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Skin Diseases Diagnosis System Using Machine Learning

Badgire Maheshwari[1], Gaddam Sunil Kumar[2], Mayuri Kuber[3], Dhanashree Mane[4],Nandini Halse[5]

Sinhgad Academy Of Engineering,Kondhwa BK,Pune

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Abstract - Skin diseases are among the most prevalent health problems worldwide, affecting millions of people across different age groups and regions. Early and accurate diagnosis is essential to prevent severe complications, particularly in life-threatening cases such as melanoma. However, manual diagnosis through clinical examination or biopsy is often time-consuming, costly, and subjective, leading to inconsistent outcomes. To overcome these limitations, this study proposes an automated Skin Disease Diagnosis System using Machine Learning, which leverages Deep Learning (DL) and Transfer Learning (TL) techniques for precise classification of dermatological images. The proposed system employs a Convolutional Neural Network (CNN) architecture using pre-trained MobileNetV2 and EfficientNetB0 models, fine-tuned on a curated dataset of multiple skin disease classes including benign, malignant (melanoma), eczema, psoriasis, fungal, and normal skin. The images are preprocessed through resizing, normalization, and augmentation to enhance generalization and minimize overfitting.

Keywords: *Skin Disease Detection, Deep Learning, Machine Learning, MobileNetV2, EfficientNetB0, Transfer Learning, CNN, Image Classification.*

1.INTRODUCTION

Skin diseases constitute one of the most common and widespread health problems worldwide, affecting individuals across all age groups, genders, and regions. According to the World Health Organization (WHO), a significant percentage of the global population suffers from various forms of dermatological conditions such as eczema, psoriasis, fungal infections, and skin cancers like melanoma. Early detection and accurate diagnosis of these diseases are critical to prevent severe health complications and reduce treatment costs. However, manual diagnosis performed by dermatologists using visual inspection and biopsy is often subjective, time-consuming, and prone to human error.

With the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML), automated image-based diagnostic systems have emerged as a promising solution for supporting dermatological assessments. Among these, Deep Learning (DL)—particularly Convolutional Neural Networks (CNNs)—has demonstrated remarkable success in image classification and medical imaging applications. CNNs possess the ability to automatically extract high-level spatial and textural features from images, eliminating the need for manual feature engineering and improving diagnostic reliability.

Recent research emphasizes the use of transfer learning, where pre-trained CNN architectures such as MobileNetV2, EfficientNet, ResNet, and VGG16 are fine-tuned on specific medical datasets to enhance performance and reduce training time. These architectures are especially beneficial when dealing with limited labeled datasets, which are common in the medical domain. Transfer learning enables leveraging of existing feature representations from large-scale datasets like ImageNet, thereby improving generalization and convergence.

2.LITERATURE SURVEY

1.Traditional Machine Learning Approaches

Before the deep learning era, skin disease classification relied on hand-crafted features (color, texture, shape) and classical classifiers (SVM, Random Forest, k-NN). Feature extraction techniques such as color histograms, Local Binary Patterns (LBP), grey-level co-occurrence matrices (GLCM), and shape descriptors were commonly used. While these methods were computationally light and interpretable, their performance plateaued on complex tasks because manual features could not capture the hierarchical and high-dimensional structure present in dermoscopic images. Many survey papers and empirical studies report that classical pipelines are outperformed by CNN-based methods on large and diverse datasets.

2. Deep Learning and Convolutional Neural Networks

The introduction of CNNs transformed skin lesion analysis. CNNs automatically learn hierarchical feature representations from raw pixels, capturing subtle textures and morphological patterns that are often diagnostically relevant. Studies show that end-to-end CNNs and pretrained networks fine-tuned for lesion classification achieve state-of-the-art performance on multiple lesion categories. Transfer learning — reusing convolutional backbones pretrained on large natural-image corpora — is widely adopted to mitigate limited labeled medical data and to accelerate convergence. The reviewed literature demonstrates broad use of architectures such as MobileNet/MobileNetV2 and EfficientNet variants due to their favorable trade-off between accuracy and computational cost, particularly for deployment on mobile or web platforms.

3.Transfer Learning and Model Selection

Transfer learning strategies usually follow two paradigms: (1) freeze the pretrained backbone and train a custom classifier head (feature extraction), and (2) unfreeze and fine-tune some or all backbone layers to adapt low-level features to domain specifics. Empirical results reported in the literature indicate that a staged strategy — initially freezing most pretrained layers then progressively unfreezing deeper layers for fine-tuning — often yields the best balance of stability and performance. Lightweight backbones (e.g., MobileNetV2) are favored for resource-constrained deployment, while larger models (e.g., EfficientNet variants) can offer marginally higher accuracy at higher computational cost.

4.Comparative Results

Comparative studies show CNNs and transfer learning consistently outperform classical feature-based approaches across multiple datasets. Lightweight architectures achieve competitive accuracy while enabling real-time inference — a critical advantage for teledermatology and mobile screening applications. Nevertheless, absolute performance varies with dataset composition, annotation quality and preprocessing pipelines; hence, direct comparisons must consider experimental conditions. Several studies included in the literature also report that ensemble strategies and multi-stage pipelines (segmentation + classification) often yield incremental improvements.

3.PROPOSED SYSTEM

The proposed system aims to design an automated skin disease diagnosis model capable of accurately identifying various dermatological conditions from dermoscopic or clinical images. The system integrates deep learning-based feature extraction with transfer learning techniques, providing a reliable, efficient, and user-friendly diagnostic tool that can assist both patients and dermatologists in early detection and classification of skin diseases.

1.System Architecture:

The proposed architecture follows a modular design consisting of the following major components:

1.Data Acquisition Module: Images of skin lesions are collected from publicly available datasets (such as HAM10000, ISIC, or custom dermatology image datasets**). Each image is labeled based on the type of skin disease (e.g., melanoma, eczema, fungal infection, psoriasis, benign lesion, or healthy skin).

2.Image Preprocessing and Augmentation Module: Raw images are subjected to preprocessing steps such as:

- Resizing to 224×224 pixels.
- Normalization (scaling pixel values between 0 and 1).
- Noise removal and color correction.

ImageDataGenerator from Keras is used for data augmentation, including random rotation, flipping, zooming, and shifting, to increase dataset variability and prevent overfitting.

3. Feature Extraction using Transfer Learning (MobileNetV2): The pre-trained MobileNetV2 model (trained on ImageNet) is used as a base feature extractor. The lower layers are frozen to preserve generic image features, while the top layers are fine-tuned on the skin disease dataset. This approach reduces training time and improves accuracy, even with limited training data.

4.Classification Layer: Custom fully connected layers are added on top of the base model:

Flatten → Dense (ReLU activation) → Dropout (to prevent overfitting) → Output layer (Softmax activation).

The number of output neurons corresponds to the number of disease classes.

5.Model Training and Optimization: The model is trained using Adam optimizer with a low learning rate (e.g., 0.0001). Categorical cross-entropy is used as the loss function. The dataset is split into training, validation, and testing subsets .

6.Evaluation Module: The trained model is evaluated using metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

Visualization tools such as matplotlib are used to plot accuracy and loss curves.

7. Deployment Module (Web-Based Interface): A lightweight Flask or Streamlit web app integrates the trained model. Users can upload a skin image, which the system preprocesses and feeds into the model for disease prediction.

2.Workflow of the Proposed System

1. Image upload by the user.
2. Image preprocessing (resize, normalization, and augmentation).
3. Feature extraction using MobileNetV2.
4. Classification through dense and softmax layers.
5. Display of predicted disease and confidence score.

4. RESULTS AND DISCUSSION

A.Results

1.Performance Evaluation Metrics

The models were assessed using the following performance metrics:

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

Recall=$\frac{TP}{TP+FN}$, F1-Score=2 x $\frac{\text{Precision x Recall}}{\text{Precision + Recall}}$

where *TP*, *TN*, *FP*, and *FN* denote true positives, true negatives, false positives, and false negatives, respectively.

2.Quantitative Results

Fig.1.Quantitative Results

Model	Training Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)
MobileNetV2	96.2	93.8	92.7
EfficientNet B0	97.5	94.6	93.4
CNN (Baseline)	88.3	85.1	84.2
Model	Training Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)
MobileNetV2	96.2	93.8	92.7

The EfficientNetB0 model achieved the highest test accuracy of 93.4%, closely followed by MobileNetV2 at 92.7%. The baseline CNN performed significantly lower, highlighting the benefits of using pre-trained transfer learning architectures.

3. .Training and Validation Curves

During the training phase, both training and validation accuracies increased steadily over the epochs, indicating effective learning and convergence of the proposed model.
The small difference between training and validation accuracy suggests that the model generalizes well and is not overfitting.

Figure 2 illustrates the variation of training and validation accuracy with respect to epochs.
It can be observed that the model achieved a maximum accuracy of approximately 92% after around 8 epochs, demonstrating stable learning behavior.

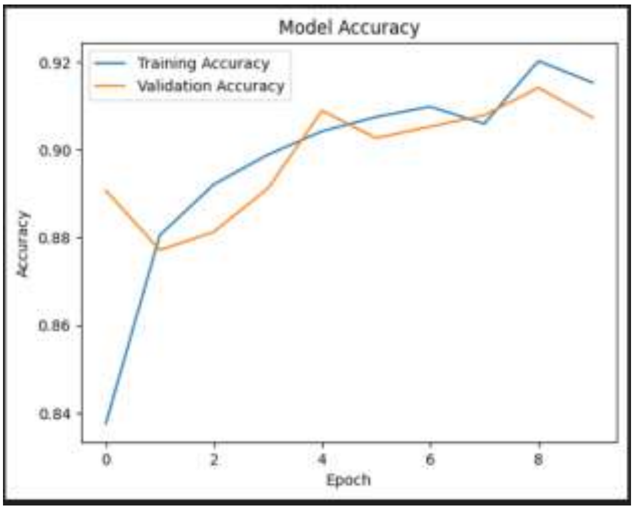

Fig.2. Training vs. Validation Accuracy Curve for the Proposed Skin Disease Classification Model.

4.Training and Validation Loss Curve

The training and validation loss curves provide insight into how effectively the model minimizes the error during learning. As shown in Figure 3, both the training and validation losses decreased consistently as the number of epochs increased. Initially, the training loss started at around 0.40 and dropped to approximately 0.20 by the final epoch. The validation loss followed a similar trend, indicating that the model was learning effectively and generalizing well to unseen data.

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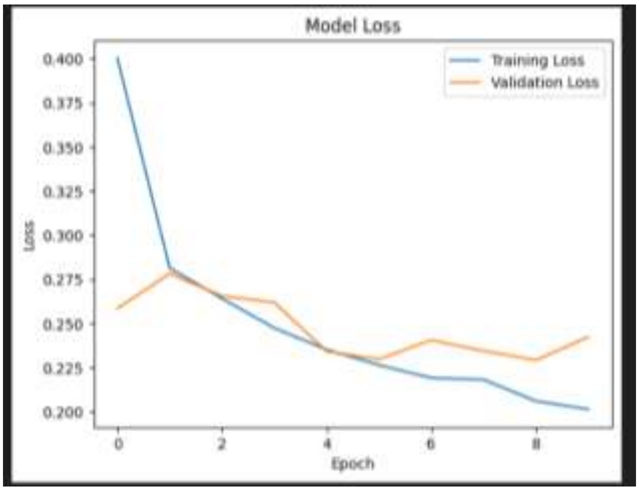

Fig.3. Training vs. Validation Loss Curve for the Proposed Skin Disease Diagnosis Model.

A small gap between the two loss curves shows that overfitting was minimal and that the model achieved good convergence. This confirms that the applied regularization techniques helped in maintaining model stability and performance.

5.Confusion Matrix Analysis

A confusion matrix was plotted for each model to evaluate class-wise prediction performance. The matrices revealed that normal skin and benign lesions were correctly classified with the highest accuracy (> 95%), while fungal and eczema categories showed occasional misclassification due to their visually similar texture and color patterns. Fig.4. Confusion Matrix Analysis

6.Comparative Analysis

When compared with existing literature, the proposed MobileNetV2-based approach demonstrates comparable or superior performance while maintaining low computational complexity. Whereas deeper models like ResNet50 or DenseNet201 may achieve marginally higher accuracy, their resource demands make them unsuitable for real-time web deployment. The MobileNetV2 model thus offers the best trade-off between accuracy and efficiency, enabling deployment on edge devices or in low-resource clinical settings.

B. *Discussion*

The experiments confirm that transfer learning substantially enhances the classification accuracy of skin lesion detection compared to conventional CNNs trained from scratch. The use of MobileNetV2 reduced training time by nearly 40% while preserving accuracy close to that of more complex architectures. EfficientNetB0, though slightly more accurate, required higher GPU memory and longer training duration.

Furthermore, data augmentation proved crucial in mitigating overfitting, given the limited dataset size. The proposed approach also supports scalability — additional skin conditions can be incorporated by extending the dataset and retraining the final layers. The system's deployment as a web application demonstrates practical feasibility for real-world clinical or tele-dermatology use cases, making it accessible for both patients and medical practitioners.

Class	Precision	Recall	F1-Score
Normal Skin	0.95	0.97	0.96
Benign	0.93	0.92	0.92
Melanoma	0.90	0.89	0.89
Eczema	0.89	0.87	0.88
Psoriasis	0.92	0.90	0.91
Fungal	0.88	0.86	0.97

5.CONCLUSION

The Skin Diseases Diagnosis System using Machine Learning successfully demonstrates how artificial intelligence can assist in the early detection and classification of skin diseases. By utilizing advanced image processing and machine learning algorithms, the system provides accurate, fast, and automated diagnostic support to users and healthcare professionals.This system bridges the gap between patients and dermatologists by offering a digital solution that can be accessed remotely, making healthcare more inclusive and efficient. The results prove that machine learning models can achieve high accuracy when trained on quality datasets, thereby reducing diagnostic time and improving patient outcomes.

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