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# Early Detection of Diabetic Foot Ulcers Using Image Classification and Segmentation

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*Abstract— One of the most severe complications of diabetes is the Diabetic Foot Ulcers (DFUs). Otherwise, they may cause infection, or even amputation. The timely diagnosis is vital to successful treatment and avoiding acute health conditions. Old ways of diagnosis rely on clinical examination by experts, which may be lengthy, subjective, and even inaccessible in the rural or remote regions. The project presents a deep learning solution that is based on the automatic detection, segmentation, and classification of diabetic foot ulcers based on Convolutional Neural Network (CNN) architectures. YOLOv8 is employed in detection, and U-Net is employed in segmentation. The system is trained with DFU_4Class (Wagner-Meggitt) data, that contains different ulcer cases which are divided into None, Infection, Ischemia, and Both. The given model gives an opportunity to analyze ulcers early, accurately, and automatically by using images taken by cameras or smartphones. It is developed to be efficient and lightweight and can be deployed on the web platforms and is suitable in a clinical and telehealth environment.*

*Index Terms— Diabetic Foot Ulcer, YOLOv8, U-Net, Deep Learning, Image Segmentation, Medical Imaging*

## I. INTRODUCTION

Diabetic Foot Ulcer (DFU) is a complication that is prevalent and severe to individuals with long-term diabetes. It occurs primarily due to nerve damage, lack of blood circulation and slow healing of wounds. These reasons may result in chronic infections or tissue loss. Otherwise, DFUs may progress rapidly, cause hospital admission, or even amputation of lower limbs. Globally, approximately one out of four diabetic patients are susceptible to incur a foot ulcer, and the causative agents of the majority of non-traumatic amputations are caused by the ulcer. These consequences are not only affecting the physical condition, but also cause serious psychological and economic problems to the patients and health systems.

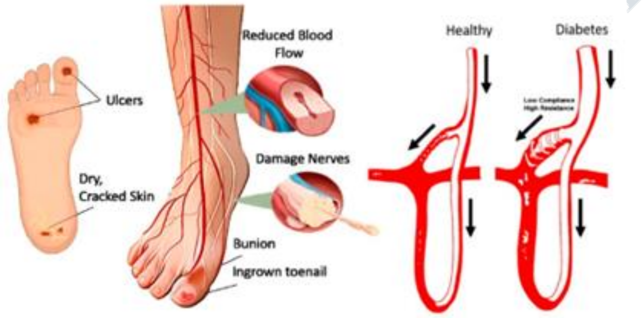


**Fig. 1.** Pathophysiology of diabetic foot ulcers (DFUs)

Historically, doctors or podiatrists can make a diagnosis of DFUs through manual inspection. Although this approach is effective in clinics, it is subjective and consumes a considerable amount of time. It is frequently relative to the availability and experience of the clinician. Even such factors as lighting, skin color, shape of wounds, and quality of images complicate correct assessment even more. In remote locations or telehealth appointments, where specialists are not readily available, the problems will slow the response to early detection and treatment, increasing the risk of severe infection.

The increase in digital medical imaging has led to the application of computer analysis to wound photographs to perform more rapid and consistent analysis. Among them, the deep learning methods, which are particularly the convolutional neural networks (CNNs), have demonstrated tremendous potential to detect more intricate features of a visual object and detect disease patterns with accuracy. Such techniques are able to provide details that matter like wound edges, texture and minute differences in the colors that are difficult to detect with the naked eye.

Researchers expect to accelerate the process of diagnosing the presence of a foot ulcer, increase the accuracy, and reliability by applying deep learning to foot ulcer images. This will assist the clinicians to make earlier and better decisions. The current increase in the development of these computer-aided diagnostic tools has a high potential to reduce amputation rates, increase patient outcomes, and access to diabetic care in every healthcare setting.

## II. EXISTING SYSTEMS

Detection and classification of the Diabetic Foot Ulcer (DFUs) has been investigated using different computational and clinical techniques in the last decade. Current systems can be classified into three broad categories, namely, manual diagnosis, classical machines learning techniques, and deep learning-based frameworks.

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### A. Specialist Diagnosis in Manual

Traditional approach to evaluation of DFUs is based on clinical establishment and physical examination by trained medical professionals. Although such method is useful in a controlled environment, it is very subjective and time consuming. It is very dependent on the experience of the clinician. Manual diagnosis can lead to poor results in terms of timeliness and unreliability in the case of specialists who are difficult to reach.

### B. Basic Machine Learning Systems

Early algorithms approximately relied on manually-constructed features of images such as texture, color, and edge descriptions as well as image classifier models such as Support Vector Machines (SVM) or k-Nearest Neighbors (k-NN). Nevertheless, despite being an early step in automation, these systems demonstrated poor accuracy, less robustness and low versatility with variations in patient groups and imaging cases.

### C. Basic Deep Learning Models

The development of Convolutional Neural Networks (CNNs) transformed the analysis of medical images, as it gave an opportunity to extract features automatically. Such models as VGGNet, ResNet, and AlexNet were able to enhance the accuracy of detection and classification. Nevertheless, their work was dependent strongly on massive labelled datasets and hardware capacity. They tended to have issues with the change of the ulcer appearance, lighting, and skin color.

### D. Hybrid and Lightweight Models

Subsequently, there were research works into hybrid CNN and lightweight networks like MobileNetV2 and EfficientNet. These were meant to be tradeoffs between accuracy and efficiency. Although these models were more efficient in inference, they needed hyperparameters to be carefully tuned and needed a high-end GPUs to perform optimally, which restricted their application in a clinical or mobile context. By exploring object detection and segmentation, it becomes possible to identify questions and concepts that facilitate the growth of one's professional activities, as well as to develop practices and procedures that are both effective and efficient for adoption in teaching and research disciplines.

### E. Object Detection and Segmentation Models

Investigating the object detection and segmentation, one will be able to find questions and concepts that could help to pursue the development of his or her professional activity, to create the practices and procedures that are effective and efficient to be adopted in the field of teaching and research. DFU detection and segmentation has been done with deep learning structures such as YOLO (You Only Look Once) and U-Net. YOLO gives the localization of objects in real-time whereas U-Net can map wound boundaries on the pixel-level. Nevertheless, models relying on these models have problems in identifying small or irregular ulcers. The real time deployment is challenging because they require a vast amount of GPU resources.

### F. Sensors and Multimodal Systems

Besides RGB imaging, more sophisticated methods employ thermal, infrared or hyperspectral sensors to detect ulcers depending on physiological indications such as variation in temperature or blood flow in tissues. Although such methods enable a thorough non-invasive analysis, they are expensive, complicated, and cannot be used in the majority of healthcare institutions on a regular basis.

## III. PROPOSED SYSTEM

The paper introduces an integrated hybrid system in the early detection and segmentation of Diabetic Foot Ulcers (DFUs) using deep learning. It uses YOLOv8 to localize ulcers accurately and U-Net to follow up the segmentation of borders with high precision and accuracy even in problematic situations.

This system is unlike the existing ones that depend on manual examination or single model processing since the detection and segregation take place in a single architecture. The YOLOv8 is very efficient in finding the regions of interest, whereas U-Net refines these localizations with pixel-based segmentation. These models combined enhance the accuracy of diagnosis, reduce the necessity of manual labor, and enable the analysis of a large number of medical images.

The system is trained on the DFU 4Class dataset that comprises different types of ulcers including none, infection, ischemia, and both. The framework offers high accuracy, generalization, and computational efficiency as achieved through standardization of preprocessing and optimized training methods, which is appropriate to be used in real-time or clinical applications.

### A. Objectives

- To come up with a single deep learning model that combines both YOLOv8 and U-Net to detect and segment DFUs at DFU.
- To obtain proper localization and boundary mapping of ulcer areas in different sample images.
- To facilitate early diagnosis and classification of severity of ulcers by use of standardized grading criteria.
- To maximize the model efficiency in clinical and research applications as well as minimum computational requirements.

## IV. METHODOLOGY

The suggested model will be a pipeline of deep learning modules, which will be implemented to treat Diabetic foot ulcers (DFUs) into segments, classifications, and automated

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detection. It is the procedure comprised of 6 significant modules as shown below.

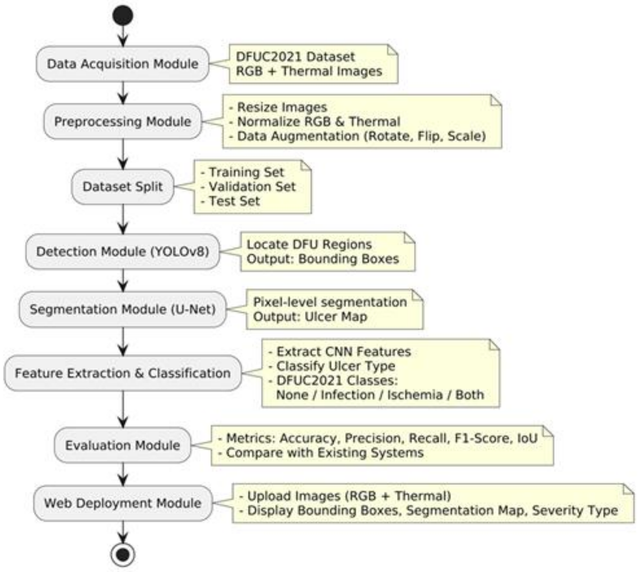


**Fig. 2.** Proposed Methodology for Diabetic Foot Ulcer Detection

### A. Data Acquisition

The data to be used in this attempt is the DFU_4Class data which embraces four distinct classes of ulcer severity according to the Wagner-Meggitt system which includes: Neither, Infection, Ischemia and Both. This data takes into consideration the RGB data as well as thermal foot images which offer a supplement of data in effective determination of ulcers. Photos will be made of different lighting, skin color, and appearance of ulcers in order to render the model powerful.

### B. Preprocessing

All the images are subjected to an equal preprocessing before training the models so that the uniformity of all images and higher learning efficiency are achieved.

- Resizing: The size of each image is reduced to the fixed size of 512x512 pixels.
- Normalization: The values of pixels are normalized to normal distribution in order to make the gradient change constant throughout the training process.
- Data augmentation: Data augmentation will involve rotation, flipping and scaling of data to enhance variance of the data and prevent overfitting.

### C. Dataset Split

The processed information is split into three:

Training Set: This is applied in order to train the U-Net and YOLOv8 models.

- Validation Set: This may be applied both to hyperparameter tune and to keep track of generalization by models.
- Test Set: This can be used to test how final models are performing on new information.

### D. Detection (YOLOv8)

The stage of detection is an application of the YOLOv8 model, which speedily and precisely locates the areas of ulcers in RGB and thermal images of the foot. YOLOv8 provides bounding boxes of the possible ulcer sites and also the confidence scores. This is the first step which is effective in the reduction of the area of interest to the other segmentation.

### E. Segmentation (U-Net)

The U-Net segmentation model is used to address the area detected with the assistance of YOLOv8 to get the appropriate boundaries of the ulcers. U-Net performs pixel-based segmentation in order to obtain an ulcer mask that informs about the precise shape and size of the wound. This will achieve precision in calculation of ulcer area and severity which is a major component of a clinical examination.

### F. Features Extraction and Classification

When the ulcers are segmented, CNN is used to obtain high-level texture and spatial features. They are applied in classifying each of the samples in the four levels of severity: None, Infection, Ischemia or Both.

Under this multi-class system, one can be able to diagnose and rank the treatments according to their severity in the early stages.

### G. Evaluation

Quantitative measures of performance of a model are common metrics that they include:

- Correctness - The sum total of agreement in classifications.
- Precision - Fraction of accurate samples that are called positive.
- Recall (Sensitivity) Ability to detect ulcer true positive.
- F1-Score - Pre and recall harmonic mean.
- Intersection over Union (IoU)- The intersection of the predicted and the ground-truth segmentation masks.
- It is as well compared to other state of art visual deep architecture learning systems to ensure that the performance is boosted.

### H. Web Development

The electronic interface is created in the form of a web-based interface to be practical and applicable in practice. The system is capable of capturing RGB pictures or thermal foot, which are uploaded by users and automatically scanned and identified. Bounding boxes, segmented ulcer area and predicted severity class are given in the interface, making it an easy and easy-to-use diagnostic tool.

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Volume 13 Issue 02 February 2026

## V. RESULTS AND DISCUSSIONS

### A. Preprocessing

The entire dataset of DFU was resized to 224x224 pixels in order to be compatible with deep learning. Horizontal and vertical flipping, rotation, zooming, and contrast adjustment are data augmentation methods that were used to enhance diversity in the dataset and avoid overfitting. Images were all normalized to a pixel range between [0, 1], before conversion to RGB so that all models could be consistent. Training, validation and testing then had separate directories, with the ratio being 80:10:10.

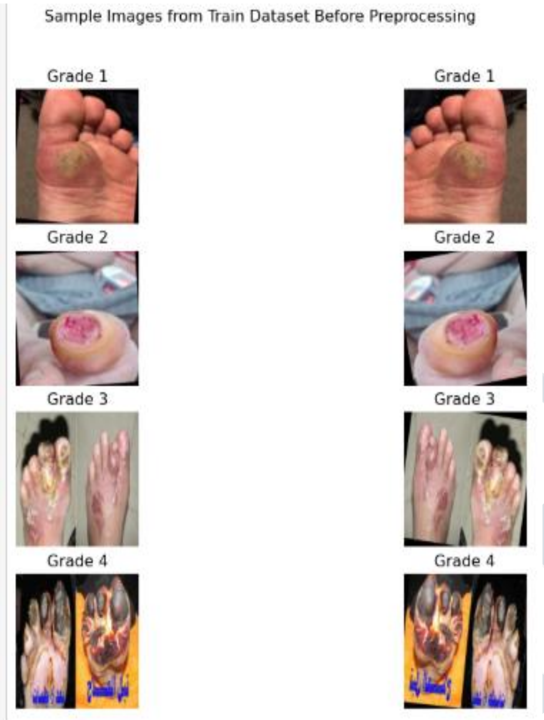


**Fig. 2.** Sample Images Before Preprocessing

```
--- TRAIN ---
Grade 1: 10875
Grade 2: 11121
Grade 3: 11883
Grade 4: 11045
Total images in train: 44924

--- VALID ---
Grade 1: 86
Grade 2: 78
Grade 3: 40
Grade 4: 78
Total images in valid: 282

--- TEST ---
Grade 1: 44
Grade 2: 37
Grade 3: 18
Grade 4: 42
Total images in test: 141

=== TOTAL IMAGES IN DATASET AFTER AUGMENTATION: 45347 ===
```

**Fig. 3.** Class Distribution Before/After Augmentation

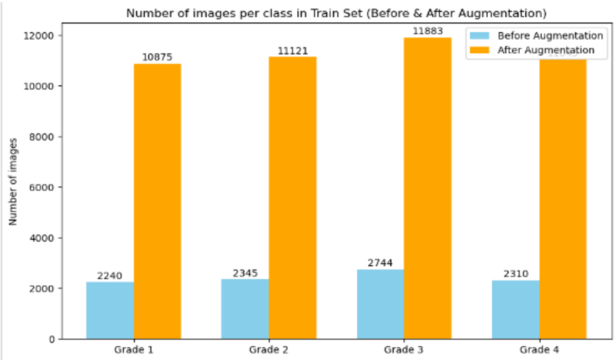


**Fig. 4.** Dataset Size After Augmentation

### B. Detection (YOLOv8)

The YOLOv8 model detects diabetic foot ulcer regions by producing accurate bounding boxes that box the infected areas which exist in both RGB and thermal images. The detection process creates two benefits through its ability to restrict the area of interest and its capacity to deliver exact location information which boosts the effectiveness of the upcoming segmentation work. The model shows strong ability to detect different types of ulcers which have distinct sizes and different visual characteristics.

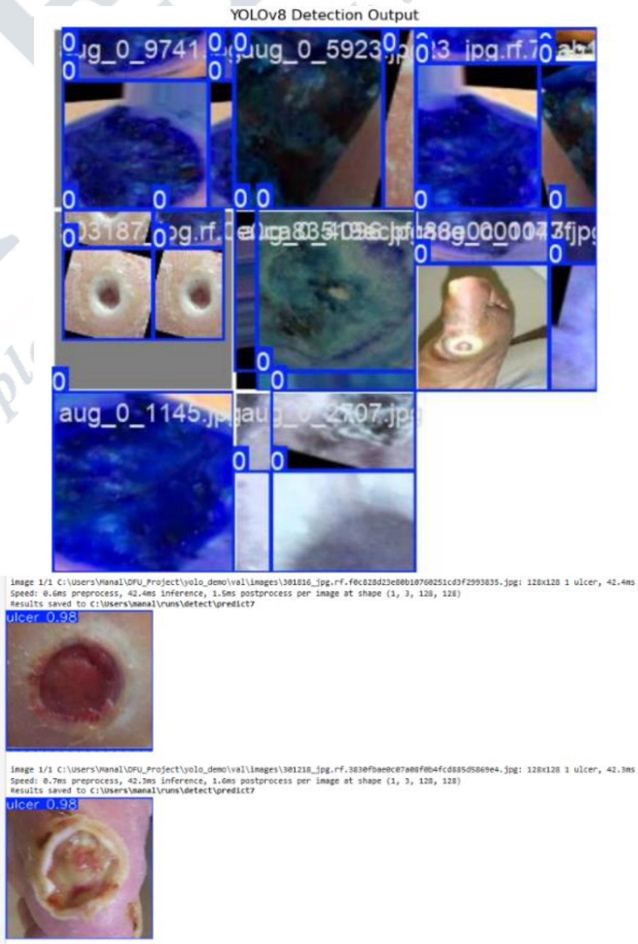


**Fig. 5.** YOLO model detection output on sample DFU image.

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Volume 13 Issue 02 February 2026

### C. Segmentation (U-Net)

The U-Net model uses pixel-based segmentation to precisely identify ulcer boundaries from the regions which it has detected. The segmentation results because of their resemblance to the ground truth masks represent a reliable boundary delineation. The segmentation process demonstrates its effectiveness through performance metrics which include Dice coefficient and IoU that show continuous growth.

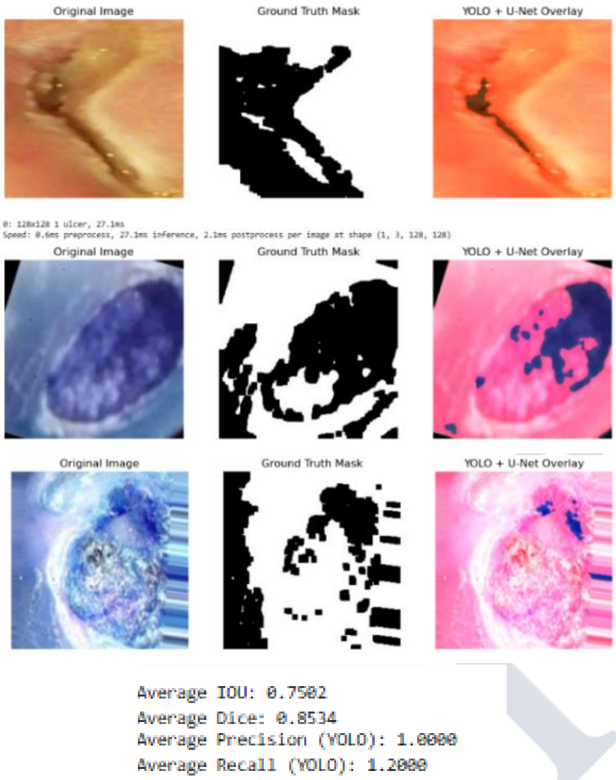


**Fig. 6.** Segmentation Output Example

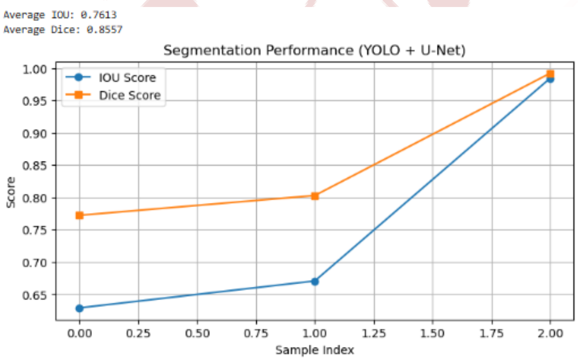


**Fig. 7.** Segmentation Performance Chart

### D. YOLO + U-Net Pipeline

The YOLOv8 and U-Net system combines quick detection capabilities with accurate segmentation results deliver complete ulcer assessment. YOLOv8 detects the ulcer area through its localization system while U-Net generates detailed segmentation masks to improve output results. The combination of these methods enhances the diagnostic accuracy allowing the clinician to diagnose an ulceration in its early stages.

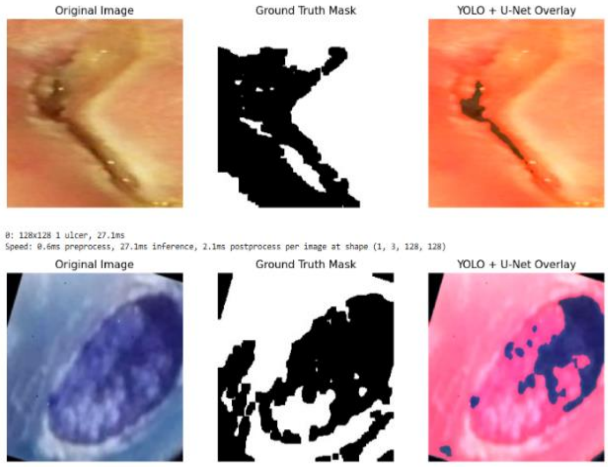


**Fig. 8.** Combined Detection and Segmentation

### E. Comparative Performance

To test the effectiveness of the modifications made to the system, a comparison analysis was done between the baseline system and the system with changes under the same conditions. The results show improvements made to the segmentation accuracy and are evident.

**Table 1.** Existing vs. Proposed System

| System | Description | Dice / Accuracy |
|---|---|---|
| **Existing System** | Standard U-Net (baseline, no augmentation) | **82.4%** |
| **Proposed System** | Optimized U-Net with augmentation | **85.6%** |

The projected model obtained 3.2% absolute improvements that further proved the efficacy of utilized training strategies on DFU segmentation.

## VI. CONCLUSION

This study proposes a deep learning-based solution to identify, segment, and classify Diabetic Foot Ulcers (DFUs) earlier. The proposed system is an effective means to address some of the limitations that have been mentioned in over 50 research papers reviewed, including dependence on human diagnosis, inaccuracy in the traditional machine learning methods, limited scalability of CNN-based systems, and the processing capacity of hybrid or sensor-based systems. With a fast ulcer localization by YOLOv8 and precise pixel-level segmentation by U-Net, the system offers a high detection velocity with accurate segmentation, which is why it is reliable and consistent in categorizing the severity of ulcers across a broad range of datasets.

The findings are enough to confirm that multiplexing detection and segmentation in an end-to-end pipeline can overcome the challenges of long ulcer boundaries, dynamic changes in lighting, and realistic variability of skin hue, which typically bedevil conventional approaches. The web-based hosting also and defeats the obstacle of accessibility and scalability, permitting the system to be accessible to the remote healthcare professionals and clinicians and does not require specific hardware.

**Future directions** are to integrate multimodal imaging information (e.g., thermal or infrared images) with it to facilitate a more robust detect, and to study more complicated deep learning models to provide better feature representation. Incorporating explainable deep learning techniques will lead to a more interpretable and clinician-confident model, and optimization of pipelines to be able to run in real-time on mobile devices will allow more extensive applications in telemedicine and in rural health settings. Besides, the dataset size can be increased and the data augmentation methods are more complex, which may also lead to improved generalization, class imbalance, and additional accuracy of classification.

Overall, the proposed framework presents an effective, precise, and scalable early DFU diagnosis system that has the potential to reduce the likelihood of delayed treatments, amputation causes, and patient outcomes by a significant margin. Use of effective detection, precise segmentation, and severity classification would be a sensible and clinical gain on the existing systems.

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