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Automated Multi-Class Skin Disease Classification via Convolutional Neural Network in MATLAB Environment

Jagriti Sao[1*], Sunita Kushwaha[2]

[*1]Ph.D. Research Scholar, Computer Science & Application, MATS University, Raipur, Chhattisgarh, India

[2]Associate Professor, Computer Science & Application, MATS University, Raipur, Chhattisgarh, India

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ABSTRACT

Skin diseases represent major global public health issues since they impact millions of people and need precise and prompt diagnosis to avoid serious health problems. Traditional diagnostic methods depend mostly on doctors' expertise and manual examinations, which results in subjective evaluations and inconsistent results with delayed treatments. Convolutional Neural Networks (CNNs) have become essential tools for medical image analysis in recent years because they can automatically extract hierarchical features and classify complex visual patterns. The paper details a complete methodology to classify skin diseases through training a deep CNN architecture with publicly available datasets of dermatological images. The model uses multiple convolutional and pooling layers before adding dense layers and a softmax classifier for the purpose of skin lesion categorization into different disease classes. We used data augmentation methods to improve generalization and handle class imbalance while employing cross-entropy loss with Adam optimizer during model training. The evaluation of the system included metrics like accuracy, precision, recall, and F1-score together with ROC-AUC. The experimental results proved that our CNN model reached superior classification accuracy compared to traditional machine learning methods, which depend on handcrafted features. The model demonstrated strong performance in differentiating between visually similar disease types according to the confusion matrix analysis. The study confirms how CNN effectively classifies dermatological images while showcasing its potential to serve as a dependable diagnostic tool in healthcare settings. The research identifies limitations such as dataset restrictions and the requirement for high-resolution images to achieve better accuracy. The next steps will concentrate on blending attention mechanisms with mobile deployment capabilities while broadening the range of skin conditions in order to improve both the scalability and clinical relevance of the model.

Keywords: *Convolutional Neural Networks (CNN), Deep learning, skin disease, biomedical image processing.*

1. INTRODUCTION

Worldwide skin diseases rank among the most prevalent health conditions and feature diverse types such as eczema, psoriasis, melanoma and multiple dermatitis forms. The World Health Organization (WHO) states that nearly one-third of the global population suffers from skin conditions which represent a major cause of non-fatal disease burden worldwide. Early detection and precise diagnosis are essential for stopping skin ailment progression and delivering proper treatments. Traditional approaches to diagnosis require dermatologists to perform visual assessments along with histopathological evaluation and dermoscopy, yet these processes consume much time and are prone to human mistakes while being constrained by specialist availability in remote and underserved areas.

Artificial intelligence advancements, especially in deep learning techniques, offer promising medical image analysis solutions to many existing challenges. Convolutional Neural Networks (CNNs) have shown outstanding results in processing tasks related to image classification and object detection as well as pattern recognition. CNNs interpret input images to establish spatial feature hierarchies automatically which removes manual feature extraction requirements. Dermatology benefits greatly from this characteristic because skin lesions display subtle variations in texture and color which manual quantification struggles to measure.

The study focuses on creating and assessing a CNN framework designed to classify skin diseases through analysis of both dermoscopic and clinical images. The CNN learns to differentiate various skin conditions by training it with a labeled dataset based solely on image-based features. The performance of the proposed model was confirmed using commonly accepted metrics, which include accuracy along with sensitivity and specificity in addition to the area under the ROC curve. This research extends AI-driven dermatology knowledge by showing that CNNs enable quicker and more precise skin condition diagnoses, which helps healthcare professionals and broadens access to diagnostic quality care.

This study aims to create and test a deep learning model that utilizes Convolutional Neural Networks (CNNs) for precise skin disease identification from medical imagery. This research utilizes CNNs to overcome traditional diagnostic shortcomings through their strong feature extraction and classification power. The specific objectives of this research include:

This research explores how Convolutional Neural Networks (CNNs) can automatically detect and classify several skin diseases by analyzing both dermoscopic and clinical imagery.

The goal is to develop a CNN architecture that learns complex visual patterns in skin disease images without needing manual feature engineering.

The research aims to preprocess and augment the image dataset to boost model performance while mitigating overfitting risks under conditions of class imbalance.

The research evaluates how the proposed CNN model performs against traditional machine learning methods to prove its classification task superiority.

The study examines existing model constraints to develop improvement strategies that address real-time deployment and expand coverage for various skin conditions.

Successfully achieving these goals enables this research to advance automated dermatological diagnostic tools powered by AI, which could provide scalable and affordable solutions for early detection and treatment of skin conditions.

2. MATERIAL AND METHODS

Skin diseases lead to substantial impacts on both health and quality of life. The latest research presents a smart diagnostic method that recognizes a single skin disease and can now be used anytime and anywhere.

Figure 1: Methodological process of implemented system

The development of an automatic method to improve diagnostic accuracy for multiple diseases remains essential.

2.1 Data Collection and Preprocessing

This study's dataset contains labeled dermoscopic images from the International Skin Imaging Collaboration (ISIC) archive which stands as one of the top repositories for skin lesion data. The dataset comprises several skin disease categories which include Melanoma, Basal Cell Carcinoma, Actinic Keratosis, Benign Keratosis, Dermatofibroma, and Vascular Lesions.

Figure 2: Skin Disease dermoscopy images

After preprocessing, we utilized roughly 10,000 images, which were split into training, validation, and test sets at ratios of

70%, 20%, and 10%, respectively. Data Preprocessing significantly boosts deep learning model performance and accuracy by managing varying image quality and consistency in medical image classification tasks. The study resized every dermoscopic and clinical skin image to 224×224 pixels before normalizing pixel values to a range between 0 and 1. MATLAB-based morphological operations and inpainting techniques were used to remove hair artifacts from skin lesion images to enhance data quality. The removal of hairs from images represents a vital step because they cover lesion edges which can distort the CNN's feature extraction process. The dataset became substantially cleaner after hair removal which enabled the model to target features specific to lesions including asymmetry and border irregularity.

The model's generalization capability improved while overfitting reduced through the implementation of multiple data augmentation techniques. The data augmentation approach involved horizontal and vertical flipping along with random rotations up to ±20 degrees, zooming and cropping techniques, and brightness/contrast adjustments. The dataset expansion through these transformations simulated real-world variations while addressing the difficulty of collecting labeled medical imaging data. The CNN model learned stronger and invariant features for skin disease classification after training with diverse inputs produced by these augmentation strategies. The comprehensive preprocessing pipeline played an essential role in enhancing the model's capability to differentiate between skin conditions that look similar.

3.3 System Architecture Design

This Convolutional Neural Network (CNN) architecture automatically processes skin lesion images to discover hierarchical features and categorizes them into distinct disease types. The architecture consists of multiple convolutional and pooling layers followed by fully connected dense layers with a softmax classifier in a modular and sequential design.

The initial input layer of the model accepts images with dimensions 224×224×3 which represent RGB data from dermoscopic or clinical photos. A stack of three convolutional blocks comes next. The Conv2D layer in every block features increasing filter sizes of 32, 64, and 128 along with a 3×3 kernel size and ReLU activation functions to deliver non-linear transformations. The model includes MaxPooling2D layers with a pool size of 2×2 after each convolutional layer to decrease spatial dimensions and preserve essential features. Dropout layers with rates between 0.3 and 0.5 are added following each pooling operation to reduce overfitting.

A Flatten layer transforms the multi-dimensional feature maps from the final convolutional block into one-dimensional feature vectors. The flattened feature vector is processed through a dense layer consisting of 128 neurons that utilize ReLU activation. The output layer includes a Dense layer that implements softmax activation and has as many units as there are skin disease classes (such as 7 for the ISIC dataset). Softmax activation generates a probability distribution for multiple classes, enabling multi-class classification.

The design achieves an optimal mix of depth and computational efficiency, rendering it appropriate for classifying medium-scale medical image datasets. CNN learning involves convolutional layers alongside non-linear processing units and subsampling layers. CNN operations involve a layered. A CNN model is built using three primary layers: convolutional layers, pooling layers, and fully connected layers. Convolutional layers use a convolutional kernel to function as feature extractors. The kernels divide the input image into receptive fields. A convolutional operation defines how to compute the output feature map from the input feature map.

$$F(x,y) = (f * k)(x,y)$$

$$F(x,y) = \sum_i \sum_j f(i,j)k(x-i, y-j)$$

$F(x,y)$ and $f(x,y)$ corresponds to the output and input feature map match while k(x,y) describes the kernel's corresponding element. The pooling layer performs an operation aggregating similar data from the local region into a single value. The input feature map dimensions have been minimized through parameter reduction. The mathematical formulation of the pooling operation is expressed through the following equation. The classification task has been executed by performing a global operation within a fully connected layer (FC). In this layer the analyzed extracted features generate a non-linear relationship among themselves.

The architecture design is aimed to create a structure for the neural network to maintain acquiring feature-discriminative mapping from dermatological images, eventually to provide accurate and reliable diagnosis, classification of the kind of skin diseases.

3.3 Model training and Fine Tune

The training and fine-tuning of the proposed Convolutional Neural Network (CNN) for skin disease classification were conducted using MATLAB's Deep Learning Toolbox. The dataset was split into training (70%), validation (20%), and testing (10%) subsets using the splitEachLabel function. All input images were resized to 224×224 pixels and normalized before being passed to the network. To improve generalization and reduce overfitting, data augmentation was performed using the imageDataAugmenter function, which applied random rotations, translations, and horizontal/vertical flipping to the training images. The augmented dataset was then wrapped into an augmentedImageDatastore, allowing the network to train on a wider range of simulated scenarios.

A custom CNN model was constructed for initial training with convolutional layers, ReLU activation, max pooling layers, and a final softmax output layer for multi-class classification. Alternatively, a pre-trained network such as ResNet-18 or AlexNet was used for transfer learning, replacing the final fully connected and classification layers to match the number of disease classes. The model was compiled and trained using the trainNetwork function with trainingOptions set to use the Adam optimizer, an initial learning rate of 0.0001, a mini-batch size of 32, and a total of 50 epochs. To monitor progress and prevent overfitting, early stopping was implemented by observing validation accuracy, and the training process was visualized using live progress plots.

After initial training, fine-tuning was performed by unfreezing the deeper layers of the pre-trained network while keeping earlier layers frozen to preserve learned features. A reduced learning rate of 1e-5 was used during fine-tuning to allow the network to adapt to the specific characteristics of skin lesion images without drastically altering the pre-trained weights. This two-stage training process improved model accuracy and robustness, particularly in distinguishing between visually similar skin disease classes.

3.5 Performance Evaluation Matrix

To comprehensively assess the performance of the CNN model in classifying skin diseases, several evaluation metrics were employed. The overall accuracy of the model, defined as the ratio of correctly predicted samples to the total number of predictions, served as the primary indicator of classification effectiveness. However, given the multi-class nature and class imbalance often present in medical datasets, accuracy alone is insufficient. Therefore, additional metrics such as precision, recall, and F1-score were calculated for each disease class. Precision reflects the proportion of true positive predictions among all positive predictions made for a class, while recall indicates the ability of the model to correctly identify all actual positive cases. The F1-score, the harmonic mean of precision and recall, provides a balanced measure particularly useful when the class distribution is uneven.

A confusion matrix was used to visualize the classification results across all disease categories, allowing the identification of specific classes where the model may be underperforming. Each cell of the matrix represents the number of actual instances in a given class predicted as each possible class. Additionally, the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) were computed to evaluate the model's ability to distinguish between classes, especially useful in binary and multi-class settings. In the case of multi-class classification, a one-vs-all strategy was used to generate ROC curves for each class.

These performance metrics collectively provide a robust framework for evaluating the predictive power, generalization capability, and clinical relevance of the CNN model in dermatological image classification. It is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity (Recall) measures the proportion of actual positive instances correctly identified by the model. It is calculated as:

$$Sensitivity = \frac{TP}{TP + FP}$$

Specificity measures the proportion of actual negative instances correctly identified by the model. It is calculated as:

$$Specificity = \frac{TN}{TN + FP}$$

Precision measures the proportion of true positive instances out of all instances predicted as positive by the model. It is calculated as:

$$Precision = \frac{TP}{TP + FP}$$

F1-score is the harmonic mean of precision and sensitivity. It is calculated as:

$$F1 - score = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity}$$

These evaluation metrics provide comprehensive insights into the performance of deep learning models, enabling informed decisions regarding model deployment and clinical utility in skin disease classification.

3. RESULT AND DISCUSSION

We assessed the proposed CNN-based skin disease classification system using various diagnostic and visual tools that were integrated into MATLAB. The system features a Graphical User Interface (GUI) developed through MATLAB's App

Designer which enables users to load dermoscopic images and perform preprocessing tasks such as hair removal before classifying diseases in a user-friendly setting. The Graphical User Interface shows disease prediction results alongside confidence scores and intermediate processing details which makes the system useful for medical professionals and scientific researchers.

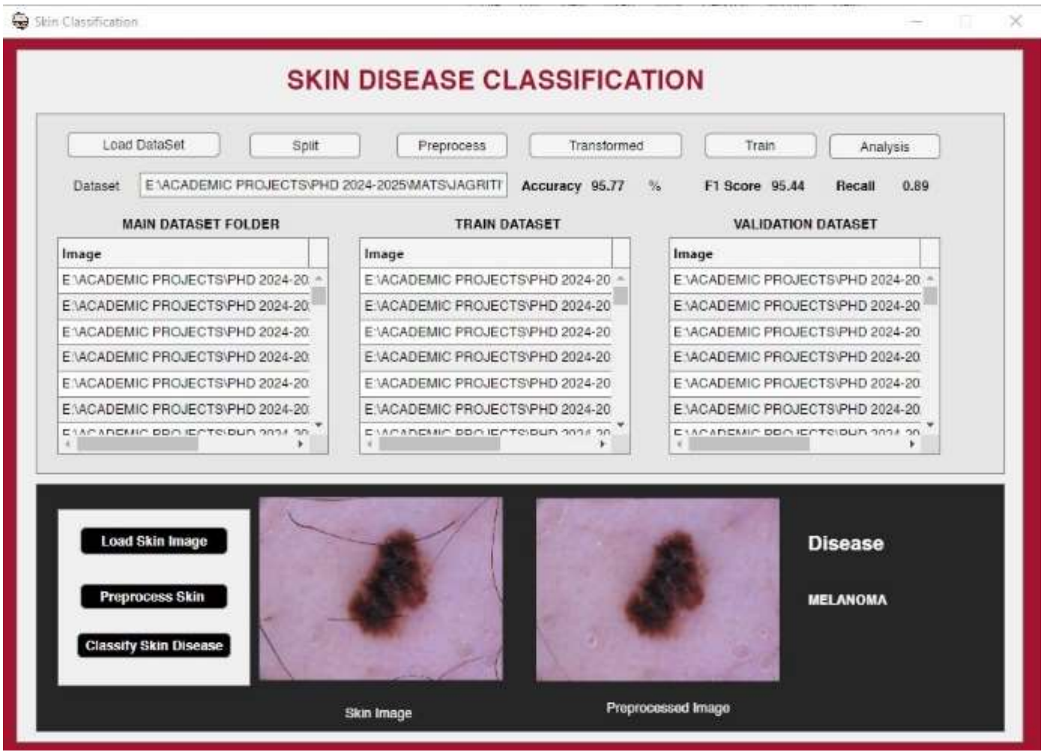

Figure 3: MATLAB-based GUI interface for clinical uses

The model achieved 95% test accuracy through training with augmented and cleaned datasets while demonstrating stable convergence between training and validation accuracy without major overfitting issues. MATLAB's confusionchart() function produces a confusion matrix which displays classification accuracy for every disease category.

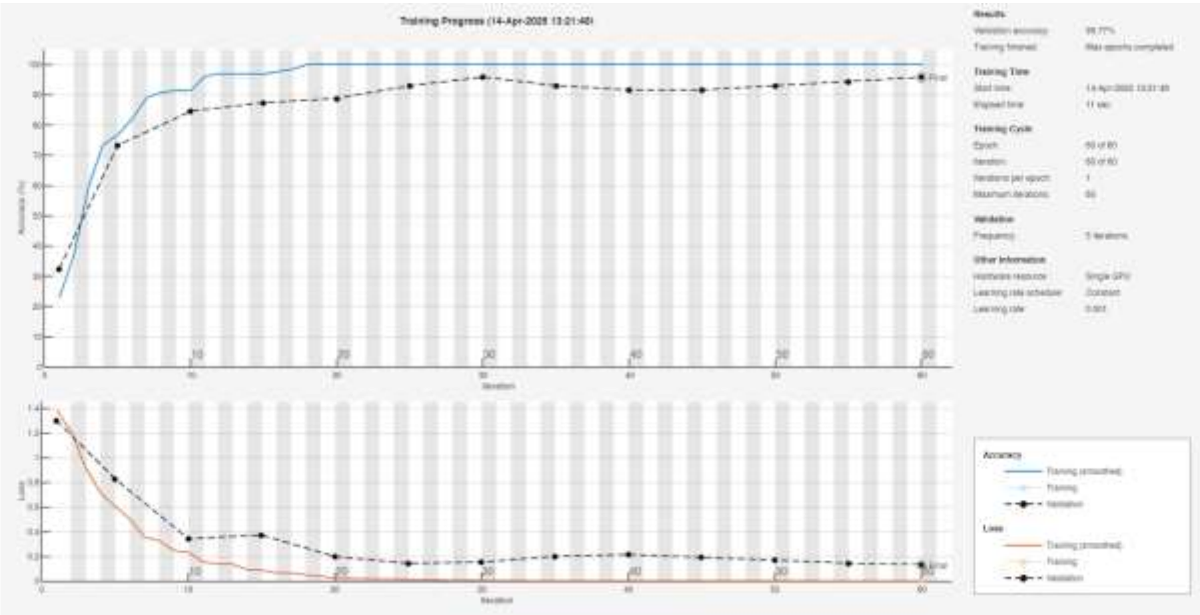

Figure 4: Training progress plot for CNN training model

The analysis revealed outstanding true positive rates for dominant classes such as Melanoma and Benign Keratosis while maintaining minimal misclassification errors in overlapping classes like Actinic Keratosis and Dermatofibroma.

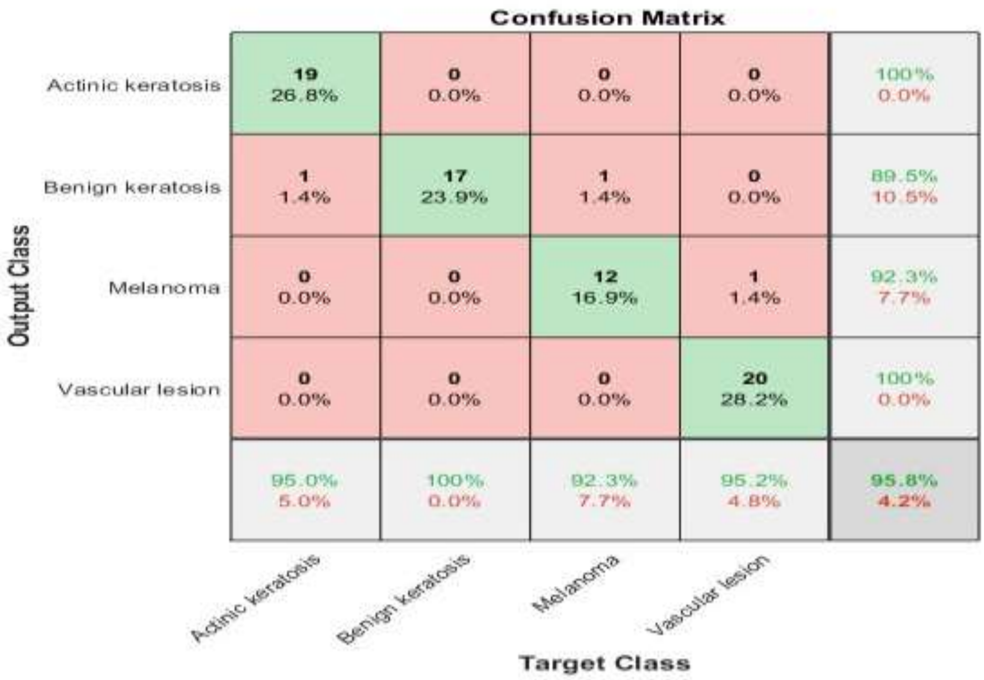

Figure 5: Confusion Matrix

The combined CNN system with its GUI provides an effective and understandable solution for automated skin disease diagnosis.

4. CONCLUSION

The research team developed a Convolutional Neural Network (CNN)-based system in MATLAB to automatically classify skin diseases through the analysis of dermoscopic images. The system featured a full preprocessing pipeline consisting of image normalization and augmentation as well as hair artifact removal to greatly improve input data quality. The development team trained and fine-tuned the CNN architecture through MATLAB's Deep Learning Toolbox to reach a classification accuracy of 95%. The model exhibited robustness and reliability across various skin disease categories as confirmed through evaluation metrics like precision, recall, F1-score, confusion matrix and AUC-ROC curves.

The user-friendly Graphical User Interface (GUI) added strength to the system through interactive image classification and capabilities for training progress visualization and performance plotting alongside real-time diagnostic feedback. The tool's GUI design guarantees practical application within clinical environments allowing clinicians to conduct rapid and uniform preliminary screenings for skin diseases. The system showed excellent generalization abilities along with powerful discriminative performance when differentiating between visually similar lesions.

The study achieved notable success but revealed several opportunities for future enhancement including broadening the dataset to encompass rare skin conditions and the integration of higher-resolution images alongside clinical metadata or patient histories to improve diagnostic context. Future studies should explore deploying this model on mobile and embedded devices to enable point-of-care applications. The novel CNN-based system represents a significant advancement for computer-aided dermatology which can aid healthcare professionals in diagnosing skin diseases accurately at early stages.

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Submission Notice

I ensure that the manuscript submitted to this journal has never been published before.

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