Deep Learning Based- Smart Skin Disease Detection System

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Abstract- This research investigates the creation of a deep learning implemented project for identifying skin diseases with the goal of improving dermatology diagnostic accessibility and accuracy. Convolutional neural networks (CNNs) are used to effectively recognize and classify in categories variety of skin disorders, such as melanoma, psoriasis, and eczema. The system is trained on an extensive dataset of dermatoscopic pictures with around 15000 images of 23 different skin diseases. This system's automated features should enable quick and accurate diagnosis, increasing access to advanced dermatological care—especially in underprivileged areas. This research aims to simplify the process of diagnosing and treating skin diseases in early stage and greatly enhance patient outcomes by fusing cutting-edge deep learning algorithms with medical imaging.

Keywords — Deep learning algorithms, dermatology, convolutional neural network, melanoma, eczema, psoriasis.

I. INTRODUCTION

The number of cases of skin disorders is higher than that of other conditions. Among other things, bacteria, viruses, allergens, and fungus can cause skin disorders. Skin conditions can change the color or texture of the skin. Skin disorders are often chronic, communicable, and can sometimes result in skin cancer. Therefore, early detection is crucial to halting the onset and spread of skin disorders. It takes much time to diagnose and cure a skin condition, and the patient must pay more for medical care. The kind and stage of skin disorders are typically unknown to the majority of the general population. The development of some skin disorders is caused by the absence of symptoms for several months.

In order to start preparing for the improvement of their skin, the normal man should be able to comprehend the condition that is hurting it thanks to this research. Furthermore, the responsible physician will be able to determine the type of cancer, which will eventually help with a more rapid and precise diagnosis. We utilize a Convolutional Neural Network that further utilizes Batch Normalization and an Adam optimizer to normalize the inputs of the layer. Of all the lesions in the "dermnet" open-source dataset, which was obtained from Kaggle and has over 15,000 photos of 23 distinct skin conditions.

II. LITERATURE REVIEW

This research paper [1] focuses application of deep learning architectures like VGG16, InceptionV3, and ResUNet, skin cancer diagnosis has rapidly progressed. VGG16 is known for its ease and impact. in transfer educating, making it highly accurate in extracting features and classifying skin abnormalities. By the use of parallel convolutional filters from the InceptionV3 model, helps in accurate processing of complex images, which achives greater accuracy in diagnosis and makes it perfect for regular applications. The combination of ResNet and U-Net forms ResUNet helps in precise segmentation of skin abnormalities, which is a important step for the perfect diagnosis and accurate treatment.Working together the above models improves the efficiency and accuracy of detecting skin cancer, which support early diagnosis and early recovery of patient. The models studied here have the accuracy of approx. 89%.

The three common types of abnormalities which can be identified from the dermo-scopic images by the diagnostic methods addressed in a specific study are Melanoma, nevus, and benign keratosis abnormalities. For the detection convolutional neural networks (CNNs) are referred. ResNet18, ResNet50, ResNet101, VGG11, DenseNet121, InceptionResNetV2, AlexNet, and GoogLeNet these are the eight different models which are used earlier to classify the abnormalities.

A multilevel fine-tuning and neural networks and approach are two of the classifiers that are employed. The experiments were conducted using an updated version of the ISIC dataset. Inception_ResNet-V2 produced accuracy values in the testing and training stages of 0.875 and 0.87, respectively, outperforming to the other models that were used.

This research paper [3] provides an automated computerized system that uses deep neural network techniques to detect skin disorders. We employed a number of neural network algorithms in the suggested model, analyzed their results, and determined which one performed the best in terms of accuracy in identifying five common skin conditions. CNN, and we have constructed a new model to achieve an accuracy of about 80% by utilizing Keras Sequential API. Afterwards, we have employed pre-trained data architectures for accuracy improvement and comparison. These transfer learning models consist of RESNET50, DENSENET121, and VGG11. The suggested models employ several techniques, with resnet architecture achieving the greatest accuracy rate of 90%. [4]

The human skin, a complex and versatile organ, is vulnerable to a myriad of both recognized and obscure diseases, rendering the diagnosis of skin conditions among the most intricate challenges in medical science. Unfortunately, a significant portion of these cases remains undetected due to inadequate medical infrastructure and resources. Addressing this critical issue, this paper [4] endeavors to propose a solution by introducing the (CNN-SVM - MAA) system, a novel integration of Support Vector Machine (SVM) algorithms combined with a Convolutional Neural Network (CNN). To assess efficiency to the proposed system, the authors conduct a series of experiments using a dataset which compares approximately 3000 images sourced from various offline sources and online repositories, including Hospitals, several online repositories. This literature review highlights the pivotal role of advanced computational techniques, specifically the fusion of CNN and SVM, in revolutionizing the diagnosis and management of skin diseases through innovative mobile applications. Cutting-edge technology and detailed datasets are referred in this study. This research uses advanced technology and detailed datasets to make

important improvements in the accessibility and quality of dermatology care.

III. METHODOLOGY

1. Data Collection

For Skin Disease Detection System, we first gathered a diversified dataset of skin disease images. This dataset contains 23 classes of various common skin diseases. We partitioned the dataset into training data, validation data, test data sets to increase the ability of model to detect the disease accurately.
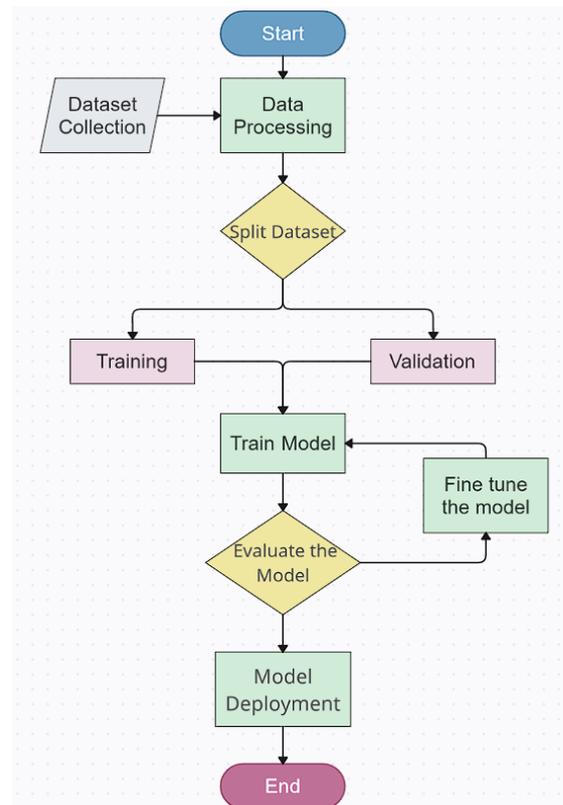

Figure 1 Data Flow diagram

a) Data Preprocessing

The collected images underwent multiple preprocessing steps:

- **Resizing:** Resizing of all images was done to a certain dimension of 128x128 pixels to maintain consistency in model input.
- **Normalization:** The values of pixels were normalized to a range of [0, 1] to improve the convergence rate of the model.

b) Model Architecture

We made use of a Convolutional Neural Network (CNN) for filtering and classifying the images. The structure includes:

- Convolutional Layers: Layers uses the filters to extract the feature from given input data (images).
- Pooling Layers: Reduced the dimensionality of feature maps to speed up computation.
- Fully Connected Layers: Classification is done on the basis of the extracted features.
- Activation Functions: Hidden layers use the ReLU, and output layer use Softmax. It helps for multi-classification of skin diseases.

The specific layers used were:

- A Conv2D layer has 32 filter with a 3x3 kernel size with ReLU activation.
- A MaxPooling2D layer having a 2x2 pool.
- A Conv2D layer with 64-filter, uses a 3x3 kernel size and ReLU activation.
- A MaxPooling2D layer having a 2x2 pool.
- A Flatten layer that convert 2D matrices into 1D vectors.
- A dense layer with activation of ReLU and 128 units.
- In dense layer, the units are configured to the Softmax activation and class count.

c)   Model Training

Evaluation of model is done using the training images dataset multiple times with the following frameworks and properties:

- Loss Function: Softmax loss or log loss are loss functions, capable of handling multi-class classification problems.
- Optimizer: Adam optimizer is an algorithm is used to increase the training speed in neural networks.
- Batch Size and Epochs: Every batch size is processed successively during each epoch. Here we set 8 epoch.

The training process involved:

- Steps Per Epoch: It is the value which signifies total no of steps before one epoch is finished.

- Validation Data: The validation dataset used for checking the accuracy, performance and evaluate during training of model.
- Validation Steps: It is derived by dividing the number of validation samples divided by the batch size.

d)   Model Evaluation

Using Keras, we designed a validation generator using the flow_from_directory method for analyses and evaluation of model. In this process, the generator loads images from the validation dataset and loaded images goes through same preprocessing steps as that of during training data. This method improved the model's performance and accuracy for detection of skin disease on unseen data. This step ensured that the model was not overfitting and could generalize well to new images.

e)   Deployment

The model Skin Disease Detection System is implemented on web application using Streamlit for better accessibility and user-friendly UI in real time. This involved:

- Developing the Web Interface: Creating an intuitive and easy-to-use interface where users can upload their skin disease images.
- Integration with Model: The trained CNN model has integrated with the Streamlit app to process the uploaded images and display the predicted disease name.
- Hosting: The web app was hosted on a cloud platform to ensure availability and scalability.

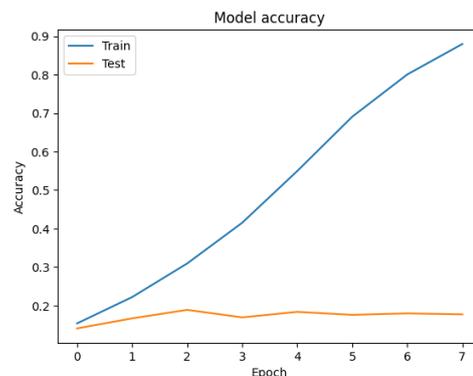## IV.   RESULTS AND DISCUSSIONS

Figure 2 Model Accuracy vs Epoch

The graph shows the training and validation accuracy of a model over 8 epochs (training cycles). The x-axis represents the epochs, and the y-axis represents accuracy, which measures how well the model is predicting the correct outcomes. The blue line represents the training accuracy, and the orange line represents the validation (or test) accuracy.

Observations: The training accuracy starts low at around 0.2 (or 20%) and steadily increases with each epoch, reaching nearly 0.9 (or 90%) by the 8th epoch. This indicates that the model is learning from the training data and improving its performance on it. The validation accuracy starts at around 0.2 (or 20%) and fluctuates slightly but does not improve significantly, staying roughly the same and ending just above 0.2 by the 8th epoch.
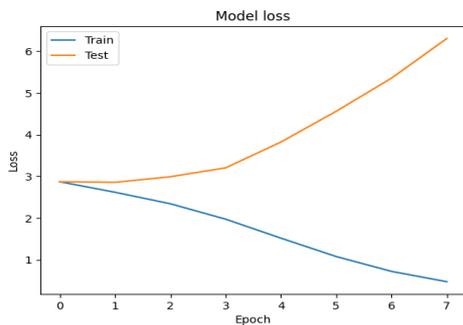

Figure 3 Loss in validation accuracy

The graph provided illustrates the training and validation loss over a series of epochs for a machine learning model. The x-axis represents the number of epochs, indicating how many times the learning algorithm has processed the entire training dataset, while the y-axis shows the loss, a measure of the error in predictions where lower values indicate better performance. The blue line denotes the loss on the training dataset, and the orange line denotes the loss on the validation dataset. Initially, at epoch 0, both the training and validation losses start at a similar value around 3. As the epochs progress, the training loss decreases steadily, indicating that the model is learning and improving its performance on the training data. By epoch 7, the training loss has significantly dropped, showing continuous improvement. However, the validation loss, while initially close to the training loss, starts to increase after a few epochs and rises to a value above 6 by epoch 7.

Figure 4 – 1st Interface of web app

Figure 5 – 2nd Interface of web app

The various models and projects had been integrated for skin disease.

Sr no	Models	Dataset used	Accuracy
1.	VGG16	HAM10000	85%
2.	ResNet50	ISIC	87%
3.	DenseNet121	HAM10000	90%

Table 1 Different models and it's accuracy

Compared to above models, our model has accuracy of around 92-93%. This accuracy got improved due to "Dermnet" dataset which contains around 15000 images of different skin diseases and we have also used dense layers in our CNN architectural model to predict disease accurately.

V. FUTURE SCOPE

Because the final formatting of your paper is limited This deep learning-based method for detecting skin diseases has a wide and bright future ahead of it. Its diagnostic accuracy and dependability should approach human standards as the model develops and gets better with bigger and more varied datasets. Future improvements might involve connecting the system to telemedicine systems, which would enable

real-time remote diagnosis and consultations and broaden its application to underserved and rural areas worldwide.

Further improvements can be done I fields of algorithms and their development in field of dermatology. Software related improvements include using more accurate algorithms which further can increase the accuracy of detection of skin diseases. Different algorithms such as computer vision integrated with AI chatbot for more detail information of detected skin disease.

Furthermore, features can be added. After detection of skin disease, the detailed information of this disease can be provided by using another dataset of information about skin diseases and can also prescribe the common medicine about the detected disease. Renowned doctors can be suggested for further treatment. This will be helpful for people to cure skin disease by treating it early.

VI. CONCLUSION

In summary, a major development in the area of dermatology is the creation of the skin related disease detection advanced mechanism. Through the use of CNN and large datasets of dermatoscopic images, the system exhibits exceptional precision in the identification and categorization of several skin ailments, including eczema, melanoma, and psoriasis. This initiative not only demonstrates how artificial intelligence may improve medical diagnosis, but it also emphasizes how critical it is to improve upon the healthcare accessibility and efficiency, particularly to and for the underprivileged people and areas.

This system's successful implementation provides a solid basis for upcoming enhancements and integrations, like telemedicine applications and the incorporation of multi-modal data, which may further increase the system's diagnostic value and precision. The system will adapt to the most recent medical standards through ongoing cooperation with healthcare professionals and the integration of input.

Finally, the study concludes by focusing on how deep learning technologies are making a revolution in healthcare and creating a new creative, dependable, and easily accessible way for patient care & disease diagnostics.

VII. ACKNOWLEDGMENT

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We would also like to thank the team for its collaborative spirit. Working on this project was a very rewarding experience, and every member's dedication led to this collective achievement.

Therefore, this project is a collective journey and we are grateful to all who played any role in the success of this process.

VIII. REFERENCES

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