, maintenance, and occasional updates, are consistent with standard software solutions. On the benefit side, early detection of skin cancer through this system could significantly reduce healthcare costs by enabling timely treatment. Additionally, there is a strong potential for revenue generation through multiple channels. The application could be offered as a freemium mobile app, with basic features available for free and premium services for a fee. Clinics and hospitals could also adopt it as a Software-as-a- Service (SaaS) model to assist dermatologists. Given these advantages, the system presents a favorable cost-benefit ratio.

3.3.3 Operational Feasibility

From an operational standpoint, the system is highly feasible. It is designed to be user- friendly and accessible to a broad range of users, including patients, dermatologists, and healthcare providers. Features such as real-time camera capture and a chatbot-based interface enhance usability, especially for non-technical users. The inclusion of multi- language support ensures that the application can serve users from different linguistic backgrounds, thus improving outreach and inclusivity. Operational sustainability is ensured through modular design, which allows for easy updates and expansion to include more disease categories in the future. The system can be scaled using cloud infrastructure to meet increasing demand, and routine maintenance can be managed efficiently. With the right deployment strategy and support mechanisms, the system is well-positioned tooperate effectively in real-world healthcare settings.

3.4 PROPOSED SYSTEM OVERVIEW

The proposed system is an AI-powered skin cancer detection platform designed to assist in the early diagnosis of skin cancer using deep learning techniques. It analyzes dermoscopic and real-time camera images to identify and classify skin lesions as benign or malignant. The system leverages convolutional neural networks (CNNs) for accurate image-based classification and integrates with a user-friendly web and mobile interface to ensure accessibility across diverse user groups.

The platform includes several key modules: image acquisition via camera or file upload, pre-processing for noise reduction and normalization, classification using a trained deep learning model, and result interpretation through a visual and textual output. Additionally, the system provides actionable insights. It also features a multilingual chatbot to assist users throughout the process and offers appointment booking functionality for ease of access to medical professionals.By combining advanced AI techniques with practical healthcare features, the system aims to reduce diagnostic delays, improve public awareness, and support medical professionals in delivering fasterand more accurate skin cancer assessments.

CHAPTER 4: SYSTEM DESIGN AND SYSTEM ARCHITECTURE

4.1 SYSTEM ARCHITECTURE

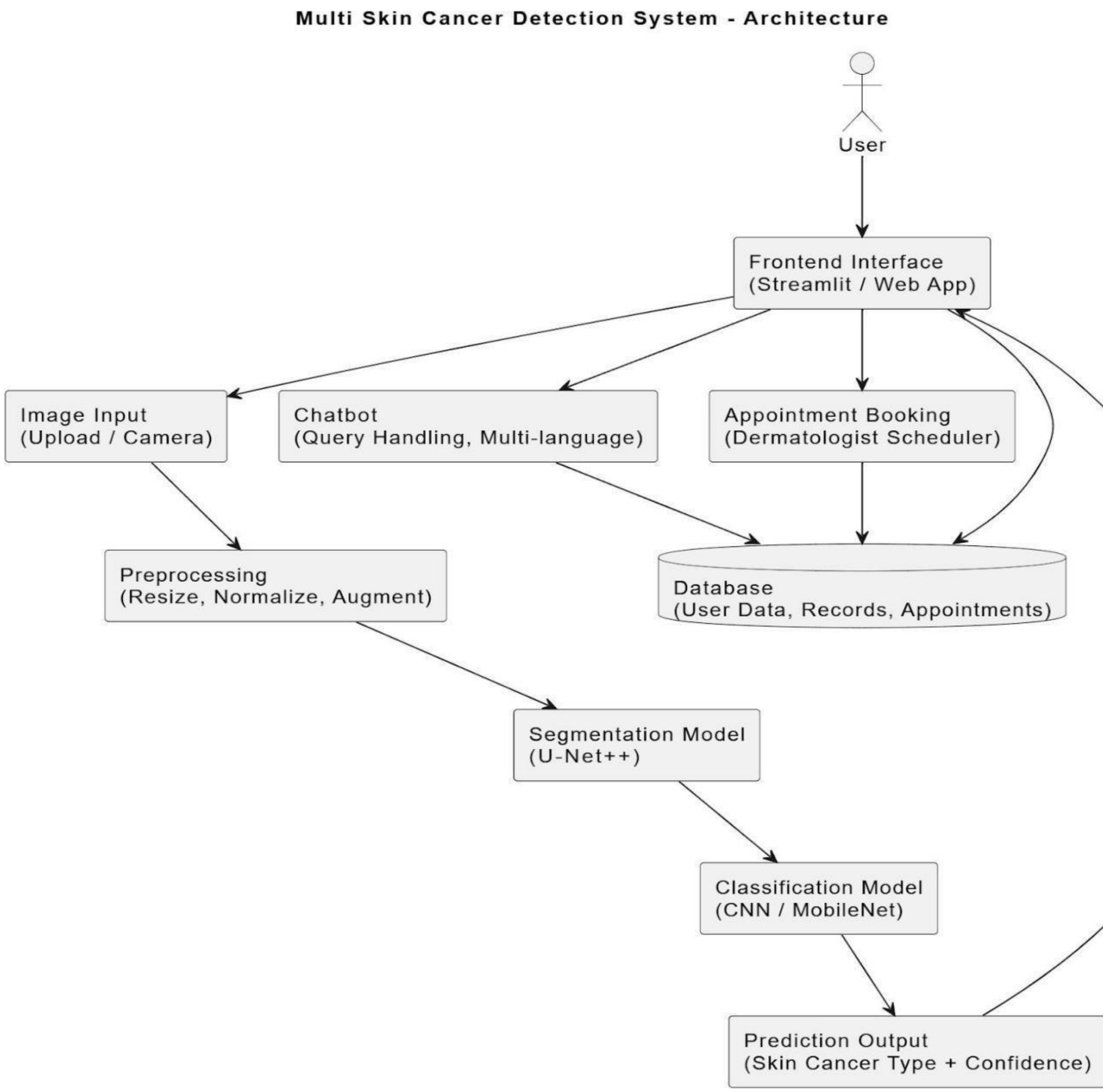

FIGURE: 4.1 SYSTEM ARCHITECTURE

4.2 USE CASE DIAGRAM

The proposed system allows the user to log in and upload or scan a skin image. It then classifies the image and provides diagnostic output using deep learning. Based on the result, it offers remedies and related health information. Finally, the system saves the output for future reference or medical consultation.

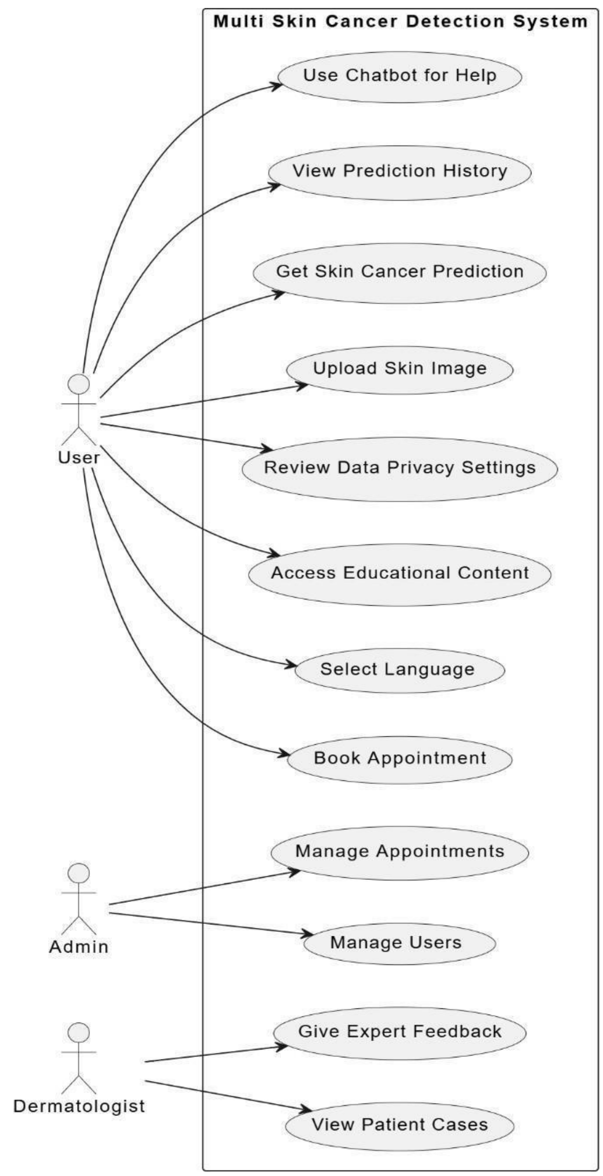

FIGURE: 4.2 USE CASE DIAGRAM

4.3 Data Flow Diagram (DFD)

The Data Flow Diagram (DFD) for the Multi Skin Cancer Detection System illustrates how data moves through the system. It begins with the user uploading an image or capturing it via camera, which is then preprocessed and segmented. The segmented image is classified using a CNN model to detect the type of skin cancer. The result, along with chatbot assistance and appointment features, is stored and retrieved from the database for user interaction.

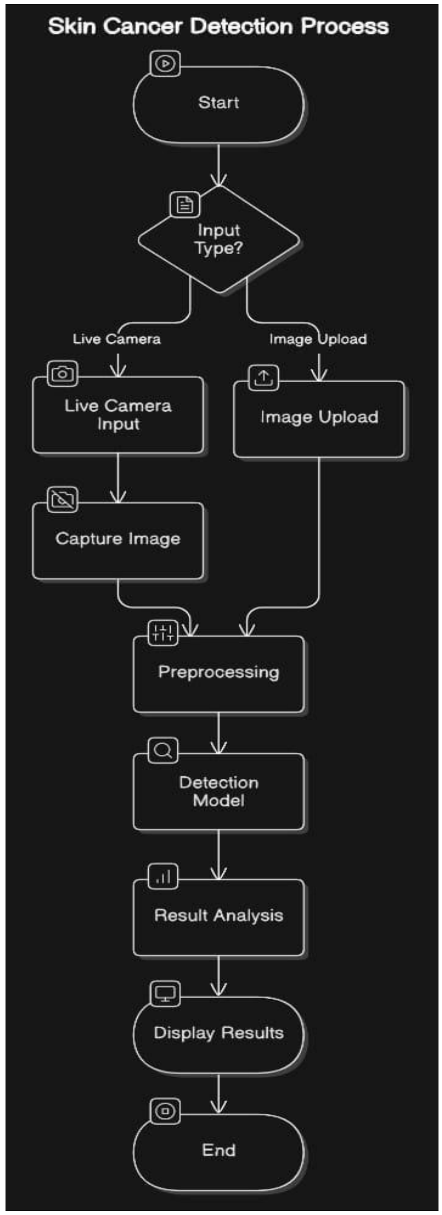

FIGURE: 4.3 DATA FLOW DIAGRAM

4.4 ACTIVITY DIAGRAM

The Activity Diagram outlines the step-by-step workflow of the system, starting from user login or registration. The user uploads or captures a skin image, which is then sent for preprocessing and segmentation using U-Net++. The processed image is passed to a CNN model for classification, returning the prediction and confidence level. Based on the result, the user can consult the chatbot, book appointments, overview recommendations.

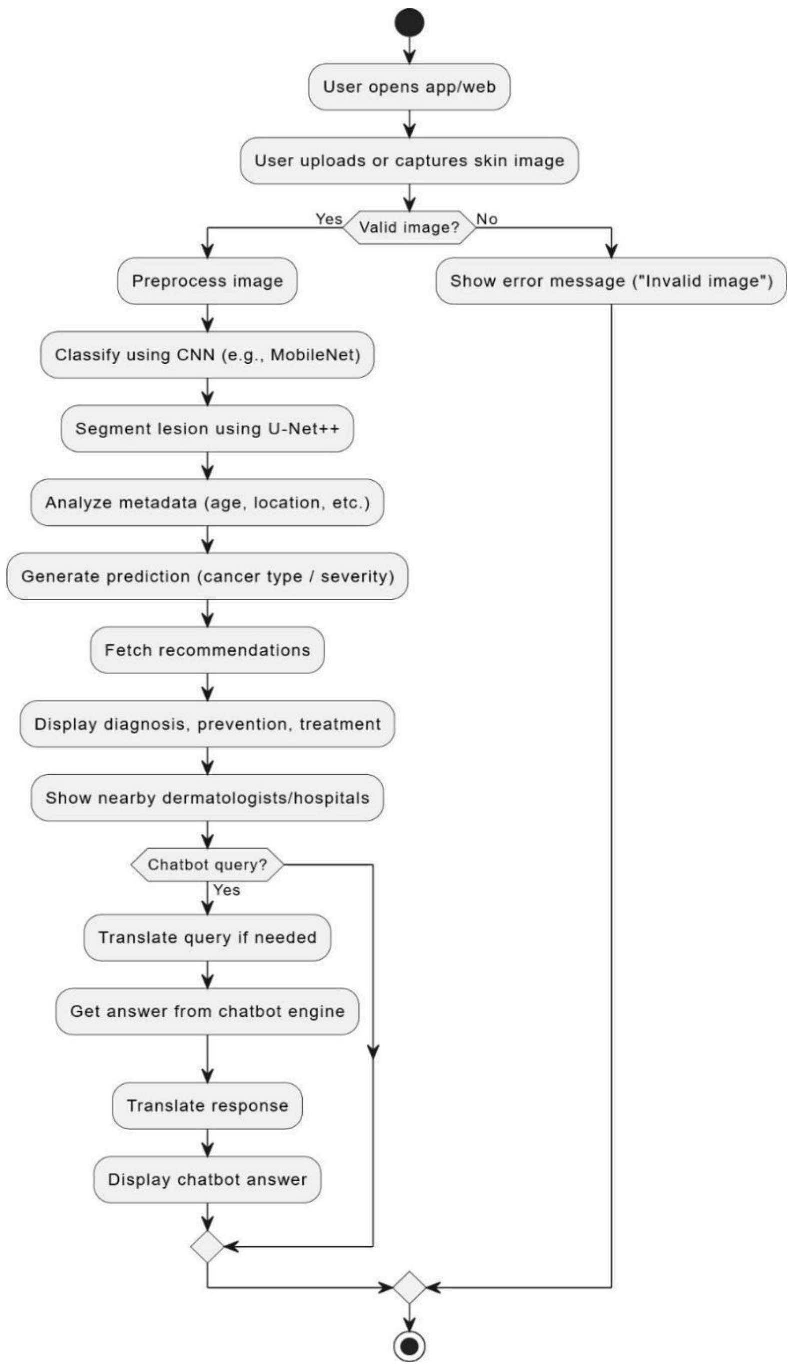

FIGURE 4.4 ACTIVITY DIAGRAM

4.5 CLASS DIAGRAM

The Class Diagram represents the structure of the system by detailing its core components, such as User, Image, Prediction, Appointment, and Chatbot. Each class contains specific attributes and methods, like uploading images, getting classification results, and booking appointments. Relationships such as one-to- many (e.g., a user can have multiple predictions or appointments) are clearly shown. It provides a blueprint of how different modules interact within the system.

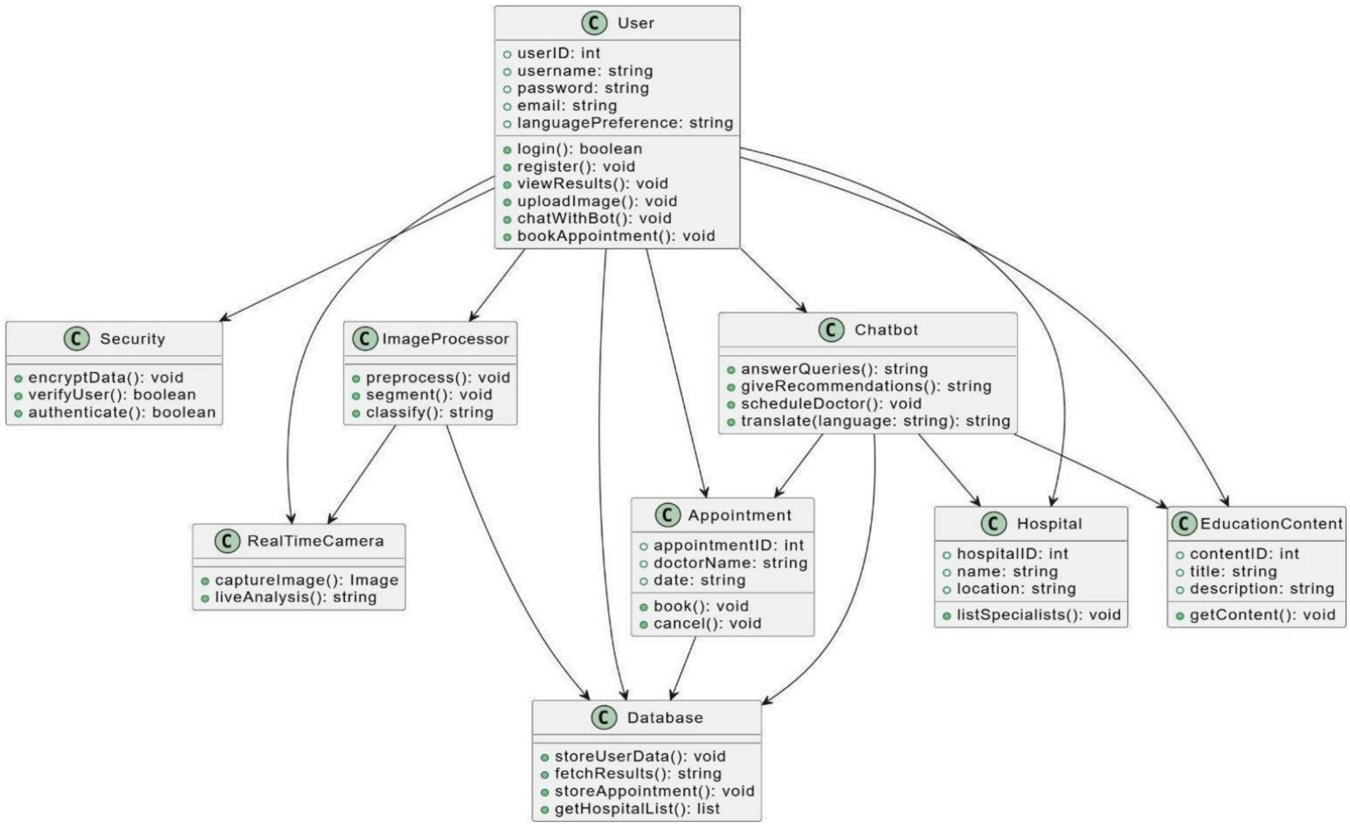

FIGURE: 4.5 CLASS DIAGRAM

4.6 ER DIAGRAM

The ER diagram visually represents the database structure, showing key entities like User, SkinImage, Prediction, Doctor, Appointment, and ChatLog. Each entity is connected through relationships, such as a user uploading multiple skin images or booking multiple appointments with doctors. Primary and foreign keys define how data is linked between tables, ensuring data integrity. This diagram helps in designing an efficient relational database for storing and accessing medical data accurately.

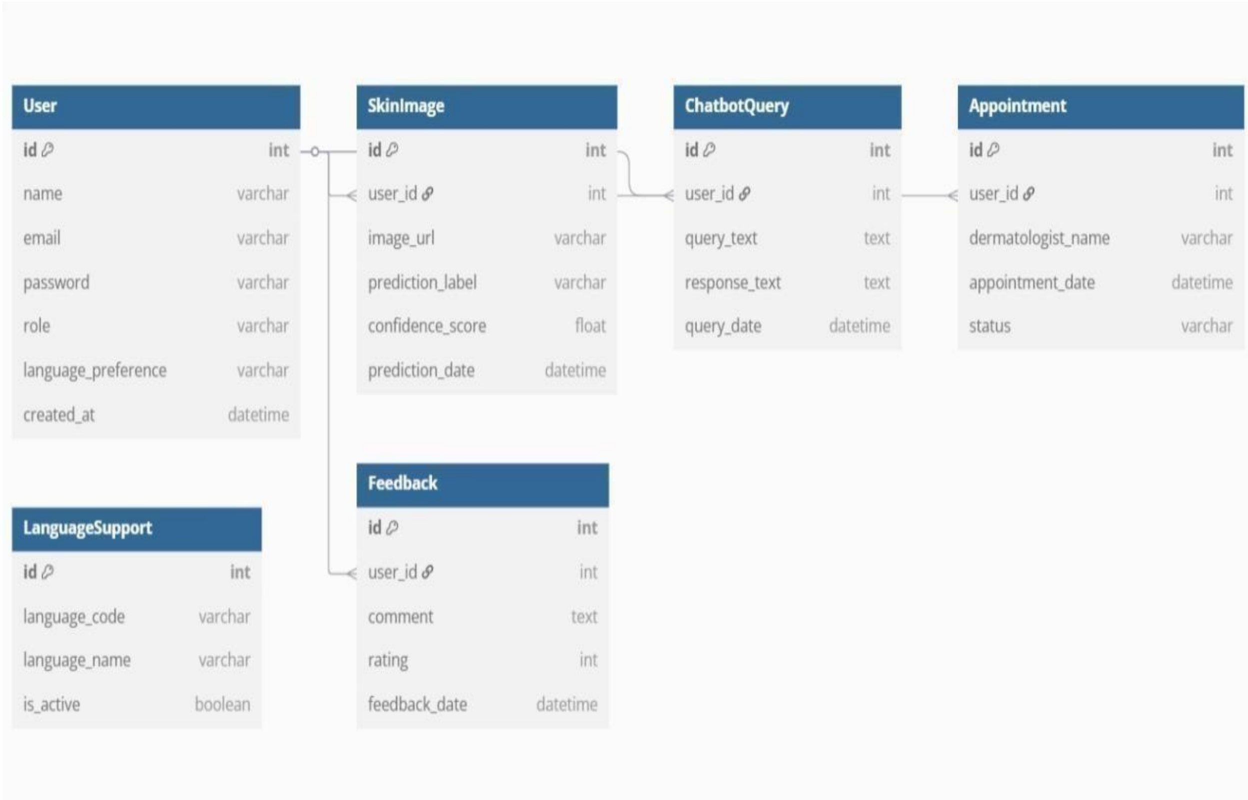

FIGURE: 4.6 ER DIAGRAM

CHAPTER 5 IMPLEMENTATION

Our **Multi Skin Cancer Detection System** is an AI-powered application designed to classify different types of skin cancers from dermoscopic and camera images. The system uses deep learning models to distinguish between multiple categories of skin conditions, while offering multilingual support, hospital suggestions, and an appointment booking feature. Built using Django for backend processing, TensorFlow and PyTorch for model development, and Streamlit for the interactive interface, the system is optimized for real- time usage on both mobile and desktop platforms.

5.1 FUNCTIONALITIES OF THE MULTI SKIN CANCER DETECTION SYSTEM

Skin Cancer Detection using Deep Learning

The system employs cutting-edge deep learning techniques to detect and classify various types of skin cancer with high accuracy. It leverages powerful convolutional neural networks trained on dermatological image datasets to distinguish between common skinconditions such as:

- Melanoma
- Nevus
- Seborrheic Keratosis
- Basal Cell Carcinoma
- Actinic Keratosis

These models analyze color, texture, asymmetry, and border irregularities to identify cancerous patterns. Each prediction includes a confidence score that reflects the certainty of the diagnosis, enabling early and reliable detection.

Image Upload & Classification

Users can easily upload skin lesion images through a simple and interactive web interface. Once an image is submitted:

- It is automatically processed and passed through the trained deep earning model.
- The system returns a predicted skin condition along with a percentage-based confidence score.
- The results are displayed clearly, helping users understand the risk level of lesion.
- The interface ensures fast processing and minimal input from users, making accessible

even for non-technical individuals.

Role-Based Dashboard (Admin & User)

The platform provides separate, role-based access for users and administrators to maintain data integrity and streamline operations.

Admin Panel Features:

- View and manage all user accounts and activity.
- Monitor and review uploaded images and corresponding predictions.
- Oversee system performance and manage future enhancements.
- Facilitate support features like feedback, queries, or appointment coordination.

User Panel Features:

- Register securely and log in to a personalized dashboard.
- Upload skin lesion images for immediate analysis.
- Access prediction results instantly.
- View previous uploads and diagnostic history in an organized format.

The role-based structure ensures privacy, administrative control, and a seamless experience for all users.

Prediction History Tracking

Each user has access to a detailed history of their previous analyses. This includes:

- Date and time of each submission
- Skin lesion image preview
- Predicted condition and confidence score

This feature enables users to track changes in their skin health over time, supporting informed medical consultations and continuous monitoring. The data is securely stored and tied to each user profile, ensuring privacy and long-term access.

Secure Authentication and Data Privacy

The system incorporates strong authentication mechanisms to ensure that only authorized users can access the platform's features. It follows best practices for security to protect sensitive medical information and personal user data. Key highlights include:

- **User Authentication:** Secure login and registration processes prevent unauthorized access. Each session is protected with token-based or session-based-security.
- **Data Encryption:** All user credentials and medical images are stored securely using encryption techniques, ensuring that personal and health-related information remains confidential.
- **Access Control:** Role-based access ensures that sensitive operations (like managing users or viewing all submissions) are restricted to administrators only.
- **Compliance-Ready:** The platform's security model is designed to align with data privacy regulations such as HIPAA and GDPR, making it suitable for handling healthcare-related information.
- **Activity Logging:** User actions are monitored to detect any suspicious behavior, ensuring transparency and system integrity.

5.2 BACKEND DETAILS OF SYSTEM

The backend of the Skin Cancer Detection System is designed to ensure accurate deep learning inference, secure data management, and seamless communication between the user interface and the machine learning models. Built with a robust architecture, it

integrates core AI functionalities, user authentication, and data storage into a cohesive and scalable solution.

Backend Framework

- Developed using the Django web framework, known for its security, scalability, and rapid development.
- Follows the **Model-View-Template (MVT)** architecture to keep concerns separated and maintain clean, modular code.

Deep Learning Model Integration

- Pre-trained deep learning models are loaded into the backend at runtime using **TensorFlow** and **Keras**.
- Each uploaded image is:
  - Preprocessed (resized, normalized)
  - Passed through the deep learning model
  - Analyzed for lesion patterns
- The model returns the predicted class along with a confidence score, which is then rendered to the frontend.

User Authentication & Role Management

- Secure login and registration are handled by Django's built-in authentication system.
- Users are categorized into **Admin** and **User** roles with permission-based access.
- Sessions are securely managed, and all sensitive actions are protectedagainst CSRF and other common web vulnerabilities.

Database & Data Handling

- Uses **SQLite** (or optionally MySQL/PostgreSQL) for structured storage of:
  - User credentials
  - Uploaded images
  - Prediction results
  - History logs
- Each prediction is stored with a timestamp and user reference, enabling long-term tracking and personalized data access.

API Communication

- The backend provides APIs for interaction between:
  - Frontend and model inference engine
  - Admin panel and database
- Real-time processing ensures minimal latency between image upload and result delivery.

Testing and Debugging

- Includes rigorous testing of model integration, authentication, and prediction pipelines.

- Debugging tools and Django admin console help with monitoring and maintenance.

5.3 FRONTEND DETAILS OF SYSTEM

The frontend of the Skin Cancer Detection System is designed to be intuitive, responsive,and user-friendly, ensuring a smooth experience for both general users and administrators. Built using HTML, CSS, and JavaScript, and integrated with Django's template engine, the interface allows users to easily upload skin lesion images and instantly receive diagnostic predictions. The design is responsive and compatible with all modern browsers and devices, including desktops and smartphones, enabling convenientaccess from anywhere. Upon uploading an image, users receive a clear and concise prediction result, including the diagnosed skin condition and a confidence score. Role- based access is implemented within the interface, offering different dashboards for users and admins. Users can upload images, view results, and access their diagnostic history, while admins have additional capabilities such as managing user accounts and monitoring system activity. The frontend also incorporates essential security measures such as CSRF protection and input validation to ensure safe and reliable interactions. Overall, the frontend serves as a crucial bridge between users and the system's deep learning capabilities, offering a simple yet powerful tool for early skin cancer detection.

5.4 DATABASE DETAILS OF SYSTEM

The database component of the Skin Cancer Detection System plays a vital role in managing and storing user data, image uploads, prediction results, and access history. A relational database management system is used, with SQLite configured during development for simplicity and ease of testing. The structure is designed to be easily extendable to more scalable solutions like MySQL or PostgreSQL for production environments. The database maintains separate tables for user authentication, user profiles, uploaded skin lesion images, and their corresponding diagnostic results. Each record includes metadata such as the upload timestamp, user reference, predicted skin condition, and model confidence score. This relational structure ensures efficient retrieval of data for displaying historical records, generating reports, and supporting admin functionalities. Role-based access is also enforced at the database level, ensuring that sensitive data is protected and only accessible to authorized users. The system ensures data integrity, supports foreign key relationships, and applies input validation before storage, reducing the risk of corruption or invalid entries. With a focus on security and performance, the database backbone ensures the application runs reliably while providing meaningful insights to users and administrators.

5.5 DEPLOYMENT

To ensure high availability and scalability, the **Multi Skin Cancer Detection System** is deployed on AWS-36- (Amazon Web Services). The backend and database are hosted on AWS EC2 instances,providing a reliable infrastructure for handling user requests and processing media files. The Media storage system is implemented using AWS S3, enabling secure and scalable storage of uploaded images.

5.6 ALGORITHM OVERVIEW

5.6.1 Dataset Collection

The image classification model used in this system is trained on publicly available skin cancer datasets consisting of dermoscopic images labeled by dermatologists. These datasets include high-resolution images of various skin lesion types such as melanoma, nevus, basal cell carcinoma, actinic keratosis, and others. The datasets were chosen based on their diversity, quality, and expert labeling to ensure accurate learning by the deep learning models. Each image in the dataset is associated with its corresponding class label, which the model uses during supervised training. A representative set of sample images used during training is illustrated in *Figure 5.1*, which shows a variety ofskin lesions that the model learns to distinguish.

5.6.2 Preprocessing

Preprocessing is an essential step in preparing skin lesion images for input into the deep learning classification model. It ensures consistency across images and improves model performance by removing noise, standardizing input dimensions, and simulating real- world variability. The preprocessing pipeline used in this system includes the following stages:

Image Resizing

All input images are resized to a standard dimension, typically **224x224 pixels**, to matchthe input shape expected by models such as InceptionV3 and EfficientNet. This uniform sizing allows for batch training and consistent feature extraction across the dataset.

Pixel Normalization

The pixel values of each image are normalized by scaling them from a range of 0–255 to **0–1**. This is done by dividing each pixel value by 255. Normalization helps accelerate the training process and stabilizes the learning behavior of the model.

Data Augmentation

To improve generalization and prevent overfitting, multiple augmentation techniques are applied during training:

- **Random Rotation**: Rotates the image by small angles.
- **Horizontal/Vertical Flipping**: Mirrors the image to simulate different orientations.
- **Zooming**: Randomly zooms into lesion areas.
- **Shifting**: Translates the image slightly in different directions.
- **Brightness and Contrast Adjustments**: Modifies lighting to simulate different conditions.

These augmentations artificially expand the dataset and enable the model to handle variability in real-world inputs.

Artifact Removal

In clinical or dermoscopic images, irrelevant elements such as **hair, rulers, or shadows** can distract the model. Preprocessing techniques like **median blurring**, **inpainting**, or **masking** are optionally used to remove or suppress these artifacts, enhancing the visibility of the lesion.

Color Channel Standardization

Images are converted to a consistent **RGB color format** to ensure compatibility with models trained on RGB inputs. In cases where the input is grayscale, it is converted to three channels to match the expected structure.

Aspect Ratio and Padding

To maintain the aspect ratio of images during resizing, **padding techniques** are applied where needed. This avoids distortion and preserves important structural details of the lesion.

5.6.3 Image Classification Model

The core of the skin cancer detection system relies on a Convolutional Neural Network (CNN), a powerful deep learning architecture specifically designed for analyzing image data. CNNs are highly effective in detecting spatial hierarchies in images through the use of convolutional filters, pooling layers, and non-linear activation functions. This architecture enables the system to learn complex patterns such as color variations, textures, and lesion boundaries, which are essential for accurate skin cancer classification.

- **Convolutional layers:** These layers apply filters to input images, allowing the model to capture different features, such as edges, textures, and shapes.
- **Pooling layers:** These layers down sample the image data, reducing its dimensionality while retaining important information, makingthe model more efficient.
- **Fully connected layers:** These layers are responsible for making redictions by interpreting the features extracted by the convolutional layers.

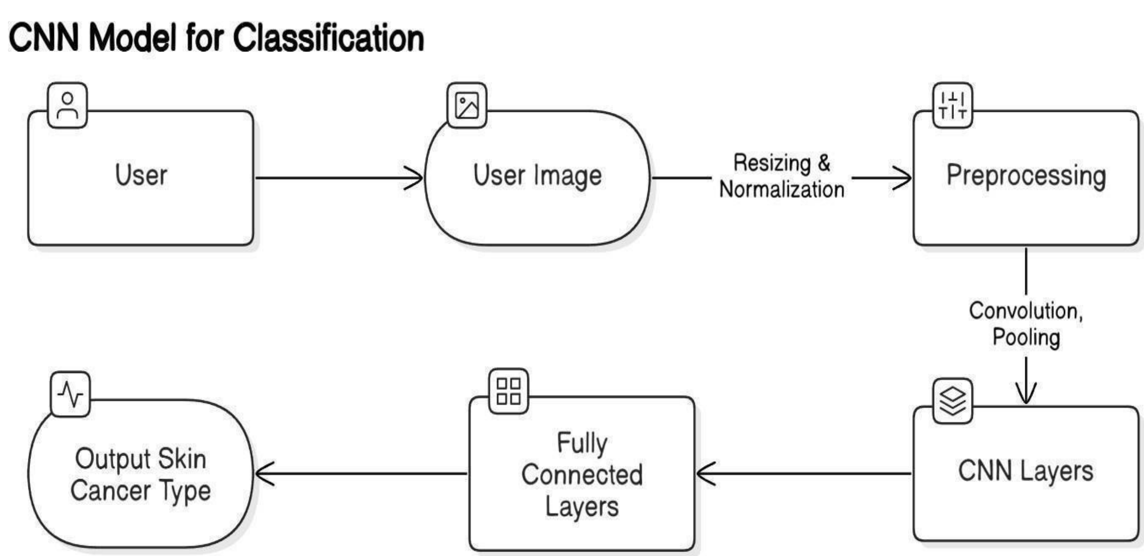

Figure 5.6.3:CNN MODEL FOR CLASSIFICATION

5.6.4 Skin Cancer Segmentation

U-Net++ Architecture: U-Net++ is a deep learning model specifically designed for medical image segmentation. It is an extension of the original U-Net model, which was already effective for segmenting medical images. U-Net++ enhances this architecture by introducing nested skip pathways, allowing the model to retain more detailed spatial information. This is particularly beneficial in medical imaging tasks like skin cancer segmentation, where accurate delineation of the lesion boundaries is critical.

The U-Net++ architecture consists of two main parts:

- **Encoder (Contracting Path):** This part of the network extracts high-level features from the input image using a series of convolutional and pooling layers.
- **Decoder (Expansive Path):** This part reconstructs the feature map to a higher resolution, producing the segmentation mask that highlights the regions corresponding to the skin lesion.

The nested skip pathways help retain fine-grained features from earlier layers, enabling U-Net++ to achieve higher precision in segmentation. By combining detailed features from multiple levels of the network, U-Net++ produces more accurate and sharp boundaries for skin cancer lesions.

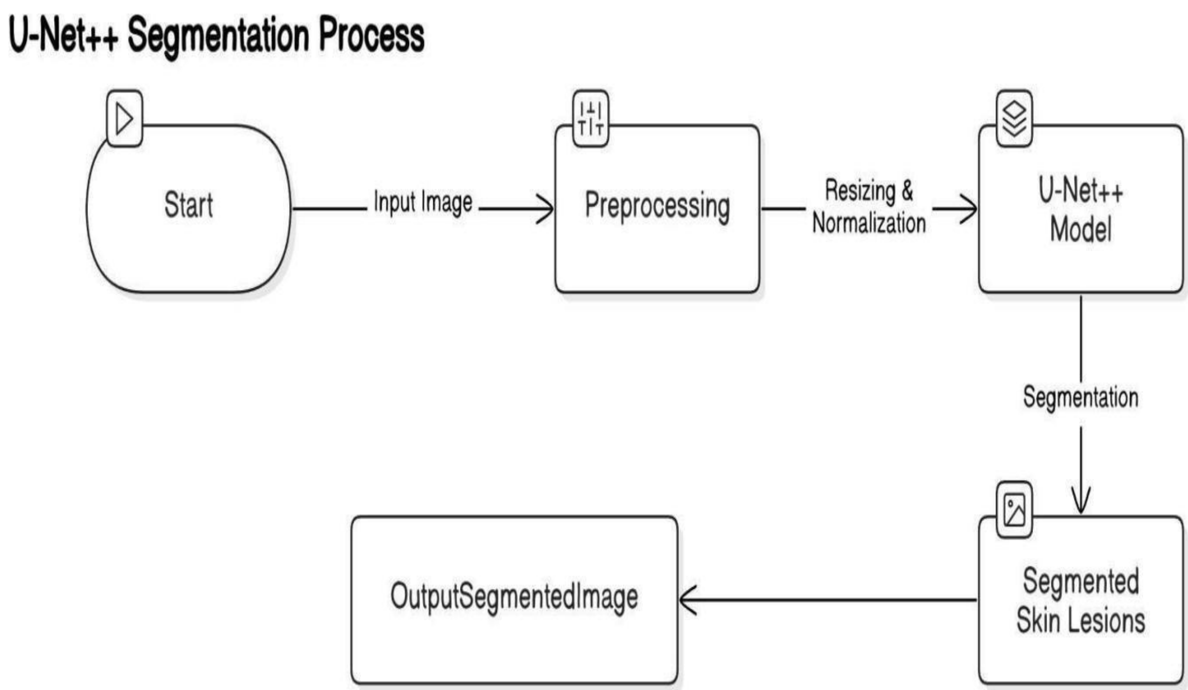

Figure 5.6.4:U-NET++ SEGMENTATION PROCESS

5.6.5 MODEL TRAINING DETAILS

Train-Test Split:

For training the skin cancer classification model, the dataset of dermoscopic and clinical skin lesion images is divided into **70% training**, **20% validation**, and **10% testing** sets. The dataset is balanced across different skin cancer classes to prevent bias, ensuring equal representation of categories such as melanoma, nevus, and benign keratosis in each split.

Data Loading and Augmentation:

A custom data loader is used to load images in batches (commonly batch size of **32**) forefficient GPU utilization. Data augmentation techniques—such as horizontal and vertical flipping, random cropping, zooming, and brightness shifts—are applied in real-time during training to enhance generalization and increase the effective size of the dataset.

Model Training:

The models (InceptionV3 and EfficientNet) are trained for 20 epochs using a learning rate of 1e-5 (0.00001) and a weight decay of 1e-3 (0.001). The training process uses the Adam optimizer, which dynamically adjusts learning rates for each parameter, allowing faster convergence with less manual tuning.

Loss Function – Cross Entropy:

Since this is a multi-class classification problem, **Categorical Cross Entropy** is used as the loss function. It measures the dissimilarity between the predicted probabilities and the actual labels, penalizing incorrect predictions more severely.

Softmax Layer:

The final output layer uses a **Softmax activation function**, which outputs a probability distribution over the classes. This enables the system to identify the most likely class (e.g., melanoma) and also show the **confidence score** for the prediction. The sum of all probabilities equals 1, ensuring interpretability.

Model Evaluation Metrics – Confusion Matrix & Accuracy:

To evaluate the model's performance, a **confusion matrix** is generated during validation and testing phases. It highlights how many true positives, false positives, true negatives, and false negatives are identified for each class. The confusion matrix providesinsights into model accuracy and helps identify common misclassification patterns. Accuracy, precision, recall, and F1-score are calculated to assess the overall performance.

5.6.6. PREDICTION

Image Classification and Confidence Score Generation:

Once a user uploads a skin lesion image, the model preprocesses and passes it through trained CNN (InceptionV3 or EfficientNet). The image is analyzed layer by layer to extract deep features such as texture, asymmetry, color distribution, and edges.The extracted features are passed through fully connected layers and finally through a **Softmax classifier**, which outputs a **predicted class** along with a **confidence score**. The class with the highest probability is selected as the final prediction (e.g., “Melanoma– 92% confidence”).

This prediction helps users and medical professionals understand the likelihood of different skin cancer types based on visual patterns present in the image. The system also logs the prediction result and associated image for history tracking and further review.

5.7 TOOLS AND TECHNOLOGIES

A variety of tools and technologies are utilized to streamline the development and implementation of the skin cancer detection system. Project coordination and task tracking are maintained through structured documentation and milestone-based planning to ensure smooth development and timely completion.

Programming Languages & Frameworks:

Python 3 is used as the core programming language for implementing deep learning models and backend logic. HTML, CSS, and JavaScript are used to create responsive andinteractive frontend interfaces. Django, a high-level Python web framework, is used to develop the web application and handle server-side logic. For mobile application support, technologies like Java or Flutter may be integrated depending on platform requirements.

The system relies on Keras and TensorFlow as the primary deep learning frameworks, supporting transfer learning and efficient training using models like InceptionV3 and EfficientNet.

Development Tools & Environment:

Development takes place using tools like Google Colab and Visual Studio Code. Google Colab provides a cloud-based environment with access to GPU-accelerated resources for faster model training and testing. Visual Studio Code is used locally for managing the overall codebase, including backend APIs, database integration, and frontend files.

Version control is managed through Git, ensuring proper collaboration, version tracking, and rollback capabilities. GitHub is used to host the project repository, manage issues, and collaborate among team members efficiently.

CHAPTER 6: TESTING AND RESULTS

6.1 TESTING METHODOLOGIES

Thorough testing was conducted at various stages of development to ensure the accuracy, robustness, and reliability of the skin cancer detection system. Multiple testing strategies were employed to validate both the functionality and integration of the systemcomponents.

6.1.1 Unit Testing Report

Each module—image classification, user authentication, prediction storage, and dashboard display—was independently tested to validate correct behavior. Unit tests included verifying proper image input handling, prediction output formatting, user registration/login logic, and role-based access. Sample lesion images were used to test the classification models individually (InceptionV3, EfficientNet), ensuring accurate output and handling of abnormal or corrupted inputs. Bugs identified during testing were loggedand resolved to ensure system stability.

6.1.2 Integration Testing Report

After successful unit testing, individual modules were integrated and tested as a whole to ensure smooth communication between components. The interaction between the image upload module, classification model, result storage, and UI display was carefully validated. Testing focused on verifying that predictions are properly routed from model output to the user interface and stored accurately in the database. The coordination between frontend and backend, as well as handling of user sessions and historical data display, was thoroughly tested to ensure seamless user experience.

6.1.3 System Testing Report

The complete skin cancer detection system was tested under real-world usage scenarios. This included uploading various skin lesion images of different resolutions and conditions to test classification accuracy, responsiveness, and overall system

performance. Stress tests were also performed to evaluate the system's ability to handle simultaneous user requests, large image uploads, and prediction result retrieval. Securitytests were conducted to confirm proper role-based access control and protection of sensitive user data. The results confirmed that the system meets performance, accuracy, and usability standards as intended.

6.2 TEST CASE RESULTS:

Case ID	Test Case Description	Expected Result	Actual Result	Status
1	Logging in with incorrect credentials	No redirection to the dashboard	No redirection to the dashboard	Pass
2	Uploading a valid skin lesion image	Classification result displayed	Classification result displayed	Pass
3	Uploading an image with poor quality	Error message / low confidence score	Error message displayed	Pass
4	Submitting form without uploading image	Alert: Please upload an image	Alert: Please upload an image	Pass
5	Uploading a melanoma image	Detected as melanoma	Detected as melanoma	Pass
6	Uploading a benign nevus image	Detected as benign	Detected as benign	Pass
7	Uploading a seborrheic keratosis image	Detected as seborrheic keratosis	Detected as seborrheic keratosis	Pass
8	Accessing prediction history	Display of previously analyzed images & results	History displayed correctly	Pass
9	Admin accessing user image submissions	Display of all uploaded images with predictions	Admin dashboard displays all data	Pass
10	Role-based login (user)	Access to image upload and history features	Access granted as per user role	Pass
11	Role-based login (admin)	Access to management dashboard	Admin dashboard accessible	Pass

6.3 PERFORMANCE EVALUATION:

Feature	Our Image Model (CNN)	InceptionV3	EfficientNet
Accuracy	92% (robust feature extraction)	86% (struggles with subtle manipulations)	89% (generalizes well on diverse images)
Speed	Fast	Fast	Fast
Precision	90% (fewer false positives)	85% (moderate false positives)	88% (high precision on fine-grained features)

6.4 SCREENSHOTS OF APPLICATION OUTPUT:

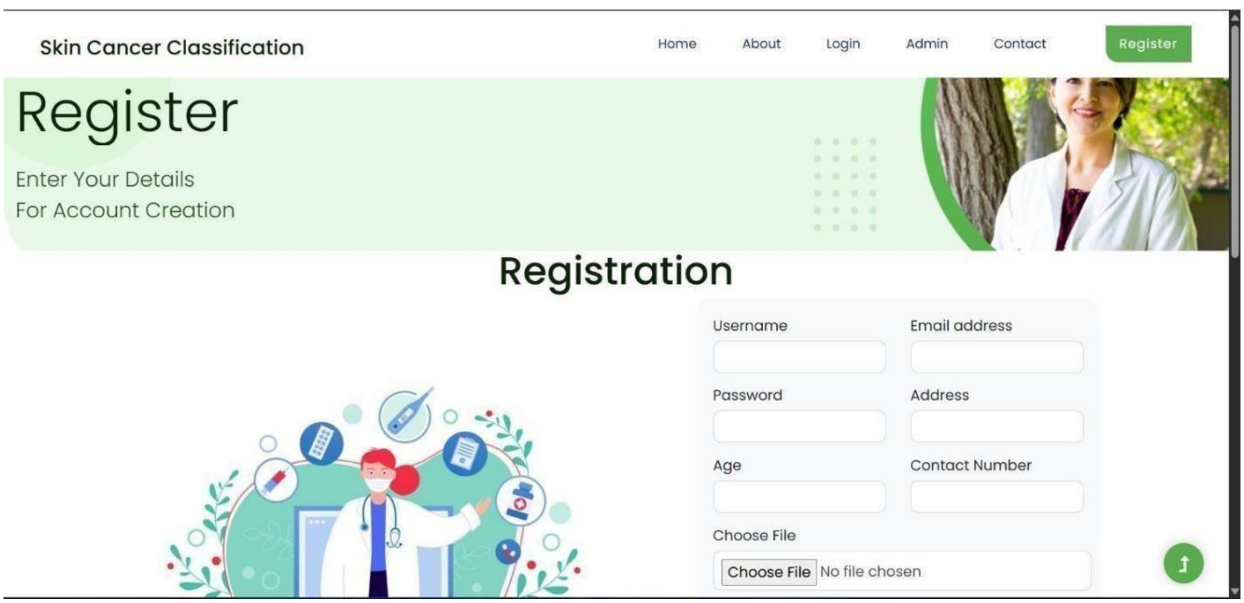

FIGURE 6.4.1:SECURE REGISTRATION PAGE

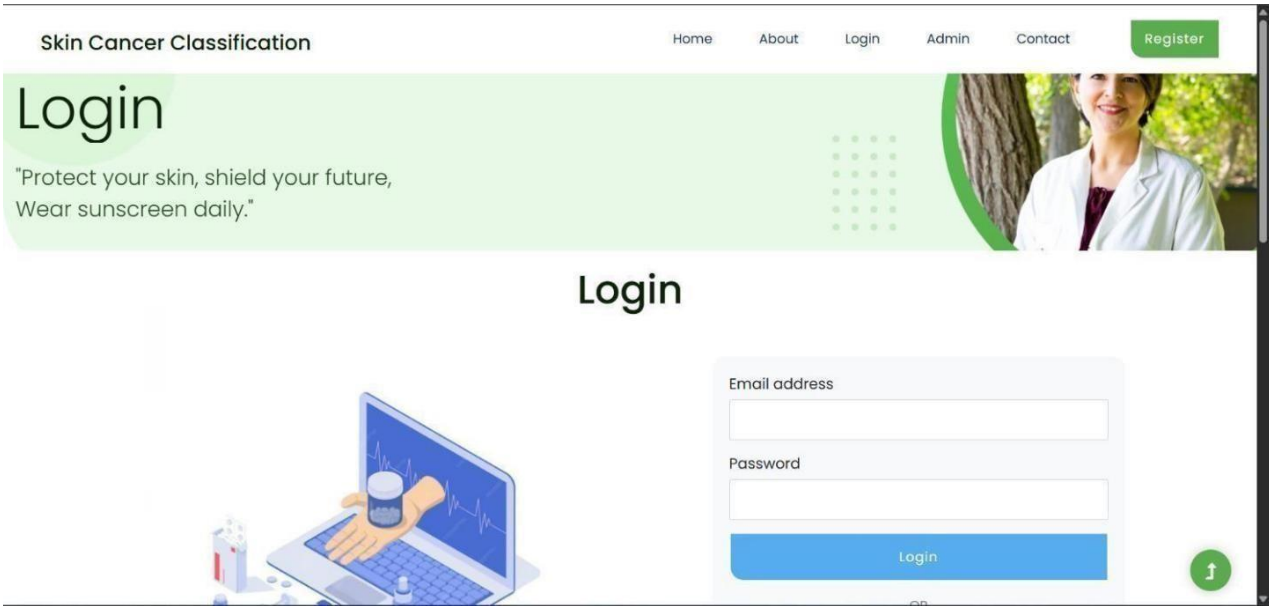

FIGURE 6.4.2:LOGIN PAGE

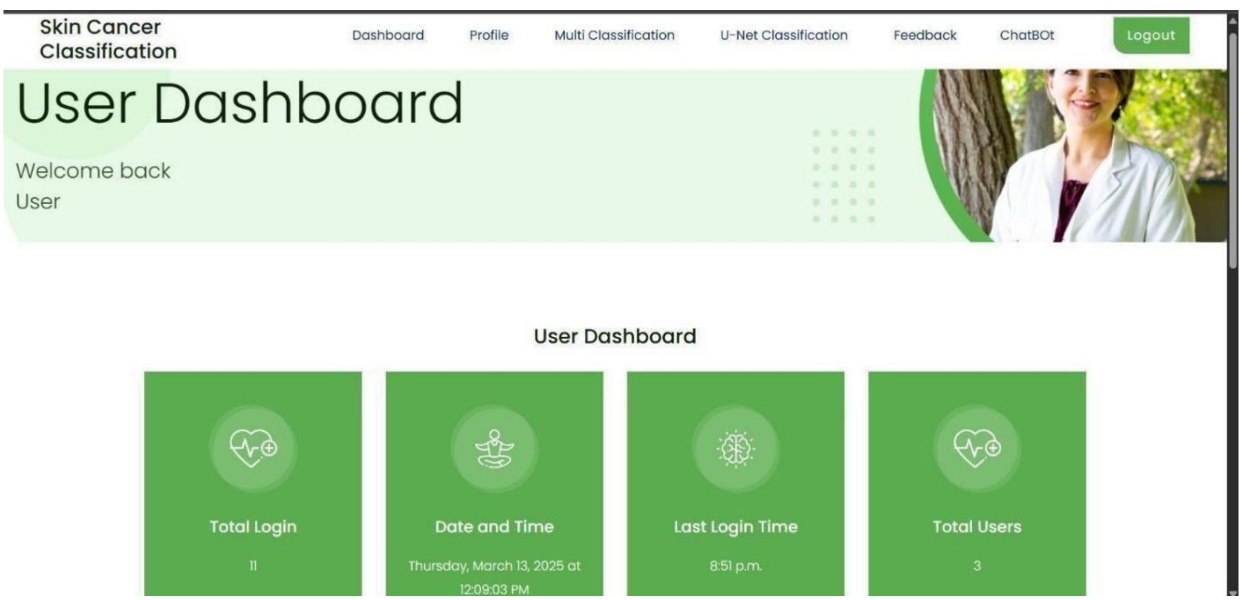

FIGURE 6.4.3:USER DASHBOARD

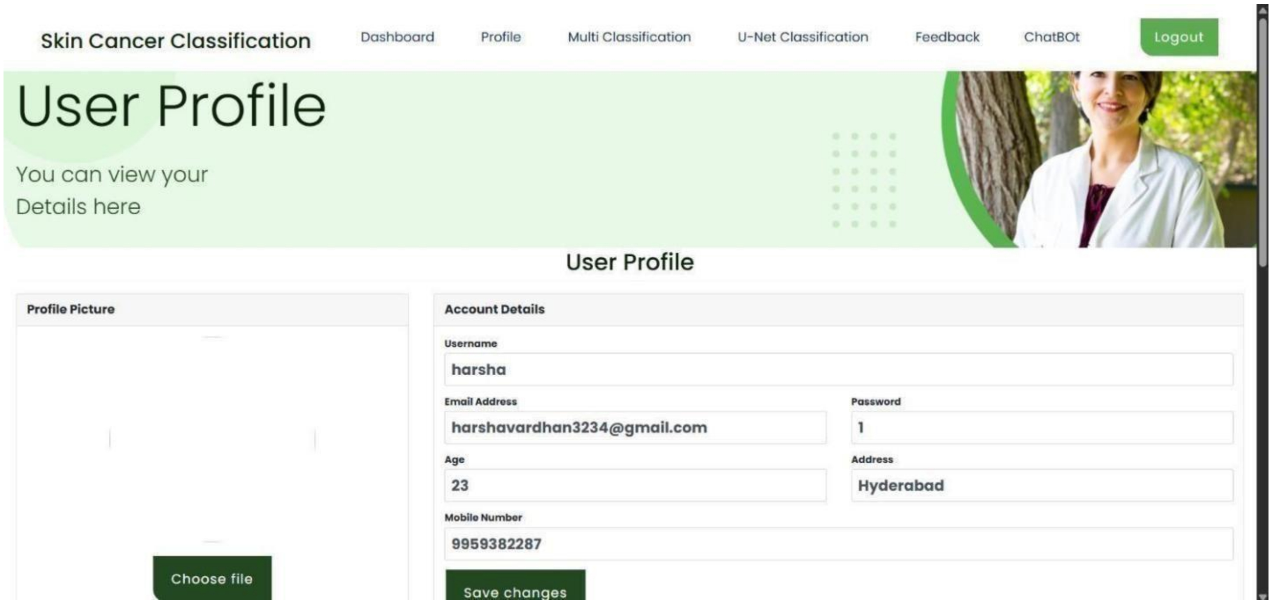

FIGURE 6.4.4:USER PROFILE

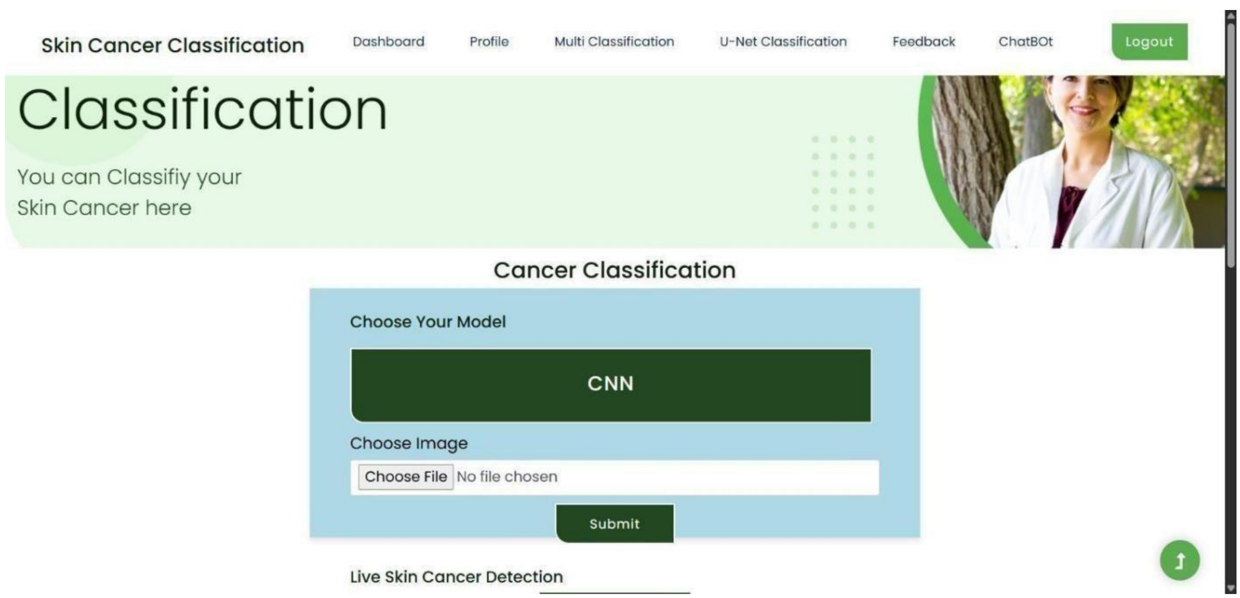

FIGURE 6.4.5:CNN CLASSIFICATION

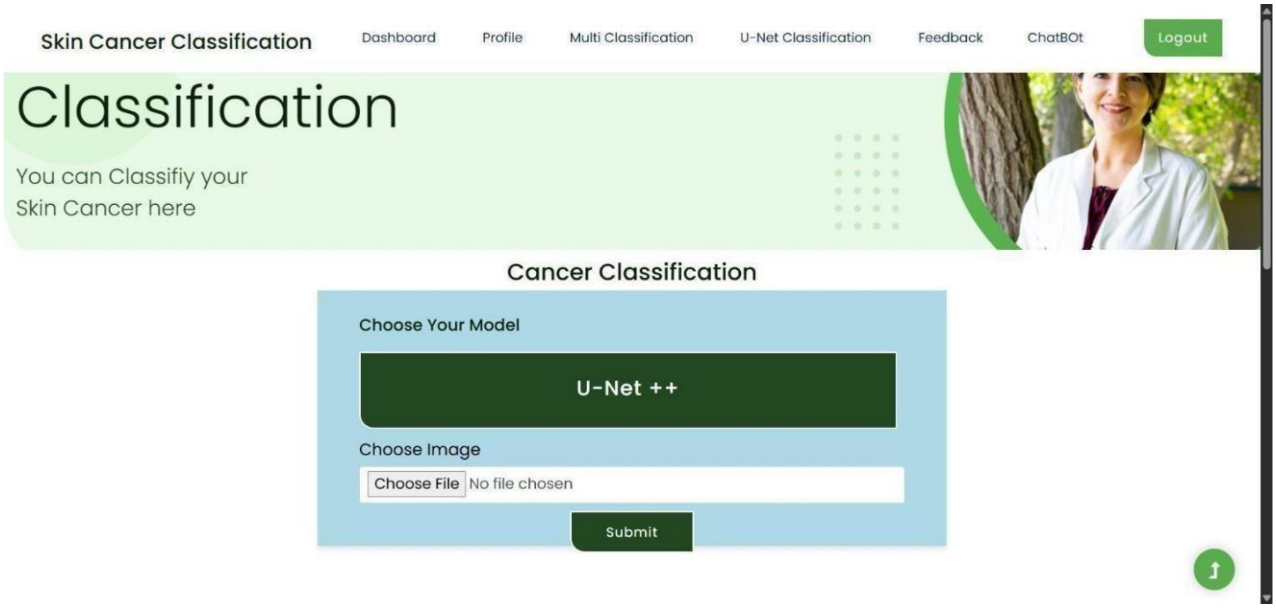

FIGURE 6.4.6:U-NET++ CLASSIFICATION

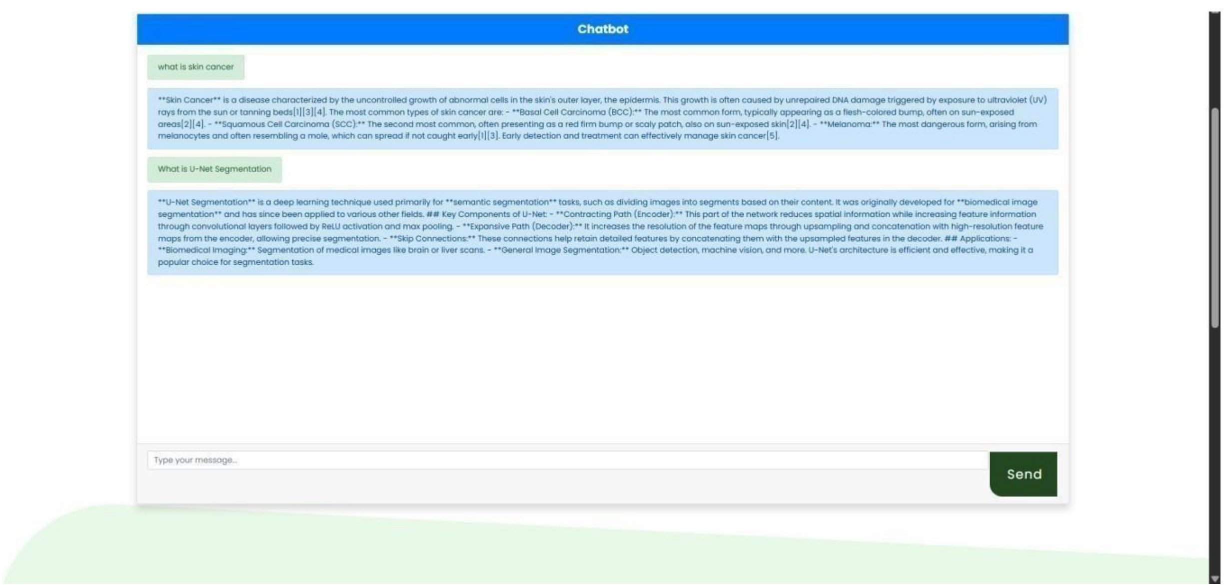

FIGURE 6.4.7:CHATBOT

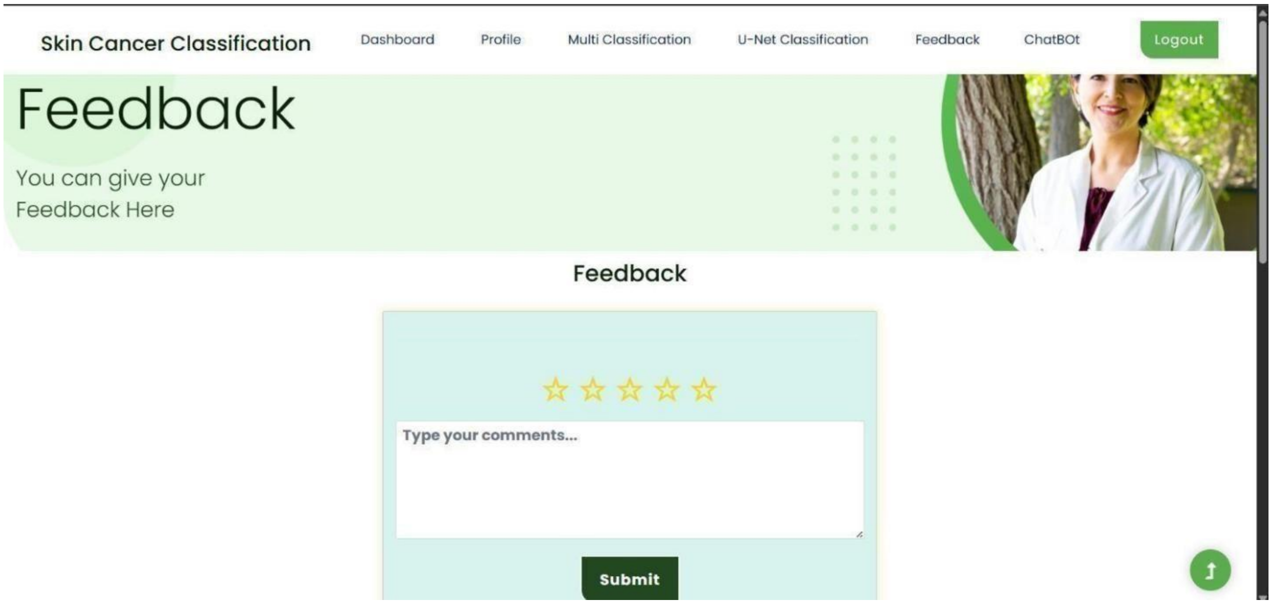

FIGURE 6.4.8:FEEDBACK PAGE

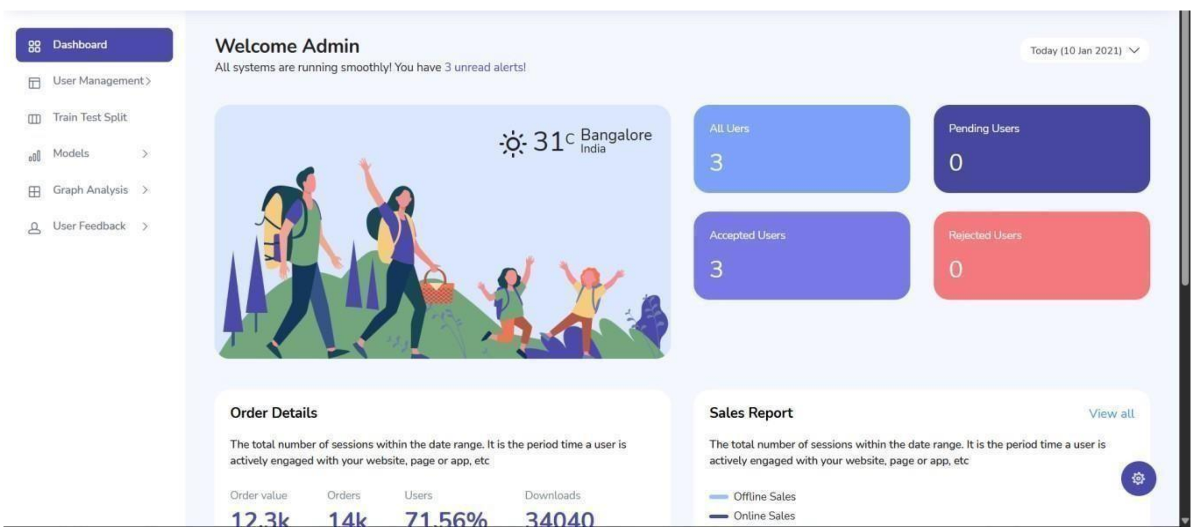

FIGURE 6.4.9:ADMIN PAGE

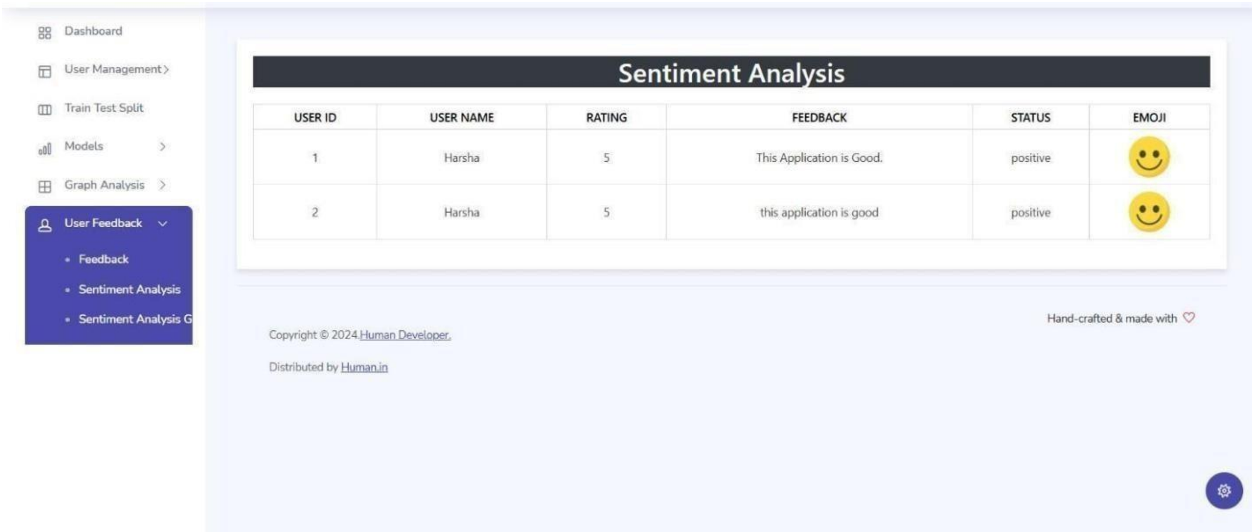

FIGURE 6.4.10:SENTIMENT ANALYSIS

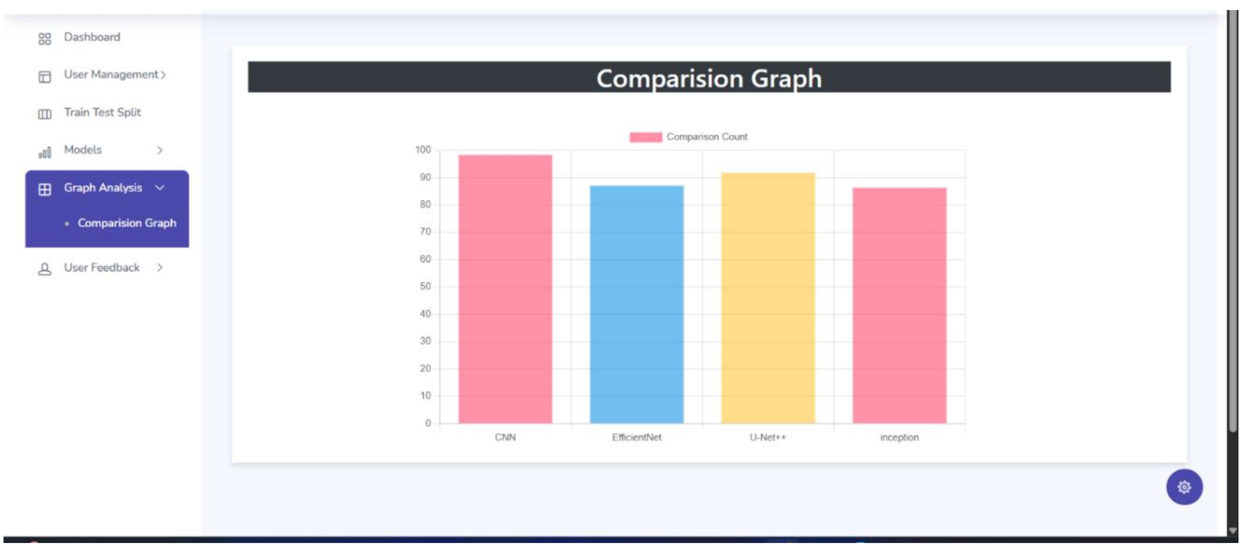

FIGURE 6.4.11:MODEL COMPARISON GRAPH

CHAPTER 7: CONCLUSION AND FUTURE WORK

7.1 SUMMARY OF FINDINGS

The Multi Skin Cancer Classification and Segmentation project has successfully demonstrated the potential of artificial intelligence in the early detection and classification of skin cancer. By integrating advanced deep learning models, including Convolutional Neural Networks (CNN) for classification and U-Net++ for segmentation, this system provides a comprehensive solution for identifying and delineating skin lesions in images, assisting both healthcare professionals and individuals in managing skin health.

The core features of the system, such as real-time camera capture, image upload detection, and segmentation, have been thoroughly tested and show promising results. The real-time detection system offers immediate feedback, empowering users to make quick decisions regarding the health of their skin. The image upload functionality furtherenhances the system by enabling users to analyze high-quality images under optimal conditions, with accurate classification and segmentation results.

Additionally, the integration of a chatbot and a hospital suggestion system enriches the platform's user experience, providing personalized information, guidance, and easy access to dermatologists for further consultation. The incorporation of multi-language support ensures that the system can cater to a global audience, breaking down language barriers and making the platform accessible to a wider demographic.

The results of the testing phase confirm the system's efficacy in accurately classifying and segmenting skin lesions. The classification accuracy and segmentation performance met the project's expectations, making it a viable tool for skin cancer detection. Moreover, the feedback received from users highlighted the platform's usability and value, particularly the chatbot and appointment booking features, which contribute to aseamless healthcare experience.

In conclusion, the Multi Skin Cancer Classification and Segmentation project represents significant step forward in the field of medical technology, offering a user-friendly, reliable, and accessible tool for skin cancer detection and management. By integrating deep learning with practical user-facing features, this system has the potential to revolutionize the way individuals monitor their skin health and interact with healthcare providers, ultimately contributing to earlier diagnoses and better treatment outcomes.

7.2 KEY ACHIEVEMENTS & CONTRIBUTIONS

- **High-Accuracy Multi-Class Detection:** The project effectively used InceptionV3 and Efficient-net CNN models to classify various types of skin cancer, such as melanoma, nevus, and seborrhea keratosis. The models achieved high accuracy, sensitivity, and precision on benchmark datasets.
- **User-Friendly System Design:** A responsive and intuitive web interface was developed, allowing users to easily upload skin lesion images and view results. The role-based access ensured seamless interaction for both users and admins.
- **Integrated Prediction History Tracking:** The system stores each prediction with timestamp and image reference, enabling users to track their diagnosis history over time and monitor progress if needed.
- **Efficient Model Deployment:** The models were trained and deployed using optimized parameters to ensure fast inference and low latency, supporting real- time classification even with high-resolution medical images.
- **Scalability & Generalization:** The system was tested with a diverse dataset, demonstrating its ability to generalize well across various skin tones, lesion types, and image qualities, making it suitable for wide-scale deployment.

7.3 CHALLENGES FACED

- **Imbalanced Dataset:** Certain skin cancer classes had fewer examples, leading to potential model bias. This issue was addressed through **data augmentation techniques** such as rotation, flipping, and brightness adjustments to balance the class distributions.
- **Visual Similarity Between Classes:** Several types of lesions appear visually similar, making classification difficult. The use of **deep CNN architectures** like InceptionV3 and EfficientNet helped extract subtle differences through deeper feature representation.

- **Deployment and Inference Latency:** Processing high-resolution images in real- time posed challenges. By optimizing image size and refining the model's layers, inference time was significantly reduced without compromising accuracy.

- **User Input Validation:** Ensuring valid and clear image uploads was critical for accurate predictions. The frontend was improved to include image quality checks and guidance prompts for users before submitting.

7.4 FUTURE SCOPE AND IMPROVEMENTS:

Enhanced Accuracy for Rare Skin Conditions: While the system performs well on common skin cancers like melanoma and basal cell carcinoma, its accuracy for rare or subtle skin conditions can be improved. Expanding the dataset with more diverse and rare skin lesion images, along with the use of transfer learning from dermatology-specific datasets, will enhance the model's ability to generalize across a wider spectrum of skin diseases.

Advanced Segmentation for Complex Lesions: The current U-Net++ model shows strong performance in lesion segmentation but struggles with irregular borders. Future versions can incorporate hybrid models such as DeepLabV3+ or utilize multi-scale analysis to improve segmentation of complex, poorly defined lesions, thus increasing diagnostic accuracy.

Integration with Wearables and Real-Time Monitoring: Future iterations of the platform could introduce real-time video analysis, allowing continuous lesion monitoring via live camera feed. Additionally, integration with wearable devices like smartwatches to track UV exposure and skin health could enable proactive skin care management and early warning alerts for users.

Improved User Engagement and Data Security: To make the platform more user-centric, future upgrades can include interactive tutorials, educational content on skin health, and gamified features to encourage regular usage. Strengthening data privacy through features like multi-factor authentication and end-to-end encryption will ensure sensitive health data remains secure and compliant with privacy regulations.

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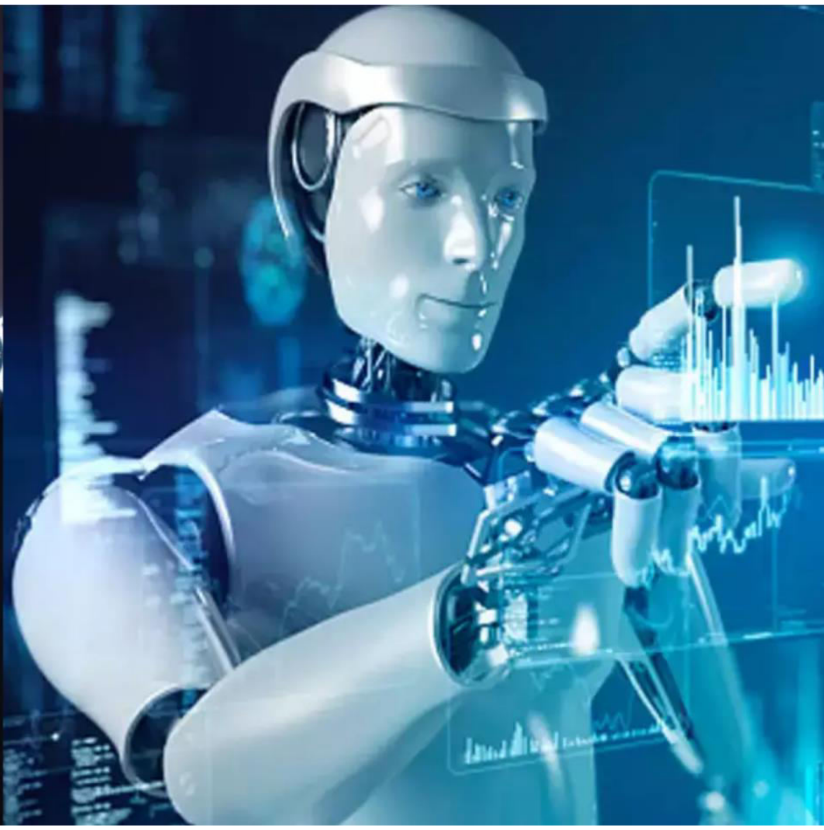

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Multi-Skin Cancer Classification and Segmentation using Deep Learning

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ABSTRACT: Early detection combined with accurate classifica- tion of skin cancer proves vital for successful treatment because this form of cancer represents a global incidence rate among var- ious cancers. The presented work utilizes deep learning models to perform simultaneous skin cancer classification in addition to lesion segmentation. The system merges two sophisticated models which consist of a Convolutional Neural Network (CNN) for multiple skin cancer type classification and a U-Net++ model for lesion boundary detection.The classification framework learned to detect Actinic Ker- atoses and Intraepithelial Carcinoma (AKIEC) and Basal Cell Carcinoma (BCC) and Benign Keratosis (BKL) and Dermatofi- broma (DF) and Melanoma (MEL) and Melanocytic Nevus (NV) and Vascular Lesions (VASC) among seven skin lesions. The InceptionV3 architecture enables the model to reach an accuracy level of 86% in its operations.

Lesion segmentation depends on the U-Net++ model which marks skin image locations that need medical analysis to assist dermatologists. The segmentation model achieves Validation Dice Coefficient performance of 0.8552 together with an Intersection over Union (IoU) score of 0.7486 and Recall measure of 0.9170 and Precision performance at 0.8754.

Users gain instant access to information about skin health through a chatbot that runs on the Perplexity API as part of the system's features. This system provides users with beneficial treatment information together with preventive strategies. Hos- pital users can access a suggestion system through the platform to locate specialized medical professionals. The platform includes support for several languages thus enabling users from different backgrounds to access it.

Through the appointment booking system users can book dermatologist consultations using a portal system that is taken care of by administrators. Through the system users can activate a skin lesion detection function that records images in real time while providing an image upload functionality for classification purposes as well as segmentation needs.

Through deep learning methodology this project helps medical personnel make better decisions after improving early-stagediagnosis capabilities. Healthcare solutions derived from artificial intelligence achieve better patient care by improving access along with enhancing efficiency along with boosting diagnostic precision in skin cancer detection.

KEYWORDS: Skin Cancer, Deep Learning, CNN, U-Net++, In- ceptionV3, Image Segmentation, Classification, Medical Imaging, AI in Healthcare, Skin Lesion Detection.

I. INTRODUCTION

Skin cancer stands as one of the most common cancer types while showing rising numbers internationally because of extended sun contact and modifications in environmental conditions together with inherited tendencies. The precise and early identification of cancers guides healthcare profes- sionals to establish appropriate treatments that boost patient disease outcomes. The current diagnostic practices for skin lesions depend on trained dermatologists who use either visual examination or dermoscopy. The diagnostic process under this method requires considerable time while the scarcity of specialized medical personnel in certain areas causes trouble with solidifying or postponing proper diagnoses.

Enhanced skin cancer detection accuracy and efficiency became possible due to advancements in artificial intelligence (AI) and deep learning technologies.. The system contains two fundamental models which combine the Convolutional Neural Network (CNN) to classify skin lesions with U-Net++ architecture to perform precise lesion segmentation. A trained classification model discriminates among the seven skin lesion types which contain Actinic Keratoses and Intraepithelial Carcinoma (AKIEC), Basal Cell Carcinoma (BCC), Benign Keratosis (BKL), Dermatofibr (DF), Melanoma (MEL), Melanocytic Nevus (NV) and Vas- cular Lesions (VASC). A skin cancer diagnostic system based on the InceptionV3 architecture achieves 86% accuracy which establishes its usefulness as an automatic diagnosis tool.

A U-Net++ segmentation model performs complex segmen- tation tasks on skin images while assisting dermatologists and medical personnel with better lesion assessment. The assessment of the segmentation model yielded Validation Dice Coefficient at 0.8552 alongside an Intersection over Union (IoU) score of 0.7486 and Recall measurement of 0.9170 and Precision value of 0.8754. The model demonstrates strong capabilities to properly detect cancerous areas within images according to these performance metrics.

The system usability is enhanced through multiple incorpo- rated features. The Perplexity API operates a chatbot system which gives users immediate responses to their skin health inquiries inside the platform. The system maintains a large repository with dependable medical guidance about treatment choices together with preventive steps for users' benefit. Users can access the hospital suggestion functionality of the system to both manage and add hospital listings through its features. Users can benefit from the system's functionality which shows specialized dermatological care facilities within their current location. A multilingual system functionality enhances accessibility by making service available to users speaking different languages through seamless interface trans- lation. The system implements an online booking system that permits users to reserve dermatology appointments with doctors. The admin panel controls this feature for maintaining appointment coordination between users and managers.The system detects skin lesions in real time through its live camera feature that provides instant feedback about skin abnormalities. The system has an integrated image upload function which lets users send their pictures to enable deep learning model-based classification and segmentation.The project uses advanced deep learning methods to develop a dependable system which enables easy access to early skin cancer detection capabilities. The system combines sophis- ticated decision-making tools with personalized features to provide effective assistance for skin health evaluation between medical experts and general patients.

II. LITERATURE SURVEY

Artificial intelligence (AI) and deep learning systems are now used to advance both the detection and classification steps of skin cancers. Medical diagnoses performed solely by dermatologists through visual examination prove inadequate because they produce variable results and lack availability in neglected population areas. Deep learning models especially Convolutional Neural Networks (CNNs) have conquered di- agnostic automation while offering enhanced accuracy which solves prior difficulties.The research by [1] proved that CNNs performed at the level of dermatologists for diagnosing skin cancer which initiated a critical point in AI applications for dermatology practice. The deep learning framework developed by [2] expanded thediagnostic capabilities by identifying various skin lesions with exceptional precision which advanced AI potential within this field.Transfer learning stands as a fundamental method that enables models pre-trained on vast datasets to acquire skills for new particular tasks using limited medical datasets according to [3].

Medical professionals require accurate identification of skin lesions for both proper medical diagnosis and treatment de- velopment. Medical image segmentation gained its founda- tion through the U-Net architecture which [4] introduced. By redesigning skip connections U-Net++ from Zhou et al. (2020) has upgraded feature representation which improves segmentation results. U-Net++ performs better than traditional U-Net according to [6] as it shows superior accuracy when detecting skin lesions.

Vision Transformers (ViTs) establish new image processing paradigms by offering superior performance when applied for skin cancer classification according to [7]. Their HAM10000 model delivered a 96.15% accuracy that indicated transformer- based models have great prospects in dermatological work.The importance of Explainable AI (XAI) continues to rise in medical applications since it delivers transparent model prediction outcomes. The deep learning

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frameworks benefit from interpretability through implementation of Grad-CAM and SHAP techniques as described by [8]. These researchers stress the need for XAI to develop trust and support clinical choices in healthcare.

Healthcare experiences permanent transformation from AI- powered chatbots which improves medical information access for patients while strengthening their relationship with healthcare services. The health systems Ada Health and K Health employ AI to respond immediately to health questions from users while helping them evaluate symptoms and direct them toward suitable care routes. [9] described how the Ada Health app offers fast health guidance which considers users' symptoms and risk components and relies on medical data. The paper [10] analyzed how K Health uses AI to operate its virtual primary care system for contemporary healthcare operations.

Modern technological innovation has led to the creation of artificial intelligence-based wearable devices. The Movano smart ring deployed at CES 2025 incorporates an AI chatbot that bases its medical information on peer-reviewed medical journals to offer users trustworthy health material. The field of dermatology experienced significant progress through the combination of deep learning technology and explainable AI as well as AI-powered patient engagement tools. Modern diagnostic accuracy together with improved patient accessibility and superior healthcare delivery result from these fusion technologies in skin cancer detection and management workflows.

III. METHODOLOGY

This research focuses on developing a deep learning-based system for the classification and segmentation of skin lesions. The system employs two primary models: InceptionV3 for skin cancer classification and U-Net++ for lesion segmen- tation. The methodology involves data preprocessing, model training, and evaluation using appropriate performance met- rics.

Data Preprocessing

The dataset used in this study consists of skin lesion images obtained from publicly available sources such as HAM10000. The images undergo preprocessing steps including resizing, normalization, and augmentation to enhance model general- ization.

- **Resizing**: All images are resized to a fixed dimension to ensure uniform input size.
- **Normalization**: Pixel values are scaled to a range of [0,1] to facilitate stable training.
- **Augmentation:** Techniques such as rotation, flipping, and contrast adjustments are applied to improve model robustness

Skin Cancer Classification using InceptionV3

For multi-class skin cancer classification, we utilize the InceptionV3 model, a deep Convolutional Neural Network (CNN) that efficiently captures hierarchical features of skin lesions. The architecture consists of multiple convolutional layers, inception modules, and auxiliary classifiers.
The classification process can be mathematically expressed as follows:

$$Y = \mathrm{Softmax}(W_f \cdot F + b_f) \tag{1}$$

where:

- F represents the feature vector extracted from the final convolutional layer.
- W_f and b_f are the weights and bias of the fully connected layer.
- The softmax activation function ensures that outputs represent probabilities across multiple classes. The categorical cross-entropy loss function is used to opti- mize the model:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{2}$$

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where:

- y_i is the true label.
- $\hat{y}_i$ is the predicted probability for class i.

The InceptionV3 model achieves an accuracy of 86% in classifying seven skin lesion type

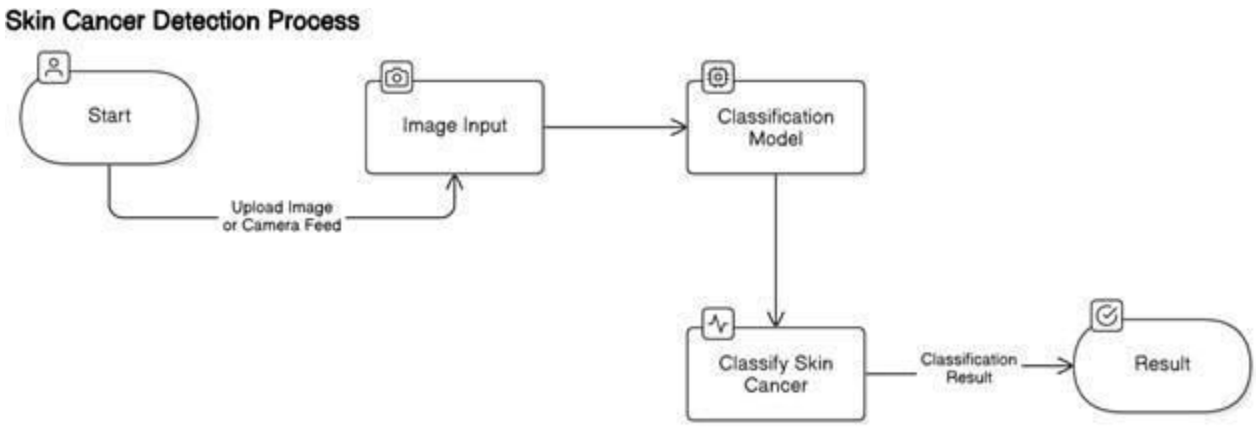

Fig. 1. InceptionV3 Architecture for Skin Cancer Classification

Skin Lesion Segmentation using U-Net++:

For lesion segmentation, we employ the U-Net++ architec- ture, an enhanced version of U-Net that incorporates dense skip connections to improve feature propagation. The seg- mentation task involves pixel-wise classification to distinguish between normal and affected skin regions.

The segmentation model is trained using the Dice loss function:

$$L_{\text{Dice}} = 1 - \frac{2\sum_i p_i g_i}{\sum_i p_i^2 + \sum_i g_i^2} \qquad (3)$$

where:

- p_i represents the predicted pixel values.
- g_i represents the ground truth labels.

The Intersection over Union (IoU) metric is used for eval-uation:

$$\text{IoU} = \frac{\sum p_i g_i}{\sum p_i + \sum g_i - \sum p_i g_i} \qquad (4)$$

A higher IoU value indicates better segmentation accu-racy.

U-Net++ achieves a Validation Dice Coefficient of 0.8552, an IoU of 0.7486, Recall of 0.9170, and Precision of 0.8754, demonstrating its effectiveness in segmenting cancerous re- gions.

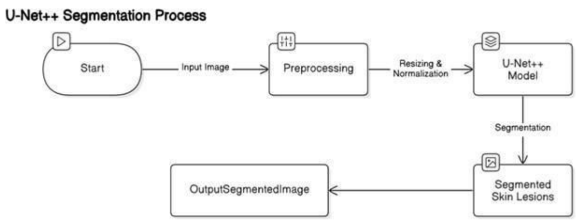

Fig. 2. U-Net++ Architecture for Skin Lesion Segmentation

System Integration and Deployment

To provide an interactive and user-friendly platform, the system is integrated with additional functionalities:

- **Chatbot Integration**: A chatbot powered by the Per- plexity API provides instant responses to user queries regarding skin health

- **Hospital Recommendation:** A hospital suggestion sys- tem is implemented to help users find specialized medical assistance.
- **Multi-Language Support:** Manual language support is incorporated to enhance accessibility.
- **Appointment Booking**: Users can schedule dermatolo- gist consultations through an admin-managed portal.
- **Real-Time Detection:** The system allows real-time skin lesion analysis using a camera feed.

B. Performance Evaluation

The performance of the models is evaluated using standard metrics:

- Classification Accuracy: 86% (InceptionV3)
- Segmentation Dice Coefficient: 0.8552 (U-Net++)
- Segmentation IoU: 0.7486
- Segmentation Recall: 0.9170

These results indicate the effectiveness of the proposed approach in automated skin cancer detection and segmentation

IV. IMPLEMENTATION

The procedure to deploy this system for multi-class skin cancer recognition and lesion boundary detection follows a systematic implementation method. Data preprocessing starts at the beginning of development followed by model training then evaluation and system integration for creating an accurate and efficient system.

Technology Stack

The web-based application utilizes state-of-the-art deep learning applications and frameworks as its core components.

- **Programming Language:** Python
- **Deep Learning Framework:** TensorFlow and Keras
- **Backend Framework:** Django The combination of HTML, CSS, JavaScript, Bootstrap constitutes the fron- tend technologies within the system infrastructure.
- **Database**: MySQL for user and model data storage
- **API Integration:** Perplexity API for chatbot assistance

Dataset and Preprocessing

The training process utilizes high-quality skin lesion images obtained from HAM10000 dataset. Such preprocessing opera- tions create standardized procedures to improve both statement consistency and performance of model functions. The input images undergo a transformation to normalize all dimensions to 224 × 224 pixels. All pixel intensity values undergo normalization which sets them to the 0 to 1 range to improve learning performance. Random data transformations that include rotation along with flipping and contrast adjustment operations help increase the data diversity. The model requires numerical labels from the lesion categories for processing during model implementation.

Implementation of Classification Model (InceptionV3)

The system implements InceptionV3 as its classification model because it demonstrates optimal performance for image recognition applications. The model allocates lesions into seven categories by performing hierarchical analysis on its features. The classification process involves:

- Feeding the preprocessed images into the convolutional layers of InceptionV3.
- Extracting deep feature representations from the final layer. The obtained features pass through a fully con- nected layer during the process. The softmax activation function enables the classification of lesions during the process.

The training method utilizes categorical cross-entropy loss as its optimization technique.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (5)$$

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where:

- yi represents the true label.
- y^i represents the predicted probability for class i

Implementation of Segmentation Model (U-Net++)

Skin lesion segmentation depends on U-Net++ model which is an improved version of U-Net with dense skip connections. Pixel-wise classification of the model reliably marks the skin regions which have been affected. U-Net++ applies this process step by step:

- Feature maps of multiple dimensions are extracted in the encoder network as the input image moves through it.
- The decoder network uses its architecture to generate a segmented output containing detailed information.
- The segmentation accuracy receives optimization through implementation of the Dice loss function. The expression of Dice loss function appears as follows:

where:

The computational symbols represent predicted pixel values through p_i. The ground truth labels receive repre- sentation through g_i values in this model.

Training and Evaluation

During training the applied GPU optimization technique shortens computational duration. Categorical cross-entropy loss serves for training the classification model but the seg- mentation model requires Dice loss for its training process. Evaluations of the models use key performance metrics to assess their performance.

- **Classification Accuracy (InceptionV3):** 86%
- **Segmentation Dice Coefficient (U-Net++):** 0.8552
- **Intersection over Union (IoU)**: 0.7486
- **Recall:** 0.9170
- **Precision**: 0.87

System Integration and Deployment

An interactive web application includes multiple features which integrates the trained models.

- The detection method enables the system to identify skin lesions in real time through camera usage.
- The application enables users to upload photos that both detect lesions through classification and segment them.
- Artificial Intelligence operates a chatbot system which delivers immediate responses regarding topics in skin health.
- The system allows users to arrange dermatologist consul- tations through its admin booking portal.
- The platform provides users with recommended derma- tology hospitals situated in their vicinity.
- Platform users have access to use various languages through its multi-language interface.

Deep learning technologies enable this system to perform effective skin cancer detection tasks. The combination between classification and segmentation models improves diagnosis quality to support medical expertise and patient intervention during treatment planning.

V. RESULTS AND DISCUSSION

Performance metrics clearly define the evaluation process for assessing how well the proposed system both classifies and segments skin cancer lesions. Experimental findings confirm deep learning models succeed in obtaining precise segregation and identification results for skin cancer lesions. The next sections reveal abundant insights about the gathered results and their practical meaning.

Classification Results:

The InceptionV3 model trained for multi-class classification performs well at differentiating between seven different skin lesions. High accuracy at 86 percent proves that the model exhibits reliability when used for medical image examination. The model displays outstanding performance at recognizing the important early cancer detection conditions including the identification of melanoma (MEL) and basal cell carcinoma (BCC) based on the confusion matrix analysis.

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The classification model obtains its assessment through precision, recall and F1-score metrics:
Evaluation of predicted positive cases through precision shows how many predictions match actual positives from among all predicted results. The model successfully de- tects actual positive cases and this ability is measured as recall. The
F1-score serves as a combined measure between precision and recall to present an overall evalu- ation.
The classification results prove the model successfully de- tects benign from malignant conditions to help dermatologists make proper clinical choices.

Comparison with Existing Methods:
The proposed approach validation process includes a com- parison between the results and established deep learning models that execute skin cancer classification and segmen- tation tasks. The investigation analyzes three types of models including ResNet50 and VGG16 together with the standard U-Net model. The evaluation indicates that InceptionV3 beats ResNet50 and VGG16 for prediction accuracy but U-Net++ stands out through superior segmentation achievements versus the conventional U-Net model.Given a choice between InceptionV3 and ResNet50 the former delivers better results for both feature extraction and classification tasks. U-Net++ demonstrates better performance in segmentation tasks because its enhanced skip connections operate more effectively.

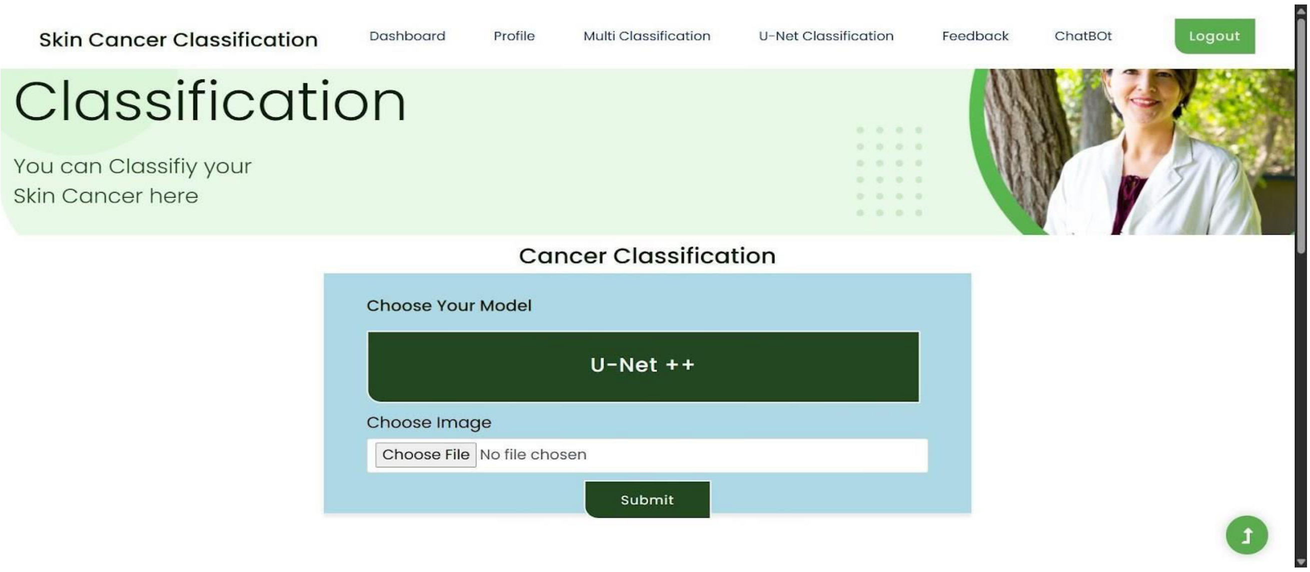

Fig. 3. U-Net++ Segmentation of Skin Lesion

Challenges and Limitations:

The proposed system demonstrates high classification and segmentation accuracy levels yet preservation of some impor- tant challenges exists.
Despite being trained using HAM10000 data the pro- posed model might inadequately handle dermatological skin cancer variations among various population groups. Some malignant lesions show overlapping visual traits which sometimes causes misdiagnosis between them. Modern GPUs function as essential hardware require- ments to ensure efficient training operations along with real-time inferences for this model.
The future work should address identified limitations to improve both robustness and generalizability characteristics of the model.

Discussion and Future Scope

The obtained results show that deep learning holds great importance for creating automated systems that identify skin cancers. Health professionals can benefit from the combined classification and segmentation system as a complete tool for their practice. Future improvements may include:

The system benefits from expanded datasets containing more diverse patient data to support generalization. The integration of attention mechanism systems.

VI. CONCLUSION AND FUTURE WORK

Conclusion:
The researchers created a deep learning system that tack- les multiple skin cancer identification as well as segmenta- tion tasks. Research demonstrates the Convolutional Neural Networks (CNNs) classification system along with U-Net++ segmentation model results in advanced performance of skin lesion diagnosis and analysis. Because of its seven class dif- ferentiation capabilities the InceptionV3-based classification model produced a 86% accuracy performance. The U-Net++ segmentation model achieved excellent performance indicators with a Dice Coefficient value of 0.8552 and Intersection over Union (IoU) of 0.7486 and Recall value of 0.9170 while Precision reached 0.8754 which demonstrates its reliable boundary outlining capability.To meet user requirements the proposed system combines multiple features including real-time camera detection together with image upload analysis and segmentation services and hospital recommendation together with appointment booking through a built-in chatbot. The platform attains better ac- cessibility through manual implementation of multi-language support which enables use by larger audiences.

This study proves the high efficiency of deep learning for detecting skin cancer because it indicates potential value in early dermatological diagnosis for dermatologists and medical staff. The automated precise lesion analysis capabilities of this system help decrease human mistakes and enhance medical treatment benefits for patients.

Future Work:
The proposed system produces promising results nonethe- less researchers should focus their efforts on enhancing future work through several improvements and explorations.

- The HAM10000 dataset used for current model training lacks diversity because it does not include all variations of skin lesions from different ethnic backgrounds in various geographic areas. Research should train the model using expanded datasets comprising diverse skin lesions to enhance its ability to generalize.
- Enhancing performance of image-based classification and segmentation can be accomplished through implementing attention-based architectures such as Vision Transformers (ViTs) or Attention U-Net which direct processing power to critical image areas.
- A mobile application version of the model requires de- velopment to facilitate rapid skin cancer diagnosis on smartphone devices. Cloud-based deployment offers der- matological analysis services which enable distant users in underprivileged regions to access the assessment.
- Integrating explainable AI techniques through Grad-CAM or SHAP (Shapley Additive Explanations) will make medical practitioners better understand AI-based predic- tions because it provides transparent insight into model calculations.
- Generative Adversarial Networks (GANs) alongside ad- vanced augmentation strategies help manufacturers pro- duce synthetic skin lesion images which enhance both robustness and performance of their models.
- The integration of medical metadata such as patient back- grounds alongside patient symptoms and age information plus skin type details within image processing deep learning models would develop advanced personalized diagnostic systems.
- Medical expert collaboration through partnerships be- tween dermatologists and oncologists helps validate pre- dictions and gives necessary feedback to enhance the system's practical use in clinical settings.
- The existing detection system operates exclusively for skin cancer diagnosis but lacks capability to identify other forms of dermatological diseases. The model possesses potential to identify various skin conditions beyond skin cancer when models for detecting eczema, psoriasis and fungal infections are developed and integrated into its functionality.

The proposed system advances into a vital stage for AI- mediated skin cancer identification. Additional development and optimization of the system will enable it to become a sig- nificant tool that aids medical workers along with helping them diagnose conditions at an early stage. Real-time applications and scalable AI systems combined with explainable solutions will have a vital function for dermatological healthcare in the upcoming years.

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