Skin Diseases Classification

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***Abstract*—This project focuses on improving medical image classification for skin diseases, enhancing diagnostic accuracy for conditions such as Eczema, Seborrheic Keratoses, and Melanocytic Nevi. By collaborating with domain experts and using data augmentation techniques, the study addresses dataset imbalances and simulates real-world conditions. The approach involves transfer learning and customized CNNs, achieving notable results: an 85.12% accuracy for skin disease classification, 99.73% for binary classification with Efficient Net, and 98.45% for cancer type classification with a 6-layer ReLU CNN. MobileNet V3 was the most effective, achieving 90.24% accuracy, while EfficientNet reached 98.05% accuracy in multiclass classification. The system uses validation splits and callbacks such as Reducing Learning Rate and Early Stopping for optimal training. These advancements could improve diagnostic accuracy and support clinical decision-making, with potential benefits for healthcare accessibility and efficiency, especially in resource-limited settings.**

Keywords—medical image classification, skin diseases, data augmentation, transfer learning, convolutional neural networks (CNNs), EfficientNet, MobileNet V3, diagnostic accuracy, healthcare, resource-limited settings

I. INTRODUCTION

This research aims to develop machine learning-based classification models for early and precise diagnosis of skin diseases, aiming to reduce healthcare costs associated with untreated or misdiagnosed conditions.

This research is motivated by the critical need for accurate and fast detection of complex dermatological conditions, which present significant challenges to modern healthcare systems. The advanced intelligent diagnostic model will analyze dermatoscopic images. This innovative approach aims to enhance early anomaly detection, speed up treatment decisions, improve clinical results, reduce healthcare resource usage, and enhance patient health.

The objectives of this research include developing a robust skin disease detection system, a user-friendly interface, the use of comprehensive datasets, validation of AI system performance, assessment of the system's potential impact on dermatological care accessibility, and distribution of findings and the AI model as open-source resources. This research aims to change the diagnostic area of dermatological diseases and improve patient care and healthcare standards.

The research team developed a CNN-based skin disease classification model to detect dermatological conditions. A user interface was designed for easy use and seamless integration into the medical field. A comprehensive dataset of skin images was used for training and validation. Performance evaluations were performed to compare the AI system's diagnostic accuracy with traditional methods. Impact assessments were performed to evaluate the system's impact on healthcare accessibility. Robust security protocols were implemented to safeguard patient data.

The project employed transfer learning to improve skin disease classification using pre-trained models like EfficientNet and MobileNet V3. Performance optimization techniques included validation split, learning rate reduction, model checkpointing, and early stopping to prevent overfitting. These techniques ensured efficient training and optimal performance.

II. LITERATURE REVIEW

A. Overview

Literature Review provides a comprehensive overview of dermatological diagnostics, highlighting the complexities and challenges of accurately detecting skin diseases. It explores the anatomy of the skin, common dermatological conditions, and diagnostic methodologies used in the field. It surveys existing research and literature, highlighting primary studies and improvements in skin disease detection.

B. Related Work

Vatsala Anand., [2] et al., in 2022, focused on the integration of U-Net and CNN models for the segmentation and classification of skin lesions from dermoscopy images. The CNN model successfully classified images into seven different skin disease classes, achieving an accuracy of 97.96% with the Adadelta optimizer.

Gan Cai., [9] et al., explored the use of a multimodal transformer to fuse images and metadata for skin disease classification. The study led to an accuracy of 93% using CNN, ViT, and SLE classifiers. The specifics of these are summarized in ***Table 1***

TABLE 1. SUMMARIZED RELATED WORK TABLE

Author	Year	Methodology	Data sets	Results
C.Gan et.al	2022	CNN,VIT,SLE	ISIC 2018	92%
C. Viswantha Reddy Allugunti	2021	Decision Tree, Random Forest, Gradient Boosting Tree and CNN	DermNet	88.83%
C.Mostafiz Ahammed	2022	SVM, Decision Tree, KNN	ISIC 2019	93%
C.Manu Goyal	2020	Inception, ResNet, VGG	ISIC Challenges	90%
C.Mohamed et.al	2019	CNN, SVM, Google-Net, Resnet, VGG	ISIC 2019	93.20%

C. *Similar Systems*

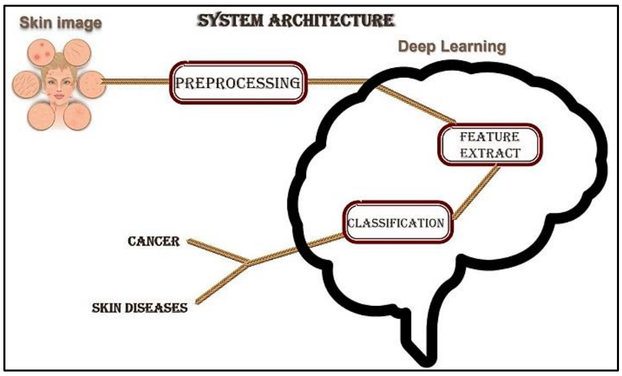
Similar systems in skin disease classification employ various methodologies and datasets to achieve accurate diagnostic results. These systems typically leverage machine learning algorithms, such as Convolutional Neural Networks (CNN), Decision Trees, Support Vector Machines (SVM), and ensemble methods like Random Forest and Gradient Boosting Trees. The variety of these approaches comforts the robustness of the research, with results consistently showing high accuracies, often exceeding 90%, showing the effectiveness of machine learning approaches in classifying various dermatological conditions.

III. SYSTEM ARCHITECTURE AND ALGORITHMS

A. *System Architecture*

The system architecture, designed for skin disease detection, highlights the critical roles of the preprocessing, feature extraction, and classification modules in ensuring diagnostic precision and reliability. The architecture diagram (Figure 1) illustrates the seamless flow from preprocessing through feature extraction to the classification stages.

Figure 1. System Architecture



B. *System Functions*

1) *Preprocessing:*

a) Preparing raw images by regularising their size

b) Augmenting data to enhance model performance

c) Removing noise and watermarks

2) *Feature Extraction:* It is important to use Convolutional Neural Networks (CNNs) to extract complex patterns and essential characteristics from preprocessed images for accurate disease classification.

3) *Classification:* Categorizing images into classes using either Hierarchical or Multi-class single classification.

a) Hierarchical approaches: begins with binary classification to differentiate cancerous from non-cancerous conditions, followed by multi-class classification for specific diseases like eczema and melanoma.

b) Multi-class single approaches: differentiating among all available disease categories.

4) *User Interface:* This module encourages seamless interaction with healthcare professionals by enabling image upload, displaying diagnostic results, and supporting integration systems.

C. *Techniques and Approaches*

The description of functions and techniques includes preprocessing steps such as image rescaling, reshaping, data splitting, and augmentation, which ensures input consistency and enhances model performance.

Feature extraction via CNN captures hierarchical features essential for disease classification.

Various deep learning models such as AlexNet, EfficientNet, Inception, MobileNetV2, MobileNetV3, and ResNet50 are employed, each chosen for its specific architecture and capabilities to optimize performance in dermatological image classification tasks.

IV. SYSTEM IMPLEMENTATION AND RESULTS

A. *Dataset*

The Skin Diseases Image Dataset is a collection of high-resolution images of 5 different skin diseases, including:

- Eczema,
- Melanoma,
- Basal Cell Carcinoma,
- Melanocytic Nevi,
- Seborrheic Keratoses

Its purpose is to enhance the accuracy and reliability of machine learning models in identifying and diagnosing various skin diseases, improving model generalization across different skin conditions.

B. *Software Programs Used*

a) Flutter: A UI toolkit developed by Google for building natively compiled applications for mobile, web, and desktop from a single codebase.

b) Google Colab: A cloud-based environment for running Python code, offering powerful computational resources and seamless integration with Google Drive, allowing execution of Python scripts without local setup.

c) Visual Studio: Used for running parts of the project locally on laptops, involving setting up the necessary environment and dependencies on personal machines to execute and test code efficiently.

C. *Experimental and Results*

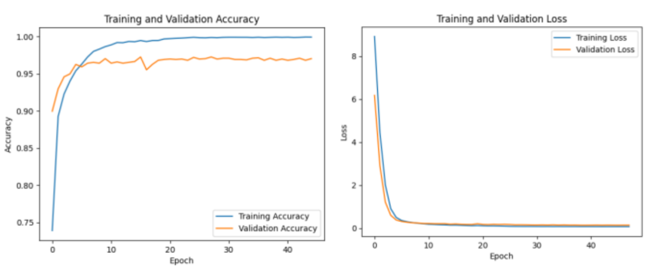
This project focuses on developing an advanced skin disease detection system using deep learning techniques, particularly Convolutional Neural Networks (CNNs) and various models like AlexNet, EfficientNet, Inception, MobileNetV2, and MobileNetV3. The experiments aim to accurately classify skin diseases and cancer types through hierarchical and multi-class single classification approaches.

1) *CNN Performance*
   a) *Binary Classification (5 classes):* Best accuracy 96.79%.
   b) *Skin Classification (3 classes):* Best accuracy 69.39%.
   c) *Cancer Classification (2 classes):* Best accuracy 98.45%.
2) *AlexNet Performance*
   a) *Binary Classification (5 classes):* Best accuracy *98.18%.*
   b) *Skin Classification (3 classes):* Best accuracy *71.13%.*
   c) *Cancer Classification (2 classes):* Best accuracy *98.04%.*
3) *EfficientNet Performance*
   a) *Binary Classification (5 classes):* Best accuracy 99.73%.
   b) *Skin Classification (3 classes):* Best accuracy 60.42%.
   c) *Cancer Classification (2 classes* Best accuracy 89.86%.
4) *Inception Performance*
   a) *Binary Classification (5 classes):* Best accuracy 99.00%.
   b) *Skin Classification (3 classes):* Best accuracy 50.00%.
   c) *Cancer Classification (2 classes):* Best accuracy 93.00%.
5) *MobileNetV2 Performance*
   a) *Binary Classification (5 classes):* Highest validation accuracy 95.88%, training accuracy 97.71%.
   b) *Skin Classification (3 classes):* Training accuracy 98.65%, validation accuracy 66.67%.
   c) *Cancer Classification (2 classes):* Highest validation accuracy 96.85%, training accuracy 97.85%.
6) *Hierarchical Classification*
   a) *EfficientNet (Binary):* Best accuracy 99.73%.
   b) *6-layer ReLU CNN(Cancer):* Best accuracy 98.45%.
   c) *MobileNetV3(Skin):* Best accuracy 90.45%.
7) *Multi-Class Single Classification*
   a) *Dataset:* 5 classes (Eczema, Melanoma, Basal Cell Carcinoma (BCC), Melanocytic Nevi (NV), Seborrheic Keratoses, and other benign tumors).
   b) *Model:* EfficientNetV2B0.
   c) *Results:* Achieved 98.05% accuracy with data split into 80% training, 10% validation, 10% test; image size 224, batch size 16, and 70 epochs. Results are shown in ***Table 2*** and ***Figure 2***.

TABLE 2. ACCURACY AND LOSS OF EFFICIENTNETV2B0

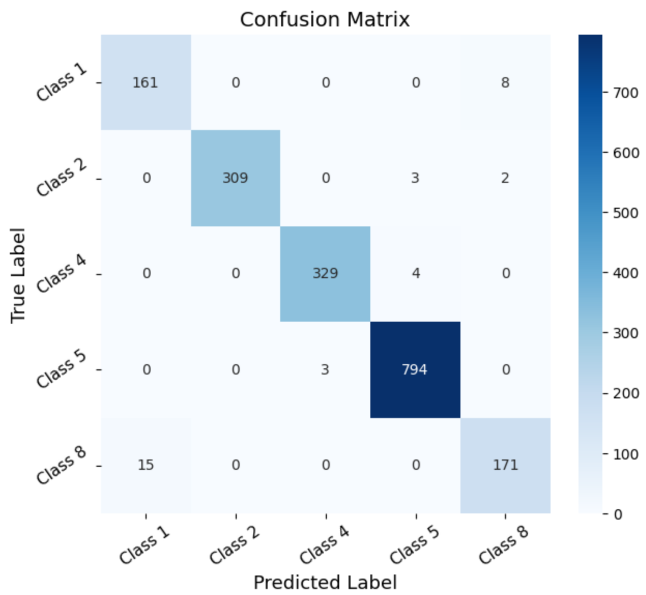
Metric	Training Set	Validation Set	Test Set
Accuracy	99.99%	97.94%	98.05%
Loss	0.065075	0.133585	0.133833

Figure 2. Accuracy and loss of EfficientNetV2B0



The project successfully demonstrated the potential of deep learning models in skin disease and cancer classification, achieving high accuracy through optimized preprocessing, data augmentation, and model configurations. EfficientNetV2B0 emerged as the best model for multi-class single classification with an accuracy of 98.05%, highlighting its effectiveness for practical dermatological diagnostics. Using, Transfer Learning: Significantly improved model accuracy. Early Stopping and Learning Rate Adjustment: Prevented overfitting and optimized training efficiency. Confusion Matrix is shown in ***Figure 3***.

Figure 3. Confusion Matrix of EfficientNetV2B0



Other models in Multi Class Single Classification were tried, such as ResNet50, whose accuracy was 94.11%, and MobileNet(V3), whose accuracy was 97.13%.

So far Using Multi Class Single Classification, the best model for classification: EfficientNet (98.05% accuracy).

In our skin disease classification project, our results show significant advancements over previous research methodologies. For multi-class single classification tasks, EfficientNet achieved an outstanding accuracy of 98.05%, surpassing methodologies reported by other researchers such as C.Gan et al. (92% using CNN, VIT, SLE), C.Viswantha Reddy Allugunti (88.83% using Decision Tree, Random Forest, Gradient Boosting Tree, CNN), C.Mostafiz Ahammed (93% using SVM, Decision Tree, KNN), C.Manu Goyal (90% using Inception, ResNet, VGG), and C.Mohamed et al. (93.20% using CNN, SVM, Google-Net, ResNet, VGG). In binary classification within a hierarchical framework, EfficientNet also excelled with 99.73% accuracy, while a specialized 6-layer ReLU CNN achieved 98.45% accuracy for cancer classification. Overall, skin disease classification using MobileNetV3 achieved a robust accuracy of 90.45%. These findings highlight the effectiveness of deep learning models like EfficientNet in achieving high accuracy rates, underscoring their potential for improving diagnostic capabilities in dermatological applications. Results are summarized in ***Table 3***.

TABLE 3. COMPARING RESULTS

Comparison	Accuracy
Other Researchers	88.83% - 93.20%
Our Work	98.05%

V. Conclusions

The project introduces a skin disease detection system using deep learning techniques. It includes preprocessing, feature extraction, and classification modules. Preprocessing improves image quality, while feature extraction uses CNNs to capture hierarchical features. The classification module differentiate between cancerous and non-cancerous conditions and identifies specific diseases. This system enhances diagnostic accuracy, supporting clinicians in making informed decisions. However, it faces limitations such as image quality variability and imbalanced datasets. The project's importance lies in its potential to improve skin disease diagnosis accuracy and efficiency, support healthcare professionals and improve patient outcomes. Integrating the system into clinical environments could help dermatologists and clinicians.

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