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# Skin Cancer Multi-Class Classification Using Deep Convolutional Neural Networks and Transfer Learning

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**Abstract:** *Skin cancer is one of the most dangerous diseases due to its slow progression and high treatment cost when diagnosed at an advanced stage. Early detection is crucial for improving patient survival rates and reducing medical expenses. This study proposes an automated framework for multi-class skin cancer classification using deep convolutional neural networks (CNNs) and transfer learning. The HAM10000 dermoscopic image dataset is used for model development. Image preprocessing and data augmentation techniques are applied to address environmental variations and class imbalance. Several pre-trained deep learning models—ResNet-150, Xception, VGG-16, VGG-19, and Dense Net—are employed for feature extraction and classification. Furthermore, a weighted ensemble learning approach is introduced to improve overall model performance. The proposed system requires only a digital camera to capture skin images, making it a cost-effective diagnostic support tool. Performance is evaluated using accuracy, precision, recall, and F1-score. The weighted ensemble model achieves the highest recall of 0.93, outperforming individual models. The results demonstrate that ensemble-based transfer learning significantly enhances multi-class skin cancer detection.*

**Keywords:** Skin cancer, Deep learning, Transfer learning, Image processing, Convolutional neural network

## I. INTRODUCTION

Skin diseases can become life-threatening if not diagnosed at an early stage. Skin cancer not only affects physical health but also has a significant emotional and psychological impact on patients. It is among the leading causes of non-fatal disease burden worldwide. Factors such as poor dietary habits, environmental changes, genetic predisposition, stress, bacterial or fungal infections, and viral exposure contribute to the prevalence of skin diseases.

Many individuals hesitate to consult dermatologists in the early stages due to lack of awareness or social stigma. As symptoms often appear gradually, patients frequently misinterpret early signs as minor infections, leading to delayed diagnosis and increased treatment cost. Accurate diagnosis is challenging due to the visual similarity between different skin lesions, requiring extensive clinical experience and patient history.

Recent advancements in machine learning and computer vision have enabled automated skin cancer detection systems that assist dermatologists in early diagnosis. Deep learning, particularly convolutional neural networks (CNNs), has shown remarkable performance in medical image analysis. However, multi-class skin cancer classification requires large datasets and effective feature extraction techniques.

In this work, transfer learning and ensemble learning are employed to classify seven types of skin cancer using the HAM10000 dataset. The paper is organized as follows: Section II reviews related work, Section III explains the methodology and dataset, Section IV discusses implementation details, Section V presents experimental results, and Section VI concludes the study.

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## II. LITERATURE REVIEW

Numerous researchers have explored image processing and machine learning techniques for skin disease detection. Traditional approaches include segmentation, texture analysis, and feature extraction using methods such as GLCM and SVM classifiers. Bayesian models have also been applied to probabilistic skin disease classification, achieving accuracies of up to 93%.

With the rise of deep learning, CNN-based models such as Mobile Net, ResNet, VGG, and Dense Net have been widely adopted for skin lesion classification. Transfer learning enables the reuse of knowledge from large-scale datasets like ImageNet, improving accuracy and reducing training time. Ensemble learning techniques—such as bagging, boosting, and weighted averaging—further enhance classification performance by combining predictions from multiple models.

Generative Adversarial Networks (GANs) have been used for data augmentation to address class imbalance, improving model robustness. Several studies report accuracies exceeding 90% using deep ensemble frameworks for multi-class skin cancer classification. Despite these advances, distinguishing visually similar lesions remains a challenge, motivating the proposed ensemble-based transfer learning approach.

## III. METHODOLOGY

The proposed framework consists of image preprocessing, feature extraction using pre-trained CNNs, multi-class classification, and ensemble learning. The workflow is illustrated in Figure 1.

### 3.1 Preprocessing and Data Augmentation

Hair removal is performed using black-hat morphological filtering to enhance lesion visibility. Data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment are applied to address class imbalance and prevent overfitting.

### 3.2 Transfer Learning Models

The following pre-trained CNN models are used:

- ResNet-150: Residual network with 150 layers, addressing vanishing gradient issues.
- VGG-16 and VGG-19: Deep CNNs with 16 and 19 layers, respectively, using small 3×3 convolution filters.
- Inception-V3: Google-developed architecture with multi-scale convolution operations.
- DenseNet: Dense connectivity between layers for improved feature propagation. Each model is fine-tuned on the HAM10000 dataset.

### 3.3 Ensemble Learning

A weighted average ensemble method combines probability outputs from individual models:

Prediction=1MΣj=1MSjPrediction = \frac{1}{M} \sum_{j=1}^{M} S_jPrediction=M1 j=1ΣMSj

where SjS_jSj is the probability vector from model jjj, and MMM is the number of models.

## IV. DATASET DESCRIPTION

The HAM10000 dataset contains 10,015 dermoscopic images of seven skin lesion classes:

| Class | Images |
|---|---|
| NV | 6705 |
| MEL | 1113 |
| BKL | 1099 |
| BCC | 541 |
| AKIEC | 327 |
| DF | 115 |
| VASC | 142 |


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The dataset exhibits significant class imbalance, addressed through data augmentation and class weighting.

## V. IMPLEMENTATION DETAILS

The experiments were conducted on Google Colab using Keras with GPU acceleration (12 GB RAM). The optimal hyperparameters were:

- Learning rate: 0.001
- Batch size: 32
- Epochs: 30–40
- Dropout: 40%

ReLU activation was used in hidden layers, and Softmax was used for final classification.

## VI. EVALUATION METRICS

Performance was evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC

## VII. RESULTS AND DISCUSSION

The ensemble model achieved superior performance compared to individual models.

| **Model** | **Recall** | **Precision** |
|---|---|---|
| ResNet-150 | 0.83 | 0.71 |
| Xception | 0.84 | 0.83 |
| VGG-16 | 0.81 | 0.71 |
| VGG-19 | 0.83 | 0.76 |
| DenseNet | 0.91 | 0.80 |
| **Weighted Ensemble** | **0.93** | **0.88** |

The ensemble model achieved 92–93% accuracy, demonstrating improved discriminative capability as shown by ROC-AUC curves.

## VIII. CONCLUSION

This study presents an effective multi-class skin cancer classification system using deep CNNs and transfer learning. Data augmentation and ensemble learning significantly improve performance on the imbalanced HAM10000 dataset. The proposed framework achieves 93% accuracy, making it a reliable and cost-effective diagnostic support tool for dermatologists. Future work will focus on real-time mobile deployment and integration with clinical decision support systems.

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