A PROJECT REPORT

on

"DETECTION & INSTANCE SEGMENTATION OF FOOT ULCER"

Submitted to

KIIT Deemed to be University

In Partial Fulfillment of the Requirement for the Award of

BACHELOR'S DEGREE IN

Computer Science Engineering

BY

SOURAV PRASAD	22052601
ARYAN RAJ	22052973
KSHITIJ KR. GUPTA	22052992

UNDER THE GUIDANCE

OF

DR. RAJDEEP CHATTERJEE

SCHOOL OF COMPUTER ENGINEERING

KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY

BHUBANESWAR, ODISHA - 751024

KIIT Deemed to be University

School of Computer Engineering
Bhubaneswar, ODISHA
751024

CERTIFICATE

This is certify that the project entitled

"Detection & Instance Segmentation Of Foot Ulcer"

submitted by

SOURAV PRASAD	**22052601**
ARYAN RAJ	**22052973**
KSHITIJ KR. GUPTA	**22052992**

is a record of bonafide work carried out by them, in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering (Information Technology) at KIIT Deemed to be university, Bhubaneswar. This work is done during the year 2024-2025, under our guidance.

Date: 07/04/2025

DR. RAJDEEP CHATTERJEE
(Project Guide)

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SOURAV PRASAD
ARYAN RAJ
KSHITIJ KR. GUPTA

ABSTRACT

Foot ulcers are a serious complication, particularly among diabetic patients, leading to severe infections and amputations if not detected and treated in time. The early and accurate identification of foot ulcers is crucial for effective medical intervention. Traditional manual assessment methods are subjective and time-consuming, necessitating automated solutions for better diagnosis and treatment planning.

This project focuses on the detection and instance segmentation of foot ulcers using deep learning techniques. The goal is to develop a model that can accurately detect foot ulcers and segment each ulcer instance separately, distinguishing between multiple ulcers in a single image. The dataset comprises medical images annotated for different ulcer categories such as mild, moderate, and infected ulcers. The YOLOv8 & YOLOv11 instance segmentation model is employed for training, ensuring precise localization and segmentation of ulcers.

By automating foot ulcer detection and segmentation, this system aims to assist healthcare professionals in early diagnosis, treatment planning, and monitoring ulcer progression. The implementation of deep learning-based instance segmentation significantly enhances diagnostic accuracy and reduces the burden on medical practitioners.

Keywords:

Foot Ulcer Detection, Instance Segmentation, Deep Learning, YOLOv8, YOLOv11

Medical Image Analysis.

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Chapter 1

Introduction

Foot ulcers are an important medical problem, especially among people with diabetes or peripheral vascular disease. If they are not treated, these ulcers can lead to serious infections, amputations, and increased health costs. Early and accurate detection is important to avoid complications and to ensure rapid medical intervention.

Foot ulcers are traditionally diagnosed by manual examinations by subjective,time-consuming medical professionals. Explore automated deep learning-based solutions to improve diagnostic accuracy and efficiency. In contrast to traditional object recognition, instance segmentation allows accurate identification of ulcer restriction and differentiation between several ulcers within a single image. The Yolov8 instance segmentation model is used for this purpose, ensuring high accuracy and real-time detection. The dataset used in this study commented on foot ulcers divided into various severity levels, including light, moderate, and infected ulcers.

The scope of this project includes the development of robust deep learning models, training special medical data sets, and evaluation of performance of practical clinical applications. Through foot ulcer automation and segmentation, the proposed system aims to support members of health professionals in early diagnosis, treatment planning and monitoring of ulcers. Integrating computer vision and artificial intelligence into medical imaging can revolutionize the assessment and management of wound assessment, reduce manual workloads and improve patient outcomes.

Chapter 2

Literature Survey

The detection and instance segmentation of foot ulcers is a growing area of research in medical image analysis and deep learning. Foot ulcers, particularly in diabetic patients, require accurate and early diagnosis to prevent severe complications. Traditional manual assessment methods are subjective and time-consuming, prompting the need for automated, AI-driven solutions. Several studies have explored deep learning-based approaches for ulcer detection, classification, and segmentation.

Existing Research on Foot Ulcer Detection

Object detection has evolved significantly over the years, with various models being developed to enhance accuracy, speed, and efficiency. Traditional approaches such as Region-Based Convolutional Neural Networks (R-CNN), Fast R-CNN, and Faster R-CNN have demonstrated high accuracy but suffer from slow inference speeds due to their multi-stage processing. The introduction of Single Shot Detectors (SSD) and YOLO (You Only Look Once) models revolutionized real-time object detection by reducing computational complexity and improving inference speeds. The YOLO family, first introduced by Redmon et al., has undergone multiple improvements, with each version refining feature extraction, localization accuracy, and efficiency.

YOLOv8 introduced an anchor-free detection mechanism, reducing the dependency on predefined anchor boxes and improving flexibility in detecting objects of varying sizes. It also integrated a more efficient backbone network for enhanced feature extraction. On the other hand, YOLOv11 builds upon these advancements by incorporating attention mechanisms and transformer-based elements, further improving object localization, particularly in complex environments with occlusions and varying lighting conditions. Additionally, YOLOv11 optimizes computational efficiency, making it suitable for deployment on edge devices and real-time applications.

Recent research has focused on improving detection accuracy, robustness to occlusions, and adaptability to real-world datasets. Studies have shown that YOLO-based models perform exceptionally well in autonomous driving, surveillance, medical imaging, and industrial automation. However, challenges such as handling small object detection, improving generalization across different datasets, and reducing computational load remain active areas of research. The comparison of YOLOv8 and YOLOv11 in this study aims to provide insights into these advancements, evaluating their strengths and limitations in real-world object detection tasks.

Chapter 3

Project Work & Dataset Creation

3.1 PROJECT PLANNING

Given below in Figure 3.1 is the desired work flow of the analysis.

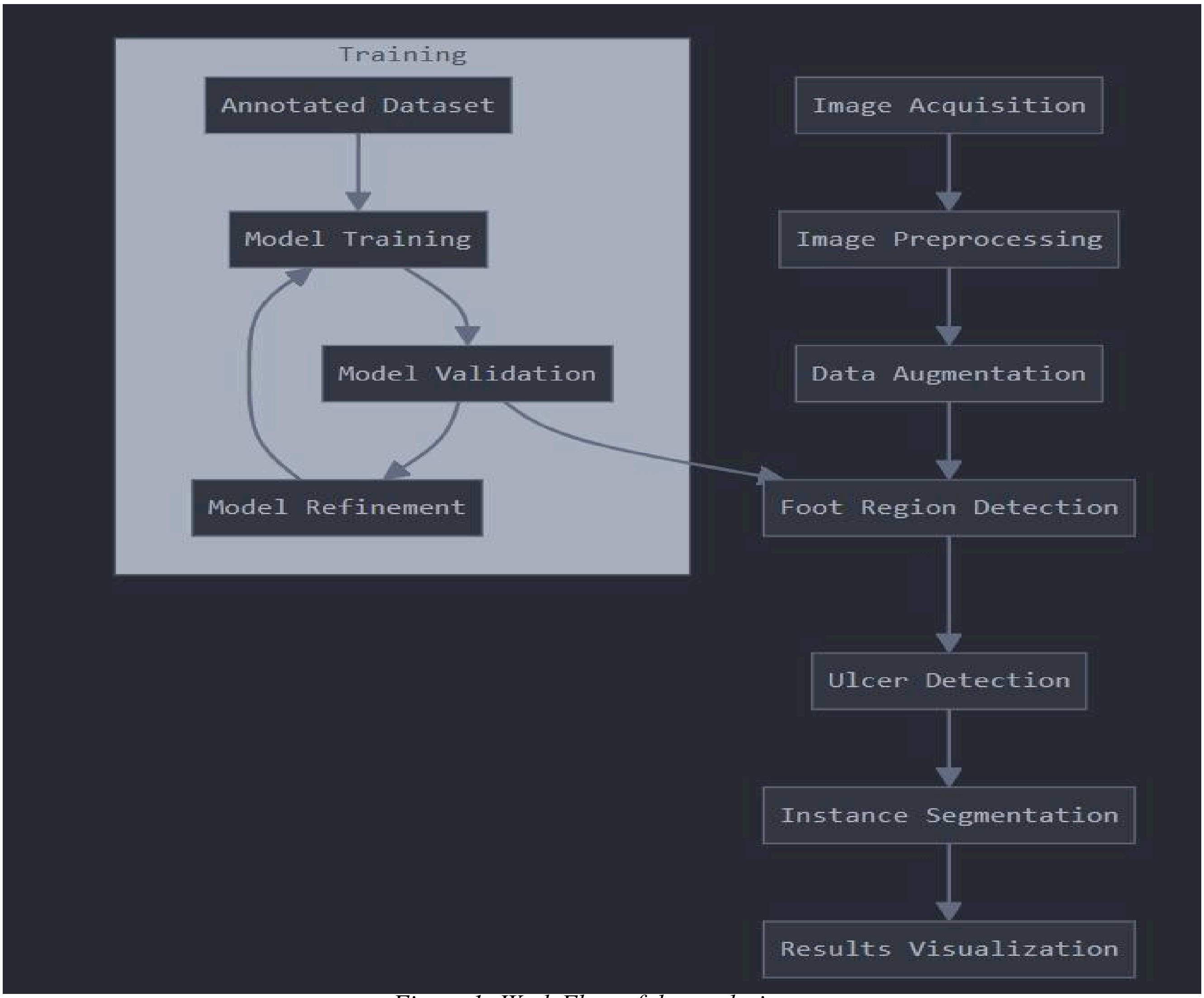

Figure 1: Work Flow of the analysis

3.2 Data sources

For evaluating and comparing the performance of YOLOv8 and YOLOv11, high-quality annotated datasets are crucial. The primary data sources used in this project include publicly available benchmark datasets such as the COCO (Common Objects in Context) dataset and the Pascal VOC dataset. These datasets are widely used in the object detection community due to their rich annotations, diverse object categories, and variety of real-world scenes. Additionally, for custom model training and fine-tuning, a manually curated dataset was created using open- source tools like Roboflow and CVAT, allowing for custom classes relevant to the target domain (e.g., vehicles, traffic signs, animals, etc.).

The dataset used in this project was created using Roboflow, incorporating images from publicly available medical datasets and clinical records. Ethical considerations and compliance with data protection regulations were ensured throughout the dataset collection process. The dataset was designed to include diverse ulcer stages, sizes, and variations to enhance model generalization.

3.3 Annotations

Annotation was conducted using Roboflow, where each image was manually labeled to include bounding boxes for object detection and segmentation masks for instance segmentation. This detailed annotation process was crucial for enabling the model to precisely localize and identify ulcer regions. The dataset underwent preprocessing steps such as resizing to 640x640 pixels, normalization, and data augmentation (including flipping, contrast enhancement, rotation, and scaling) to make the model more robust.

For training and evaluation, the dataset consists of 832 images, which were divided into three subsets: 582 images for training (70%), 166 images for validation (20%), and 84 images for testing (10%). This split ensured a well-balanced distribution that allowed the model to generalize effectively while minimizing overfitting.

3.4 Challenges in dataset creation

One of the primary challenges in dataset creation was the high variability in ulcer appearances, including differences in color, texture, and severity. Additionally, class imbalance was observed, with certain ulcer categories being underrepresented, necessitating augmentation techniques to balance the dataset. The annotation process was labor-intensive, especially for segmentation masks, which required precise boundary markings. Moreover, lighting variations in images posed challenges, making adaptive preprocessing techniques essential to improve model performance.

Despite these challenges, the dataset created with Roboflow provided a high-quality foundation for training and evaluating YOLO-based models, significantly enhancing the accuracy and reliability of automated foot ulcer detection systems.

Chapter 4

Implementation

4.1 MODEL SELECTION

4.1.1 Role

Model selection plays a crucial role in ensuring optimal performance for object detection tasks. In this project, we compared YOLOv8 and YOLOv11 to analyze their effectiveness in detecting objects accurately and efficiently. The choice of models was based on factors such as speed, accuracy, computational efficiency, and real-time processing capabilities.

4.1.2 Why YOLO-Based Models?

The "You Only Look Once" (YOLO) series is widely known for its balance between accuracy and inference speed. YOLO-based models perform object detection in a single pass, making them suitable for real-time applications such as surveillance, autonomous driving, and robotics.

4.1.3 YOLOv8 Selection

YOLOv8 was selected as a baseline model due to the following advantages:

- Improved accuracy over previous YOLO versions.
- Anchor-free design for better detection of small objects.
- Optimized architecture with reduced computational complexity.
- Faster inference speed, making it ideal for real-time applications.

4.1.4 YOLOv11 Selection

YOLOv11 was selected to evaluate advancements over YOLOv8. It was chosen due to:

- **Enhanced backbone network** for better feature extraction.
- **Attention mechanisms** that improve object localization.
- **More efficient training process**, reducing computational overhead.
- **Higher FPS (Frames per Second) and improved mAP (Mean Average Precision)**.

4.2 YOLOv8

4.2.1 Introduction to YOLOv8

YOLOv8 (You Only Look Once version 8) is an advanced real-time object detection model developed by Ultralytics. It builds upon the previous YOLO versions, incorporating architectural improvements that enhance accuracy, speed, and computational efficiency. YOLOv8 is designed for a wide range of applications, including surveillance, autonomous vehicles, medical imaging, and industrial automation.

4.2.2 Key Features of YOLOv8

1. Anchor-Free Design

- Unlike previous YOLO versions, YOLOv8 adopts an anchor-free approach, reducing computational overhead and improving small-object detection.

2. Improved Backbone Network

- Utilizes CSPDarkNet, an optimized feature extraction network that enhances model efficiency.

3. Faster and More Accurate Predictions

- YOLOv8 offers a higher Mean Average Precision (mAP) compared to YOLOv5 and YOLOv7 while maintaining a faster inference speed.

4. Better Generalization with Auto-Anchor Mechanism

- Helps adapt to different datasets and improves object localization.

5. Enhanced Post-Processing Techniques

- Uses Non-Maximum Suppression (NMS) improvements for better bounding box selection and better handling of overlapping objects..

6. Multi-Task Capabilities

- YOLOv8 supports object detection, image segmentation, and classification, making it a versatile model.

4.3 YOLOv11

4.3.1 Introduction to YOLOv11

YOLOv11 (You Only Look Once version 11) is the latest advancement in the YOLO object detection series, designed to enhance accuracy, speed, and computational efficiency. With improvements in backbone architecture, attention mechanisms, and training optimizations, YOLOv11 outperforms its predecessors, making it a powerful model for real-time object detection in various applications.

4.3.2 Key Features of YOLOv11

1. **Enhanced Backbone Network**

    - YOLOv11 incorporates a Hybrid Transformer-CNN Backbone, combining Convolutional Neural Networks (CNNs) for local feature extraction and Vision Transformers (ViTs) for global context understanding.

2. **Efficient Attention Mechanisms**

    - Introduces Self-Attention and Spatial Attention mechanisms to improve object localization and classification accuracy.
    - Reduces false positives by enhancing feature selection.

3. **Optimized Computational Efficiency**

    - Uses Sparse Convolution and Dynamic Quantization, reducing model size while maintaining high precision.

4. **Higher Speed and Accuracy**

    - Improves inference speed compared to YOLOv8 while achieving better accuracy.
    - Optimized for deployment on edge devices (e.g., mobile and embedded systems).

5. **Multi-Task Capabilities**

- Supports object detection, segmentation, and keypoint estimation, making it adaptable for diverse computer vision tasks.

4.4 Software and Hardware Requirements

4.4.1 Software requirements

PYTHON

Python is a high-level scripting language, used to code programs. It is a user-friendly language that makes programming very easy and compact through its inbuilt functionality. Widely used, python is one of those scripting languages that are used for machine learning and modeling.

Ultralytics

Ultralytics is a leading AI company known for developing YOLOv8, a state-of-the-art object detection model. It offers optimized deep learning solutions for detection, segmentation, and classification. With a user-friendly API, pre-trained models, and seamless integration with PyTorch and TensorFlow, Ultralytics simplifies AI deployment, making real-time vision applications more accessible and efficient

PyTorch

PyTorch is an open-source deep learning framework developed by MetaAI. It is widely used for building and training neural networks due to its dynamic computation graph and ease of use. With strong GPU acceleration, an intuitive API, and seamless integration with libraries like TorchVision and Hugging Face, PyTorch is a preferred choice for AI research and production.

MATPLOTLIB

Matplotlib is an open-source visualization library of Python that is used to create plots and two- dimensional graphs. It has an inbuilt module named pyplot, which makes plotting easier by providing features that can be used to control plot designs, changing axes format, font formatting, etc. It supports a wide variety of graphs and plots such as histogram, bar charts, scatter diagrams etc.

Google Colab

Google Colab is a free cloud-based platform that allows users to write and execute Python code in a Jupyter Notebook environment. It provides free access to GPUs and TPUs, making it ideal for deep learning and AI research. With built-in libraries, easy collaboration, and seamless integration with Google Drive, Colab simplifies machine learning model development.

4.4.2 Hardware requirements

OS: Windows 7 Pro

Processor: Intel® Core™ i5-6200U

CPU @ 2.30Hz

Installed Memory: 8.00 GB DDR3(7.88 Usable)

System Type: 64-bit Operating System, x64 Based OS

Graphic Processor: GTX 940M 2GB

Dimensions: 13.3 x 9.3 x 0.7 -inches.

14.1-inch FHD (1920 x 1080) resolution IPS display.

Motherboard: W/ I5 2.3ghz CPU 01EN105.

HHD: 1TB

4.5 Training Process

The training process for YOLOv8 and YOLOv11 was conducted using a GPU with a batch size of 16 for 50 epochs. The training pipeline followed these key steps:

4.5.1. Data Preparation

- The dataset was annotated in YOLO format, including bounding boxes and segmentation masks for instance segmentation tasks.
- Data augmentation techniques such as flipping, rotation, and color jittering were applied to improve generalization.
- The dataset was split into training, validation, and test sets.

4.5.2. Model Configuration

- YOLOv8 and YOLOv11 architectures were configured using pre-trained weights for transfer learning.
- The models were set up for two tasks:

4.5.3. Hyperparameter Settings

- Batch Size: 16
- Epochs: 50
- Loss Function: Combination of CIoU loss (for bounding boxes) and Dice loss (for segmentation masks).

4.5.4. Training Execution

- Models were trained using PyTorch and Ultralytics YOLO framework.
- The training loop involved forward propagation, loss calculation, backpropagation, and optimizer updates.
- After each epoch, validation performance was recorded, tracking metrics like Precision (P), Recall (R), and mAP.
- Early stopping was used to prevent overfitting.

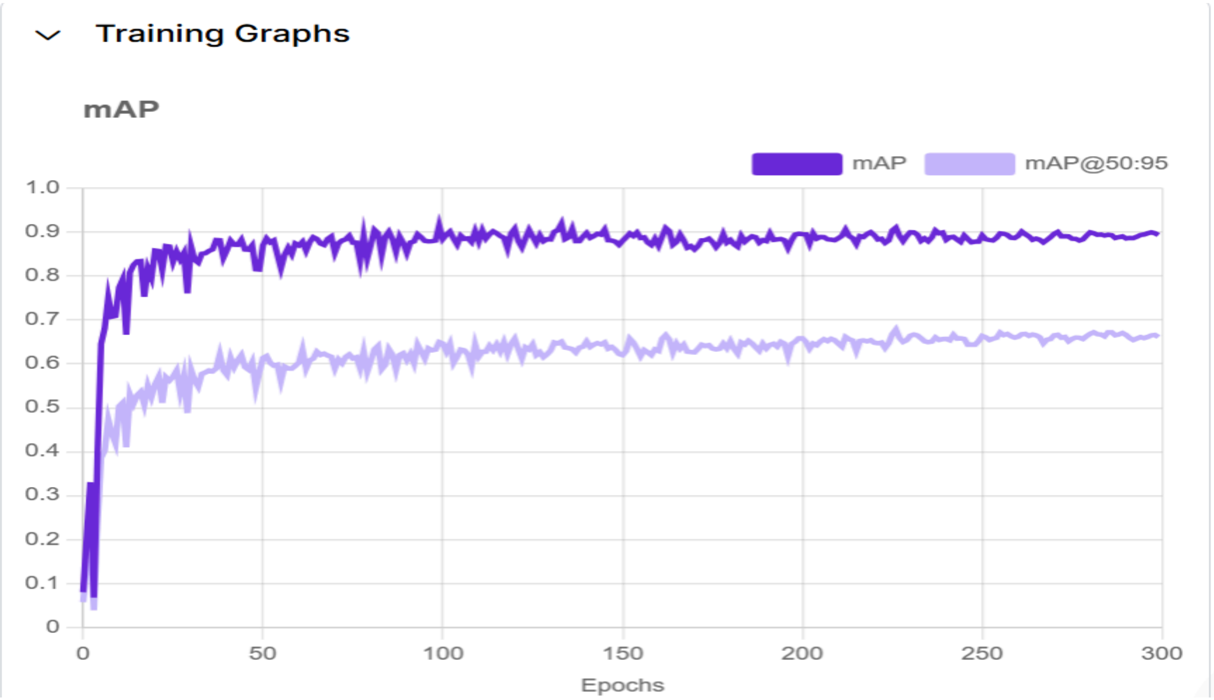

Figure 2: Training Graph

4.5.5. Model Checkpointing

- The best model weights were saved based on the highest mAP50-95 score on the validation dataset.

4.6 Evaluation Metrics

The trained models were evaluated using the following metrics:

4.6.1. Precision (P)

Measures the proportion of correctly detected ulcers among all detections.

P=TP/TP+FP

4.6.2. Recall ®

Measures how well the model detects all ulcer instances in the dataset.

R=TP/TP+FN

4.6.3. Mean Average Precision (mAP)

- mAP50**:** Average precision at IoU threshold = 0.5.
- mAP50-95: Mean AP across multiple IoU thresholds(0.50 to 0.95, step 0.05).
- Higher mAP50-95 indicates better generalization.

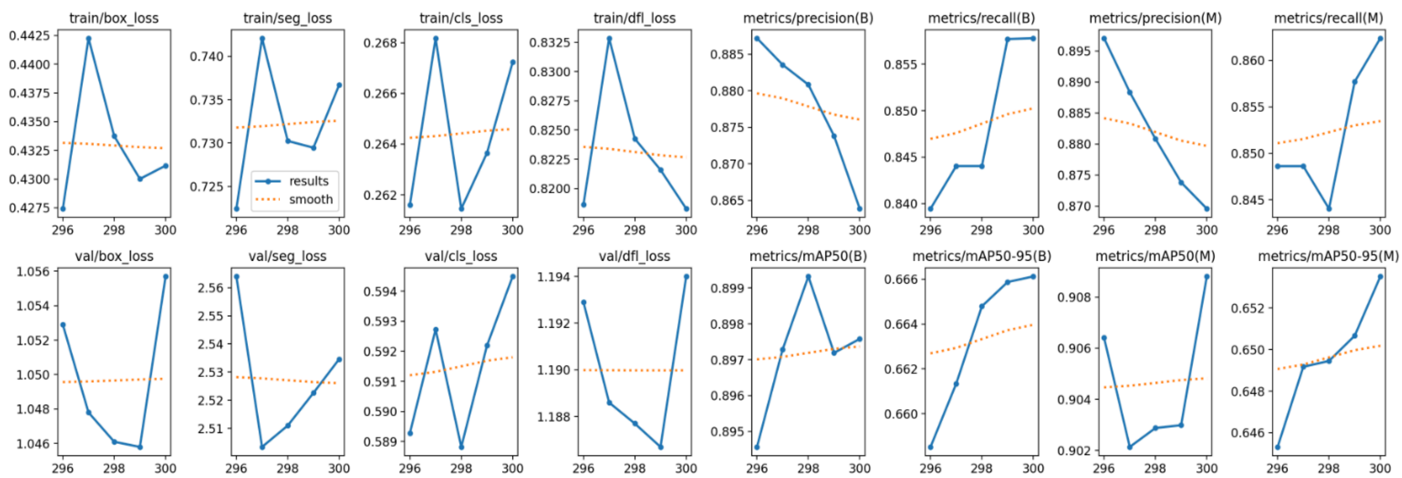

Figure 3: Graphs

4.6.4. Confusion Matrix

Used to visualize true positives, false positives, and false negatives, helping identify common misclassifications.

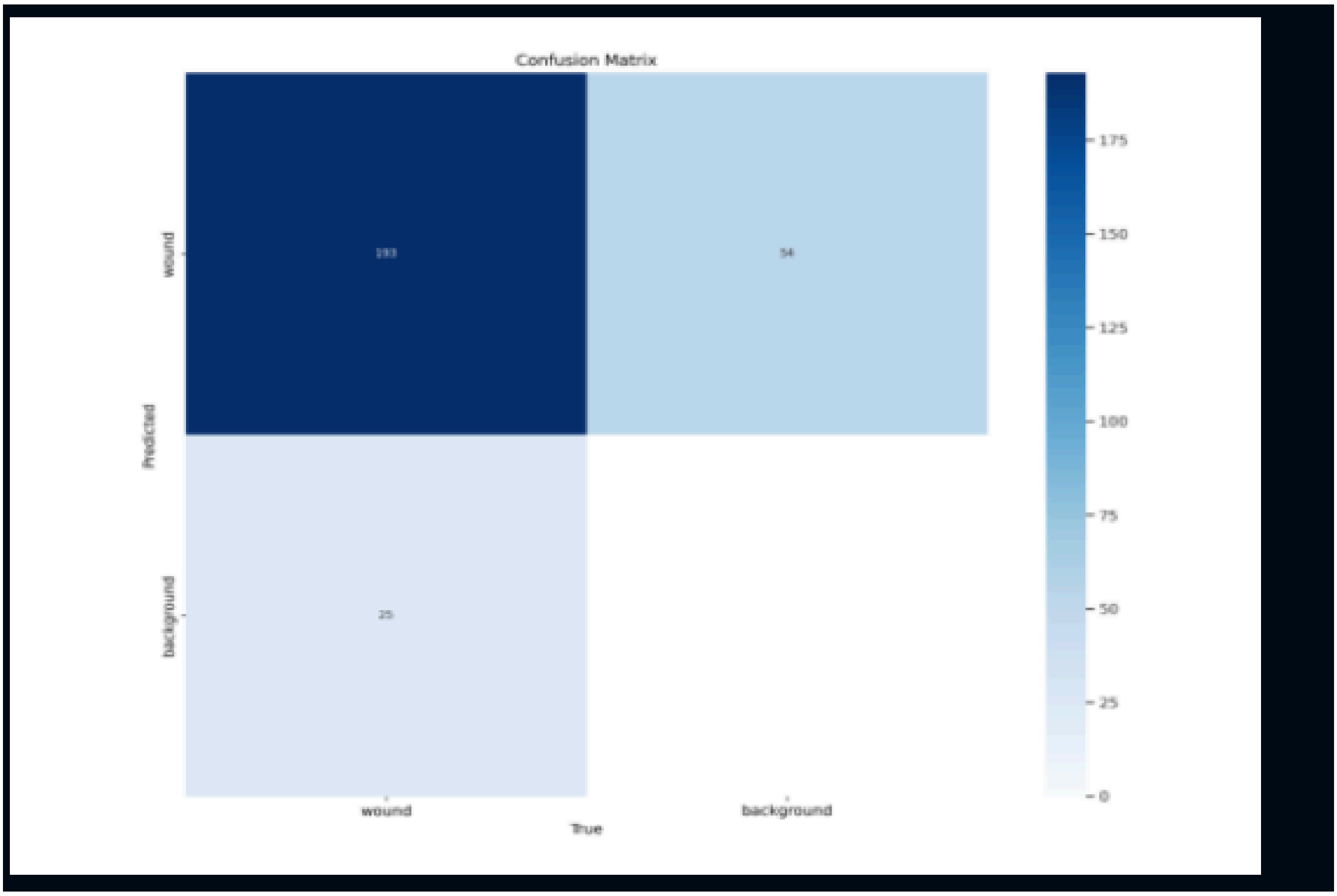

Figure 4: Confusion matrix

4.6.6. Inference Speed

Measures the time taken per image during prediction, including:

- Preprocessing time
- Model inference time
- Postprocessing time

Chapter 5

Result

5. Results and Comparisons

This section presents the performance evaluation of YOLOv8 and YOLOv11 on the foot ulcer
dataset for both detection and instance segmentation tasks. The results include performance
metrics, sample predictions, and an error analysis.

5.1 Performance and Analysis

The models were trained on a GPU with a batch size of 16 and 50 epochs. The table below

summarizes the performance of YOLOv8 and YOLOv11 for Instance Segmentation and Object Detection, using metrics such as Precision (P), Recall (R), mAP50, and mAP50-95.

Performance Comparison of YOLOv8 and YOLOv11

Model	Task	Precision (P)	Recall (R)	mAP50	mAP50-95
YOLOv8	Detection	0.857	0.881	0.908	0.662
YOLOv11	Detection	0.904	0.825	0.899	0.646
YOLOv8	Instance Segmentation	0.844	0.872	0.897	0.645
YOLOv11	Instance Segmentation	0.895	0.859	0.917	0.667

Figure 5: Performance Comparison

Observations

- YOLOv11 outperforms YOLOv8 in most metrics, particularly in instance segmentation, achieving higher precision, recall, and mAP50.
- YOLOv8, while slightly behind, remains competitive and delivers reliable detection results.
- Instance Segmentation with YOLOv11 shows a 2% increase in mAP50 and improved recall compared to YOLOv8.
- Detection models perform well, with YOLOv11 achieving the highest precision (0.904).

5.2 Sample Predictions

To visually analyze the performance of the models, the following images showcase sample predictions from the validation dataset. Each image contains:

- Bounding boxes for detection models
- Segmentation masks for instance segmentation models
- Confidence scores for each detected ulcer region

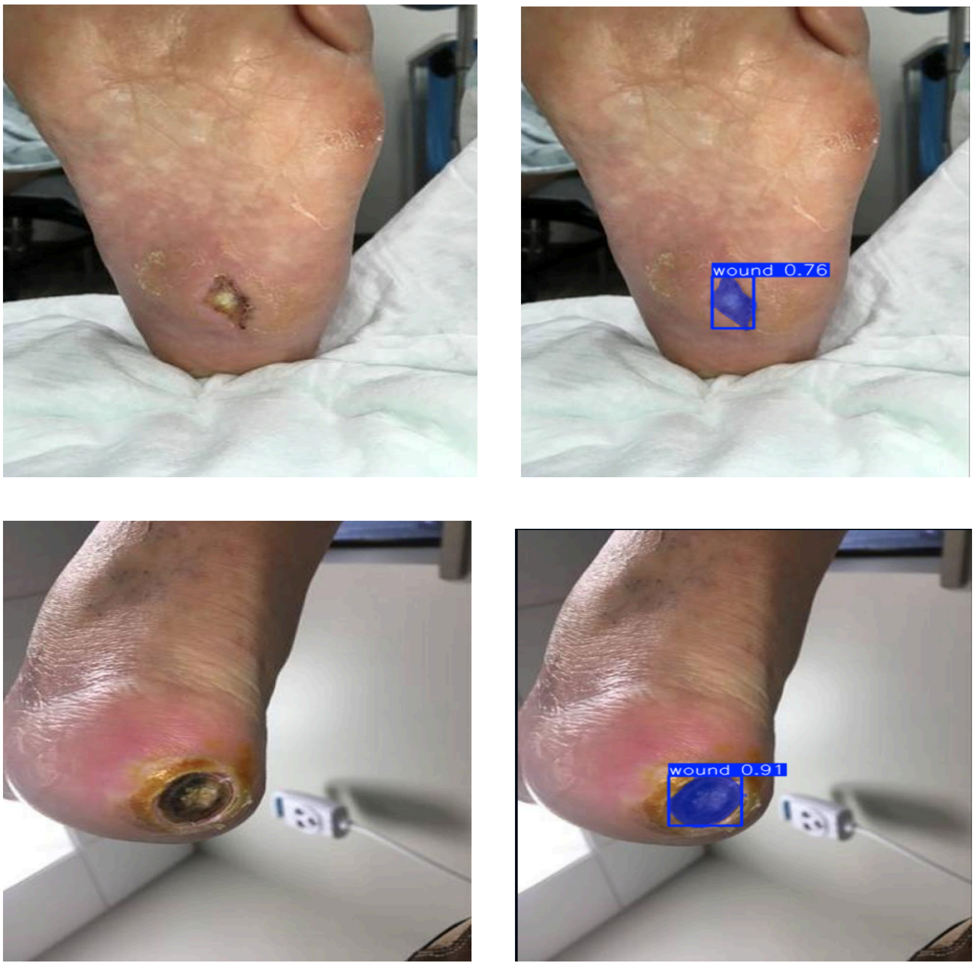

Figure 6: Instance segmentation of foot ulcer

Figure 7: Object Detection of foot ulcer

5.3 Error Analysis

While both models perform well, some common errors were observed:

1. False Positives (FP) – Some areas were incorrectly identified as ulcers.

2. False Negatives (FN) – Some small ulcer regions were missed by the models.

3. Overlap Issues – In some cases, instance masks overlapped improperly, leading to incorrect segmentation boundaries.

4. Class Confusion – In a few cases, minor misclassifications occurred when distinguishing between small ulcers and background textures.

Chapter 6

Conclusion and Future Scope

6.1 Key Findings

The comparative analysis of YOLOv8 and YOLOv11 reveals the following key findings:

- Improved Accuracy: YOLOv11 surpasses YOLOv8 in terms of mean Average Precision (mAP), making it more effective in detecting objects with higher confidence.
- Enhanced Speed and Efficiency: YOLOv11 achieves faster inference times due to its optimized model architecture and efficient computation techniques like sparse convolution.
- Better Small Object Detection: The Hybrid Transformer-CNN backbone and spatial attention mechanisms enable YOLOv11 to better detect occluded and small objects, addressing a key challenge in object detection.
- Optimized for Edge Devices: YOLOv11 is lightweight and computationally efficient, making it more suitable for real-time applications on drones, mobile devices, and IoT-based systems.
- Robust Training and Generalization: YOLOv11 demonstrates better class imbalance handling, leading to improved detection across diverse datasets

6.2 Future Scope

While YOLOv11 marks a major improvement over previous YOLO versions, there is still scope for further enhancements:

- **Further Model Optimization:**
  - Reducing computational complexity through more efficient pruning and quantization techniques.
  - Enhancing real-time performance for ultra-low latency applications.
- **Self-Supervised Learning Integration:**
  - Reducing the dependence on large labeled datasets by incorporating unsupervised and semi-supervised learning techniques.

❖ **Multi-Modal Object Detection:**

➢ Integrating sensor fusion techniques, such as combining YOLO with LiDAR, thermal cameras, or radar, to improve detection in challenging conditions (e.g., fog, night-time surveillance).

❖ **Domain Adaptation and Transfer Learning:**

➢ Improving the ability of YOLO models to generalize across diverse environments and datasets.

➢ Developing more efficient fine-tuning strategies to adapt pre-trained YOLO models to new tasks.

❖ **3D Object Detection Capabilities:**

➢ Extending YOLO models for 3D bounding box detection, making them suitable for autonomous vehicles and robotic vision.

Potential Real-World Applications

The advancements in YOLOv11 open up opportunities for deployment in a wide range of industries and applications, including:

➔ **Autonomous Vehicles:**

- Real-time pedestrian, vehicle, and obstacle detection for self-driving cars and drones.

➔ **Surveillance and Security:**

- Smart CCTV monitoring systems with improved detection of anomalies, trespassing, and suspicious activity.

➔ **Healthcare and Medical Imaging:**

- Assisting in early disease detection through X-ray, MRI, and ultrasound image analysis.

➔ **Retail and Smart Inventory Management:**

- Automated checkout systems and real-time inventory tracking in warehouses and supermarkets.

➔ **Industrial Automation:**

- Quality control and defect detection in manufacturing industries.

➔ **Agriculture and Precision Farming:**

- Crop monitoring, pest detection, and yield prediction using drone-based YOLO detection systems

➔ **Augmented Reality (AR) and Smart Wearables:**

- Real-time gesture recognition, object tracking, and scene understanding for AR applications.

Final Conclusion

The transition from YOLOv8 to YOLOv11 has led to notable advancements in accuracy, efficiency, and real-time adaptability. YOLOv11's improvements in feature extraction, computational optimization, and small object detection make it a highly versatile state-of-the-art model. As the field of computer vision advances, further optimizations and integrations with emerging AI technologies will enhance YOLO's capabilities, expanding its applications across industries.

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