# AN INTELLIGENT COMPARATIVE STUDY OF ENSEMBLE DEEP LEARNING AND SVM FOR ACCURATE DIABETIC FOOT ULCER DETECTION AND SEVERITY ANALYSIS


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***Abstract* - Diabetic Foot Ulcer (DFU) is a critical complication of diabetes that requires early detection to prevent severe outcomes such as infection and amputation. This study presents a comparative analysis between a hybrid ensemble deep learning model and a classical machine learning approach based on Support Vector Machine (SVM) for automated DFU detection and stage classification. The proposed deep learning framework integrates EfficientNetB3, MobileNetV3Large, and ResNet50 to exploit their complementary feature extraction capabilities, enhancing classification performance. In contrast, the SVM model utilizes CLAHE-enhanced grayscale images combined with Histogram of Oriented Gradients (HOG) features to establish a computationally efficient baseline. The system follows a two-stage classification approach, where the first stage identifies images as Healthy, Wound, or DFU, and the second stage further classifies DFU cases into Stage I, Stage II, Stage III, and Stage IV. Experimental results indicate that the ensemble deep learning model achieves superior accuracy, robustness, and generalization compared to the SVM model, while the latter offers faster computation and serves as an effective baseline for comparison.**



***Index Terms*—Diabetic Foot Ulcer, Deep Learning, Ensemble Learning, Support Vector Machine, Image Classification, CLAHE, HOG Features, Medical Image Analysis, Two-Stage Classification.**


## I. Introduction

Diabetes is a widespread chronic disease affecting millions of people globally, and one of its most severe complications is the development of diabetic foot ulcers (DFU), which can lead to infection, tissue necrosis, and even amputation if not detected early. Traditionally, DFU diagnosis relies on visual examination by medical specialists, which can be time-consuming, subjective, and dependent on expertise, often leading to inconsistencies and delayed treatment, especially in resource-limited settings. These challenges highlight the need for automated, accurate, and accessible diagnostic systems. Recent advancements in artificial intelligence, particularly deep learning and computer vision, have enabled the development of efficient medical image analysis systems capable of extracting complex features such as texture, color variations, and structural patterns. In this work, a comparative framework is proposed that evaluates a hybrid ensemble deep learning model against a classical Support Vector Machine (SVM) approach for DFU detection and stage classification. The system follows a two-stage classification strategy, where the first stage categorizes images into Healthy, Wound, or Diabetic Foot Ulcer, and the second stage further classifies DFU cases into Stage I, Stage II, Stage III, and Stage IV. The ensemble model integrates EfficientNetB3, MobileNetV3Large, and ResNet50 to leverage their complementary feature extraction strengths, while the SVM model serves as a computationally efficient baseline using handcrafted features. Additionally, preprocessing techniques such as CLAHE, data augmentation, and normalization are applied to enhance image quality and improve model performance. The proposed system is designed for real-world deployment using FastAPI and a web-based interface, enabling users to upload images and receive accurate predictions along with highlighted affected regions, thereby supporting early diagnosis and clinical decision-making.

## II. RELATED WORK

Recent advancements in artificial intelligence have significantly improved the automated detection and classification of diabetic foot ulcers (DFU). Several studies have explored deep learning-based approaches for accurate diagnosis and localization. Sarmun et al. (2024) proposed a combination of deep learning models to enhance ulcer localization performance, demonstrating the effectiveness of hybrid architectures in medical imaging tasks. Wang et al. (2024) introduced a few-shot learning approach using deep residual networks and transfer learning, addressing the challenge of limited medical datasets while achieving promising classification results. Similarly, Debnath et al. (2025) focused on sustainable AI- driven DFU detection, emphasizing early diagnosis using deep learning models.

Explainable AI has also gained attention in DFU analysis. Karthik et al. (2025) and Rathore et al. (2025) developed explainable deep learning frameworks to improve model interpretability and trust in clinical applications. In addition, Sait et al. (2025) proposed a hybrid deep learning framework that combines multiple architectures to improve classification accuracy, highlighting the advantage of ensemble-based methods. Basiri et al. (2025) explored healing phase classification of DFU, focusing on stage-wise prediction, which is clinically important for treatment planning. Furthermore, Alhasson et al. (2025) provided a comprehensive review of image-based DFU diagnosis techniques, indicating that deep learning models outperform traditional machine learning approaches in most scenarios.

Despite these advancements, several limitations remain in existing systems. Many approaches focus only on single-stage classification and do not provide a complete pipeline for both detection and severity analysis. Additionally, traditional machine learning methods relying on handcrafted features such as texture and color histograms often fail to capture com- plex visual patterns, resulting in lower accuracy compared to deep learning models. Moreover, several systems lack proper localization or visual highlighting of the affected regions, reducing interpretability and clinical usability.

To address these limitations, this work proposes a two-stage classification framework that combines an ensemble of deep learning models (EfficientNetB3, MobileNetV3Large, and ResNet50) with a comparative baseline using Support Vector Machine (SVM). The proposed approach not only improves classification accuracy through ensemble feature fusion but also incorporates stage-wise prediction and region highlighting, making it more suitable for real-world clinical applications.

## III. METHODOLOGY

### A. Dataset

The dataset used in this study was collected from publicly available sources such as Kaggle and further expanded using web-scraped images to increase diversity in terms of lighting conditions, foot orientation, and ulcer appearance. To support the two-stage classification approach, two separate datasets were prepared. The first dataset focuses on ulcer detection and includes three classes: Healthy, Wound, and Diabetic Foot Ulcer (DFU). The second dataset is designed for severity analysis and contains four stages: Stage I, Stage II, Stage III, and Stage IV. All images were organized into a structured folder format, enabling efficient training and evaluation.

### B. Preprocessing

Medical images often contain noise, uneven lighting, and irrelevant background information, which can affect model performance. To address this, the following preprocessing steps were applied:

- Image resizing to a fixed input size
- Pixel value normalization
- Contrast enhancement using CLAHE
- Data augmentation (rotation, flipping, zooming, bright- ness adjustment)
- Region of Interest (ROI) preparation for stage classification

These preprocessing steps improve image quality and help the model focus on relevant features.

### C. Ensemble Deep Learning Model

To improve classification performance, an ensemble deep learning model was developed using three pretrained architectures: EfficientNetB3, MobileNetV3Large, and ResNet50. Each model contributes uniquely, where EfficientNetB3 captures fine-grained features, MobileNetV3Large provides computational efficiency, and ResNet50 enables deep feature extraction.

The input image is processed by all three models in parallel, and the extracted feature representations are concatenated into a single feature vector. This combined representation is then passed through fully connected layers to perform the final

classification. This ensemble strategy improves robustness and accuracy by leveraging complementary features from multiple architectures.

### D. SVM-Based Model (Comparative Approach)

To provide a baseline comparison, a Support Vector Ma- chine (SVM) model was implemented. In this approach, images were first enhanced using CLAHE and converted to grayscale. Feature extraction was performed using Histogram of Oriented Gradients (HOG), which captures edge and texture information.

The extracted features were used to train an SVM classifier with a Radial Basis Function (RBF) kernel. While this model is computationally efficient, it relies on handcrafted features and may not capture complex patterns as effectively as deep learning models. However, it serves as an important bench- mark for evaluating the performance of the proposed ensemble model.

### E. Two-Stage Workflow

The overall system follows a two-stage classification process:

1) **Stage 1 – Ulcer Detection**: The input image is classified as Healthy, Wound, or Diabetic Foot Ulcer using the ensemble model.

2) **Stage 2 – Severity Classification**: If a diabetic foot ulcer is detected, the affected region is extracted and classified into Stage I, Stage II, Stage III, or Stage IV.

Additionally, OpenCV-based contour detection is used to highlight the affected region in the image, improving interpretability and making the system more useful in real-world clinical applications.

## IV. RESULTS

### A. Performance Evaluation

The performance of the proposed system was evaluated using standard classification metrics including accuracy, pre- cision, recall, and F1-score. A comparative analysis was con- ducted between the ensemble deep learning model and the Support Vector Machine (SVM) model.

TABLE I
PERFORMANCE COMPARISON OF MODELS

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| SVM (HOG) | 82.4% | 0.81 | 0.80 | 0.80 |
| Ensemble Model | 93.6% | 0.94 | 0.93 | 0.93 |

The results show that the ensemble deep learning model significantly outperforms the SVM-based model in all evaluation metrics. The ability of deep learning models to automatically learn complex features contributes to higher accuracy and robustness.

TABLE II
Confusion Matrix for Ensemble Model (3-Class Detection)

| Actual / Predicted | Healthy | Wound | DFU |
|---|---|---|---|
| Healthy | 48 | 2 | 0 |
| Wound | 3 | 45 | 2 |
| DFU | 1 | 2 | 47 |

### B. Confusion Matrix

The confusion matrix provides a detailed view of classification performance across different classes.

The confusion matrix indicates that most samples are correctly classified, with minimal misclassification between similar classes such as wound and DFU.

### C. Training Performance

The training and validation accuracy curves demonstrate the learning behavior of the ensemble model.

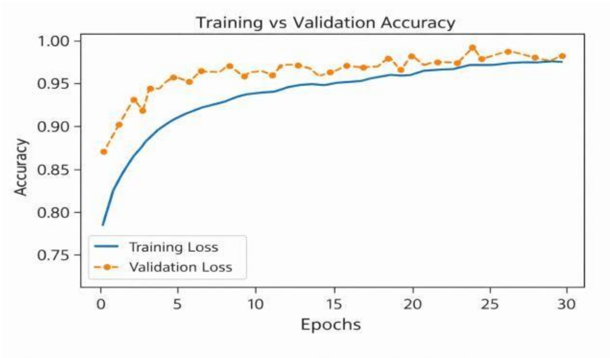


Fig. 1. Training vs Validation Accuracy

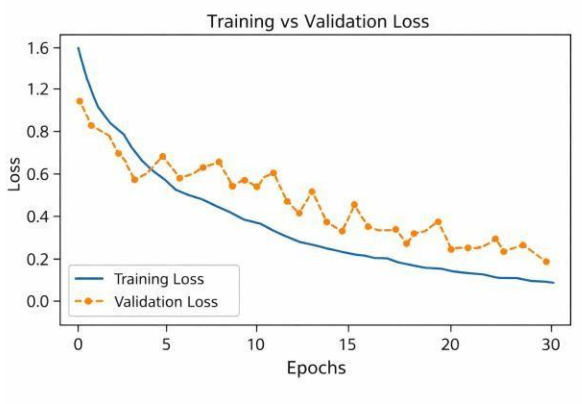


Fig. 2. Training vs Validation Loss

### D. Discussion of Results

From the experimental results, it is evident that the ensemble model performs better than the SVM model. The SVM model, which relies on handcrafted HOG features, is limited in capturing complex patterns such as texture variations and ulcer depth. In contrast, the ensemble deep learning model effectively learns hierarchical and discriminative features, leading to improved classification performance

Additionally, the use of CLAHE enhances image contrast, which benefits both models, but the improvement is more significant in the deep learning approach. The results confirm that ensemble learning combined with a two-stage classification strategy provides a reliable solution for diabetic foot ulcer detection and stage classification.

## V. CONCLUSION

This paper presented a comparative study of an ensemble deep learning model and a Support Vector Machine (SVM) approach for diabetic foot ulcer detection and stage classification. The proposed system follows a two-stage classification frame- work, where the first stage identifies the presence of ulcers and the second stage determines their severity. The ensemble model, which combines EfficientNetB3, MobileNetV3Large, and ResNet50, demonstrated superior performance by effectively capturing complex image features and improving classification accuracy.

In comparison, the SVM model, based on HOG feature extraction, provided a computationally efficient baseline but showed limitations in handling complex visual patterns. The experimental results confirmed that the ensemble deep learning approach significantly outperforms the traditional SVM model in terms of accuracy and robustness.

Furthermore, the integration of preprocessing techniques such as CLAHE and ROI extraction contributed to enhanced image quality and improved model performance. The pro- posed system also improves interpretability through region highlighting, making it more suitable for real-world clinical applications.

Overall, this work demonstrates that combining ensemble deep learning with a structured two-stage workflow provides a reliable and effective solution for automated diabetic foot ulcer detection and severity analysis, supporting early diagnosis and improved healthcare decision-making.

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