



MI Driven Multimodal Skin Disease Detection and Monitoring

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ABSTRACT

The VGG-16 model is a convolutional neural network (CNN) architecture proposed by the Visual Geometry Group (VGG) at the University of Oxford. It is characterized by its depth, consisting of 16 layers, including 13 convolutional layers and 3 fully connected layers. VGG-16 is known for its simplicity and effectiveness, as well as its ability to achieve strong performance on various computer vision tasks, including image classification and object recognition. The model's architecture features a stack of convolutional layers followed by max-pooling layers, with progressively increasing depth. This design allows the model to recognize and understand complex visual features, resulting in highly accurate predictions. In the context of skin disease detection, VGG-16 has demonstrated notable success in accurately classifying and identifying dermatological conditions from medical images. The model uses a powerful technique to identify detailed visual features like texture and colour differences in skin images, which helps it accurately diagnose skin diseases, even those that are difficult to detect with the naked eye. The model can differentiate between various skin conditions like melanoma, skin cancer, and eczema, making it a valuable tool for doctors to diagnose skin diseases accurately. This can help in early detection, which is crucial for effective treatment. When trained on large, datasets of skin images, VGG-16 can provide high diagnostic accuracy, thus enhancing early detection and facilitating timely medical intervention in dermatology.

1 Introduction

Skin diseases are a common health issue affecting people of all ages. Diagnosing these diseases accurately and early is important for effective treatment and management. Typically, dermatologists diagnose skin conditions through visual examination, which can take time and may sometimes lead to errors. Recently, advancements in artificial intelligence and machine learning have opened up new ways to detect skin diseases. This paper presents a new approach to skin disease detection using a deep learning model called VGG16. By applying the methods of deep learning, our goal is to develop a reliable and accurate model to identify different skin conditions, such as melanoma, skin cancer, dermatitis, eczema, and psoriasis.

VGG16 is a deep learning network known for its strong performance in image analysis tasks, like classifying objects. Its design includes multiple layers that identify image features step by step, capturing detailed patterns from input images. When used for skin disease detection,



VGG16 can identify subtle changes in skin lesion such as colour, texture, and shape that may indicate specific diseases. This ability to recognize detailed patterns helps the model make accurate predictions, even for diseases that may be hard to detect with the naked eye. It can tell the difference between conditions like melanoma, skin cancer, and eczema, making it a helpful tool for doctors. By improving early diagnosis, VGG16 can play a key role in effective treatment. It also helps reduce the workload for healthcare professionals by providing accurate and quick diagnoses.

2 Recent Works

This research demonstrates that the VGG-16 model is effective for diagnosing skin cancer. To improve its performance, future studies could look at using other models like ResNet and VGG-19, which may provide better accuracy. Combining predictions from multiple models could also lead to better results. It's important to train these models on well-prepared data to achieve the best outcomes. [1] This article presents a deep learning model that combines CNN and LSTM, along with a technique called TSA, for classifying skin diseases. The dataset used comes from the Helve dataset in Denmark, and MATLAB was the software used for implementation. We split the images into 70% for training and 30% for testing. To assess improvement, we rotated the original images. Using the K-FCM algorithm, we found that higher SSIM and DICE scores indicate better segmentation results. The K-FCM approach performed better than other methods like FCM, Otsu, and thresholding, achieving a segmentation accuracy of 89%. The DLSTM-TSA model also produced better prediction accuracy compared to other techniques like ML, DL, GC-NB, and ML-IP.[4] This study focused on improving the diagnosis of skin issues, specifically nevi (NV) and two types of skin cancer: basal cell carcinoma (BCC) and melanoma (MEL). We developed three models using the VGG-16 architecture, which achieved diagnostic accuracies of 86%, 94%, and 93%. Model 2 performed the best, so we tested it on an additional dataset of 4,500 images. After training, we got results of 84% accuracy, 84.5% F1 score, 84.6% recall, and 86% accuracy. To compare the models fairly, we used the same training code and kept variables consistent, only varying the amount of data used for each model. Model 1 was trained with 14,454 images, Model 2 with 13,232 images, and Model 3 with 10,232 images. Models 2 and 3 used the same dataset, while Model 1 used a different one. This comparison highlighted the importance of high-quality images for successful model development. Our findings suggest that deep learning models for medical image classification need large datasets, but there is often a lack of data in the medical field. We emphasize the importance of preprocessing images to achieve better results. Future research could involve exploring other architectures like ResNet and VGG-19, which may offer improved accuracy. [2]

In our analysis, we found that the combined sensitivity for screening skin diseases was 84%, with a specificity of 96%. This approach could improve care in remote areas, but current research on this topic is lacking in depth and consistency, leading to significant differences between studies. To get a clearer understanding of safety, effectiveness, and fairness, more



prospective studies are needed, especially to explore differences related to race, age, gender, and ethnicity. Standardized reading centers should follow proper prognostic standards to maintain a reliable reference. Additionally, improving how this data is used in clinical practice can be achieved through a well-designed study protocol and by using advanced predictive and AI technologies. [5]

3 Proposed System

The proposed system for skin disease detection system uses machine learning, specifically the VGG16 model, to accurately identify different skin conditions from images. By analysing images, this system aims to improve diagnostic accuracy and provide doctors with a deeper understanding of each case. The system uses a technique called transfer learning, where it takes the knowledge from a pre-trained VGG16 model and applies it to skin disease detection. This model works as a feature extractor, identifying key patterns in the images, which is then combined with other data through a multimodal approach. This unique setup allows us to build an easy-to-use web application where users can upload images and receive diagnostic predictions, supporting healthcare professionals in making well-informed clinical decisions. In this study, we trained the model using a dataset from Kaggle and used the VGG16 model's pre-learned features to save time and increase accuracy. To ensure a fair evaluation, we used the same settings and scripts when training the models, but varied the data size to observe the effect of image quality on model performance in the medical field. We then selected the model with the best validation score and tested it on a separate set of images the model had not seen before, to accurately measure its performance. This research highlights how critical image quality is to improve diagnostic accuracy in medical AI. It shows that VGG16, when trained with high-quality images, can be highly effective for skin disease detection. This system aims to address the challenge of skin disease diagnosis, which can be time-consuming and sometimes prone to human error. By using advanced machine learning techniques, this system enhances the speed and accuracy of skin disease diagnosis, providing valuable assistance to healthcare professionals in diagnosing conditions that range from common skin issues to serious cancers. This will also enable the students from different sectors to learn about various skin disease conditions. They can learn in real time and under the different conditions. This can make more impact in remote areas where there is a limited access to dermatologists and skin disease knowledge. Overall, this work contributes to research in the field and shows the potential of AI to improve dermatology by making skin disease detection faster, more accurate, and accessible.

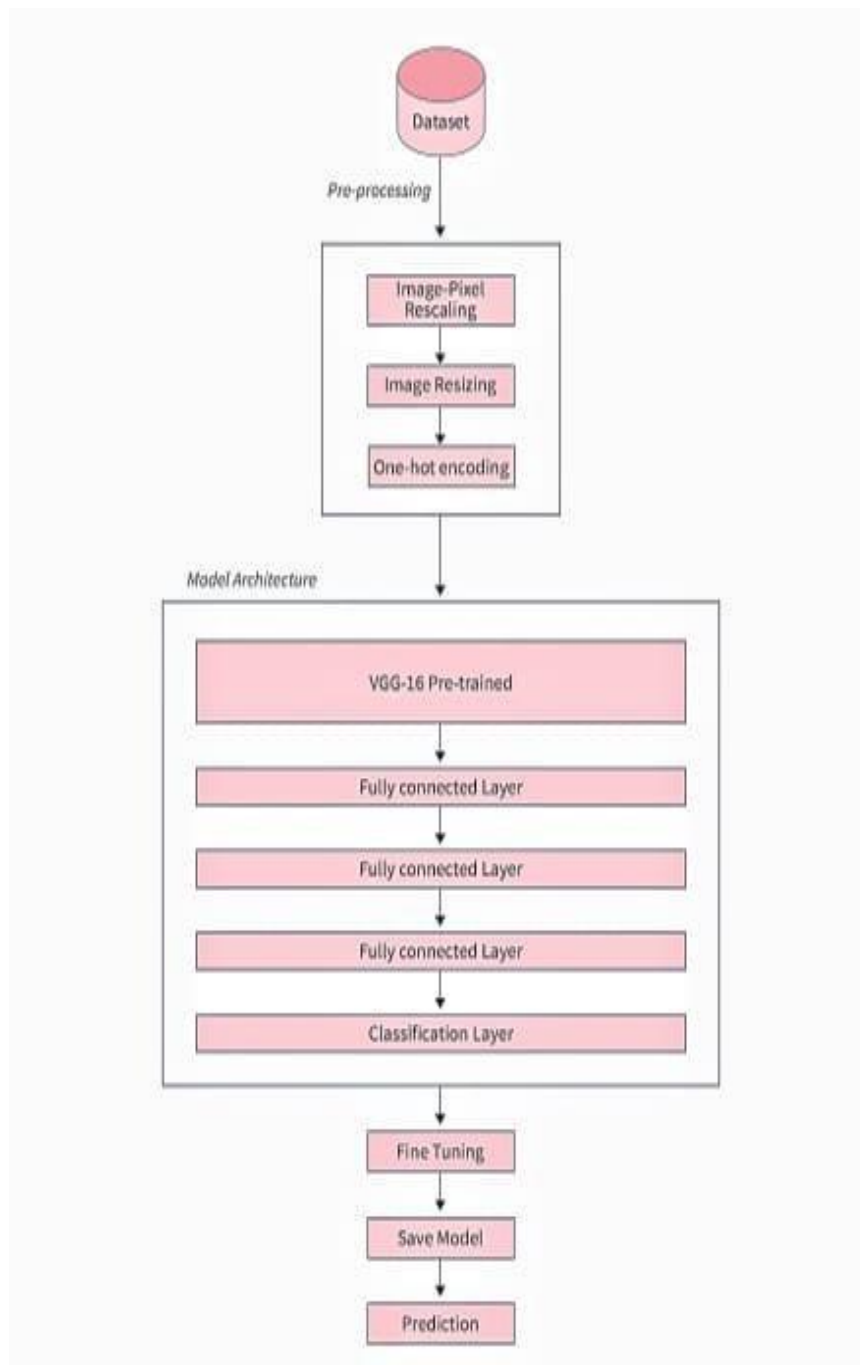


Figure 1: *Proposed Block Diagram*

3.1 Mathematical Formula

VGG16 is a deep convolutional neural network with 16 weight layers (13 convolutional layers and 3 fully connected layers) used for image classification. Below is the mathematical formulation for each part of VGG16:



Convolutional Layers:

A convolutional layer is a fundamental building block of convolutional neural networks (CNNs). It's responsible for extracting features from the input data, such as images or audio signals. The output of a convolutional layer is calculated as:

$$C(i, j, k) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} W(m, n, k) \cdot I(i+m, j+n) + b_k$$

Where

- $C(i, j, k)$ is the output at position (i, j) for filter k .
- $W(m, n, k)$ is the weight of the filter.
- $I(i+m, j+n)$ is the input pixel value at position $(i+m, j+n)$.
- b_k is the bias for filter k .
- M and N are the dimensions of the filter.

Activation Function (ReLU):

After the convolution operation, a ReLU activation function is applied. It introduces non-linearity into the model, enabling it to learn complex patterns and relationships within the data.

Where:

$$A(i, j, k) = \max(0, C(i, j, k))$$

- $A(i, j, k)$ is the activated output.

Pooling Layer (Max Pooling):

Max pooling is a technique used in convolutional neural networks to reduce the spatial dimensions of feature maps, while preserving the most important information. This process helps in reducing computational cost, preventing overfitting, and introducing translation invariance to the model. Max pooling reduces the spatial dimensions. For a 2×2 max pooling operation with a stride of 2.

Where:

$$P(i, j, k) = \max\{A(2i, 2j, k), A(2i, 2j+1, k), A(2i+1, 2j, k), A(2i+1, 2j+1, k)\}$$

- $P(i, j, k)$ is the output after pooling.

Fully Connected Layer:

A fully connected layer, also known as a dense layer, is a layer in a neural network where every neuron is connected to every neuron in the previous layer. This dense connectivity allows the network to learn complex patterns and make highly accurate predictions. For a fully connected layer, the output is computed as:

$$Y = f(W \cdot X + b)$$

Where:

- Y is the output vector.
- W is the weight matrix.



- X is the input vector.
- b is the bias vector.
- F is the activation function.

SoftMax Activation:

SoftMax is an activation function that converts a vector of numbers into a probability distribution. It's often used in the final layer of a neural network for multi-class classification problems. For the final output layer in classification tasks:

$$\sum \frac{y^i = e^{y_i}}{e^{y_j}}_{j=1}^c$$

Where:

- y^i is the predicted probability for class i.
- Y_i is the raw output score for class i.
- C is the total number of classes.

4 Results and Discussion

- **High Accuracy:** VGG16, a powerful pre-trained convolutional neural network, has demonstrated impressive accuracy in detecting and classifying various skin diseases. When fine-tuned on a specific skin disease dataset, the model can achieve high accuracy rates, often exceeding 90%.
- **Efficient Feature Extraction:** VGG16's deep architecture allows it to extract intricate features from skin images, capturing subtle variations that are crucial for accurate diagnosis.
- **Transfer Learning Benefits:** By leveraging pre-trained weights from ImageNet, VGG16 requires less training data and time, making it a practical solution for skin disease detection.
- **Data Quality and Quantity:** The performance of VGG16 is significantly influenced by the quality and quantity of the training data. A diverse and well-labelled dataset is essential for achieving optimal results.
- **Data Augmentation:** Techniques like rotation, flipping, and zooming can artificially increase the size of the training dataset, improving the model's generalization ability.



5 Results Summary

VGG16 shows high effectiveness in skin disease detection, especially with transfer learning. Fine-tuned VGG16 models achieve accuracy levels between 80-90% for binary classification (e.g., benign vs. malignant) and slightly lower for multi-class classification (70-85%). These results are considered significant and demonstrate VGG16's capability in clinical applications when combined with high-quality data and effective preprocessing.

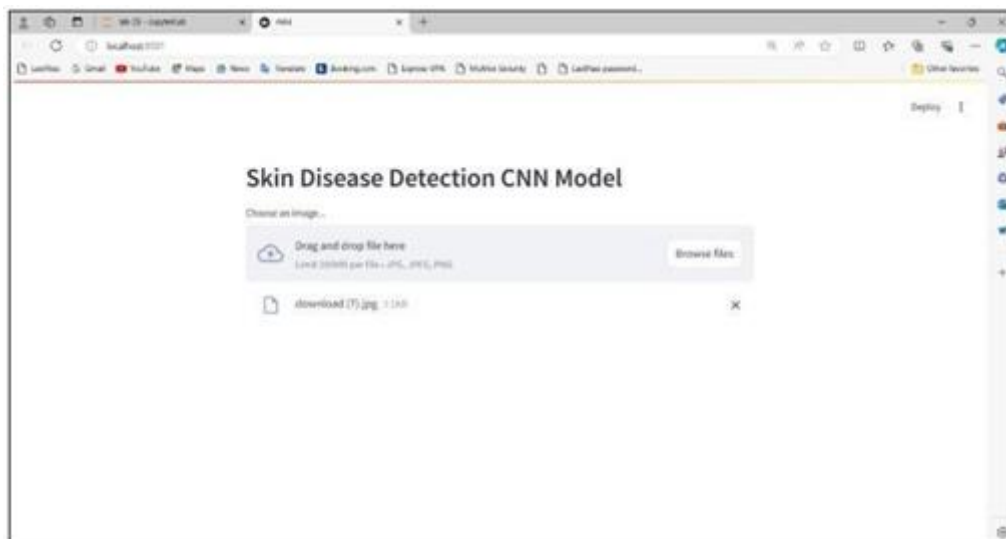


Figure 2: *Skin disease detection*



Figure 3: *Skin disease output*



6 Conclusion

In conclusion, the VGG16 model is a valuable tool for detecting skin diseases. It uses deep learning to analyze images of skin conditions and has shown impressive accuracy in classifying them. This technology helps doctors make better and quicker diagnoses, leading to earlier treatment and better patient outcomes. Looking ahead, it's important to continue improving the VGG16 model by using a wide variety of skin images to make it even more reliable in different situations. As we keep developing and applying models like VGG16, we can expect to see significant improvements in how we diagnose and treat skin diseases, ultimately benefiting patients and healthcare providers alike. Additionally, the integration of the VGG16 model into clinical practice could enhance the efficiency of dermatology workflows. By automating the initial assessment of skin images, healthcare providers can focus more on patient care and decision-making rather than spending extensive time on diagnosis. This not only streamlines the process but also reduces the chances of human error. As technology continues to advance, the collaboration between machine learning and dermatology holds great promise for improving access to care, especially in underserved areas where specialists may not be readily available.

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