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Skin Disease Detection Using Deep Learning

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Abstract: Cutaneous diseases rank as a leading global health issue and many of them should be diagnosed in time to treat them appropriately. With the development of deep learning, automated skin disease diagnosis is now possible and has been improved to be more accurate. In this paper, we propose a deep-learning methodology based on the VGG16 CNN model for classifying skin diseases from the DERMNET dataset. Preprocessing and data augmentation steps are employed to enhance the robustness and generalization ability of the model. The above system effectively demonstrated a diagnostic accuracy of around 90% indicating that it can provide great support for dermatologists and reduce diagnostic errors. In addition, to provide real-time diagnostic assistance, a Streamlit tool is implemented as an interface to invoke the trained model.

Keywords: Deep Learning, Skin Disease Detection, VGG16, Convolutional Neural Network, Data Augmentation, Stream lit.

I. INTRODUCTION

Diseases of the skin are prevalent in the general population to a large extent in the forms of infections, inflammatory diseases and cancers. Diagnosis frequently requires expert dermatologic evaluation, which may not be easily available. With the advent of deep learning, and CNN, medical image classification has been significantly enhanced in terms of accuracy and efficiency.

The goal of this paper is to examine the use of VGG16 model, deep CNN architecture as a popular and wide-open source available for the application of detecting skin diseases. We preprocess and augment data on the DERMNET dataset for better quality of the training. We want to create a strong classifier that will reliably diagnose different skin conditions and assist dermatologists.

II. LITERATURE SURVEY

Deep learning-based skin disease classification has also received much attention over the last few years because of its efficiency in automatizing medical diagnosis. Various researchers have applied convolutional neural networks (CNNs) and machine learning models in the recognition of skin diseases. Esteva et al. showed that deep learning could be utilized through the Inception V3 model with an accuracy of approximately 55.4% on nine classes of tumors. Codella et al. used a non-linear SVM method for melanoma detection and obtained accuracy of up to 76%. Zhang et al. also used the Inception V3 network for dermoscopic image classification and obtained a better accuracy of 87.25%.

To build on previous work, our project centres on a stronger and more generalizable solution using the VGG16 architecture that has been pretrained on ImageNet. We make use of the DERMNET dataset and strengthen it via preprocessing and augmentation. In contrast with earlier models, our solution includes two-stage training with fine-tuning, class balance with resampling, and deployment via a user-friendly Streamlit interface. This not only maximizes accuracy (~90%) but also real-world usability for real-time prediction.

In addition, though certain research has investigated federated learning for privacy-conserving training, our interest in this work is still to enhance classification performance based on a centralized model. Extensions in the future may look into federated methods for protection of sensitive dermatological information.

III. METHODOLOGY

This research adopts a skin disease classification system based on the VGG16 convolutional neural network (CNN) architecture. The architecture involves a sequence of layers that increasingly extract and classify image characteristics.

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The methodology describes the design elements of the CNN and their function to learn visual patterns from dermatological images.

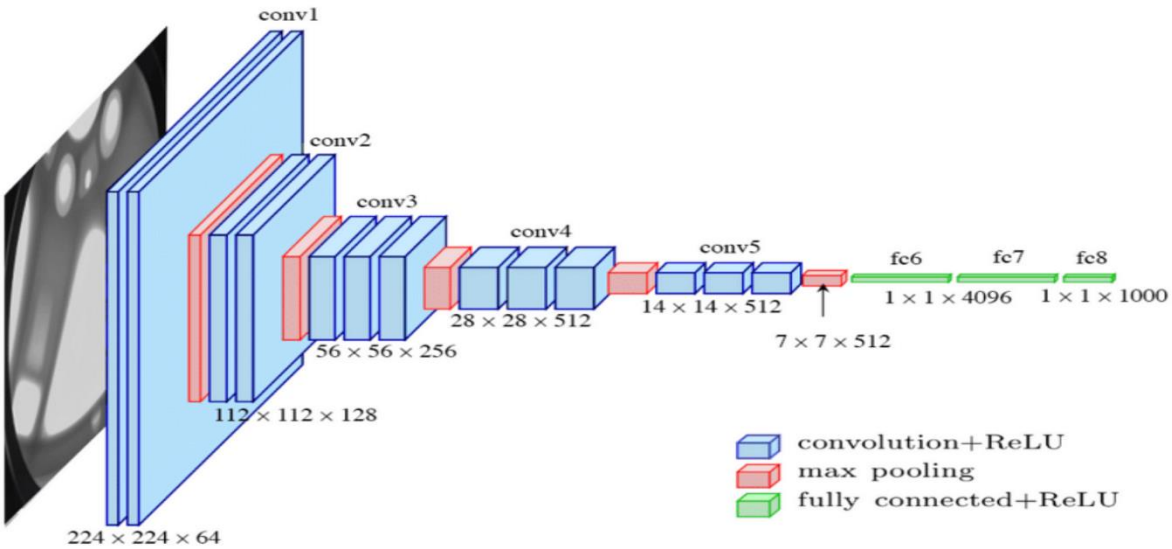

Fig 1. VGG – 16 Architecture

A. Convolution Layer

The VGG16 convolutional layers are tasked with extracting the spatial features from the skin images. One 3×3 filter is used in each convolution operation to identify patterns like edges, texture, and color changes. The filters move over the input image with a stride of 1, and 'same' padding is used to maintain spatial sizes. Each convolution layer produces a feature map that indicates salient visual information for the identification of disease.

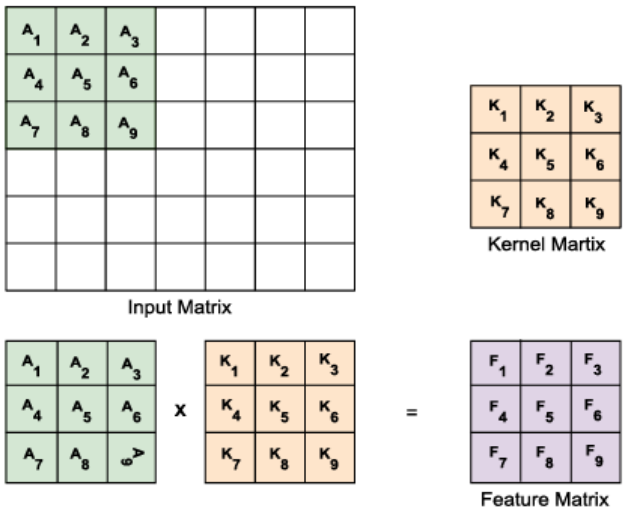

Fig 2. Convolution layer operation

B. Pooling Layer

Max-pooling layers then come after some of the convolution layers to downsample the spatial sizes of the feature maps. The layers employ a 2×2 window to take into consideration the most important features as the spatial dimensions are minimized. Pooling also provides translation invariance and thereby ensures that small input image shifts don't impact the model's predictions. This aids in helping the model generalize more across diverse clinical images.

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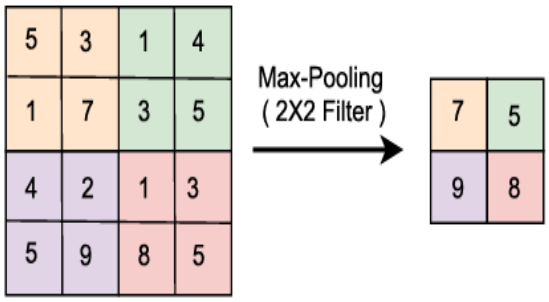

Fig 3. Pooling layer operation

C. Activation Function

ReLU (Rectified Linear Unit) activation function is utilized after each convolutional layer. It brings non linearity in the network so that the model can learn complex patterns. ReLU can be described as:

$$\text{ReLU}(x) = \max(0, x)$$

This function helps speed up convergence while training and prevents the vanishing gradient problem.

D. Fully Connected Layer

Following the convolution and pooling operations, the feature maps are flattened and fed through fully connected layers. These constitute a high-level classifier. In our case, two dense layers with 1024 and 512 neurons respectively are utilized along with batch normalization and dropout for regularization. The output layer makes use of the softmax function to provide class probabilities for five skin disease classes.

IV. IMAGE DATASET

The DERMNET skin disease dataset, which includes thousands of excellent photos of different skin conditions, was used for this investigation. Five distinct disease classes were chosen for this project. To guarantee a balanced class distribution across training and validation sets, the dataset was arranged into training and testing directories using an 80:20 stratified split.

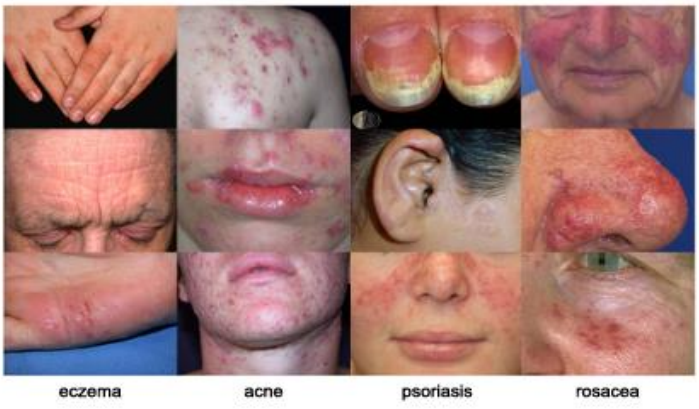

Fig 4. Some sample images of different classes

V. IMPLEMENTATION

The system of detection for skin diseases proposed was developed with Python incorporating TensorFlow, Keras, and OpenCV. The dataset, which was divided into five classes from the collection of DERMNET images, was preprocessed by converting all images to 168×168 pixels and boosting contrast through CLAHE. A data generator in the form of a custom function was developed to introduce real-time data augmentation in terms of flips, rotations, and change of brightness. Minority classes were upsampled to the majority class to counter class imbalance using resampling.

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The VGG16 model, pre-trained on ImageNet, was altered by adding custom dense layers with batch normalization and dropout. To start with, only classifier layers were trained keeping the VGG16 base frozen. In the second phase, selective VGG16 layers were left unfrozen for fine-tuning. The model was trained in two stages using Adam optimizer with early stopping and learning rate reduction callbacks. It reached a validation accuracy of around 90%. The training and validation loss/accuracy trends validated successful learning without overfitting.

Lastly, the trained model was deployed on Streamlit, allowing users to upload images of skin and obtain real-time classification of disease using a web interface.

VI. RESULTS AND DISCUSSION

The model was able to obtain a validation accuracy of about 90%, reflecting excellent generalization capability. Learning trends were visualized through performance graphs:

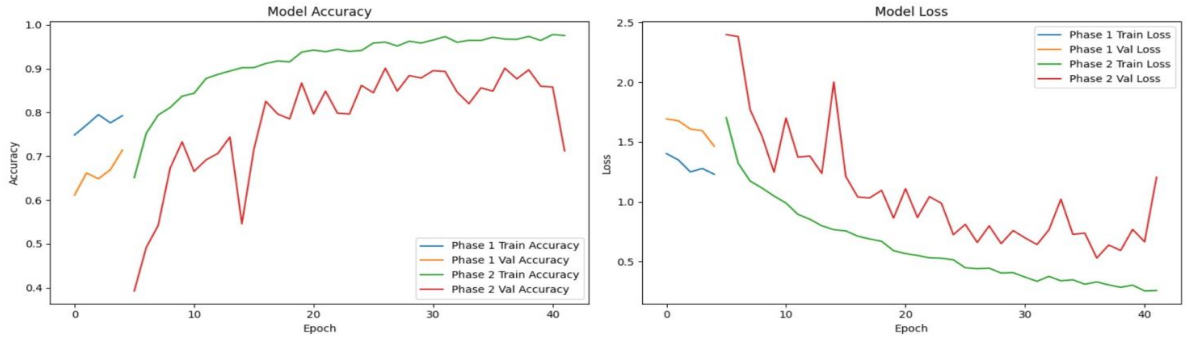

Fig 5. Training and validation set accuracy and loss graphs through phases.

Training and validation accuracy consistently improved through both training phases.
Loss values reduced steadily without any indications of overfitting.

The data generator and augmentation used had the effect of improving robustness, with fine-tuning deepening feature extraction that applies to skin disease patterns.

VII. CONCLUSION

This work proposes a deep-learning method for skin disease classification based on the VGG16 model. With efficient preprocessing, data augmentation, and fine-tuning the VGG16 architecture, the system was able to attain a validation accuracy of around 90%. The strong performance justifies its potential as a tool to help dermatologists in initial screening and diagnosis.

Aside from training and testing the model, the system was also implemented with Streamlit, providing an interactive web interface for real-time prediction of skin disease. This allows the solution to be more accessible to patients and medical professionals. Potential improvements in the future could be the integration of model explainability (e.g., Grad-CAM), moving to more categories of disease, and enhanced transparency of predictions.

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