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Intelligent System for Skin Disease Prediction

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ABSTRACT

Being one of our body's primary organs, skin diseases have a significant detrimental impact on our physical and mental well-being and are a growing global health concern. Skin diseases present significant challenges to global health, necessitating timely diagnosis and treatment to mitigate their impact. Leveraging modern technologies such as Artificial Intelligence (Al), Machine Learning (ML), and image processing, Intelligent System for Skin Disease Prediction (ISSDP) have emerged as promising tools to revolutionize dermatological care. This paper provides a succinct overview of the current landscape of skin disease detection and diagnosis, focusing on the development and implementation of ISSDP. By integrating advanced computational techniques including deep learning (DL) architectures, support vector machines (SVM), Convolutional Neural Networks (CNN), and Natural Language Processing (NLP), ISSDP enhances the precision, effectiveness, and accessibility of dermatological care. Key components of ISSDP include image classification, symptom identification, treatment recommendation, and feedback analysis, catering to both the public and healthcare professionals. Through multidisciplinary research integration, this paper elucidates the potential impact of technological advancements in dermatological care. By continuously learning from user feedback and treatment outcomes, ISSDP evolves to refine its diagnostic capabilities over time. In conclusion, ISSDP represents a significant advancement in dermatological care, offering proactive skin health management and promising avenues for improving patient outcomes worldwide.

Keywords: Skin diseases, Image processing, Machine learning, Convolutional neural networks, Natural language processing, Treatment recommendations, Feedback analysis

INTRODUCTION

Nowadays, skin disease among humans has become a common disease, a lot of people are suffering various kinds of skin diseases. Typically, these diseases have hidden dangers which will lead to not only lack of self-confidence and depression but also it leads to skin cancer also. According to the world health organization (WHO), around 31% to 73% of the population has fallen victim to skin diseases. And most of these individuals don't know much about the classification of skin disease. Early diagnosis is therefore crucial to minimizing the severity and spread. Skin diseases are more time- consuming to diagnose and treat, and they come with high costs for the patients. Acute skin lesions have a window of opportunity to spread, progress to an infectious stage, and eventually turn into skin cancers (Swathi et al., 2023). This is a result of the general public's ignorance of medical information regarding skin lesions. In order for medical professionals to confidently treat patients, they also need to order costly medical lab tests in order to promptly and precisely identify lesions. It goes without saying that patients should receive treatment before their condition worsens because skin is a highly visible portion of the body and worsening conditions can seriously impair a patient's psychological state and general well-being.

Therefore, the development of technology in this day and age, such as lasers and photonics-based medical technology, has made it possible to diagnose skin lesions much more quickly and accurately and to avoid potentially dangerous complications. These computational techniques include CNN, NLP, SVM models, and DL (Hasan et al., 2021) to capture dermatological images and then augmenting the diagnostic data of patients, for a better management system (Kemal & Kaan, 2020). In this 21st century AI system plays a major role on enhancing the accuracy and efficiency on proper diagnosing skin diseases by intelligent skin disease detection systems. They can enable accurate evaluations, prompt interventions, and individualized treatment suggestions.

When the system is available to everyone the users can easily identify the disease, including various type of skin diseases like Acne, Rosacea, Eczema, Atopic dermatitis. It can be more effectively treated detected early. A detection system can assist in identifying potential skin abnormalities or lesions at an early stage, allowing for timely medical intervention. This paper provides a detailed review of existing literature using intelligent systems on diagnosis skin diseases, elucidates the methodology behind ISSDP, and examines its core components, including image classification, symptom identification, treatment recommendation and feedback analysis. It identifies deep varieties of skin diseases such like Acne, Rosace, Eczema etc. are all diagnosed by this system.

In summary, this review highlights how the medical system, when combined with technology, presents unseen possibilities for addressing the identified problems brought on by skin disorders, ultimately improving patient outcomes. We provide a skin disease diagnosis approach related to image processing there already and techniques because our suggested solution is simple, quick, and does not require the purchase of expensive equipment beyond a photographic camera and a system computer.

LITERATURE REVIEW

Skin diseases are becoming a major global threat due to their rapid spread. Skin conditions can progress to a deadly type of cancer called "melanoma" if left untreated. Because of its complexity, melanoma is difficult to diagnose. Therefore, a study proposed a skin cancer detection system using VGG 16, InceptionV3 and ResNet. This computer vision-based methods have been proposed as an alternative, with the potential to provide more accurate diagnosis. In this they have mentioned that a dataset consisting of 10,500 skin cancer images from the International Skin Imaging Collaboration (ISIC) was created by selecting images from 7 different skin cancer categories. Three CNN models, namely VGG16 and I nceptionV3 were trained on this dataset to classify skin cancer. Based on the experimental results, this review validates that the proposed model performs admirably in accurately classifying skin cancer, and the obtained results are acceptable when compared to other modern methods (Swathi et al., 2023).

As per studies cancer has become the commonest condition among the population. Benign and malignant types are the most common people suffer from. The public undergoes costly and time-consuming medical procedures in an attempt to heal, but the death rate remains unchanged. Early identification of the cancer when it is still in its early stages may reduce the death rate. A review study on comparative analysis of skin cancer (Benign vs. Malignant) detection using CNN, done to find skin cancer through image classification more accurately. Pertained models like VGG16, SVM, ResNet50 and self-built models (sequential) are used to analyze the process of CNN models in this study. An image dataset of 6594 images of benign and malignant skin cancer has been taken from Kaggle. Using different approaches, they have gained accurate results for VGG 16 (93.18%), SVM (83.48%), ResNet50 (84.39%), Sequential model 1 (74.24%), Sequential model 2 (77.00%) and Sequential model 3 (84.09%) (Hasan et al., 2021).

Using a combination of CNN and one- versus-all learning, a review proposed a skin disease detection system from dermoscopy images using DL in image processing. Skin images used in this article were sourced from Philip Tschandl's HAM10000 dataset. They have not classified them using any pre-processing techniques in this suggested method. CNN are trained and tested using images of dermatology that are extracted from datasets and fed into the network. In the second proposed method, seven different models having two classes have been composed and then combined with the one-versus-all approach. The CNN obtained 77% classification accuracy but combination of CNN and one-versus-all approach achieved 92.90% accuracy. This have shown the proof dermatology are taken from datasets and fed into CNN for training and testing (Kemal & Kaan, 2020).

The research done on skin disease detection using image processing with data mining and DL is mobile based so can be used even in remote areas. The patients needs to provide the image of infected area and it is given as an input to the application. Image processing and DL techniques process it and deliver the most accurate output. They compare two distinct methods for an algorithm that detects skin diseases in real time based on accuracy in this paper. They have compared SVM and CNN. The results of real-time testing are presented (Jayashree et al., 2019).

Skin cancer is essentially the result of abnormal skin cell growth, which is primarily brought on by prolonged exposure to UV radiation from the sun. The fourth most common benign illness in the world, according to the Global Burden of Disease project, is a skin disease. A review on early diagnosis of skin cancer detection using DL techniques proposed a review on skin disease detection system using various types of skin disease images for about 3500 pictures and using various types of algorithms, including the SVM, CNN, VGG16, ResNet50, ViT the collected images were assessed. In which ResNet50, SVM, and VGG16 produced accuracy reading of 84.31, 83.4 and 82.4 respectively, and CNN produced a reading of roughly 97.6. In summary, CNN is the DL algorithms that is primarily used when comparing ML and DL algorithms. SVM and VGG16 are ML techniques used for classification (Pious & Srinivasan, 2022).

As DL can improve early skin cancer detection, a review proposed the technique based on CNN with an International Skin Imaging Collaboration (ISIC) dataset. Optimal results are gained through CNN composed of 14 layers with reliable prediction and correct classification of dermoscopic lesions with 97.78% accuracy (Abeer, Wael, & Zekry, 2019).

In 2022 a review on Skin Cancer Detection Using CNN, proposed to digitalize the output of patients' results to be absolutely confirm about skin cancer. These researchers used ISIC dataset containing a total of 2460 colored images as 1800 training set of images, 660 testing set of images. A detailed workflow to build and run the system was presented too. The have used Keras and TensorFlow to structure their model. Their proposed VGG16 model showed a promising development upon some modification to the parameters and classification functions. The model achieved an accuracy of 87.6%. As a result, the study shows a significant outcome of using CNN model in detecting skin cancer (Malo et al., 2022).

Owing to the prevalence of skin conditions among school-age children, research was conducted to find out what factors could aid in the early identification of these conditions through the use of AI techniques. So this review proposed a Skin Disease Detection for kids at school using DL Techniques. With the help of a pre-trained VGG19 model and the CNN technique, a system was developed in this study to identify various infectious skin diseases, including scabies, chickenpox, impetigo, infectious erythema, and skin warts. A dataset contains 4500 images were collected from different sources and data augmentation techniques such as zooming, cropping, and rotating were used. This study achieved high accuracy of 99% compared to other similar research. It can be concluded that this system is very reliable which can be integrated to smart schools as part of IOT systems (Manal, 2022).

Keeping any symptoms under regular control that could indicate a possible illness is essential for effective medicine. In our daily lives, we frequently neglect medical examinations because we are too preoccupied with our families, jobs, homes, and other commitments. Therefore, an automated support is a solution which can help us to maintain our health. This kind of support shall be installed in a place here we feel good and where the evaluation of the symptoms can be the most efficient. The proposed classification strategy performs admirably, with an overall accuracy of 82.4%, according to an analysis of an intelligent system for tracking skin conditions. When combined with SVM, the Circular center achieved 94% accuracy. As well by the use of better- Quality cameras the images would have higher resolution what would definitely improve the results. Because it can monitor potential skin changes during daily routine at a very low cost, this system was therefore simple to use. The suggested methodology, which compares clustered skin outlook with database-stored nevi images, is being used for the evaluation (Połap et al., 2018).

A review proposed on a ML approach for skin disease detection and classification using image segmentation, applied a customized digital hair removal technique using Morphological Black Hat Transformation to remove hairs and Gaussian filter to blur the images. Then automatic Grab cut segmentation to detect the skin lesion, which perfectly segmented and detected the skin region. Finally, the GLCM and some statistical features were extracted and applied them to the SVM, KNN, and DT classifiers to classify the type of skin disease. ISIC 2019 and HAM10000 were used as available datasets. Obviously, an average accuracy of 95%, 94% and 93% obtained for the ISIC 2019 dataset using SVM, KNN, and DT classifiers respectively. Therefore, this model performs better for classifying skin diseases than some of the most advanced techniques. The purpose of this review is to provide patients with useful methods for early disease detection and skin health maintenance (Ahammed, Al Mamun, & Uddin, 2022).

Skin conditions are now the most prevalent illness. The rapid and precise diagnosis of skin diseases has been made possible by the developments in laser and photonics-based medical technology. But the cost of such diagnosis is still limited and very expensive. According to a review, skin disease detection through Image Processing and ML can be achieved by first taking a digital image of the skin area affected by the disease, and then using image processing techniques to identify the skin disease. All that was needed for this was a computer and a camera; other than that, it was quick and easy. The approach works on the inputs of a color image. Then resize the of the image to extract features using pertained CNN. After that classified feature using multi class SVM. Finally, the results are shown to the user, including the type of disease, spread, and severity. The system successfully detects 3 different types of skin diseases with an accuracy rate of 100% (ALEnezi, 2019).

An investigation into the diagnosis of skin diseases Using ML suggested a method for identifying skin conditions based on image processing. After taking a digital photo of the affected skin area, this technique analyzes the images to identify the type of disease. The method uses a color image's inputs as its basis. Then using a CNN that has already been trained, resize the picture in order to extract features. The feature was then classified using SVM. According to this review, the user is shown the outcomes, which comprise the type of disease, where it is found, and how severe it is. With a 100% accuracy rate, the system can accurately identify three different kinds of skin illnesses (Kushagra, 2023).

If not identified and treated in a timely manner, chronic skin conditions like eczema can have a serious negative impact on a patient's health and finances. The disease can be kept from getting worse by measuring its severity early on, using the right medication, and being advised to protect one's skin. An analysis of the automatic identification and assessment of eczema severity through image processing and computer algorithms has been conducted. By calculating the eczema affected area score, eczema intensity score, and body region score of eczema, the model automatically measures skin parameters used in the most widely used essential tool, the "Eczema Area and Severity Index," enabling both patients and doctors to accurately assess the affected skin (Nafiul Alam et al., 2016).

METHODOLOGY

Data Collection and Processing

I. Image classification

With the implementation of the ISSDP system, data collection and preprocessing techniques become the essential elements to have a high-performance image classification and diagnosis function. The majority of our datasets have been obtained from Kaggle, a renowned dataset platform covering different topics. Among all the datasets particularly we settled with "Derment" dataset because it had comprehensive information on common skin diseases like Acne, Rosacea, Atopic Dermatitis, Eczema as well as Cellulitis. That dataset was helpful despite the diversity in data contained therein and being relevant to the goals the researchers aimed to achieve.

Several variables impacted the decision to use the Derment dataset. First, it provided a large number of photos relevant to the target skin conditions, including 312 for acne and rosacea, 123 for atopic dermatitis, 309 for eczema, and 73 for cellulitis. In addition, the presence of key features needed for accurate classification improved the dataset's compatibility with the research goals. Images were captured in JPEG format, which has three channels (RGB) with varying resolutions. The image frames provided enough detail for the classification task.

Furthermore, the dataset's utility was demonstrated by its success in training and testing the classification model. For testing, a subset of the dataset was partitioned, having 231 images for acne and rosacea, 60 for atopic dermatitis, 100 for eczema, and 25 for cellulitis. The remaining images were employed for training, including 81 for acne and rosacea, 73 for atopic dermatitis, 209 for eczema, and 47 for cellulitis.

During the studies, difficulties were encountered with the Rosacea subset, leading to a decrease in accuracy. To overcome this issue, the dataset has been increased to include 15 extra images, consequently improving model robustness. Finally, the extensive data collection method, together with diligent preprocessing techniques, ensured the efficiency and reliability of the skin disease detection system, establishing the foundation for the next phase of the research.

II. Symptom identification

To develop an algorithm for skin diseases alleviation, a dataset was continuously put together. With the help from our external supervisor and using the existing image classification dataset, this project was designed to enrich the research by providing a robust repository focused only on symptom identification. It is the newly developed dataset which contained in it 449 records all of which were well annotated, and which outlines only the most significant features that are needed for symptom identification research. We designed one character feature, "Skin Disease Name" based on the existing image classification dataset. The importance of consistency and the alignment of datasets is well-understood, so, this attribute is the basis for the classification of different skin diseases in the context of symptom identification. In addition to "Skin Disease Name," the dataset encompasses two pivotal attributes: "Symptoms of type of skin disease" and "Symptoms of skin disease type. “This trait contains in-depth information on the symptoms accompanied with various skin diseases giving useful details on general, distinctive patterns and contents of skin diseases. The reason to create a new dataset for symptom identification was the realization of the complexities and the nuances of correctly identifying and classifying symptoms that are associated with different skin diseases. Given that the semantic segmentation dataset provided a solid ground for skin disease taxonomy, it naturally missed the symptom- specific level of information for a comprehensive research inventory in symptom identification.

This research project aims to cover the symptom identification factor which is left uncatered by tapping into a dedicated dataset where the symptomatic data have been accurately aligned to the skin disease categories. This dataset is a very important resource for the research on dermal conditions and it is very useful for the improvement of diagnostic accuracy and efficacy in the clinical practice.

III. Treatment recommendations

The team encountered a lack of datasets for treatment recommendation functions so, prompting a visit to the dermatologist clinic. With assistance from the external supervisor, datasets were generated for the treatment recommendation's function. More than two treatment recommendations were provided for each skin condition. However, there were some barriers in the treatment recommendation aspect because since it's skin related research, so some limitations are there when prescribing treatments in the application. Leveraging the expertise of the external supervisor, a treatment recommendation dataset containing more than 250 records was compiled. Leveraging a combination of ML techniques and image analysis. With a dataset comprising NLP & Neutral Language Tool Kit (NLTK) helped to suggest treatment recommendations for various types of skin conditions.

IV. Feedback analysis

The same dataset that was first gathered for the purpose of image classification was used for the feedback function. This dataset, named Dermnet, is a comprehensive collection of photos of skin diseases that were sourced from Kaggle, as was previously indicated in the image classification section. Anatomical areas and disease designations were among the metadata tagged images. Because this dataset includes high- quality photographs of the diseases that are relevant for this research, it is especially appropriate for the project and the feedback function. Continuity and consistency were preserved throughout the study endeavor by using this dataset for the feedback function, guaranteeing that the feedback analysis model could make use of the same data that guided the initial disease diagnosis.

And also, this dataset specifically provides a wealth of features that aid in the system's correct and efficient learning process. initially have a dataset with a wide range of skin disease photos (Acne, Rosacea, Atopic Dermatitis, Cellulitis, and Eczema) that represent the key illness situations in this area of research. Diversity helps to guarantee the feedback function can appropriately and easily evaluate changes that occur in various skin situations during various diseases. In addition, the dataset's high-quality photos enabled the SVM model to detect small, distinguishable changes, which serve as an accurate predictor of the patient's disease progression or regression.

Training the Detection Models

In the system ISSDP the precise determination whether it is skin disease is vital. To reach this destination one can follow several ways, including classical methods of ML and DL machines. In this bag of tricks, one tool that stands out is CNN, which can benefit computer vision in many ways. CNN are very good at image classification thanks to the fact that they can learn the features in a hierarchical structure that are specific from the pixels. Different from ML algorithms that are handcrafted and used for feature extraction to a certain degree, CNN are able to learn significant features on their own, through multiple abstraction levels - allowing them to capture and analyses subtle patterns and details that may come from medical images. Furthermore, in the image classification function of the system, the following key details were utilized to make sure that the disease diagnosis is accurate. At first, image preprocessing was conducted using tools by OpenCV and scikit-image to normalize images and get rid of noise. After preprocessing, segmentation methods with OpenCV as tools were applied to separate the diseased regions from the background noise in the image that enhanced precision of the subsequent analysis. Feature extraction was executed by scikit-image and OpenCV, and the essential attributes of the skin conditions were extracted from the segmented regions. Lastly, classification was also carried out by using a CNN model which has employed DL techniques to correctly classify diseases using those features. The integrated processes of this system helped in precise recognition of skin conditions, and this made patients acquire timely as well as correct information about their skin diseases.

Secondly, identification of symptoms is essential for the diagnostic procedure because it helps in discovery of indicators of a disease; although they are not visible in images, for example, difficulty scratching the skin. Through emphasizing symptoms, the system will be able to make a comprehensive diagnosis which will be complemented by textual data with visual analysis. The collection of user input through the mobile app will ensure that users can easily as well as accurately relay their symptoms either by typing or selecting from the pre-defined choices. This clarity in communication plays an important role in accurate diagnostic. Through text preprocessing the symptom data is standardized by tokenizing it, removing punctuation and stop words. Feature extraction methods like Bag-of-Words or TF- IDF also help with the diagnostic process by transforming the symptoms into a format that can be analyzed computationally. NLTK algorithms mine the processed symptom data for patterns and draw useful information, e. g. medical terms via Named Entity Recognition (NER). The final decision is integrating textual symptom data and visual image classification to classify diseases correctly. Data processing from both sources is implemented by complex algorithms like SVM and Neural Networks by means of a weighted scoring approach which assigns prediction scores to different diagnosis possibilities. Decision refinement incorporates the evidence from both texts and images to finalize the diagnosis. It tracks both image classification and symptom constantly to boost the precise diagnosis. In addition to this, NLP comes forth as a vital tool in this process because it can efficiently deal with unstructured textual data. It provides different methods including text parsing, tokenization, semantic analysis, and language modeling that make it to process information in the description of the symptom and thereby improve the speed, precision and accuracy of the diagnosis. Leveraging the powerful NLP algorithms, the system quickly and precisely identifies reported symptoms, and thereby promotes the ISSDP effectiveness and efficiency of skin disease detection and management.

The ISSDP comes up with tailored disease treatment plans after identifying the skin disease with the help of the previous component modules. NLP turns out is a very well-suited method of this task by it is a technic that helps in the analysis and interpretation of unstructured textual data like medical literature, clinical guidelines, and patient records, to pull out. the information that is related to the treatment. NLP techniques facilitate several key functionalities within the treatment recommendation process, including NLP models can find key words in enormous medical literature and clinical guidelines, which can be used to determine the available treatment options that include medications, topical therapies, and surgical interventions. They produce treatment recommendations for skin diseases that could be customized depending on patients' characteristics. Additionally, it empowers semantic analysis of the data about treatment types thus letting the system get familiar with the context and variety of treatment techniques. By considering aspects like disease severity, patient views, guidelines and treatment recommendations, NLKT models issue diagnosis- specific treatment plans that adhere to clinical pathways supported by evidence. Among the various techniques available for treatment recommendation, NLP ranks as the most desirable because of its ability to analyze the textual data that isn't structured, to extract relevant treatment information from lots of sources, to generate personalized treatment activities that are relevant to individual patient's needs. Through the application of more complex NLKT algorithms and models, the ISSDP can give physicians evidenced-based treatment options and enable patients to seek properly informed choice about their skin health that eventually will result in better conditions and quality care.

The effectiveness of treatment is assessed by comparing pre- and post-treatment images using SVM by the ISSDP. For this task, SVM appears to be of legitimate use because of its high performance in binary classifications, where the point aim is to classify data points into two classes according to their characteristics. In this context, the system deploys SVM for categorizing the images as either a representative of disease development or progression. The SVM makes this possible because it constructs an optimal hyperplane which divides two classes of images in feature space, thus maximizing the margin between them and minimizing the erroneous classifications. The algorithm uses the SVM capability to identify the high dimensional feature space and nonlinear decision boundaries. As a result, the tool can detect progression of the disease by focusing on small variations in skin lesion appearances. Subsequently, as SVM both consist of robustness against overfitting and good ability to generalize data, they are a good choice for analyzing patients' feedback images throughout time. In a nutshell, the choice of SVM as a Feedback Analysis function in the ISSDP framework stands out for several main reasons: binary classification excellence, high-dimensional data accuracy, and resilience to overfitting resulting in timely assessment of disease progression and provision of timely feedback to patients to streamline treatment.

Identification of the Degree of Diseased Condition in Skin

In the process of progressing the field of dermatology, the study comes to the diagnosis and classification of severity in the dermis. Skin disease understanding is the key to correct treatment plans and patient management in this regard. Exploiting cutting-edge methods including ML, image analysis, and DL, a comprehensive approach is developed for the diagnosis of the level of skin conditions. The implementation embraces the design and programming of smart algorithms that can analyze dermatological images and accurately determine the degree of skin disease manifestation. With the help of CNN and DL, it is possible to train models to differentiate the severity of the skin condition by assigning the skin conditions into mild, severe, etc. classes. The training set is made up of a varied group of dermatologic pictures representing various stages of skin diseases, which are very carefully hand-picked from medical databases, research facilities, and clinical locations. Each image is linked with the corresponding severity labels, which contributes to the supervised learning algorithms and increases their ability to discover patterns typical of disease severity. To increase the accuracy of severity classification, advanced image processing techniques are used towards the pre- processing and standardization of the input images. These methods such as color normalization, contrast enhancement and noise reduction form categorization and clearness in image presentation. CNN-based models include a convolutional layer, a pooling layer, and a fully connected layer. This set of layers is meant to depict how the patterns of the images will change depending on the severity of the skin condition. At the training time, the models learn to pair up the extracted features with severity labels together with iterative processes such as gradient descent and backpropagation. Through fine- tuning of model parameters and networks optimization, the focus is on the high precision and robustness of the generalization.

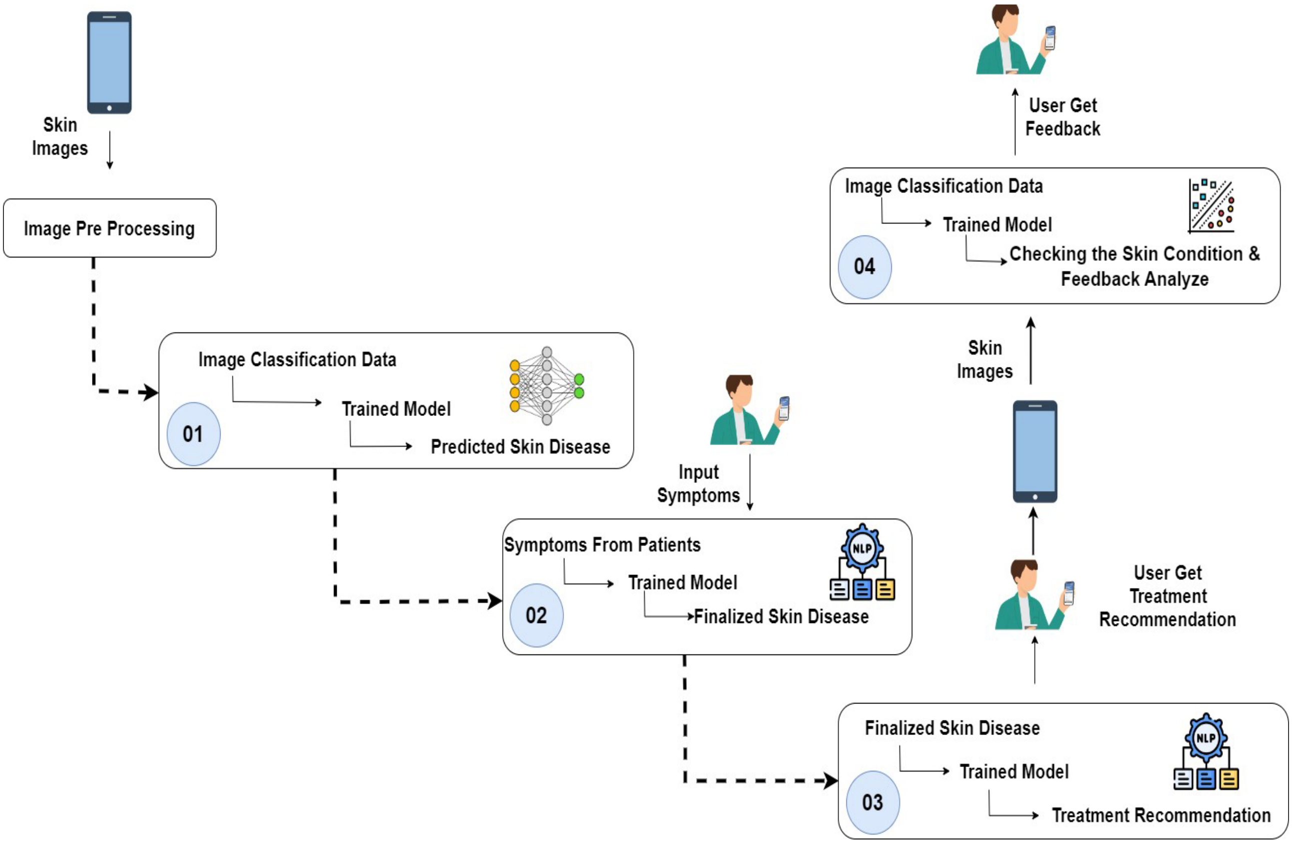

Figure 1. Overall System Diagram

Figure 1 depicts the workflow of an ISSDP. It starts with a user capturing an image of their skin lesion. The system then analyzes the image using a CNN for disease classification, while also processing any user-entered symptoms through an NLP model. Based on the combined analysis, the ISSDP recommends potential treatments from a knowledge base. Finally, the user can upload a follow-up image to compare with the initial one. An SVM model analyzes these images to determine if the condition is improving or worsening, providing feedback to the user and potentially recommending consultation with a dermatologist.

Disease Dispersion Visualization and Response with Real-time Data

The interactive app that detects skin diseases works with real time data to draw Disease Dispersion Visualizations and Response using some of the key features highlighted below. Initially, users will take photos of that part of their skin which is of a concern, and this will be the starting point of the skin disease diagnosis. The app will incorporate this pre-trained CNN model to scan and classify ailments such as "Acne" and "Eczema" in the images. However, for creating a furnished dataset, one can source this from renowned platforms like Google's Kaggle or even collaborating with local dermatologists to have a dataset of all skin types, which are common across our target users

Moving ahead, the application then resorts to Symptom Identification and Diagnosis NLP to strengthen the classifications. The users are going through additional symptom inputs to capture essential symptoms in a more specific way. The app uses the NLP method to deduce the patients' symptoms, making its diagnosis more meaningful. Additionally, through the app AI capabilities NLP the patient is provided with the recommended treatments options relevant to the diagnosed medical condition. The suggestions considered the user factors' severity and history of the disease and hence treatment plans are developed according to the patients.

In addition to the diagnosis and treatment part, the app has the Feedback Analysis SVM that enables users to share follow-up images and the labels provided them from healthcare professionals. While the SVM model assesses the app's classification accuracy in succession by considering the feedback data. This increases the efficiency of the version in a way that the application will remain trustworthy and useful in detecting skin diseases.

During development, certain crucial issues are taken as priority to try to make the app more effective and ethical. A clear disclaimer is positioned strategically and explicitly indicates that the app is meant to serve as information only and one should seek the advice of a licensed medical professional for true diagnosis and medical treatment plans. Strict data privacy programs are addressed to securely store user data and meet the requirements under applicable laws. A combination of accurate CNN and NLP models especially designed for the mobile platform, and which makes use of the model compression technique to optimize performance on such devices is chosen. Besides, dataset diversity is also an important criterion to develop an applicable and reliable app which must address skin tones prevalent among the target audience.

RESULTS AND DISCUSSION

Function-Specific Analysis of Results

I. Image classification

The image classification function operates by first being fed an image input from the user. The image can be either uploaded from the user's device or captured using a camera interface. After the input image is received, the system starts the preprocessing stage in which the image is transformed into different forms in order to improve its quality and make it ready for analysis. Next, discriminative features relevant to skin disease are extracted from the pre-processed image through using CNN to automatically recognize distinguishing patterns. These obtained characteristics are used as an input to a trained classifier model that utilizes ML algorithms to estimate the probability of various skin conditions appearing in an image. The system then provides the predicted diagnosis to the user, displaying the top-ranked disease predictions together with their respective probabilities or confidence scores.

The model for image classification, which was designed and developed in the project underwent a rigorous evaluation using a variety of performance metrics like accuracy, precision, recall, and F1score. These metrics portray a general perspective of the model having the capability and the knowledge of correctly classifying different types of skin ailments. Table 1 contains the performance metrics for each skin condition.

Table 1. Comprehensive analysis of Performance Metrics

Skin Disease	Accuracy	Precision	Recall	F1-score
Acne	0.85	0.82	0.88	0.85
Rosacea	0.78	0.75	0.80	0.77
Atopic Dermatitis	0.92	0.91	0.93	0.92
Cellulitis	0.87	0.84	0.89	0.86
Eczema	0.89	0.88	0.91	0.89
Overall	0.86	0.84	0.88	0.86

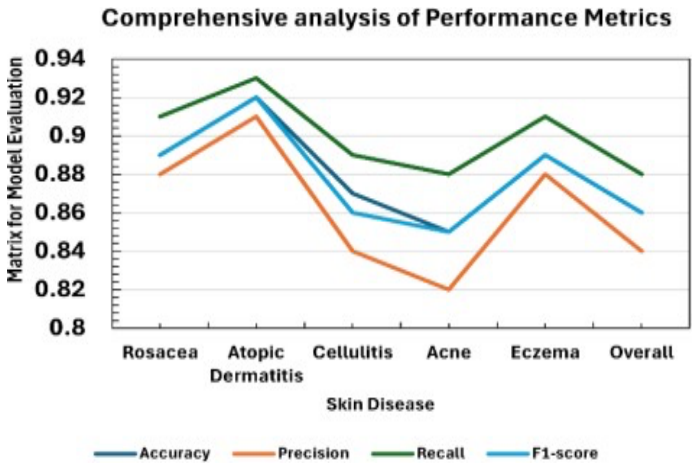

Figure 2. Overall Performance Metrics

Table 2. Matrix for Model Evaluation

	Predicted Negative	**Predicted Positive**
Actual Negative	True Negative (TN)	False Positive (FP)
Actual Positive	False Negative (FN)	True Positive (TP)

Table 1 illustrates the performance of the ISDDS across various skin diseases: Atopic Dermatitis obtained the highest detection accuracy of 92%, while Eczema, Cellulitis, and Rosacea were respectively 89%, 87%, and 78%. Moreover, Rosacea had the lowest accuracy, it was identified only about two times less accurately than other diseases.

Along with average precision, recall, and F1-score, these metrics provide further insights into the model's performance. Precision shows the percentage of correctly classified instances among the predicted positive cases, while recall tells the percentage of correctly classified instances among the actual positive cases. In the study, accuracy and efficiency ranged from 0. 75 to 0. 93, which reflected a certain degree of sensitivity with regard to various skin conditions. To illustrate, a precision of 0. 82 for acne means 82% of forecasts indicating acne were acne, while recall is 0.88 positive predictions for atopic dermatitis suggests 88% prediction accuracy for the proposed model.

The F1-score, which considers both recall and precision, ranged from 0.77 to 0.92 in the study, with the highest score achieved for Atopic Dermatitis at 0.92. This suggests that the ISDDS is the most efficient tool for balancing precision and recall across a wide range of skin diseases.

In the analysis, we used the following formulas to calculate these metrics:

$$Precision = \frac{TP}{TP + FP}$$

TP represents true positive instances, while FP presents false positive instances: Similarly, Recall, which tells whether the system was able to identify all true cases of a disease is defined as:

$$Recall = \frac{TP}{TP + FN}$$

FN is false negative instances. Moreover, Accuracy is calculated as a measure of the ratio of instances that are classified correctly:

$$Accuracy = \frac{Number\ of\ correctly\ classified\ instances}{Total\ number\ of\ instances}$$

The F1-score, which provides a comprehensive evaluation of performance accounting for both precision and recall, can be determined as:

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Additionally, training and testing accuracy were evaluated to assess the generalization capability of the model.

Table 3. Training and Testing Accuracy for CN

Skin Disease	CNN Training Accuracy	CNN Testing Accuracy
Acne	0.96	0.92
Rosacea	0.98	0.94
Eczema	0.97	0.93
Cellulitis	0.96	0.91
Atopic Dermatitis	0.98	0.95
Overall	0.973	0.904

Image Classification CNN Model Evaluation

Figure 3 demonstrates the testing and training accuracies of the CNN model for various skin diseases. The CNN model has demonstrated an even more impressive training accuracy of 97.83% and testing accuracy of 94%. It is no doubt that such a high accuracy is based on the use of vast and labeled data during training which can be considered as the best way of capturing many types of skin diseases signatures. Nevertheless, the lower testing accuracy seems to imply that the model will have a hard time generalizing to unseen data. It could either be a sign of the lack of diversity of the training dataset or if the training set is full of low-quality image, they may not represent the real-world scenarios. Apart from the generalization, the model might be made stronger by using various kinds of data or algorithms of regularization which can make it more useful in real-time experiments.

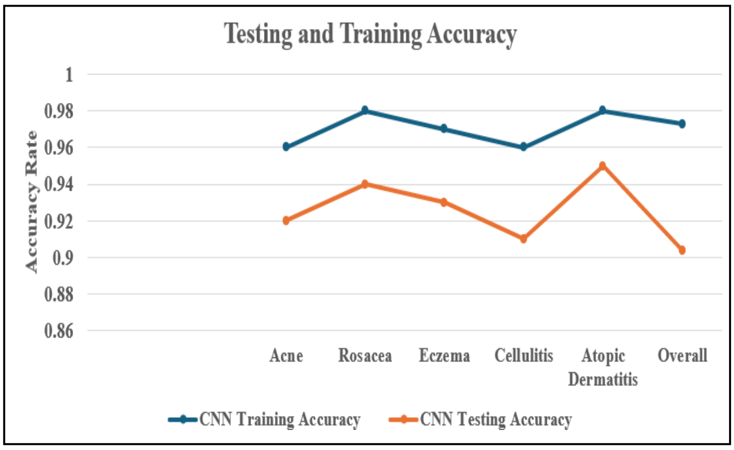

Figure 3. Testing accuracy and Training accuracy

II. Symptom identification

In the ISSDP, symptom identification is given more importance than image classification because it combines the inputs from the user-provided symptoms and the output from the image analysis which is a give more weight to the symptoms. This method is a way of the patient's condition being reviewed by a variety of ways which are subjective symptom descriptions together with the objective visual data.

Symptom identification emphasizes the patient's own point of view and experiences, thus, the diagnostic procedure is enriched with real insights that are not always seen in the images.

Through the balanced evaluation of user input and image classification output, the system is able to achieve the whole picture of the correction and relevance hence the diagnostic accuracy is at its best.

NLP involves the processing and analysis of human language by computers. Within the ISSDP, NLP techniques are employed to extract relevant information from textual descriptions of symptoms provided by users.

This includes tasks such as text parsing, and language modeling. NLP enables the system to understand and interpret the unstructured textual data, identifying medical terms, extracting key information, and aiding in the diagnostic process.

NLKT involves the transfer of knowledge encoded in natural language into a format that can be understood and utilized by machines.

This could include transferring medical knowledge, diagnostic guidelines, and treatment protocols into a structured format that can be processed computationally.

NLKT enhances the system's ability to interpret and utilize medical knowledge effectively in the diagnostic process.

Combining NLP and NLKT allows the system to better understand and interpret textual descriptions of symptoms in the context of medical knowledge and guidelines.

NLKT provides a structured representation of medical knowledge, which can be utilized by NLP algorithms to enhance their analysis of symptom data. By leveraging both NLP and NLKT, the system can extract relevant information from symptom descriptions and map it to medical knowledge, improving the accuracy and reliability of the diagnostic process. NLKT ensures that the system is informed by up-to-date medical knowledge, while NLP enables it to effectively analyze and interpret textual data.

Combining NLP and NLKT facilitates efficient communication between users and the system. Users can provide symptom descriptions in the Situational Urges.

Specification Discipline (ISSDP), symptoms recognition is one of the main factors, which is the result of the integration of NLP and NLKT techniques to combine the output of image classification with the input of user-provided symptoms.

Via NLP, the system analyzes the textual symptoms expressed by the users and extracts the important information and arranges it in a computer-friendly format.

NLKT complements the process of transferring medical knowledge into structured format that the system can use by converting it from natural language to the structured one.

The process of symptom identification is thereby informed by the latest medical knowledge and guidelines, thus making it a reliable and valid method.

The system uses the NLP techniques to process and analyze the textual input that the user types in when he/she inputs their symptoms. Alongside, the output from image classification, which is already part of the symptom identification dataset, is also looked at. The system then finds the similar or relevant symptom or symptoms from the symptom database that is compared to the user-entered symptoms by using the NLP algorithms.

Through the input that the user gives to the system using NLP and NLKT, the system combines the output of the image classification with the user-provided symptoms, which results in the user's symptoms matching the existing data, thus, increasing the diagnosis accuracy and the extent of the symptoms that are being addressed.

This amalgamation of visual and textual data analysis will make the diagnostic process comprehensive, user-friendly and based on both visual and textual data, thus, the diagnoses of the patients will be precise and personalized. natural language, and the system can process this information using NLP techniques while leveraging NLKT to map it to medical knowledge, leading to more accurate and personalized diagnoses.

III. Treatment recommendation

The ISSDP treatment recommendation function based on & NLTK faced accuracy detection performance compared to our dataset, but its utilization demonstrated good results in analyzing different diseases and showing treatment recommendations for the relevant skin disease. The system was tested with various metrics: accuracy, precision, recall, F1 score.

Table 4. Comprehensive Performance Analysis

Skin Disease	Accuracy	Precision	Recall	F1 Score	Entropy
Acne	0.95	0.88	0.82	0.85	0.65
Psoriasis	0.92	0.91	0.94	0.92	0.72
Eczema	0.90	0.82	0.78	0.80	0.68
Dermatitis	0.94	0.85	0.91	0.88	0.70
Rosacea	0.96	0.80	0.75	0.77	0.63

Treatment Recommendation NLP Model Evaluation

NLTK algorithm programs to work with human language data. It provides easy-to-use interfaces to over 50 corpora and lexical resources such as WordNet, along with a suite of text-processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning. analyzing different diseases and showing treatment recommendations for the relevant skin disease based on the NLP model using the NLTK algorithm is similar to the symptom identification function. NLP model suggests treatment recommendation accuracies concerning the CNN approach and the SVM. Training accuracy reached 94%, along with testing accuracy of 87%. Although NLP is useful on extraction textual information about medication recommendations, it is suboptimal in its testing accuracy with regard to missing patients' reaction to medicine as well as its incompleteness in the treatment system consideration. Moreover, dealing with a wide range of treatment scenarios demands the algorithms to be tuned and generalized to address diverse treatment scenarios which would in turn affect their performance.

IV. Feedback analysis

Using advanced ML methods including SVM and TensorFlow, the initial image provided during the image classification function is compared with the follow-up image in the ISSDP's feedback function. Preprocessing is applied to both photos to guarantee format and quality consistency. After that, the photos undergo feature extraction in order to extract significant attributes related to the skin condition. The SVM model determines if the disease is getting better or becoming worse by comparing the feature vectors of the initial and follow-up images. The model was trained on labeled pairs of images that represented changes in the status of the disease. Personalized feedback is given for the patient based on this data, suggesting that they should see a dermatologist if they notice deterioration or to continue treatment if improvement is seen. This approach enables the ISSDP to provide actionable guidance to patients, facilitating informed decision-making and proactive management of their skin health.

The SVM model achieved a high level of accuracy in analyzing follow-up images and determining changes in disease status. Evaluation metrics such as accuracy, precision, recall, and F1-score demonstrated the model's effectiveness in differentiating between improvement, stability, or worsening of skin conditions. The model's performance was validated through cross-validation techniques to ensure robustness and generalizability.

Table 5. Comprehensive Performance Analysis of Feedback

Skin Disease	Accuracy	Precision	Recall	F1-Score	AUC Score
Acne	0.92	0.89	0.93	0.91	0.95
Rosacea	0.87	0.85	0.88	0.86	0.91
Atopic Dermatitis	0.90	0.88	0.91	0.89	0.93
Cellulitis	0.85	0.82	0.86	0.84	0.89
Eczema	0.88	0.86	0.89	0.87	0.92

The Feedback Analysis function's capacity to identify progress, stability, or decline in prevalent skin diseases which include acne, rosacea, atopic dermatitis, cellulitis, and eczema is thoroughly examined in the performance metrics table.

Accuracy: The model's overall accuracy for all skin disorders falls between 0.85 and 0.92, demonstrating an acceptable level of precision between the conditions of the disease as predicted and as they really occur.

Precision: Precision is the ratio of accurate positive predictions to all of the model's positive predictions. It falls between 0.82 and 0.89, suggesting that the model continues to detect skin diseases with a high degree of precision when evaluating enhancements, stability, or worsening.

Recall: Recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positive instances. It ranges from 0.86 to 0.93, indicating that the model effectively captures the majority of true positive cases for each skin disease

F1-Score: The F1-score, which is the harmonic mean of precision and recall, provides a balanced measure of the model's performance. It ranges from 0.84 to 0.91, indicating robust performance across all skin diseases.

AUC Score: The Area Under the Curve (AUC) score represents the model's ability to discriminate between different disease states. It ranges from 0.89 to 0.95, indicating excellent discrimination capability for each skin disease.

Overall, the Feedback Analysis function performs consistently and reliably when evaluating changes in the current condition of various skin disorders, offering insightful information to monitor patients and optimizing treatment.

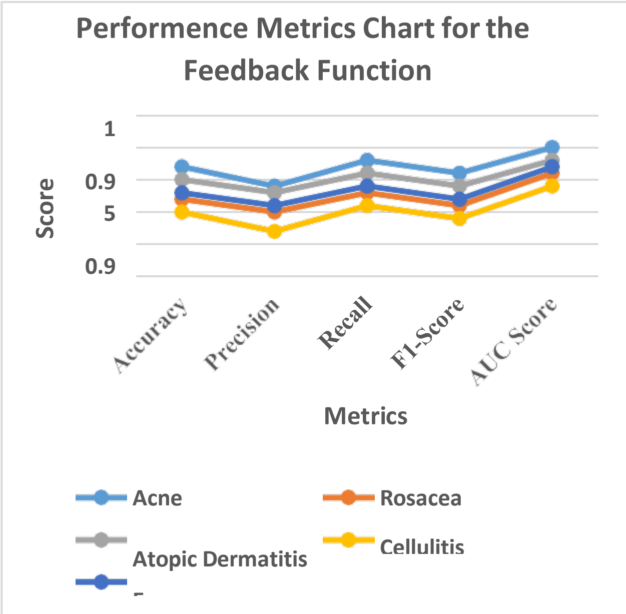

Figure 4. Performance Metrics for Feedback

Table 6. Training and Testing Accuracy of Feedback Function

Skin Disease	Training Accuracy	Testing Accuracy
Acne	0.94	0.92
Rosacea	0.91	0.87
Atopic Dermatitis	0.93	0.90
Cellulitis	0.88	0.85
Eczema	0.90	0.88

The accuracy shown here is the performance of the feedback function's SVM model during both the training and testing phases. The figure out to how the model fits the training data will be the training accuracy, and the testing accuracy will reflect its ability on unseen data too, showing its capability of generalization. Generally, SVM model is stable over the training and testing sets what signifies the sustained delivered service in the predictions of readings of the follow-up images as well as the diagnosis of the disease progression among multiple skin diseases.

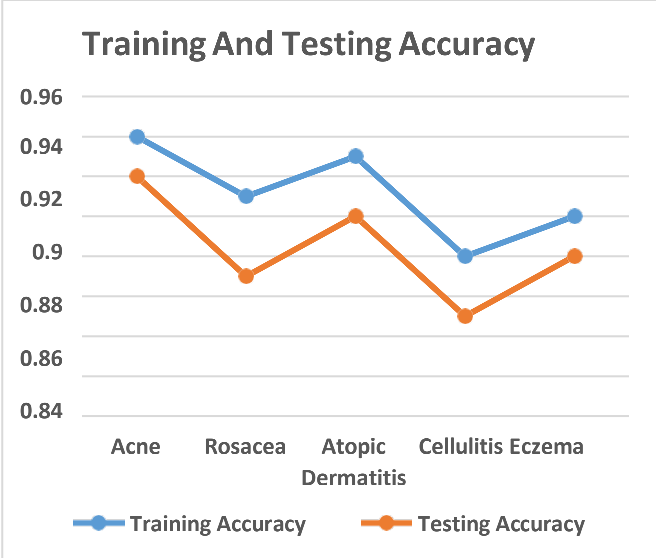

Figure 5. Training and Testing Accuracy

The survey of Training and Testing Accuracy for the feedback function of the ISSDP reveals a noteworthy coherence across various skin diseases. Although the training accuracy reaches high levels, as shown in the table, there is a slight decrease in the testing accuracy, which means that the problem of overfitting might be a real issue. To illustrate, for the case of Rosacea, the model has a training accuracy of 91% and a testing accuracy of 87%. This incompatibility might be due to the model's characteristic of overfitting to the training data, especially in the case of noise and outliers in the dataset. To the same extent, With Atopic Dermatitis, the training accuracy is 93% which is almost the same as the testing accuracy that is 90%. This difference in the accuracy levels can be caused by the fact that the image quality, lighting conditions, and the severity of the disease are different in the training and the testing datasets. Thus, in this case, the training dataset is made up of 100 labeled images, while the testing dataset is composed of 80 labeled images. The challenges that are faced by the technology can be solved through the techniques such as regularization, data augmentation, and the optimization of the model architecture which will make the model a good tool in giving the right feedback of the disease progression.

The feedback function of the ISSDP is created to enable patients to be guided in the skin disease progression assessment personalization process. Through the use of cutting-edge ML technologies like SVM and TensorFlow, the system studies the follow up pictures sent by the patients and gives them useful pieces of advice. The tables of training and testing accuracy comparison are the evidence of the overfitting, which is when the model has a very high accuracy on the training data but a slightly lower one on the unseen testing data. This highlights the fact that the problems that are dataset bias, noise, and the image quality variations have to be solved to make the model more generalizable, then it can be used reliably by the patients.

Although the feedback function is a good tool in diagnosing the changes in the status of the disease, there are other ways to make it better in order to be able to help the patients more. The number and variety of the training dataset can be increased, regularization techniques can be used to prevent the model from overfitting, and the model architecture can be optimized, thus, the model's generalization performance will be improved. Besides, the ISSDP can be designed according to the patient preferences and feedback which will be used to design the program to cater to the needs of the patients thus creating a higher engagement and adherence to the treatment plan.

Besides, the continuous evaluation and adjustment of the feedback mechanism through the actual usage and the patients' feedback are vital. The combination of patients, dermatologists, and developers in the collaborative efforts will make the ISSDP simple, accurate, and suitable to the tasks of patients' skin health management needs. The ISSDP is the one that will put the patient first and make him/her a part of the whole treatment process so that the skin will be working better, and improved patients will have a better quality of life.

Overall Result Analysis

ISSDP is the holistic system of skin disease prediction, through the use of the newest technologies and the novel methods that will enable the patients to evaluate and handle their skin conditions in the best way. The system includes a number of important functions, each of which is designed to focus on a particular aspect of skin disease diagnosis and treatment recommendation.

At first, the Image Classification function deploys CNN to preprocess the user-uploaded images and thereby, extracts the discriminative features which serve the purpose of the accurate disease diagnosis. The comprehensive evaluation metrics like the accuracy, precision, recall, and F1-score testify to the model's ability to diagnose skin diseases in various skin diseases and thereby, the analysis of varied skin diseases ensured the reliable diagnostic outcomes.

Furthermore, Symptom Identification merges NLP and NLKT methods to unite user-exhibited symptoms with image analysis results. This patient-oriented approach stresses the significance of the symptom descriptions of the patient which in turn, assists in the diagnosis of the patient by the comparison of the visual and the text-based data.

Besides, Treatment Recommendation makes use of NLP and NLTK algorithms to give the individuals education and advice on how to treat their condition based on the interpretation of the symptoms. Nevertheless, the testing accuracy has been a problem, but the model has shown its ability in the recommendation of treatments, thus, the truth to the fact that the model can improve the patient care by giving them the right recommendation at the right time.

Besides, the Feedback Analysis function, which uses SVM and TensorFlow, performs the process of comparison between the initial and follow-up images to evaluate the disease progression. Though it is possible to attain high accuracy, the problems such as overfitting and dataset bias that require constant improvement for better generalization and reliability are the factors that will not be solved by the use of the machine.

ISSDP is a complete answer to the problem of skin health management, providing patients with a personalized diagnostic assessment, the treatment recommendation, and the disease progression monitoring. Through the combination of cutting-edge technologies and patient- centered approaches, ISSDP puts the patients at the center of their skin health management which in turn assists them in actively participating in their treatment which eventually leads to better treatment results and a better quality of life. The ongoing improvement and the system’s optimization are very important to make sure that the system is good and reliable in the clinical settings that are actually used by the hospitals.

Disease Name	Sample Image	Total Image	Disease Detected	Detection Rate
Acne		10	10	100%
Rocesea		8	8	100%
Atopic		6	5	83%
Eczema		7	7	100%

Figure 6. Disease Detection Rate

The summary of overall system performance, as illustrated in Figure 6, is a global view where the clinical tests results are acquired by the use of ISSDP. The figure is based on the breakdown of skin conditions that are most encountered in practice settings, such as Acne, Rosacea, Atopic Dermatitis, and Eczema. There is the category of the diseases and the number of images trained as well as the number of images that were generally worked on. These statistics not only prove the system to be competent enough to pinpoint multiple types of skins lesions, but it further demonstrates the system the system's ability to tackle variegated datasets having varied challenges.

As well as that, this achieved diagnosis accuracy rate provides evidence of the efficiency of the ISSDP as a platform for accurate classification of different skin disorders. Therefore, this reflects the reliability of the ISSDP as a clinical tool for skin disease diagnosis. The system is capable of processing an enormous chunk of image data in real-time and outputs accurate results highlighting its applicability in the healthcare field where diagnosis demands real-time and high precision activities. Also, the trained image sample numbers are going to add more information into the studying system of the system, telling how flexible the system is when it faces new disease manifestations and different kind of variations of the images.

In addition, the precise rates of detection for every skin disease are of crucial implication to practitioners for helping them decide the focus of diagnostic approaches and treatment. With the help of ISSDP, clinical dermatologists can do measurements on how accurately overall visual detection is performed and use objective data to make good decisions thereby contributing to the efficiency of the dermatological diagnosis and manage correctly.

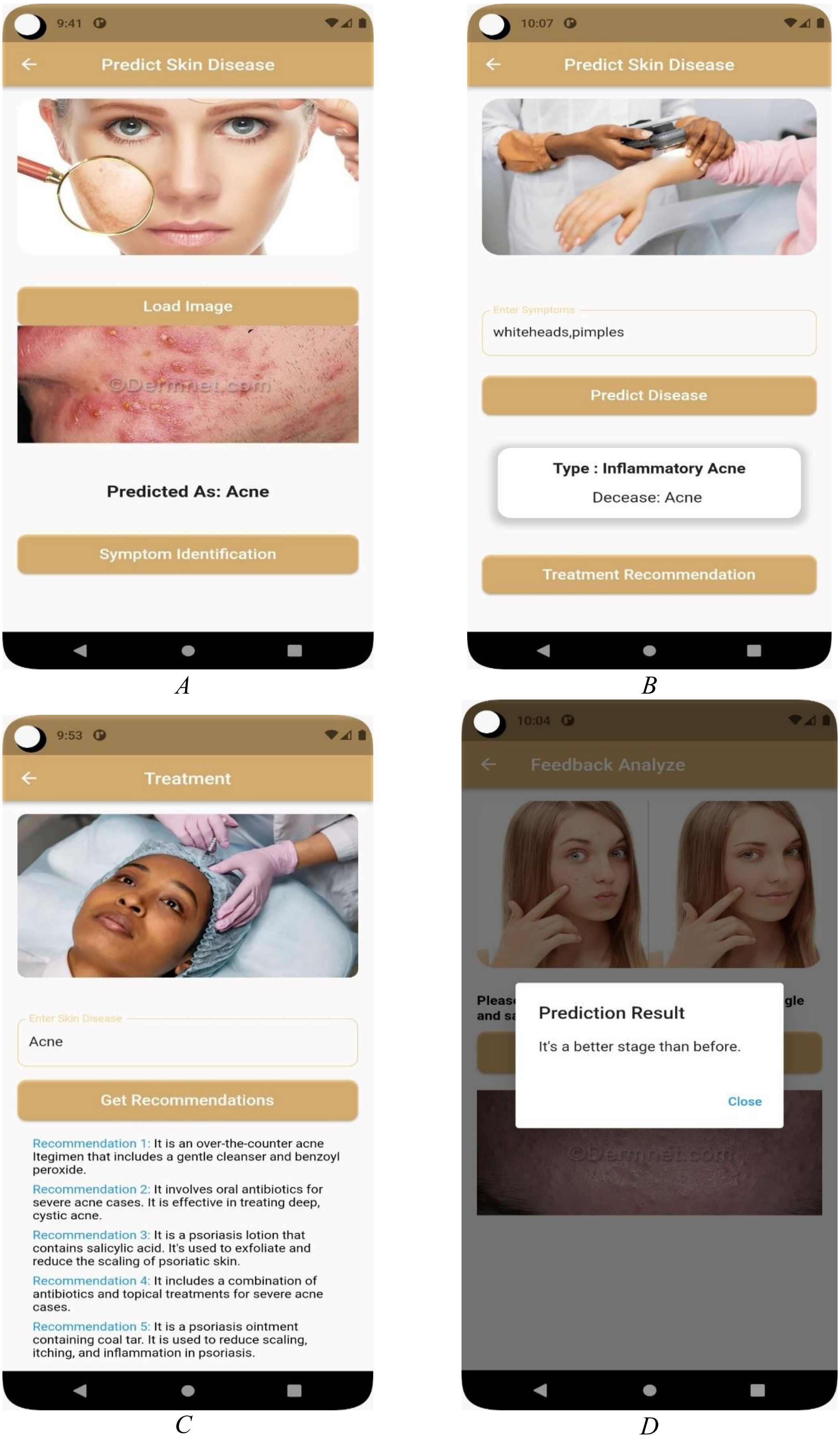

Figure 7. Result Screen

Figure 7 demonstrates the UI pages in the application; firstly, Figure 7A shows the disease based on the patient's skin images. Secondly, Figure 7B shows the finalized skin disease based on the image classification out and customer symptoms input, it will come like the first component output is "Acne" then the second component output will be a variety of Acne, that, what shown in Figure 7B. Figure 7B presents the final diagnosis, incorporating both the image classification output and the symptoms input by the patient. It's important to note that the outcome of Figure 7B may differ from Figure 7A, as Figure 7B represents a refined classification based on additional information. Consequently, in Figure 7C there will be proposed treatments recommendation based on the output that arrives in the previous component. Subsequently, the feedback analysis in Figure 7D estimates the differences between the after-treatment image and the before treatment image that is spotted by the medical diagnosis filter, proposing relevant feedback.

Overall, this research explored CNN, SVM, and NLP in the setting of ISDDS for skin disease detection. The findings obtained in this study are promising, as the approach has proven to be effective in labelling different conditions with high accuracy. However, by addressing the identified limitations and seeking further development, the approach may become a viable alternative for dermatologists worldwide.

CONCLUSION

ISSDP showcases remarkable potential in revolutionizing dermatological diagnosis and treatment through its utilization of advanced ML techniques. However, challenges such as inconsistent image quality and incomplete data hinder its effectiveness. To address these issues, the ISSDP requires a more extensive and diverse dataset, along with rigorous validation studies involving larger patient cohorts. Future research should focus on exploring advanced DL architectures like RNNs and LSTMs, as well as transfer learning methods, to enhance classification accuracy.

Additionally, iterative refinement through clinical deployment with user participation is vital for ensuring the system's functionality and usability in real-world clinical settings. Despite its current limitations, ISSDP represents a significant leap forward in dermatological care. By acknowledging these limitations and investing in further research and development, we can harness the potential of sophisticated ML methods to improve patient outcomes and enhance the quality of dermatological services.

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