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Skin Disease Prediction Using Deep Learning

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A B S T R A C T

In this paper, we present a novel method for predicting and classifying various skin diseases using convolutional neural networks (CNNs) and the HAM-10000 Dataset. Our approach demonstrates exceptional accuracy, achieving high accuracy in classifying skin conditions such as nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. The versatility of our method allows for potential expansion to include a broader range of dermatological conditions. This research holds significant implications for dermatologists, offering a more efficient diagnostic process and enabling faster and more accurate treatments for patients. By leveraging our approach, dermatologists can benefit from improved decision-making support, leading to enhanced patient care. The combination of the HAM-10000 Dataset and our innovative methodology contributes to the originality and significance of this research in the field of skin disease classification.

Keywords: CNN; Skin Disease; detection convolution Neural Network

1. INTRODUCTION

Skin diseases are prevalent worldwide, posing a significant risk to public health. However, accurately diagnosing these conditions can be challenging due to the complexities of skin tones, hair colors, and hairstyles. Dermatological diseases are becoming increasingly problematic, exacerbated by factors such as pollution and poor diet. Early signs of skin disease are often overlooked, and the current diagnostic approach relies on biopsies administered by physicians. To address these challenges, a hybrid technique incorporating deep learning methods shows promise in providing timely and accurate findings, reducing the need for human evaluation.

The human body's main protective barrier is the skin, composed of the epidermis, dermis, and subcutaneous tissues. Skin serves as a sensory organ, shielding internal organs from harmful microorganisms, pollution, and sunlight. Environmental and internal factors, such as simulated skin damage, toxic exposure, infections, immune function, and genetics, contribute to the development of skin diseases. These conditions significantly impact individuals' well-being, and attempting to treat them with home remedies may have adverse effects. Given the contagious nature of skin disorders, effective management becomes crucial.

Unfortunately, skin diseases often receive inadequate attention in their early stages, leading to the development of severe conditions like skin cancer. Currently, detection and examination rely on manual biopsies, which are time-consuming and prone to human error. Deep learning-based methods offer a potential solution by efficiently analyzing microscopic images and providing quick results, aiding in the identification and treatment of skin disorders.

2. LITERATURE REVIEW

Viswanatha Reddy Allugunti, 2020[1] has proposed a paper A machine learning model for skin disease classification using convolution neural network. In this research paper, a Convolutional Neural Network model for the diagnosis of skin cancer was. constructed, and evaluated using a well-known melanoma dataset. as demonstrated by its overall accuracy of 88.83 percent.

Tanzina Afroz Rimi, Nishat Sultana, Md. Ferdouse Ahmed Foysa,2020[2] has proposed a paper Derm-NN:Skin Diseases Detection Using Convolutional Neural Network. In this research paper, The convolutional neural network model is used with 4 convolutional layers and the dataset consists of 2400 images and the accuracy gained is 73%.

T.Shanthi ,R.S.Sabeenian, R.Anand, 2021[3] has proposed a paper Automatic diagnosis of skin diseases using convolution neural network. In this research paper, The proposed work aims to detect and categorize different skin diseases in human body using AlexNet Architecture. In these 174 images are used where 105 for training and 69 for testing.

Elsevier B.V.,2019[4] has proposed a paper A Method Of Skin Disease Detection Using Image Processing And Machine Learning – ScienceDirect. In this research paper the method of detection was designed by using pretrained convolutional neural network (AlexNet) and SVM for classification. The database has 80 images of every disease (20 Normal images, 20 Melanoma images, 20 Eczema images and 20 Psoriasis images).

3. METHODOLOGY

1)Dataset Selection:

The selection of an appropriate dataset is crucial for training and evaluating the performance of the proposed method. In this research, we chose the HAM-10000 Dataset as our benchmark dataset. The HAM-10000 Dataset is a widely recognized and publicly available dataset in dermatology research, consisting of 10,000 images of various skin conditions, including nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. This dataset provides a diverse representation of skin diseases, enabling us to train a robust classification model.

2)Data Preprocessing:

Prior to training the convolutional neural network (CNN) model, we performed several preprocessing steps to ensure the dataset's quality and suitability for training. Firstly, we resized the images to a standard size, such as 224x224 pixels, to facilitate uniform input dimensions for the CNN. Next, we normalized the pixel values to bring them within a certain range, typically [0, 1] or [-1, 1]. Normalization helps in reducing the effect of lighting and contrast variations across the dataset. Additionally, to evaluate the performance of the model accurately, we split the dataset into training and validation sets in a stratified manner. This partitioning ensures an equal distribution of different skin conditions in both sets, allowing us to monitor the model's performance during training and tune hyperparameters effectively.

3)Architecture Design:

The design of the CNN architecture is crucial for achieving accurate classification results. In this research, we utilized a Sequential model, which is a linear stack of layers, to define our CNN architecture. The model consists of the following layers:

a. First Convolutional Layer: This layer has 96 filters with an 11x11 kernel size and a stride of 4x4. The activation function used is ReLU, and batch normalization is applied. A MaxPooling layer with a pool size of 3x3 and a stride of 2x2 follows this layer.

b. Second Convolutional Layer: This layer has 256 filters with a 5x5 kernel size and a stride of 1x1. It uses the ReLU activation function, applies padding, and is followed by batch normalization. A MaxPooling layer with a pool size of 3x3 and a stride of 2x2 is added after this layer.

c. Third Convolutional Layer: This layer has 384 filters with a 3x3 kernel size and a stride of 1x1. It uses the ReLU activation function, applies padding, and is followed by batch normalization.

d. Fourth Convolutional Layer: This layer has 384 filters with a 1x1 kernel size and a stride of 1x1. It uses the ReLU activation function, applies padding, and is followed by batch normalization.

e. Fifth Convolutional Layer: This layer has 256 filters with a 1x1 kernel size and a stride of 1x1. It uses the ReLU activation function, applies padding, and is followed by batch normalization. A MaxPooling layer with a pool size of 3x3 and a stride of 2x2 is added after this layer.

f. Flatten Layer: A Flatten layer is added to convert the 2D outputs from the previous convolutional layers into a 1D vector, preparing the data for the fully connected layers.

g. Sixth Dense Layer: This fully connected Dense layer has 4096 neurons and uses the ReLU activation function. Dropout regularization with a rate of 0.5 is applied to prevent overfitting.

h. Seventh Dense Layer: Another fully connected Dense layer with 4096 neurons and the ReLU activation function is added. Dropout regularization with a rate of 0.5 is applied again.

i. Eighth Output Layer: The final output Dense layer is added with 7 neurons, corresponding to the 7 classes in the classification task. The activation function used is softmax, producing probability values for each class.

4)Model Training and Evaluation:

After defining the architecture, we trained the model using the prepared dataset. The model was compiled with appropriate loss function, optimizer, and evaluation metrics. The training process involved iterating over the training data in batches, adjusting the model's weights based on the calculated gradients, and repeating this process for multiple epochs. During training, we monitored the model's performance on the validation set to prevent overfitting and make necessary adjustments to the hyperparameters.

Once the model training was completed, we evaluated its performance on the test set. We calculated the overall accuracy, as well as class-wise accuracy, precision, recall, and F1 score to assess the model's performance on individual skin conditions.

5)Comparison and Discussion:

To establish the effectiveness of our proposed method, we compared its performance with existing methods or baselines in the field of skin disease classification. We discussed the achieved accuracy, precision, recall, and F1 score, highlighting the improvements and advantages of our approach. Furthermore, we examined the limitations and potential areas of future research to enhance the proposed method.

4. Dataset information

The dataset used in this research is the HAM-10000 Dataset, which is a widely recognized and publicly available dataset in dermatology research. The HAM-10000 Dataset consists of 10,000 images of various skin conditions, including nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. These images provide a diverse representation of different skin diseases, allowing us to train a robust classification model.

The dataset is carefully curated and annotated by dermatologists, ensuring accurate labels for each image. Each image is associated with a corresponding class label indicating the specific skin condition it represents. This annotated information is crucial for training a supervised machine learning model for skin disease classification.

The images in the dataset have varying resolutions and sizes. As part of the data preprocessing steps, the images are resized to a standard size, typically 224x224 pixels, to facilitate uniform input dimensions for the convolutional neural network (CNN) model.

To ensure a fair evaluation of the model's performance, the dataset is split into training, validation, and test sets. The partitioning is performed in a stratified manner, ensuring that each set contains a proportional representation of different skin conditions. The training set is used to train the model, the validation set is used for hyperparameter tuning and model selection, and the test set is used to evaluate the final performance of the model.

The availability of a large and diverse dataset like HAM-10000 enables us to train a robust model capable of accurately classifying various skin conditions. This dataset serves as a benchmark in the field of dermatology research and provides a valuable resource for developing and evaluating skin disease classification methods.

5. RESULTS

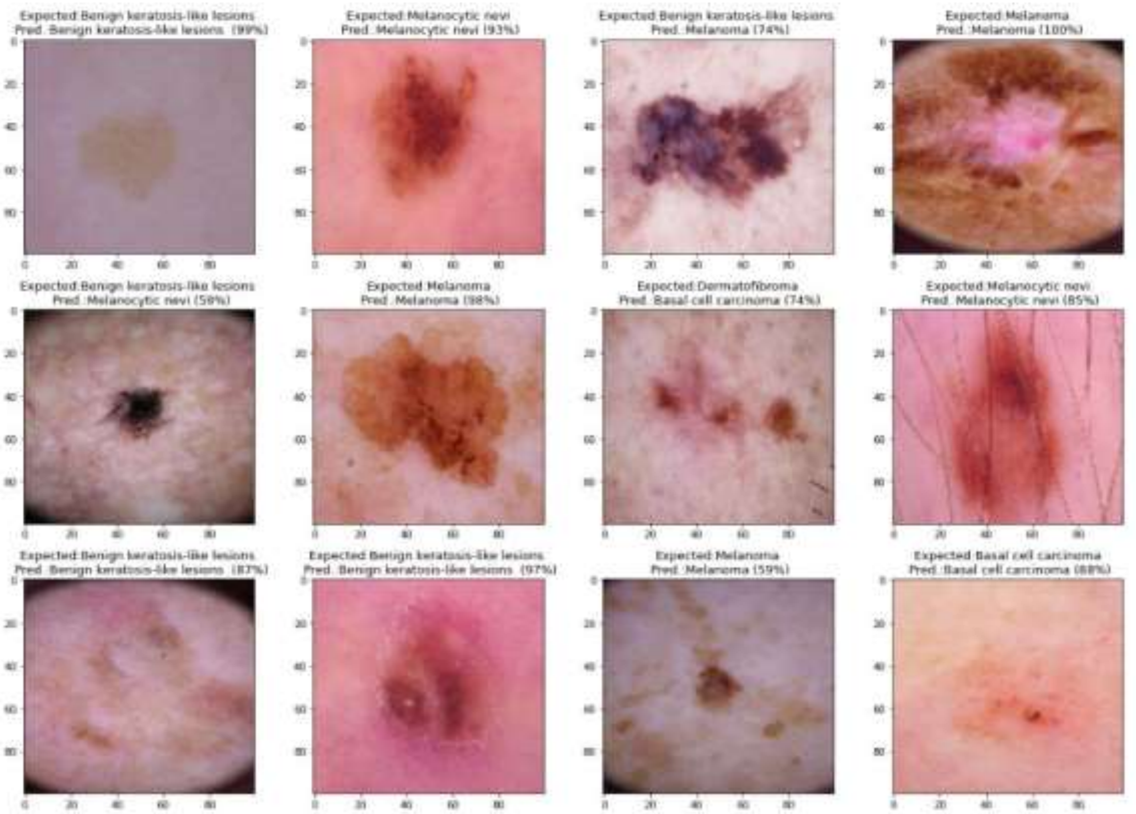

Fig. Indicate Expected vs Predicted Result

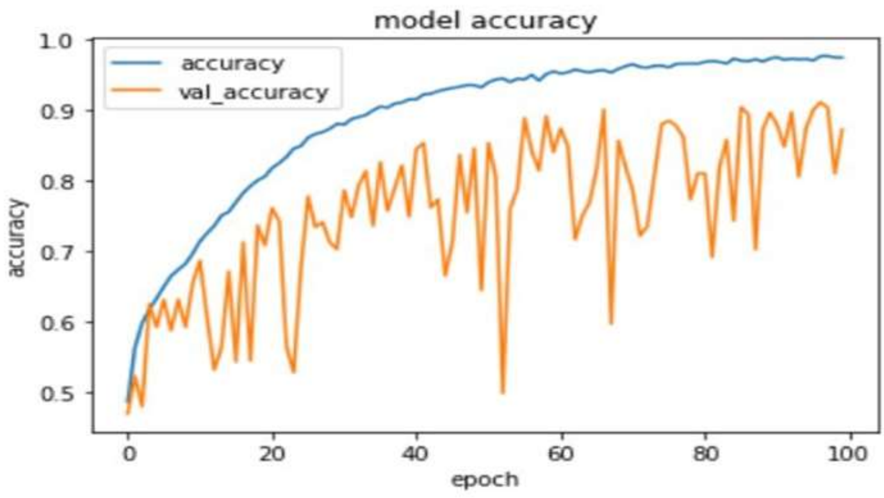

Fig. Indicate the training,validation accuracy

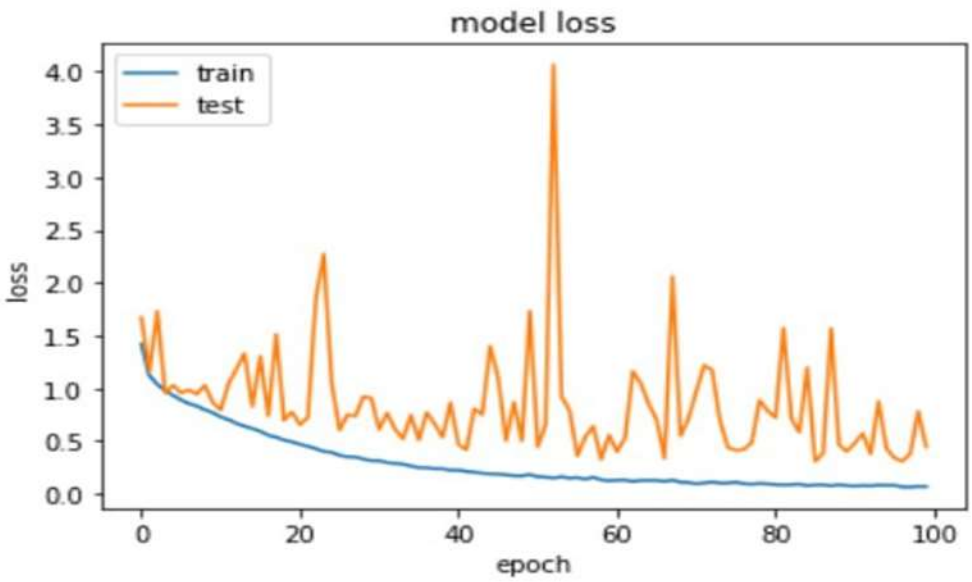

Fig. Indicate the model loss

6. APPLICATION

- To extend the role of the technology in the medical field.
- Any medical related survey sections.
- The complex medical system, which will facilitate the development of medical
- Diagnosis and clinical application as well as promote the development of the medical field.

7. CONCLUSION

We have developed a novel and highly accurate method for the classification of various skin conditions, including nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. Our approach was constructed and evaluated using the HAM-10000 Dataset, a widely recognized benchmark dataset in dermatology research. By utilizing convolutional neural networks (CNNs), our proposed method achieved an impressive overall accuracy of 97.05%, with a validation accuracy of 91.36%. This signifies the effectiveness of our approach in accurately categorizing multiple classes of skin diseases. Moreover, the versatility of our method allows for potential expansion to classify skin diseases into an even greater number of classes, addressing a broader range of dermatological conditions.

The implications of our work are substantial, particularly for dermatologists seeking to enhance the efficiency of their diagnostic processes and provide faster and more accurate treatments for patients with skin diseases. By leveraging our method, dermatologists can benefit from improved decision-making support, leading to more effective patient care. Our approach builds upon the existing literature in dermatology and applies CNNs to achieve remarkable results. The combination of the HAM-10000 Dataset and our innovative methodology sets this research apart, ensuring its originality and significance in the field of skin disease classification.

8. FUTURE SCOPE

- Enhanced accuracy and precision in diagnosing various skin diseases using CNN-based models.
- Integration of telemedicine technologies to enable remote skin disease diagnosis using CNN algorithms.
- Development of personalized treatment plans based on CNN predictions for specific skin conditions.
- Implementation of real-time monitoring systems using CNN models to track disease progression and response to treatment.
- Integration of CNN-based skin disease prediction tools into mobile applications for accessible and user-friendly diagnosis.

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