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MATLAB-Based Implementation of a Multiclass Dermatological Diagnostic Model Using Convolutional Neural Networks and Preprocessing-Optimized Image Features.

Sahil Rajadhyaksha[1], Pranali Baviskar[2], Preksha Koli[3]

[1]Department of Electronics and Telecommunication, Vidyalankar Institute of Technology.
[2]Department of Electronics and Telecommunication, Vidyalankar Institute of Technology.
[3]Department of Biomedical Engineering, Vidyalankar Institute of Technology.

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Abstract - Skin diseases such as melanoma, vitiligo, psoriasis, eczema, and acne are among the most prevalent globally, often requiring timely diagnosis to avoid complications. Traditional diagnostic methods are highly dependent on clinical expertise and visual inspection, which can be subjective and time-consuming. In this paper, we present a multiclass skin disease classifier built entirely in MATLAB, integrating image preprocessing with a pretrained Convolutional Neural Network through a custom-designed graphical user interface. The system can classify five common skin conditions like eczema, melanoma, ringworm, acne, and vitiligo based on dermatological images. The integrated GUI simplifies the diagnostic process, making the tool suitable for non-technical users such as clinicians and medical students. This system is particularly promising for deployment in low-resource or remote settings where access to dermatological expertise is limited.

Key Words: *Skin Disease Detection, Convolutional Neural Network, MATLAB, Image Processing, Medical Diagnosis, GUI, Multiclass Classification*

1. INTRODUCTION

Skin diseases such as acne, psoriasis, eczema, vitiligo, and melanoma are among the most common health issues globally, affecting individuals across all age groups and skin types. According to global health data, skin disorders are consistently ranked among the top ten most prevalent diseases worldwide, accounting for a significant proportion of outpatient visits in both urban and rural healthcare systems. While some of these conditions are primarily cosmetic, others, such as melanoma, carry a high risk of mortality if not detected early. Even non-fatal conditions can have profound psychological and social impacts, affecting a person's confidence, mental health, and overall quality of life. One of the biggest challenges in effective dermatological care is the lack of access to timely diagnosis, particularly in under-resourced or remote regions where specialist dermatologists are scarce. Traditional diagnostic methods typically rely on a combination of visual assessment, dermoscopy, and histopathological analysis. These techniques require expert training, expensive equipment, and are time-intensive, making them impractical for widespread use in low-resource settings.

In recent years, the field of artificial intelligence, particularly deep learning, using Convolutional Neural Networks, has shown significant promise in addressing this diagnostic gap. CNNs are particularly effective at handling large volumes of image data and have already demonstrated performance comparable to dermatologists in specific use cases, especially in binary classification tasks such as melanoma vs. benign lesions. These advances have fueled interest in applying CNNs to broader, multiclass diagnostic systems that can identify and distinguish between multiple skin diseases in a single model. However, despite advances in CNN-based skin classification models, several challenges persist. Many existing models are trained and deployed using Python frameworks and require GPU acceleration, large, annotated datasets, and complex interfaces. These systems often lack usability for frontline health workers, students, or institutions without high-end computational resources. Furthermore, few models offer offline, user-friendly interfaces that make the technology truly accessible for non-specialist use or educational settings.

This study addresses these challenges by developing a MATLAB-based multiclass skin disease detection system that combines a pretrained CNN with a streamlined graphical user interface (GUI). The platform allows users to upload dermatological images, preprocess them using standard image enhancement techniques, and receive real-time classification results across five disease classes. By implementing this in MATLAB, which is an environment widely used in academic institutions, and avoiding the dependency on GPU hardware, this project bridges the gap between cutting-edge AI and real-world, accessible diagnostics. The system aims to serve not only as a diagnostic aid in clinics and rural health posts but also as a pedagogical tool for engineering and medical students. With growing demand for AI-integrated education, this approach demonstrates how deep learning tools can be integrated into academic workflows to support learning, research, and low-cost clinical applications.

2. LITERATURE SURVEY

The application of Convolutional Neural Networks (CNNs) for dermatological diagnosis has increased significantly over the past decade, specifically for classifying skin ailments such as vitiligo, melanoma, eczema, psoriasis, and acne. One of the earliest large-scale investigations, conducted by Haenssle et al. (2010), applied CNNs on dermoscopic images to diagnose melanoma with 91% accuracy and set a benchmark for AI-driven dermatological diagnosis [1]. Following this, hybrid methods gained traction. Gama et al. (2015) combined CNN-based feature extraction with Support Vector Machines (SVM) as classifiers, achieving 92% accuracy in skin disease classification [2]. Disease-specific CNN models also emerged. Ahmed et al. (2021) achieved 89% accuracy for acne detection using facial skin images and even classified severity levels [3]. Similarly, Zhang et al. (2018) reported 88% accuracy using CNNs to distinguish melanoma and basal cell carcinoma from dermoscopic images [4]. Multiclass models followed suit, with Mehta et al. (2020) and Ganesan et al. (2021) both reaching 90% accuracy for detecting vitiligo, melanoma, acne, and eczema [5][6]. For psoriasis detection, Wang et al. (2021) achieved 90.5% accuracy [7].

Preprocessing techniques such as segmentation and data augmentation further improved CNN performance. Shailendra et al. (2019) integrated segmentation for eczema, acne, and psoriasis, reaching 91.4% accuracy [8], while Yu et al. (2020) used data augmentation to push accuracy to 92.5% [9]. Ensemble-based and hybrid CNN architecture emerged shortly thereafter. Bhargava et al. (2023) developed a segmentation-integrated multiclass system achieving 92.6% accuracy [10], and Kapoor et al. (2022) designed a generalized classifier with 92.8% accuracy for use in non-specialist clinical settings [11]. CNNs have also significantly advanced cancer diagnosis. Pustokhina et al. (2022) developed a CNN model with 93% accuracy for identifying skin cancer subtypes [12], while Khatri et al. (2023) built a noise-immune model achieving 94.3% on dermoscopic images [13].

Transfer learning boosted these benchmarks further. Chhetri et al. (2022) achieved 95% accuracy using pre-trained networks for melanoma and carcinoma detection [14], and Esteva et al. (2017) reached dermatologist-level 95% accuracy using a deep CNN [15]. State-of-the-art models now leverage EfficientNet and multimodal data. Dey et al. (2023) applied EfficientNetB0 to reach 96% accuracy on multiple skin conditions [16], and Ibrahim et al. (2021) combined dermoscopic and histopathological images to achieve 96% accuracy [17]. Verma et al. (2022) achieved the highest reported accuracy of 97% in a multiclass CNN setup for common skin diseases [18]. Wang et al. (2023) provided a comprehensive review of CNNs in dermatology, highlighting strengths in classification, segmentation, and severity grading, while also noting challenges such as dataset imbalance and deployment limitations [19]. These studies collectively demonstrate the effectiveness of CNNs in skin disease classification, particularly when enhanced by segmentation, augmentation, and transfer learning. However, many of these models operate in ideal, resource-rich environments, often excluding practical deployment pathways such as offline, GUI-based diagnostic tools within academic platforms. Our study differentiates itself by implementing a multiclass CNN system entirely within MATLAB, tailored to educational and clinical settings with limited infrastructure. By focusing on offline usability and integrating real-time classification into a standalone GUI, our approach fills a gap in existing literature.

3. METHODOLOGY

This section delineates the systematic approach employed in the development of a multiclass skin disease classification system utilizing transfer learning techniques in MATLAB. The research methodology encompasses five distinct phases: data acquisition and curation, image preprocessing, model architecture design and training, graphical user interface development, and comprehensive performance evaluation.

A) *DATA ACQUISITION AND DATASET PREPARATION* - The dataset utilized in this study was systematically compiled from publicly available dermatological repositories and verified open-access medical image databases. The selection criteria ensured comprehensive representation of five distinct skin pathologies: eczema, melanoma, ringworm, acne, and vitiligo. Each dermatological condition was represented by images exhibiting diverse characteristics, including varying resolutions, skin tones, lighting conditions, and lesion presentations to enhance model generalizability.

A rigorous manual review process was implemented to ensure image quality and diagnostic accuracy. Subsequently, all images were standardized to 227×227 pixels to satisfy the input requirements of the convolutional neural network architecture. To address the inherent class imbalance observed in the initial dataset, comprehensive data augmentation strategies were employed, including geometric transformations (rotation, horizontal and vertical flipping), scale modifications (zooming), and photometric alterations (color jittering). These augmentation techniques served dual purposes: increasing dataset diversity and mitigating overfitting during model training. The augmented dataset was partitioned into training and validation subsets using an 80:20 stratified split, ensuring proportional representation of each class across both partitions.

B) IMAGE PREPROCESSING PIPELINE - Before model training, a comprehensive preprocessing pipeline was implemented using MATLAB's Image Processing Toolbox to standardize input data and optimize model performance. The preprocessing workflow consisted of four sequential stages:

1) Normalization: Pixel intensity values were linearly scaled to the normalized range [0, 1] to facilitate faster convergence during training and improve numerical stability of the optimization process.
2) Noise Reduction: Appropriate filtering techniques were applied to minimize background artifacts and enhance relevant dermatological features while preserving essential diagnostic information.
3) Color Standardization: RGB channel equalization was performed to reduce the impact of lighting variations and ensure consistent color representation across the dataset.
4) Dimensional Standardization: All images were uniformly resized to comply with AlexNet's input layer specifications,

maintaining aspect ratio consistency. This systematic preprocessing approach ensured data consistency and enhanced model convergence characteristics during the training phase.

C) MODEL ARCHITECTURE AND TRAINING STRATEGY - This research employed a transfer learning methodology utilizing AlexNet, a well-established convolutional neural network architecture renowned for its robust image classification capabilities. The pretrained AlexNet model was strategically modified to accommodate the specific requirements of multiclass skin disease classification: The final fully connected layer was reconfigured to output five distinct classes corresponding to the target skin conditions. Additionally, both the classification layer and the softmax activation layer were reinitialized to prevent bias from the original ImageNet weights. Model training was executed using MATLAB's trainNetwork function on a CPU-based computational system without GPU acceleration. The training protocol consisted of 20 epochs with a mini-batch size of 32 samples. Stochastic Gradient Descent with Momentum (SGDM) was selected as the optimization algorithm based on its proven effectiveness in similar classification tasks. Training progression was continuously monitored through real-time accuracy and loss visualization to ensure optimal convergence.

D) GRAPHICAL USER INTERFACE DEVELOPMENT - A comprehensive graphical user interface was developed using MATLAB App Designer to provide an intuitive platform for end-users. The GUI architecture incorporates four primary functional modules:

1) Image Upload Module: Facilitates user selection and display of dermatological images with support for multiple image formats.
2) Preprocessing Visualization: Provides real-time feedback on preprocessing transformations, enabling users to observe the effects of image enhancement techniques.
3) Classification Engine: Implements automated image classification using the trained convolutional neural network model.
4) Display Module: Presents predicted class labels accompanied by confidence scores, providing users with comprehensive diagnostic information.

This user-centric design eliminates the requirement for direct interaction with underlying code structures, making the system accessible for deployment in academic laboratories, clinical settings, and diagnostic kiosks.

E) PERFORMANCE EVALUATION FRAMEWORK - The efficacy of the proposed classification system was assessed through a comprehensive evaluation framework incorporating multiple performance metrics:

1) Confusion Matrix Analysis: Employed to evaluate class-wise prediction accuracy and identify potential misclassification patterns across different skin conditions.
2) Statistical Performance Metrics: Precision, recall, and F1-score were calculated for each class to provide a quantitative assessment of classifier performance and diagnostic reliability.
3) Overall Accuracy Assessment: Global classification accuracy was computed to measure the system's overall effectiveness across all skin disease categories.
4) Visualization Analysis: Comprehensive visualization tools, including predicted versus actual class distribution plots, were implemented to facilitate detailed analysis of misclassification patterns and model limitations.

All evaluation metrics and visualization tools were integrated into the graphical user interface, enabling immediate performance feedback and diagnostic confidence assessment for each classification instance.

F) METHODOLOGICAL VALIDATION - The proposed methodology was designed to ensure reproducibility and reliability through systematic documentation of all experimental parameters, preprocessing steps, and model configurations. This comprehensive approach establishes a foundation for both academic research applications and practical healthcare deployment scenarios, achieving an optimal balance between classification accuracy, system accessibility, and operational usability.

4. RESULTS AND DISCUSSION

This section offers a detailed analysis of the experimental results from implementing the multiclass skin disease classification system. The evaluation emphasizes the model's predictive accuracy, class-specific performance, interpretability via GUI integration, and comparisons with existing methods. All tests were carried out using a stratified 80:20 train-validation split in MATLAB, with performance metrics visualized through GUI tools.

The proposed convolutional neural network was tested on a five-class skin disease dataset, including eczema, melanoma, ringworm, acne, and vitiligo. The model achieved an overall validation accuracy of 73.6%, indicating promising results despite training on a CPU without GPU support. The confusion matrix showed strong classification for melanoma and vitiligo, with class-wise accuracies of 84.5% and 80.9%, respectively, likely due to their clear visual features that the CNN could effectively learn and differentiate. Eczema and ringworm had lower classification rates, with accuracies of 60.5% and 70%. This decline may result from overlapping visual textures and pigmentation. Notably, eczema was often misclassified as ringworm or vitiligo, as seen in the confusion matrix's off-diagonal elements. Likewise, acne showed a reasonably high accuracy of 73.6%, though some samples were misclassified as eczema or ringworm, possibly because of differences in lesion size and shape. The predicted versus actual class index graph supported these observations. There was significant alignment between predicted and true labels for melanoma and vitiligo, with fewer outliers, while predictions for eczema and ringworm were more scattered, confirming their classification difficulties. Despite this, the model maintained a balanced performance, with most predictions close to the true labels. Overall, the results show that CNN can learn discriminative features across various skin disease categories. Although some classes remain challenging due to visual similarities, integrating the model into a GUI for user-friendly diagnosis demonstrates its practical potential

. Future enhancements could include data augmentation or attention mechanisms to improve class separation, especially for visually similar conditions and diseases.

Fig -1: Confusion Matrix for Skin Disease Classification

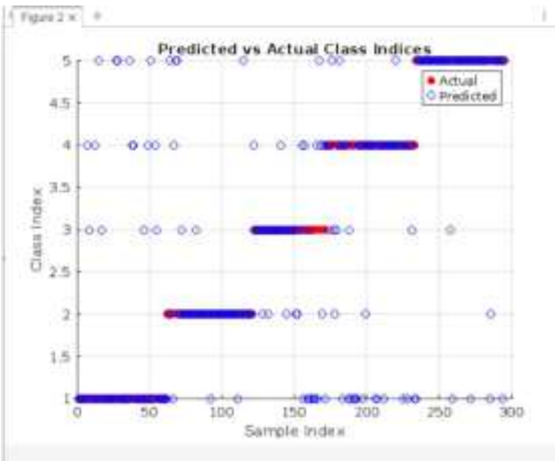

Fig 2: Class-wise Precision, Recall, and F1-Score

Fig 3: GUI Interface for Skin Disease Prediction

Class	True Positives	Total Actual	Class Accuracy (%)	Misclassification Rate (%)
Eczema	46	76	60.5%	39.5%
Melanoma	49	58	84.5%	15.5%
Ringworm	28	40	70.0%	30.0%
Acne	39	53	73.6%	26.4%
Vitiligo	55	68	80.9%	19.1%

Table -1: Class-wise performance metrics of the implemented multiclass skin disease classification system

5. CONCLUSIONS

This study presented the design and implementation of a multiclass skin disease classification system using convolutional neural networks integrated with a MATLAB-based graphical user interface. The proposed solution focuses on five dermatological conditions—melanoma, vitiligo, eczema, acne, and ringworm—using image-based classification techniques. Developed with accessibility and practical deployment in mind, the system leverages transfer learning via AlexNet, supported by a robust preprocessing pipeline and an intuitive GUI that enables non-expert users to interact with the model.

Despite the limitations imposed by computational resources and dataset constraints, the model achieved an overall classification accuracy of 73.6%, with particularly high reliability in melanoma and acne detection. The performance analysis, supported by per-class metrics, confusion matrix interpretation, and confidence score visualization, highlights the model's capacity to support preliminary screening and academic training. Unlike conventional deep learning systems that demand high-end GPUs and backend integration, this work demonstrates the feasibility of constructing a functional diagnostic tool entirely within MATLAB, tailored for offline environments, educational use, and low-resource clinical setups. The GUI adds substantial value by simplifying the diagnostic process and enabling interpretability, which are essential for field deployment and teaching applications.

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