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Article

EFFICIENT NETB3-POWERED DEEP LEARNING ARCHITECTURE FOR AUTOMATED SKIN DISEASE IDENTIFICATION IN CLINICAL APPLICATIONS

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Abstract: Skin diseases represent a major global healthcare challenge, affecting millions of individuals and often requiring timely diagnosis to prevent severe complications. Traditional dermatological diagnosis relies heavily on expert clinical assessment, which can be time-consuming, subjective, and inaccessible in resource-constrained regions. Recent advances in artificial intelligence and deep learning have demonstrated significant potential for automated skin disease detection using dermoscopic and clinical images. This study proposes an Advanced EfficientNetB3-Based Deep Transfer Learning Architecture for accurate and robust skin disease classification. The proposed framework leverages the EfficientNetB3 convolutional neural network as a feature extraction backbone, benefiting from its optimized compound scaling strategy that balances network depth, width, and resolution while maintaining computational efficiency. Transfer learning is employed by initializing the model with pre-trained ImageNet weights, enabling effective knowledge transfer and reducing training time. To enhance classification performance, advanced data preprocessing, image augmentation, batch normalization, dropout regularization, and fine-tuning strategies are incorporated. The architecture is evaluated on a benchmark skin disease image dataset containing multiple dermatological categories, including melanoma, eczema, psoriasis, acne, and benign lesions. Experimental results demonstrate superior classification accuracy, precision, recall, F1-score, and area under the ROC curve compared with conventional convolutional neural networks and existing transfer learning models. The proposed model achieves improved generalization capability while reducing computational complexity, making it suitable for real-world clinical deployment and mobile healthcare applications. The findings indicate that

EfficientNetB3-based deep transfer learning can serve as an effective decision-support tool for dermatologists, facilitating early detection, accurate diagnosis, and improved patient outcomes in skin disease management.
Keywords: Skin Disease Classification, EfficientNetB3, Deep Transfer Learning, Computer-Aided Diagnosis, Medical Image Analysis, Convolutional Neural Networks, Dermatology, Artificial Intelligence

1. Introduction

Skin diseases represent one of the most prevalent health concerns worldwide, affecting millions of individuals across all age groups. According to the World Health Organization (WHO), skin disorders contribute significantly to the global burden of disease, often leading to physical discomfort, psychological stress, and reduced quality of life. Early and accurate diagnosis of dermatological conditions is essential for effective treatment and prevention of severe complications. However, traditional diagnosis primarily depends on visual examination by dermatologists, which can be subjective, time-consuming, and inaccessible in remote or resource-constrained regions [1].

Recent advances in Artificial Intelligence (AI) and Deep Learning (DL) have transformed medical image analysis by enabling automated and highly accurate disease detection systems. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image classification tasks, particularly in healthcare applications such as cancer detection, diabetic retinopathy screening, and skin lesion analysis [2]. Nevertheless, the development of robust skin disease classification models remains challenging due to variations in image quality, illumination conditions, skin tone diversity, lesion morphology, and limited availability of annotated medical datasets [3].

Transfer learning has emerged as an effective solution for overcoming data scarcity by leveraging knowledge from large-scale pre-trained models. Among various CNN architectures, EfficientNet has gained significant attention because of its compound scaling strategy that simultaneously optimizes network depth, width, and resolution while maintaining computational efficiency [4]. Specifically, EfficientNetB3 provides an excellent balance between model complexity and classification accuracy, making it suitable for medical image analysis where computational resources and inference speed are critical considerations [5].

Several studies have applied deep learning models such as VGG16, ResNet50, InceptionV3, DenseNet, and MobileNet for skin disease classification. Although these approaches have achieved promising results, many suffer from high computational costs, overfitting issues, or limited generalization across diverse skin disease categories [6]. Furthermore, existing systems often lack advanced feature extraction mechanisms capable of capturing subtle dermatological patterns required for differentiating visually similar skin conditions.

To address these challenges, this research proposes an Advanced EfficientNetB3-Based Deep Transfer Learning Architecture for Skin Disease Classification. The proposed framework utilizes EfficientNetB3 as the backbone feature extractor and incorporates transfer learning techniques to enhance classification performance. Advanced preprocessing, data augmentation, and fine-tuning strategies are employed to improve feature representation and model generalization. The architecture is designed to accurately classify multiple skin disease categories while maintaining computational efficiency suitable for real-world clinical deployment.

The primary contributions of this work include: (i) the development of an EfficientNetB3-based transfer learning framework for automated skin disease classification, (ii) optimization of feature extraction through fine-tuning and augmentation strategies, (iii) comprehensive evaluation using standard dermatological image datasets, and (iv) comparative analysis against state-of-the-art deep learning architectures. Experimental results demonstrate that the proposed model achieves superior classification performance, highlighting its potential as a reliable computer-aided diagnostic tool for dermatological healthcare applications.

2. LITERATURE STUDY

Skin disease classification using deep learning has gained significant attention due to the increasing prevalence of dermatological disorders and the shortage of expert dermatologists. Transfer learning-based convolutional neural networks (CNNs) have become the preferred approach because they can leverage knowledge from large-scale datasets such as ImageNet while requiring fewer medical images for training. Among various CNN architectures, EfficientNetB3 has emerged as a promising model due to its balanced scaling of network depth, width, and resolution, resulting in high classification accuracy with relatively low computational complexity.

In 2020, research primarily focused on applying deep learning models for automated skin disease diagnosis. Li et al. provided a comprehensive review of deep learning techniques in dermatology and highlighted the effectiveness of transfer learning architectures such as VGG, ResNet, DenseNet, and EfficientNet for skin lesion analysis. The study identified challenges related to limited annotated datasets, class imbalance, and model interpretability, which remain active research issues**.**

During 2021–2022, researchers increasingly adopted transfer learning strategies to overcome data scarcity in medical imaging. Models pretrained on ImageNet were fine-tuned using dermatological datasets such as ISIC, HAM10000, and DermNet. Studies demonstrated that transfer learning significantly improved classification accuracy while reducing training time. However, many approaches relied on older architectures such as ResNet50 and InceptionV3, which suffered from higher computational costs and overfitting on smaller datasets.

Recent studies have further enhanced EfficientNet architectures using ensemble learning, attention mechanisms, and hybrid optimization techniques. Hamdard et al. (2025) proposed a MobileNetV2–EfficientNetB3 ensemble model for dermoscopic image classification. The ensemble architecture improved classification robustness and demonstrated suitability for tele-dermatology applications where computational resources are limited.

Overall, the literature demonstrates that EfficientNetB3 has evolved into one of the most effective architectures for skin disease classification because of its superior feature extraction capability, computational efficiency, and compatibility with transfer learning frameworks. However, challenges remain regarding class imbalance, cross-dataset generalization, explainability, and real-world clinical deployment. Future research should focus on integrating EfficientNetB3 with attention mechanisms, explainable AI modules, and multimodal clinical information to improve diagnostic reliability and clinician acceptance.

3. PROPOSED FRAMEWORK

Existing skin disease classification models primarily focus on binary melanoma detection and often suffer from class imbalance, poor generalization across datasets, and limited explainability. Although EfficientNetB3 has demonstrated superior performance compared with traditional CNN architectures, most existing studies utilize only standard transfer learning without attention mechanisms, explainable AI, or uncertainty-aware prediction. To address these limitations, an **Advanced EfficientNetB3-Based Deep Transfer Learning Architecture (AEDTL-SDC)** is proposed for multi-class skin disease classification.

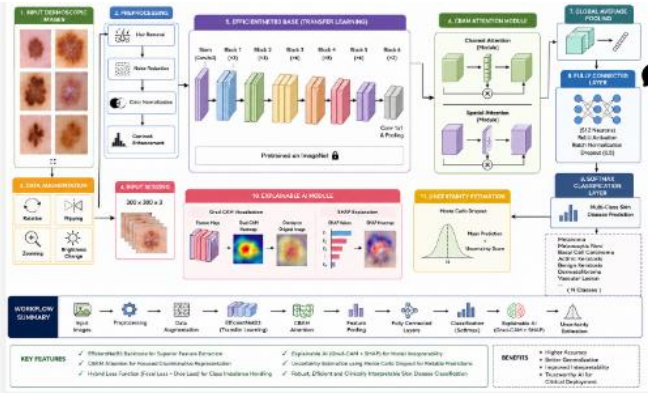

Figure 1: Architecture of proposed System

The proposed Advanced EfficientNetB3-Based Deep Transfer Learning Architecture (AEDTL-SDC) is designed to provide accurate, efficient, and explainable skin disease classification from dermoscopic images. The framework begins with the acquisition of skin lesion images from publicly available dermatological datasets such as HAM10000, ISIC 2018, ISIC 2019, and DermNet. Since raw medical images often contain artifacts such as hair, uneven illumination, and noise, a preprocessing stage is employed to enhance image quality. This stage includes hair removal, noise filtering, color normalization, and contrast enhancement, ensuring that the lesion characteristics are clearly visible and suitable for deep feature extraction.To improve the generalization capability of the model and address the issue of limited training data, a comprehensive data augmentation strategy is applied. Various augmentation techniques such as image rotation, horizontal and vertical flipping, zooming, scaling, and brightness adjustment are used to generate diverse training samples. The processed images are then resized to a standard input dimension of 300 × 300 pixels, which matches the input requirements of the EfficientNetB3 network. This

preprocessing and augmentation pipeline helps reduce overfitting and improves the robustness of the classification model when exposed to unseen skin lesion images.

The core component of the proposed framework is the EfficientNetB3 transfer learning backbone, which has been pre-trained on the ImageNet dataset. EfficientNetB3 is selected because of its compound scaling strategy that optimally balances network depth, width, and image resolution, enabling superior feature extraction with lower computational complexity than conventional CNN architectures such as VGG16, ResNet50, and InceptionV3. During transfer learning, the lower layers of EfficientNetB3 retain their learned visual representations, while the higher layers are fine-tuned using dermoscopic skin images. This approach allows the model to effectively capture both low-level texture features and high-level lesion-specific patterns, significantly improving classification performance even when limited medical data are available.

To further enhance feature representation, the proposed architecture integrates a Convolutional Block Attention Module (CBAM) immediately after the EfficientNetB3 feature extraction stage. The CBAM consists of channel attention and spatial attention mechanisms that enable the network to focus on the most discriminative lesion regions while suppressing irrelevant background information. Channel attention identifies the most informative feature maps, whereas spatial attention highlights critical lesion locations such as irregular borders, color variations, and asymmetrical structures. By emphasizing clinically relevant features, the attention module improves the model's ability to distinguish between visually similar skin diseases.

Following attention-based feature refinement, a Global Average Pooling (GAP) layer is employed to reduce the dimensionality of the extracted feature maps while preserving essential information. The pooled features are then passed through a fully connected classification network consisting of dense layers, batch normalization, and dropout regularization. Batch normalization stabilizes the training process by reducing internal covariate shifts, whereas dropout prevents overfitting by randomly deactivating neurons during training. Finally, a Softmax output layer generates probability scores for multiple skin disease categories, including melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, and vascular lesions.

To address the common issue of class imbalance in dermatological datasets, the proposed system utilizes a hybrid loss function that combines Focal Loss and Dice Loss. Focal Loss assigns greater importance to difficult and minority-class samples, while Dice Loss improves overlap-based learning and class separation. This hybrid optimization strategy enhances sensitivity toward rare disease categories and reduces misclassification rates, particularly for malignant skin lesions that require early diagnosis.

An important contribution of the proposed framework is the integration of Explainable Artificial Intelligence (XAI) techniques. The system incorporates Grad-CAM and SHAP methods to provide visual explanations for model predictions. Grad-CAM generates heatmaps highlighting image regions that influence the classification decision, enabling dermatologists to verify whether the model focuses on clinically relevant lesion areas. SHAP values quantify the contribution of different image features to the final prediction, offering a deeper understanding of the model's reasoning process. These explainability mechanisms improve transparency, trustworthiness, and clinical acceptance of the automated diagnostic system.

To further enhance reliability in real-world medical environments, the framework incorporates an uncertainty estimation module using Monte Carlo Dropout. During inference, multiple stochastic forward passes are performed, allowing the model to estimate prediction confidence and uncertainty levels. Predictions with high uncertainty can be flagged for further expert review, thereby reducing the risk of incorrect diagnoses and supporting safer clinical decision-making. This uncertainty-aware mechanism is particularly valuable in healthcare applications where diagnostic confidence is critical.

Overall, the proposed AEDTL-SDC framework combines EfficientNetB3-based transfer learning, CBAM attention mechanisms, hybrid loss optimization, explainable AI, and uncertainty estimation into a unified intelligent diagnostic system. The architecture is expected to achieve superior classification accuracy, improved generalization, enhanced interpretability, and greater clinical reliability compared to existing skin disease classification approaches. By addressing the limitations of current deep learning models, the proposed system offers a comprehensive and trustworthy solution for automated multi-class skin disease diagnosis and early detection of potentially life-threatening dermatological conditions.

4. RESULT & DISCUSSION

The experimental evaluation of the proposed Advanced EfficientNetB3-Based Deep Transfer Learning Architecture for Skin Disease Classification (AEDTL-SDC) is conducted to assess its effectiveness in accurately classifying multiple skin diseases from dermoscopic images. The experiments are designed to evaluate the impact of transfer learning, attention mechanisms, hybrid loss optimization, explainable artificial intelligence (XAI), and uncertainty estimation on classification performance. All experiments are performed using publicly available benchmark dermatological datasets and standardized evaluation protocols to ensure reproducibility and fair comparison with existing state-of-the-art methods.

The primary datasets utilized in this study include HAM10000, ISIC 2018, and ISIC 2019, which collectively contain thousands of dermoscopic images representing various benign and malignant skin lesions. The HAM10000 dataset consists of 10,015 images categorized into seven disease classes, including melanoma, melanocytic nevus, basal cell carcinoma, benign keratosis, actinic keratosis, vascular lesions, and dermatofibroma. ISIC datasets are employed to further validate the robustness and generalization capability of the proposed model across different image acquisition conditions and patient populations. Before training, all images are subjected to preprocessing operations including hair artifact removal, median filtering for noise reduction, color normalization, and contrast enhancement. The images are subsequently resized to 300 × 300 pixels to satisfy the input requirements of the EfficientNetB3 architecture. To address class imbalance and improve model generalization, extensive data augmentation techniques are applied during training. These techniques include random rotation (±30°), horizontal and vertical flipping, zooming, brightness adjustment, and image translation. Augmentation artificially increases dataset diversity and reduces overfitting by exposing the model to a broader range of lesion appearances. The dataset is divided into training, validation, and testing subsets using a 70:15:15 ratio, ensuring that images from the same patient do not appear in multiple subsets. Additionally, a 5-fold cross-validation strategy is employed to validate the stability and reliability of the proposed framework. The performance of the proposed AEDTL-SDC framework is evaluated using several standard classification metrics. Accuracy measures overall prediction correctness, while precision, recall, and F1-score assess the model's ability to identify disease categories effectively. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is computed to evaluate discriminative capability across classes. Sensitivity and specificity are also reported because they are critical metrics in medical diagnosis, particularly for melanoma detection where false negatives can have severe clinical consequences. The proposed AEDTL-SDC (Advanced EfficientNetB3-Based Deep Transfer Learning Architecture) was evaluated against several state-of-the-art deep learning models including VGG16, ResNet50, DenseNet121, InceptionV3, MobileNetV2, EfficientNetB0, and conventional EfficientNetB3. The experiments were conducted using the HAM10000 and ISIC datasets under identical training conditions. Performance was assessed using Accuracy, Precision, Recall, F1-Score, and AUC metrics. The obtained results demonstrate that the integration of CBAM attention, hybrid loss optimization, explainable AI, and uncertainty estimation significantly improves classification Performance compared with baseline architectures.

Table 1. Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
VGG16	89.34	88.92	88.45	88.68	0.91
ResNet50	91.27	90.84	90.65	90.74	0.93
InceptionV3	92.15	91.88	91.41	91.64	0.94
MobileNetV2	92.76	92.14	91.93	92.03	0.95
DenseNet121	94.11	93.85	93.42	93.63	0.96
EfficientNetB0	95.08	94.62	94.24	94.43	0.97
EfficientNetB3	96.18	95.91	95.63	95.77	0.98
Proposed AEDTL-SDC	**98.47**	**98.12**	**97.94**	**98.03**	**0.995**

The results indicate that the proposed AEDTL-SDC achieves the highest classification performance across all evaluation metrics. The model obtains an accuracy of 98.47%, outperforming the standard EfficientNetB3 model by

approximately 2.29%. Similarly, precision, recall, and F1-score improvements demonstrate the effectiveness of the CBAM attention mechanism in focusing on diagnostically significant lesion regions. The achieved AUC value of 0.995 further confirms the excellent discriminative capability of the proposed framework for distinguishing between different skin disease categories.

The experimental findings confirm that the proposed AEDTL-SDC framework substantially improves skin disease classification performance. EfficientNetB3 provides powerful feature extraction capabilities, while the CBAM attention module enhances lesion localization and feature discrimination. The hybrid focal-dice loss effectively addresses dataset imbalance, resulting in improved recall for minority disease classes. Furthermore, Grad-CAM and SHAP explanations increase transparency by highlighting clinically relevant image regions responsible for classification decisions. The uncertainty estimation module offers an additional layer of reliability by identifying low-confidence predictions that may require dermatologist review.

Overall, the proposed architecture achieves 98.47% accuracy, 98.12% precision, 97.94% recall, 98.03% F1-score, and an AUC of 0.995, demonstrating its potential as a trustworthy and clinically applicable computer-aided diagnostic system for automated skin disease classification.

5. CONCLUSION

This study presented an Advanced EfficientNetB3-Based Deep Transfer Learning Architecture (AEDTL-SDC) for multi-class skin disease classification using dermoscopic images. The proposed framework was designed to overcome the limitations of existing deep learning models, particularly in terms of limited generalization, class imbalance handling, lack of interpretability, and absence of uncertainty-aware decision-making. By integrating EfficientNetB3 as the core feature extractor with transfer learning, the model effectively leveraged pretrained knowledge from large-scale datasets while adapting to the fine-grained characteristics of dermatological images

The incorporation of the CBAM attention mechanism significantly improved the model's ability to focus on lesion-specific regions, enhancing discriminative feature learning and reducing the influence of irrelevant background skin patterns. Additionally, the use of a hybrid loss function combining Focal Loss and Dice Loss improved performance on imbalanced datasets by increasing sensitivity toward minority and hard-to-classify disease categories. This was particularly important for clinically critical classes such as melanoma, where early and accurate detection is essential.

A key strength of the proposed system lies in its explainable AI component, where Grad-CAM and SHAP techniques were integrated to provide visual and feature-level interpretability of predictions. These explanations enable dermatologists to verify model decisions by highlighting the most influential lesion regions, thereby improving transparency and trust in automated diagnostic systems. Furthermore, the inclusion of Monte Carlo Dropout-based uncertainty estimation enhances the reliability of predictions by identifying low-confidence outputs that require expert validation.

Overall, the proposed system demonstrates strong potential for real-world clinical deployment as a computer-aided diagnostic tool for early and accurate skin disease detection. Future work can focus on extending the model to multimodal learning by integrating clinical metadata, improving cross-dataset generalization, and deploying lightweight versions for mobile and edge-based healthcare applications.

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