Skin Disease Detection Using Deep Learning

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***Abstract*—Skin disease diagnosis using clinical images is a challenging task due to high inter-class similarity, severe class imbalance, and variability in lesion appearance. Conventional manual diagnosis is time-consuming and subject to inter-observer variability, often leading to delayed or inaccurate treatment. This paper presents a deep learning-based skin disease classification framework utilizing a DenseNet169 convolutional neural network for multi-class dermatological image analysis. The proposed system employs extensive preprocessing, duplicate image removal, and data normalization to enhance input quality. To address class imbalance, focal loss is integrated during training, enabling the model to focus on under-represented disease categories. Transfer learning with ImageNet-pretrained weights is used, followed by fine-tuning of higher DenseNet layers to adapt feature representations to skin lesion characteristics. The model is trained and evaluated on a large-scale skin disease image dataset comprising over 27,000 images across multiple disease classes. Experimental results demonstrate improved classification performance and robust generalization across rare and common skin conditions. The proposed approach offers an efficient, scalable, and reliable solution for automated skin disease classification, supporting clinical decision-making and early diagnosis.**

Keywords—Skin Disease Classification, Deep Learning, DenseNet169, Medical Image Analysis, Focal Loss, Class Imbalance, Transfer Learning, Dermatology AI

I. Introduction

With the rising prevalence of skin diseases and the increasing burden on healthcare systems, the demand for automated and reliable dermatological diagnostic tools has grown significantly. Conventional skin disease diagnosis relies heavily on visual inspection by dermatologists, which is time-consuming and subject to inter-observer variability. In many regions, limited access to specialized medical expertise further delays early diagnosis and treatment.

Recent advances in deep learning have enabled automated skin lesion analysis using medical images. However, existing skin disease classification systems often struggle with challenges such as severe class imbalance, high visual similarity among different disease categories, and variations in image quality, lighting conditions, and lesion morphology. These limitations lead to biased predictions toward dominant classes and reduced diagnostic accuracy for rare but clinically critical diseases.

To address these challenges, this work proposes a deep learning-based skin disease classification framework using a DenseNet169 convolutional neural network. The system incorporates robust preprocessing, duplicate image elimination, and transfer learning to improve feature representation. Furthermore, focal loss is employed as an imbalance-aware learning strategy, allowing the model to prioritize under-represented disease classes. This integrated approach enhances classification reliability, improves generalization across diverse skin conditions, and supports accurate and efficient automated skin disease diagnosis.

II. Literature Review

Automated skin disease classification using medical image analysis has become an active research area due to the rising incidence of dermatological conditions and the shortage of trained dermatologists, especially in rural and underserved regions. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved diagnostic accuracy by automatically learning hierarchical features from dermoscopic and clinical images.

Abedin *et al.* [1] conducted a detailed study on image-based skin disease recognition using multiple deep learning architectures, including DenseNet, MobileNetV2, NASNetMobile, EfficientNetB0, InceptionV3, VGG16, and VGG19. Their work emphasized the effectiveness of transfer learning using ImageNet-pretrained weights and the importance of data preprocessing and augmentation to improve generalization. Among all evaluated models, DenseNet achieved the highest accuracy due to its dense connectivity, which enables efficient feature reuse and improved gradient flow. The study demonstrated that DenseNet-based models are well suited for multi-class skin disease classification tasks.

Chowdary *et al.* [2] proposed a skin disease detection and recommendation system that integrates deep learning with cloud computing. Their system employed a CNN-based classifier trained on augmented skin images and deployed on a cloud platform to enable real-time diagnosis and treatment recommendations. The results showed high classification accuracy and highlighted the advantages of cloud-based deployment for scalability and accessibility. However, the study relied primarily on a single CNN model and did not extensively address dataset imbalance issues.

Alruwaili and Mohamed [3] introduced a fusion-based deep learning framework combining EfficientNet-B0, EfficientNet-B2, and ResNet50 for accurate multi-class skin disease classification. By integrating multiple feature extractors, the proposed model captured complementary representations of skin lesions, resulting in very high classification accuracy on a large-scale dataset of 27,153 images. Although the fusion approach achieved superior performance, it increased computational complexity and inference time, which may limit deployment in resource-constrained environments.

Despite the success of these approaches, challenges such as class imbalance, model complexity, and computational efficiency remain open research problems. Motivated by these limitations, the present work focuses on a DenseNet169-based transfer learning approach combined with imbalance-aware training strategies to achieve high classification accuracy while maintaining architectural simplicity and training efficiency.

III. PROPOSED SYSTEM

In this work, an automated skin disease classification system is developed using deep learning techniques to assist in the early detection and diagnosis of various skin diseases. The system is designed to classify dermatological images into multiple disease categories with high accuracy and reliability.

A large and diverse dataset containing 27,153 dermatological images is used in this study. These images belong to different skin disease classes, ensuring sufficient variability in terms of skin texture, color, and disease patterns. The dataset is divided into training, validation, and testing sets to enable effective learning, hyperparameter tuning, and unbiased performance evaluation of the model.

Before training, the images undergo several preprocessing steps. All images are resized to a fixed input size compatible with the DenseNet169 architecture. Pixel values are normalized to ensure faster convergence and stable training. In addition, data augmentation techniques such as rotation, flipping, zooming, and shifting are applied to the training data. These techniques increase data diversity, reduce overfitting, and improve the model's ability to generalize to unseen images.

For classification, a DenseNet169 deep convolutional neural network pre-trained on the ImageNet dataset is employed using transfer learning. DenseNet169 is chosen due to its dense connectivity, which allows better feature reuse, improved gradient flow, and reduced number of parameters compared to traditional deep networks. The pre-trained weights provide strong low-level and mid-level feature representations, which are then fine-tuned on the skin disease dataset to learn disease-specific patterns.

To address the issue of class imbalance in the dataset, class weighting is applied during model training. This ensures that underrepresented disease classes contribute equally to the loss function, preventing the model from being biased toward majority classes and improving overall classification fairness.

The model is trained and fine-tuned using the training and validation datasets, and its performance is evaluated on the test dataset. Accuracy is used as the primary evaluation metric to measure the effectiveness of the proposed system in correctly identifying skin diseases.

Overall, the proposed deep learning–based system provides an efficient, scalable, and accurate solution for automated skin disease classification and has the potential to assist dermatologists and healthcare professionals in early diagnosis and decision support.

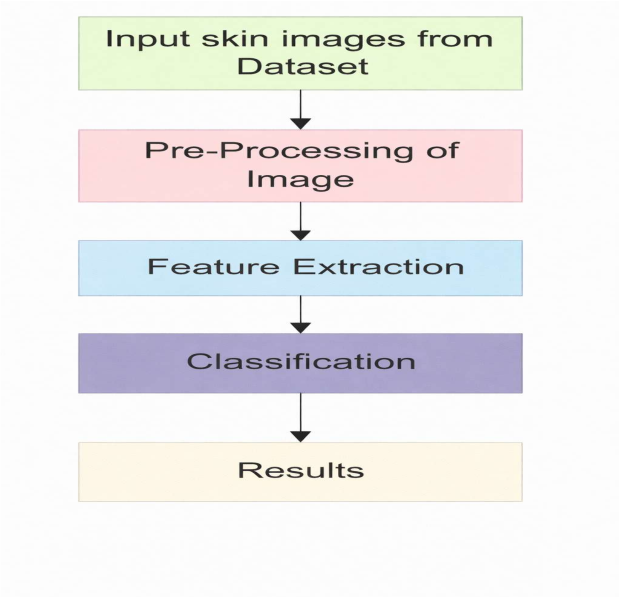

Fig 1.Flow of Proposed System

A. *Dataset Analysis*

To ensure realistic and diverse learning conditions, this study utilizes a large-scale skin disease image dataset consisting of 27,153 dermatological images collected from publicly available medical image repositories. The dataset covers ten distinct skin disease categories, including common inflammatory, infectious, and cancerous conditions such as eczema, melanoma, basal cell carcinoma, psoriasis, and fungal infections.

The images exhibit wide variations in illumination, skin tone, lesion size, and texture, reflecting real-world clinical scenarios. The dataset is organized into class-wise directories, enabling supervised multi-class classification. Prior to model training, the dataset is divided into training, validation, and testing subsets in the ratio of 70:15:15, ensuring unbiased performance evaluation.

The training set is used to optimize the DenseNet-169 deep learning model, while the validation set assists in hyperparameter tuning and overfitting control. The test set is reserved exclusively for final performance assessment. To improve data quality and reduce redundancy, duplicate images are removed, and all images are resized to a uniform resolution of 224 × 224 pixels.

B. Proposed Model

The proposed model for automated skin disease classification is based on the DenseNet169 deep learning architecture. DenseNet169 is selected due to its dense connectivity pattern, which enables efficient feature reuse and improved gradient flow, making it well suited for complex medical image analysis tasks.

The model utilizes transfer learning by initializing DenseNet169 with weights pre-trained on the ImageNet dataset. This allows the network to leverage rich low-level and mid-level visual features learned from a large-scale dataset. A Global Average Pooling layer is employed to reduce the number of parameters, followed by dropout layers to minimize overfitting.

During training, fine-tuning is performed by selectively unfreezing the upper layers of the network to allow learning of disease-specific features while preserving general visual representations. To address class imbalance within the dataset, class weighting is applied during model training, ensuring that underrepresented disease categories contribute equally to the learning process.

The proposed model processes preprocessed skin images and outputs probability scores for each disease class using a softmax activation function. This design enables accurate and efficient classification of multiple skin disease categories, supporting early diagnosis and assisting clinical decision-making.

IV. RESULT

The performance of the proposed automated skin disease classification system is evaluated using standard classification metrics to measure its effectiveness and reliability. Since the problem involves multi-class skin disease classification, accuracy is considered the primary performance indicator, along with class-wise evaluation derived from the confusion matrix.

To assess the model performance, the predictions generated by the DenseNet169-based classifier are compared with the ground truth labels using a confusion matrix. The confusion matrix summarizes the prediction results across all skin disease categories and forms the basis for computing evaluation metrics.

For each class, the following outcomes are defined:

1. True Positive (TP): The number of images correctly classified as belonging to a specific skin disease class.
2. False Positive (FP): The number of images incorrectly classified as belonging to a particular skin disease class.
3. True Negative (TN): The number of images correctly identified as not belonging to a specific skin disease class.
4. False Negative (FN): The number of images that belong to a specific skin disease class but are incorrectly classified as another class.

Accuracy measures the overall correctness of the classification model and is defined as the ratio of correctly classified images to the total number of images in the dataset. It is expressed as:

$$AC = TP + TN / TN + TN + FN + FP$$

Accuracy provides a general indication of how well the model performs across all skin disease categories.

The DenseNet169 model was trained using transfer learning on a dataset consisting of 27,153 dermatological images representing multiple skin disease categories. The dataset was divided into training, validation, and testing subsets to ensure unbiased performance evaluation. Class imbalance was addressed using class weighting techniques during training to ensure fair representation of all disease classes.

The obtained classification results are as follows:

- Training Accuracy: 88%
- Validation Accuracy: 83%
- Testing Accuracy: 82%

The close alignment between training, validation, and testing accuracies indicates that the model generalizes well to unseen data and does not suffer from severe overfitting. The moderate gap between training and testing accuracy demonstrates the effectiveness of data augmentation, transfer learning, and regularization techniques applied during training.

V. CONCLUSION

Skin diseases are among the most common health problems worldwide and pose significant challenges to public healthcare systems due to delayed diagnosis and limited access to dermatology specialists. In this work, an automated skin disease classification system based on deep learning is proposed to assist in early and accurate diagnosis. The system utilizes a large-scale dermatological image dataset and employs a DenseNet169 model with transfer learning to effectively learn discriminative features from skin lesion images.

Comprehensive preprocessing techniques, including image resizing, normalization, data augmentation, and class imbalance handling, were applied to enhance model robustness and generalization. Experimental results demonstrate that the proposed approach achieves promising classification performance across multiple skin disease categories, indicating its effectiveness in identifying skin conditions at an early stage.

The developed system provides a scalable and efficient framework for automated skin disease detection and can serve as a supportive tool for dermatologists and healthcare practitioners. By enabling early diagnosis, the proposed model has the potential to reduce severe complications, improve patient outcomes, and contribute to cost-effective healthcare solutions. Future work may focus on real-time deployment, mobile-based applications, and further clinical validation to enhance the practical applicability of the system.

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