

AI-powered Django Framework for Multi-class Classification of Skin Disease for Enhanced Diagnosis

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ABSTRACT

Skin cancer and related dermatological conditions are among the most common health issues worldwide. Early detection is critical for effective treatment, yet manual diagnosis relies heavily on specialist availability and subjective visual assessment. Dermoscopic imaging has improved diagnostic accuracy but still depends on expert interpretation, limiting accessibility and consistency. Therefore, this research presents an AI-powered web application for automated skin disease classification, integrating a Django-based user interface with a deep Convolutional Neural Network (CNN) for image analysis. The core CNN, implemented in Keras with TensorFlow, comprises two convolutional layers (32 filters, 3×3 kernels) each followed by 2×2 max-pooling, a flattening layer, a dense layer with 256 neurons (ReLU activation), and a softmax output layer classifying nine skin disease categories (e.g., Melanoma, Basal Cell Carcinoma). Proposed model performance is evaluated using accuracy, precision, recall, and F1-score computed via scikit-learn, and a confusion matrix visualized with Seaborn. Upon prediction, the system annotates the original image with the detected disease label and displays it to the user. This end-to-end solution addresses limitations of manual dermatological diagnosis, such as subjectivity, limited access, and high costs, by offering rapid, consistent, and scalable screening. The modular design separates web and AI components, facilitating maintenance and future enhancements. Ultimately, the application demonstrates how deep learning and web technologies can converge to provide accessible, accurate diagnostic support in dermatology.

Keywords: Dermoscopic images, Skin disease, Artificial intelligence, Deep learning, Convolutional neural networks.

1. INTRODUCTION

Since the 1970s, skin cancer has held the title of the most prevalent disease globally. Over the previous several decades, there has been an uptick in people diagnosed with nonmelanoma and melanoma skin cancers, respectively. Melanoma can be identified in that only one in three cases of cancer, as stated by the World Health Organization (WHO), and according to statistics provided by the Skin Cancer Foundation, one out of every five people in the United States will develop skin cancer at some point during their lifetime. For the past several centuries, the incidence of skin cancer has risen at a relatively constant rate, particularly in the Western hemisphere. Countries such as the United States, Canada, and Australia are just some of the places where this trend has been observed. Infectious diseases of the skin typically have the potential to have a significant detrimental effect on the overall health of people all over the world. According to one piece of a study released in 2017, multiple studies have demonstrated that skin cancer is responsible for 1.79 percent of the disease burden assessed in disability-adjusted life years on a global scale [1]. The incidence of skin cancer accounts for around 7 percent of all newly diagnosed instances of cancer worldwide [2], resulting in a loss of more than \$8 billion for the Medicare program in the United States in 2011. Clinical data suggest that there are such disparities in results based on race in the case of skin cancer: Even though people with darker skin tones are approximately

20 to 30 times as likely to develop melanoma than those who have lighter skin tones, it has been discovered that people with darker skin tones either have a higher or lower mortality risk for specific types of melanomas, depending on their skin tone.

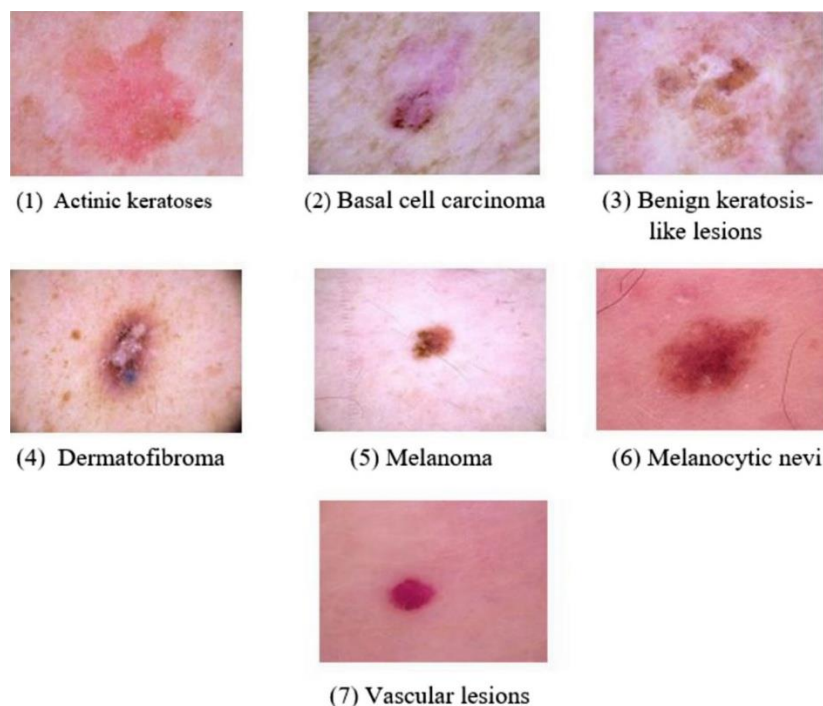


Fig. 1: Types of skin cancers.

The motivation behind this research is driven by the need to leverage advances in artificial intelligence and deep learning to enhance the accuracy and efficiency of skin disease diagnosis. With the proliferation of digital imaging and the availability of large datasets, deep Convolutional Neural Networks (CNNs) have shown remarkable success in image classification tasks. This project aims to harness these advancements to build an AI-powered system capable of detecting skin cancer and other skin conditions from images. The prospect of reducing diagnostic errors, supporting clinicians, and facilitating early intervention serves as a powerful incentive to pursue this research, as it promises to bridge the gap between complex visual diagnosis and accessible healthcare solutions.

2. LITERATURE SURVEY

Hameed et al. [3] implemented using a hybrid approach i.e. using deep convolution neural network and error-correcting output codes (ECOC) support vector machine (SVM). The proposed scheme is designed, implemented and tested to classify skin lesion image into one of five categories, i.e. healthy, acne, eczema, benign, or malignant melanoma. Experiments were performed on 9,144 images obtained from different sources. AlexNET, a pre-trained CNN model was used to extract the features. For classification, the ECOC SVM classifier was used. Using ECOC SVM, the overall accuracy achieved is 86.21%. 10-fold cross validation technique was used to avoid overfitting. The results indicate that features obtained from the convolutional neural network can enhance the classification performance of multiple skin lesions.

Aldhyani et al. [4] proposed a CNN-based model with efficient utilization of kernels and activation functions. The proposed model has shown a remarkable class-wise (seven classes) accuracy and overall accuracy of 97.85% on the test dataset with fewer parameters than is standard (172,363). The proposed model can also be used for disease classification with a dataset that has more classes. The model still has room for more accurate prediction of benign keratosis-like lesions, melanoma, and melanocytic

nevi classes of skin lesions. Vakili et al. [5] focused on primary skin lesion classification, particularly early-stage detection, and present a deep learning approach to classify images containing skin lesions, macule, nodule, papule, plaque pustule, wheal, and bulla. This framework applied deep learning techniques for classifying such images into seven classes covering the types of lesions. This work performed experiments on pre-trained deep convolutional neural network models to find the most accuracy one. The result showed that the pre-trained model ResNet-50 after the training and testing can achieve satisfactory accuracy of 85.95%.

Iqbal et al. [6] developed, implemented, and calibrated an advanced deep learning model in the context of automated multi-class classification of skin lesions. The proposed Deep Convolutional Neural Network (DCNN) model is carefully designed with several layers, and multiple filter sizes, but fewer filters and parameters to improve efficacy and performance. Dermoscopic images are acquired from the International Skin Imaging Collaboration databases (ISIC-17, ISIC-18, and ISIC-19) for experiments. The experimental results of the proposed DCNN approach are presented in terms of precision, sensitivity, specificity, and other metrics. Specifically, it attains 94 % precision, 93 % sensitivity, and 91 % specificity in ISIC-17. It is demonstrated by the experimental results that this proposed DCNN approach outperforms state-of-the-art algorithms, exhibiting 0.964 area under the receiver operating characteristics (AUROC) in ISIC-17 for the classification of skin lesions and can be used to assist dermatologists in classifying skin lesions. As a result, this proposed approach provides a novel and feasible way for automating and expediting the skin lesion classification task as well as saving effort, time, and human life.

Chaturvedi et al. [7] proposed an automated computer-aided diagnosis system for multi-class skin (MCS) cancer classification with an exceptionally high accuracy. The proposed method outperformed both expert dermatologists and contemporary deep learning methods for MCS cancer classification. This work performed fine-tuning over seven classes of HAM10000 dataset and conducted a comparative study to analyse the performance of five pre-trained convolutional neural networks (CNNs) and four ensemble models. The maximum accuracy of 93.20% for individual model amongst the set of models whereas maximum accuracy of 92.83% for ensemble model is reported in this paper. This framework proposed use of ResNeXt101 for the MCS cancer classification owing to its optimized architecture and ability to gain higher accuracy.

Anjum et al. [8] proposed the ensemble CNN models for skin lesion detection. In the localization method, ONNX and squeeze Net model is used as a backbone of the YOLOv2 model. The configuration parameters of the segmentation model are selected after the extensive experiment for accurate lesion segmentation. The segmentation method achieves Global Accuracy of 0.93, 0.95 on ISBI 2017, and ISBI 2018 respectively. The skin lesion classification is performed by applying ResNet-18 model and deep features are extracted by cross entropy activation function. Later, extracted features vectors are enhanced by using ACO method. The hybrid classification approach provided good classification results compared to the recent existing work.

Anand et al. [9] proposed a transfer learning-based model with help of pre-trained Xception model. The Xception model was modified by adding layers such as one pooling layer, two dense layers and one dropout layer. A new Fully Connected (FC) layer changed the original Fully Connected (FC) layer with seven skin disease classes. The proposed model has been evaluated on a HAM10000 dataset with large class imbalances. The data augmentation techniques were applied to overcome the unbalancing in the dataset. The new results showed that the model has attained an accuracy of 96.40% for classifying skin diseases. The proposed model is working best on Benign Keratosis and the values of precision, sensitivity and F1 score are 99%, 97% and 0.98 respectively. This method can provide patients and

doctors with a good notion of whether or not medical assistance is required, thus avoiding undue stress and false alarms.

Srinivasu et al. [10] proposed a computerized process of classifying skin disease through deep learning based MobileNet V2 and Long Short-Term Memory (LSTM). The MobileNet V2 model proved to be efficient with better accuracy that can work on lightweight computational devices. The proposed model is efficient in maintaining stateful information for precise predictions. A grey-level co-occurrence matrix is used for assessing the progress of diseased growth. The performance has been compared against other state-of-the-art models such as Fine-Tuned Neural Networks (FTNN), Convolutional Neural Network (CNN), Very Deep Convolutional Networks for Large-Scale Image Recognition developed by Visual Geometry Group (VGG), and convolutional neural network architecture that expanded with few changes.

Shanthi et al. [11] utilized the Convolutional Neural Network (CNN) used in this paper around 11 layers viz., Convolution Layer, Activation Layer, Pooling Layer, Fully Connected Layer and Soft-Max Classifier. Images from the DermNet database are used for validating the architecture. The database comprised all types of skin diseases out of which we have considered four different types of skin diseases like Acne, Keratosis, Eczema herpeticum, Urticaria with each class containing around 30 to 60 different samples. The challenge in automating the process includes the variation of skin tones, location of the disease, specifications of the image acquisition system etc., The proposed CNN Classifier results in an accuracy of 98.6% to 99.04%.

Allugunti et al. [12] shown a deep learning technique for reliably diagnosing the type of melanoma present at a preliminary phase. The proposed model makes a distinction between lesion maligna, superficial spreading, and nodular melanoma. This permits the early diagnosis of the virus and the quick isolation and therapy necessary to stop the transmission of infection further. Deep learning (DL) and the standard non-parametric machine learning method are exemplified in the deep layer topologies of the convolutional neural network (CNN), which are neural network algorithms. The effectiveness of a CNN classifier was evaluated using data retrieved from the website <https://dermnetnz.org/>. The outcomes of the experiments show that the proposed method is superior in terms of diagnostic accuracy compared to the methodologies that are currently considered state of the art.

3. PROPOSED SYSTEM

In this project we are using CNN (convolution neural networks) to classify skin diseases from images as CNN gains lots of success and popularity in the field of image classification as shown in Fig. 2. To train CNN we have used skin disease dataset which contains 9 different types of diseases such as 'Actinic Keratosis', 'Basal Cell Carcinoma', 'Dermatofibroma', 'Melanoma', 'Nevus', 'Pigmented Benign Keratosis', 'Seborrheic Keratosis', 'Squamous Cell Carcinoma' and 'Vascular Lesion'. After training CNN algorithm, we can upload any test image then CNN will detect and classify disease from that image. The overview of proposed skin disease detection and classification system is as follows:

1. Web Application Framework: The project is built using the Django web framework, a high-level Python web framework that encourages rapid development and clean, pragmatic design.
2. Skin Disease Classification: The core functionality of the project involves skin disease prediction and classification using a pre-trained Convolutional Neural Network (CNN) model.
3. Model and Training:

— The CNN model is trained and saved using the Keras library. The model architecture is defined with convolutional layers, pooling layers, dense layers, and activation functions.

- The training data (X and Y) is loaded from files, and the model is either trained or loaded from existing files.
4. Image Processing: The project involves image processing using OpenCV (cv2). Images are resized, normalized, and used as input to the CNN model for disease classification.
 5. Database Integration:
 - The application interacts with a MySQL database to manage user registration and login information.
 - The skindisease database is created, and a register table is defined to store user details, including username, password, contact, email, and address.
 6. User Authentication and Authorization:
 - User registration and login functionality is implemented.
 - Usernames are checked for uniqueness, and registration details are stored in the MySQL database.
 7. Web Templates: The application uses Django templates for rendering HTML pages. Templates like DiseasePrediction.html, ViewOutput.html, index.html, Login.html, and Register.html are mentioned.
 8. Data Visualization: The project uses libraries like seaborn and matplotlib for visualizing the confusion matrix and other metrics related to the CNN model's performance.
 9. Project Structure: The code is organized into functions, each handling specific aspects of the project, such as disease prediction, model evaluation, and user authentication.
 10. External Libraries: The project utilizes various external libraries such as pymysql for MySQL database interaction, numpy for numerical operations, scikit-learn for machine learning metrics, and others.

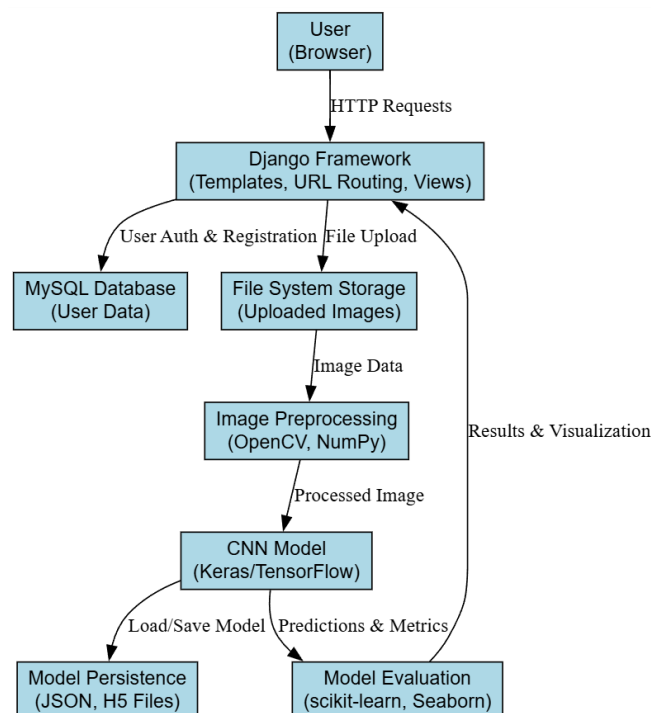


Fig. 2: Block diagram of proposed skin cancer prediction system.

3.1 Proposed CNN model

The deep CNN model as shown in Fig. 3 is designed to classify skin disease images into one of nine classes. It begins with an input layer that accepts images resized to 32×32 pixels with three color channels (RGB). The network then passes the input through a series of layers that progressively extract and refine features:

1. **Convolutional Layers:** The first convolutional layer applies 32 filters of size 3×3 with a ReLU activation function to extract low-level features (such as edges and textures) from the input image. This is followed by a max-pooling layer (pool size of 2×2) that downsamples the feature maps to reduce spatial dimensions and computational complexity. A second set of convolution and max-pooling layers further refines the features by capturing more complex patterns in the image.
2. **Flattening:** After the convolutional and pooling layers, the multidimensional feature maps are flattened into a one-dimensional vector. This transformation prepares the data for the dense (fully connected) layers.
3. **Dense Layers:** The flattened vector is passed to a fully connected (dense) layer with 256 neurons, using ReLU activation. This layer learns complex, non-linear combinations of the features extracted by the previous layers.
4. **Output Layer:** Finally, the model includes a dense output layer with a softmax activation function. This layer produces a probability distribution over the nine skin disease classes, with the highest probability indicating the predicted class.

The model is compiled using the Adam optimizer and categorical cross-entropy loss, and it is trained on preprocessed image data. Once trained, the model can be saved and later loaded for predictions on new images.

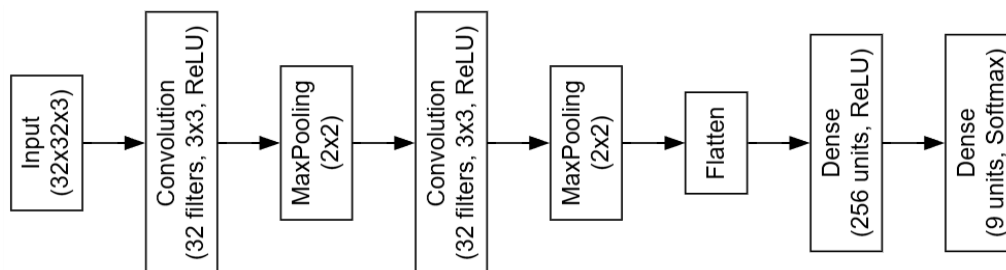


Fig. 3: Proposed deep CNN architecture.

4. RESULTS AND DISCUSSION

This work has a database named skindisease and a table named register. Here's a detailed description of the database and table:

- Create Database: This SQL statement creates a new database named skindisease.
- Use Database: This statement selects the skindisease database for subsequent operations.
- Create Table: The register table is created with the following columns:
 - username: A variable character (VARCHAR) field with a maximum length of 30 characters, used as the primary key.
 - password: A VARCHAR field with a maximum length of 30 characters to store user passwords.

- contact: A VARCHAR field with a maximum length of 12 characters to store contact information.
- email: A VARCHAR field with a maximum length of 30 characters to store user email addresses.
- address: A VARCHAR field with a maximum length of 40 characters to store user addresses.

The username field is defined as the primary key, ensuring that each username is unique in the table. This database schema is designed to store user registration information, including usernames, passwords, contact details, email addresses, and addresses. The username field serves as a unique identifier for each user in the register table. Fig. 4 presents the overall user interface of the web application. It showcases a clean, intuitive layout where users can navigate through various functionalities such as account management, image upload for disease prediction, and viewing performance metrics. The design emphasizes ease of use, ensuring that even non-technical users can interact with the system effectively. The user signup page is depicted in Fig. 5. It provides input fields for new users to enter details such as username, password, contact information, email, and address. This page is designed to ensure that all required information is captured accurately, with validation mechanisms in place to prevent duplicate registrations or incomplete submissions.

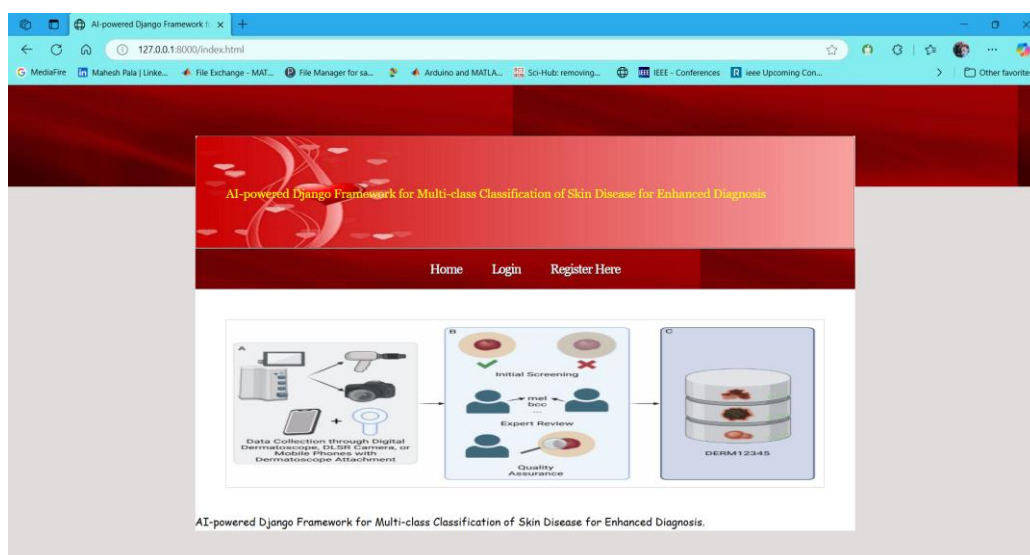


Fig. 4: Web application of proposed AI-powered skin cancer prediction system.

Fig. 6 shows the confirmation page that appears once a user successfully completes the signup process. The page typically displays a success message along with further instructions, ensuring that users are informed that their account creation was successful and may now proceed to log in. The user login page shown in Fig. 9.4 provides a secure entry point into the system. It contains fields for the username and password. The design is streamlined to focus on authentication and secure access. After a successful login, the system displays an updated user interface with a navigation bar (navbar) that includes tasks such as "Build and Train Deep CNN," "Disease Prediction," and "Logout." Fig. 9.5 illustrates the post-login state where users have access to key functionalities, enabling them to either train the model, make predictions, or exit the system.

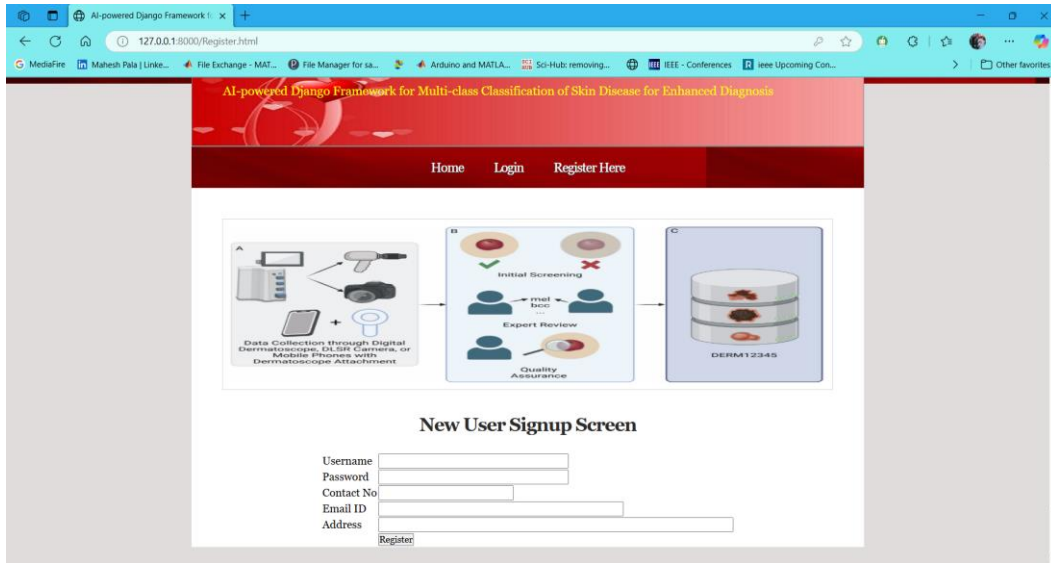


Fig. 5: User signup page.

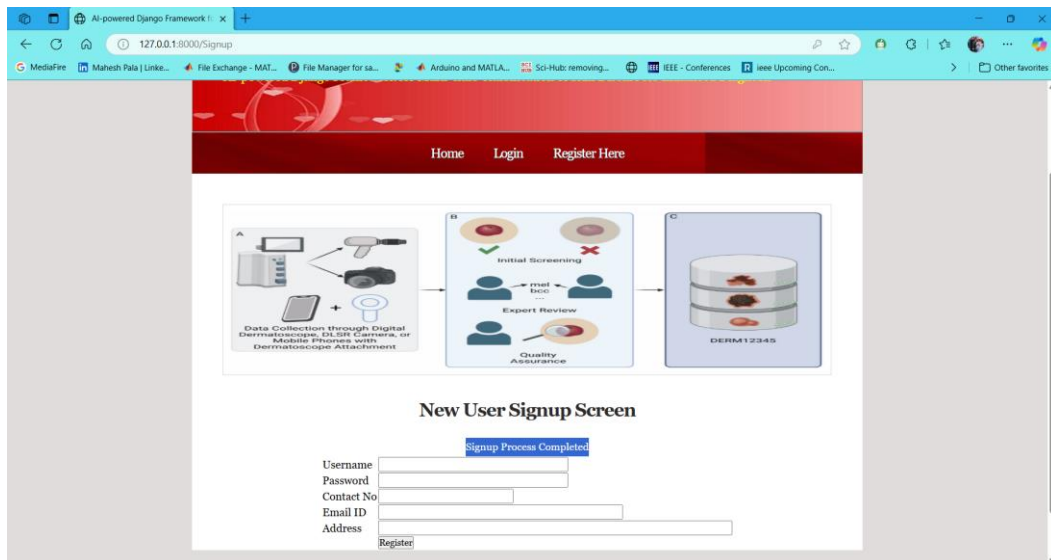


Fig. 6: Successful signup completion page.

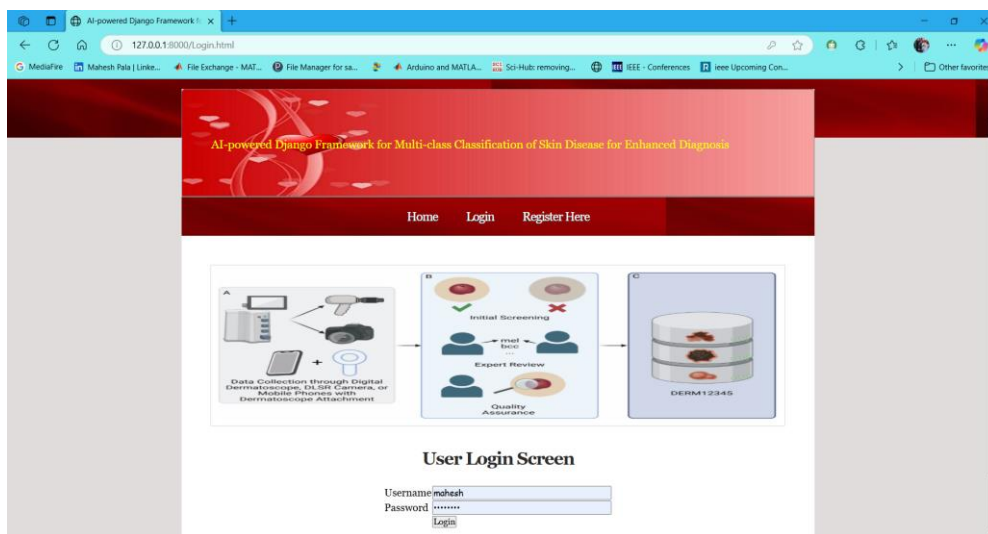


Fig. 7: User login page.

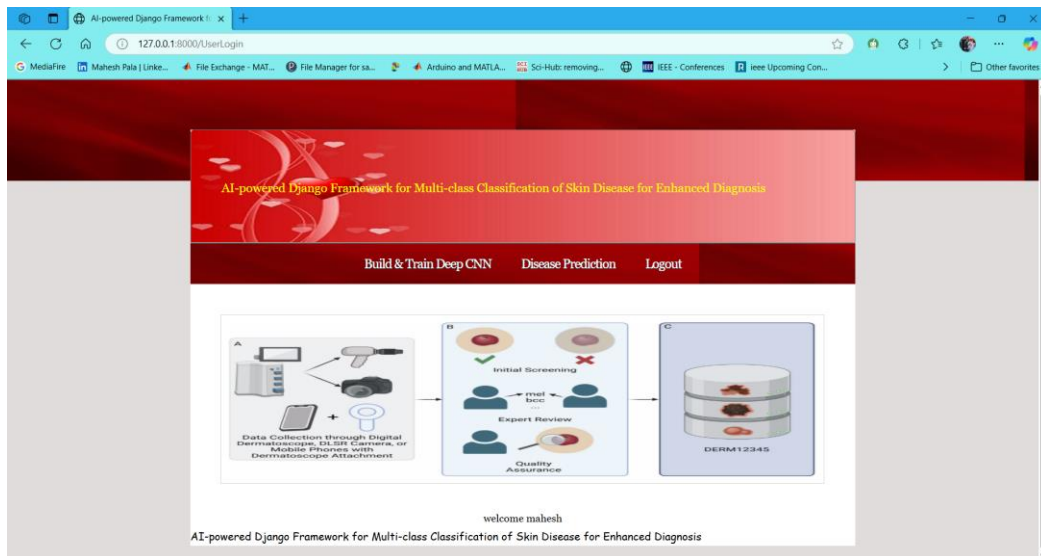


Fig. 8: User login page showing navbar tasks build and train deep CNN, disease prediction, and logout after successful login of user.

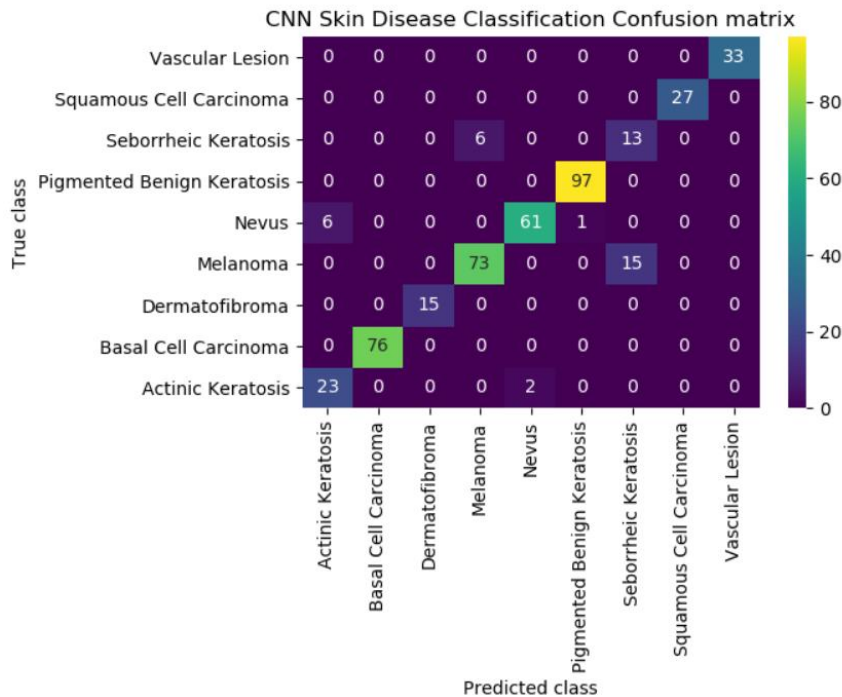


Fig. 9: Confusion matrix obtained using proposed deep CNN model.

The confusion matrix is visualized in Fig. 9, offering insight into the performance of the deep CNN model across different skin disease classes. The matrix helps to identify how often predictions are correctly made versus misclassifications, making it a critical tool for evaluating model accuracy and diagnosing areas for improvement. Fig. 10 presents the performance metrics generated by the deep CNN model, such as accuracy, precision, recall, and F1-score. The metrics are displayed in a tabular format within the web application, providing users and developers with a clear summary of the model’s effectiveness in classifying skin diseases.

Fig. 11 displays the console output or diagram that illustrates the layered architecture of the deep CNN model. It typically details the sequence of layers—from input through convolutional, pooling,

flattening, and dense layers—demonstrating the internal structure and flow of data within the model. In Fig. 12, the disease prediction page is designed for users to upload skin images and initiate the prediction process. This page guides the user through selecting an image, submitting it for analysis, and then receiving a visual result with an overlay that indicates the predicted skin disease class. Fig. 13 showcases examples of the system’s output when test images are processed. The images are annotated with the predicted disease labels, allowing users to see the practical application of the model. This figure serves as a demonstration of the system’s predictive capability and its real-world relevance for skin disease diagnosis.



Fig. 10: Web application displaying the performance metrics of deep CNN model.

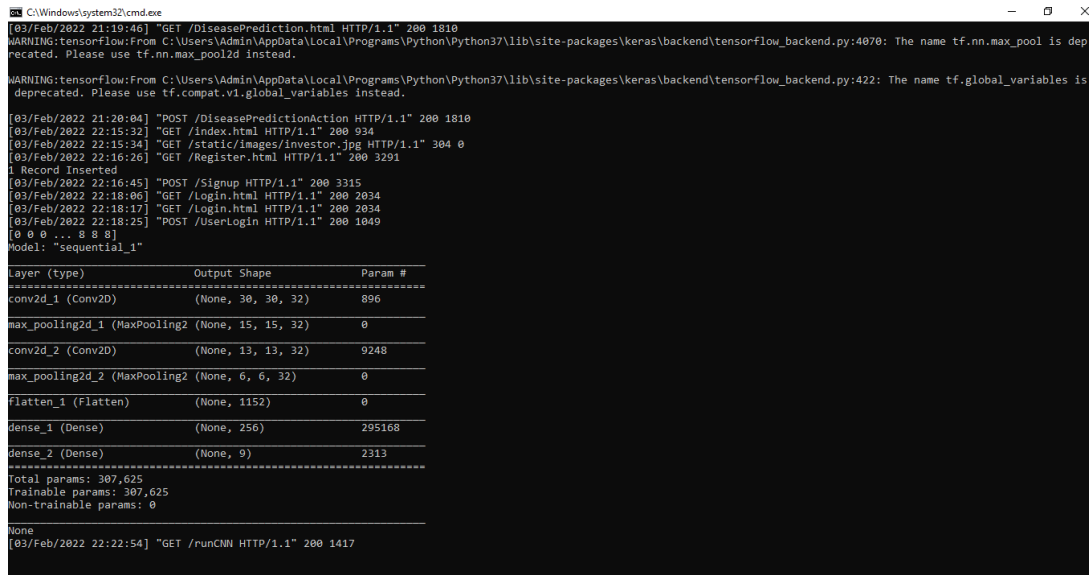


Fig. 11: Console showing the layered architecture of proposed deep CNN model.

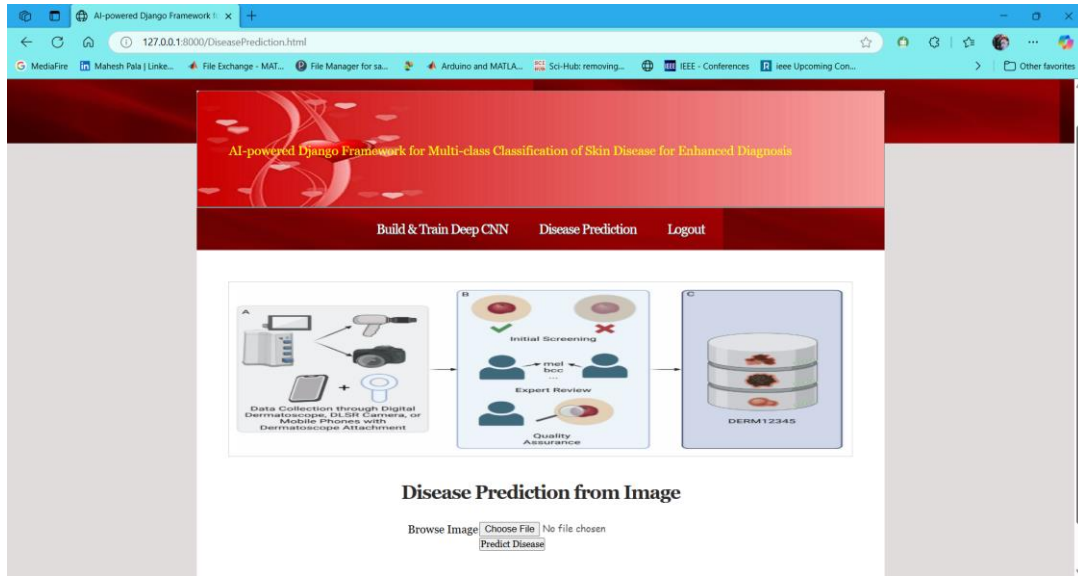


Fig. 12: Disease prediction page.

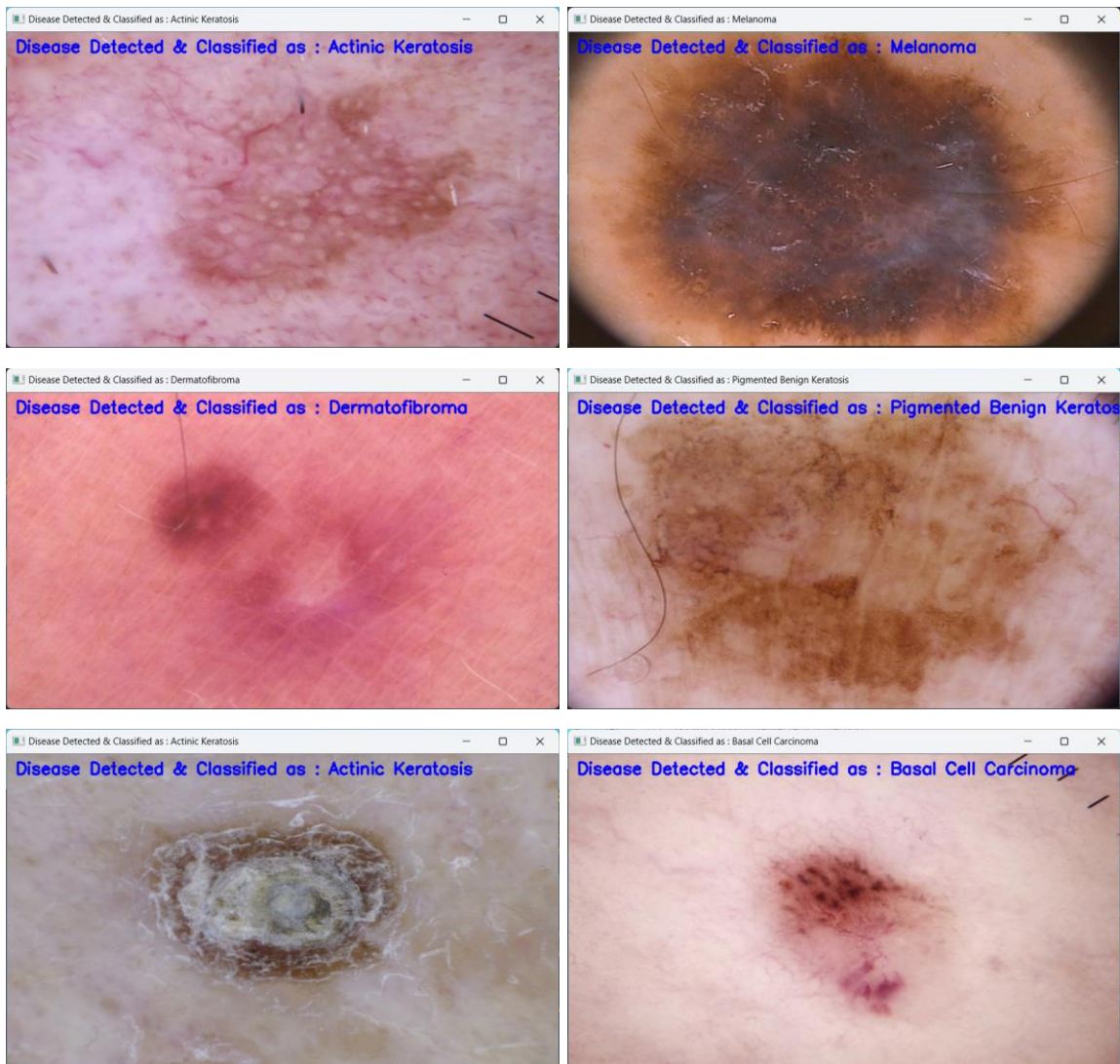


Fig. 13: Sample predictions on test images.

5. CONCLUSION

This research is a comprehensive web application designed for skin disease prediction and classification. Leveraging the Django web framework, it seamlessly integrates machine learning capabilities, user authentication, and MySQL database management. The core functionality centers around a deep CNN trained on skin disease images to provide accurate predictions. The CNN model is equipped with image processing features, employing OpenCV for tasks such as image resizing and normalization. User interaction is a key aspect of the application, featuring a user-friendly interface for disease prediction. Users can input images to receive dynamic and real-time classification results. The project incorporates user authentication through a MySQL database, ensuring secure user registration and login functionalities. The database stores user details, including usernames, passwords, contact information, email addresses, and physical addresses. In addition to disease prediction, the application includes comprehensive machine learning metrics such as precision, recall, F1 score, and accuracy. Visualizations, powered by libraries like scikit-learn, seaborn, and matplotlib, present a clear understanding of the CNN model's performance, with a focus on the confusion matrix. The code structure adheres to best practices in Django development, with functions logically organized to handle diverse aspects of the application. Overall, this project serves as a powerful tool for both healthcare professionals and technology enthusiasts, offering an efficient and interactive solution for skin disease analysis.

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