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Hybrid Approach for Skin Disease Classification: Integrating Machine learning and Deep Learning

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Abstract: Skin infections are more common than many other diseases, and they can be caused by various factors such as infectious pollution, microorganisms, awareness, and infections. With the advancement of lasers and photonics-based medical technology, the diagnosis of skin infections has become faster and more accurate. However, the cost of such diagnosis is still limited and expensive. Therefore, image processing techniques are used to develop an automated assessment system for dermatology at an early stage. The extraction of features plays a crucial role in accurately and quickly diagnosing skin diseases. PC vision plays an important role in the detection of skin diseases in various ways. This study focuses on four skin diseases: ringworm, nail parasite, psoriasis, and atopic dermatitis. Convolutional neural networks have achieved close to or even better performance than humans in the imaging field. The skin diseases are classified using a machine learning algorithm, i.e., random forest, which achieves an accuracy of 98.23% after 100 epochs.
Keywords: Skin Disease Detection, Convolutional Neural Network, Image Processing, Deep Learning, Machine Learning, Random Forest.

I. INTRODUCTION

Skin diseases can pose risks to individuals with insufficient melanin, making them vulnerable to sunburn and harmful sun radiation. Early intervention is crucial for accurate outcomes and effective treatment by clinicians and dermatologists. Clinical data technology plays a significant role in healthcare systems, enabling early disease detection and improved patient care. However, accurate diagnosis is essential, as incorrect diagnoses can lead to fatalities in skin-related diseases. Therefore, precise diagnostic aids are needed. Skin disorders such as acne, alopecia, ringworm, and dermatitis can significantly impact a person's appearance, emphasizing the importance of skin protection. Computer-assisted analysis has become increasingly relied upon in the medical field. Deep neural networks (DNN) have proven effective in feature learning and classification tasks. While advancements in artificial intelligence have improved the efficiency of skin disease detection, accuracy regarding specific skin diseases remains a challenge. Skin diseases have a significant impact globally, affecting millions of people and placing a burden on communities and healthcare providers. Skin diseases can lead to economic, social, and psychological burdens, including depression and suicidal ideation. The prevalence of skin diseases varies due to environmental factors, hygiene standards, cultural practices, and genetics. Diagnosis traditionally relies on patient history, symptom analysis, and physical examinations, but these methods can be time-consuming and subject to interpretation. Advanced imaging technologies offer potential solutions but are often complex, expensive, and limited to specialized healthcare facilities, leaving underserved populations without access to dermatological care. Smartphone-based imaging and sensing platforms have emerged as an alternative for disease diagnosis, leveraging the capabilities of high-definition cameras, large storage capacity, and powerful processors. These smartphones enable the capture of digital images and videos for analysis using computer-aided diagnosis (CAD) systems.In recent years, there has been a growing interest in using artificial intelligence (AI) and machine learning (ML) for skin disease diagnosis and treatment. One of the most promising applications of AI in dermatology is computer-aided diagnosis (CAD), which involves the use of algorithms and software to analyze medical images of skin lesions and provide a diagnosis.By using machine learning-based systems, dermatologists can analyze a vast amount of data in a short period of time and make more accurate diagnoses. This can lead to earlier detection and treatment of skin diseases, which can be life-saving in some cases. Additionally, It can help to reduce the number of unnecessary biopsies and improve the accuracy of skin cancer diagnosis.Smartphone-based imaging and sensing platforms have also emerged as an alternative method for skin disease diagnosis.

With the increasing availability of high-quality cameras and high-performance processors on smartphones, dermatologists can now use them to capture digital images and videos of skin lesions and use computer-aided diagnosis to analyze the images. This can make skin disease diagnosis more accessible and affordable for people who may not have access to specialized medical facilities.
Despite the potential benefits of using deep learning and machine learning in dermatology, there are still challenges that need to be addressed. Overall, DL and ML have the potential to revolutionize dermatology and improve patient outcomes. As the technology continues to advance, it is important for researchers, clinicians, and policymakers to work together to address the challenges and ensure that theses technologies is used in a responsible and ethical manner.

II. LITERATURE SURVEY

Zhe Wu et al. [1], In this paper various CNN algorithms were explored for the classification of face skin diseases using clinical images. They curated a dataset from Xiangya-Derm, China's largest clinical image dataset of skin diseases, which consisted of 2656 face images representing six common skin diseases, including seborrheic keratosis (SK), actinic keratosis (AK), rosacea (ROS), lupus erythematosus (LE), basal cell carcinoma (BCC), and squamous cell carcinoma (SCC).
Nawal Soliman ALKolifi ALEnezi [2] proposed an image processing-based approach for skin disease detection. This approach involves capturing high-resolution images of affected skin and performing image analysis to identify the type of disease. The proposed method is simple, fast, and does not require expensive equipment other than a camera and a computer. It handles the variations in image composition by resizing the image and extracting features using a pretrained convolutional neural network. These features are then used for classification using a multiclass support vector machine (SVM).
Masum Shah Junayed and Abu Noman Md Sakib [3] proposed an intelligent CNN-based approach for classifying five different classes of skin diseases using a curated dataset. Data augmentation techniques were employed to enhance the performance of the models. Regularization techniques such as batch normalization and dropout were utilized to reduce overfitting. The proposed model achieved an accuracy of 96.2%, surpassing the state-of-the-art performance in skin disease classification.
Seunghyeok Back [4] aimed to establish a specialized deep neural network (DNN) capable of distinguishing herpes zoster (HZ) from other skin diseases using user-submitted images. To improve efficiency while maintaining low computational cost, the author proposed a data refinement method called knowledge distillation ensemble training (KDE-CT), in which a student network learns from a stronger teacher network.
Neha Agrawal et al. [5] employed transfer learning techniques to identify three skin diseases, namely melanoma, vitiligo, and vascular lesions. The initial V3 model served as a base model, which was then fine-tuned. Significant improvements in training accuracy and testing accuracy were achieved.
Milton and Md Ashraful Alam [6] extensively focused on various deep learning-based models for the detection of melanoma and skin lesion malignancies. Early and accurate diagnosis of melanoma, a type of malignant skin cancer, is crucial for successful treatment. Dermoscopic images depicting benign and malignant skin lesions were analyzed using computer vision techniques. Different deep learning models, such as PNASNet-5-Large, InceptionResNetV2, SENet154, and InceptionV4, were experimented with. The dermoscopic images were appropriately preprocessed and augmented before feeding them into the models. The proposed methods were evaluated on the International Skin Imaging Collaboration (ISIC) 2018 test dataset, achieving a top validation score of 0.76 for the PNASNet-5-Large model. Further improvements and optimizations with larger training datasets and carefully selected hyperparameters could enhance the performance of the proposed methods
Jainesh Rathod and Vishal Waghmode et al. [7] highlighted the complexity of dermatology and the challenges associated with diagnosing skin conditions. In the field of dermatology, multiple examinations and assessments are often required to determine the specific skin condition a patient may be facing. This process can vary from one expert to another, depending on their experience and expertise.
Therefore, there is a need for an automated image-based system for the diagnosis of skin diseases using artificial intelligence techniques. The proposed system utilizes computational methods to analyze, process, and interpret image data based on various features extracted from the images. Skin images are filtered to eliminate unwanted noise and enhance image quality. Feature extraction techniques, such as convolutional neural networks (CNNs), are employed to describe the image, and a softmax classifier is used for classification, generating a diagnostic report.
This system aims to provide higher precision and faster results compared to traditional methods, making it an efficient and reliable tool for dermatological disorder diagnosis. Additionally, it can serve as a valuable learning resource for medical students specializing in dermatology.

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III. PROPOSED METHOD AND ALGORITHM

A. Proposed Method

In our proposed system, we plan to conduct experiments focused on skin diseases, specifically atopic dermatitis, psoriasis, ringworm, and nail fungus. Due to limited availability of supervised data, we aim to develop a multimodal disease risk prediction model using a combination of convolutional neural network and random forest algorithms. The primary objective is to achieve higher accuracy in the prediction of these limited skin diseases. Additionally, we aim to address the accuracy challenges associated with the diagnosis of psoriasis by providing accurate stage predictions.

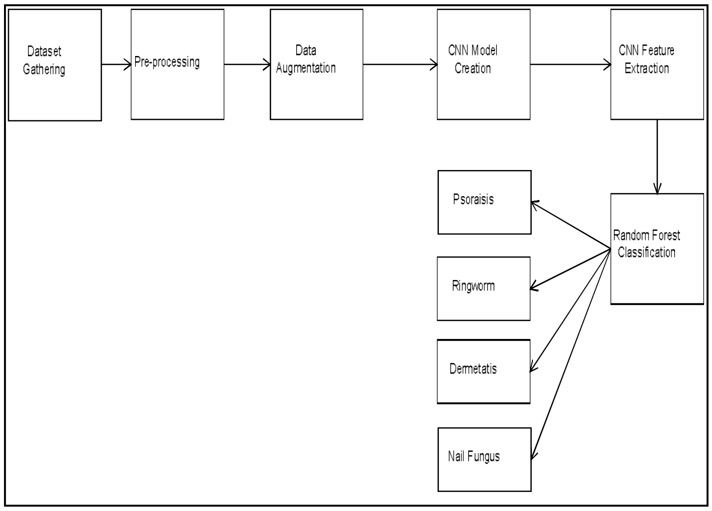

Fig1. Proposed Architecture

1) Data Gathering

The initial step in our research involved the collection of a dataset. The dataset was carefully compiled, and we subsequently divided it into two distinct sets: a training set and a testing set. The training set comprised 600 images, while we reserved 60 images for the testing set. This division allowed us to effectively train and evaluate our models.

2) Data Preprocessing

Once we had gathered the data, we took several preprocessing steps to ensure optimal training on the dataset. One such step was resizing the images to a standard size, typically 224x224 pixels. This resizing process helped to normalize the images and create consistency in the dataset. Additionally, we performed thorough screening of the data to identify and eliminate any redundancy or noise present. By removing these unwanted elements, we aimed to improve the accuracy and reliability of our training process.

3) Data Augmentation

Applying data augmentation techniques can effectively reduce overfitting and enhance the accuracy of both training and testing processes. By augmenting the data, we increase the size of the training dataset by incorporating variations of the original images. This includes operations such as rotating, zooming, shearing, and adjusting the brightness of the images. These transformations introduce diversity into the dataset, allowing the model to learn from a wider range of examples and generalize better to unseen data. As a result, data augmentation helps to improve the model's performance by mitigating overfitting and enabling more robust training and testing.

B. Algorithm

1) Convolutional Neural Networks(CNN)

Convolutional Neural Networks (CNNs), also known as ConvNets, have emerged as powerful architectures for various applications in image analysis and recognition. These networks have been extensively employed in the fields of object detection, image classification, and other related tasks. The fundamental operations involved in Convolutional Neural Networks can be summarized as follows:

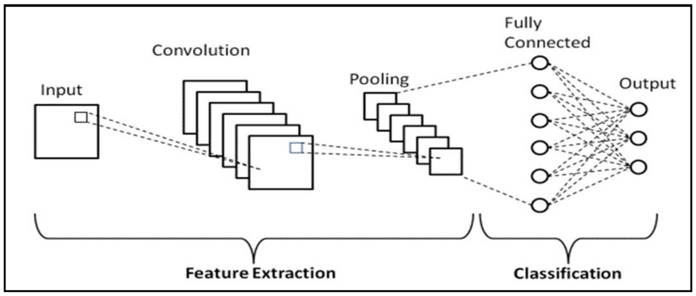

Fig2. CNN Architecture

a) Convolution

In the case of a CNN, the primary application of the Convolution operation is to extract relevant features from the image, serving as input to the subsequent layers. Convolution helps preserve the spatial relationships between pixels by applying small filters or kernels across the image to capture image features. This process involves convolving the filters with the image to extract important information.

b) Rectified Linear Unit (ReLU)

The Rectified Linear Unit (ReLU) function is a simple activation function commonly used in neural networks. It operates on a per-pixel basis and sets all negative pixel values in the feature map to zero, effectively eliminating any negative activations. This non-linear activation function helps introduce non-linearity to the network and allows it to learn more complex representations.

c) Pooling Or Subtesting

Pooling, also known as subsampling or downsampling, is a technique used in convolutional neural networks to reduce the size of feature maps while preserving important information. Specifically, spatial pooling reduces the dimensions of each feature map by selecting representative values through a pooling operation. This process helps to summarize the essential information from the input while maintaining the key features of the original data.

2) Random Forest

A "Random Forest" is an artificial intelligence algorithm used for solving classification and regression problems. It uses ensemble learning, which combines multiple decision trees to provide solutions for complex problems. A Random Forest algorithm consists of several decision trees. The decision tree generated by the Random Forest algorithm is trained through a process called bagging or bootstrap aggregating. Bagging is a meta-learning technique that improves the accuracy of AI algorithms. The Random Forest algorithm produces a result based on the predictions of the decision trees. It predicts the output by taking the average or mean of the result from multiple trees. Increasing the number of trees improves the accuracy of the output.

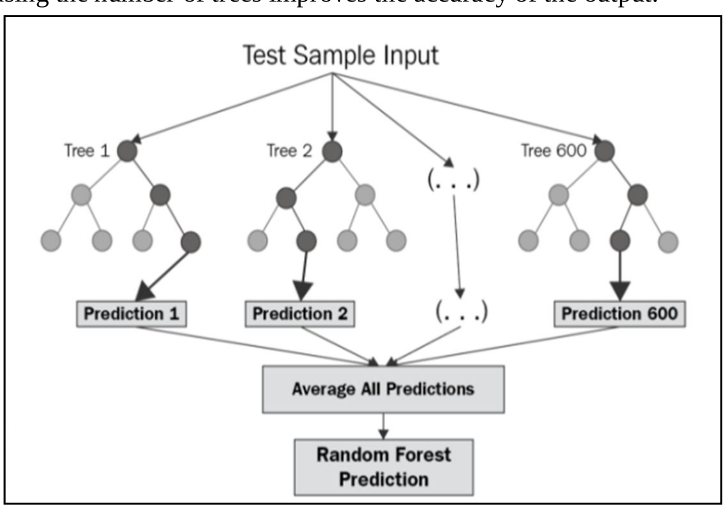

Fig3. Random Forest Architecture

IV. RESULTS AND DISCUSSION

In our experimental setup, as shown in table 1 ,we conducted tests on a total of 287 trained images belonging to four categories: ringworm, Nail fungus, Psoriasis, and atopic dermatitis. Additionally, we tested 56 new images. These images were processed through our CNN framework, which involved feature extraction using our image processing module. The images were then classified using a random forest model. Our trained model successfully classified the images into their respective categories of skin diseases We get the accuracy **98.23%** at 100 epochs as shown in figure4 and figure5

Table 1. Classification Of Data

Sr. No.	Category	Number of Images
1	Training	287
2	Testing	56

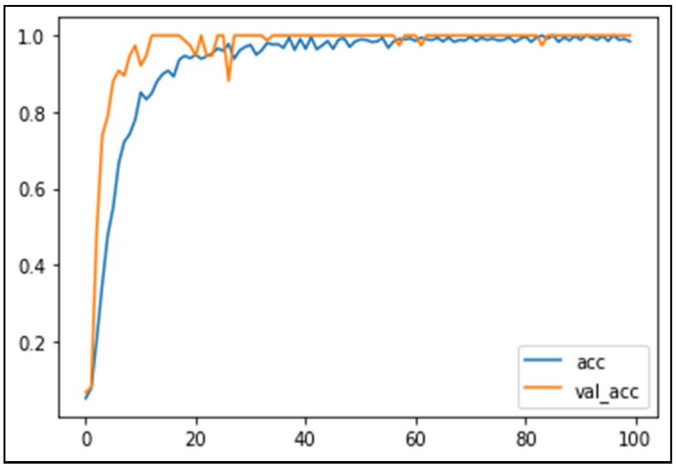

Fig4. Accuracy Graph

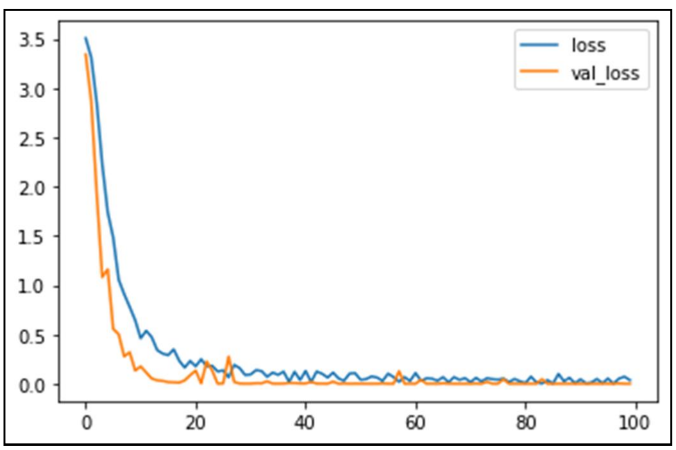

Fig5. Loss Graph

V. CONCLUSION

We have developed a multi-disease detection system using AI and CNN methods, aiming to improve the accuracy and reduce mortality rates associated with skin diseases such as Psoriasis, Ringworm, Atopic Dermatitis, and Nail Growth. Our research paper focuses on the utilization of AI and deep learning models for skin disease detection. By increasing the number of diseases considered and expanding our dataset, we have enhanced the accuracy of our system. Our approach incorporates two algorithms: random forest and CNN. The CNN is responsible for extracting features, which are then classified using the random forest algorithm. Through our experiments, we have achieved an impressive accuracy of 98.23% after 100 epochs. In our future work, we plan to extend our research to include additional skin diseases.

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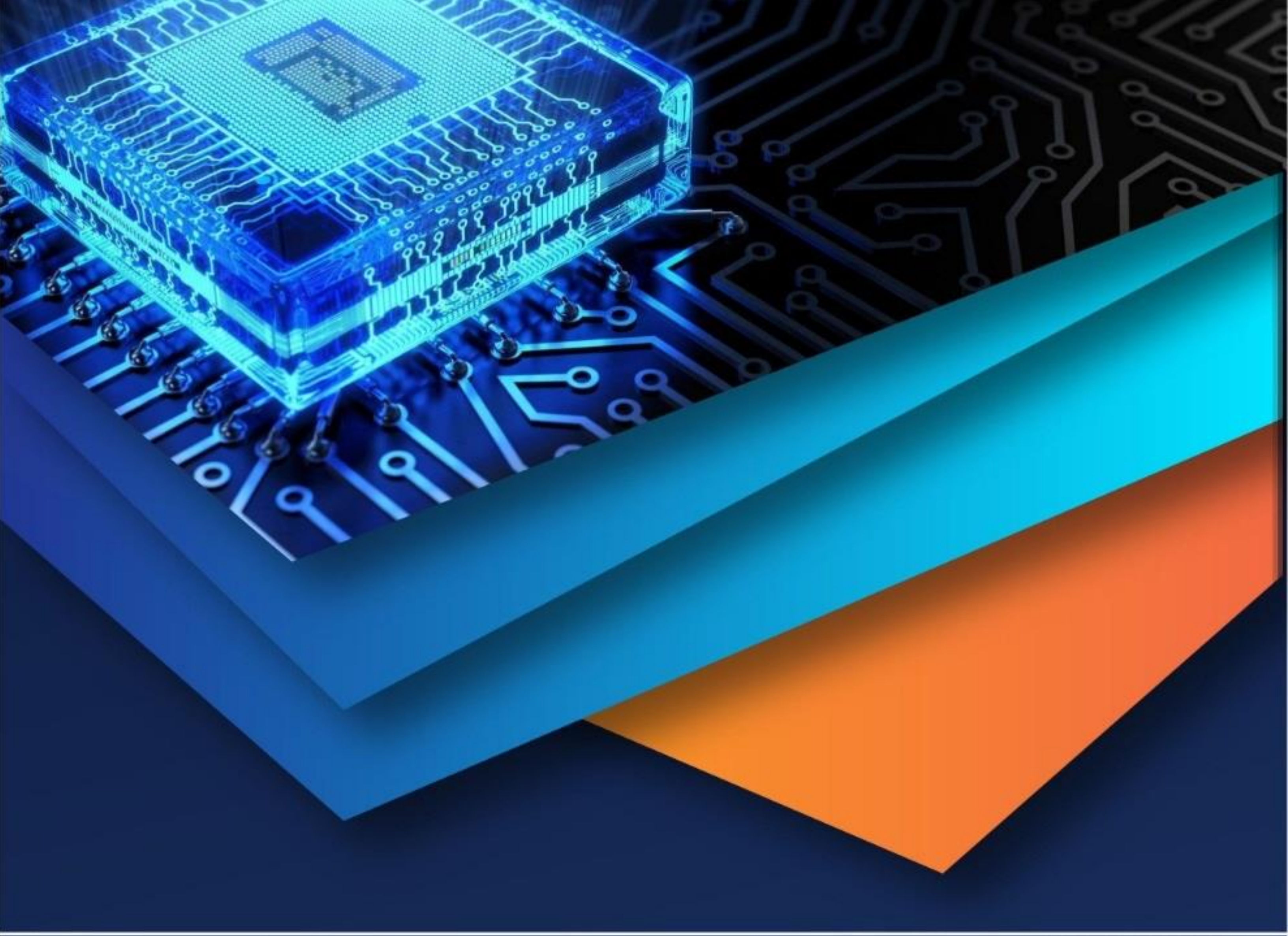

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