

Efficient Net-Based Deep Learning Model for Real-Time Diabetic Foot Ulcer Detection

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ABSTRACT

Diabetic foot ulcers (DFUs) are among the most serious complications of diabetes and can lead to severe infections, tissue damage, and amputations if not detected early. Early and accurate diagnosis is essential for improving patient outcomes and reducing healthcare risks. Traditional methods of DFU diagnosis mainly depend on manual examination by healthcare professionals, which can be time-consuming, subjective, and inconsistent. To address these challenges, this research proposes an automated diabetic foot ulcer detection system using the EfficientNet deep learning model. The proposed model utilizes transfer learning techniques to extract important and discriminative features from medical foot images for accurate classification of ulcer and non-ulcer cases. Several preprocessing techniques, including denoising, normalization, and data augmentation methods such as rotation, flipping, and scaling, are applied to improve image quality and reduce overfitting. Experimental results show that the EfficientNet-based model achieves a high detection accuracy of 97.5%, demonstrating its effectiveness and reliability in medical image classification. proposed approach can serve as a valuable decision-support tool for healthcare professionals by enabling early diagnosis and better management of diabetic foot ulcers. This system has the potential to improve clinical efficiency and reduce complications associated with delayed detection of DFUs.

Keywords: Diabetic foot ulcer (DFU); Deep Learning; EfficientNet; Transfer Learning; Convolutional Neural Network (CNN); Image Classification; Early Diagnosis.

1. Introduction

Diabetic Foot Ulcer (DFU) detection has become an important research area in modern healthcare and medical image analysis because it enables automated assistance for the early identification of ulcerative conditions in diabetic patients. Early diagnosis of DFUs is essential to reduce severe complications such as infections, tissue damage, and lower-limb amputations. Automated DFU detection systems also support clinical decision-making, remote patient monitoring, and telemedicine services, particularly in rural and resource-limited healthcare environments.

Traditionally, diabetic foot ulcer diagnosis relies on manual visual examination performed by healthcare professionals. Although effective, this process is often subjective, time-consuming, and prone to inter-observer variability. Earlier machine learning approaches based on handcrafted features and conventional classifiers achieved moderate success in DFU detection. However, these techniques struggle to capture the complex and high-dimensional characteristics of ulcer images, thereby reducing classification accuracy and generalization capability.

Recent advancements in Deep Learning (DL), especially Convolutional Neural Networks (CNNs), have significantly improved medical image analysis and classification tasks. CNN-based models automatically learn hierarchical feature representations from images, making them highly effective for identifying subtle abnormalities in diabetic foot ulcer images. Compared to traditional machine learning methods, deep learning approaches provide improved robustness, scalability, and classification performance.

Several studies have investigated automated DFU detection using computer vision and deep learning techniques. Image enhancement methods combined with texture feature extraction and Support Vector Machine (SVM) classifiers have shown promising results for early-stage ulcer detection (Khandakar

et al., 2021). However, traditional approaches are limited in scalability and robustness when compared with deep learning-based frameworks. Diabetic foot ulcers are commonly caused by peripheral neuropathy, poor blood circulation, and impaired immune response, which delay wound healing and increase the risk of infection (Boulton et al., 2008; Singh et al., 2005). Due to the increasing global prevalence of diabetes, DFUs have become a major public health concern associated with high treatment costs, hospitalization rates, and reduced quality of life.

In this study, a transfer learning-based EfficientNet-B0 model is proposed for binary classification of diabetic foot images into Normal and Ulcer categories. The proposed framework integrates image preprocessing, data augmentation, and transfer learning techniques to improve feature extraction and classification accuracy. The main objective of this research is to develop an accurate, computationally efficient, and reliable automated DFU detection system that can assist healthcare professionals in early diagnosis and effective clinical management.

2. Literature Review

Recent advancements in machine learning and deep learning have significantly improved the automated detection and classification of Diabetic Foot Ulcers (DFUs). These intelligent systems assist healthcare professionals in early diagnosis, reduce clinical workload, and improve patient management. This section reviews important research contributions related to DFU detection and highlights the limitations of existing approaches.

Robert Singh et al. (2020) proposed a multimodal diabetic foot ulcer detection framework using RGB and thermal images collected from the STANDUP database. Their method integrated ResNet50 for feature extraction and SegNet for image segmentation within a federated learning architecture. The proposed system achieved an accuracy of 98.55%. However, the framework required extensive manual annotation and high computational resources, limiting its practical use in low-resource healthcare environments.

Shiva Mehta et al. (2021) utilized the DFUC2021 dataset containing 2,000 diabetic foot images categorized into Normal, Mild, and Severe classes. The authors combined ResNet50 with a Support Vector Machine (SVM) classifier using an RBF kernel to improve classification performance. Their hybrid approach achieved an accuracy of 95.2%. Despite achieving good performance, the model increased computational complexity and reduced deployment efficiency.

Sengottaiyan N. et al. (2021) introduced a real-time diabetic foot ulcer classification framework based on EfficientNet-B0 and Siamese Neural Networks (SNN). The model was trained using approximately 4,000 augmented images and achieved 91% accuracy. Although the system provided effective fine-grained classification, dependence on cloud infrastructure increased latency and reduced offline usability.

S. Geeitha et al. (2022) applied the InceptionV3 model with Particle Swarm Optimization (PSO) for hyperparameter tuning and utilized deep sparse autoencoders for classification. Using 1,979 images, the proposed framework achieved 93.3% accuracy. However, the model required high computational power, which limited its deployment on lightweight medical devices and edge computing systems.

Ezhilan R. et al. (2021) implemented transfer learning techniques using ResNet152, EfficientNet-B7, and SEResNeXt architectures on the DFU2020 dataset containing more than 7,000 image patches. Their framework achieved 98.48% accuracy with high sensitivity and specificity. Nevertheless, the complex model architecture reduced interpretability and required extensive clinical validation before practical implementation.

Muthuraja M. et al. (2022) evaluated EfficientNet-B0, EfficientNet-B3, and ResNet50 models using a combined dataset collected from Kaggle and clinical sources. The proposed system achieved 90.18% classification accuracy for binary DFU detection. Although the framework demonstrated effective ulcer identification, inference speed and computational cost remained significant challenges.

Chalmani et al. (2021) proposed a multimodal diabetic foot ulcer classification framework integrating RGB, infrared, and thermal imaging techniques using the DFUC2021 dataset containing more than

15,000 images. Their DenseNet-201 and EfficientNet-B3-based models achieved nearly 97% accuracy. Despite the improved classification performance, the framework heavily relied on curated and pre-labeled datasets, which affected scalability in real-world clinical applications.

Gottumukkala Gayatri et al. (2022) developed a custom 11-layer Convolutional Neural Network (CNN) for diabetic foot ulcer classification using approximately 1,500 images. The proposed model achieved 95% accuracy and supported real-time web deployment. However, the relatively small dataset size limited the model's generalization capability compared with transfer learning-based pretrained architectures.

From the reviewed studies, it is evident that deep learning-based methods significantly outperform traditional machine learning approaches in diabetic foot ulcer detection tasks. However, several limitations still exist, including high computational complexity, limited interpretability, cloud dependency, and insufficient validation using diverse clinical datasets. To address these challenges, the present study proposes a transfer learning-based EfficientNet-B0 framework for binary classification of diabetic foot ulcer images. The proposed model focuses on achieving high classification accuracy while maintaining computational efficiency and practical applicability in real-world healthcare environments.

Research Gap Analysis

Table 1 summarizes the key research gaps identified from existing studies.

Table 1. Research Gap Analysis

No	Author	Algorithm Used	Merits	Identified Gaps
1	Robert Singh et al. [7]	ResNet50 + SegNet (Federated Learning)	Very high accuracy	High computational cost; manual annotation required
2	Shiva Mehta et al. [8]	ResNet50 + SVM	Improved classification accuracy	Increased model complexity; limited interpretability
3	Sengottaiyan N. et al. [9]	EfficientNet-B0 + SNN	Real-time fine-grained detection	Cloud dependency; latency issues
4	S. Geeitha et al. [10]	InceptionV3 + PSO + Autoencoder	Strong optimization	High resource requirements
5	Ezhilan R. et al. [11]	ResNet152, EfficientNet-B7	High sensitivity and specificity	Limited explainability; needs large-scale validation
6	Muthuraja M. et al. [12]	EfficientNet variants, ResNet50	Effective detection	Needs faster and lightweight deployment

Table 1 summarizes the key limitations identified in existing DFU detection approaches. Although many studies report high classification accuracy, several challenges remain unresolved. These include reliance on computationally intensive architectures, dependence on large or multimodal datasets, limited model interpretability, insufficient validation across diverse clinical settings, and lack of lightweight deployment-ready solutions. Additionally, some studies do not clearly describe experimental configurations, which affects reproducibility.

To address these limitations, the present study proposes a transfer learning-based EfficientNet-B0 model for binary classification of DFU images using a publicly available Kaggle dataset. The proposed framework emphasizes computational efficiency, balanced dataset utilization, standardized training configuration, and fair comparative evaluation to ensure reproducibility and practical applicability.

3. Methodology

The proposed system presents a transfer learning-based deep learning framework for binary classification of Diabetic Foot Ulcer (DFU) images into Normal and Ulcer categories. The framework utilizes EfficientNet-B0 as the backbone architecture due to its computational efficiency and strong feature extraction capability.

The overall pipeline consists of image preprocessing, data augmentation, dataset splitting, model training, and performance evaluation. Transfer learning is applied using ImageNet-pretrained weights to enhance feature representation and improve convergence on the relatively small DFU dataset.

3.1 System Architecture

The overall architecture of the proposed Diabetic Foot Ulcer (DFU) detection system is illustrated in **Fig.1**. The framework follows a structured deep learning pipeline consisting of image preprocessing, dataset preparation, model training, and final classification.

The process begins with the acquisition of input diabetic foot images from the publicly available Kaggle DFU dataset. These images are first subjected to preprocessing to ensure uniformity and improve feature extraction quality. Preprocessing includes resizing all images to 224×224 pixels to match the EfficientNet-B0 input requirements, pixel normalization to scale intensity values between 0 and 1, and noise reduction to enhance wound visibility.

To increase dataset diversity and reduce overfitting, data augmentation techniques are applied. These include rotation, horizontal flipping, zooming, and brightness adjustments. Augmentation improves model generalization, particularly given the moderate dataset size.

Following preprocessing and augmentation, the dataset is divided into training, validation, and testing sets. The training set is used to optimize model parameters, the validation set monitors performance during training to prevent overfitting, and the testing set is reserved for final unbiased evaluation.

The core classification component employs EfficientNet-B0 using transfer learning with pretrained ImageNet weights. The final fully connected layer is modified to perform binary classification (Normal vs Ulcer). During training, the model learns discriminative features relevant to ulcer detection. After training, the model outputs class probabilities, and the image is categorized based on the higher probability score.

The final output of the system is a binary decision:

- Normal Foot
- Abnormal Foot (Ulcer)

This structured architecture ensures consistent data handling, computational efficiency, and reliable classification performance while maintaining reproducibility under standardized experimental settings.

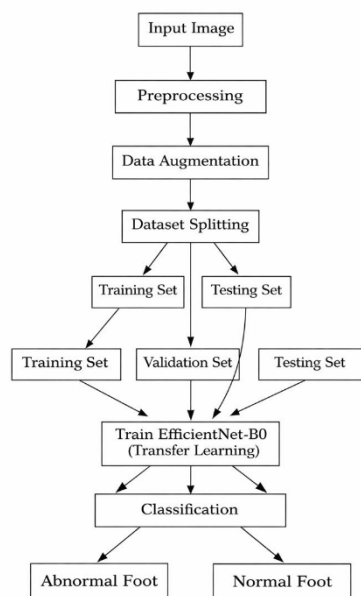


Figure 1. Proposed System Architecture for Binary DFU Classification

3.2 Methodology used

The proposed methodology employs a transfer learning-based EfficientNet-B0 model for binary classification of diabetic foot ulcer (DFU) images into Normal and Ulcer categories. A publicly available Kaggle dataset is used for training and evaluation.

All images are resized to 224×224 pixels and normalized to improve training stability. Data augmentation techniques such as rotation, flipping, and zooming are applied to enhance generalization and reduce overfitting. The dataset is divided into training, validation, and testing sets to ensure unbiased performance evaluation.

EfficientNet-B0, pretrained on ImageNet, is fine-tuned for binary classification by modifying the final output layer. The model is trained using the Adam optimizer and binary cross-entropy loss function. Performance is evaluated using accuracy, precision, recall, and F1-score.

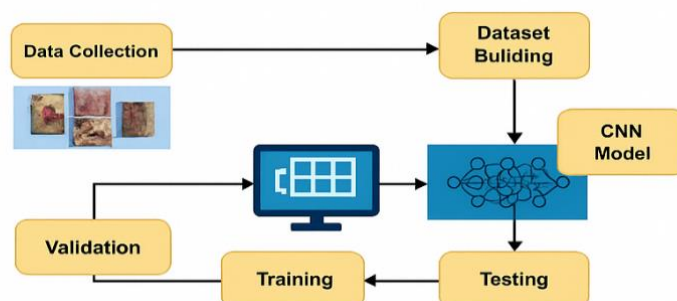


Figure 2. Proposed Methodology for Binary DFU Classification

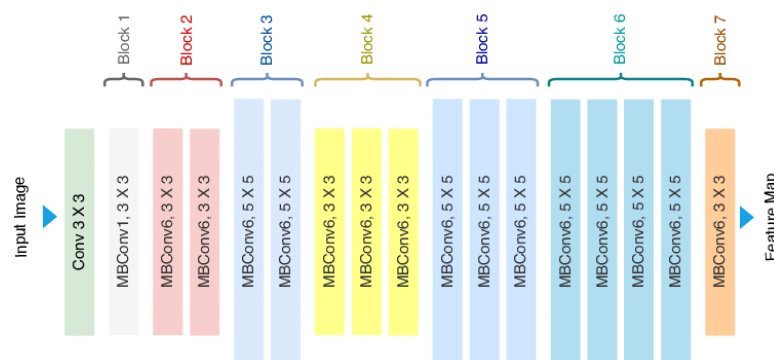
Fig.2 illustrates the proposed methodology adopted for binary classification of diabetic foot ulcer images. The process begins with acquisition of the publicly available Kaggle DFU dataset. The images undergo preprocessing and data augmentation to enhance quality and diversity. The dataset is then

divided into training, validation, and testing subsets. The EfficientNet-B0 model, initialized with ImageNet pretrained weights, is trained using the training set and monitored using validation data. Finally, model performance is evaluated on the testing set to classify images into Normal and Ulcer categories.

EfficientNet is a convolutional neural network architecture designed to achieve high accuracy while maintaining computational efficiency. Unlike conventional CNN models that increase performance primarily by scaling depth or width independently, EfficientNet introduces a compound scaling method that uniformly scales network depth, width, and input resolution. This balanced scaling strategy enables improved accuracy with fewer parameters and reduced computational cost.

EfficientNet provides multiple variants ranging from EfficientNet-B0 to EfficientNet-B7, each offering a trade-off between model size and performance. In this study, EfficientNet-B0 is the selected due to its lightweight architecture and suitability for moderate-sized medical image datasets. The architecture consists of stacked mobile inverted bottleneck convolution (MBConv) blocks, which enhance feature extraction efficiency while minimizing parameter growth. The structure illustrated in Fig.3 provides overview of the hierarchical feature learning process used for diabetic foot ulcer classification.

Figure 3. EfficientNet-B0 Architecture Used in the Proposed Model (PM)



3.3. Image Preprocessing

Before training the CNN model, image preprocessing is performed to ensure consistency, improve data quality, and enhance feature extraction. All images resized to 224×224 pixels to match the input requirements of EfficientNet-B0. Pixel intensity the values are normalized to the range $[0,1]$ to facilitate stable and faster convergence during training. Noise reduction is applied using Gaussian filtering to suppress background variations and enhance relevant wound features.

To improve model generalization and mitigate the overfitting, data augmentation techniques are applied, including random rotation, horizontal flipping, zooming, cropping, and brightness adjustments. These transformations increase dataset diversity without altering class labels.

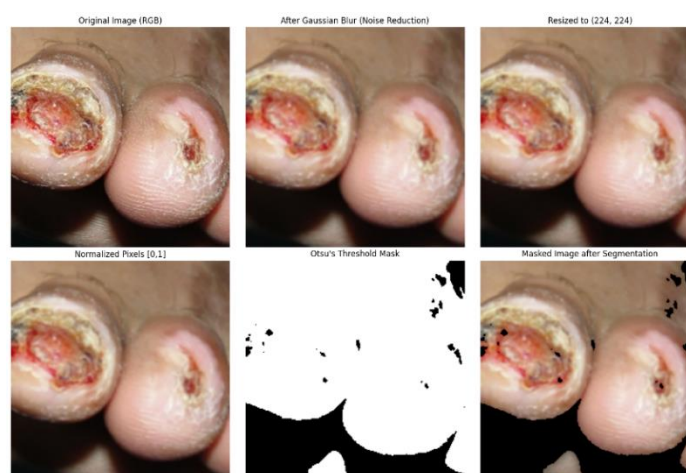


Figure 4. Image Preprocessing and Segmentation Workflow

Fig.4 illustrates the preprocessing and segmentation workflow applied to a sample DFU image. The process includes the original RGB image, Gaussian the blur for noise reduction, resizing, normalization, Otsu's thresholding for mask generation, and the segmented output. It be should be noted that Otsu-based segmentation used for visualization and analysis purposes and is not directly integrated into the model training pipeline.

3.4 Dataset Description

Dataset used in this study was obtained from publicly available Diabetic Foot Ulcer (DFU) dataset on Kaggle. The dataset contains clinical foot images categorized into two classes: Normal (Healthy) and Ulcer. As the dataset is publicly accessible and anonymized, it does not include identifiable patient information, and separate the ethical approval was not required.

The dataset comprises a total of 900 images, equally distributed between the two classes (450 Normal and 450 Ulcer images). An 80:20 stratified split is applied to maintain class balance, resulting in 360 images per class for training and 90 images per class for testing.

Although the dataset size is moderate, transfer learning using pretrained ImageNet weights enables effective feature extraction. Data augmentation further enhances generalization capability and reduces overfitting.

3.5 Training Configuration and Hyperparameters

EfficientNet-B0 was selected due to its lightweight architecture and computational efficiency, making it suitable for moderate-sized medical image datasets. The model was initialized with ImageNet-pretrained weights and fine-tuned for binary classification.

The training configuration includes an input the image size of 224×224 pixels, Adam optimizer with a learning rate of 0.0001, a batch size of 16, and a total of 10 training epochs. Binary cross entropy was used as the loss function. Regularization techniques such as dropout and data augmentation were applied to reduce overfitting. Early stopping based on validation loss was implemented to prevent performance degradation.

For fair comparison, AlexNet and ResNet50 models we trained under identical experimental conditions, including dataset splits, optimizer settings, batch size, and learning rate.

4. Results

The EfficientNet-B0 model with the transfer learning was trained for binary classification of diabetic foot images into Normal and Ulcer categories. Dataset was divided into training, validation, and testing subsets using a stratified split to maintain class balance. All preprocessing and hyperparameter configurations described in Section 3 were consistently applied across comparative models to ensure fairness.

4.1 Evaluation metrics

Model performance was evaluated using the standard classification metrics including Accuracy, Precision, Recall, and F1-score. These metrics were computed from the confusion matrix, where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

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

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

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2TP}{2TP + FP + FN}$$

4.2 Comparative Performance Analysis

Table 2 presents the comparative results of EfficientNet-B0, AlexNet, and ResNet50 trained under identical experimental conditions.

Table 2. Comparative Performance Analysis

Model	Accuracy	Precision	Recall	F1-score
AlexNet	91.05%	90%	89%	89%
ResNet50	93.20%	92%	91%	91%
EfficientNet-B0	97.51%	97%	97%	97%

EfficientNet-B0 achieved the highest classification accuracy of 97.51%, outperforming AlexNet and ResNet50. The improvement that can be attributed to EfficientNet's compound scaling strategy and efficient feature extraction capability.

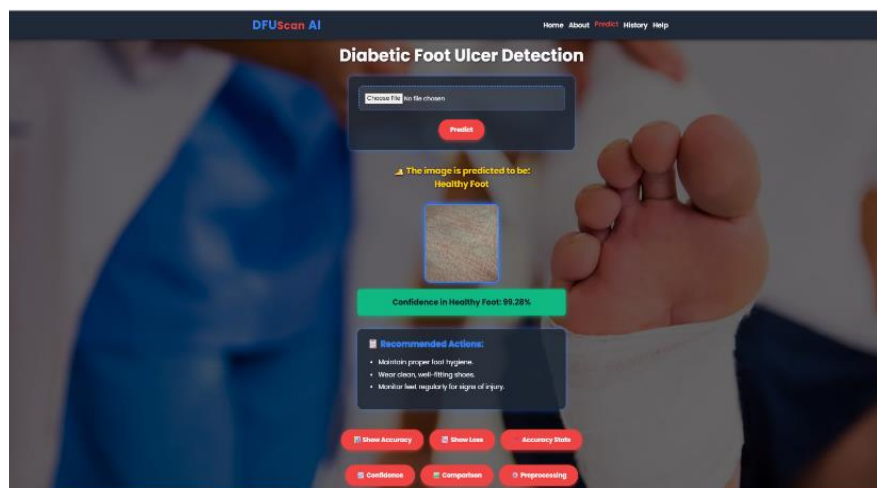


Figure 5. Web-Based Interface for DFU Classification

Fig.5 presents the developed web-based interface designed for diabetic foot ulcer (DFU) classification. The interface allows users to upload a foot image, after which the trained EfficientNet-B0 model performs binary classification and displays the predicted result along with the corresponding confidence score. In the illustrated example, the uploaded image is classified as “Healthy Foot” with a confidence score of 99.28%. The interface also provides general foot care recommendations for informational purposes.

The web application serves as a demonstration of the trained model's inference capability and does not represent a clinically validated diagnostic tool.

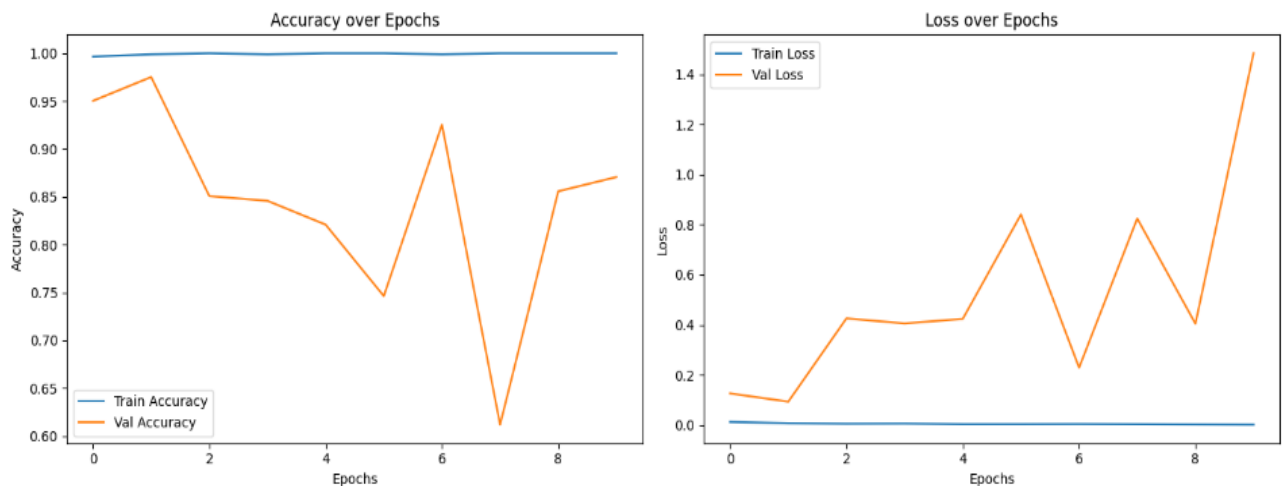


Figure 6. Training and Validation Accuracy and Loss Curves

Fig.6 illustrates training and validation accuracy and loss across 10 epochs. The training accuracy approaches near 100%, while validation accuracy exhibits fluctuations during early epochs. This behaviour indicates potential overfitting.

To mitigate overfitting, data augmentation, dropout regularization, and early stopping were applied. Although minor validation fluctuations remain due to dataset size limitations, the final model demonstrates stable generalization performance.

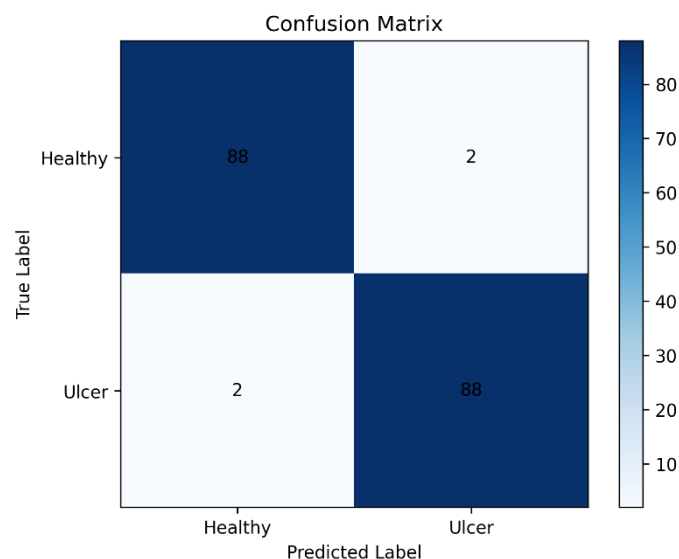


Figure 7. Confusion Matrix for Binary DFU Classification

Fig.7 presents the confusion matrix of the proposed EfficientNet-B0 model on test dataset. The model correctly classified 88 Healthy and 88 Ulcer images, with only 2 false positives and 2 false negatives. The results indicate balanced performance across both classes and support the reported overall accuracy of approximately 97.5%.

4.3 Classification Report

Table 3. Classification Report

Class	Precision	Recall	F1-score	Support
Healthy	0.98	0.98	0.98	90
Ulcer	0.98	0.98	0.98	90
Accuracy	–	–	0.98	180
Macro Avg	0.98	0.98	0.98	180
Weighted Avg	0.98	0.98	0.98	180

The classification report confirms balanced model performance across both categories.

5. Discussion

The experimental results demonstrate that the proposed EfficientNet-B0 model outperforms AlexNet and ResNet50 in terms of classification accuracy, precision, recall, and F1-score. The improved performance can be attributed to EfficientNet's compound scaling strategy, which balances network depth, width, and resolution efficiently.

Compared to traditional CNN architectures, EfficientNet-B0 provides better feature extraction while maintaining lower computational complexity. The confusion matrix and classification report confirm balanced performance across both Normal and Ulcer classes, indicating reliable generalization capability.

Despite achieving high accuracy, the study has certain limitations. The dataset size is moderate and limited to a publicly available Kaggle dataset. Additional validation using larger and multi-center clinical datasets is required to improve robustness and real-world applicability.

The proposed framework demonstrates the potential of deep learning-based automated DFU detection systems for supporting early clinical diagnosis and improving healthcare accessibility. The lightweight nature of EfficientNet-B0 also makes the system suitable for deployment in telemedicine and resource-constrained healthcare environments.

6. Conclusion

This study presented a transfer learning-based EfficientNet-B0 framework for the binary classification of diabetic foot ulcer (DFU) images into Normal and Ulcer categories. Proposed system integrates preprocessing, the data augmentation, and standardized training procedures to improve feature extraction and classification performance. Experimental results demonstrate that the model achieves strong classification accuracy on the publicly available Kaggle DFU dataset, indicating its effectiveness for automated DFU image analysis.

Compared to traditional machine learning approaches based on handcrafted features, the proposed deep learning framework provides improved feature representation and classification consistency. The use of EfficientNet-B0 enables computational efficiency while maintaining high predictive performance, making it suitable for moderate-sized medical image datasets.

Although the obtained results are the promising, this study has certain limitations. The dataset size is relatively moderate, and evaluation was performed on a single publicly available dataset. Further validation using larger, multi-center clinical datasets is necessary to assess generalization performance and real-world applicability.

Future work may focus on expanding the dataset, incorporating cross-institutional validation, and exploring multi-class DFU severity classification. Additionally, the research may also investigate explainable AI that the techniques to enhance model interpretability and clinical transparency.

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