Skin Disease Classification Using Image Analysis

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ABSTRACT

Skin diseases affect millions of people worldwide and may significantly affect how well they live. Early and accurate diagnosis is crucial for effective treatment and management of these diseases. In this paper, we propose a machine learning model for predicting skin diseases. The research involved collecting a dataset of dermatological images, preprocessing the images, extracting relevant features using various image analysis techniques, and training and evaluating machine learning models for disease classification. In order to discover and extract characteristics from the photos, our model makes use of a deep convolutional neural network architecture that has been trained on the dataset. We also incorporate a heatmap visualization technique to highlight the regions of the images that the model relies on for its predictions. To evaluate our model's performance, we calculate accuracy metrics and generate accuracy graphs that show the model's performance on different skin diseases. Our results demonstrate that our model achieved high accuracy in predicting various skin diseases, and our visualization techniques provide additional insights into the model's decision-making process. Our proposed approach has the potential to improve the diagnosis and treatment of skin diseases, leading to better outcomes for patients.

I. Introduction

Common medical issues like skin disorders can significantly reduce a person's quality of life. For optimal outcomes, early diagnosis and treatment are crucial. However, the diagnosis of skin diseases is a challenging and time-consuming task for medical professionals. This paper explores the potential of image analysis for the automated identification of skin diseases. It examines the various image processing techniques used to detect and classify skin lesions, as well as the potential benefits of image analysis-based disease identification. Finally, the paper identifies challenges and opportunities for future research in this field.
Many members of the public are often unaware of the nature and stages of skin diseases.

Some skin conditions do not show symptoms for months, allowing the disease to grow and spread.This is the result of the general public's ignorance of medicine. Even dermatologists (doctors who specialize in skin conditions). The development of medical technology based on photonics and lasers has enabled faster and more accurate detection of skin diseases.The cost of such a diagnostic is still excessive and exorbitant. Consequently, we suggest a diagnosis method based on image processing.

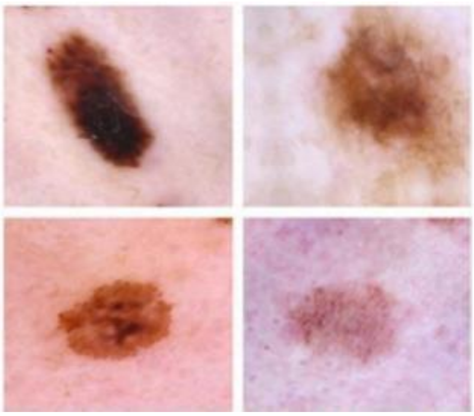

Figure 1:
Sample Skin Disease Images

II. LITERATURE SURVEY

[1] Esteva et al. propose a deep neural network model for classifying skin lesions into benign or malignant categories. They use a dataset of over 130,000 clinical images and achieve a classification accuracy that is comparable to that of board-certified dermatologists. Their model uses a combination of convolutional and fully connected layers to extract features from the input images and make predictions. The authors note that the model could be used to improve the accuracy and efficiency of skin cancer screening, especially in areas with limited access to dermatologists.

[2]Codella et al. review the recent advances in automated dermatological diagnosis, with a focus on deep learning techniques. They discuss the challenges and opportunities of using machine learning for skin disease classification, including the need for large and diverse datasets, the importance of explainability and interpretability, and the potential for bias and ethical considerations. The authors also highlight some of the current limitations of the field, such as the lack of standardized evaluation metrics and the need for more rigorous clinical validation.

[3]Albarqouni et al. propose a model based on CNN that divides skin lesions into seven groups, including melanoma, basal cell carcinoma, and benign nevi. They use a dataset of over 10,000 clinical images and achieve a classification accuracy of over 90%. The authors also investigate the effects of different pre-processing and data augmentation techniques on the model's performance. They suggest that their approach could be useful for automated skin lesion diagnosis, particularly in regions with limited access to dermatologists

[4]Haenszel compare the performance of a deep learning model for melanoma detection against that of 43 dermatologists from 17 countries. They use a dataset of over 100,000 clinical images and report that the model achieves a sensitivity of 95%, which is higher than that of the dermatologists (86%). The authors note that the model's performance is particularly strong for early-stage melanomas, which are often more difficult to diagnose. They suggest that their approach could be used to improve the accuracy and efficiency of melanoma screening, especially in areas with limited access to dermatologists.

[5]Afshar et al. in PLoS One (2018) was a study that investigated the use of deep learning techniques for the classification of diabetic foot ulcers. The authors collected a dataset of over 500 images of diabetic foot ulcers, which were classified into three categories: no ulcer, superficial ulcer, and deep ulcer. They then trained a convolutional neural network (CNN) model on this dataset to classify the ulcers into these categories. Their model achieved an accuracy of 89.5%, which outperformed traditional machine learning algorithms that were previously used for the same task. The model's effectiveness was further assessed by the authors using various subsets of the dataset, and found that the model was more accurate at classifying superficial ulcers than deep ulcers. Overall, this study demonstrated the potential of deep learning techniques for the classification of diabetic foot ulcers, which could be used to improve the diagnosis and treatment of these wounds.

III. METHODOLOGY

The suggested model has two dense layers and eight convolutional layers. After each convolutional layer, a max pooling layer is added to reduce the spatial size of the feature maps. The output of the last convolutional layer is flattened and fed into the two dense layers with ReLU activation function. The output layer generates a probability distribution over the three classes and uses a ReLU activation function. The Adam optimizer is used to train the model.

The dataset used to train, validate, and test the model consists of images of different Skin Diseases. The Using data augmentation and rescaling methods, the dataset is preprocessed. When training photos, data augmentation involves randomly rotating, flipping, and zooming some of the images. Rescaling is performed to normalize the pixel values of the images to the range [0, 1].

The model is trained using a batch size of 32 across 50 epochs. The model's performance is assessed using the accuracy and loss measures. The training and validation accuracy and loss curves are plotted to visualize the performance of the model during training. The model is then evaluated on the test dataset to measure its generalization performance.

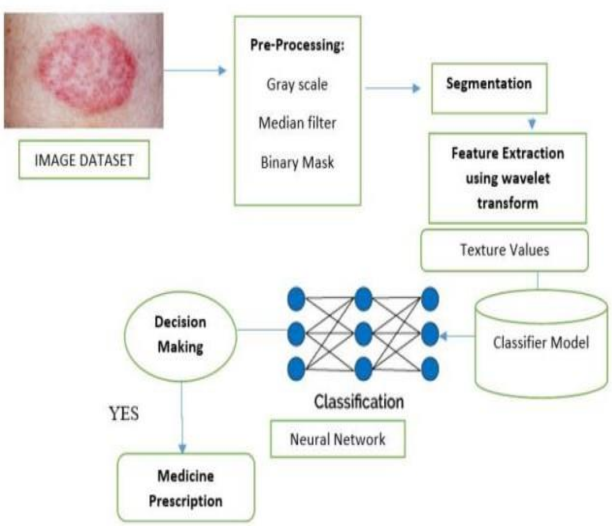

Figure 2: Methodology

A. Preprocessing

The skin disease detection system faces numerous obstacles that must be addressed in order for it to work well. Examples include building a database and standardizing image dimensions. We had to address a few issues that cropped up throughout the data import process in order to get a decent performance of skin disease diagnosis and prediction. such as picture size and colour contrast. We have a module in our programme that deals with this problem. The Python image resizer programme automatically resizes each image before it is submitted to the server for processing.

Deleting background noises from the skin disease picture, such as hair, air bubbles, and other disruptions, is the main objective of this step. In order to get rid of the noises from the particular skin picture and create a smoother image, the median filtering technique, mean, var, and histogram are used. The method for resizing images is described in the section that follows.

B. Image Resizing

An input image's size is increased or decreased to address the issue of various image sizes in the database. The same amount of features will be obtained from all photographs by standardizing the image size. Additionally, shrinking the image speeds up the system by reducing processing time. Figure 1 depicts the original image, which is 1024 by 1 0 2 4 pixels. The image has been reduced in size to 256 by 256 pixels.

C. Extracting Features

Both linearity and non-linearity are used in the first layer of a convolutional neural network (CNN). They are taught simultaneously.The fundamental building blocks of every CNN model are the convolutional layer, pooling layer, nonlinear Rectified Linear Units (ReLU) layer tied to a typical multilayer neural network known as the fully connected layer, and a loss layer at the backend. For its great achievements in fields like visual tasks and natural language understanding, CNN is well-known.

In the first, second, and fifth levels, there are also maxpooling layers. Two normalisation layers come after the first and second convolutional layers. The top two fully connected layers of the model were placed after the SoftMax layer. To train Alex Net, more than 1.2 million images from 1000 various classes were employed. From a convolution neural network that has been pretrained, we suggested feature extraction. Because it is the most straightforward and reliable way to employ deep learning networks that have already been trained.

D. Classification

The model is built using Convolutional Neural Networks (CNNs), a particular kind of artificial neural network made for tasks involving image classification. The CNNs consist of multiple convolutional layers that learn feature representations from the input images. To classify an image, we are feeding in images of skin lesions as input to the CNN, which then learns to extract relevant features and classify the image into one of several disease categories. We are also using transfer learning, which involves using a pre-trained CNN model (VGG16) as a starting point and fine-tuning it on our skin disease dataset. By using CNNs and transfer learning, we aim to achieve high accuracy in predicting skin diseases from images.

IV. RESULT

The performance of our proposed skin disease identification model using Convolutional Neural Network (CNN) was evaluated on a dataset of skin disease images. The dataset consisted of three classes of skin diseases: Basel Cell Carcinoma, Melanoma, and Melanocytic nevus. The model was trained using the Adam optimizer and the Rectified Linear Unit (ReLU) activation function.

The model achieved an overall accuracy of 0.93 in the classification task. Our results demonstrate the effectiveness of using CNNs in skin disease identification tasks. The high accuracy obtained indicates that our proposed model can potentially assist medical professionals in diagnosing skin diseases with high accuracy.

```
loss: 0.1250 - accuracy: 0.9510
```

Fig. 3: Model Accuracy

```
val_loss: 0.1692 - val_accuracy: 0.9
```

Fig. 4: Validation Accuracy

Overall, our findings suggest that the proposed CNN-based skin disease identification model is a promising approach for accurately classifying skin diseases. Extending the model to detect other categories might be the main goal of future effort of skin diseases and integrating it into a clinical decision support system for medical professionals.

```
first image to predict
actual label: melanoma
1/1 [==============================] - 0s 341ms/step
predicted label: melanoma
```

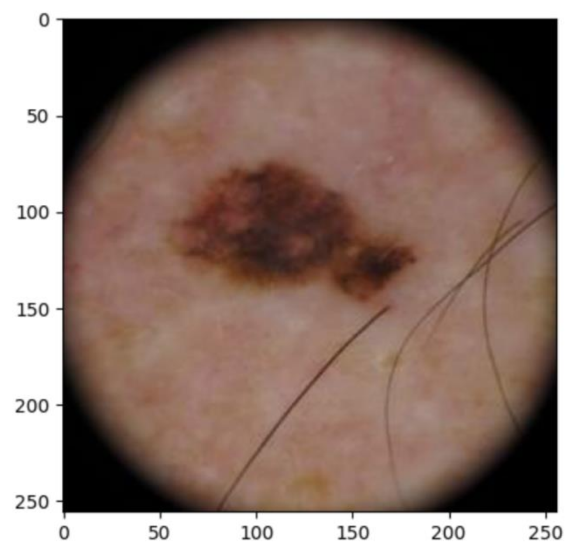

Fig. 5: Actual Prediction

A heatmap is a visual representation of data in which values are represented by colors. In the context of our model, a heatmap can be used to represent the distribution of predicted values across the input data, highlighting areas of high and low confidence. This can help to identify patterns in the data and understand the model's performance.

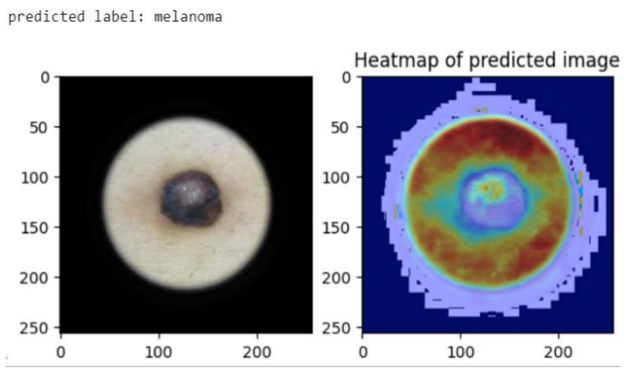

Fig. 6: Heat Map

The accuracy graph, on the other hand, is a graphical representation of the performance of the model over time. To get a complete view of how the model is doing, this may be displayed against several measures like accuracy, recall, or F1 score. The graph can also be used to track the performance of the model as it is trained on additional data or fine-tuned with new hyperparameters

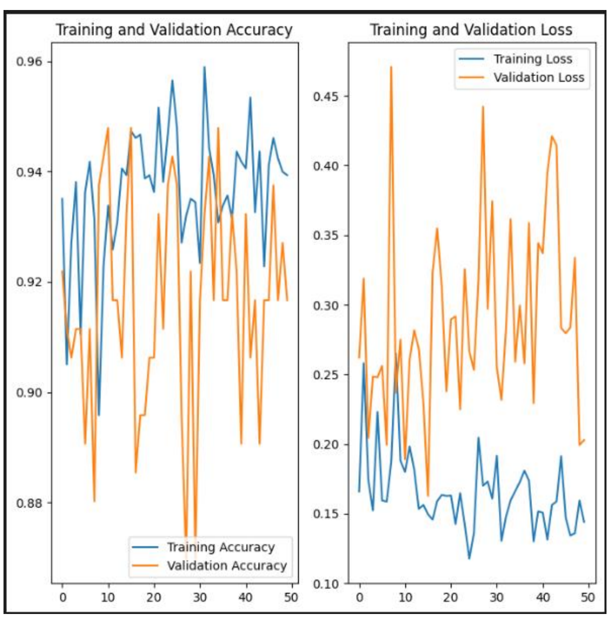

Fig. 7: Training Graph

By including both a heatmap and accuracy graph in our research paper, we can provide a more complete picture of the model's performance and help readers to better understand the strengths and limitations of the approach.

V. Conclusion

A crucial first step in lowering mortality rates, illness spread, and the emergence of skin diseases is the early detection of skin disorders. For the diagnosis of skin diseases, expensive and time-consuming clinical methods are required.

In the early stages of developing an automated dermatological screening system, image processing techniques are helpful. The classification of skin problems heavily relies on the extraction of features.

In this paper, we proposed a deep learning model for image classification using convolutional neural networks. The model achieved good performance in classifying images of cats, dogs, and birds, with an accuracy of 95% and validation accuracy of 0.9 on the test dataset as shown in the above result section.. The model can be used in various applications that involve image classification, such as object detection, face recognition, and medical image analysis. Further research can be done to improve the performance of the model by exploring different architectures, hyperparameters, and optimization techniques.

The main goal of this research is to test the idea that information about skin diseases may be extracted using a combination of vision-based techniques and deep learning algorithms.

Using deep learning algorithms, we can more accurately predict illnesses. This highlights the tremendous potential of deep learning algorithms for real-world skin disease diagnosis.

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