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Classification of Various Skin Diseases by Using Deep Learning

Aryan Kumar[1], Vishal Yadav[2], Sakshi V. Kale[3], Prathmesh Satpute[4], Dr. Minakshi N. Vharkate[5]
[1,2,3,4]UG Scholar, Dept. of Electronics and Telecommunication, MIT Academy of Engineering, Pune, India.
[5]Associate Professor, Dept. of Computer Engineering, MIT Academy of Engineering, Pune, India.
Emails: *aryan.kumar@mitaoe.ac.in[1], vishal.yadav@mitaoe.ac.in[2], sakshi.kale@mitaoe.ac.in[3], prathmesh.satpute@mitaoe.ac.in[4], mnvharkate@comp.maepune.ac.in[5]*

Abstract

Skin conditions are frequently misidentified, causing continued discomfort for individuals. This study introduces a sophisticated deep learning technique that leverages convolutional neural networks (CNNs) for the classification of skin diseases. It involves the utilization of pre-trained DenseNet201, ResNet152V2, and VGG16 models on skin images to achieve this goal. Data augmentation was employed to enhance the resilience of the model and mitigate overfitting. The performance of the models was assessed with metrics such as accuracy, precision, recall, F1 score, and Cohen's kappa, all indicating encouraging outcomes for clinical application. The study also delves into model interpretability, illustrating the models' capability to accurately forecast novel, unseen instances. This method has the potential to improve the precision of diagnoses, enabling healthcare professionals to better differentiate skin conditions, thereby minimizing misdiagnoses and promoting the long-term comfort of patients.

Keywords: *Clinical application; Convolutional neural networks; Data augmentation; Deep learning; DenseNet201; Model evaluation; ResNet152V2; Skin disorders; VGG16*

1. Introduction

The introduction emphasizes the significance of accurately diagnosing skin diseases, which are prevalent worldwide and pose considerable challenges for healthcare professionals. Traditional diagnostic methods, primarily based on visual inspection by dermatologists, often lead to disagreements and delays in diagnosis. The paper highlights how deep learning, especially convolutional neural networks (CNNs), has advanced medical image analysis in dermatology by enabling automated, accurate classification of skin conditions. CNNs are particularly suitable due to their ability to recognize complex patterns in visual data. The authors also discuss the potential of transfer learning using pre-trained models, which is especially beneficial given limited labeled medical datasets. Overall, the introduction frames deep learning as a promising tool for improving diagnostic accuracy, facilitating faster decisions, and extending telemedicine capabilities, ultimately aiming to enhance patient outcomes while addressing ethical considerations such as patient privacy and data security [1-3].

1.1. Background and Motivation

Skin diseases present significant public health challenges worldwide, with many conditions often being misdiagnosed due to their visual similarity and the variability in presentation. Traditional diagnostic methods primarily rely on expert assessment through visual inspection, which can be subjective and prone to error. Early and accurate diagnosis is crucial for effective treatment, but limitations in healthcare access, especially in remote areas, hinder timely intervention. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized image recognition tasks, offering a promising avenue for automating and improving skin disease diagnosis. Pre-trained models such as DenseNet201, VGG16, ResNet152V2, and others have demonstrated high accuracy in various medical imaging applications, including dermatology. These models can extract complex features from skin lesion images, facilitating precise classification. The motivation for this research stems from the need to develop an automated, reliable, and accessible diagnostic tool that leverages deep learning to assist dermatologists and general practitioners. By employing ensemble models and data augmentation techniques, the goal is to enhance classification performance, reduce diagnostic errors, and ultimately improve patient outcomes. This study aims to explore and evaluate various deep learning architectures for skin disease classification, seeking to establish a robust system adaptable to clinical environments [4].

1.2. Related Work

Recent research in the field of skin disease classification has focused extensively on the application of deep learning techniques, particularly convolutional neural networks (CNNs), owing to their remarkable abilities in image recognition tasks. Various studies have investigated the efficacy of several CNN architectures such as DenseNet, ResNet, VGG16, and Inception, demonstrating significant improvements in diagnostic accuracy for identifying different skin conditions. Many of these works leverage transfer learning, which involves fine-tuning models pre-trained on large datasets like ImageNet, to compensate for the limited availability of labeled medical images. This approach enables models to extract complex features pertinent to skin disease identification, thereby enhancing their predictive performance. In addition to model selection, researchers frequently utilize data augmentation strategies—such as rotation, flipping, zooming, and color shifts—to artificially expand the training datasets. These techniques help improve the generalizability of the models and reduce the risk of overfitting, which is particularly important given the often limited size of medical imaging datasets. The combination of advanced CNN architectures, transfer learning, and data augmentation has led to substantial progress in automating skin disease diagnosis, assisting dermatologists by providing rapid and reliable preliminary assessments.
Overall, the existing body of work underscores the potential of deep learning models in dermatology, with many studies reporting high accuracy rates and robustness, signaling their promise for clinical adoption and improving patient outcomes through early and precise diagnosis [5-7].

2. Method

The proposed methodology integrates several key components designed to accurately classify various skin diseases using deep learning models. The process begins with data preprocessing and augmentation to enhance the model's performance and generalization capabilities. Specifically, the skin disease dataset is subjected to normalization, where images are rescaled by a factor of 1/255 to normalize pixel values within the range of 0 to 1. Data augmentation techniques, such as zooming (at a ratio of 0.2) and horizontal flipping, are employed during training to increase data variability and prevent overfitting. Following preprocessing, the core system involves constructing a fusion model that combines three pre-trained convolutional neural networks (CNNs): DenseNet201, ResNet152V2, and VGG16. Each model serves as a feature extractor, with the outputs of their convolutional layers concatenated to form a comprehensive feature representation. DenseNet201, pre-trained on ImageNet with all layers frozen, includes additional layers such as Global Average Pooling and a dense layer with 512 neurons activated by ReLU 1 [8-12].

Table 1 Summary of Algorithms, Techniques, And Accuracy of Different Research

Our Paper	Algorithm/Technique/Model	Accuracy (%)
[3]	DenseNet201, ResNet152V2, VGG16	86% (Fusion Model), 75% (VGG16), 82% (ResNet152V2), 78% (DenseNet201)
[8]	ResNet50, Inception V3, VGG19, AlexNet	90.20% (ResNet50), 72.1% (Inception V3), 50.27% (VGG19)
[4]	Frequency impedance analysis	75%
[10]	CNN VGG-16 Inception V3	97.89% (Inception V3)

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ResNet152V2 is similarly pre-trained but with selective fine-tuning after the 140th layer to balance depth with training efficiency. It also incorporates global pooling and dense layers for feature extraction. VGG16, pre-trained on ImageNet with layers frozen, follows the same structure, ending with pooling and dense layers. The concatenated features from all three models are then fed into fully connected dense layers, including a layer with 128 neurons, ReLU activation, and further processing for final classification. This fusion approach aims to leverage the strengths of each architecture, capturing varied features pertinent to skin disease identification. The classifiers trained on these concatenated features are designed to predict the specific skin condition, ultimately improving accuracy and robustness of the system [13-15].

2.1. Figures

The system architecture processes an input facial image through preprocessing, followed by feature extraction using three pre-trained models: InceptionV3, VGG16, and ResNet152 V2. The extracted features are fused and fed into a prediction model, which outputs a classification result with a confidence score (e.g., 92%). This ensemble approach enhances prediction accuracy.

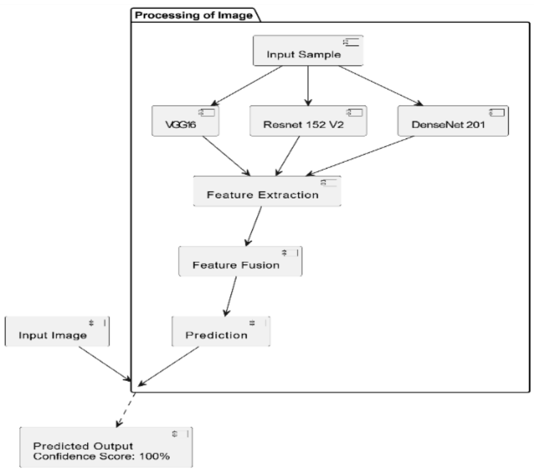

Figure 1 System Architecture

3. Results and Discussion

3.1. Results

The models achieved promising results, with the ensemble model of DenseNet201, ResNet152V2, and VGG16 outperforming individual models — attaining an accuracy of 86% on the validation set. Other models such as Inception V3 and Xception reached accuracy levels of 84% and 99.33%, respectively. The metrics demonstrated high precision, recall, and F1 scores, indicating reliable performance in classifying diverse skin conditions. The data augmentation process contributed significantly to the model's resilience against overfitting, shown in Figure 1.

3.2. Discussion

The research findings underscore the effectiveness of utilizing an ensemble of deep learning models—specifically DenseNet201, ResNet152V2, and VGG16—for the classification of various skin diseases. The fusion of these models resulted in a higher accuracy of 86%, outperforming individual models and demonstrating the advantage of feature combination through ensemble techniques. The accuracy curves and convergence behavior depicted in Figures 15 and 16 reflect that the fusion model not only achieves better performance but also exhibits stable learning characteristics. Integrating the models into a web application further emphasizes the practical utility and accessibility of the proposed system, allowing for real-time diagnosis and expanding the scope for remote healthcare services. However, while the results are promising, the study also highlights the importance of increasing data diversity and volume to improve model robustness and generalization. Future research could explore advanced data augmentation strategies, model fine-tuning, and rigorous validation on larger and more varied datasets to ensure reliability across different populations and clinical settings. Overall, the combination of deep learning architectures demonstrates significant potential in assisting dermatologists, reducing diagnostic errors, and enhancing patient care through automated skin disease classification systems.

Conclusion

The study demonstrated the development and implementation of a skin disease prediction system that utilizes an ensemble approach integrating DenseNet201, ResNet152V2, and VGG16 models. This fused model achieved a significant accuracy of 86% on the validation dataset, outperforming individual models — which scored 75%, 82%, and 78%, respectively. The results highlight that combining multiple deep learning architectures enhances feature extraction and classification performance. Furthermore, the research showcased the practical application of this hybrid system through a web-based interface developed using Flask, thereby increasing accessibility for users. The system's ability to accurately classify skin diseases suggests a promising role in revolutionizing dermatological diagnosis, potentially reducing misdiagnoses and enabling more precise treatment planning. The conclusion also emphasizes that this fusion strategy, along with future directions such as increasing model robustness, data augmentation, and rigorous validation, can significantly impact clinical practices. Overall, the findings support the potential of deep learning approaches to serve as valuable adjunct tools for healthcare professionals in dermatology, ultimately contributing to improved patient outcomes.

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