AI-BASED TOOL FOR PRELIMINARY DIAGNOSIS OF DERMATOLOGICAL MANIFESTATIONS

A Mini Project report submitted
in the partial fulfilment of the requirements for the award of the degree of

Bachelor of Technology

in

Computer Science & Engineering

(Artificial Intelligence and Machine Learning)

by

21071A6609	Bhogi Tanuja
21071A6636	Merugu Sriram
21071A6639	Mucharla Likitha
21071A6659	Tagor Ganesh

Under the Guidance of

Dr. N. Sandhya

Associate Professor

CSE – AIML & IoT, VNR VJIET

Submitted to

DEPARTMENT OF

CSE- (ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING & INTERNET OF THINGS)

Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology,

Hyderabad, Telangana

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VignanaJyothi Nagar, Pragathi Nagar, Nizampet (S.O), Hyderabad – 500 090, TS, India.
Telephone No: 040-2304 2758/59/60, Fax: 040-23042761

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CERTIFICATE

This is to certify that **BHOGI TANUJA (21071A6609), MERUGU SRIRAM (21071A6636), MUCHARLA LIKITHA (21071A6639), TAGOR GANESH (21071A6659)** have successfully completed their Mini project work at CSE-(AIML & IoT) Department of VNRVJIET, Hyderabad entitled **"AI-BASED TOOL FOR PRELIMINARY DIAGNOSIS OF DERMATOLOGICAL MANIFESTATIONS"** in partial fulfilment of the requirements for the award of B. Tech degree during the academic year 2023-2024.

This work is carried out under my supervision and has not been submitted to any other University/Institute for award of any degree/diploma.

Guide
Dr.N Sandhya
Associate Professor
Dept. of CSE (AIML & IoT)

Head of the Department
Dr. Sagar Yeruva
Associate Professor
Dept. of CSE (AIML & IoT)

DECLARATION

This is to certify that our project titled "**AI-BASED TOOL FOR PRELIMINARY DIAGNOSIS OF DERMATOLOGICAL MANIFESTATIONS**" submitted to Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology in complete fulfilment of the requirement for the award of Bachelor of Technology in CSE- (Artificial Intelligence and Machine Learning) is a bonafide report to the work carried out by us under the guidance and supervision of Dr. N. Sandhya, Professor, Department of CSE-(AIML & IoT), Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology. To the best of our knowledge, this has not been submitted in any form to another University/Institute for an award of any degree/diploma.

Bhogi Tanuja
21071A6609
Dept. of CSE (AIML&IoT)

Merugu Sriram
21071A6636
Dept. of CSE (AIML&IoT)

Mucharla Likitha
21071A6639
Dept. of CSE (AIML&IoT)

Tagor Ganesh
21071A6659
Dept. of CSE (AIML&IoT)

ABSTRACT

The accurate diagnosis of dermatological manifestations is crucial for effective treatment and patient care. However, access to dermatologists can be limited, leading to delayed diagnoses and potential complications. This project aims to develop an AI-based tool to assist healthcare professionals in the preliminary diagnosis of dermatological conditions. By leveraging machine learning algorithms and image recognition techniques, the proposed system will analyze and classify skin lesions, rashes, and other skin abnormalities, providing potential diagnoses and recommendations for further evaluation. The tool will serve as an initial screening aid, enabling timely and informed decision-making while increasing accessibility to specialized dermatological expertise

TABLE OF CONTENTS

TABLE OF FIGURES

1 INTRODUCTION

Dermatological manifestations encompass a wide range of skin conditions, from common rashes and infections to more serious diseases like melanoma. Early and accurate diagnosis is essential for successful treatment and prevention of complications. However, access to dermatologists can be limited, particularly in remote or underserved areas, leading to delays in diagnosis and treatment. This project proposes the development of an AI-based tool to assist healthcare professionals in the preliminary diagnosis of dermatological manifestations. By leveraging machine learning algorithms and advanced image recognition techniques, the tool will analyze and classify skin lesions, rashes, and other skin abnormalities, providing potential diagnoses and recommendations for further evaluation. The ultimate goal of this project is to increase accessibility to specialized dermatological expertise, enabling timely and informed decision-making, and improving patient outcomes.

1.1 EXISTING SYSTEM

Currently, the diagnosis of dermatological manifestations primarily relies on visual examination by dermatologists or other healthcare professionals with specialized training. This process can be time-consuming and subject to human error or biases. In some cases, teledermatology services are available, where patients can submit images of their skin conditions for remote evaluation by dermatologists. However, these services are often limited in availability and accessibility, particularly in resource-constrained settings.

1.2 PROPOSED SYSTEM

The proposed AI-based tool for the preliminary diagnosis of dermatological manifestations will consist of the following key components:

1. Image Acquisition: A user-friendly interface for healthcare professionals to upload or capture images of skin lesions, rashes, or other skin abnormalities.
2. Image Preprocessing: Techniques for enhancing image quality, segmentation, and feature extraction to optimize the input for the machine learning model.

3. Machine Learning Model: A deep learning model trained on a large dataset of annotated skin images, capable of classifying and identifying various dermatological manifestations.
4. Diagnostic Output: The system will provide potential diagnoses, along with confidence scores and recommendations for further evaluation or referral to a dermatologist.
5. User Interface: An intuitive and user-friendly interface for healthcare professionals to interact with the system, upload images, and receive diagnostic outputs.

2 LITERATURE SURVEY

2.1 RELATED WORK

We referenced fifteen distinct research papers encompassing autism screening, disease diagnosis, and early detection using machine learning algorithms. These studies shed light on various methodologies, pros, and cons associated with their respective approaches.

2.1.1 Skin Disease Recognition Method Based on Image Color and Texture Features

The article addresses the need for automatic methods to accurately diagnose multitype skin diseases.The objective is to develop a method for identifying three types of skin diseases (herpes, dermatitis, and psoriasis) using image color and texture features.The paper discusses preprocessing techniques, image segmentation using the grey-level co-occurrence matrix (GLCM), feature extraction of texture and color features, and classification using the Support Vector Machine (SVM) method.The paper proposes an efficient method for identifying skin diseases based on image color and texture features, demonstrating its effectiveness through experimental results

2.1.2 A Method Of Skin Disease Detection Using Image Processing And Machine Learning

The article addresses the need for cost-effective and accurate methods for diagnosing skin diseases, particularly in regions like Saudi Arabia where skin diseases are common due to hot weather.The objective is to propose an image processing-based method for detecting skin diseases that is simple, fast, and cost-effective, using techniques like convolutional neural networks (CNN) and support vector machines (SVM)

2.1.3 A machine learning approach for skin disease detection and classification using image segmentation

The article addresses the challenge of diagnosing skin diseases from clinical images, which is time-intensive and subjective when done manually by medical experts. It highlights the need for automatic skin disease prediction to speed up treatment plans.The paper discusses the use of morphological 9filtering (Black-Hat transformation, inpainting algorithm), Gaussian filtering for de-blurring and denoising images, automatic Grabcut segmentation, and feature extraction techniques like Gray Level Co-occurrence Matrix (GLCM) and statistical features. Machine learning classifiers such as Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) are applied for classification.

2.1.4 Hybrid Methodologies for Segmentation and Classification of Skin Diseases: A Study

Skin disorders pose a significant global health concern, especially when they progress to malignant stages. Early detection is crucial to prevent complications, but existing methods may not be sufficient. The paper addresses the need for an automated skin disease detection system using mobile technology to enable early diagnosis and treatment.The paper employs advanced machine learning algorithms to develop a mobile-based automated skin disease detection system. It integrates segmentation techniques like K-means clustering and Watershed algorithm, feature extraction methods including Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP), and classification algorithms such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Random Forest, and k-Nearest Neighbors (k-NN). These techniques enable accurate detection of skin disorders, with treatment plans delivered to individuals via SMS or email for enhanced accessibility to healthcare resources.

2.1.5 Detection of Skin Diseases Using Matlab

The paper addresses the challenge faced by doctors in accurately diagnosing skin diseases, despite the availability of advanced technology. It highlights the inconvenience and expense of traditional diagnostic methods, which often require multiple medical examinations over several days. The proposed work aims to mitigate these challenges by developing a MATLAB-based program for the automated detection of three common skin diseases: Acne, Cancer, and Psoriasis dermatitis. By utilizing image segmentation and classification techniques, the program seeks to provide quick and intuitive diagnoses, thereby improving the efficiency of medical care. In summary, the paper presents a solution to the challenge of accurate skin disease diagnosis by developing a MATLAB program. By integrating image processing and machine learning techniques, the program can quickly identify symptoms of Acne, Cancer, and Psoriasis dermatitis from input images. The proposed system offers a user-friendly interface for medical professionals, potentially improving diagnostic efficiency and patient outcomes.

2.1.6 A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks

The traditional diagnosis of skin diseases is laborious, time-consuming, and requires extensive expertise. There is a lack of automated systems in Ghana for skin disease diagnosis, leading to complexity and delays in diagnosis.Utilizes Convolutional Neural Networks (CNNs) built upon the Tensorflow framework for skin disease detection.Develops a web- based system named "medilab-plus" specifically for detecting atopic dermatitis, acne vulgaris, and scabies.Achieves high classification accuracies: 88% for atopic dermatitis, 85% for acne vulgaris, and 84.7% for scabies.Demonstrates computational efficiency with a processing time of 0.0001 seconds, enabling rapid diagnosis.

2.1.7 Skin disease detection using deep learning

Traditional methods for diagnosing skin diseases rely heavily on the expertise of dermatologists and may involve extensive testing, leading to delays in diagnosis and treatment. Additionally, access to specialized medical equipment for diagnosis is limited in many regions, hindering early detection and intervention.The paper utilizes a dataset of skin disease images, obtained from the Xiangya-Derm collection, to train a CNN model for skin disease diagnosis. Pre processing techniques, including image scaling and feature extraction, are employed to enhance the quality of the input images and extract relevant features for classification. The CNN model, along with the softmax classifier algorithm, is then used to classify the images into different skin disease categories. Additionally, the paper discusses the use of pre-trained models, such as VGG16 and VGG19, for efficient feature learning and classification.

2.1.8 Artificial Intelligence Application in Prediction of Diagnosis in Dermatological Conditions.

In this perspective, Predictions given by the AI application were compared with diagnosis done by the dermatologist. The performance of AI application was evaluated using accuracy, precision, and recall. The AI works on the principle, the convolutional neural network (CNN) of AI takes an image and converts it into numerical forms and retrieves from its own memory similar images from which it can generate a diagnosis.

2.1.9 Intelligent System for Skin Disease Prediction using Machine Learning

Skin diseases are prevalent and challenging to diagnose accurately, often leading to delayed treatment due to limited medical resources and infrastructureThe paper utilizes a dataset of around 3000 skin disease images collected from various sources. It employs feature extraction algorithms and classifiers, including CNN and SVM, to detect and classify skin diseases. The proposed (CNN-SVM - MAA) system is evaluated through experiments to demonstrate its efficiency

2.1.10 Skin Disease Detection Using Machine Learning

The article addresses the challenges in traditional skin disease diagnosis methods, including subjectivity, time consumption, and reliance on dermatologists, and proposes a machine learning-based approach for automated and accurate diagnosis.Utilizes diverse datasets of skin images from medical databases and health institutions.Employs Convolutional Neural Networks (CNNs) and transfer learning for feature extraction and classification.Integrates interpretable deep learning models for insights into the decision- making process and enhancing trust in automated diagnostics.

2.1.11 Artificial intelligence in dermatology

A guide for the dermatologist Limited understanding and integration of artificial intelligence (AI) tools in dermatology practice. The paper reviews the current state of AI applications in dermatology and provides insights into how dermatologists can incorporate AI tools into their practice.

2.1.12 A Dermoscopic Skin Lesion Classification Technique Using YOLO-CNN and Traditional Feature Model

The early detection of skin cancer is crucial for better treatment planning. However, existing methods for detecting and classifying skin lesions may have limitations in terms of accuracy and performance.The paper investigates the use of a Convolutional Neural Network (CNN), specifically the You Only Look Once (YOLO) algorithm, to extract features from skin lesions. These features are then concatenated with traditional features such as texture and colour features extracted from the lesion region of the input images. The concatenated features are fed into a Fully Connected Network, which is trained with specific ground truths to achieve higher classification accuracy.

2.1.13 Detection of Skin disease using Metaheuristic supported Artificial Neural Networks

Developing automated, efficient, and accurate techniques for classifying skin diseases from digital images is crucial for biomedical image analysis.Employed Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for training the ANN (NN-NSGA-II).Extracted different features to train the classifier.Compared the proposed NN-NSGA-II model with NN-PSO (ANN trained with Particle Swarm Optimization) and NN-GA (ANN trained with Genetic Algorithm).

2.1.14 Artificial Intelligence in Dermatology Image Analysis

Current Development The integration of artificial intelligence (AI) and deep learning algorithms into the healthcare field, particularly in image recognition and dermatological diagnosis, has become a modern focus and future trend.Discusses the use of 3D imaging systems and dermatoscopes combined with intelligent software for screening, labeling, and documenting skin lesions.Explores the potential of AI in prosthetics and rehabilitation for patients with skin tumors and amputations. Analyzes the application of emerging AI in dermatology for diagnosis, treatment, and evaluation of skin conditions, inflammatory diseases, and beauty assessments.

2.1.15 Detection of Skin disease using Metaheuristic supported Artificial Neural Networks

Automated skin lesion diagnosis from dermoscopic images is challenging due to artifacts, blurry boundaries, poor contrast, and variable lesion sizes/shapes.Pre-processing: Top-hat filtering and inpainting technique. Segmentation: Mayfly Optimization with multilevel Kapur's thresholding for determining infected regions. Feature Extraction: Inception v3 based feature extractor for deriving valuable feature vectors. Classification: Gradient boosting tree (GBT) model for classification.The IMLT-DL model addresses challenges through a multi-stage approach. Achieved maximum accuracy of 0.992 on ISIC dataset, outperforming existing methods. Future work aims to enhance segmentation using advanced deep learning technique

2.2 SYSTEM STUDY

In this comprehensive project focused on disease classification and prediction, the primary objective is to leverage the power of Machine Learning (ML) techniques to accurately identify and predict three distinct diseases: sepsis, diabetes, and autism. The project entails a meticulous system study that involves several crucial components. First, a robust and accurate dataset containing relevant medical data for each disease will be curated. The data will encompass both clinical and patient-specific attributes to ensure the models' effectiveness. Second, a well-defined system architecture will be established, incorporating various ML algorithms such as support vector machines, logistic regression, K-nearest neighbors, and random forest. Each algorithm will be rigorously tested and evaluated to identify the best-performing ones tailored to each disease. Third, hyperparameter tuning will be conducted to finetune the models' parameters and optimize their predictive capabilities. This step aims to enhance the models' accuracy and generalizability. Additionally, a comprehensive analysis of the most significant features and predictors for each disease will be carried out, shedding light on the underlying factors contributing to disease classification and prediction. Ultimately, this project aspires to provide valuable insights into the effective utilization of ML techniques for disease diagnosis, offering a pathway towards more accurate and timely healthcare interventions.

A comparative study of various machine learning algorithms was conducted for diagnosing diabetes mellitus. The study's advantages lie in its insights gained from the comparison of different algorithms. However, the study's focus solely on diabetes mellitus and omission of other diseases, along with the possibility of not considering recent advancements in machine learning techniques, are considered drawbacks.

This systematic review delves into the use of machine learning algorithms for early detection of sepsis. The approach offers non-invasiveness and high accuracy, but its limitations include a small size and limited diversity among the data source.

3 DESIGN

3.1 SYSTEM REQUIREMENTS

3.1.1 Software Requirements:

- **OS:** Windows 11
- **Programming Language:** Python
- **Libraries:** Matplotlib, sklearn, numpy, pandas, Yolo, shutil
- Algorithms: Cosine Similarity
- **Editor:** Pycharm, Jupyter Notebook

3.1.2 Hardware Requirements:

3.1.2.1 Computing Power:

- A reasonably powerful computer with a multi-core CPU is necessary for training ML models, especially if you're working with large datasets or complex deep learning models.

3.1.2.2 GPU : T4-GPU

- Having access to a GPU (Graphics Processing Unit) can significantly speed up training deep learning models.

3.1.2.3 RAM:

- Adequate RAM, typically 16 GB or more, is essential for handling large datasets and training complex models.

3.1.2.4 Storage: 32GB

- Sufficient storage space for datasets and model checkpoints. SSDs are preferable for faster data access.

3.1.2.5 Internet Connection:

- A reliable internet connection is necessary for downloading datasets, libraries, and collaborating with team members if applicable.

3.2 UML

3.2.1 Use case:

They are usually used to illustrate the various actions taken by the application. They also show the several users who can carry out these functions. Use-case diagrams fall under behaviour diagrams due to their emphasis on the tasks carried out and the users (actors) who carry out these tasks.

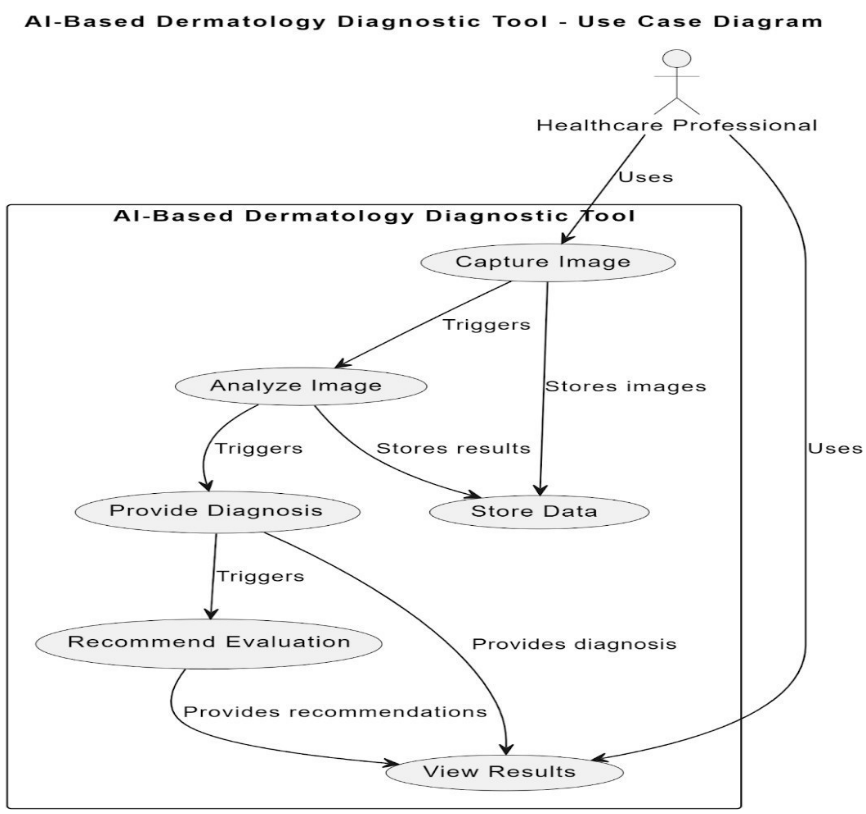

Figure 3.1 Use Case Diagram

3.2.2 Activity Diagram

An activity diagram visually presents a series of actions or flow of control in a system like a flowchart or a data flow diagram. Activity diagrams are often used in business process modelling.

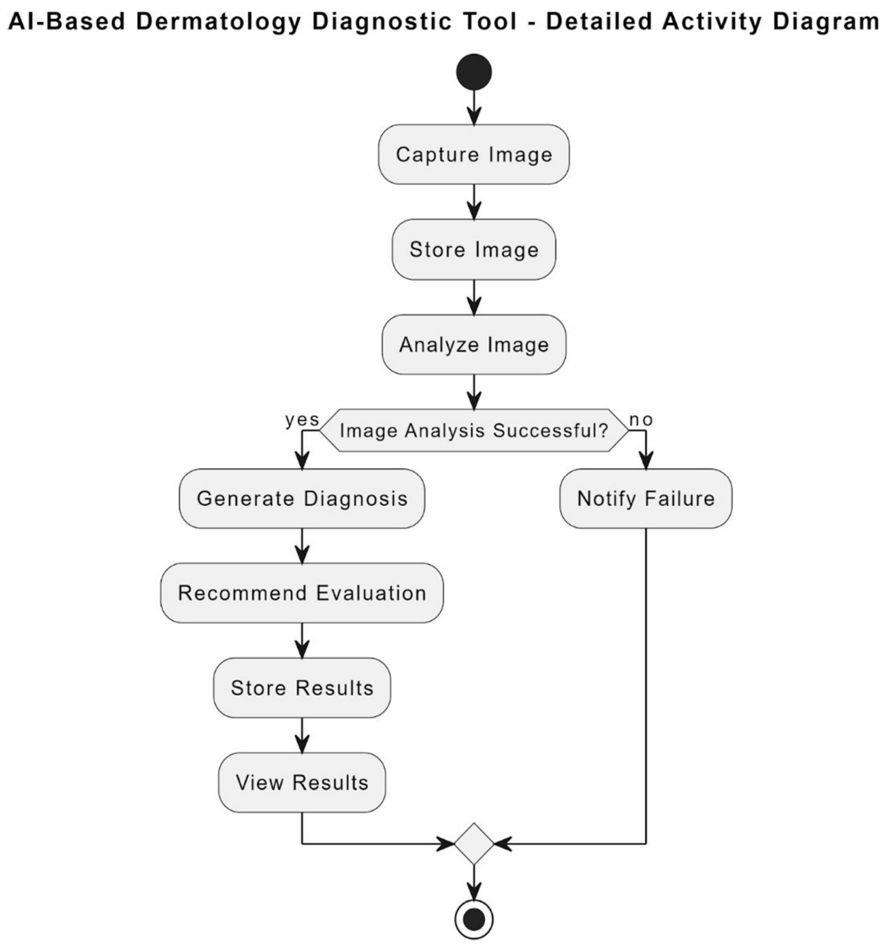

Figure 3.2 Activity Diagram

3.2.3 Class Diagram

Class diagram is a static diagram. It represents the static view of an application. Class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable code of the software application.

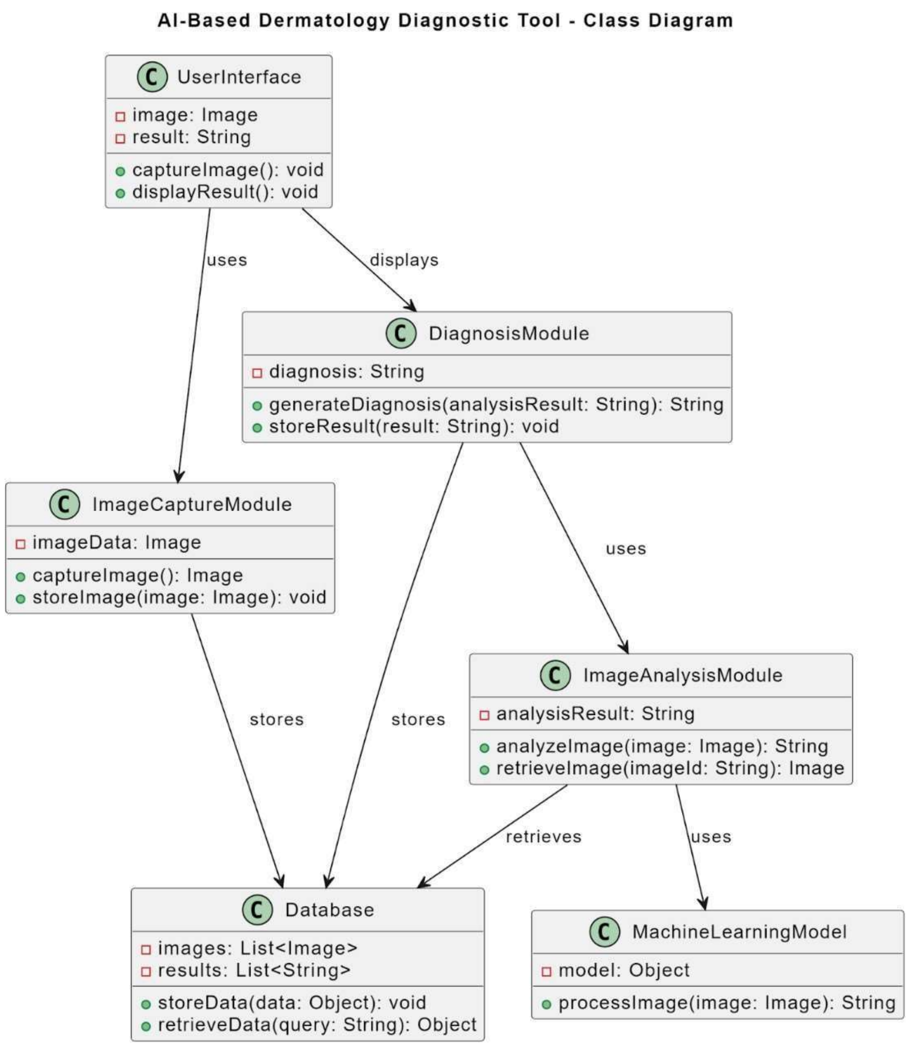

Figure 3.3 Class Diagram

4 IMPLEMENTATION

4.1 MODULES

4.1.1 Dataset

HAM10000 ("Human Against Machine with 10000 training images") dataset - a large collection of multi-source dermatoscopic images of pigmented lesions

The dermatoscopic images are collected from different populations, acquired and stored by different modalities. The final dataset consists of 10015 dermatoscopic images.

It has 7 different classes of skin cancer which are listed below :

- Melanocytic nevi
- Melanoma
- Benign keratosis-like lesions
- Basal cell carcinoma
- Actinic keratoses
- Vascular lesions
- Dermatofibroma

4.1.2 Models

We conducted a comparative analysis of VGG19, YOLOv8 algorithms for disease prediction. Through extensive hyperparameter tuning, we identified the algorithm delivering the highest predictive accuracy across diverse datasets.

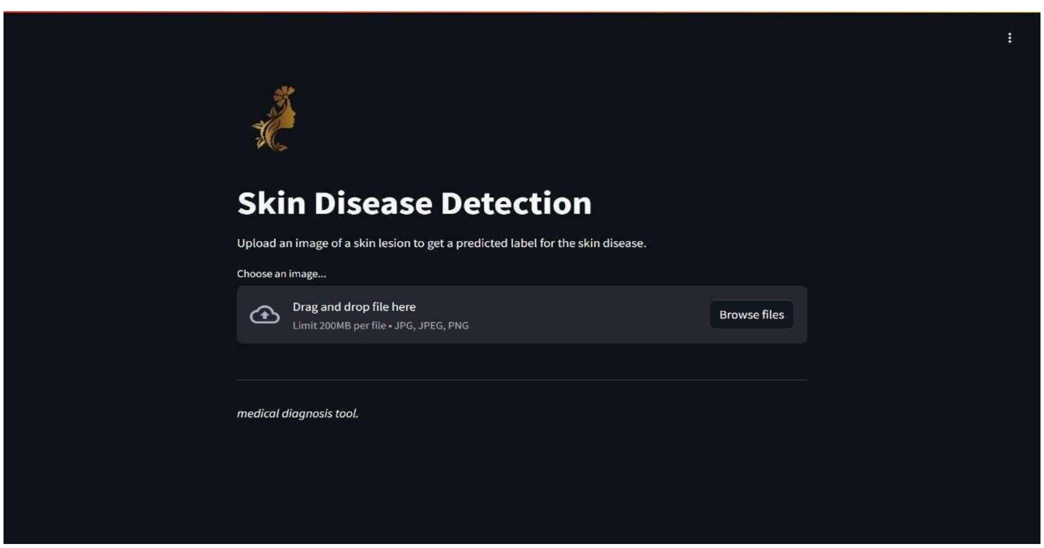

Figure 4.1 User Interface

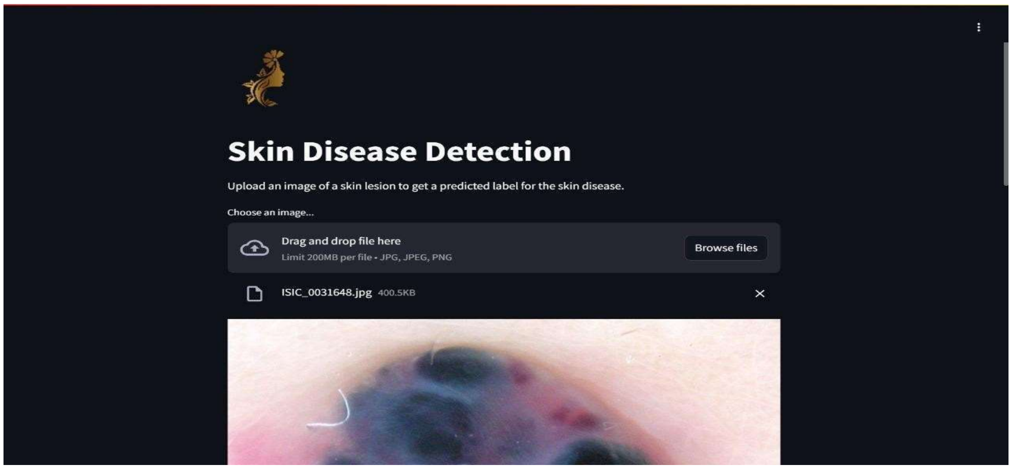

Figure 4.2 Uploading image

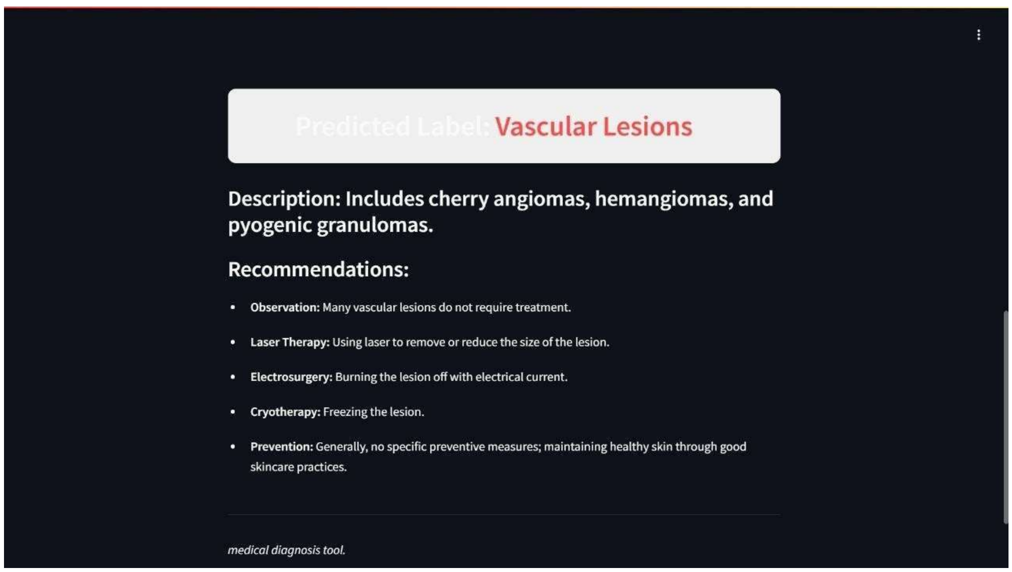

Figure 4.3 Output of the prediction

4.1.2.1 Deep Learning Models

4.1.2.1.1 VGG19

VGG19 is a deep convolutional neural network (CNN) architecture developed by the Visual Geometry Group at the University of Oxford. It consists of 19 layers, including 16 convolutional layers and 3 fully connected layers, designed to classify images into 1000 categories. VGG19 is known for its simplicity and depth, using small 3x3 convolutional filters throughout the network, which allows it to capture intricate features in images. This model has been extensively used for image classification, feature extraction, and transfer learning due to its high performance on the ImageNet dataset.

4.1.2.1.2 YOLO

YOLO (You Only Look Once) is a state-of-the-art, real-time object detection algorithm developed by Joseph Redmon and his collaborators. Unlike traditional object detection methods that apply the model to an image at multiple locations and scales, YOLO frames object detection as a single regression problem, predicting bounding boxes and class probabilities directly from full images in one evaluation. This approach allows YOLO to achieve high speed and accuracy, making it suitable for real-time applications. YOLO's architecture processes images at an impressive rate of 45 frames per second, and its ability to generalize well to new domains has made it a popular choice for various applications, from autonomous driving to surveillance.

4.1.3 Performance Metrics

Performance metrics provide a quantitative assessment of model effectiveness. Key metrics include accuracy, measuring overall correctness; precision, indicating true positive rate; recall, gauging the ability to identify positives; and F1 score, blending precision and recall.

- **Accuracy:** Measures the ratio of correctly predicted instances to the total instances.
  Formula: (TP + TN) / (TP + TN + FP + FN)

4.2 OVERVIEW TECHNOLOGY

Embarking on a meticulous journey towards accurate disease prediction, our methodology seamlessly integrates various essential steps. From meticulous data preprocessing and strategic data splitting to rigorous hyperparameter tuning and methodical model testing, this orchestrated approach culminates in results that are robust, reliable, and clinically relevant. Each step harmonizes to form a comprehensive framework that not only showcases the potential of deep learning but also contributes to the advancement of medical diagnosis and treatment.

4.2.1 Data Preprocessing

Data preprocessing forms the bedrock of our project, ensuring data quality and relevance. Through meticulous cleaning, normalization, we ensure the integrity of our datasets. This phase lays the foundation for accurate disease prediction by providing our models with clean and consistent input.

4.2.2 Data Splitting

Our dataset partitioning adheres to an 80:20 split, with 80% of the data allocated for training and 20% for testing. This stratified division safeguards a robust representation of disease classes within both subsets, avoiding bias and optimizing model performance across various scenarios.

Training Set and Testing Set: The training set, comprising the larger portion of our data, serves as the material for model learning. It enables our algorithms to grasp underlying patterns and relationships within the data. The testing set, held separate, acts as an independent evaluation ground, validating model generalization and predictive capabilities.

4.2.3 Algorithm selection

In the pursuit of accurate disease prediction, the selection of appropriate deep learning algorithms is paramount. YOLO model performed well on our dataset. Other model couldn’t able to detect the underlying patterns in the dataset accurately

5 TESTING

5.1 TEST CASES

5.1.1 Test Case 1: Image Upload and Display

- **Objective:** Ensure the user can upload an image and that it is displayed correctly.
- **Input:** Upload a valid image file (e.g., a JPEG of a skin lesion).
- **Expected Output:** The image is displayed on the UI immediately after upload.
- **Pass/Fail Criteria:** The image appears correctly without distortion.

5.1.2 Test Case 2: Diagnosis Display

- **Objective:** Verify that the system displays the diagnosis correctly below the uploaded image.
- **Input:** Upload an image that the model has been trained to diagnose (e.g., an image of eczema).
- **Expected Output:** The diagnosis (e.g., "Eczema") appears below the image along with a confidence score.
- **Pass/Fail Criteria:** The correct diagnosis is displayed with the confidence score.

5.1.3 Test Case 3: Unsupported File Type Handling

- **Objective:** Ensure the system handles unsupported file types gracefully.
- **Input:** Attempt to upload a non-image file (e.g., a PDF or text file).
- **Expected Output:** The system displays an error message indicating that the file type is not supported.
- **Pass/Fail Criteria:** The user is informed of the issue, and no image or diagnosis is displayed.

5.1.4 Test Case 4: High-Resolution Image Handling

- **Objective:** Verify that the system can handle and process high-resolution images without issues.
- **Input:** Upload a high-resolution image of a skin lesion.
- **Expected Output:** The image is processed correctly, and the diagnosis is displayed without significant delay.
- **Pass/Fail Criteria:** The image is displayed, and the diagnosis is provided promptly.

5.1.5 Test Case 5: Low-Resolution Image Handling

- **Objective:** Assess how the system handles low-resolution images.
- **Input:** Upload a low-resolution image (e.g., a blurry or pixelated image).
- **Expected Output:** The system attempts to provide a diagnosis or informs the user if the image quality is too low for accurate analysis.
- **Pass/Fail Criteria:** Either a diagnosis is provided, or the user is informed of the image quality issue.

5.1.6 Test Case 6: Incorrect Image Upload Handling

- **Objective:** Ensure the system handles situations where the uploaded image does not depict a skin condition.
- **Input:** Upload an image of an object (e.g., a book).
- **Expected Output:** The system either provides a message indicating the image is not suitable for diagnosis or fails to provide a diagnosis.
- **Pass/Fail Criteria:** The system does not produce an incorrect diagnosis and handles the situation appropriately.

5.1.7 Test Case 7: Diagnosis Accuracy Check

- **Objective:** Test the accuracy of the model by uploading known images of skin conditions.
- **Input:** Upload images of various known skin conditions that the model has been trained on.
- **Expected Output:** The correct diagnosis is displayed for each image.
- **Pass/Fail Criteria:** The diagnoses match the known conditions with reasonable accuracy.

5.1.8 Test Case 8: User Interface Usability

- **Objective:** Ensure the UI is user-friendly and easy to navigate.
- **Input:** Simulate user interaction by uploading an image and viewing the diagnosis.
- **Expected Output:** The user can easily upload an image and view the diagnosis without confusion or errors.
- **Pass/Fail Criteria:** The process is straightforward, and no usability issues are encountered.

5.2 TEST RESULTS

The culmination of our deep learning model development lies in the rigorous testing and evaluation phase. This pivotal step aims to ascertain the predictive capabilities and performance of our models, further contributing to the refinement of disease prediction accuracy.

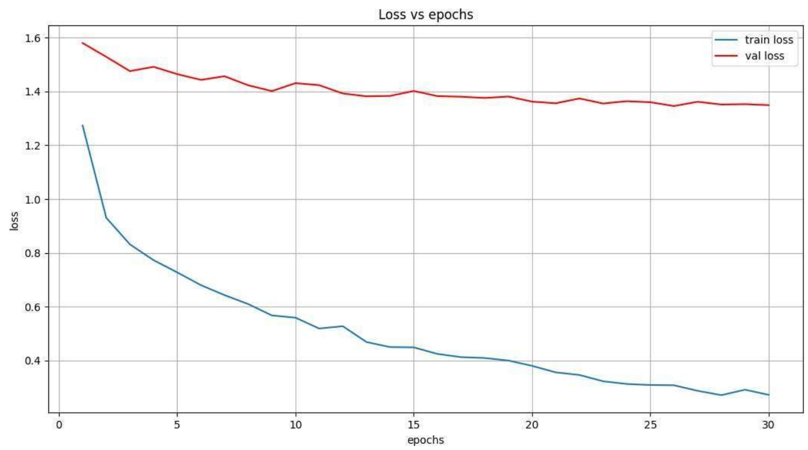

Figure 5.1 Loss vs Epochs

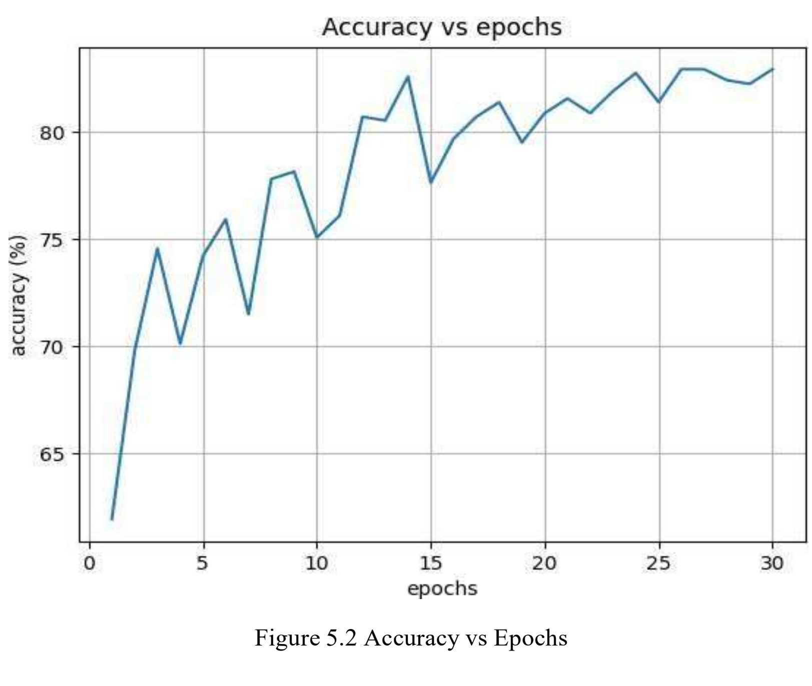

Figure 5.2 Accuracy vs Epochs

5.2.1 Accuracy

Accuracy showcases the proportion of correctly predicted outcomes. A high accuracy rate signifies the models precision in differentiating disease classes and underscores their potential as diagnostic tools.

Formula: (TP + TN) / (TP + TN + FP + FN)

Model	**Accuracy**
VGG19	62.35
YOLO	82.25

Figure 5.3 Accuracy of models

6 RESULTS

The AI-Based Tool for Preliminary Diagnosis of Dermatological Manifestations, which employs the YOLOv8 model trained over 30 epochs, achieved an accuracy of 82% in classifying skin conditions. This outcome highlights the model's effectiveness in analyzing dermatological images and providing preliminary recommendations. The 30 epochs of training contributed to refining the model's performance, allowing it to deliver reliable insights and support initial diagnostic efforts. The 82% accuracy underscores the model's capability to handle a range of skin conditions, enhancing its value as a tool for early assessment and decision-making in dermatological care.

7 CONCLUSION

The AI-Based Tool for Preliminary Diagnosis of Dermatological Manifestations, utilizing the YOLOv8 model, offers an efficient solution for initial skin condition assessments. By allowing users to upload images, the tool generates temporary recommendations based on the model's analysis. This provides immediate, preliminary guidance, helping users make informed decisions about seeking further medical consultation. While the tool does not replace professional diagnoses, it enhances accessibility to initial dermatological insights, showcasing the potential of advanced AI in improving early detection and healthcare efficiency.

8 FUTURE SCOPE

The AI-Based Tool for Preliminary Diagnosis of Dermatological Manifestations has considerable potential for future enhancements. Expanding the dataset and extending the model's training could improve its accuracy and robustness, enabling it to handle a broader range of skin conditions more effectively. Integrating the tool with electronic health records (EHRs) and teledermatology platforms could streamline the diagnostic process and facilitate better follow-up care. Developing mobile and web applications would enhance accessibility, allowing users to easily upload images from various devices. Future iterations could also include real-time feedback, extended condition coverage, and user customization options to improve interactivity and relevance.Collaborating with dermatologists for continuous validation will ensure the tool's recommendations remain accurate and aligned with clinical standards. These advancements could significantly enhance the tool's utility and impact in dermatological care.

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