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Identify Skin Disorder Using Dermoscopic Analysis Through Federated Learning

Yerramsetti Bhargavi
PG scholar, Department of MCA, DNR collage, Bhimavaram, Andhra Pradesh.
K.SRI DEVI
(Assistant Professor), Master of Computer Applications, DNR collage, Bhimavaram, Andhra Pradesh.

Abstract: Skin disorders affect millions of individuals worldwide, necessitating accurate and early diagnosis for effective treatment. Traditional machine learning-based medical image classification often requires centralized data storage, raising concerns about data privacy and security. To address this issue, this project implements Federated Learning (FL) for skin disorder detection using dermoscopic images. The proposed system utilizes YOLOv8 for object detection and CNN for classification. The HAM10000 dataset is used for training, with data distributed across two federated clients. Each client trains locally, and the trained model weights are aggregated at a central federated server, ensuring data privacy while enhancing model generalization. The CNN model achieves a global accuracy of 95%, outperforming the VGG19 model (65%). A Flask-based web application is deployed to enable real-time skin disorder detection, offering a scalable and secure AI-driven diagnostic solution.

I. INTRODUCTION

In recent years, artificial intelligence (AI) has gained popularity as a potent tool for resolving a wide range of contemporary issues. Artificial Neural Networks (ANNs) are used in Deep Learning (DL), a kind of Machine learning (ML) to learn models and patterns rather than begin expressly programmed for a Job. To identify various illnesses, machine learning and deep learning techniques have been embraced by several medical fields. Using two of the largest publicly available skin image datasets, Derment and ISIC Archive, they applied the state-of-the-art Deep Neural Networks and the deep learning approach. They also used disease taxonomy, where available, to enhance the classification performance of these models.

For the classification of 23 illnesses, they develop new state-of-art on DermNet with 80% accuracy and 98% Area Under the Curve (AUC). They established standards for the categorization of all 622 distinct subclasses [1]. The classification of psoriasis skin sickness was assessed using a convolutional neural network, since plaque and guttate are the common causes of psoriasis.

A total of 187 images were contributed by the Psoriasis Image Library, the international Psoriasis Council (IPC) and DermNet NZ; 82 of these images were used for Plaque Psoriasis and 105 for Guttate Psoriasis. Skin illnesses such as psoriasis are classified by the analysis and extraction of information using Convolutional Neural Networks (CNNs). It yielded results similar to CNN, with an accuracy rate of 72.4% for guttate and 82.9% for plaque [2]. Evaluated the dermoscopic diagnosis of the International Skin Imaging Collaboration (ISIC) and Shinshu datasets to classify malignant melanoma, melanocytic nevus, basal cell carcinoma, and benign keratosis on the non-volar skin. Thirty Japanese dermatologists were compared to a DNN in this regard. 12,234 photos from the ISIC set and 594 images from the Shinshu set were used to train the DNN.

The Shinshu set had a sensitivity for malignancy prediction by the dermatologists than the ISIC set (0.853[95% confidence range, 0.820-0.885] versus 0.608[0.553- 0.664], P<0.001). When compared to the human readers, the DNN's specificity was much greater, measuring 0.962 for the Shinshu set and 1.00 for the ISIC set at the dermatologists' mean sensitivity threshold [3]. In order to create classifiers that can distinguish between regular globules and typical networks, scientists utilized a dataset of high-resolution skin photos. They built deep Convolution neural networks this purpose, and the networks showed state-of-the-art performance in picture categorization tasks.

They used the dataset—which included 211 lesions that were manually annotated by domain experts—acquired through a collaboration with the International Skin Imaging Collaboration (ISIC) for the evaluation, producing approximately 2000 samples of each class of networks and globules. Three unsupervised feature extraction and classification algorithms K-means clustering, sparse coding, and Fisher Kernel encoding—are used as a comparison [4]. Using EfficientNet-b4 to develop a deep learning framework that was trained on a real clinical dataset from a Chinese tertiary hospital. The system was able to classify 14 common dermatoses with high accuracy, outperforming previous CNN models and matching dermatologists' diagnostic performance [5].

This dataset has been used to build numerous machine learning models aimed at the diagnosis of skin disorders. Two local clients (Client 1 and Client 2) trained convolutional neural networks (CNNs) on multiple dataset segments during the investigation. The results demonstrated a remarkable capacity for classification. Moreover, federated learning generates a global CNN model by combining data from both local clients. This federated approach improves accuracy while ensuring better security and privacy of sensitive data. When the performance of CNN models is compared to that of VGG19.

Skin disorders affect a significant portion of the global population, with conditions ranging from common infections to life-threatening diseases such as melanoma. Early and accurate diagnosis is crucial for effective treatment and improved patient outcomes. Traditionally, machine learning models have been employed for automated skin disease detection using dermoscopic images. However, these models often require centralized data storage, which raises concerns about data privacy, security, and regulatory compliance in healthcare settings.

To address these challenges, this project introduces a Federated Learning (FL)-based framework for skin disorder detection. Federated Learning enables multiple clients (hospitals, clinics, or research centers) to train models locally on their data without sharing it, thereby preserving data privacy. The system utilizes YOLOv8 for skin disorder region detection and CNN for classification, leveraging distributed training across multiple clients to enhance model generalization. The model is integrated into a Flask-based web application, allowing real-time skin disorder detection from uploaded images.

II. LITERATURE SURVEY

1. M.N. Bajwa et al., "Computer-Aided Diagnosis of Skin Diseases Using Deep Neural Networks", Applied Sciences, 2020

This study explores the application of deep neural networks (DNNs) for computer-aided diagnosis (CAD) of skin diseases. The research focuses on leveraging convolutional neural networks (CNNs) for feature extraction and classification of skin lesions. A large dataset of dermatological images is used to train and evaluate the model, achieving high classification accuracy across multiple skin disease categories. The study demonstrates the potential of AI-driven dermatology in improving diagnostic precision, reducing human error, and supporting telemedicine applications.

2. R.B. Roslan et al., "Evaluation of Psoriasis Skin Disease Classification Using Convolutional Neural Networks", IAES International Journal of Artificial Intelligence, 2020

This paper presents a CNN-based classification model for psoriasis skin disease detection. The study compares different CNN architectures to determine the most efficient model for distinguishing psoriasis from other skin conditions. The proposed CNN model achieves significant improvements in accuracy, demonstrating its efficacy in dermatological image analysis. The results indicate that deep learning techniques can assist dermatologists in early detection and classification of psoriasis, thereby enhancing patient management and treatment planning.

3. A. Minagawa et al., "Dermoscopic Diagnostic Performance of Japanese Dermatologists for Skin Tumors Differs by Patient Origin: A Deep Learning Convolutional Neural Network Closes the Gap", Journal of Dermatology

This study investigates the impact of patient origin on dermoscopic diagnostic accuracy among Japanese dermatologists. A deep learning-based CNN model is employed to standardize and improve diagnostic performance, addressing variations in human diagnostic accuracy across different patient groups. The results demonstrate that CNN models can bridge the diagnostic gap by providing consistent and objective analysis, making AI a valuable tool in reducing diagnostic biases and improving skin cancer detection rates.

4. S. Demyanov et al., "Classification of Dermoscopy Patterns Using Deep Convolutional Neural Networks", IEEE International Symposium on Biomedical Imaging, 2016
This research presents a deep convolutional neural network (DCNN) approach for classifying dermoscopy patterns in skin images. The model is trained on a large-scale dataset of labeled dermoscopic images and achieves high classification accuracy in distinguishing different lesion patterns. The study highlights the potential of DCNNs to automate dermatological diagnostics, aiding clinicians in early detection of malignant melanoma and other skin disorders.

5. C-Y Zhu et al., "A Deep Learning-Based Framework for Diagnosing Multiple Skin Diseases in a Clinical Environment", Frontiers in Medicine, 2021

This study introduces a deep learning-based framework for diagnosing multiple skin diseases in clinical settings. The model integrates CNN and transfer learning techniques, utilizing a diverse dataset of skin lesion images to improve classification performance. The proposed framework is tested in real-world clinical environments, demonstrating high sensitivity and specificity in detecting various dermatological conditions. The research highlights the viability of AI-powered diagnostic systems in healthcare applications.

6. M.A. Hashmani et al., "An Adaptive Federated Machine Learning-Based Intelligent System for Skin Disease Detection: A Step Toward an Intelligent Dermoscopy Device", Applied Sciences, 2021

This study explores **Federated Learning (FL) for skin disease detection**, emphasizing **data privacy and decentralized AI training**. The proposed **adaptive FL model** allows multiple medical institutions to collaboratively train deep learning models **without sharing sensitive patient data**. The results show that **federated CNN models achieve comparable accuracy to centralized models**, making FL a **promising approach for AI-driven dermatology in privacy-sensitive applications**.

7. A. Kumar Vermaa et al., "Comparison of Skin Disease Prediction by Feature Selection Using Ensemble Data Mining Techniques"
This paper presents a comparative analysis of skin disease prediction models using ensemble data mining techniques. The study evaluates multiple feature selection algorithms, including Random Forest, Decision Trees, and Support Vector Machines (SVM), to determine the most effective approach for dermatological classification. Results indicate that ensemble-based methods improve model performance, particularly in feature selection and disease classification accuracy.

III. PROPOSED METHOD

1. Data Collection and Preprocessing

- The **HAM10000 dataset** is used, containing **10,000 dermoscopic images** of different skin disorders.
- Images are **resized, normalized, and augmented** to improve model robustness.
- Dataset is **partitioned across two clients**, with **Client 1 having the full dataset** and **Client 2 having half the dataset**.

2. Federated Learning Setup

- A **Federated Server** is deployed to aggregate model weights from distributed clients.
- Each client **trains a CNN model independently** on its local dataset.
- After training, the **trained weights** are sent to the **federated server**, which computes the **global model** by averaging the weights.
- The **global model is distributed back** to all clients for improved learning.

3. Model Training and Evaluation

- **CNN and VGG19 models** are tested for performance.
- CNN achieves **93% accuracy on Client 1** and **87% accuracy on Client 2**.
- After federated averaging, the **global model reaches 95% accuracy**.

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- Performance metrics such as **precision, recall, F1-score, and confusion matrix** are analyzed.

4. Real-Time Prediction Using Flask Web Application

- A **Flask-based web interface** is designed for **real-time skin disorder detection**.
- Users can **upload an image**, which is processed by **YOLOv8 for object detection** and **CNN for classification**.
- The detected skin disorder is displayed along with its **classification label**.

5. Comparison with Traditional Models

- **VGG19 achieves only 65% accuracy**, proving less effective than CNN.
- The **proposed CNN-based federated model** outperforms traditional machine learning methods while preserving **data privacy**.

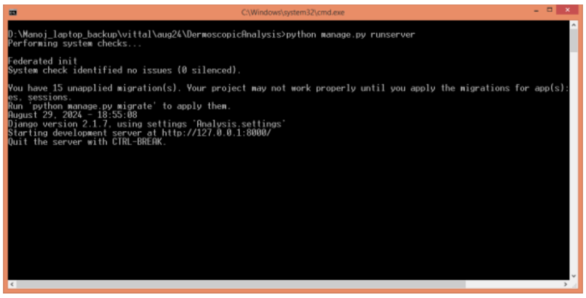
IV. RESULT

In this project we have used YOLO8 to detect and extract skin disorder from uploaded image and then employ CNN algorithm to predict type of skin disease. To secure dataset we have used two clients to train on dataset and then each client will upload its trained weights to Federated server. Federated server will take average of all weights and then send to all requesting clients. To train all algorithms we have used HAM10000 dataset and then experiment with multiple algorithms such as CNN and VGG19. Among both algorithms CNN is giving best accuracy so we have used CNN to detect skin disorder.

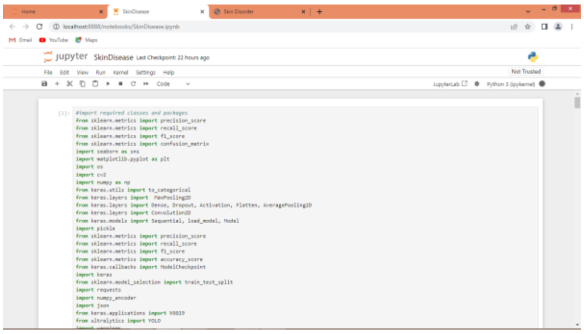
For algorithm training and testing we have used JUPYTER notebook and for prediction we have designed FLASK based web application

SCREEN SHOTS

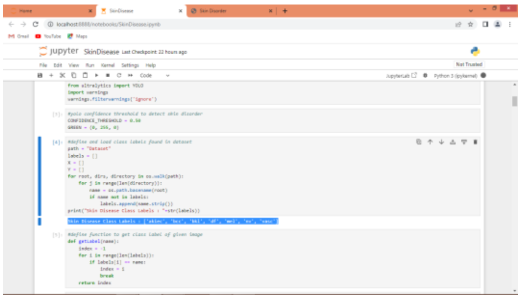
First double click on 'runFLServer.bat' file to start federated server and get below page



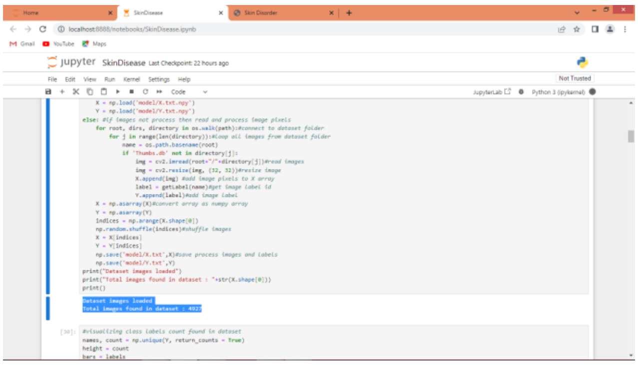
In above screen federated server started and now double clicks on 'run.bat' file to start JUPYTER notebook and will get below page



In above screen importing required packages and classes



In above screen defining code to get labels of different skin disorders available in dataset and then in blue colour text can see all skin disorders labels



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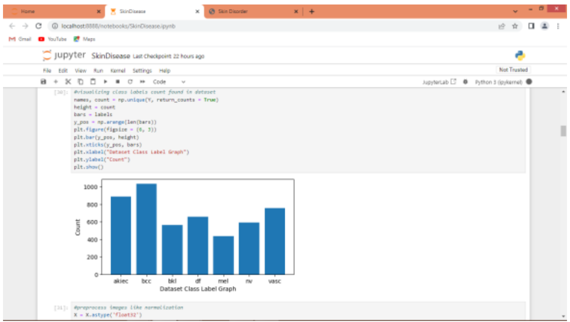
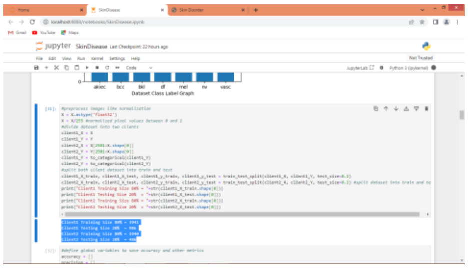
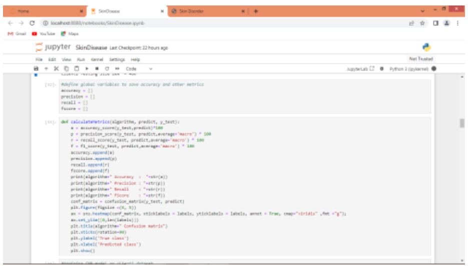
In above screen looping and reading each image from the dataset and then applying processing techniques such as resize and then extracting features and labels from each image and then adding X and Y training array and in blue colour text can see total number of loaded images



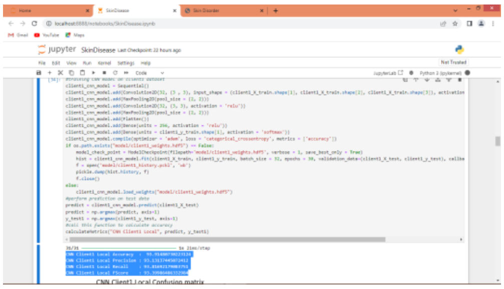
In above graph visualizing different class labels graph where x-axis represents 'Skin Disorder' class label and y-axis represents number of images



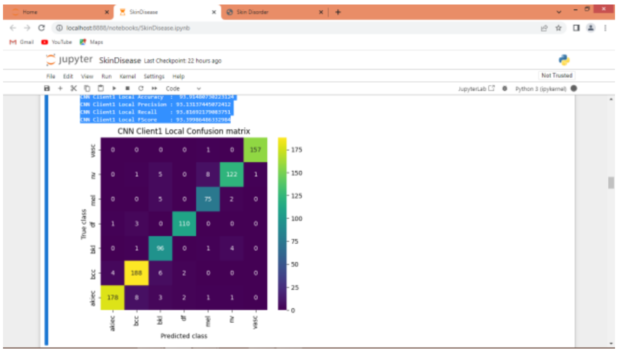
In above screen for client 1 we are taking full dataset and then for client2 we are taking half dataset and then splitting both datasets into train and test and then blue colour text can see train and test size for each client



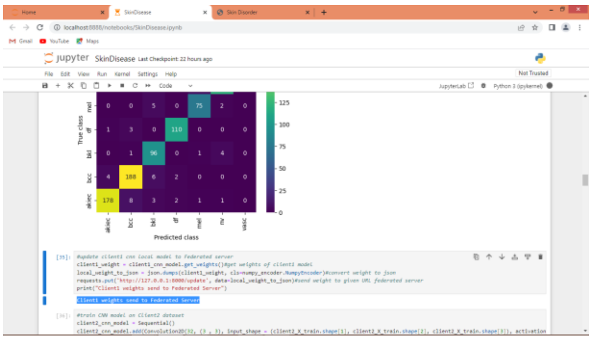
In above screen defining function to calculate accuracy and other metrics



In above screen defining CNN for client1 which will get trained on training images and then its accuracy will be calculated based on prediction of test data and then in blue colour text can see CNN on Client1 got 93% accuracy and can see other metrics like precision, recall and FCSORE. In below screen can see confusion matrix graph



In above confusion matrix graph x-axis represents predicted class labels and y-axis represents True class labels and then all different colour boxes in diagnol represents correct prediction count and remaining blue boxes got incorrect prediction count.



In above screen extracting weight of client1 CNN model and then sending that weight to federated server running on given URL

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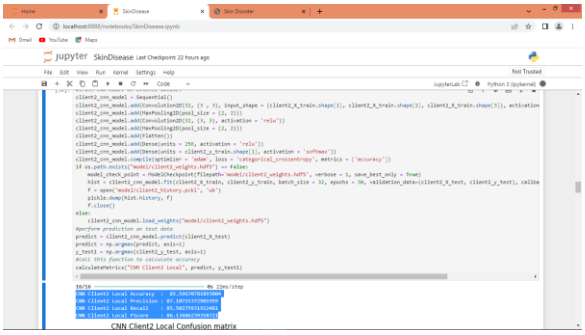
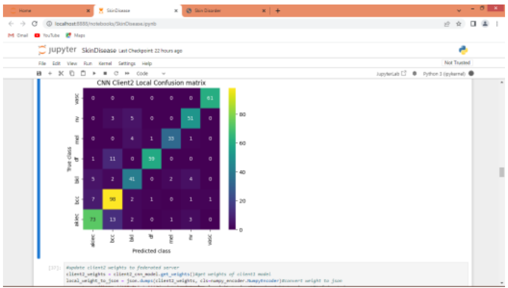
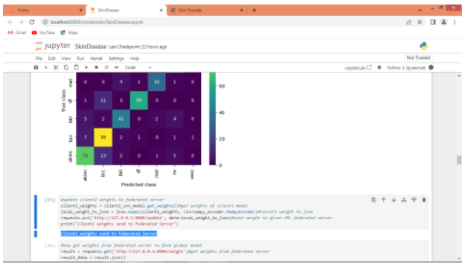


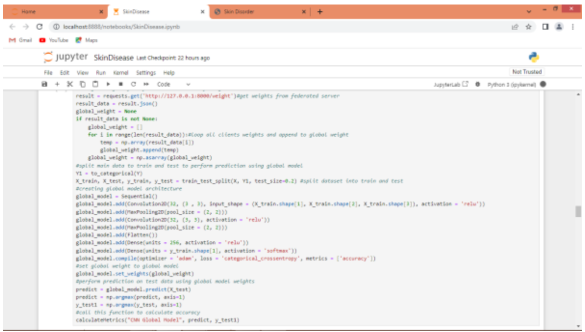
In above screen training CNN client2 model using another dataset and then in blue colour text can see client2 model got 87% accuracy



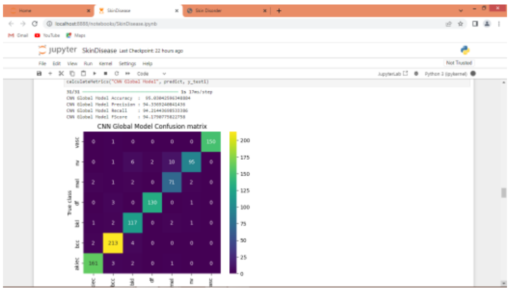
In above screen can see CNN client2 model confusion matrix graph



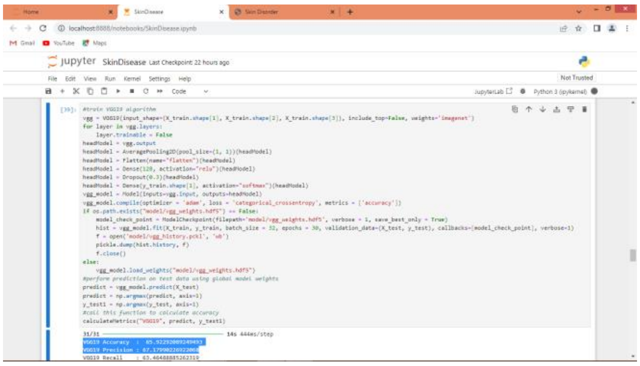
In above screen extracting weight of CNN client2 model and then sending to Federated server URL



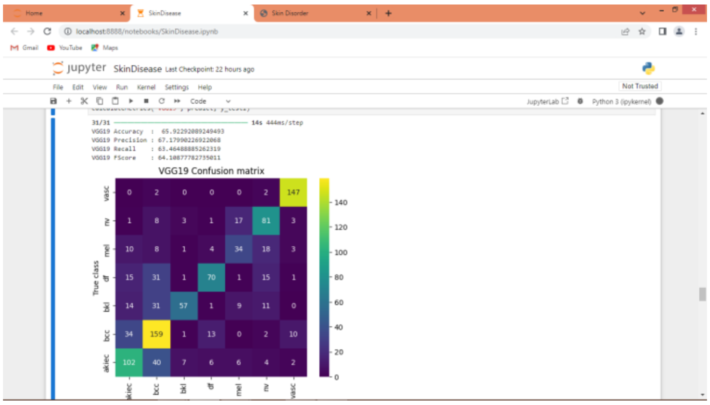
In above screen collecting weights from federated server and then generating Global model and after executing above model will get below weight



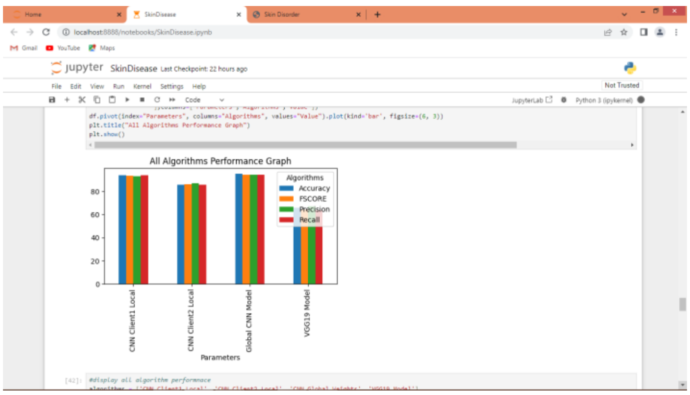
In above screen global model got 95% accuracy and can see other metrics and output for global model



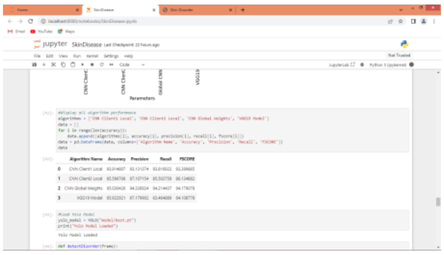
In above screen training VGG19 model and after executing this model we can see VGG19 got 65% accuracy and can see other metrics in below screen



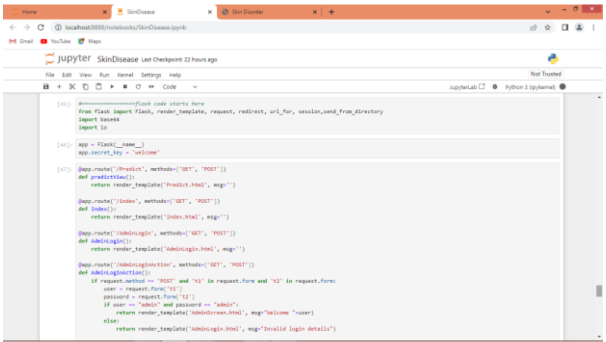
In above screen can see VGG19 performance



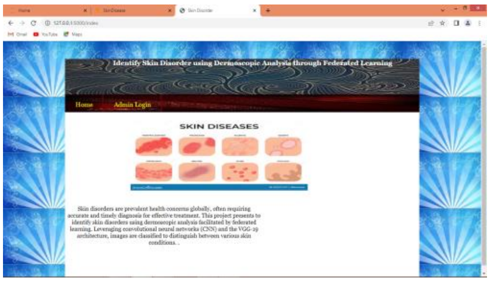
In above screen can see performance of each algorithm where x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars



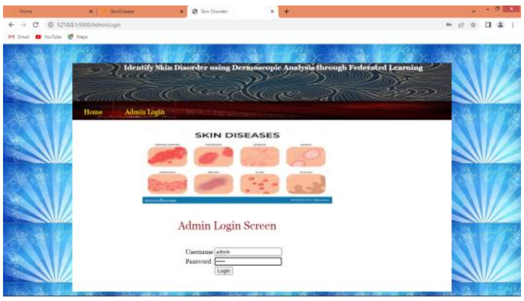
In above screen in tabular format can see performance of each algorithm



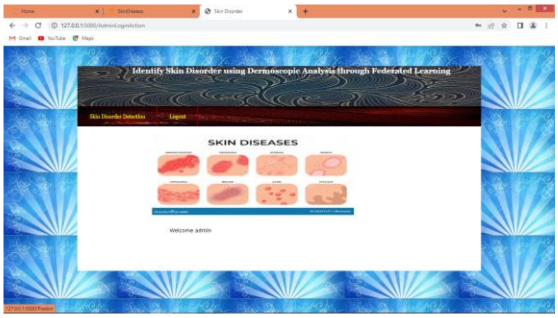
In above screen run FLASK code block to start flask server and then open browser and enter URL as http://127.0.0.1:5000/index and press enter key to get below page



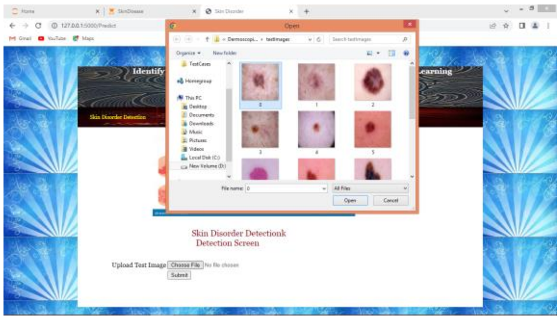
In above screen click on 'Admin Login' link to get below page



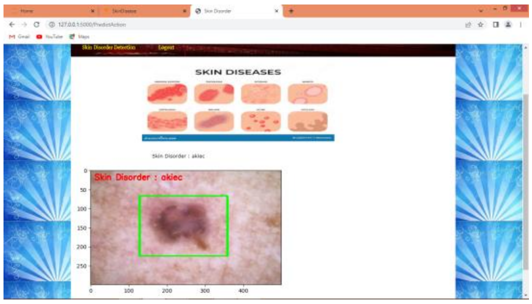
In above screen admin is login by using username and password as 'admin and admin' and then press button to get below page



In above screen click on 'Skin Disorder Detection' link to get below page



In above screen click on 'Choose File' button and then upload test image from 'test Images' folder available inside code folder and then press 'Submit' button to get below page



In above screen Yolo8 will detect skin disorder region and surrounded with green rectangle and then CNN will predict type of skin disorder and in above screen AKIEC disorder detected. Similarly you can upload and test other images and below are few other samples

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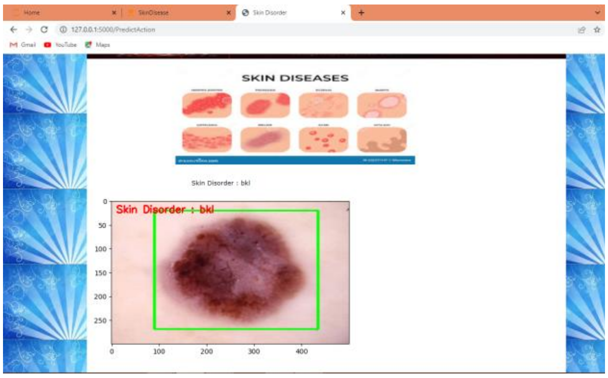
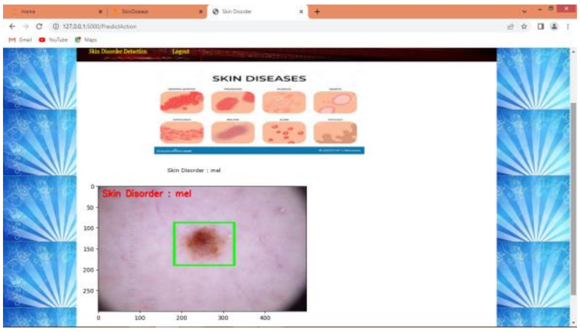


In above screen BKL disorder detected



In above screen MEL disorder detected and similarly you can test other images also.

V. CONCLUSION

This study demonstrates the effectiveness of Federated Learning for privacy-preserving skin disorder detection. By leveraging YOLOv8 for object detection and CNN for classification, the proposed system achieves a global accuracy of 95%, significantly outperforming traditional models. The federated learning approach eliminates the need for centralized data storage, ensuring patient data privacy and compliance with medical data security regulations. Additionally, the Flask-based web application enables real-time, user-friendly diagnosis, making it accessible to dermatologists and telemedicine platforms. Future work will focus on expanding the dataset, integrating explainability techniques (e.g., Grad-CAM), and optimizing model performance using advanced federated learning techniques.

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