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Multi-class skin disease classification using transfer learning architectures

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Abstract: Dermatological conditions are among the most common health problems worldwide, where delayed identification may increase disease severity and complicate treatment procedures. However, restricted access to dermatological expertise and insufficient public awareness often contribute to delayed diagnosis. This study proposes a multi-class skin disease classification approach using deep learning and transfer learning architectures based on digital skin images. The dataset, obtained from the *babaruzair/kaggle-skin-disease* repository, consists of 1,157 images categorized into eight skin disease classes. Image preprocessing techniques, including resizing, normalization, and data augmentation, were applied to improve data quality and model generalization. Three models were evaluated in this study, namely a baseline Convolutional Neural Network (CNN), MobileNetV2, and EfficientNetB0. Both transfer learning models utilized ImageNet pre-trained weights, followed by customized classification layers and fine-tuning of selected upper layers. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results show that the baseline CNN achieved an accuracy of 52.36%, while MobileNetV2 and EfficientNetB0 achieved accuracies of 88.84% and 95.28%, respectively. The findings demonstrate that transfer learning architectures significantly outperform conventional CNN models for limited medical image datasets, with EfficientNetB0 providing the best classification performance. These results indicate the potential of deep learning-based approaches to support early skin disease diagnosis and assist clinical decision-making.

Keywords: Skin diseases, CNN, MobileNetV2, EfficientNetB0

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Introduction

Dermatological disorders remain one of the most frequently encountered health problems worldwide, impacting approximately 1.8 billion individuals worldwide. According to the World Health Organization (WHO) in 2023, infections attributable to bacteria, fungi, and viruses constitute primary causes of morbidity in numerous countries [1]. In Indonesia, skin diseases remain among the most common public health problems and frequently require long-term medical treatment [2].

A common issue is the limited public understanding of skin health, causing skin diseases to often be diagnosed and treated only at advanced stages. This reliance on dermatologists, who are often limited in availability, especially in certain regions, leads to long waiting times for consultations and delayed diagnosis [3].

As digital technologies advance, artificial intelligence approaches in medical image analysis, particularly for medical image classification, offer promising opportunities for faster and more efficient diagnosis. Skin diseases exhibit visual characteristics that can be identified through digital images, making them suitable for analysis using image-processing approaches. Compared to other medical imaging methods such as histology, Magnetic Resonance Imaging (MRI), and Computer Tomography (CT), skin imaging is generally more accessible and cost-effective to obtain [4].

Convolutional Neural Networks (CNNs) have become dominant architectures for automated image analysis tasks in image processing because of their capability to learn hierarchical visual representations directly from image data without manual intervention [5]. However, the performance of CNN models is highly influenced by the quantity and quality of training data. In practical applications, skin disease datasets are often limited and moderately imbalanced, which may negatively affect model generalization performance [6].

To address these challenges, transfer learning has emerged as an effective approach for medical image classification, particularly when dealing with limited datasets [7]. MobileNetV2 has been widely utilized in image classification tasks due to its lightweight architecture, computational efficiency, and competitive performance in transfer learning applications [8]. In addition, The EfficientNetB0 architecture has demonstrated superior classification capability through compound scaling strategies that optimize network depth, width, and image resolution simultaneously, enabling more effective feature extraction while maintaining parameter efficiency [8]. Several representative studies on deep learning-based skin disease classification are summarized in Table 1.

Therefore, this study presents a comparative analysis of three deep learning architectures, namely a baseline Convolutional Neural Network (CNN), MobileNetV2, and EfficientNetB0, for multi-class skin disease classification. Unlike previous studies that mainly focused on a single transfer learning architecture or specific skin lesion datasets, this study provides a comprehensive comparison between conventional CNN and two transfer learning models under identical preprocessing, training, and evaluation settings. Furthermore, customized classification layers, dropout regularization, and fine-tuning strategies are incorporated to improve feature adaptation for relatively limited and moderately imbalanced skin disease datasets. The scientific contributions of this study are threefold. First, it provides a fair comparative evaluation of conventional CNN, MobileNetV2, and EfficientNetB0 under identical experimental settings. Second, it demonstrates the effectiveness of transfer learning for multiclass skin disease classification using a relatively limited and moderately imbalanced dataset. Third, it provides benchmark results that can serve as a reference for future research on automated dermatological diagnosis.

Table 1. Comparison of previous studies on deep learning-based skin disease classification

Authors	Dataset	Model	Main Findings
Virupakshappa et al.	DermNet, PH2, HAM10000, ISIC	Enhanced MobileNetV2	Proposed an enhanced MobileNetV2 integrated with attention mechanisms and multi-scale feature extraction, demonstrating high performance across multiple public skin disease datasets.
Taşar	HAM10000	MobileNet, DenseNet121, ResNet50, VGG16, Xception	Compared several transfer learning architectures for multiclass skin lesion classification and showed that transfer learning models consistently outperformed conventional CNN models.
Harahap and Zulkifli	HAM10000	InceptionResNetV2	Developed a transfer learning-based skin lesion classification system and demonstrated that pretrained models can effectively improve multiclass skin lesion classification.
Dhuhita et al.	HAM10000	MobileNetV2	Demonstrated that MobileNetV2 can be applied for multiclass skin cancer classification using transfer learning, although further improvements are needed to enhance performance.

As presented in Table 1, previous studies have demonstrated that transfer learning architectures achieve promising performance in skin disease classification. Nevertheless, most studies focused on evaluating a single transfer learning architecture or specific skin lesion datasets such as HAM10000, ISIC, PH2, and DermNet. Comprehensive comparisons between conventional CNN and multiple transfer learning architectures under identical preprocessing, training, and evaluation settings for multiclass skin disease classification remain limited. Therefore, a comparative evaluation is still required to better understand the effectiveness of different deep learning architectures for this task.

Methodology

This research was carried out in several phases, carefully structured to achieve its aims. It began with data collection and ended with evaluating the classification model's performance, as shown in Figure 1.

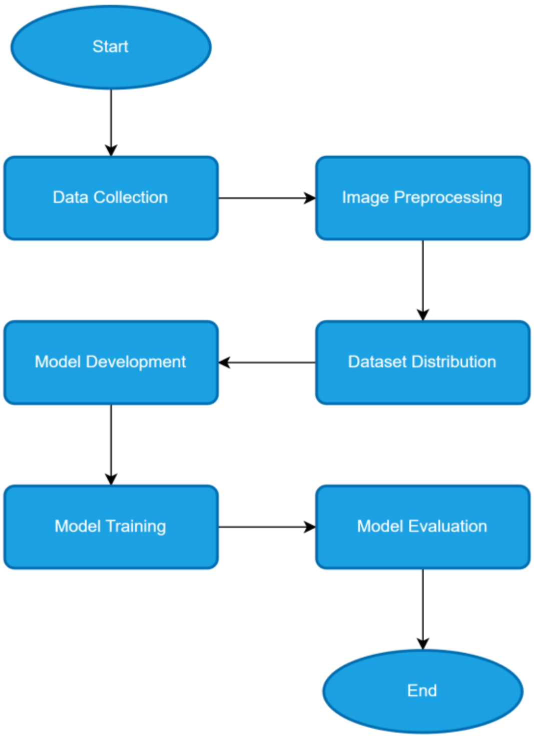


Figure 1. Research procedure

Data Collection

This study utilizes a publicly accessible dataset from Kaggle, titled 'kaggle-skin-disease.' This dataset comprises 1,157 images depicting various skin conditions, categorized into eight disease groups (Cellulitis, Impetigo, Athlete's Foot, Nail Fungus, Ringworm, Cutaneous Larva Migrans, Chickenpox, and Shingles). The distribution of images across each category in this study is outlined in Table 2.

Table 2. Distribution of skin disease images per class

No	Disease Category	Number of Images
1	Cellulitis	168
2	Impetigo	100
3	Athlete’s Foot	156
4	Nail Fungus	162
5	Ringworm	113
6	Cutaneous Larva Migrans	125
7	Chickenpox	170
8	Shingles	163
	Total	1,157

Figure 2 shows examples of images in each class to provide a visual representation of the data used.

Figure 2. Image dataset sample

Image Preprocessing

Prior to model training, all skin disease images underwent preprocessing procedures to ensure consistent input representation and improve data quality. In this stage, all images were transformed into a uniform spatial resolution of 224×224 pixels to match the standard input dimensions required by the transfer learning architectures used in this study, namely MobileNetV2 and EfficientNetB0. In addition, pixel intensity values were normalized into a numerical range between 0 and 1 to support more stable optimization during the learning process [9].

Considering the relatively limited dataset size, data augmentation techniques were employed to increase data variability and improve the model's generalization capability [10]. Several augmentation techniques, including rotation, horizontal flipping, zooming, and width and height shifting, were applied to generate more diverse training samples. This approach was intended to reduce overfitting risk and enable the models to learn more robust image features from various skin disease patterns. Figure 3 illustrates an example of the image preprocessing and augmentation results applied in this study.

Figure 3. Image preprocessing results on one image

Model Development

In this study, three deep learning architectures were employed for multi-class skin disease classification, namely a baseline Convolutional Neural Network (CNN), MobileNetV2, and EfficientNetB0. The baseline CNN was utilized as a conventional deep learning benchmark without transfer learning, while MobileNetV2 and EfficientNetB0 were implemented using transfer learning approaches with ImageNet pre-trained weights. These architectures were selected to evaluate the effectiveness of transfer learning techniques on relatively limited and moderately imbalanced skin disease datasets. Both MobileNetV2 and EfficientNetB0 utilized ImageNet pre-trained weights, enabling the models to extract representative visual features such as textures, edges, and lesion patterns from skin disease images [11].

In the initial stage of model development, the base layers of the transfer learning architectures were frozen to preserve previously learned low-level visual features and prevent excessive modification of pre-trained weights during early training. This strategy was also intended to reduce overfitting risk considering the relatively limited dataset used in this study [12]. Subsequently, customized classification layers were added on top of the pre-trained base models to adapt the architectures for multi-class skin disease classification tasks, consisting of:

1. Input Layer
   RGB images with dimensions of 224×224 pixels were provided as input to the transfer learning architectures.
2. Base Model
   The pre-trained base models were initially frozen during the early training phase to preserve previously learned low-level visual features and reduce excessive modification of pre-trained weights.
3. Global Average Pooling 2D
   A Global Average Pooling layer was applied to reduce feature dimensionality before classification.
4. Dropout (0.5)
   Dropout regularization with a rate of 0.5 was introduced to reduce excessive neuron dependency during training.
5. Dense Layer (128)
   A fully connected dense layer with 128 neurons and ReLU activation was utilized to learn discriminative feature representations.
6. Dropout (0.3)
   A second dropout layer with a rate of 0.3 was added before the output layer to further improve regularization performance.
7. Output Layer
   The final classification layer employed Softmax activation to generate probability distributions across all skin disease categories.

After the initial feature extraction stage, selected upper layers of the pre-trained architectures were unfrozen and fine-tuned using a lower learning rate.

Model Training

Model optimization was performed using the Adam optimizer with an initial learning rate of 0.001 to support stable parameter updates during the training process. Preprocessing and augmentation procedures were exclusively applied to the training subset to improve model robustness and generalization capability while preventing data leakage. The validation subset was used to evaluate learning performance throughout the training stage, as presented in Table 3. Training was conducted using mini-batches consisting of 32 images, meaning that model weight updates were performed after processing every 32 images. In addition, Adaptive training callbacks, including EarlyStopping and ReduceLROnPlateau, were incorporated to reduce overfitting risk and improve training stability.

For the transfer learning architectures, the training procedure was conducted in two phases. Transfer learning optimization was performed in two sequential stages. Initially, the pre-trained backbone networks remained frozen while only the newly added classification layers were updated. Subsequently, selected upper layers of the pre-trained architectures were unfrozen and fine-tuned using a lower learning rate of 0.0001 to improve adaptation toward dermatological image characteristics while retaining previously learned low-level visual representations [13].

Table 3. Division of train data, validation data, test data

No	Disease Category	Train (68.1%)	Validation (11.8%)	Test (20.1%)	Number of Images
1	Cellulitis	115	20	33	168
2	Impetigo	68	12	20	100
3	Athlete's Foot	105	19	32	156
4	Nail Fungus	110	19	33	162
5	Ringworm	77	13	23	113
6	Cutaneous Larva Migrans	85	15	25	125
7	Chickenpox	116	20	34	170
8	Shingles	111	19	33	163
	Total	788	136	233	1,157

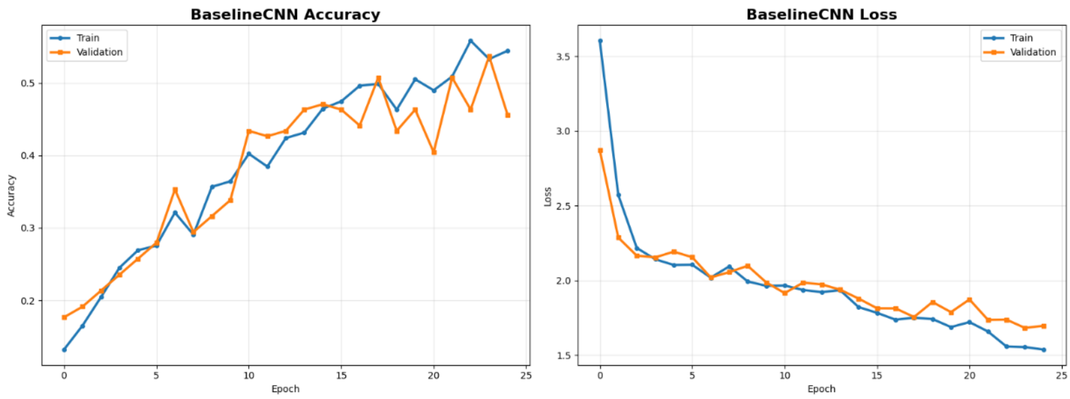
The dataset was divided into training, validation, and testing subsets with proportions of 68.1%, 11.8%, and 20.1%, respectively. Although these proportions differ slightly from commonly used split configurations such as 70:15:15 or 80:10:10, the distribution strategy was intentionally designed using a stratified approach to preserve class representation across all subsets [14]. Considering that the dataset used in this study was relatively limited and moderately imbalanced, maintaining proportional representation for each skin disease category was considered more important than strictly following conventional split ratios. In addition, allocating approximately 20% of the dataset for testing provided a sufficiently representative evaluation of the model's generalization performance on previously unseen data. This strategy was expected to reduce sampling bias and provide a more reliable and balanced assessment of classification performance across all skin disease categories [15].

Evaluation

Model evaluation was conducted using test data that had been separated from the training and validation datasets. The performance of each proposed architecture was evaluated using several classification metrics, including accuracy, precision, recall, and F1-score. In addition, confusion matrix analysis and classification reports were utilized to examine classification performance across each skin disease category. The evaluation results from the baseline CNN, MobileNetV2, and EfficientNetB0 models were further compared to analyze the effectiveness of transfer learning approaches for multi-class skin disease classification.

Results and Discussions

Results



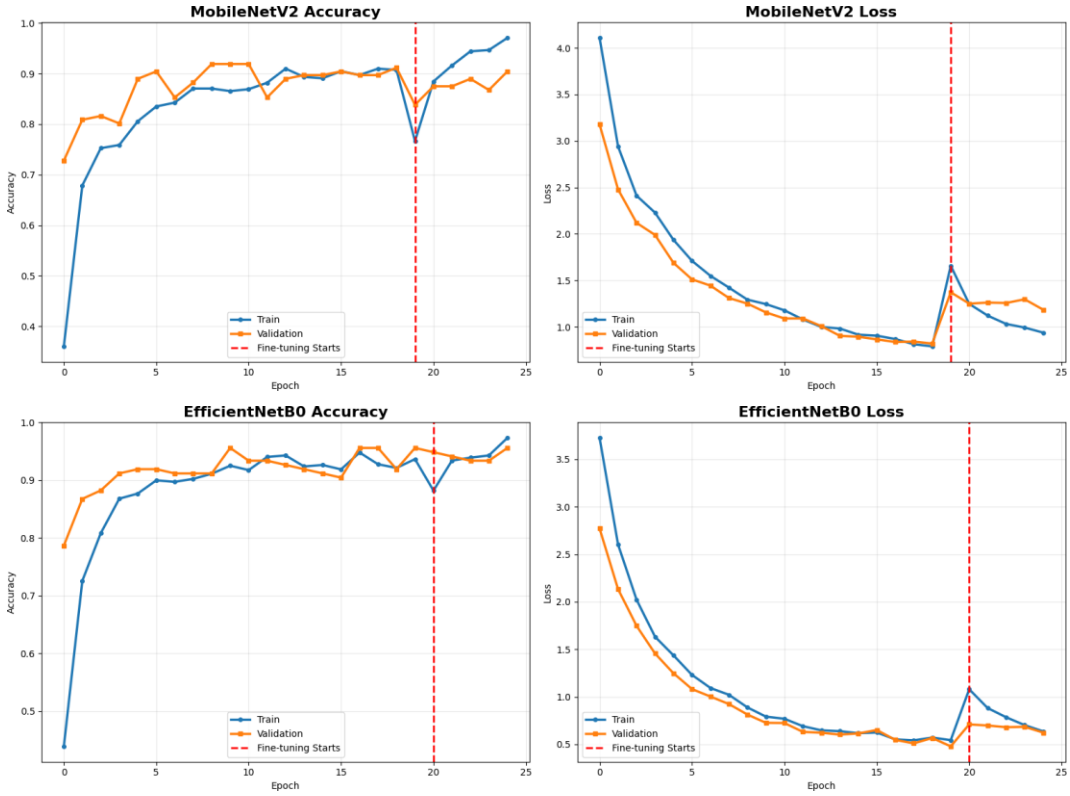


Figure 4. Model training result graph

Figure 4 illustrates the training and validation performance of the Baseline CNN, MobileNetV2, and EfficientNetB0 models during the learning process. The training and validation accuracy values showed a consistent increase during the early epochs before stabilizing in the later training stages. At the same time, both training and validation loss values gradually decreased, indicating that the model was able to effectively learn discriminative features from skin disease images. The relatively small gap between training and validation performance suggests that the implemented regularization techniques, data augmentation, and fine-tuning strategy contributed to reducing overfitting risk and improving model generalization capability. Furthermore, the stable convergence pattern indicates that EfficientNetB0 was able to extract representative image features efficiently, which may be attributed to its compound scaling strategy that balances network depth, width, and input resolution.

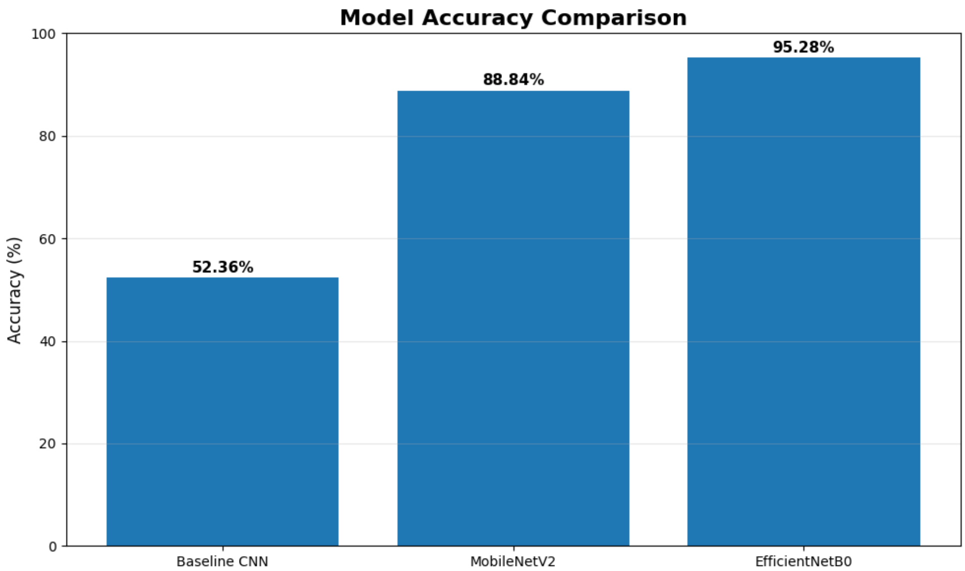


Figure 5. Model accuracy comparison

Figure 5 presents the comparison results of the proposed deep learning architectures for multi-class skin disease classification. The baseline CNN achieved an accuracy of 52.36%, while MobileNetV2 and EfficientNetB0 obtained accuracies of 88.84% and 95.28%, respectively. These results demonstrate that transfer learning architectures significantly outperformed the conventional CNN model on the limited skin disease dataset used in this study.

The relatively low performance of the baseline CNN indicates that conventional convolutional architectures without transfer learning experience difficulties in extracting robust discriminative features from limited and moderately imbalanced medical image datasets. In contrast, MobileNetV2 and EfficientNetB0 benefited from ImageNet pre-trained weights, enabling the models to utilize previously learned visual representations such as textures, shapes, and image patterns.

Among all evaluated architectures, EfficientNetB0 achieved the highest classification performance. This superior performance may be attributed to the compound scaling strategy employed by EfficientNetB0, which optimizes network depth, width, and image resolution simultaneously, allowing the model to extract more representative features from skin disease images. Although MobileNetV2 produced slightly lower accuracy compared to EfficientNetB0, it still demonstrated competitive performance while maintaining a relatively lightweight architecture suitable for resource-constrained applications.

The VI-chickenpox class achieved the highest performance with an F1 score of 90%, while FU-ringworm and VI-shingles scored 83%. This performance may still be considered reasonable considering the limited and moderately imbalanced dataset used in this study.

Table 4. Per-class F1-score comparison of Baseline CNN, MobileNetV2, and EfficientNetB0 models

Disease Category	**Baseline CNN**	**MobileNetV2**	**EfficientNetB0**
Cellulitis	0.68	0.95	0.94
Impetigo	0.41	0.90	0.98
Athlete’s Foot	0.60	0.90	0.98
Nail Fungus	0.52	0.95	1.00
Ringworm	0.38	0.82	0.88
Cutaneous Larva Migrans	0.44	0.76	0.93
Chickenpox	0.78	0.94	0.97
Shingles	0.12	0.88	0.93
Macro Avg	0.49	0.89	0.95
Weighted Avg	0.53	0.89	0.95

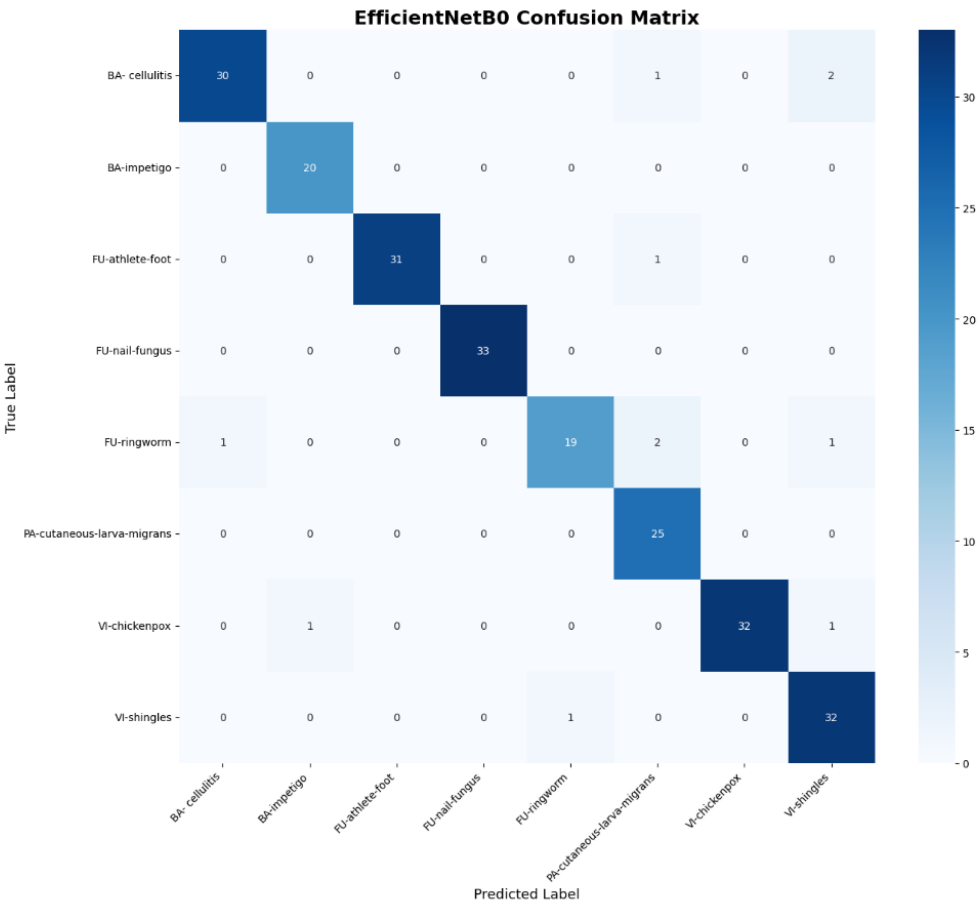


Figure 6. Confusion matrix

Table 4 presents the per-class F1-score comparison of the Baseline CNN, MobileNetV2, and EfficientNetB0 models, while Figure 6 illustrates the confusion matrix obtained from the EfficientNetB0 model. Based on the evaluation results, EfficientNetB0 achieved the highest classification performance across most skin disease categories, with weighted average precision, recall, and F1-score values of 0.96, 0.95, and 0.95, respectively. In contrast, the baseline CNN demonstrated substantially lower performance, particularly for visually similar disease categories, indicating limitations in extracting robust discriminative features from the relatively limited dataset. Meanwhile, MobileNetV2 showed considerable performance improvement compared to the baseline CNN, demonstrating the effectiveness of transfer learning approaches for skin disease classification.

The confusion matrix demonstrates that most predictions were concentrated along the diagonal region, indicating that the majority of skin disease images were classified correctly. Several classes, such as FU-nail-fungus, VI-chickenpox, and VI-shingles, achieved particularly high classification performance with minimal misclassification. These results indicate that the transfer learning approach combined with fine-tuning and customized classification layers was effective in extracting representative visual features from skin disease images.

Nevertheless, a small number of misclassifications were still observed between visually similar disease categories. This issue may have occurred due to similarities in skin texture, lesion shape, or color patterns among certain classes. In addition, although EfficientNetB0 achieved high classification accuracy, the relatively limited dataset size may still introduce potential overfitting and dataset bias. Therefore, further evaluation using larger and more diverse clinical datasets is necessary to validate the robustness and generalization capability of the proposed models in real-world applications.

Discussions

The experimental results demonstrate that transfer learning architectures significantly improved skin disease classification performance compared to the conventional baseline CNN model. The baseline CNN achieved relatively low accuracy due to its limited capability in extracting robust feature representations from a relatively small and moderately imbalanced dataset. In contrast, MobileNetV2 and EfficientNetB0 benefited from ImageNet pre-trained weights, enabling the models to utilize previously learned visual representations such as textures, edges, shapes, and lesion patterns. This transfer learning strategy substantially improved feature extraction capability and accelerated convergence during training.

Among the evaluated architectures, EfficientNetB0 achieved the highest classification performance with an accuracy of 95.28%, outperforming MobileNetV2 and the baseline CNN. The superior performance of EfficientNetB0 may be attributed to its compound scaling approach, which balances network depth, width, and image resolution simultaneously [16]. This mechanism enables the model to capture more representative and discriminative image features while maintaining efficient parameter utilization. Meanwhile, MobileNetV2 also demonstrated competitive performance with an accuracy of 88.84%, indicating that lightweight transfer learning architectures remain effective for skin disease classification tasks, particularly in resource-constrained environments [17].

The confusion matrix analysis further indicates that most skin disease categories were classified correctly, although several misclassifications were still observed between visually similar classes. Such classification errors may occur because certain skin diseases share similar visual characteristics, including lesion texture, color distribution, and skin surface patterns [18].

Despite the promising results obtained in this study, several limitations should be acknowledged. The dataset consisted of only 1,157 images distributed across eight classes, resulting in relatively limited training data for deep learning models. Although data augmentation, dropout regularization, and fine-tuning strategies were implemented to reduce overfitting risk, the possibility of dataset bias and limited generalization capability may still exist. Furthermore, the dataset used in this study originated from publicly available image collections and may not fully represent real-world clinical variations. Therefore, future studies are encouraged to utilize larger and more diverse clinical datasets, explore additional transfer learning architectures, and investigate explainable artificial intelligence (XAI) techniques to improve model interpretability and reliability in practical healthcare applications.

Conclusion

This research evaluated the comparative performance of conventional CNN and transfer learning architectures for multi-class skin disease classification. The experimental results demonstrated that transfer learning architectures significantly outperformed the conventional CNN model on a relatively limited and moderately imbalanced skin disease dataset. Among the evaluated models, EfficientNetB0 achieved the highest classification performance with an accuracy of 95.28%, followed by MobileNetV2 with 88.84% accuracy.

The findings indicate that transfer learning, combined with image preprocessing, data augmentation, dropout regularization, and fine-tuning strategies, effectively improved feature extraction capability and model generalization performance for skin disease classification tasks. Furthermore, the results demonstrate the effectiveness of transfer learning architectures in extracting representative dermatological features from limited and moderately imbalanced datasets. In addition, confusion matrix analysis showed that most skin disease categories were classified correctly, although several misclassifications still occurred among visually similar classes.

Despite the strong classification performance achieved in this study, several limitations remain. The dataset consisted of only 1,157 images distributed across eight disease categories, which may still introduce overfitting risk and limit model generalization capability in real-world clinical scenarios. Therefore, future studies are encouraged to utilize larger and more diverse clinical datasets, investigate additional transfer learning architectures, and explore explainable artificial intelligence (XAI) approaches to improve model interpretability and reliability for practical healthcare applications [19].

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