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Enhanced Skin Disease Detection and Classification System Using Deep Learning Technique

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A B S T R A C T

Even in this era of advanced technology, physicians still encounter challenges in accurately identifying skin diseases. Severe skin conditions necessitate urgent hospitalization, yet the diagnostic process involves costly tests with delayed results, exacerbating the worsening of infections. In rural areas, patients often ignore initial symptoms due to limited medical services, allowing conditions to progress unchecked. This underscores the pressing need for highly accurate automated skin disease detection systems. In response to this demand, we developed a multiclass convolutional neural network model aimed at discerning between healthy and diseased skin. Employing Python, we constructed a program utilizing this convolutional neural network with pre-trained networks- AlexNet and VGG19 to address the issue effectively. The primary objective of our project was to categorize five different skin illnesses using input images. By providing our model with pictures of affected skin regions, we aimed to detect ailments like Eczema, Nail fungus, Melanoma, Bullous, and Vascular Tumor. Upon processing the input image, our model would accurately identify and output the specific illness affecting the skin. This streamlined approach significantly aids in timely and accurate diagnosis, crucial for early intervention and treatment of various skin conditions

INTRODUCTION

Skin disease, being the most widespread affliction globally, demands precise diagnosis by dermatologists, prompting the suggestion of a computer-aided diagnostic model for unbiased and reliable assessments. Despite various studies conducted to identify skin conditions such as cancer and tumors, accurate diagnosis remains challenging due to factors like poor lesion contrast and visual similarities between affected and unaffected areas. To aid in skin illness diagnosis from images, this article proposes filtering and grayscale conversion to eliminate unwanted elements. Ignoring skin ailments isn't viable, especially with their high prevalence, notably among children, adding strain to vulnerable populations [1-3].

The impact of skin diseases is significant, leading to deformities, impairments, persistent itching, and reduced quality of life, as seen in conditions like lymphatic filariasis causing secondary cellulitis. The financial burden of treating such conditions limits families, forcing them to cover expenses from already constrained budgets, affecting their ability to afford basic necessities [4,5].

Skin screening is crucial for various disorders like leprosy, yet primary care providers often lack essential knowledge about these conditions manifesting on the skin [6,7]. In India, a considerable portion of the population suffers from severe skin issues, inflicting emotional and psychological distress, often outweighing the physical effects [8]. The heightened awareness of appearance and well-being among young individuals exacerbates anxiety, making the situation more challenging.

LITERATURE REVIEW

Numerous scholars have suggested diverse image processing with deep-learning techniques for the identification of various skin disorders. In this regard, T. Shanthi et al. [9] present a novel convolutional neural network (CNN) architecture that identifies 4 selected classes like acne, keratosis, Eczema herpeticum and utricaria obtained from DermNet dataset and shows that it can recognize skin conditions with improved accuracy 98.6% to 99.04%.

A further research contribution by Jessica S. Velasco et. al [10] and Agarwal et al. [11] investigates how transfer learning might be integrated, using trained models to improve classification performance on a variety of datasets. In the field of dermatology, where it might be difficult to gather a large and diverse labeled dataset, this method is especially helpful. The model's outstanding performance in accurately classifying a variety of skin illnesses using pertinent dermatological datasets. Pretrained CNNs speed up the training process and improve the model's ability to capture complex characteristics and patterns unique to skin pathologies.

Bhadoria et. al [12] presents a compelling approach to skin disease classification by harnessing the power of pretrained convolutional neural networks (CNNs). The authors effectively leverage transfer learning, demonstrating the model's ability to benefit from the knowledge acquired during training on large datasets for general image recognition tasks. This strategy is particularly advantageous in the context of dermatology, where obtaining a large and diverse labeled dataset can be challenging. The paper rigorously evaluates the proposed model on relevant dermatological datasets, highlighting its superior performance in accurately classifying various skin diseases. The use of pretrained CNNs not only expedites the training process but also enhances the model's capacity to capture intricate patterns and features specific to skin pathology.

Another research method proposed by Alenezi et. al [13] and Hameed et.al [14] used pre-trained convolutional neural networks and SVM for disease detection. The authors showcase the effectiveness of their model through extensive experimentation on diverse datasets. The integration of attention mechanisms enhances feature extraction, yielding state-of-the-art performance. A real-time and dynamic system for skin disease detection was suggested by Min Chen et al. [15]. It combines self-learning with a large data collection to facilitate effective user interaction. To remove irrelevant data and provide the network with useful data, a data filter algorithm was used. For this filtering operation, information entropy was applied. LeNet-5, AlexNet, and VGG-16 are the three CNN learning models that were employed in the classification and prediction test. By examining the system's computation and transmission delays, the authors further assess the authenticity and dependability of the suggested solution. According to this investigation, the LeNet and AlexNet models have communication delays of 63 ms and 75 ms, respectively.

A deep CNN-based approach was suggested by Liao et. al [16]. Advanced CNN architecture, including VGG-16, VGG-19, and GoogleNet, was used in this investigation. Dermnet and OLE are the two distinct datasets used in the experiment, and the models' performances were compared. The ImageNet dataset was utilized to pretrained each model employed in this investigation. Using the VGG-16 model, the top-5 accuracy on the DermNet dataset was 91%, while the top-5 accuracy on the OLE dataset was 69.5%.

MobileNet V2 and LSTM were coupled by Srinivasu et al. [17] to classify skin diseases. This experiment employed the HAM10000 dataset, with a claimed accuracy of 85%. A web application for the classification of skin reductions has also been proposed by them.

Skin diseases pose a significant global burden, prompting the development of robust automated systems to aid early assessment of skin lesions. While most existing systems mainly focus on skin diseases classification, the project presented by K. S. Rao et. al [18] aimed to detect various common skin lesions using a novel approach involving pre-processing, deep learning algorithms, model training, and classification. The experiments conducted on over 10,000 images achieved a 93% accuracy for seven-class classification using Convolutional Neural Networks (CNN) with the Keras Application API.

The latest findings presented by N. Nigar et al. [19] are appealing because they address the black-box character of deep learning models by adding visualization techniques and attention mechanisms, hence focusing on interpretability. In order to increase diagnostic accuracy, there is also a discernible trend toward multimodal techniques, which combine imaging and clinical data. A clear decision-making process is ensured using explainable AI approaches, which is important for winning over healthcare experts. Nevertheless, issues still exist, including the requirement for extensive and varied datasets, moral issues, and the necessity of real-world validation. Together, these studies represent a promising new phase in the use of deep learning for the diagnosis of skin diseases, highlighting both technological developments and an increasing understanding of the real-world applications in clinical settings.

METHODOLOGY

The system for automated diagnosis was created by employing Convolutional Neural Network (CNN) architectures, specifically based on AlexNet [20] and VGG19 pre-trained models [27 - 29]. It involved capturing an image of the diseased area using a mobile or camera and then uploading image to the proposed model. The model will identify and classify skin diseases and display results on screen. A visual representation of the proposed system's overall structure can be seen in Figure 1.

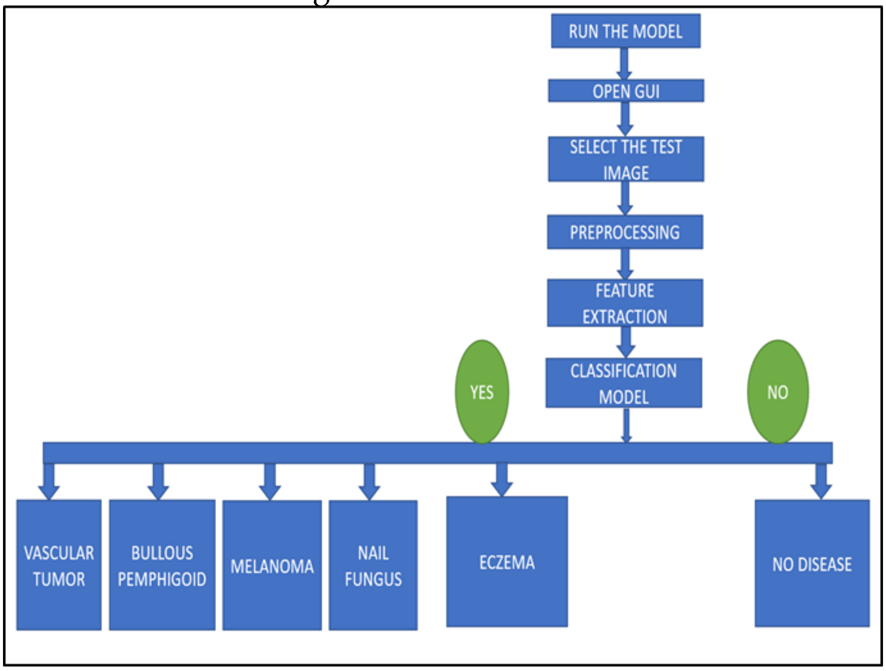

Fig. 1 – Flow Chart of the Proposed Method

A. Dataset: We prepared our dataset by gathering photos from two distinct sources named DermNet [21] and HAM10000 [22 - 26]. The DermNet is an open-access dataset including over 23,000 photos that have been collected and annotated by Dermnet Skin Disease Atlas. The connections for the remaining photographs seemed to be broken, thus we were only able to download 22,501 images. From these downloaded images, four specific types of skin diseases: Eczema, Nail fungus, Bullous, and Vascular Tumors, have been sorted and separated.

We have used the HAM10000 dataset for photos of melanoma. The data has been partitioned into three distinct sets: a training dataset with 5024 images, a validation dataset containing 1900 images, and a separate testing set comprising 576 images. The training and validation sets are primarily utilized to train our model, while the test set serves the purpose of assessing the model's performance. A preview of the photos that make up our dataset may be found in Fig. 2. Table 1 Shows How The Dataset Was Divided Into Training And Testing Datasets

Fig. 2. Sample Images of Dataset

Table 2. Overall Dataset Splitting

Skin diseases	Training images	Validation images	Test images
Eczema	1590	320	40
Nail Fungus	858	197	30
Melanoma	2578	487	60
Bullous Pemphigoid	434	107	20
Vascular tumour	478	115	25
Total	5938	1226	175

B. Image processing: Before inputting the images into the deep learning network, several image processing steps were undertaken. Image resizing was conducted to ensure all images were standardized to 224 × 224 pixels, aligning with the proposed model's input size. To eliminate any color bias in clinical images, a shades of grey color constancy algorithm was utilized during pre-processing. Additionally, augmentation techniques such as cropping, scaling, contrast and brightness adjustments, horizontal and vertical flips, and combinations of these methods were applied to enhance the dataset.
C. Label Encoding: Labels are 5 different classes of skin disease from 1-5. The labels are Eczema, Nail Fungus, Melanoma, Bullous Pemphigoid, and Vascular Tumor.
E. Feature Extraction: In this work, feature extraction utilized CNN architectures based on AlexNet and VGG19. The training phase in proposed model encompasses deep feature extraction, while the subsequent testing phase evaluates the performance of these features when diagnosing new images. The strength of deep learning models lies in their multi-layered structure for feature extraction.
This process takes place inside the CNN's convolutional layers, each of which serves as a specialized filter to extract distinguishing characteristics. Combining VGG19 and AlexNet for feature extraction guarantees a thorough examination of many attributes in the skin photos. VGG19, which excels at pattern recognition

thanks to its deep design, is complemented by AlexNet, which is well-known for its capacity to capture complex features. The network gains the ability to extract hierarchical representations of features from the skin images as they go through these coupled layers, giving it a more sophisticated knowledge of the subtleties connected to various skin disorders. The overall accuracy and dependability of the skin disease detection system are improved by the model's ability to discern minute visual cues that are symptomatic of skin disease.

F. Model Implementation: We utilized the Keras Sequential API, adding layers incrementally, starting with the input. With 32 filters operating, each applies a kernel filter to specific parts of the image, determined by the kernel size, resulting in transformed images. The subsequent pivotal layer is the pooling layer, using MaxPooling to down-sample by selecting the highest value pixel from a nearby set [30]. This step scales machine values, reducing overfitting. The combination of these layers allows CNN to learn both local and global features. We use the softmax activation function for multi-class classification and apply dropout regularization to prevent overfitting [31]. Flattening the final feature maps using the Flatten Layer is essential for subsequent fully connected layers to consolidate learned options. The Dense () layer generates the likelihood distribution for each category, serving as the final output layer. After layer addition, defining a scoring function, loss function (binary cross-entropy in our case), and selecting an optimization algorithm (such as the widely used Adam optimizer) is crucial. Employing a decreasing learning rate (LR) through annealing helps minimize loss, a critical aspect for efficient learning. Accuracy metrics are employed to evaluate the system's performance.

G. Evaluation metrics: To measure the performance of the system we calculate precision, recall, F-score, and accuracy by following formulae:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{F1 Score} = 2 * \frac{\text{P*R}}{\text{P+R}} \quad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Where TP represents True Positive, FP represents False Positive, TN represents True Negative and FN represents False Negative. Similarly, P, R, represents precision and recall respectively.the other hand, it should be

RESULTS AND DISCUSSION

The system aims to categorize a provided skin image as either 'Normal skin' or as one of five classes of skin diseases- Eczema, Nail fungus, Melanoma, Bullous, and Vascular Tumor utilizing deep learning methodologies. The dataset is partitioned into training and testing sets, and deep learning models are constructed using Convolutional Neural Networks (CNN) along with pre-trained networks, including AlexNet and VGG19. The detection rate for five different diseases are shown in Table 2.

Table 2. Test Performance of Skin Disease Detection System

Skin diseases	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
Eczema	91.85	89.02	90.89	90.27
Nail Fungus	88.27	84.51	85.82	86.75
Melanoma	99.36	94.36	96.00	96.83
Bullous Pemphigoid	87.32	84.42	86.90	85.64
Vascular tumour	85.98	82.67	84.56	84.22

The performance matrix of our system is shown in the graph (Figure 3). Examining the graph reveals that a substantial portion of the predictions align accurately with the designated categories, with only a minimal number of inaccuracies.

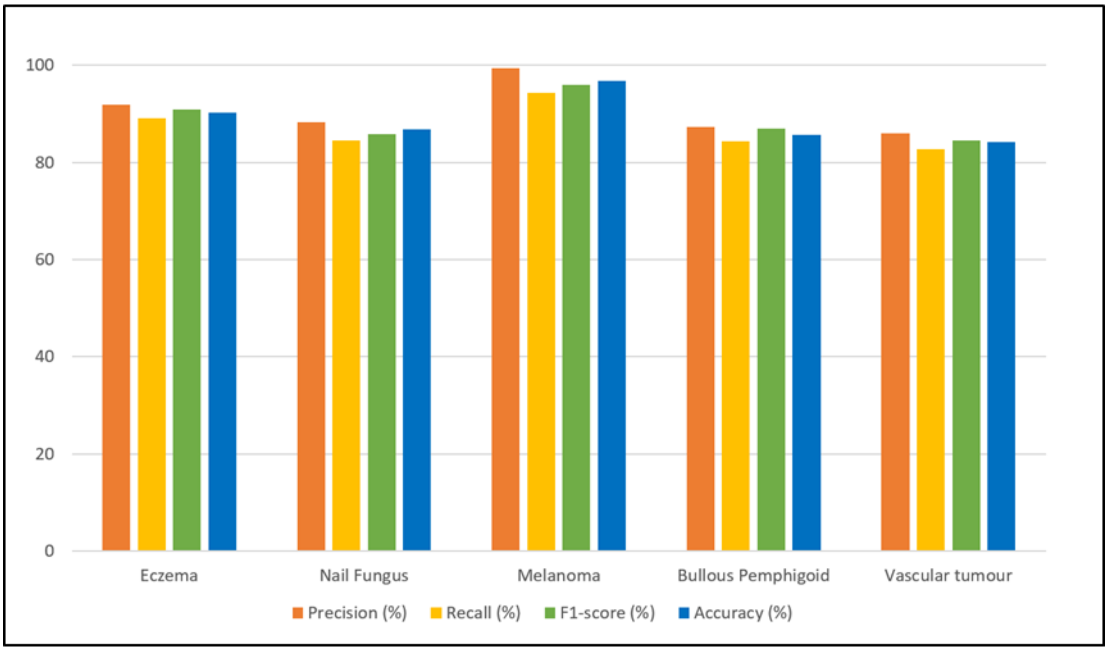

Fig. 3. Performance Graph

Results from our experiment are depicted in Figure 4, illustrating the outcomes. Our user interface allows for input of new images, with the system determining whether it is a skin disease. If identified as a disease, the system classifies it into one of the five disease categories.

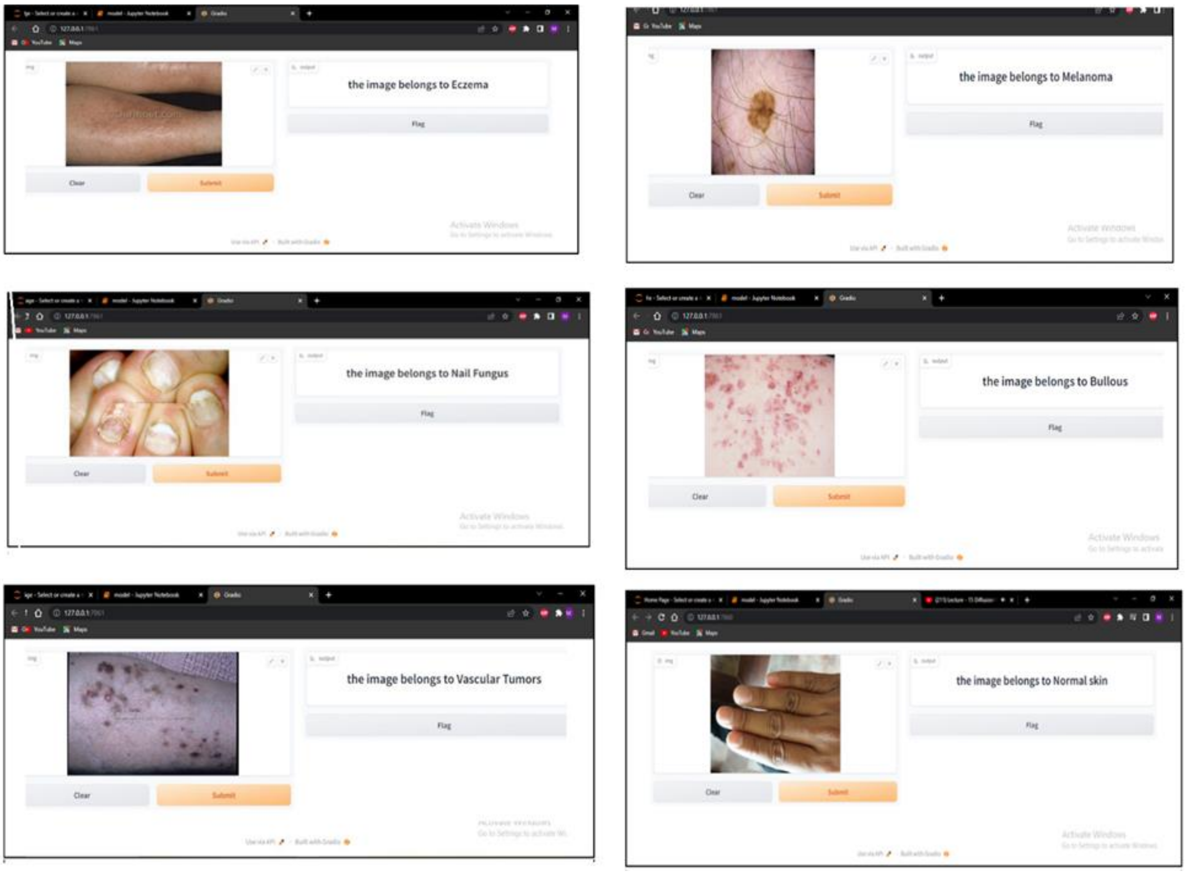

Fig. 4. Outcome of the Skin Disease Detection System

CONCLUSIONS AND RECOMMENDATIONS

Despite skin diseases being the fourth most common health issue, many individuals delay seeking medical attention. We provided a reliable and automated method for diagnosing dermatological illnesses. Skin disorders are more effective and less disfiguring when addressed early. In this paper, a model for the prediction of skin diseases is developed using deep learning techniques. It was found that employing a convolutional neural network can improve accuracy. But we only included five different skin conditions in our model: eczema, nail fungus, melanoma, bullous pemphigoid, and vascular tumor each of which has an accuracy level of 90.27%, 86.75%, 96.83%, 85.64%, and 84.22%. This demonstrates the enormous potential of convolutional neural network algorithms for diagnosing skin diseases in the real world. A very large dataset and even more sophisticated technology and software can greatly increase the accuracy, and since the model doesn't require any intrusive procedures, it can be utilized in clinical experiments. Future work can be done to make this model a routine process for preliminary skin disease diagnosis, since it will reduce the time and expense associated with treatment and diagnosis.

FURTHER STUDY

This research still has limitations, so it is necessary to carry out further research related to the topic of Enhanced Skin Disease Detection and Classification System Using Deep Learning Technique in order to improve this research and add insight to readers.

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