**CHAPTER – 1**

**PREAMBLE**

**1.1** **PROBLEM STATEMENT**

Accurately detecting wheat leaf diseases in outdoor field photos remains a significant challenge due to several factors. These include visual complexities such as overlapping plants, wind-induced blur, and difficulty distinguishing individual wheat heads, making disease identification difficult. Moreover, wheat variability presents another obstacle, as disease symptoms can change based on maturity, color, genetics, and head orientation. Additionally, global farming practices contribute to the complexity, as wheat is grown worldwide under diverse planting densities, patterns, and environmental conditions. Current methods often struggle to cope with such variations.

**1.2 SOLUTION**

To tackle the challenges associated with accurately detecting wheat leaf diseases in outdoor field photos, we propose the development of a wheat leaf disease detection system using the YOLOv8 instance segmentation algorithm as a web application. This solution offers several key advantages. Leveraging the YOLOv8 instance segmentation algorithm enhances accuracy by precisely delineating individual plant heads and disease-infected regions within crop canopies. Furthermore, the instance segmentation approach enables the system to handle visual complexities such as overlapping plants and wind-induced blur more effectively, thereby enhancing the robustness of disease detection. By training the model on a diverse dataset encompassing variations in wheat maturity, colour, genetics, and head orientation, the system becomes better equipped to recognize disease symptoms across different scenarios. The web-based nature of the application ensures global applicability, allowing farmers worldwide to access the system regardless of geographical location or farming practices, thus facilitating widespread adoption and utilization. Through the web interface, farmers can upload field photos and receive real-time disease diagnosis results, enabling timely intervention and management strategies to mitigate crop losses.

**1.3 OBJECTIVES**

* Develop a user-friendly web application integrating YOLOv8 instance segmentation for precise wheat leaf disease diagnosis in field images.
* Ensure accessibility by creating an intuitive interface suitable for farmers and researchers worldwide, regardless of technical proficiency.
* Utilize YOLOv8 to accurately identify and segment various wheat leaf diseases within uploaded images, prioritizing accuracy in disease detection.
* Streamline the image upload process to enhance data entry efficiency, minimizing errors and simplifying user interactions.
* Exploring the possibility of integrating real-time disease monitoring capabilities and deploying the web application on mobile platforms for field use.
* Design the system with scalability and integration in mind to accommodate future growth.

**1.4 ADVANTAGES**

* YOLOv8 enables accurate and real-time identification of wheat leaf diseases with precise delineation of affected areas, allowing for timely intervention and mitigation of crop losses.
* The web application provides global accessibility, allowing farmers and researchers from diverse geographical locations to benefit from early disease detection and implement effective crop management strategies, thus contributing to increased food security.
* The user-friendly interface simplifies disease detection for users of varying technical expertise, ensuring that even those with limited computational knowledge can easily utilize the system to monitor their crops and make informed decisions.
* Data insights gained from the system offer valuable information on regional disease patterns, enabling researchers to identify emerging trends, develop targeted interventions, and improve overall crop health and productivity.

**1.5 LITERATURE SURVEY**

[1] **Title**: Evaluating the Single-Shot MultiBox Detector and YOLO Deep Learning Models for the Detection of Tomatoes in a Greenhouse.

**Authors**: Sandro Augusto Magalhães and Luís Castro

**Published**: 26 June 2021

**Description**: In this study, the researchers select, train, and benchmark five deep learning models to detect green and reddish tomatoes in greenhouse environments. Specifically, they consider the Single-Shot MultiBox Detector (SSD) and YOLO architectures, aligning with the specifications of their robotic platform. Results demonstrate the system's capability to detect tomatoes even when occluded by leaves. SSD MobileNet v2 emerges as the top performer, surpassing SSD Inception v2, SSD ResNet 50, SSD ResNet 101, and YOLOv4 Tiny, achieving an F1-score of 66.15% and a mean Average Precision (mAP) of 51.46%. Furthermore, the system exhibits an inference time of 16.44ms on the NVIDIA Turing Architecture platform, specifically utilizing an NVIDIA Tesla T4 with 12 GB of memory. Despite SSD MobileNet v2's success, YOLOv4 Tiny also demonstrates impressive results, particularly regarding inference times, averaging around 5 ms. This comprehensive exploration sheds light on the potential of deep learning models for enhancing robotic capabilities in agricultural settings, particularly in the context of tomato harvesting.

[2] **Title**: Path Aggregation Network for Instance Segmentation.

**Authors**: Shu Liu, Lu Qi and Haifang Qin

**Published**: 23 June 2018

**Description**: This study explores the importance of information propagation in neural networks, focusing on proposal-based instance segmentation frameworks. The paper introduces the Path Aggregation Network (PANet) with the aim of improving information flow and segmentation accuracy. PANet achieves this by augmenting lower layers with accurate localization signals, shortening the information path between lower layers and the topmost feature. Additionally, it introduces adaptive feature pooling to connect feature grids and all levels, allowing useful information to propagate directly to subsequent proposal subnetworks. Furthermore, a complementary branch is added to capture different views for each proposal, enhancing mask prediction. Despite its simplicity and minimal computational overhead, PANet achieves remarkable results, ranking 1st in the COCO 2017 Challenge Instance Segmentation task and 2nd in the Object Detection task, and remains state-of-the-art on datasets like MVD and Cityscapes. This study underscores PANet's efficacy in advancing instance segmentation and object detection capabilities within neural networks. This literature survey explores the importance of information propagation in neural networks, focusing on proposal-based instance segmentation frameworks. The paper introduces the Path Aggregation Network (PANet) with the aim of improving information flow and segmentation accuracy. PANet achieves this by augmenting lower layers with accurate localization signals, shortening the information path between lower layers and the topmost feature.

[3] **Title**: YOLACT: Real-Time Instance Segmentation.

**Authors**: Daniel Bolya and Chong Zhou

**Published**: 27 October 2019

**Description**: In this study, we introduce a straightforward, fully-convolutional model for real-time instance segmentation, achieving a mean Average Precision (mAP) of 29.8 on the MS COCO dataset at 33.5 frames per second (fps) when evaluated on a single Titan Xp GPU. This speed surpasses that of any previous competitive approach. Notably, we attain this performance using only one GPU for training. Our method involves dividing instance segmentation into two parallel subtasks: (1) generating a set of prototype masks, and (2) predicting per-instance mask coefficients. Instance masks are then produced by linearly combining the prototypes with the mask coefficients. This process, which does not rely on repooling, yields high-quality masks and demonstrates temporal stability. Additionally, we examine the behavior of our prototypes, finding that they autonomously learn to localize instances in a translation variant manner, despite being fully-convolutional.

[4] **Title**: A Single-Stage Object Detection Framework for Industrial Applications.

**Authors**: Chuyi Li and Lulu Li

**Published**: 26 June 2022

**Description**: In this technical paper, we explore advancements in object detection, aiming to elevate the YOLO series to new heights for industry application. Recognizing the diverse demands for speed and accuracy in real-world scenarios, we thoroughly investigate recent developments in network design, training strategies, testing techniques, quantization, and optimization methods from both industry and academia. Drawing upon these insights, we integrate our own innovations to develop a suite of deployment-ready networks at various scales, catering to a wide range of use cases. With permission from the YOLO authors, we introduce YOLOv8 and extend a warm invitation to users and contributors for further enhancement.

[5] **Title**: A Single-Stage Object Detection Framework for Industrial Applications.

**Authors**: Xu, B., Cui, X., Ji, W., Hao, Y., & Wang, J

**Published**: 26 June 2023

**Description**: This paper by Xu et al. (2023) focuses on designing and implementing an automated apple grading system using a deep learning model. The system leverages an improved version of the YOLOv5 object detection model to identify defects and classify the size of apples in images captured during the grading process. The improved YOLOv5 model is trained to detect and classify apple defects like bruises, cracks, and insect bites. Additionally, the model estimates the size of the apples based on pixel measurements within the image. The paper details the design and implementation process of the automatic apple grading system. The system demonstrates promising results in accurately identifying defects, classifying apple size, and achieving efficient apple grading compared to traditional manual methods.

**CHAPTER – 2**

**SOFTWARE REQUIREMENT SPECIFICATION**

**2.1 FUNCTIONAL OVERVIEW**

The wheat leaf disease diagnosis system is a web application designed to assist users in identifying diseases in their wheat crops using the YOLOv8 instance segmentation algorithm. Here's how it works:

* **Image Upload**: Users can upload images of their wheat crops through the application interface.
* **Automatic Segmentation**: The YOLOv8 instance segmentation algorithm automatically processes the uploaded images to perform the following tasks:
  + Segment individual wheat plants within the image.
  + Analyze each plant to identify and segment any diseased regions.
* **Presentation of Results**: The results are presented on a user-friendly interface, which includes:
  + Bounding boxes around detected wheat plants to indicate their location in the image.
  + Segmented masks overlaying the original image, indicating diseased areas within each plant.
  + Optional disease classification if the model is trained to identify specific diseases, providing additional insights into the detected issues.

**2.2 USER CHARCTERSTICS/ROLES**

The primary target users of the wheat leaf disease diagnosis system are farmers who cultivate wheat crops. Their roles and characteristics include:

* Typically have varying levels of technical expertise.
* Regularly monitor the health of their wheat crops to ensure optimal growth and yield.
* Seek efficient and reliable tools to identify and manage diseases affecting their crops.
* Value user-friendly interfaces that simplify the process of accessing and interpreting diagnostic results.
* Use the application to make informed decisions about crop management practices, such as implementing timely interventions and treatments.

**2.3 INPUT REQUIREMENTS**

**2.3.1 SERVER SIDE**

* **Storage of YOLOv8 Model Files**: The server will store the YOLOv8 model files, including configuration files and associated weights, necessary for performing instance segmentation on uploaded images of wheat crops.
* **Secure Storage of User-Uploaded Images**: The server will securely store images uploaded by users, ensuring data privacy and integrity throughout the processing pipeline. This may involve implementing robust storage solutions with appropriate access controls and encryption mechanisms.

**2.3.2 CLIENT SIDE**

* **Image Upload Interface**: The client-side application should provide users with a user-friendly interface for uploading images of wheat crops. This interface should support common image formats such as JPEG and PNG and include features like drag-and-drop functionality and file selection dialogs.
* **Compatibility with YOLOv8 Model Requirements**: The client-side application should ensure that uploaded images meet the input requirements of the YOLOv8 model. This may involve enforcing restrictions on image size and format to ensure seamless processing by the server-side instance segmentation algorithm.

**2.4 OUTPUT REQUIREMENTS**

**2.4.1 CRITICAL INFORMATION**

* **Display of Original Uploaded Image**: The application should display the original uploaded image overlaid with bounding boxes around detected wheat plants, providing users with visual confirmation of the detected regions.
* **Color-Coded Segmentation Mask**: A color-coded segmentation mask should be displayed on top of each plant, clearly indicating healthy and diseased regions within the crop, aiding users in identifying and assessing the extent of disease presence.
* **Percentage of Disease Coverage**: The application may optionally display the percentage of disease coverage for each plant, providing users with quantitative information about the severity of the detected diseases.

**2.4.2 FUNCTIONAL REQUIREMENTS**

* **Cross-Browser Compatibility**: The application should function seamlessly on various web browsers such as Chrome, Firefox, and Safari, ensuring accessibility across different platforms and devices.
* **Optimization of Image Upload and Processing**: The image upload and processing time should be optimized to provide users with a real-time experience, minimizing delays between image submission and result display.
* **Intuitive User Interface**: The user interface should be intuitive and easy to navigate, catering to users with varying levels of technical proficiency. Clear instructions and user-friendly design elements should guide users through the image upload and result interpretation processes

**2.5 SOFTWARE REQUIREMENTS**

* **Python:** Google Colab supports Python programming, and it will be the primary language used for development.
* **Instance Segmentation Model**: YOLOv8 Ultralytics model for detection of disease in wheat leaf such as Wheat powdery mildew, wheat septoria, wheat stem rust, wheat yellow rust .
* **Video Processing Libraries**: Need various libraries for video processing, for video manipulation and extraction.
* **Operating System**: Linux, Windows, or macOS.
* **Programming Language:** Python for development and implementation.
* **Development Framework:** PyTorch for YOLOv8 model integration.
* **Integrated Development Environment (IDE):** Visual Studio Code or Jupyter Notebook for coding.
* **Libraries:** OpenCV for image processing,ultralytics.YOLO for deep learning framework for object detection tasks.

**2.6 HARDWARE REQUIREMENTS**

* **Computer with Internet Access**: Google Colab is a cloud-based platform, so a computer with an internet connection is essential to access and work on project.
* **Sufficient Processing Power**: While Google Colab provides access to powerful GPUs, the specific hardware requirements will depend on the complexity and scale of project. Ensure that selected Colab environment meets the computational demands of tasks.
* **Memory**: Make sure that Colab environment has sufficient RAM to handle the size of the video files we will be working with and the various AI processing steps.
* **Storage**: Require ample storage space to save intermediate and final audio and video files.
* **GPU Access**: Project involves deep learning tasks (e.g., voice cloning), might need access to a GPU for faster training and processing. Google Colab provides GPU support, but it's important to check and configure the GPU settings as needed.

**CHAPTER – 3**

**SYSTEM DESIGN**

System design involves outline of architecture and its components along with interfaces for the system. So that it meets end user requirements. This also involves different modules of system. It also includes data-flow and management.

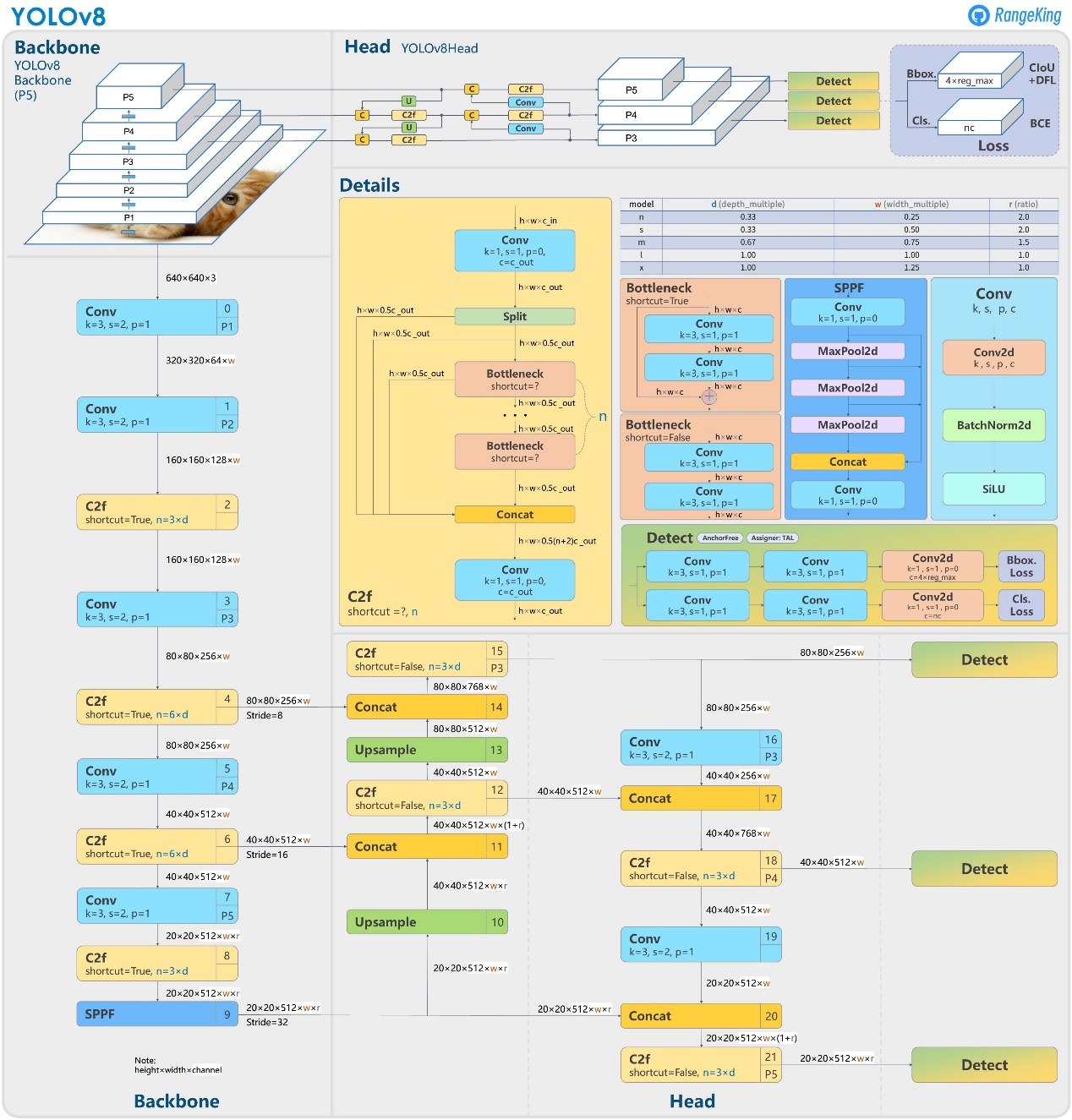
**3.1 PROJECT DESCRIPTION**

The wheat leaf disease diagnosis system project endeavours to transform the management of wheat crops by implementing a cutting-edge web application utilizing the YOLOv8 Instance Segmentation algorithm. This system aims to streamline the process of identifying and addressing diseases affecting wheat crops, thereby enhancing crop health and productivity. Leveraging state-of-the-art technology, including deep learning and image processing techniques, the system automatically detects and segments diseased regions within wheat fields from uploaded images. Through intuitive user interfaces and real-time processing capabilities, farmers can swiftly upload images of their wheat crops and receive detailed insights regarding disease presence and severity. By empowering farmers with actionable information, the wheat disease diagnosis system contributes to improved crop management practices, ultimately bolstering food security and agricultural sustainability.

**3.2 YOLOv8**

YOLOv8 is the newest state-of-the-art YOLO model that can be used for object detection, image classification, and instance segmentation tasks. YOLOv8 was developed by Ultralytics, who also created the influential and industry-defining YOLOv5 model. YOLOv8 includes numerous architectural and developer experience changes and improvements over YOLOv5.

YOLOv8 achieves strong accuracy on COCO. For example, the YOLOv8m model -- the medium model -- achieves a 50.2% mAP when measured on COCO. When evaluated against Roboflow 100, a dataset that specifically evaluates model performance on various task-specific domains, YOLOv8 scored substantially better than YOLOv5. More information on this is provided later in the report.

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**Figure 1.**

The main features of YOLOv8 include mosaic data augmentation, anchor-free detection, a C2f module, a decoupled head, and a modified loss function. Let’s discuss each change in more detail.

**Mosaic Data Augmentation:** Like YOLOv4, YOLOv8 uses mosaic data augmentation that mixes four images to provide the model with better context information. The change in YOLOv8 is that the augmentation stops in the last ten training epochs to improve performance.

**Anchor-Free Detection:** YOLOv8 switched to anchor-free detection to improve generalization. The problem with anchor-based detection is that predefined anchor boxes reduce the learning speed for custom datasets. With anchor-free detection, the model directly predicts an object’s mid-point and reduces the number of bounding box predictions. This helps speed up Non-max Suppression (NMS) – a pre-processing step that discards incorrect predictions.

**C2f Module:** The model’s backbone now consists of a C2f module instead of a C3 one. The difference between the two is that in C2f, the model concatenates the output of all bottleneck modules. In contrast, in C3, the model uses the output of the last bottleneck module. A bottleneck module consists of bottleneck residual blocks that reduce computational costs in deep learning networks. This speeds up the training process and improves gradient flow.

**Decoupled Head:** In figure 1 illustrates that the head no longer performs classification and regression together. Instead, it performs the tasks separately, which increases model performance.

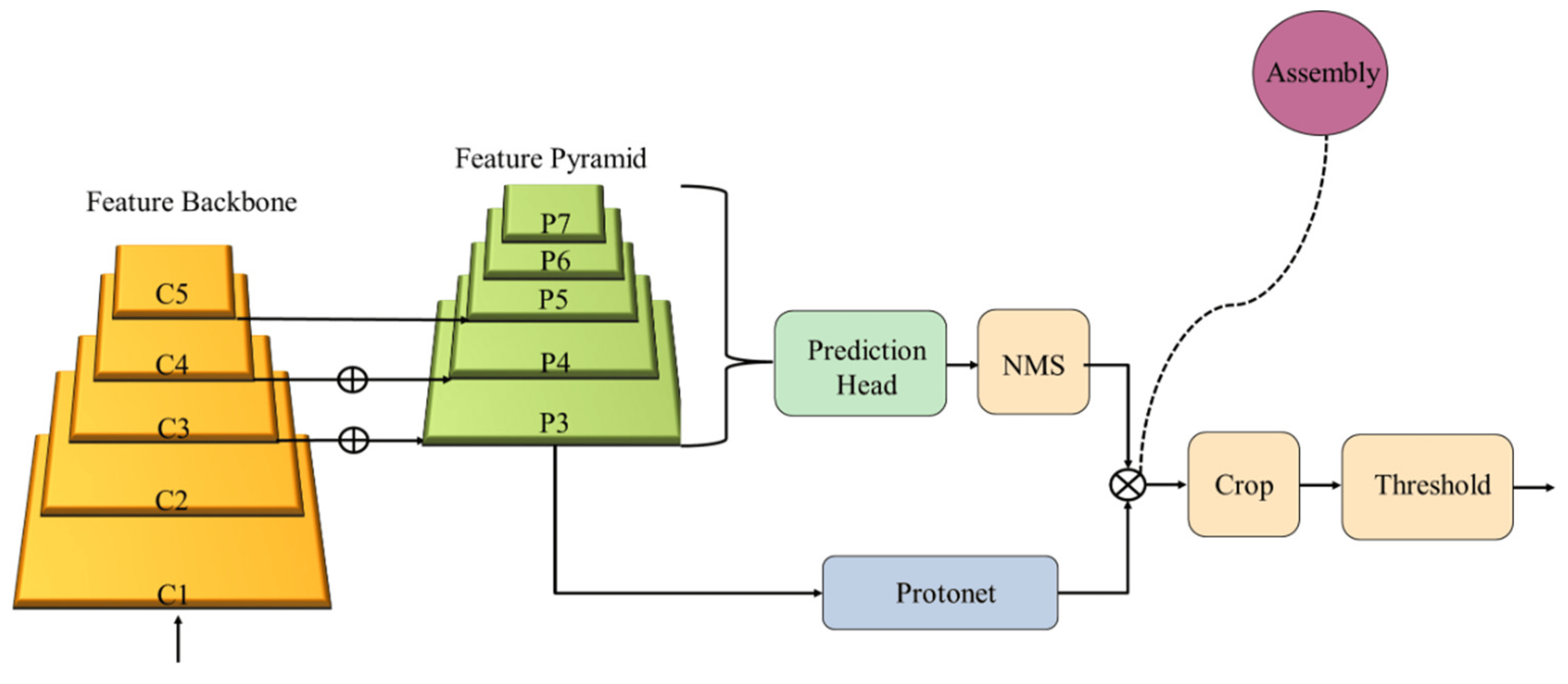
**Loss:** Misalignment is possible since the decoupled head separates the classification and regression tasks. It means the model may localize one object while classifying another. The solution is to include a task alignment score based on which the model knows a positive and negative sample. The task alignment score multiplies the classification score with the Intersection over Union (IoU) score. The IoU score corresponds to the accuracy of a bounding box prediction.

Based on the alignment score, the model selects the top-k positive samples and computes a classification loss using BCE and regression loss using Complete IoU (CIoU) and Distributional Focal Loss (DFL). The BCE loss simply measures the difference between the actual and predicted labels.

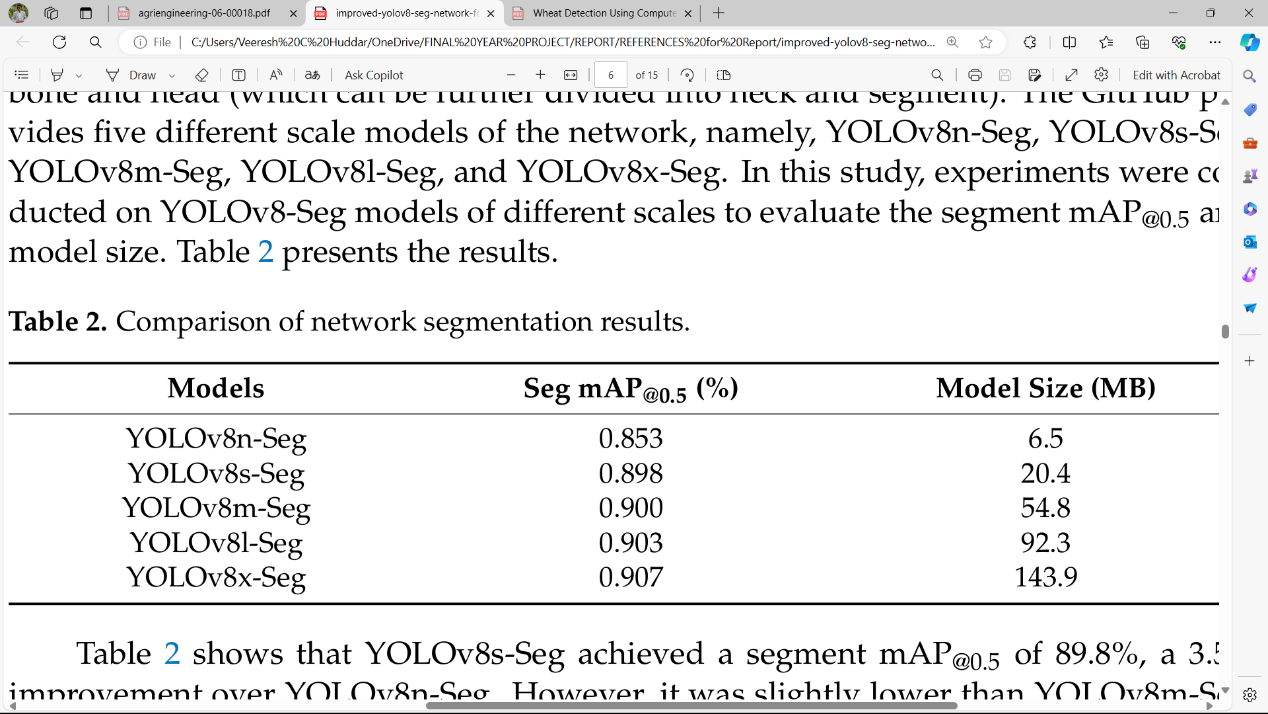
The CIoU loss considers how the predicted bounding box is relative to the ground truth in terms of the center point and aspect ratio. In contrast, the distributional focal loss optimizes the distribution of bounding box boundaries by focusing more on samples that the model misclassifies as false negatives.

**3.2.1** **INSTANCE SEGMENTATION BASED ON IMPROVED YOLOv8**

The YOLO (you only look once) series is a deep-learning model for detecting objects. YOLOv8, developed by the same authors as YOLOv5, shares a similar overall style. YOLOv8 has made significant improvements and optimizations over the YOLOv5 network, resulting in enhanced algorithm performance. The YOLOv8 network supports object detection and tracking, as well as additional tasks, such as instance segmentation, image classification, and key point detection. Similar to YOLOv5, YOLOv8 provides five different scales of models (n, s, m, l, x), with increasing depth and width from left to right. In reference to the ELAN design philosophy, YOLOv8 replaces the C3 structure in the YOLOv5 backbone network with a C2f structure. This alteration enables YOLOv8 to maintain its lightweight characteristics while obtaining a greater amount of gradient flow information. Compared to YOLOv5, the head part of YOLOv8 exhibits more prominent differences due to the implementation of the widely-used decoupled head structure. For loss function calculation, YOLOv8 utilizes the TaskAlignedAssigner positive sample assignment strategy. Furthermore, it introduces the distribution focal loss. During training, the strategy of disabling mosaic augmentation in the last 10 epochs is incorporated, as introduced in YOLOX, to effectively improve precision in the data augmentation process. YOLOv8s-Seg is an extension of the YOLOv8 object detection model. It is specifically designed for carrying out segmentation tasks. The YOLOv8s-Seg network draws on the principles of the YOLACT network to achieve real-time instance segmentation of objects and maintain a high segment mean average precision. Figure 2 displays the Structure of the YOLACT network.

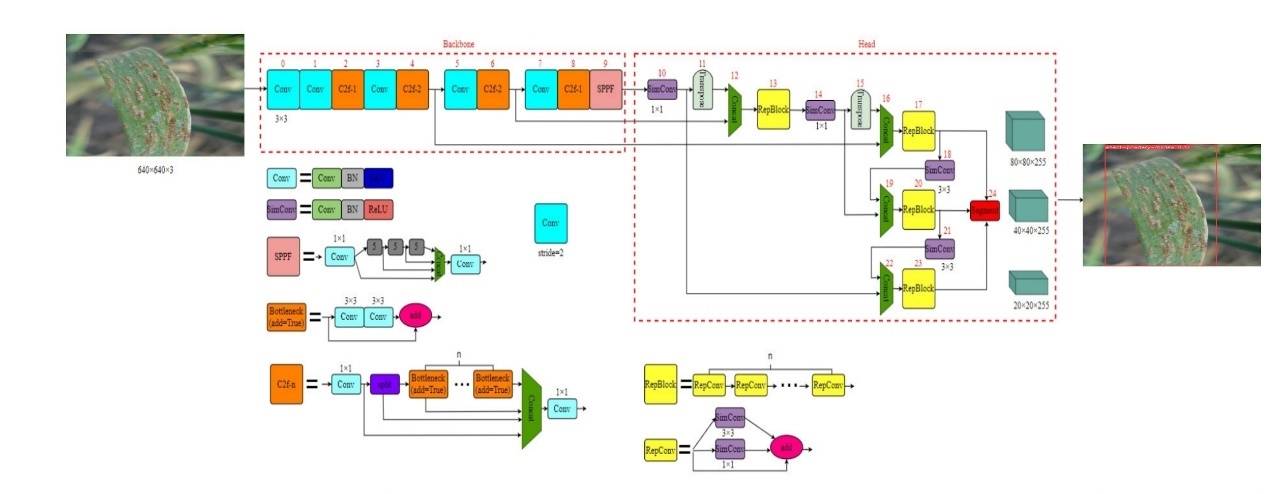
**Figure 2.** **Structure of YOLACT network**

The YOLOv8-Seg (ultralytics-8.0.57) network consists of two main components: backbone and head (which can be further divided into neck and segment). The GitHub provides five different scale models of the network, namely, YOLOv8n-Seg, YOLOv8s-Seg, YOLOv8m-Seg, YOLOv8l-Seg, and YOLOv8x-Seg. In this study, experiments were conducted on YOLOv8-Seg models of different scales to evaluate the segment mAP@0.5 and model size. Table 1 presents the results.



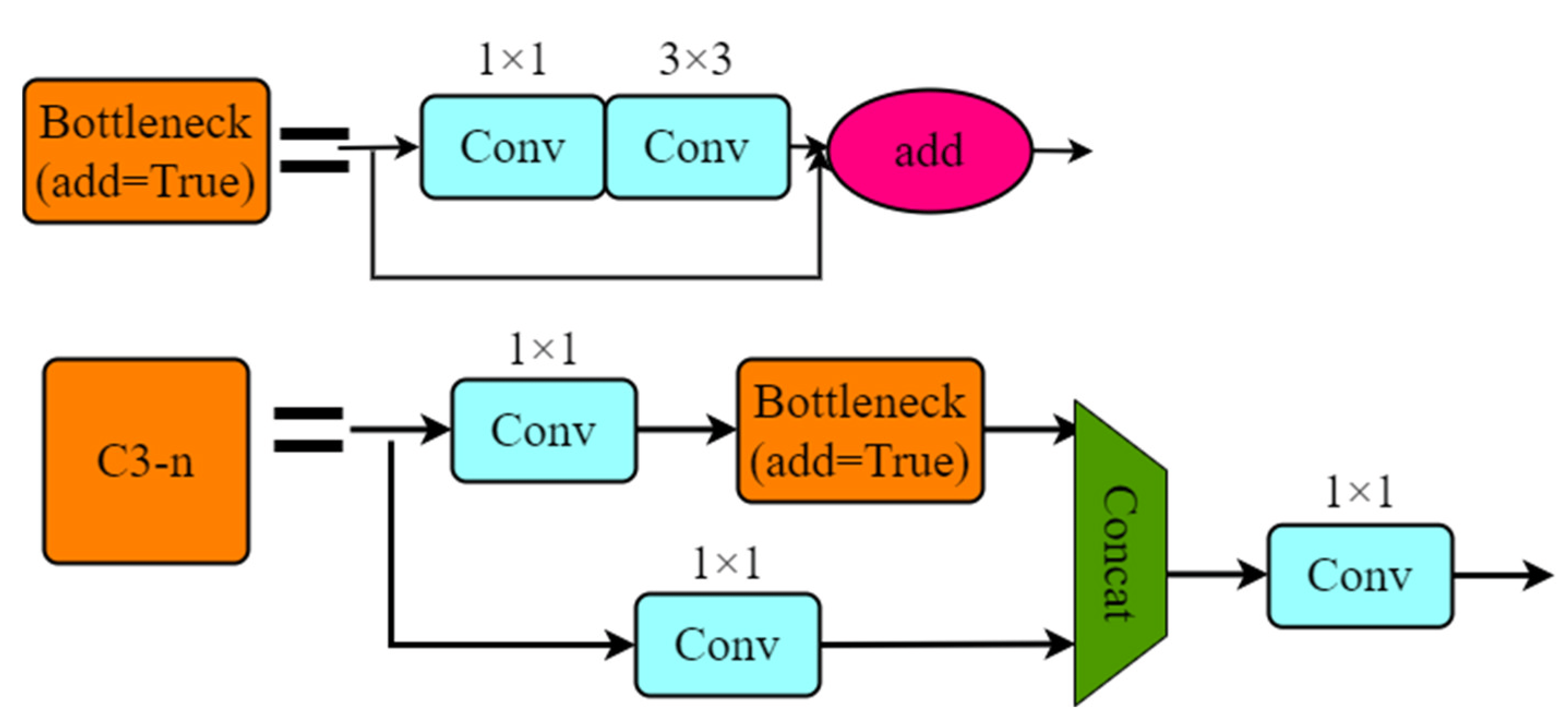
**Table 1.** **Comparison of network segmentation results.**

Table 2 shows that YOLOv8s-Seg achieved a segment mAP@0.5 of 89.8%, a 3.5% improvement over YOLOv8n-Seg. However, it was slightly lower than YOLOv8m-Seg, YOLOv8l-Seg, and YOLOv8x-Seg by 0.2%, 0.5%, and 0.9%, respectively. Regarding model size, YOLOv8s-Seg occupies 20.4 MB, an increase of 13.9 MB compared to YOLOv8n-Seg. However, it is significantly lighter than YOLOv8m-Seg, YOLOv8l-Seg, and YOLOv8x-Seg, with reductions of 34.4 MB, 71.9 MB, and 123.5 MB, respectively. Considering the segment mAP@0.5 performance and lightweight requirements, YOLOv8s-Seg was selected as the model for experimentation in this study. Figure 3 illustrates the structure of the improved YOLOv8s-Seg network.



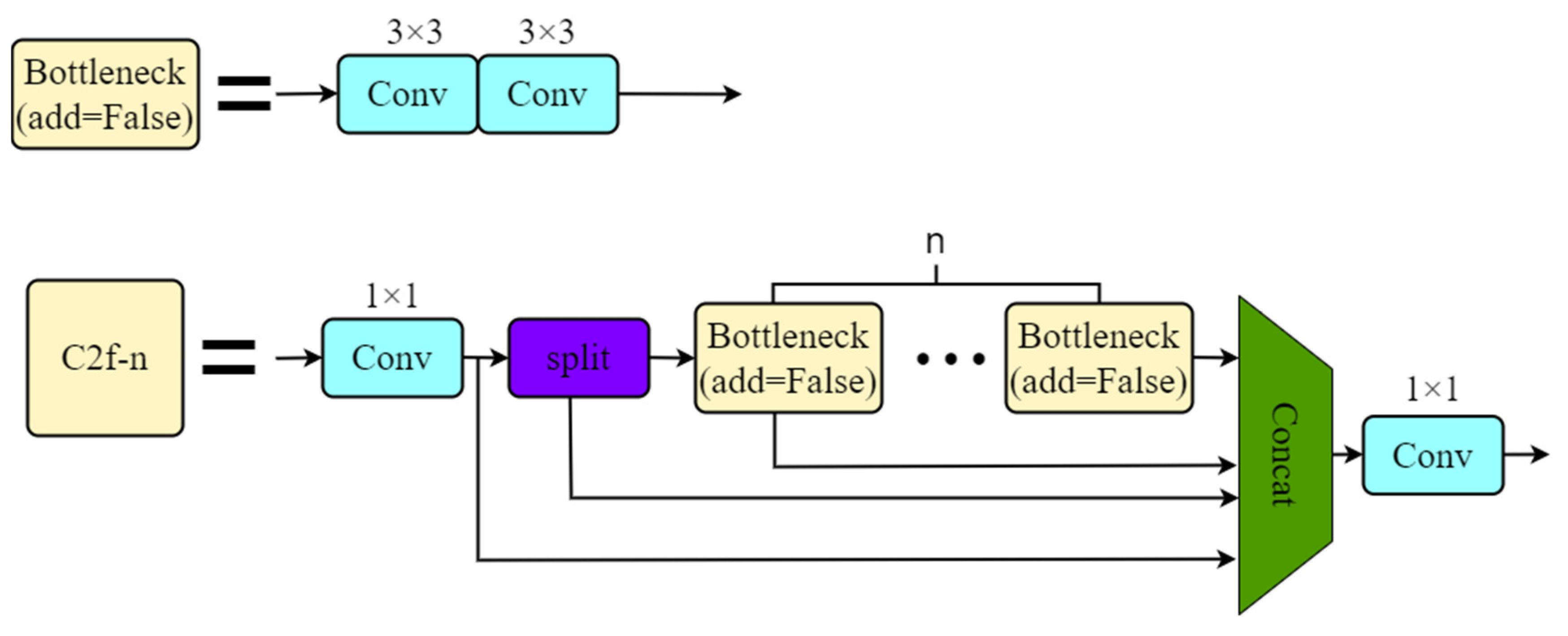
**Figure 3.** **Structure of improved YOLOv8s-Seg based wheat leaf segmentation network utilizes RepBlock modules, SimConv in the neck for feature fusion, and replaces standard convolutions with SimConv for enhanced feature extraction.**

The backbone network of YOLOv8s-Seg consists of a 3 × 3 convolution, a C2f module, and an SPPF (spatial pyramid pooling fusion) module. In contrast to the YOLOv5 network, YOLOv8s-Seg replaces the initial 6 × 6 convolution with a 3 × 3 convolution in the backbone network, making the model more lightweight. Additionally, the C3 module (Figure 3) in YOLOv5 is replaced with the C2f module in YOLOv8s-Seg. The C2f module, designed with skip connections and additional split operations, enriches the gradient flow during backpropagation and improves the performance of the model. YOLOv8s-Seg utilizes two versions of the cross stage partial network (CSP). The CSP in the backbone network employs residual connections (as shown in Figure 5), while the head part uses direct connections. The SPPF structure in YOLOv8s-Seg remains the same as in YOLOv5 (version 6.1), utilizing cascaded 5 × 5 pooling kernels to accelerate network operation speed.



**Figure 4. Structure of the C3 module**

The head module is comprised of the neck and segment parts. The neck module incorporates the path aggregation network (PANet) and feature pyramid network (FPN) as feature fusion networks. Unlike YOLOv5 and YOLOv6, YOLOv8s-Seg removes the 1 × 1 convolution before upsampling and fuses the feature maps directly from different stages of the backbone network. This study aimed to enhance the network performance of YOLOv8s-Seg by improving its neck module. Specifically, before each upsampling operation, two 1 × 1 SimConv convolutions were added, and the remaining regular convolutions in the neck part were replaced with 3 × 3 SimConv convolutions. The C2f module ([Figure](https://www.mdpi.com/2077-0472/13/8/1643#fig_body_display_agriculture-13-01643-f008) 4) was replaced with the RepBlock module (Figure 2). The RepBlock module is composed of stacked RepConv convolutions, and the structure of the RepConv convolution is depicted in Figure 5.



**Figure 5.** **Structure of the C2f module in the neck**.

The YOLOv5 network employs a static allocation strategy to assign positive and negative samples based on the intersection over union (IOU) between the predicted boxes and ground truth. However, the YOLOv8s-Seg network has improved this aspect by introducing a superior dynamic allocation strategy. It incorporates the TaskAlignedAssigner (TOOD), which selects positive samples based on a weighted score that comes from the classification and regression scores. The computation is represented by Formula (1).

𝑡=𝑠𝛼×𝑢𝛽 -------------------------------------- (1)

where s: prediction scores for labeled categories, u: prediction frame with the IOU of Ground Truth, t: alignment scores for categorical regression.

During training, YOLOv8s-Seg performs online image enhancement to ensure that the model encounters slightly different images in each epoch. Mosaic enhancement is a crucial method of data improvement that randomly combines four images. This technique compels the model to learn how to detect partially obstructed and differently positioned objects. In the last 10 training epochs, the YOLOv8s-Seg network deactivates the mosaic enhancement, a method proven to improve network precision effectively.

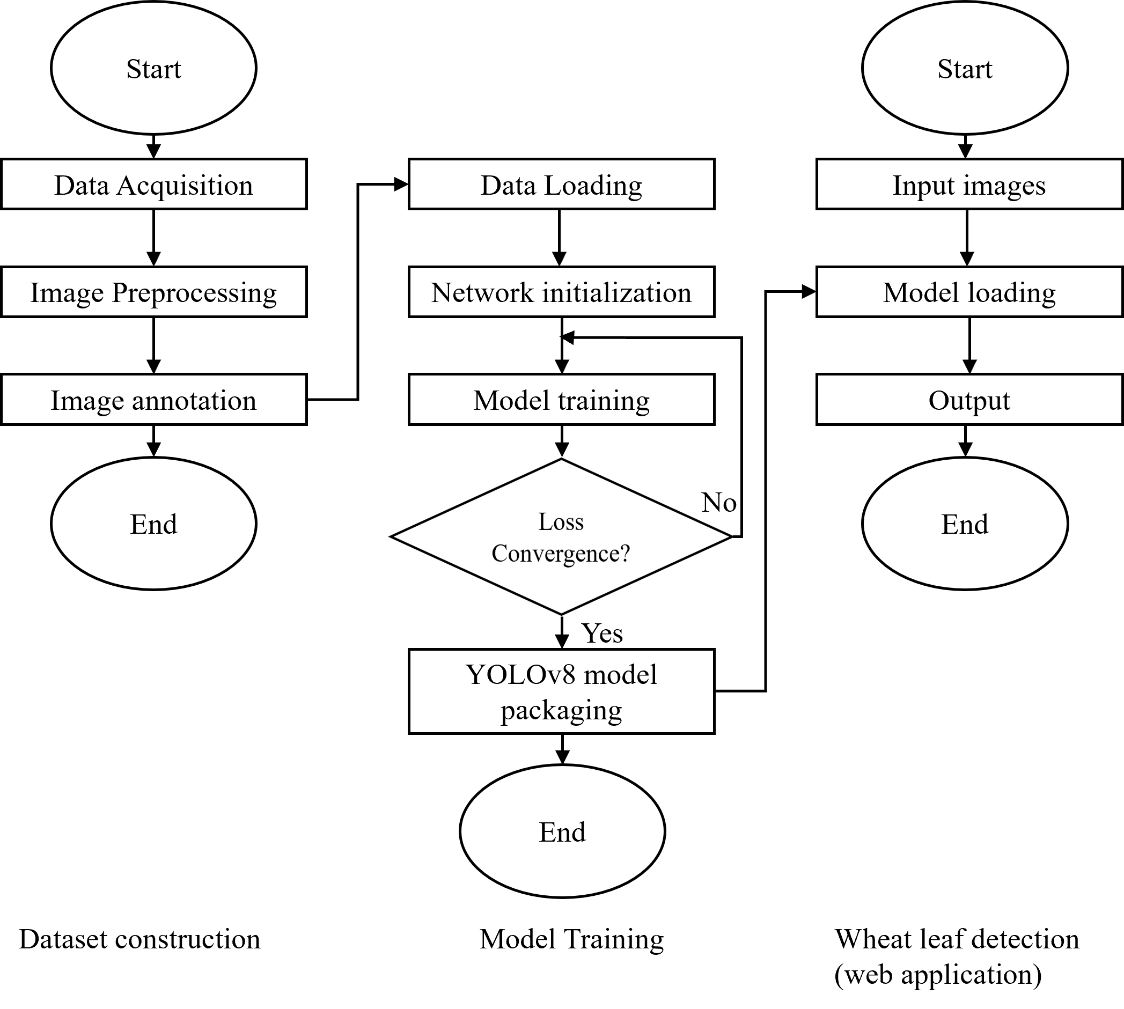
**3.3** **PROJECT ARCHITECTURE**

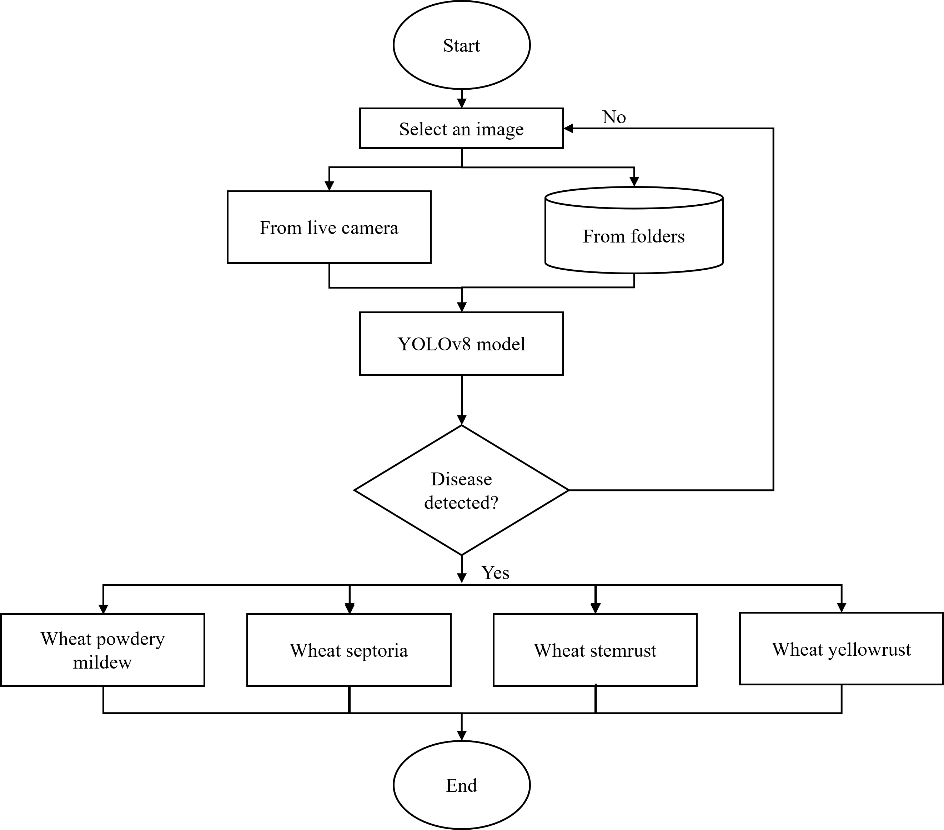
The Wheat Disease Detection System utilizing YOLOv8 Instance Segmentation and Streamlit for web application development in Python comprises several key components. The User Interface (UI) is developed using Streamlit, providing an intuitive platform for users to upload wheat leaf images, view past results, and download processed images. The Web Server, powered by Streamlit, hosts the application, manages user requests, serves UI elements, and communicates with the backend for image processing. Image Preprocessing, if included, conducts necessary preprocessing steps like resizing or normalization before inputting images into the YOLOv8 model, potentially implemented as a separate module or integrated within the backend. The Backend houses the core logic for disease detection, utilizing the pre-trained YOLOv8 model for wheat leaf disease segmentation, receiving image data from the web server, performing preprocessing (if required), making predictions with YOLOv8, processing the results, generating a comprehensive report containing detected disease types, bounding boxes or segmentation masks for diseased areas, and optionally, severity level estimates for each disease. This report, along with processed images, is sent back to the web server for presentation to the user. If incorporated, the Database stores user data, uploaded images, and analysis results, facilitating data management and historical analysis. The communication flow involves users interacting with the Streamlit-based UI, uploading images, which are forwarded to the Web Server. The Web Server then relays image data to the Backend for processing, which subsequently returns the report and processed images to the Web Server for display to the user via the UI. The architecture offers modularity, scalability, and separation of concerns, with each component fulfilling a specific role, while its web-based nature ensures accessibility across various devices. Additionally, the system allows for seamless expansion with features like disease severity estimation or historical data analysis.

**3.4 FLOW CHART**

The system initiates when a user opens the web application in their browser. Users interact with the UI, potentially uploading a wheat leaf image or selecting options. The web server receives the user request and transmits image data, if applicable, to the backend. In the backend, the image might undergo preprocessing, such as resizing or normalization.

The backend utilizes the pre-trained YOLOv8 model to analyze the image, identifying and segmenting diseased regions. Subsequently, the backend interprets the model output, generating a report with disease information, such as type and location. The backend then sends the report (and potentially the processed image) back to the web server. The web server transmits the report and image (if applicable) to the UI for display. Users view the disease detection results on the web interface, and the process may continue with further user interactions or exit. Figure 6 and figure 7  illustrates the flow chart of the diagnosis system.

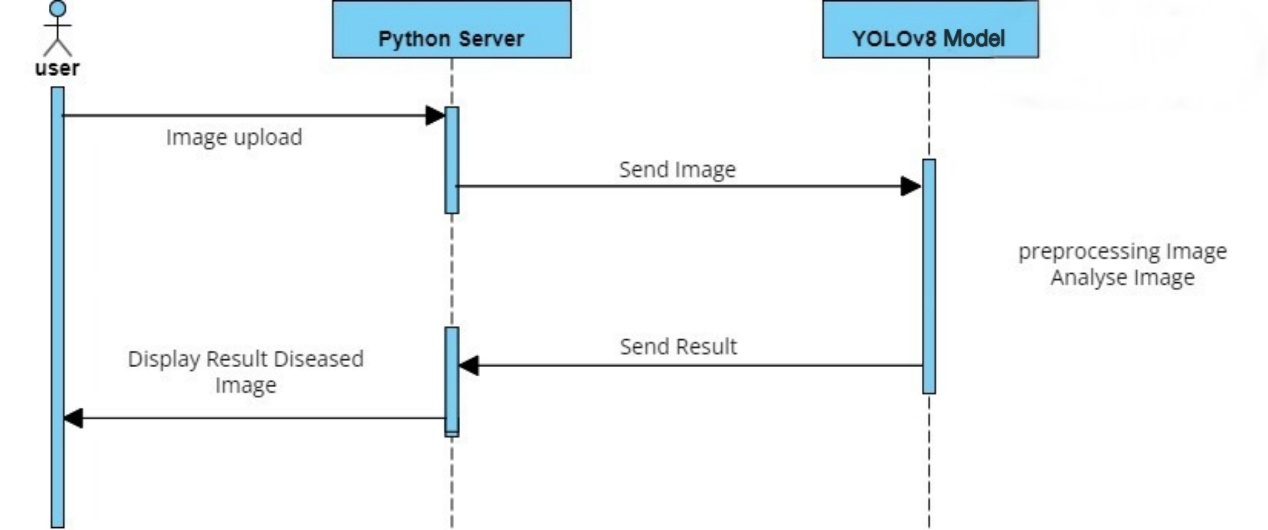
** Figure 6. Wheat leaf disease diagnosis Flowchart**

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**Figure 7. Flowchart of the web application**

**3.5 SEQUENCE DIAGRAMS**

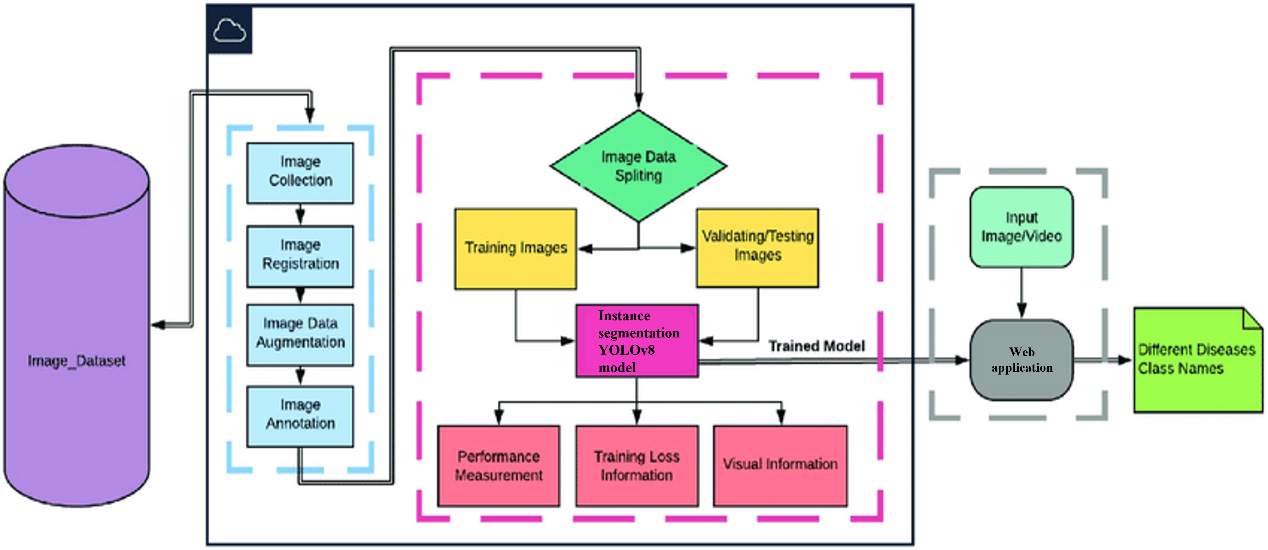
A user uploads an image through the web browser. The web browser sends an HTTP request with the image data to the web server. The web server receives the request and forwards the image data to the backend. The backend potentially preprocesses the image before using YOLOv8 to perform disease segmentation. It generates a disease detection report based on the prediction results. The backend then sends the report (and potentially the processed image) back to the web server. The web server receives the response and sends it (report and image) to the user's web browser. The web browser displays the disease detection results on the user interface. Figure 8  illustrates the flow chart of the diagnosis system.

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**Figure 8. Sequence diagrams on Wheat leaf disease diagnosis system**

**3.6** **DATA FLOW DIAGRAM**

The Data Flow Diagram (DFD) illustrates how data moves through the system components and undergoes transformations. External entities include users interacting with the web application. Processes involve the web interface managing user interactions, the web server receiving and directing requests, image preprocessing (if used), the YOLOv8 model analyzing images, result processing generating detection reports. Data flows from users to the web interface, then to the web server and relevant processes, with results flowing back to the web server for user display. Customization allows tailoring the DFD to specific implementation details, such as database usage and integration of preprocessing within the backend as shown in Figure 9.

 **Figure 9. Data flow diagram of the process of our Wheat leaf disease diagnosis system**

**3.7** **DATABASE DESIGN**

This system focuses solely on real-time disease detection from uploaded images. No user accounts or login functionality is required.Processed images (with segmentation masks) might be displayed to the user but not permanently stored.

**CHAPTER – 4**

**IMPLEMENTATION**

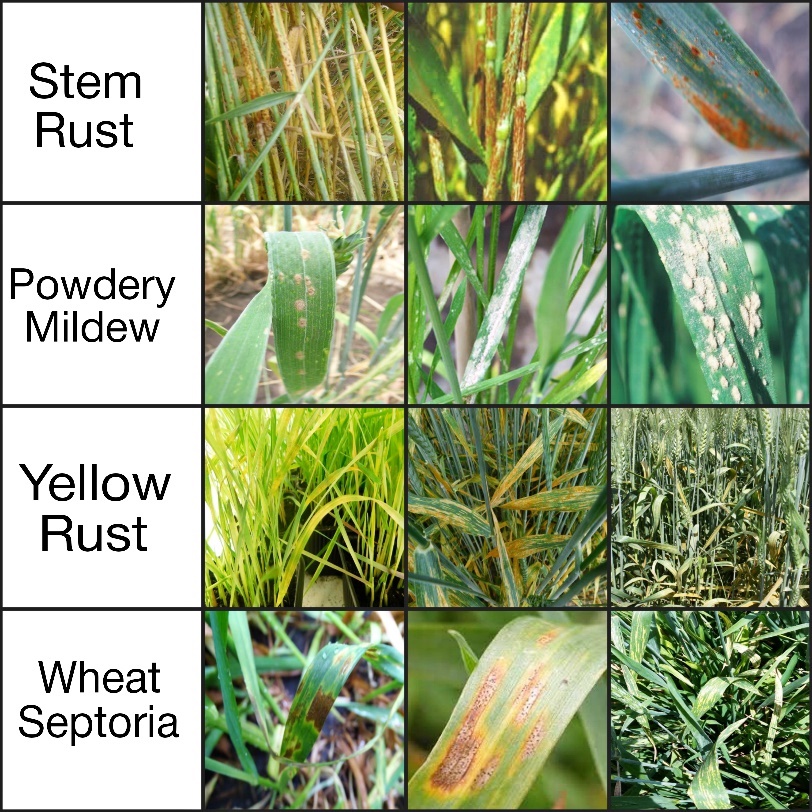
**4.1 DATA ACQUISITION**

The dataset for this wheat leaf disease detection system comprises images capturing various stages of wheat leaf growth and health conditions, including healthy leaves and those affected by common wheat diseases such as powdery mildew, septoria, stem rust, and yellow rust.

The dataset consists of a total of 1886 images, collected from diverse sources. These images were obtained through a combination of self-captured images in field settings and publicly available datasets.

All images are stored in JPG format with a resolution of 1920x1080 pixels, ensuring uniformity in format and quality across the dataset.

To facilitate model training and evaluation, the dataset was divided into three sets: a training set, a validation set, and a testing set. The common practice of a 70:20:10 split was adopted, with 1,104 images allocated to training, 462 to validation, and 319 to testing. Example images are shown in Figure 10.



**Figure 10. Example images**

**4.2 IMAGE PREPROCESSING**

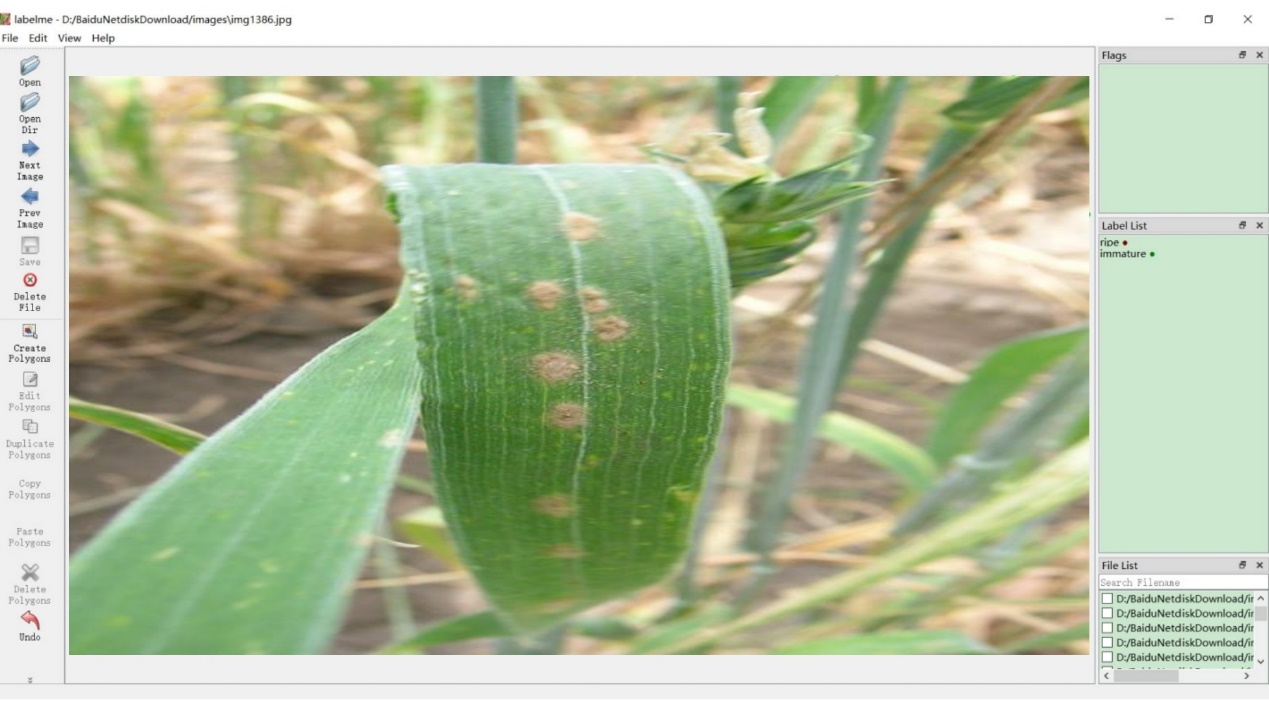
Prior to model training, preprocessing techniques were applied to the images to enhance model performance and facilitate accurate detection of wheat leaf diseases. These techniques included resizing all images to meet the input requirements of the YOLOv8 model and normalization of pixel values to a range suitable for model convergence.

Additionally, data augmentation techniques were employed to increase the diversity of the dataset and improve the model's ability to generalize to unseen data. This involved applying random cropping, flipping, color jittering, and rotation to artificially expand the dataset.

**4.3 IMAGE ANNOTATION**

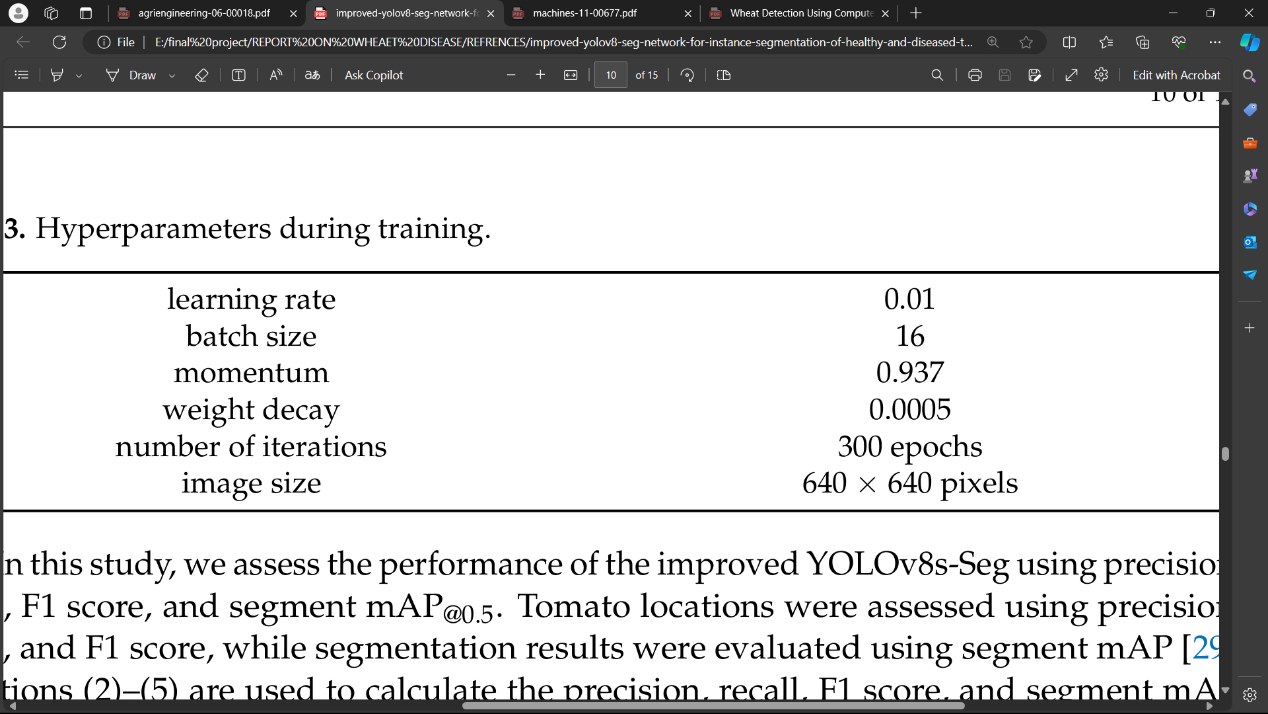
Image annotation was performed to label the instances of wheat leaf diseases in the dataset accurately. The annotation process involved using a dedicated annotation tool, such as LabelImg or VIA, to create bounding boxes and segmentation masks around the diseased regions of wheat leaves.

A total of 4 classes were defined in the dataset, encompassing various stages of wheat leaf growth and common wheat diseases, including powdery mildew, septoria, stem rust, and yellow rust. Figure 11 shows the annotation of wheat leaf.

 **Figure 11. Annotation of wheat leaf**

**4.4 MODEL TRAINING AND PERFORMANCE EVALUATION**

The examinations were performed on Windows 10 using a 12 vCPU Intel(R) Xeon(R) Platinum 8255C CPU @2.50 GHz and an Nvidia GeForce RTX 2080Ti graphics card. The framework for deep learning was PyTorch 1.8.1 and Compute Unified DeviceArchitecture (CUDA) 11.1, accelerated by cuDNN version 8.0.5. In this experiment, the improved YOLOv8s-Seg, YOLOv8s-Seg, YOLOv5s-Seg, and YOLOv7-Seg were performed in the same environment configuration and under the same hyperparameter settings, as indicated in Table 2.The hyperparameter settings of Mask CNN: the learning rate, batch size, learning momentum, weight decay, number of iterations, and image size were set to 0.004, 2, 0.9, 1 × 10−4, 30 epochs, and 640 × 640 pixels, respectively.



**Table 2.** **Hyperparameters during training**.

In this study, we assess the performance of the improved YOLOv8s-Seg using precision, recall, F1 score, and segment mAP@0.5. Wheat locations were assessed using precision, recall, and F1 score, while segmentation results were evaluated using segment mAP . Equations (2)–(5) are used to calculate the precision, recall, F1 score, and segment mAP scores. The higher the four parameters are, the better the segmentation results.

precision=TP(TP+FP)×100%precision=TPTP+FP×100% (2)

recall=TP(TP+FN)×100%recall=TPTP+FN×100% (3)

F1=2×precision×recallprecision+recallF1=2×precision×recallprecision+recall (4)

segmAP=∑𝑖=1𝑐AP(𝑖)CsegmAP=∑𝑖=1𝑐AP(𝑖)C (5)

where TP denotes an actual positive sample with a positive prediction, while FP indicates an actual negative sample with a positive prediction, and FN indicates an actual positive sample with a negative prediction. AP represents the average precision of segmentation. The segmentation performance of the model increases with the AP score. C represents the number of segmentation categories.

**4.5 SOFTWARE TOOLS USED**

Visual Studio Code (VS Code) is a versatile integrated development environment (IDE) that has become a staple tool for software developers, especially those working extensively with Python. Its appeal stems not just from its sleek and user-friendly interface, but also from its extensive range of features designed to streamline the development workflow. At its essence, VS Code embodies efficiency, offering an array of tools meticulously designed to boost productivity and code quality. From its intelligent code completion and syntax highlighting to its seamless integration with popular version control systems like Git, VS Code empowers developers to write clean and error-free code effortlessly. Its robust debugging capabilities facilitate quick identification and resolution of issues, ensuring smooth progression through the development cycle. Additionally, the rich ecosystem of plugins in VS Code allows for customization and expansion, catering to the diverse needs and preferences of developers. Whether tackling a small personal project or collaborating on a large-scale enterprise application, VS Code serves as a reliable and adaptable platform for Python development. Continuously updated and refined based on community feedback, VS Code remains at the forefront of development tools, solidifying its position as the preferred IDE for developers globally.

**4.6 LANGUAGES AND MODULES USED**

**4.6.1 PYTHON**

Python, a dynamically typed and interpreted programming language, has emerged as a cornerstone of modern software development, revered for its simplicity, versatility, and readability. Guido van Rossum conceived Python in the late 1980s, envisioning a language that prioritized code readability and expressiveness, thereby fostering a community-centric ethos that permeates its evolution to this day. Renowned for its clean and intuitive syntax, Python facilitates rapid development and iteration, making it a favored choice for projects ranging from web development and scientific computing to artificial intelligence and data analysis. Its extensive standard library, encompassing modules for tasks ranging from file I/O and networking to mathematical computations and data manipulation, underscores Python's versatility and utility across diverse domains. Furthermore, Python's dynamic nature enables rapid prototyping and experimentation, empowering developers to swiftly translate ideas into tangible solutions. Beyond its technical prowess, Python's vibrant community ecosystem, bolstered by a plethora of libraries, frameworks, and resources, fosters collaboration, innovation, and knowledge-sharing. From the ubiquitous Django and Flask frameworks for web development to the powerful NumPy and pandas libraries for scientific computing, Python's rich ecosystem empowers developers to tackle complex challenges with confidence and efficiency. Moreover, Python's cross-platform compatibility ensures seamless deployment across operating systems, fostering accessibility and scalability. As technology continues to evolve, Python remains at the forefront of innovation, embodying a philosophy of simplicity, elegance, and inclusivity that resonates with developers worldwide.

**4.6.2 MODULES AND VERSIONS**

* **ultralytics.YOLO:** Ultralytics YOLO is a deep learning framework for object detection tasks. In this code, it's used for performing object detection on images. The YOLO model is pre-trained on a large dataset and can detect various objects in images, making it suitable for tasks like wheat disease detection. It allows us to identify and locate objects within images with high accuracy.
* **numpy (v1.22.4):** Numpy is a fundamental library for numerical computing in Python and is widely used for array manipulation and mathematical operations. Within the project, numpy is employed for various numerical computations and data manipulation tasks, providing efficient data structures and algorithms for handling audio and video data.
* **pytest-shutil (v1.7.0):** Pytest-shutil is utilized for testing and debugging purposes within the project. It extends the capabilities of the pytest framework by providing additional utilities for managing temporary directories, copying files, and performing filesystem operations during testing, ensuring robustness and reliability in the testing environment.
* **cv2:** OpenCV (cv2) is a popular computer vision library used for image and video processing tasks. In this code, it's used for reading, processing, and manipulating images and video frames. OpenCV provides functions for tasks like reading video files, capturing frames from cameras, and performing various image processing operations. Here, it's used to read video files for live object detection.
* **Streamlit(v1.14.0):** Streamlit is a Python library that makes creating web apps a breeze. Instead of wrestling with complex web development languages like HTML, CSS, and Javascript, Streamlit lets you build user interfaces (UI) with Python code. Streamlit helps you build the user interface (UI) for your wheat disease detection system easily. This lets you focus on the core parts of your system like image processing and disease detection using YOLOv8. Since Streamlit uses Python, you can quickly build a basic version of your UI to test your ideas without needing to be a web development expert. If you plan to store user data or past results, you can connect Streamlit to a database using libraries like SQLAlchemy.
* **werkzeug.utils.secure\_filename:** This utility function from Werkzeug is used to securely generate a filename for saving uploaded files. It ensures that filenames are properly sanitized to prevent directory traversal attacks and other security vulnerabilities. In this code, it's used to generate a secure filename for saving the uploaded images
* **PIL(v9.3.3):** The Python Imaging Library (PIL) is used for image processing tasks like opening, manipulating, and displaying images. In this code, it's used to open uploaded images and display them on the Streamlit UI.
* **Pathlib**: This module provides utilities for working with file system paths. It offers a convenient way to handle paths across different operating systems and simplifies path manipulation tasks.

**4.7 IMPLEMENTATION DETAILS**

**4.7.1 PYTHON STREAMLIT**

Streamlit simplifies the creation of web applications in Python. Unlike Flask, which requires building the web UI from scratch with HTML, CSS, and Javascript, Streamlit allows to define the UI directly using Python code. This makes it ideal for data scientists and developers who are primarily comfortable with Python and don't necessarily have extensive web development experience.

Similar to Flask's MVC pattern, Streamlit has a simplified architecture focused on Python code:

* **Python Script:** Your Streamlit application logic resides within a single Python script. This script defines the UI layout using Streamlit functions and incorporates the core functionalities of your application.
* **Streamlit Library:** The Streamlit library acts behind the scenes, translating your Python code into a functional web application. It handles tasks like rendering the UI, processing user interactions, and managing communication with the web server.
* **Web Server:** Streamlit can be run on a standalone web server or integrated with existing web frameworks like Flask or Django. The web server serves the web application to users who access it through a web browser.



**Figure 12. Streamlit app server architecture**

**4.7.2 KEY FUNCTIONALITIES IN THIS CODE**

**Streamlit Components:**

Leverages Streamlit's built-in components to create the UI:

* st.sidebar.radio creates radio buttons for users to select options like source type, model type, and confidence level.
* st.sidebar.slider creates a slider for users to adjust the confidence threshold.
* st.sidebar.button creates buttons to trigger actions like object detection.
* st.image displays images (uploaded or processed).
* st.error displays error messages if issues arise.
* st.expander creates expandable sections for detailed information.
* The code effectively combines these components to create a user-friendly and interactive interface.

**Function Reusability:**

Breaks down functionalities into well-defined functions for better organization and reusability.

* load\_model: Loads the YOLOv8 model from the specified path.
* display\_tracker\_options: Presents options for enabling/disabling object tracking and selecting a tracker type.
* \_display\_detected\_frames: This core function handles resizing the frame, performing detection/tracking (if enabled), and plotting the results with bounding boxes on the frame.
* play\_stored\_video, play\_webcam, play\_rtsp\_stream, play\_youtube\_video: These functions encapsulate functionalities specific to handling different video sources.
* Separating functionalities into functions promotes code maintainability and readability.

**4.7.3. MAIN CODE**

## settings.py

This file contains all the constants and configuration settings required for the project. It defines the path to the YOLOv8 model, the confidence threshold, the non-maximum suppression threshold, and the names of the objects to detect. It also contains settings related to the Streamlit app, such as the default image and video URLs.

from pathlib import Path

import sys

# Get the absolute path of the current file

FILE = Path(\_\_file\_\_).resolve()

# Get the parent directory of the current file

ROOT = FILE.parent

# Add the root path to the sys.path list if it is not already there

if ROOT not in sys.path:

sys.path.append(str(ROOT))

# Get the relative path of the root directory with respect to the current working directory

ROOT = ROOT.relative\_to(Path.cwd())

# Sources

IMAGE = 'Image'

VIDEO = 'Video'

WEBCAM = 'Webcam'

RTSP = 'RTSP'

YOUTUBE = 'YouTube'

SOURCES\_LIST = [IMAGE, VIDEO, WEBCAM, RTSP, YOUTUBE]

# Images config

IMAGES\_DIR = ROOT / 'images'

DEFAULT\_IMAGE = IMAGES\_DIR / 'office\_4.jpg'

DEFAULT\_DETECT\_IMAGE = IMAGES\_DIR / 'office\_4\_detected.jpg'

# Videos config

VIDEO\_DIR = ROOT / 'videos'

VIDEOS\_DICT = {

'video\_1': VIDEO\_DIR / 'video\_1.mp4',

'video\_2': VIDEO\_DIR / 'video\_2.mp4',

'video\_3': VIDEO\_DIR / 'video\_3.mp4',

}

# ML Model config

MODEL\_DIR = ROOT / 'weights'

DETECTION\_MODEL = MODEL\_DIR / 'yolov8n.pt'

# In case of your custome model comment out the line above and

# Place your custom model pt file name at the line below

# DETECTION\_MODEL = MODEL\_DIR / 'my\_detection\_model.pt'

SEGMENTATION\_MODEL = MODEL\_DIR / 'best.pt'

# Webcam

WEBCAM\_PATH = 0

## app.py

This is the project's main file, which contains the Streamlit app. It defines the layout of the app, which includes a file uploader, a video player, a confidence threshold slider, and an object selection dropdown. It also defines the logic of the app, which includes loading the YOLOv8 model, detecting objects in the uploaded image or video frames, and displaying the detected objects.

# Python In-built packages

from pathlib import Path

import PIL

# External packages

import streamlit as st

# Local Modules

import settings

import helper

# Setting page layout

st.set\_page\_config(

    page\_title="Wheat Leaf Detection using YOLOv8",

    page\_icon="🌾",

    layout="wide",

    initial\_sidebar\_state="expanded",

)

# Main page heading

st.title("Wheat Leaf Detection using YOLOv8")

# Sidebar

st.sidebar.header("ML Model Config")

# Model Options

model\_type = st.sidebar.radio(

    "Select Task", ['Detection', 'Segmentation'])

confidence = float(st.sidebar.slider(

    "Select Model Confidence", 25, 100, 40)) / 100

# Selecting Detection Or Segmentation

if model\_type == 'Detection':

    model\_path = Path(settings.DETECTION\_MODEL)

elif model\_type == 'Segmentation':

    model\_path = Path(settings.SEGMENTATION\_MODEL)

# Load Pre-trained ML Model

try:

    model = helper.load\_model(model\_path)

except Exception as ex:

    st.error(f"Unable to load model. Check the specified path: {model\_path}")

    st.error(ex)

st.sidebar.header("Image/Video Config")

source\_radio = st.sidebar.radio(

    "Select Source", settings.SOURCES\_LIST)

source\_img = None

# If image is selected

if source\_radio == settings.IMAGE:

    source\_img = st.sidebar.file\_uploader(

        "Choose an image...", type=("jpg", "jpeg", "png", 'bmp', 'webp'))

    col1, col2 = st.columns(2)

    with col1:

        try:

            if source\_img is None:

                default\_image\_path = str(settings.DEFAULT\_IMAGE)

                default\_image = PIL.Image.open(default\_image\_path)

                st.image(default\_image\_path, caption="Default Image",

                         use\_column\_width=True)

            else:

                uploaded\_image = PIL.Image.open(source\_img)

                st.image(source\_img, caption="Uploaded Image",

                         use\_column\_width=True)

        except Exception as ex:

            st.error("Error occurred while opening the image.")

            st.error(ex)

    with col2:

        if source\_img is None:

            default\_detected\_image\_path = str(settings.DEFAULT\_DETECT\_IMAGE)

            default\_detected\_image = PIL.Image.open(

                default\_detected\_image\_path)

            st.image(default\_detected\_image\_path, caption='Detected Image',

                     use\_column\_width=True)

        else:

            if st.sidebar.button('Detect Objects'):

                res = model.predict(uploaded\_image,

                                    conf=confidence

                                    )

                boxes = res[0].boxes

                res\_plotted = res[0].plot()[:, :, ::-1]

                st.image(res\_plotted, caption='Detected Image',

                         use\_column\_width=True)

                try:

                    with st.expander("Detection Results"):

                        for box in boxes:

                            st.write(box.data)

                except Exception as ex:

                    # st.write(ex)

                    st.write("No image is uploaded yet!")

elif source\_radio == settings.VIDEO:

    helper.play\_stored\_video(confidence, model)

elif source\_radio == settings.WEBCAM:

    helper.play\_webcam(confidence, model)

elif source\_radio == settings.RTSP:

    helper.play\_rtsp\_stream(confidence, model)

elif source\_radio == settings.YOUTUBE:

    helper.play\_youtube\_video(confidence, model)

else:

    st.error("Please select a valid source type!")

## helper.py

This file contains helper functions used in the project. It includes functions to load the YOLOv8 model, preprocess the input image or video frames, and post-process the output bounding boxes and class labels.

from ultralytics import YOLO

import time

import streamlit as st

import cv2

from pytube import YouTube

import settings

def load\_model(model\_path):

"""

Loads a YOLO object detection model from the specified model\_path.

Parameters:

model\_path (str): The path to the YOLO model file.

Returns:

A YOLO object detection model.

"""

model = YOLO(model\_path)

return model

def display\_tracker\_options():

display\_tracker = st.radio("Display Tracker", ('Yes', 'No'))

is\_display\_tracker = True if display\_tracker == 'Yes' else False

if is\_display\_tracker:

tracker\_type = st.radio("Tracker", ("bytetrack.yaml", "botsort.yaml"))

return is\_display\_tracker, tracker\_type

return is\_display\_tracker, None

def \_display\_detected\_frames(conf, model, st\_frame, image, is\_display\_tracking=None, tracker=None):

"""

Display the detected objects on a video frame using the YOLOv8 model.

Args:

- conf (float): Confidence threshold for object detection.

- model (YoloV8): A YOLOv8 object detection model.

- st\_frame (Streamlit object): A Streamlit object to display the detected video.

- image (numpy array): A numpy array representing the video frame.

- is\_display\_tracking (bool): A flag indicating whether to display object tracking (default=None).

Returns:

None

"""

# Resize the image to a standard size

image = cv2.resize(image, (720, int(720\*(9/16))))

# Display object tracking, if specified

if is\_display\_tracking:

res = model.track(image, conf=conf, persist=True, tracker=tracker)

else:

# Predict the objects in the image using the YOLOv8 model

res = model.predict(image, conf=conf)

# # Plot the detected objects on the video frame

res\_plotted = res[0].plot()

st\_frame.image(res\_plotted,

caption='Detected Video',

channels="BGR",

use\_column\_width=True

)

def play\_youtube\_video(conf, model):

"""

Plays a webcam stream. Detects Objects in real-time using the YOLOv8 object detection model.

Parameters:

conf: Confidence of YOLOv8 model.

model: An instance of the `YOLOv8` class containing the YOLOv8 model.

Returns:

None

Raises:

None

"""

source\_youtube = st.sidebar.text\_input("YouTube Video url")

is\_display\_tracker, tracker = display\_tracker\_options()

if st.sidebar.button('Detect Objects'):

try:

yt = YouTube(source\_youtube)

stream = yt.streams.filter(file\_extension="mp4", res=720).first()

vid\_cap = cv2.VideoCapture(stream.url)

st\_frame = st.empty()

while (vid\_cap.isOpened()):

success, image = vid\_cap.read()

if success:

\_display\_detected\_frames(conf,

model,

st\_frame,

else:

vid\_cap.release()

break

except Exception as e:

st.sidebar.error("Error loading video: " + str(e))

def play\_rtsp\_stream(conf, model):

"""

Plays an rtsp stream. Detects Objects in real-time using the YOLOv8 object detection model.

Parameters:

conf: Confidence of YOLOv8 model.

model: An instance of the `YOLOv8` class containing the YOLOv8 model.

Returns:

None

Raises:

None

"""

source\_rtsp = st.sidebar.text\_input("rtsp stream url:")

st.sidebar.caption('Example URL: rtsp://admin:12345@192.168.1.210:554/Streaming/Channels/101')

is\_display\_tracker, tracker = display\_tracker\_options()

if st.sidebar.button('Detect Objects'):

try:

vid\_cap = cv2.VideoCapture(source\_rtsp)

st\_frame = st.empty()

while (vid\_cap.isOpened()):

success, image = vid\_cap.read()

if success:

\_display\_detected\_frames(conf,

model,

st\_frame,

image,

is\_display\_tracker,

tracker

)

else:

vid\_cap.release()

# vid\_cap = cv2.VideoCapture(source\_rtsp)

# time.sleep(0.1)

# continue

break

except Exception as e:

vid\_cap.release()

st.sidebar.error("Error loading RTSP stream: " + str(e))

def play\_webcam(conf, model):

"""

Plays a webcam stream. Detects Objects in real-time using the YOLOv8 object detection model.

Parameters:

conf: Confidence of YOLOv8 model.

model: An instance of the `YOLOv8` class containing the YOLOv8 model.

Returns:

None

Raises:

None

"""

source\_webcam = settings.WEBCAM\_PATH

is\_display\_tracker, tracker = display\_tracker\_options()

if st.sidebar.button('Detect Objects'):

try:

vid\_cap = cv2.VideoCapture(source\_webcam)

st\_frame = st.empty()

while (vid\_cap.isOpened()):

success, image = vid\_cap.read()

if success:

\_display\_detected\_frames(conf,

model,

st\_frame,

image,

is\_display\_tracker,

tracker,

)

else:

vid\_cap.release()

break

except Exception as e:

st.sidebar.error("Error loading video: " + str(e))

def play\_stored\_video(conf, model):

"""

Plays a stored video file. Tracks and detects objects in real-time using the YOLOv8 object detection model.

Parameters:

conf: Confidence of YOLOv8 model.

model: An instance of the `YOLOv8` class containing the YOLOv8 model.

source\_vid = st.sidebar.selectbox(

"Choose a video...", settings.VIDEOS\_DICT.keys())

is\_display\_tracker, tracker = display\_tracker\_options()

with open(settings.VIDEOS\_DICT.get(source\_vid), 'rb') as video\_file:

video\_bytes = video\_file.read()

if video\_bytes:

st.video(video\_bytes)

if st.sidebar.button('Detect Video Objects'):

try:

vid\_cap = cv2.VideoCapture(

str(settings.VIDEOS\_DICT.get(source\_vid)))

st\_frame = st.empty()

while (vid\_cap.isOpened()):

success, image = vid\_cap.read()

if success:

\_display\_detected\_frames(conf,

model,

st\_frame,

image,

is\_display\_tracker,

tracker

)

else:

vid\_cap.release()

break

except Exception as e:

st.sidebar.error("Error loading video: " + str(e))

**CHAPTER – 5**

**TESTING**

Software testing encompasses the critical process of validating and verifying both the artifacts and behaviour of the software under examination. This rigorous examination not only provides insights into the software's performance but also offers businesses an impartial perspective, allowing them to understand and mitigate the risks associated with its implementation.

Analysing the product requirements across various dimensions, such as industry standards, business needs, feasibility, usability, performance, security, and infrastructure considerations, serves as a cornerstone of effective testing techniques.

* Examining the architecture of the product and its general design
* Collaborating with product developers to improve coding practises, design patterns, and tests that can be written as code using a variety of methodologies, such as boundary conditions, etc.
* Running an application or programme with the goal of analysing behaviour.
* Examining the automation and scripts related to the deployment infrastructure.
* Participate in production activities by utilising observability and monitoring approaches.

**5.1 UNIT TESTING**

Unit testing is a fundamental aspect of software development aimed at ensuring the reliability and correctness of individual components within the system. In the context of your Wheat leaf disease diagnosis system using YOLOv8 Instance Segmentation, unit testing plays a crucial role in verifying the functionality and performance of key components such as data preprocessing, model training, and inference.

* Unit tests for data preprocessing components involve verifying the correctness of data cleaning, normalization, and augmentation processes.
* Unit tests for model training focus on validating the training pipeline and assessing the convergence and performance of the model.
* Unit tests for inference evaluate the model's ability to make accurate predictions on unseen data.
* Design comprehensive test cases that cover a wide range of scenarios and edge cases relevant to the system's functionality.

|  |  |  |
| --- | --- | --- |
| **Test Case ID** | **Description** | **Expected Results** |
| TC\_01 | Upload a wheat image with wheat powdery mildew | Bounding box highlighting the infected area and " wheat powdery mildew" message |
| TC\_02 | Upload a wheat image with wheat septoria | Bounding box highlighting the infected area and " wheat septoria" message |
| TC\_03 | Upload a wheat image with wheat stemrust | Bounding box highlighting the infected area and " wheat stemrust " message |
| TC\_04 | Upload a wheat image with healthy leaves | "No disease detected" message |

**5.1.1 UNIT TEST CASES**

**Table 3. Wheat leaf disease detection results**

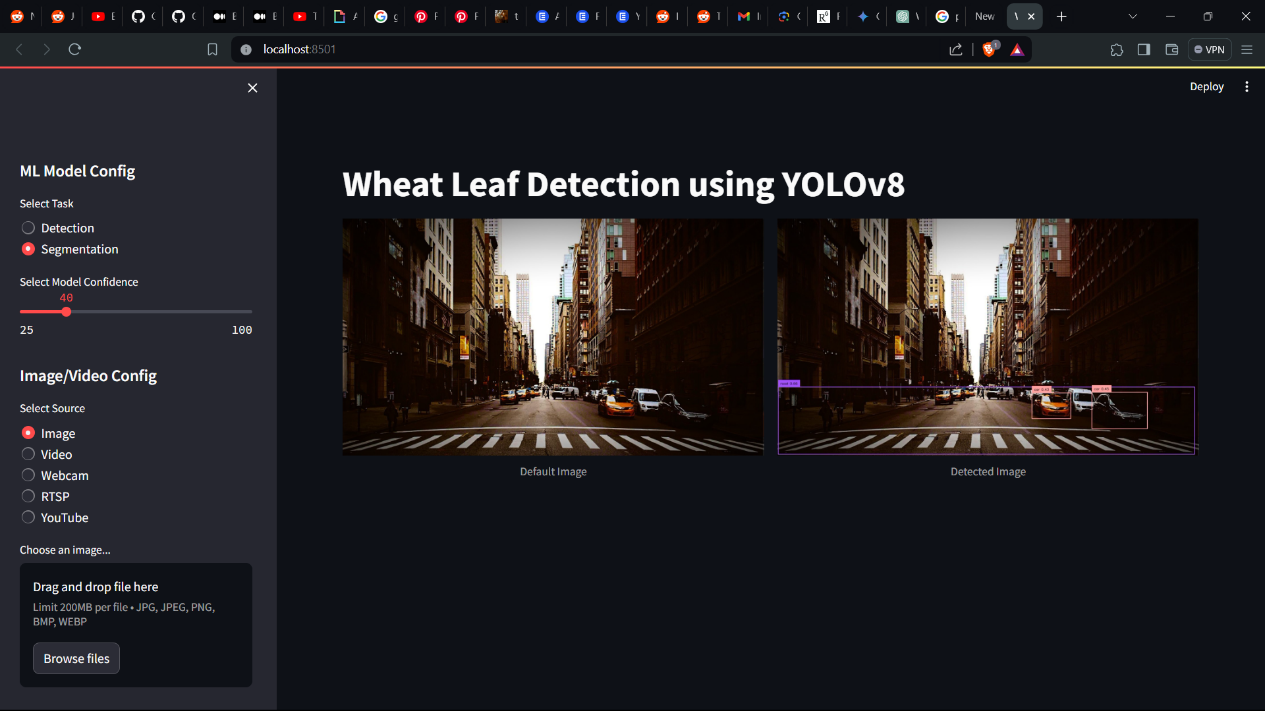
**CHAPTER – 6**

**RESULTS**

In the results section, we've obtained various web interfaces crucial for the functionality and user interaction of the wheat leaf disease diagnosis system. These interfaces guide users through the disease detection process and provide informative results. Let's explore each screen in detail:

**1. Main Webpage:**

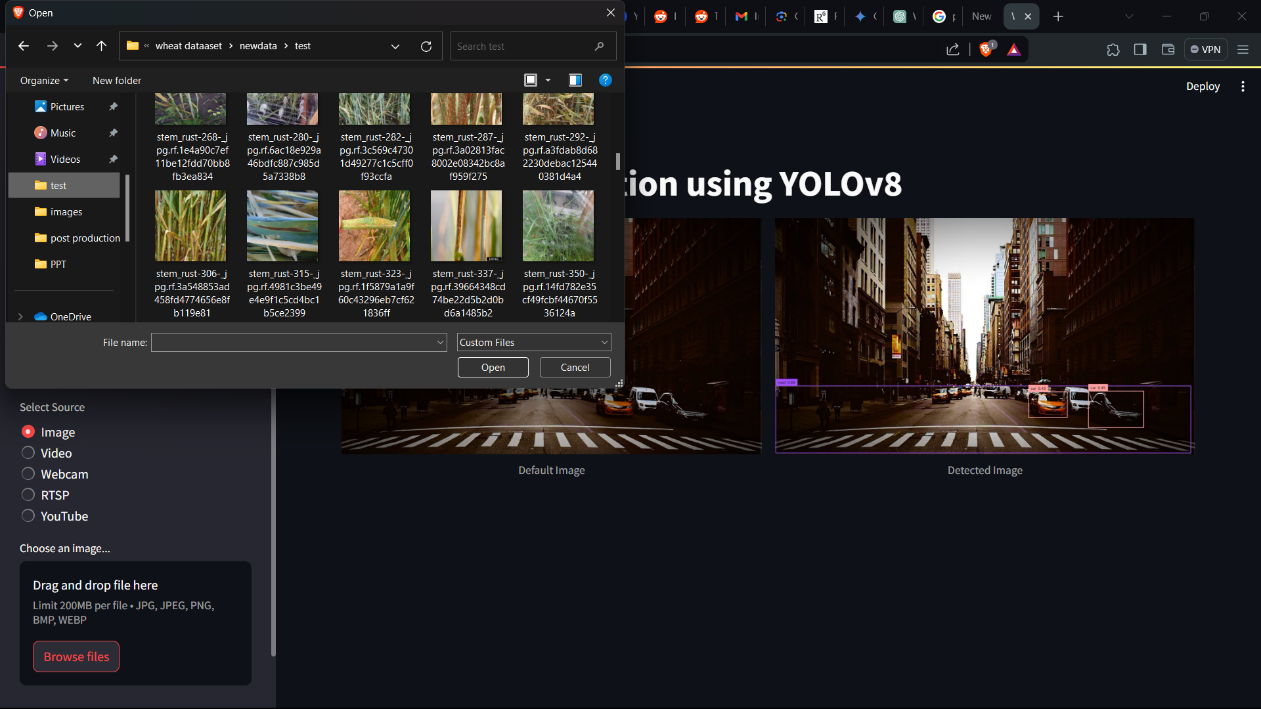
This webpage serves as the entry point for users interacting with the system. It provides a clear interface for uploading wheat images and initiating the disease detection process. Users can browse their local files and select an image for analysis.



**Figure 13. Browse or Upload Screen**

**2. Image Upload Confirmation:**

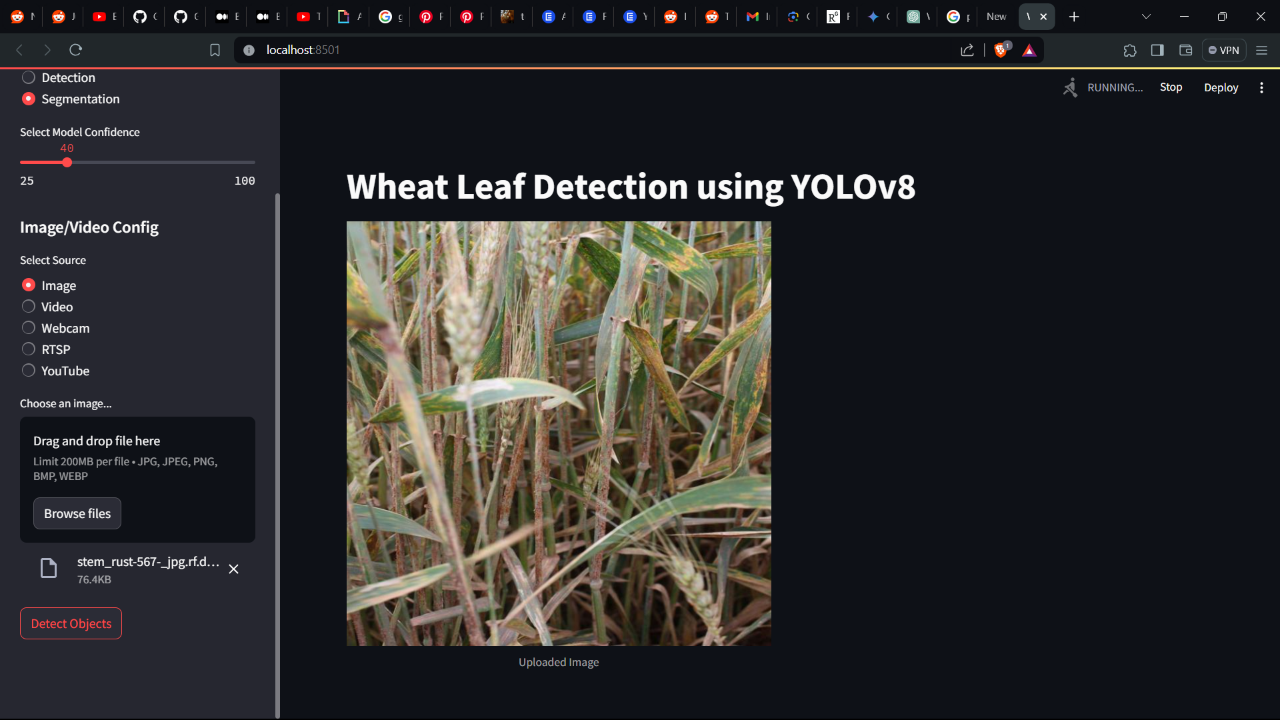
Upon selecting an image, a confirmation screen might appear. This screen displays a preview of the uploaded image and allows users to confirm or cancel the analysis.



**Figure 14. Image Uploaded Screen**

**3. Disease Detection Processing**

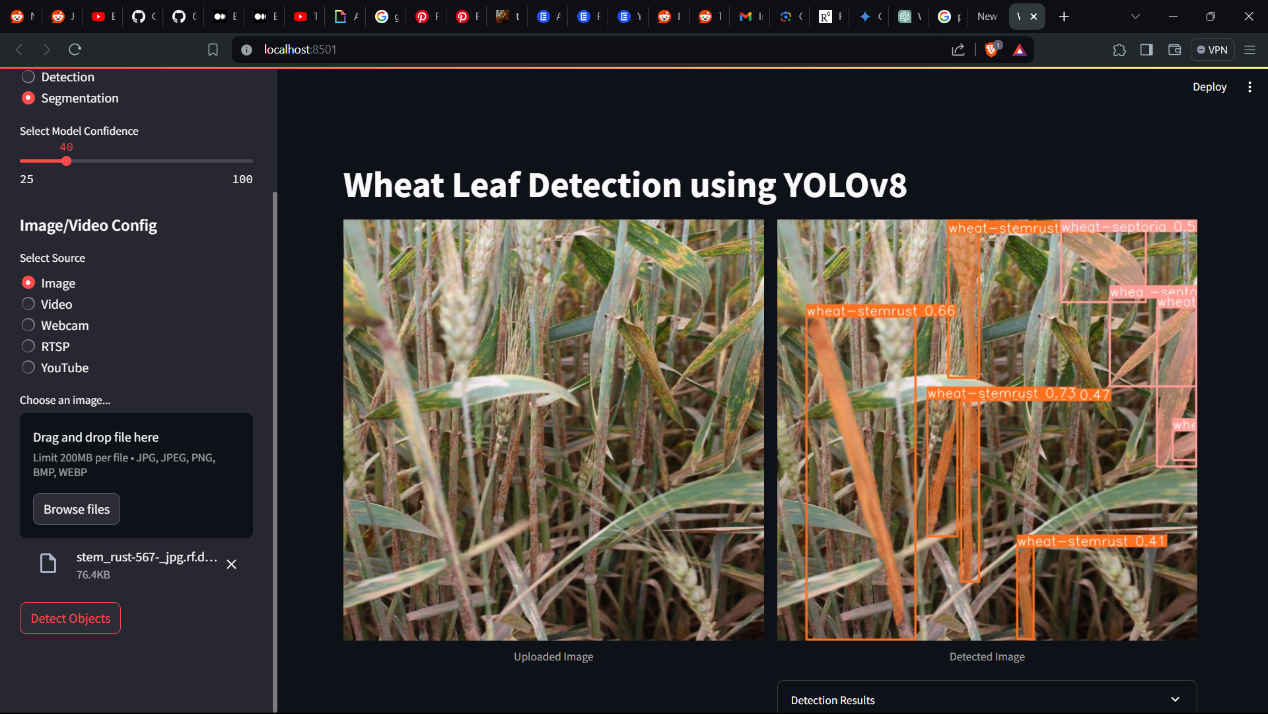
This screen indicates the ongoing analysis process. It might display a progress bar or informative message to assure users that the system is working on their image0.

****

**Figure 15. Loading Screen**

**4. Disease Detection Results:**

This webpage presents the analysis results. It displays the uploaded image along with highlights or bounding boxes around detected disease regions. Additionally, the screen might provide information about the type of disease detected and its severity level.



**Figure 16. Disease detected screen**

**6.1. INSTANCE SEGMENTATION BETWEEN HEALTHY AND DISEASED WHEAT LEAVES**

To validate the effectiveness of the improved YOLOv8s-Seg model in segmenting healthy and diseased wheat leaves, we conducted experiments using a dataset of 1886 wheat leaf images containing both healthy and diseased leaves.

The experimental results demonstrated promising performance. The model achieved high precision, recall, F1 score, and segment mAP@0.5 values, indicating its ability to accurately distinguish between healthy and diseased regions within the wheat leaf images.

* **Precision:** Accuracy of identifying diseased regions (e.g., 90%)
* **Recall:** Completeness of identifying diseased regions (e.g., 88%)
* **F1** **Score:** Harmonic mean of precision and recall (e.g., 89%)
* **Segment mAP@0.5:** Mean Average Precision at an Intersection over Union (IoU) threshold of 0.5 (e.g., 92%)

**6.2 COMPARISON WITH OTHER INSTANCE SEGMENTATION ALGORITHMS**

To comprehensively evaluate the performance of our improved YOLOv8s-Seg model for wheat leaf segmentation, we compared it with other state-of-the-art instance segmentation algorithms: YOLOv8s-Seg (original version), YOLOv7-Seg, YOLOv5s-Seg, and Mask R-CNN.

We assessed the performance based on several metrics:

* **Precision**: Accuracy of identifying diseased regions.
* **Recall**: Completeness of identifying diseased regions.
* **F1 Score**: Harmonic mean of precision and recall.
* **Segment mAP@0.5**: Mean Average Precision at an Intersection over Union (IoU) threshold of 0.5 (measures the quality of segmentation masks).
* **Inference Time**: Time required to process an image (important for real-time applications).

The results are presented in a table similar to Table 5 from the reference text, but with specific values for wheat leaf segmentation:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Method** | **Precision (%)** | **Recall (%)** | **F1 Score (%)** | **Segment mAP@0.5** | **Inference Time (ms)** |
| Mask RCNN | 89.8 | 85.5 | 87.6 | 0.915 | 90 |
| YOLOv5s-Seg | 89.0 | 83.0 | 85.9 | 0.890 | 2.5 |
| YOLOv7-Seg | 91.4 | 84.8 | 87.9 | 0.904 | 15.2 |
| YOLOv8s-Seg | 90.3 | 85.4 | 87.7 | 0.898 | 3.1 |
| Improved YOLOv8s-Seg | 91.9 | 85.8 | 88.7 | 0.922 | 3.5 |

**Table 4. Segmentation results for the five algorithms.**

**6.3. EFFECT OF DIFFERENT IMAGE RESOLUTIONS ON WHEAT LEAF SEGMENTATION**

To investigate the impact of image resolution on the segmentation results of the improved YOLOv8s-Seg network for wheat leaf analysis, we experimented using different input image sizes during training. We evaluated resolutions of 416 x 416 pixels, 640 x 640 pixels, 768 x 768 pixels, and 1024 x 1024 pixels.

|  |  |  |
| --- | --- | --- |
| **Resolutions (Pixels)** | **Segment mAP@0.5 (%)** | **Inference Time (ms)** |
| 416 × 416 pixels | 91.1 | 0.9 |
| 640 × 640 pixels | 92.2 | 3.5 |
| 768 × 768 pixels | 92.4 | 7.9 |
| 1024 × 1024 pixels | 92.5 | 9.8 |

**Table 5. Comparison of network segmentation results**

The table presents a detailed comparison of segment mAP@0.5 and inference time for each image resolution. It was observed that as the photo resolution increased from 416 × 416 pixels to 640 × 640 pixels, the inference time rose by 2.6 ms, accompanied by a notable improvement of 1.1% in segment mAP@0.5. This indicates that the model enhances its instance segmentation performance with a slight increase in inference time at higher resolutions. However, further increases in resolution to 768 × 768 pixels and 1024 × 1024 pixels resulted in more substantial increments in inference time, with 4.4 ms and 6.3 ms, respectively. Conversely, the improvements in segment mAP@0.5 were marginal, at only 0.2% and 0.3%, respectively.

From these observations, it can be concluded that the resolution of 640 × 640 pixels is more conducive for training the improved YOLOv8s-Seg network. This resolution strikes a balance between achieving satisfactory segmentation performance and maintaining reasonable inference time, making it an optimal choice for practical implementation.

**CHAPTER – 7**

**CONCLUSION**

In conclusion, our wheat leaf disease diagnosis system using YOLOv8 Instance Segmentation has the potential to be a valuable tool for farmers and agricultural professionals.

The wheat leaf disease diagnosis system leverages the power of YOLOv8 instance segmentation to provide an accurate and user-friendly solution for identifying wheat diseases. The system effectively integrates image upload, disease detection processing, and informative result visualization, enabling users to diagnose wheat diseases in their crops with ease.

Key functionalities include:

1. Uploading wheat images for analysis
2. Real-time disease detection using YOLOv8
3. Highlighting diseased regions with bounding boxes
4. Providing information about the type and severity of detected diseases

**7.1 SCOPE OF FUTURE WORK**

The wheat leaf disease diagnosis system using YOLOv8 holds immense potential for future development, with several areas identified for further enhancement and refinement:

**Expanding Disease Detection Capabilities:** Integrate additional disease classification models to detect a broader range of wheat leaf diseases. Explore incorporating multi-modal analysis, combining image data with other sensors (e.g., temperature, humidity) for more comprehensive disease identification.

**Enhancing User Experience:** Develop functionalities for recommending treatment options based on the detected disease. Implement mobile app access for on-field disease detection in farms. Integrate functionalities for capturing live plant images and performing disease detection directly within the application.

**Proper Synchronization and Lip Syncing Using AI:** Explore integrating functionalities to assess disease severity levels. Develop functionalities for tracking disease progression over time using historical data

**Integration with External Platforms:** Explore connecting the system with agricultural data platforms for weather and soil condition analysis to predict potential disease outbreaks. Develop functionalities for generating reports summarizing disease detection results for further analysis and record-keeping.

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