Skin Disease Prediction

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***Abstract*— Skin diseases affect millions of people globally, which makes precise diagnosis methods crucial. Traditional diagnostic approaches sometimes suffer from time and accuracy restrictions. To overcome these limitations, our research presents a deep learning-based prognostic model for skin conditions. To achieve better classification accuracy, we employ a range of machine learning methods in conjunction with feature selection and ensemble learning techniques. We employ a user-friendly, web-based framework created with the Python programming language Flask. Experts can instantly detect skin health issues by uploading images to this portal with ease. We achieve a high accuracy rate of 95% by combining MobileNet classifiers with Convolutional Neural Networks (CNN) to produce precise predictions.**

Keywords*— *Skin diseases, Deep learning, Disease prediction, Convolutional Neural Network (CNN), MobileNet.

I. INTRODUCTION

Skin disorders are a serious worldwide health concern because they affect people of all ages and demographics [1]. Environmental factors and changes in lifestyle have been linked to the increased prevalence of these disorders [2]. Notably, some populations like Indians carry a disproportionate amount of the load; they rank among the top ten most affected countries worldwide [3]. In contrast, studies conducted in the United States show that a significant portion of the population roughly one in five has dermatitis in one form or another [4]. Complex factors such as immune system anomalies, hormone abnormalities, and cellular dynamics may influence the development of skin issues [5]. The complexity of treating and managing severe and chronic conditions like eczema and psoriasis emphasizes the need of early detection [6].

In an attempt to address the growing need for accurate and timely diagnosis of skin disease, efforts have been focused on enhanced diagnostic technologies. Convolutional Neural Networks (CNNs) and MobileNet algorithms, two deep learning techniques, have gained popularity as potentially useful instruments for automated skin disease diagnosis [7]. These advanced models have impressive skills to analyze images of skin lesions, providing opportunities for future simplification of diagnostic procedures [8]. Nevertheless, the translation of these intricate algorithms into useful clinical tools requires intuitive user interfaces and effective implementation frameworks. In response, our study uses the Flask framework to provide a web-based diagnostic platform that integrates the latest deep learning models, such as CNNs and MobileNet [9]. Our application uses convolutional neural networks to detect skin disease categories from uploaded photos with high accuracy. Our model's scalability and computational efficiency are further improved by integrating the MobileNet architecture, which guarantees quick and accurate diagnostics[10].

Many tasks make use of deep learning neural networks, such as MobileNet and LSTM, for the categorization of skin diseases has produced encouraging results in terms of utilizing cutting-edge architectures for precise diagnosis [11]. Further research has concentrated on one area that needs improvement is the image processing protocols used to identify skin lesion in non contact diagnostic equipment, which has helped to create more efficient diagnostic methods [12]. One important area of research is investigating the effect of picture noise on deep convolutional neural networks for skin lesion classification provides insights into the possibilities and difficulties of improving diagnostic precision [13]. Convolutional neural network is also proven to be a useful and practical method for mobile-based skin lesion categorization, with the potential to provide universal accessibility and ease in diagnostic procedures [14]. The utilization of multi-scale and multi-network ensembles in transfer learning methodologies has demonstrated significant effectiveness in skin lesion classification tasks, underscoring the significance of varied approaches for enhanced diagnostic results [15].

The field of dermatological diagnosis and prediction is constantly changing, as demonstrated by the latest developments in deep learning frameworks and approaches.

II. LITERATURE SERVEY

Z. Diame et al. [1] provide an overview of “Deep Learning Architectures for Aided Melanoma Skin Disease Recognition”. They talk about many approaches and innovations that were presented at the conference held in 2021 focused on advancement in mobile, intelligent, and ubiquitous computing. Important information on melanoma skin cancer statistics is provided by this publication. Conversely, L. Li et al. [2] explore the field of "Deep Learning in Skin Disease Image Recognition: A Review," which was released in 2020 by IEEE Access. Their thorough analysis carefully looks at the developments and deep learning techniques applied practically using picture analysis to diagnose skin disease, offering priceless insights into this rapidly developing area Concurrently, A. Hartatik et al. [3] offer a groundbreaking "Decision Support System for Detection of Skin Diseases in Smart Health Development Planning," which will be showcased at the 2020 Materials Science and Engineering Conference Series, IOP press. By assisting in the diagnosis of skin conditions, this ground-breaking technology hopes to make a substantial contribution to the advancement of smart health technologies.

Going forward, "Skin Cancer Mnist: Ham10000," accessible on Kaggle dataset in September 2018, is a contribution made by K. S. Mader et al. [4] to the field. This dataset provides for training and assessment purpose, this dataset offers a large variety of annotated pictures, making it a vital resources for researchers and practitioners interested in the research of skin cancer. The 2022 Conference on Innovative Computation Technologies featured a topic on "AI Tools for Media Data Governance in the Post-Truth Era: From Abnormal Data Recognition to Intelligent Opinion Monitoring Algorithm," which Y. He et al. [5] discuss and examine. Their work explores the use of AI to media data governance, addressing the complexities of anomalous data identification and intelligent opinion surveillance in the misinformation age Furthermore, results from "Automatic Skin Lesion Segmentation Based on Saliency and Colour" which will be presented convening of the International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications in 2020, presented by G. Ramella et al. [6]. By utilizing colour and saliency information, this research focus on creating an automatic skin lesion segmentation technique that will significantly advance computer-aided diagnosis for dermatological disorders.

R. Karthik et al. [7] present "Eff2Net: An Efficient Channel Attention-Based Convolutional Neural Network for Skin Disease Classification" of Biomedical Signal Processing and Control made significant strides in 2022. In order to accurately detect skin illnesses, this new convolutional neural network architecture incorporates channel attention techniques, which is a significant development in the field of image processing for medicinal purposes. Last but not least, the study of N. B. Muhammad et al. [8] on "Computer-Aided Diagnosis of Skin Diseases using Deep Neural Networks," which was published in Applied Sciences in April 2020, advances the subject. Their research highlights the effectiveness of deep neural networks in automating and precisely diagnosing skin illnesses, providing a potential path for dermatology's computer-aided diagnosis. A. Aldwgeri et al.[9] suggests using a group of deep convolutional neural networks to categorize skin lesions in dermoscopy images. The accuracy and dependability of categorization are enhanced by this ensemble technique. A deep learning method is used by Padmavathi et al. [10] to forecast skin conditions. The paper was published in the International Journal of Recent Technology and Engineering. Their research aids in the creation of models that forecast dermatological disorders in 2020.

The review of the literature highlights important developments in dermatology, especially in recognizing and classifying skin disease. Integrating deep learning methods, such as predictive models and lesion segmentation, has the potential to transform patient care and diagnostic accuracy. These results demonstrate how AI may revolutionize dermatology and pave the way for more investigation and advancement in the field of medicine.

III.METHODOLOGY

The research methodology utilized in this consists of a sequence of procedures meant to create an effective deep learning-based method for classifying and detecting skin disease. This procedure starts with the collection of a large dataset that includes a diverse range of photos that depict various skin diseases. The basis for training and testing the deep learning model is provided by these photographs. A wide range of skin conditions, from typical dermatological problems to more uncommon conditions, are shown in the carefully chosen images.

Once the dataset is put together, the deep learning model's architecture is carefully specified. The selection of an appropriate neural network design and configuration is necessary to effectively classify skin conditions. The architecture is designed with specific consideration for dermatological imaging because of its complexity and variation. The chosen design is then adjusted and improved to satisfy the particular requirements of the classification of skin conditions. This can mean adding more layers, adjusting parameters, and including logistic regression components to increase the model's predictive potential.

To get ready for model training, the dataset is subjected to additional processing. Figure 1 represents the involves actions to guarantee consistency and improve the generalization capacity of the model, like scaling, normalization, and data augmentation. After that, several subsets of the dataset are separated out for training, validation, and testing. The validation subset is used to assess the performance of the model and modify hyperparameters to avoid overfitting, whilst the training subset teaches the model how to map input photos to the proper illness diagnoses. Lastly, the testing subset is used to evaluate how well the model generalizes and how ready it is to be used in practical situations. The intention behind this thorough approach is a solid and dependable deep learning system with precise recognition and classification of skin diseases.

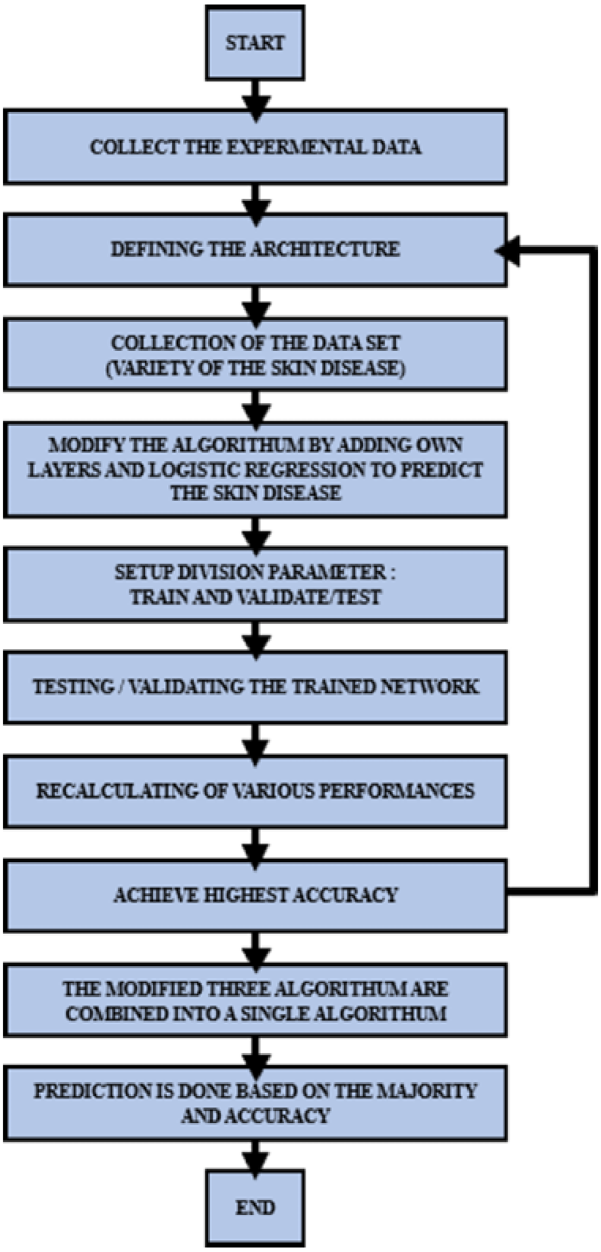

Fig. 1. Overview of the Methodology Applied

A . Dataset Analysis

The HAM10000 dataset, which includes a wide range of skin disorders such as Actinic Keratoses, Benign Keratosis, Basal Cell Carcinoma, melanoma, Dermatofibroma, melanocytic nevi, and vascular Naevus. this dataset provides an extensive picture of dermatological pathology. It is clear that every image in the dataset has a ground truth label that specifies the exact kind of skin lesion it represents. The below table 1 represents different types of Skin Disease classes represents in data set.

Table 1. Types of Skin Disease Classes

S. No	Disease Name
1	Actinic Keratoses
2	Basal Cell Carcinoma
3	Benign Keratosis
4	Dermatofibroma
5	Melanoma
6	Melanocytic Nevi
7	Vascular Naevus

B. Dataset Visualization

A Graphical representation which is visual representation of dataset is made in order to get brief understanding and visualization of different types of skin disease as shown figure 2.

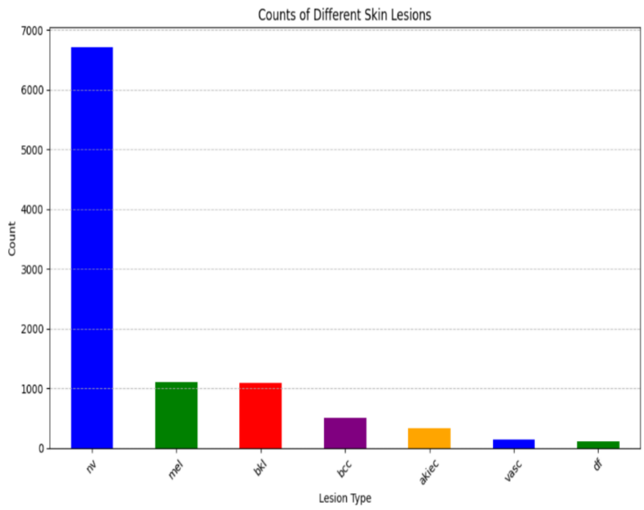

Fig. 2. Counts the Dataset Class Labels.

Figure 3 provides a comprehensive overview of various skin conditions within our dataset, including vascular lesions, dermatofibroma, melanocytic nevi, basal cell carcinoma, actinic keratoses, and intraepithelial carcinoma. To aid comprehension, displaying sample images representing each class alongside the summary would offer researchers a tangible reference for understanding the dataset's composition.

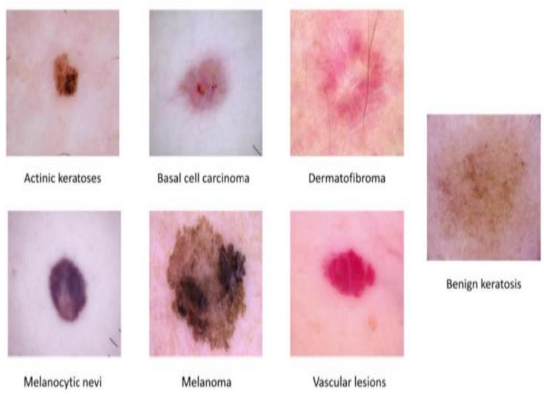

Fig. 3. Visualizing sample images in Dataset

C. Pre-Processing Technique

Preprocessing an image is a series of consecutive operations intended to improve the image's quality and remove pertinent components required for additional analysis. These processes refine the raw input data for better interpretability and effectiveness across a variety of applications, particularly computer vision, medical imaging, and remote sensing. All phases from scaling and normalization to more intricate techniques like data augmentation help to enhance the input data's quality, reduce noise, standardize features, and boost the derived features' discriminating power. This methodical approach not only offers robustness against changes in input data but also facilitates the extraction of relevant patterns and structures, which in turn enables tasks such as object detection and picture classification. Figure 4 represents the step-by-step process of the pre-processing.

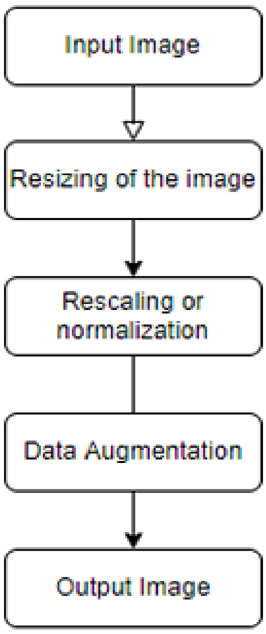

Fig. 4. Overall process of Pre-Processing.

The original image is first loaded popular preprocessing method is Gaussian filtering, which is well known for its ability to reduce noise and smooth out images. Functions for applying Gaussian filters are easily accessible in libraries such as scipy or OpenCV. High-frequency noise is reduced and the image becomes smoother and cleaner by convolving it with a Gaussian kernel.

An additional important step in preprocessing is to apply a bilateral filter, frequently with a designated Region of Interest (ROI). Effective noise reduction is achieved using bilateral filtering, which maintains the image's key edges and characteristics. Important visual features are preserved, and computational resources are used more effectively by applying the filter selectively to particular regions of interest. Figure 5 represents levels of filtered images in pre-processing.

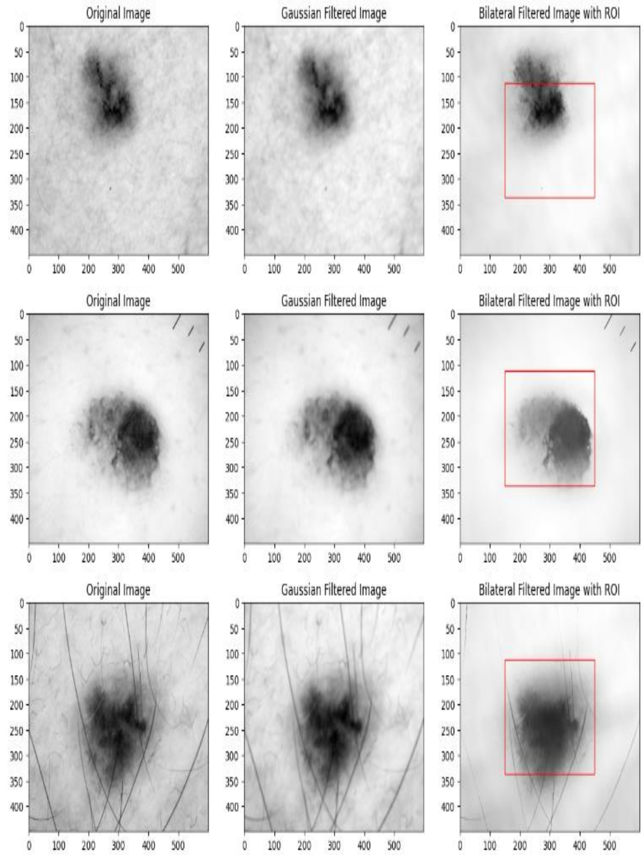

Fig. 5. Filtered Images.

D. Process of Model

The input image, which represents the unprocessed data entered into the system for analysis, is where the process starts. After that, in order to get the input data ready for model training, it goes through preprocessing, The data is divided into several subsets for training, validation, and testing following preprocessing, which includes operations like scaling, normalization, and augmentation. The training dataset is used to teach the MobileNet model how to map input photos to the appropriate labels. Concurrently, the performance of the model is evaluated using the validation dataset to adjust hyperparameters and avoid overfitting.

After training, the model is assessed on the testing dataset to ascertain its generalization ability and preparedness for deployment. Throughout this procedure, MobileNet a deep learning model architecture renowned for its effectiveness and efficiency in picture categorization tasks is employed. During training, the model's parameters are iteratively changed to extract relevant features from input photographs and generate precise predictions. Validation is required to assess the performance of the model and identify potential issues, ensuring that the final deployed model is robust and dependable for image classification tasks. Figure 6 represents overall process of the model.

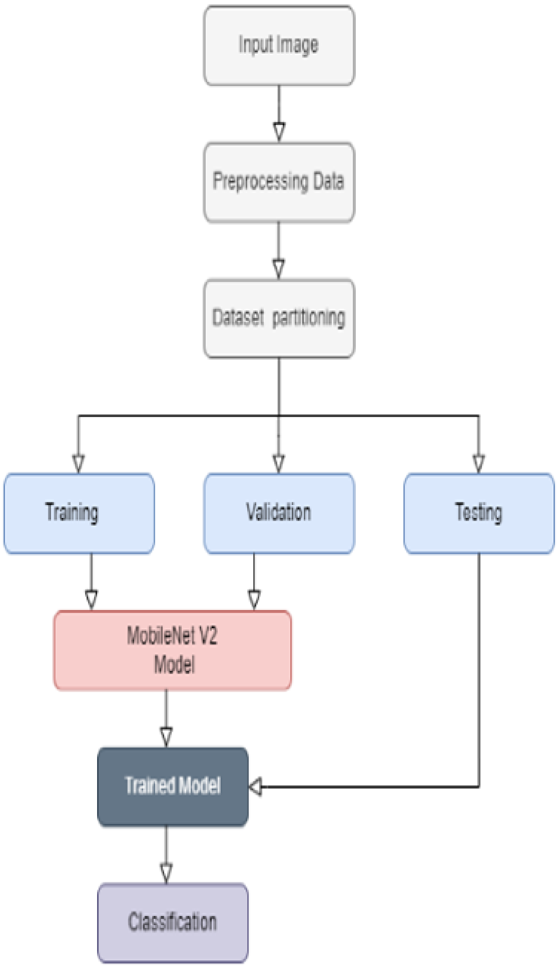

Fig. 6. Overall process of model

E. Evaluation of Model

The methodology uses MobileNet architecture in conjunction with convolutional neural networks (CNNs) to classify skin lesions. Preprocessing the dataset and performing exploratory data analysis are the first steps towards comprehending the distribution of lesion types. Using transfer learning techniques, the pre trained MobileNet model is then utilize to extract features. To further improve classification and refinement, further CNN layers are placed on top of MobileNet. Training is done on the model using dynamic learning rate modifications and adjusted hyperparameters. In order to ensure the resilience and accuracy of the model's classification of skin lesions, validation and evaluation are carried out. We hope to create a trustworthy model for identifying different skin problems with this approach.

Two different models that we have coded for are the first that uses a simple Convolutional Neural Network (CNN) that we designed from scratch, and the second that uses MobileNet, the most advanced CNN architecture, which we learned through transfer learning. Using a model that has been trained for one task as a basis for a different task transfer learning application.

When images are rotated or scaled, CNNs have trouble differentiating between them because they lack rotational and scale invariance. To enhance performance, scaled and rotated versions of the images are included to the training set.

A resilient convolutional neural network architecture called MobileNet, which performs well and is designed with mobile devices in mind. The primary distinction between using a simple CNN and more complex models such as MobileNet is that the latter is pre-trained on a large dataset of millions of photos using robust GPUs and TPUs. We use transfer learning to modify this pre-trained model to fit our particular dataset. By removing hierarchical information from the input images displayed in figure 7, the MobileNet layers allow model to recognize patterns and generate accurate predictions.

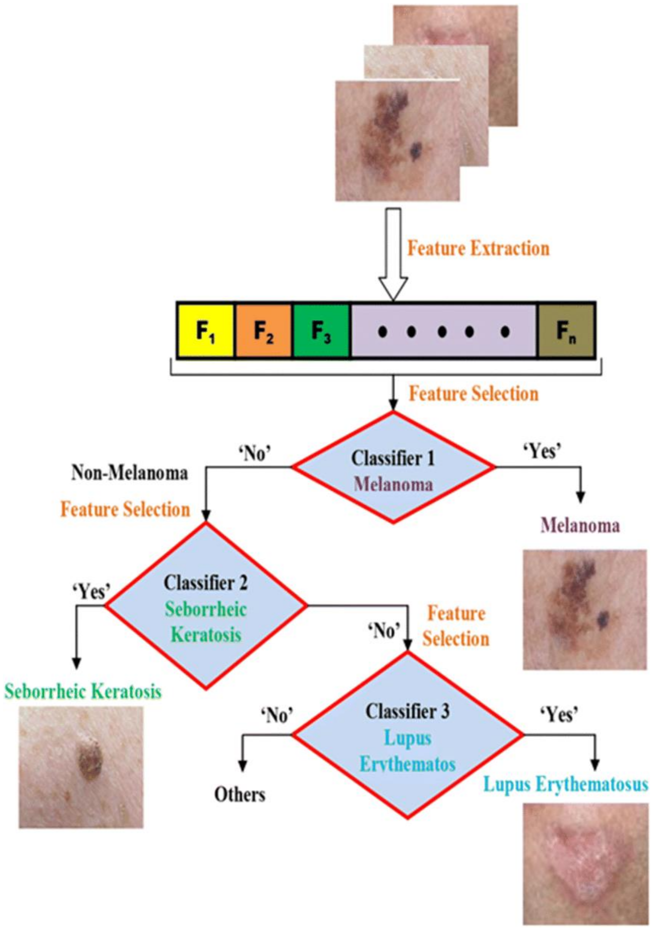

Fig. 7. Overview of Model Prediction

F. Accuracy

In this paper, two methods have been used to detect skin diseases. The system determines and forecasts the type of skin illness classification algorithms. The name of the detected ailment and suggested safety measures are shown by the system upon detection. With the use of this feature, the system can forecast skin conditions in real-world settings with an accuracy of 95%. Figure 8 represents the accuracy values in the model, and Figure 9 represents loss values in the model.

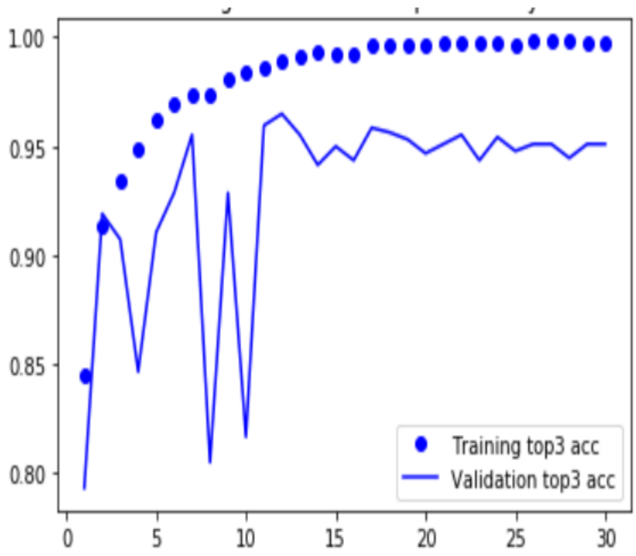

Fig. 8. Accuracy Report.

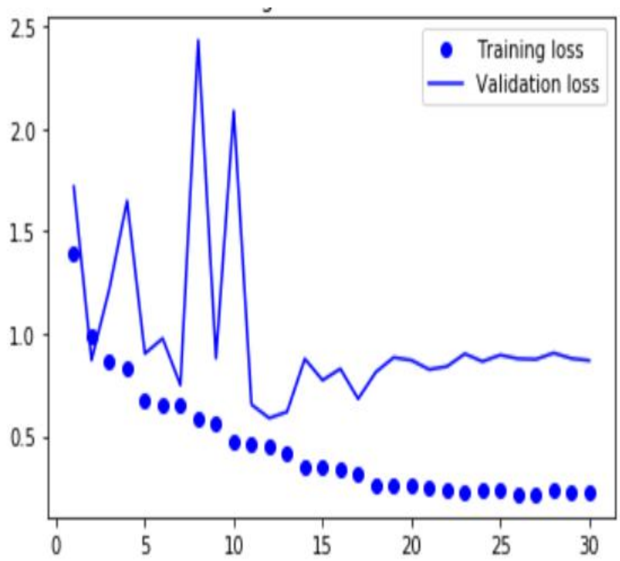

Fig. 9. Loss Report.

IV. CONCLUSION

The creation of a skin disease prediction system that combines CNNs and MobileNet with the Flask framework represents a significant improvement in healthcare accessibility. This approach enhances healthcare results by precisely diagnosing skin abnormalities based on input images, offering pertinent recommendations, and aiding the early discovery and efficient management of skin disorders.

V. RESULT

A. Image Upload

Users have the opportunity to select from pre-existing alternatives or submit an image of a skin lesion. Figure 10 represents the choosing the diseased images.

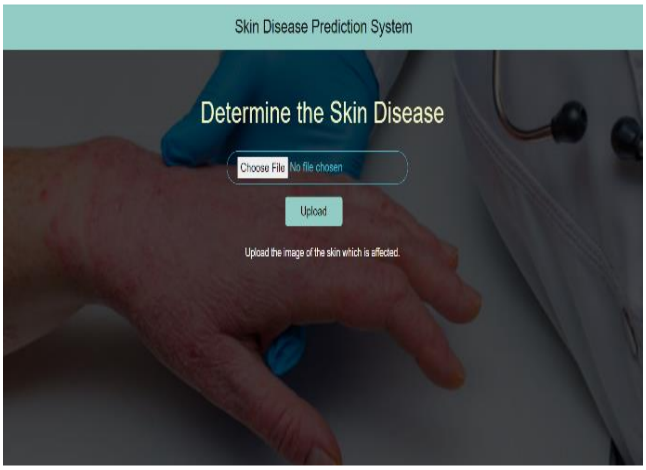

Fig. 10. Choosing file.

B. Display Predicted Image

Figure 11 represents user can click "Upload" to start the analysis after choosing or uploading the image. Upon completion of the prediction, the name of the anticipated skin illness appears on the interface.

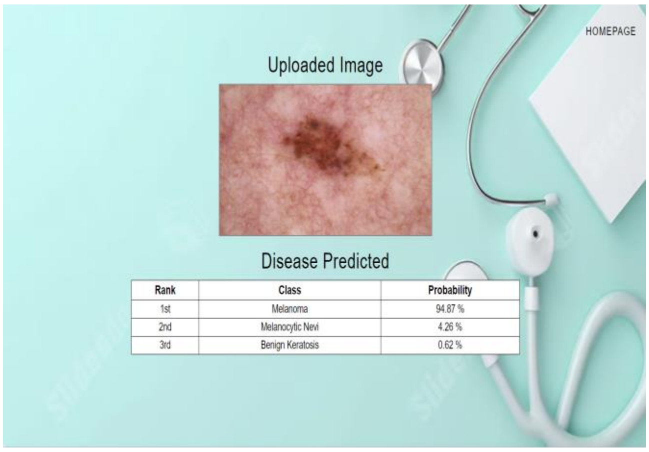

Fig. 11. Predicted Result.

C. Display Precautions.

The system creates and displays recommendations or precautions based on the expected outcome. Figure 12 represents Information regarding possible dangers related to the detected condition as well as recommendations for preventive measures or treatment alternatives may be included in these precautions.

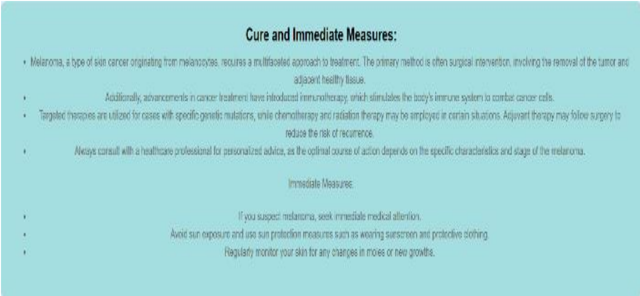

Fig. 12. Precautions.

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