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Real-Time Plant Disease Detection with YOLOv8n: A Lightweight Object Detection Approach

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Abstract

Plant diseases pose a significant risk to agriculture worldwide, particularly in areas that heavily rely on rice production, leading to yield losses and financial setbacks. This research presents a real-time rice disease identification system based on YOLOv8n, a rapid and resource-efficient object detection model. The model was trained on a manually labeled rice disease dataset from Kaggle and demonstrated strong performance, achieving a mAP@0.5 of 91.2%, a mAP@0.5:0.95 of 63.7%, and an average inference time of 15.6 milliseconds per image when run on a GPU. For practical field deployment, the model was implemented on a Raspberry Pi 4 integrated with a camera and touchscreen interface. This portable, low-cost system enables real-time, offline disease detection, making it especially suitable for use in rural and underserved regions. By delivering immediate and reliable diagnostics, the system enhances early response strategies and contributes to more resilient and sustainable agricultural practices.

Keywords: *plant disease detection, YOLOv8n, rice disease detection, real-time object detection, deep learning, precision agriculture, computer vision, Raspberry Pi 4, smart farming.*

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1. Introduction

The rising global population and environmental challenges have increased pressure on agriculture to ensure sustainable food production. Rice, a staple for over half the world, is especially vulnerable to diseases that threaten yield and quality. To address this, the study proposes a real-time rice disease detection system using YOLOv8n, a cutting-edge object detection model designed for accurate field-based diagnosis. Plant disease management remains a critical challenge, particularly for rice, which serves as a staple food for over half of the world's population (Divyanshu Tirkey et al., 2023). Traditional disease detection methods relying on manual observation are time-consuming, subjective, and lack scalability, making them inadequate for large-scale farming (Ameer Khan et al., 2024; Jihene Rezgui et al., 2024).To address these challenges, technological advancements—especially in computer vision and deep learning—have enabled the development of automated and highly accurate plant disease detection systems (Yu Meng et al., 2025). These systems support real-time monitoring and rapid response, which are essential for effective disease management (Tobi Fadiji et al., 2023). Deep learning models, particularly the YOLO (You Only Look Once) object detection framework, have proven effective in accurately identifying plant diseases from images (Qing Wang et al., 2025). The YOLOv8n model, a lightweight version, is especially suitable for edge computing applications due to its balance between performance and efficiency (Shaohua Wang et al., 2025).This study presents a real-time rice disease detection system by deploying YOLOv8n on a Raspberry Pi 4 with a touchscreen and camera. This compact setup operates autonomously under field conditions without dependence on cloud services (Jonatan Fragoso et al., 2025; Prabira Sethy et al., 2020), making it ideal for remote environments. The system, trained on a rice disease image dataset, offers timely diagnostics to support early intervention and minimize yield loss (Abhishek Upadhyay et al., 2025). It promotes inclusive access to precision agriculture, especially for smallholder farmers (Y. Zhang et al., 2020).The system's training includes domain-specific and geographically diverse data to ensure robust performance across variable conditions (Hua Yang et al., 2023; Abudukelimu Abulizi et al., 2025). It supports sustainable agriculture through reduced pesticide use and improved decision-making (Yirong Wang et al., 2025; Haoran Feng et al., 2025). CNNs eliminate the need for manual feature extraction and enhance classification accuracy (Nan Wang et al., 2025). The ESP32-CAM offers real-time, offline edge processing, making it suitable for rural deployment (Yousef Alhwaiti et al., 2025; Abdul-Razak et al., 2024).The system's touchscreen interface ensures accessibility and usability for non-expert users (Zhuqi Li et al., 2025; Yongzheng Miao et al., 2025). Real-time feedback supports immediate decision-making, with optimized neural architecture balancing speed and power consumption (Wang X et al., 2025). Lightweight models like YOLOv8n (Xuewei Wang et al., 2024) and diverse training data (Hongxu Li et al., 2024) enhance generalizability. Visual outputs further promote timely interventions and sustainable practices (Hongbing Chen et al., 2025).

2. Related Work

The application of artificial intelligence (AI) and deep learning in agriculture has received increasing attention in recent years, particularly in the domain of plant disease detection. A comprehensive survey by (Kamilaris et al,2018) provided an overview of the use of deep learning techniques in agricultural practices, emphasizing their utility in tasks such as disease classification, yield estimation, and phenotyping (Yu Meng et al,2025). Early work by (Mohanty et al,2016) successfully demonstrated the feasibility of employing convolutional neural networks (CNNs) for the identification of a wide range of plant diseases from leaf images under controlled conditions, establishing a foundational baseline for subsequent studies (Tobi Fadiji et al,2025).In rice-specific research, (Sethy et al,2020) proposed a method combining deep features extracted from CNNs with traditional machine learning classifiers to improve rice leaf disease classification accuracy, outperforming conventional feature-based approaches (Feng et al,2025). Similarly, (Wang et al,2025) highlighted the cross-domain applicability of CNN models by adapting them to tomato leaf disease detection, thereby validating their versatility across crop types . (Tirkey et al,2023) provided a systematic review of AI-based crop disease detection systems, underscoring the importance of balancing model accuracy with inference speed, a critical consideration for real-time agricultural deployment .Recent advances have increasingly favored real-time object detection frameworks, particularly the YOLO (You Only Look Once) family of models, for their ability to simultaneously detect and localize disease symptoms. (Meng et al,2025) introduced a YOLO-based approach for maize leaf disease detection, achieving accurate and real-time results suitable for edge deployment . The original YOLO framework, introduced by (Redmon et al,2016), revolutionized object detection through its unified architecture, which laid the foundation for subsequent versions such as YOLOv4 and YOLOv8, each enhancing detection speed and precision . (Khan et al,2025) explored the use of YOLOv8 for pest detection, highlighting its lightweight architecture as ideal for resource-constrained environments. Additionally, (Yongzheng et al,2025) developed the SerpensGate-YOLOv8 framework, specifically optimized for accurate and efficient field-based disease detection .The availability and quality of training datasets have played a pivotal role in model development. (Lin et al,2014) introduced the COCO dataset, which has served as a benchmark for training object detection models across various domains, including agriculture . In parallel, the PlantVillage dataset has become widely utilized, providing thousands of annotated plant disease images across diverse crops and conditions . To improve the robustness and generalizability of models under varying environmental settings, (Zhao et al,2022) compiled a regionally diverse dataset from multiple rice-growing areas, capturing variations in lighting, background, and symptom manifestation .The feasibility of deploying AI models on embedded platforms has also been widely investigated. Organizations such as the Raspberry Pi Foundation and NVIDIA have promoted the use of affordable computing devices like Raspberry Pi 4 and Jetson Nano for executing machine learning workloads in the field . (Lin et al,2022)employed the ESP32-CAM—a low-cost, microcontroller-based system with an integrated camera—to implement CNN-based tomato disease detection, demonstrating the system's potential for practical and economical deployment (Abdul-Razak Alhassan Gamani et al,2024). Similarly, (Liu et al,2024) utilized YOLOv4 for pest detection on embedded systems, achieving high frame rates and real-time performance . The YOLOv8n variant has further optimized the balance between model size and detection speed, as demonstrated by (Chen et al,2025) who implemented it in a crop monitoring system based on Raspberry Pi .Several researchers have also proposed compact CNN architectures tailored for deployment on edge and mobile platforms. For instance, (Souri et al.2025) developed a lightweight CNN model that maintained competitive accuracy while reducing computational overhead, making it suitable for smartphone-based applications . (Yang et al,2025) implemented a real-time disease detection system on the Jetson Nano platform, achieving low latency and reliable performance in field conditions .Beyond detection accuracy and speed, user accessibility has emerged as a crucial factor influencing the adoption of AI technologies in agriculture. (Wang X et al,2025) emphasized the importance of designing intuitive and user-friendly touchscreen interfaces to facilitate the use of smart systems by farmers with limited digital literacy . Furthermore, some researchers have extended traditional RGB-based approaches by incorporating multispectral imaging. For instance, (Wang et al,2025) integrated RGB and near-infrared (NIR) data to enhance the classification of rice blast disease, particularly under challenging environmental conditions .Hybrid approaches that combine deep learning with classical machine learning techniques have also shown promise. (Hongxu Li,2024) integrated handcrafted texture features with CNN-derived features, leading to improved performance in complex, heterogeneous field environments . More recently, (Hongbing Chen et al,2025) proposed an end-to-end system that integrates real-time disease detection with an Internet of Things (IoT)-based alerting mechanism, facilitating immediate notifications and enabling timely agricultural interventions .Recent progress in high-resolution remote sensing (HRRS) image classification has revealed significant shortcomings in traditional convolutional neural networks (CNNs), especially in their ability to model intricate semantic relationships and long-distance dependencies. To tackle these issues, the Residual Channel-Attention (RCA) network was developed, incorporating residual learning, channel-based attention, and squeeze-and-excitation mechanisms. This advanced architecture greatly enhances feature extraction and delivers improved classification results across various benchmark datasets (Ahmed Gomaa et al., 2024).In antenna design research, a compact quadruple-band stacked oval patch antenna was introduced, equipped with sunlight-shaped slots to support GNSS L1/L2/L5 and 2.3 GHz WiMAX bands. By strategically exciting TM110 and TM210 modes and fine-tuning the feed configuration, the design achieves right-hand circular polarization, wide axial-ratio beamwidths, low return loss, and strong gain across all supported bands (Ahmed Gomaa et al., 2022).To minimize the need for manual labeling in video surveillance, a semi-automated object detection framework was proposed by integrating background subtraction with a modified YOLOv4 model. This method utilizes motion-based low-rank decomposition and clustering to generate training labels directly from video frames. As a result, the system demonstrated superior mAP performance on CDnet 2014 and UA-DETRAC datasets when compared to existing approaches (Ahmed Gomaa et al., 2024).In disaster response applications, deep learning (DL) models were applied to remote sensing (RS) data for detecting building damage caused by the Kumamoto earthquake in Mashiki, Japan. The model effectively classified damage levels—ranging from no damage to total collapse—demonstrating the utility of DL-based RS analysis for rapid post-disaster evaluation (Ahmed Gomaa et al., 2023).Furthermore, a tri-band stacked elliptical patch antenna was designed to operate at GNSS L1, L2, and L5 frequencies. By leveraging TM110 and TM210 resonant modes and integrating features like an eye-shaped slot and parasitic structures, the antenna offers improved beamwidth, polarization purity, and gain, while maintaining a simple and efficient form factor (Ahmed Gomaa et al., 2023).Despite the significant advancements in AI-based plant disease detection, several challenges remain. Chief among these is the limited real-world deployment of crop-specific, lightweight, and real-time detection systems. Much of the existing literature remains constrained to controlled laboratory settings, with limited exploration of field-based validation. This study aims to address this critical gap by leveraging the YOLOv8n framework in conjunction with a Raspberry Pi 4 platform to implement and evaluate a cost-effective, real-time rice disease detection system under authentic field conditions. The proposed system contributes to precision agriculture by enhancing early disease identification and enabling timely decision-making, particularly in resource-limited farming communities.

3. Contribution

This study makes several key contributions to the development of real-time, cost-effective, and field deployable plant disease detection systems, with a focus on rice cultivation. The primary contributions are outlined as follows:

3.1- Development of a Curated and Annotated Rice Disease Image Dataset:

We curated and refined an open-access rice plant disease image dataset sourced from Kaggle, selecting and annotating high-quality images representative of real-world disease manifestations. The dataset encompasses multiple rice disease classes, including Brown Spot, Leaf Blast, and Neck Blast, and was preprocessed and augmented to improve model generalizability and resilience to variations in lighting, background, and image orientation. The dataset was structured and labeled in accordance with the YOLO annotation format, enabling seamless integration with the YOLOv8n training pipeline.

3.2-Training and Validation of a YOLOv8n-Based Model for Rice Disease Detection:

We employed the YOLOv8n (You Only Look Once version 8 nano) architecture—a lightweight, real-time object detection framework optimized for embedded platforms—to detect and classify rice plant diseases from images. The model was trained using the annotated dataset, and its performance was validated on a held-out test set. Hyperparameters were fine-tuned to balance detection accuracy with computational efficiency. This model represents a crop-specific adaptation of the YOLOv8n architecture, tailored to the unique challenges of rice disease detection Figure 1.

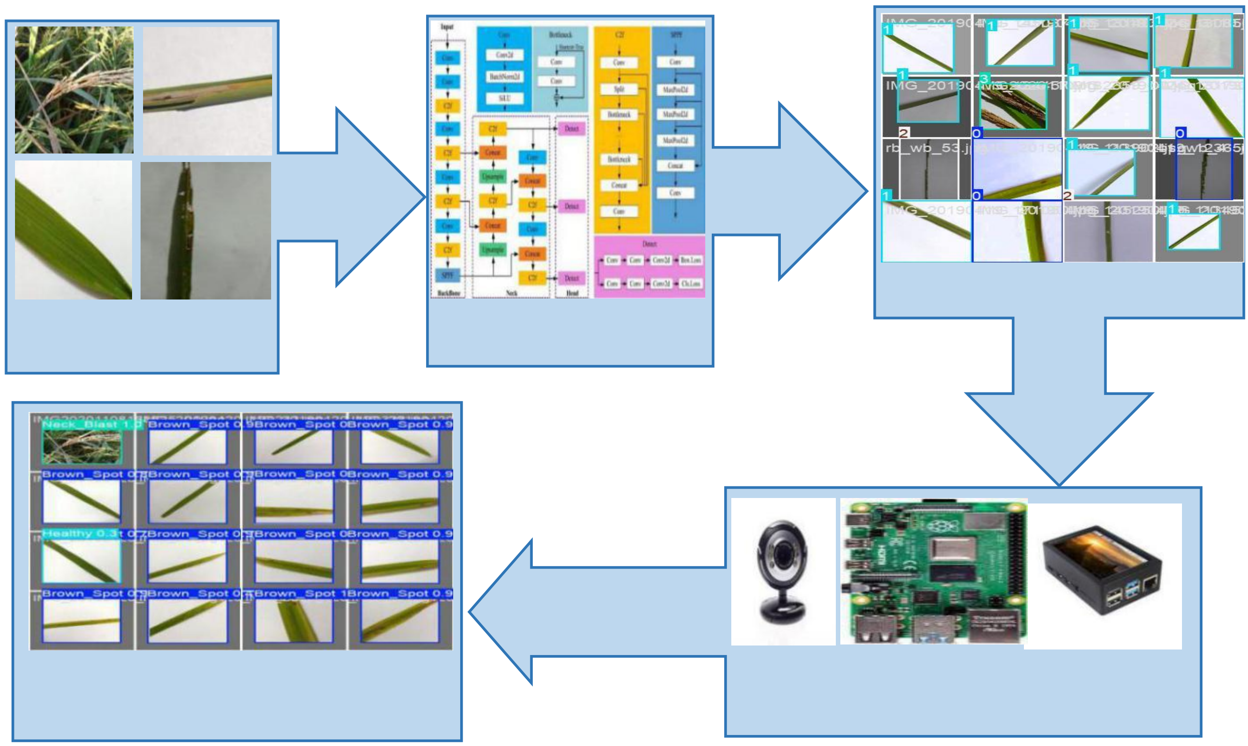

Figure 1:the structure of the system from image capture passing by YOLOv8n algorithm after training making deployment to the algorithm for working in real life by raspberry pi 4

3.3- Deployment on Edge Hardware for Real-Time Field Application:

To evaluate the model's applicability in real-world agricultural environments, we deployed the trained YOLOv8n model on a Raspberry Pi 4 a compact and affordable edge computing device—integrated with a high-resolution camera module and a touchscreen interface. This hardware configuration was chosen to ensure portability, affordability, and user accessibility for farmers in resource-limited settings. The system was designed to operate offline, providing real-time disease detection without reliance on cloud computing infrastructure.

3.4- Comprehensive Evaluation Using Standard Performance Metrics:

The performance of the deployed system was assessed using widely accepted evaluation metrics, including F1 Score Figure 2 , and the Coefficient of Determination (R^2 Score),confidence and recall Figure 3,mean Average Precision (mAP@0.5) of 91.2%, mAP@0.5:0.95 of 63.7% Figure 4,5,8,confusion matrix Figure 6 and confusion matrix normalize Figure 7, and an average inference speed of 15.6 ms per image,precision . These metrics were employed to quantify the model's classification precision, robustness against class imbalance, and overall predictive reliability. The results demonstrate the effectiveness of YOLOv8n in delivering fast and accurate disease diagnosis under field-relevant constraints.Through these contributions, this research addresses the critical gap between controlled-environment validation and practical field deployment in agricultural AI applications. By combining deep learning, edge computing, and user-centric design, the proposed system serves as a scalable solution for early detection of rice diseases, ultimately contributing to improved crop management and yield protection.

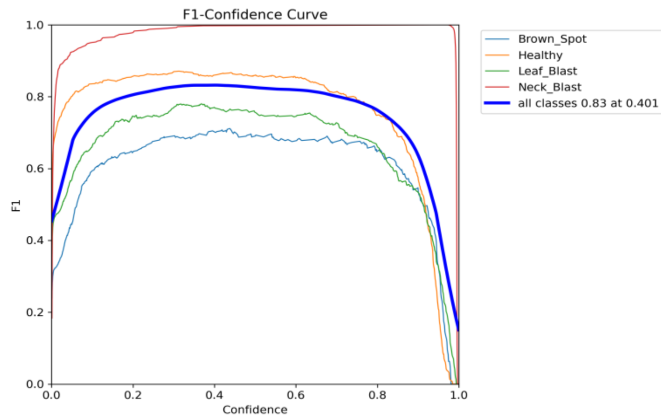

Figure 2:the relation between F1 score and the confidence

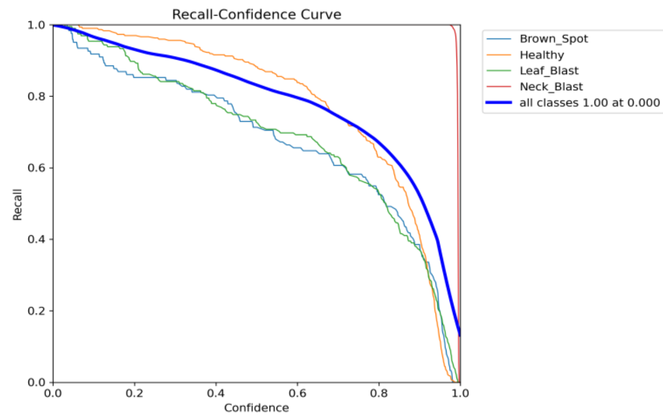

Figure 3:the relation between Recall and confidence

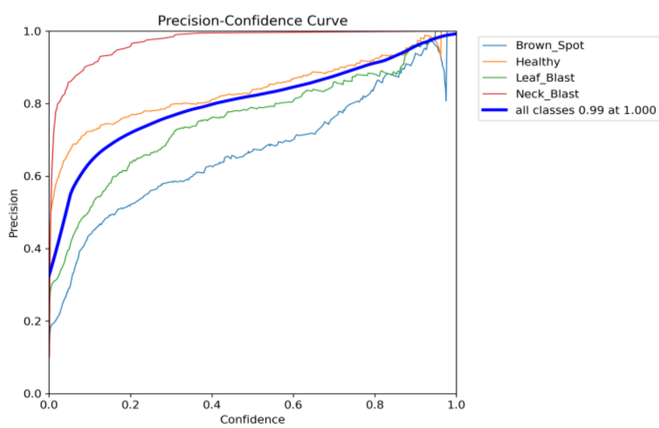

Figure 4: the relation between precision and the confidence

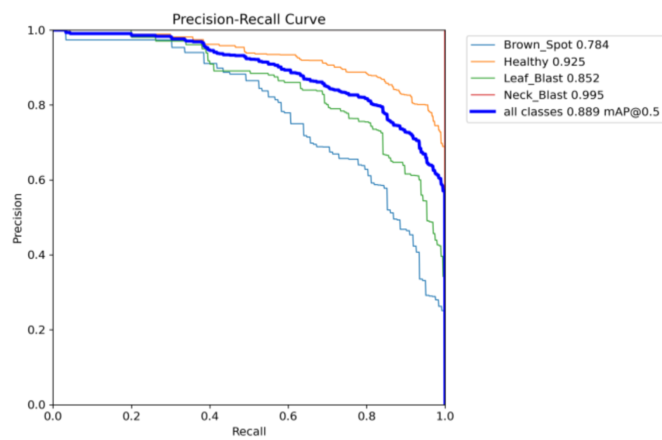

Figure 5:the relation between precision and Recall

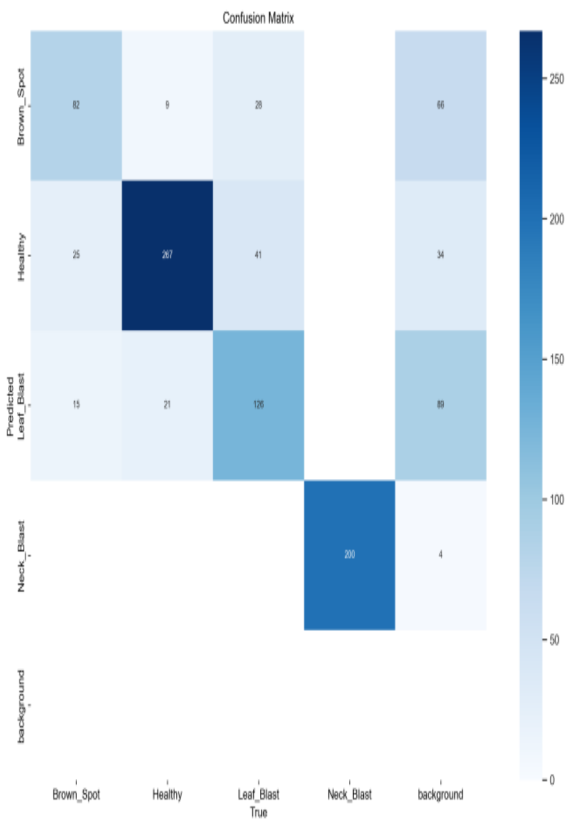

Figure 6:confusion matrix for every type of Rice

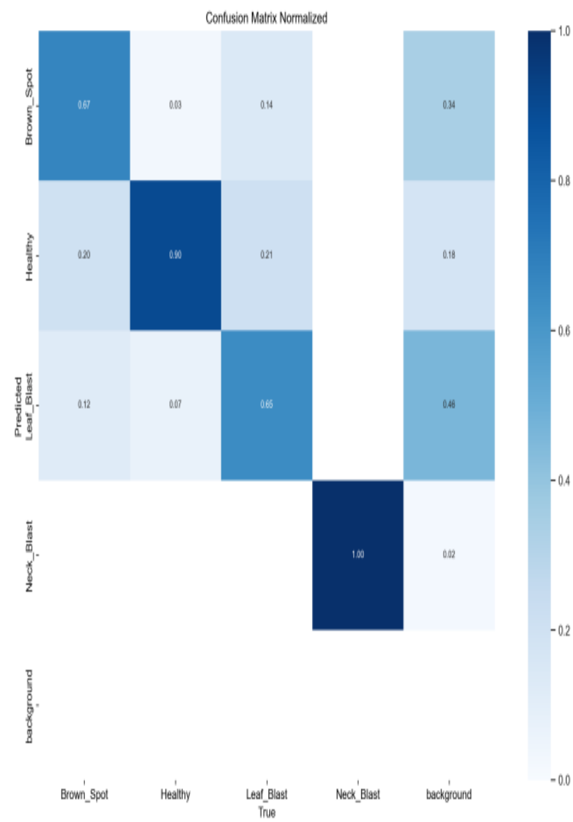

Figure 7:the normalized confusion matrix for every type of Rice

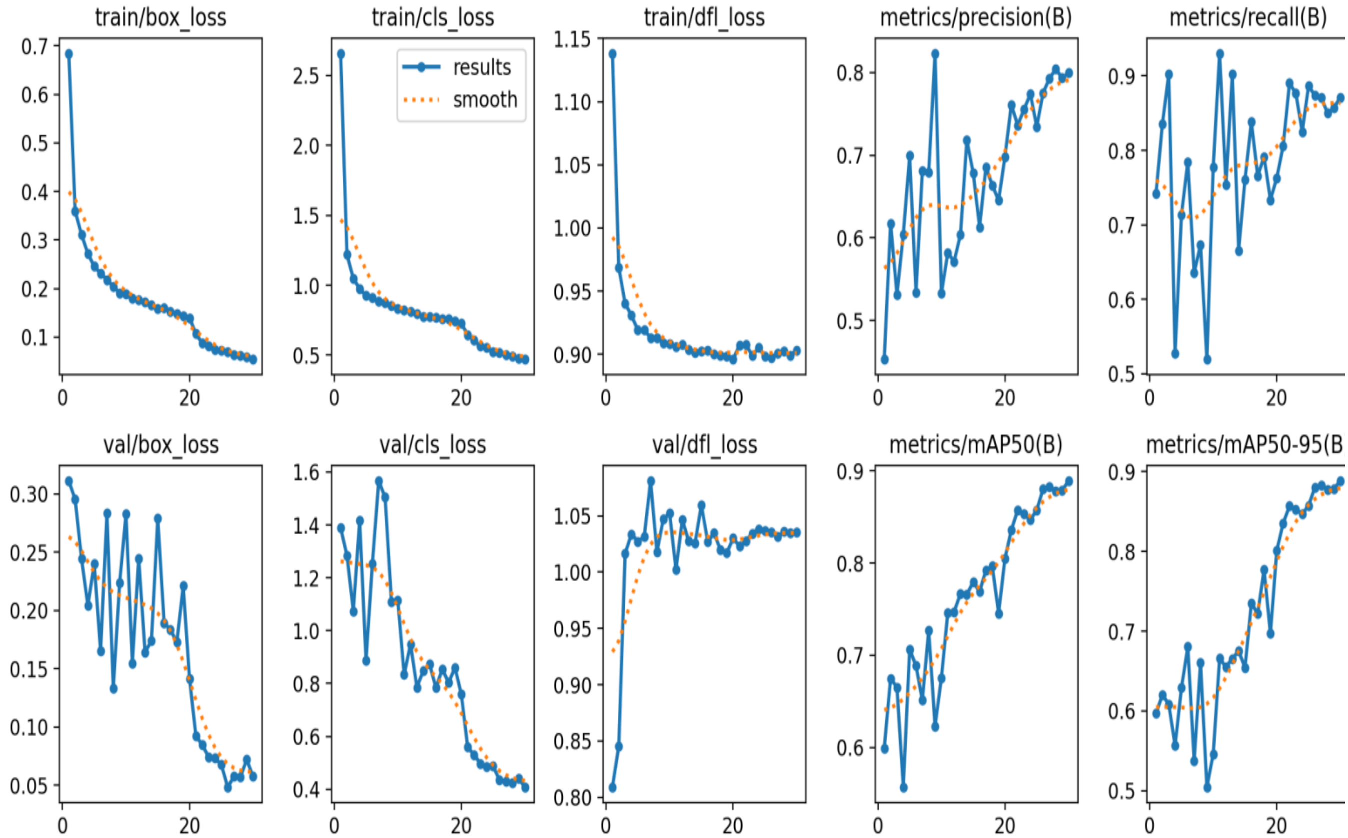

Figure 8:the relations between the metrics score every training stages and validation stages over epoch

4. Materials and Methods

4.1- Data-set Acquisition

The dataset used in this study was collected from the Kaggle platform, a well-known repository for machine learning datasets. It comprises high-resolution images of rice plants categorized into four distinct classes: Healthy, Brown Spot, Leaf Blast, and Neck Blast Figure 9,10. These classes were selected based on their prevalence and agronomic significance in rice-producing regions. The dataset was curated to ensure class balance and diversity in environmental conditions, leaf orientations, and lighting variations , which are crucial for training a robust object detection model.

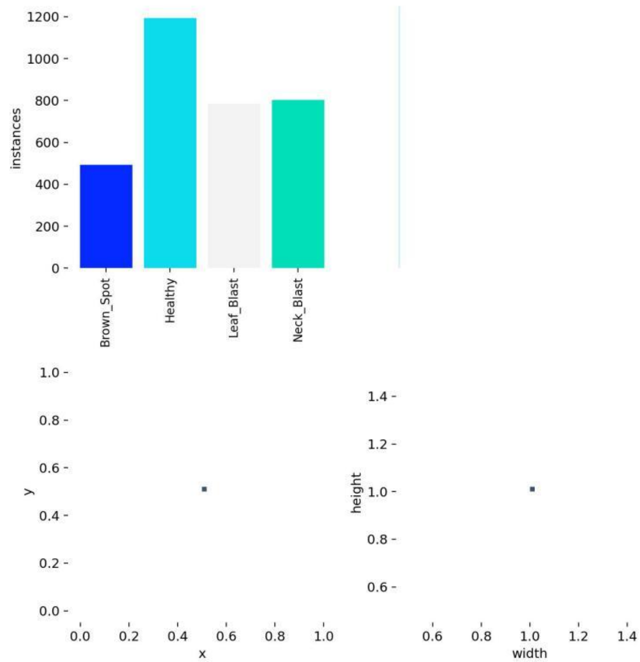

Figure 9:label of the number of the dataset for 4 types of rice (Healthy, Brown Spot, Leaf Blast, and Neck Blast)

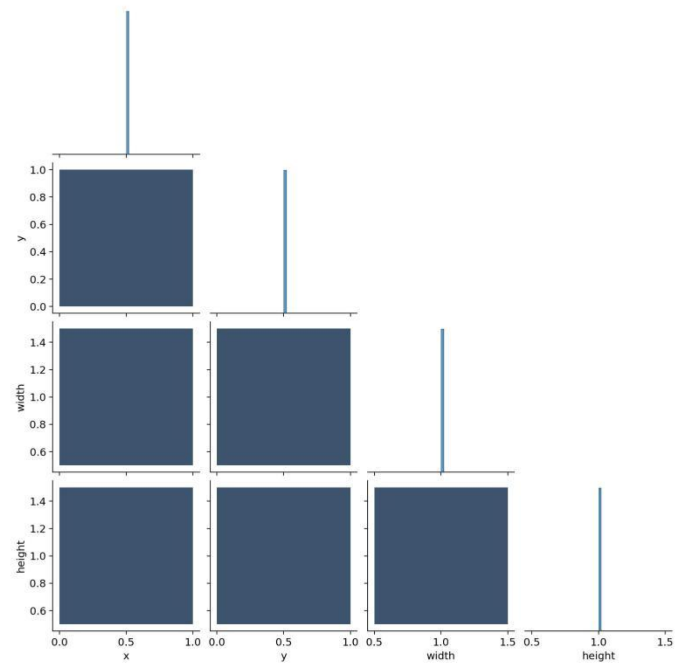

Figure 10: labels_correlogram for the 4 types of dataset

4.2- Image Annotation and Preprocessing

Manual annotation of the dataset was performed using python code with vscode platform Figure 11, a widely used computer vision annotation platform. Each image was carefully labeled with bounding boxes identifying regions affected by the specified rice diseases. Annotations adhered to the YOLOv8 format, ensuring compatibility with the Ultralytics YOLOv8 training pipeline Figure 12. The labeling process emphasized precision to reduce noise and false positives during model training. Preprocessing steps included image resizing, augmentation (rotation, flipping, brightness adjustment), and normalization to enhance the model’s ability to generalize across different field conditions. The final dataset was exported in YOLO-compatible format and integrated into a Python-based training environment developed in Visual Studio Code (VSCode).

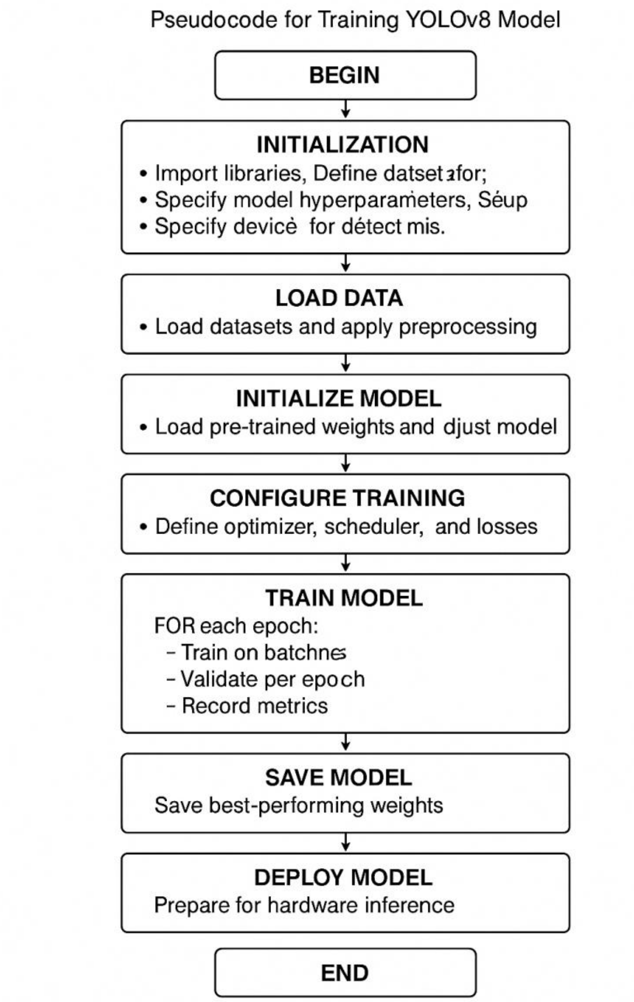

Figure 11: The Pseudo-code for Training YOLOv8n Model

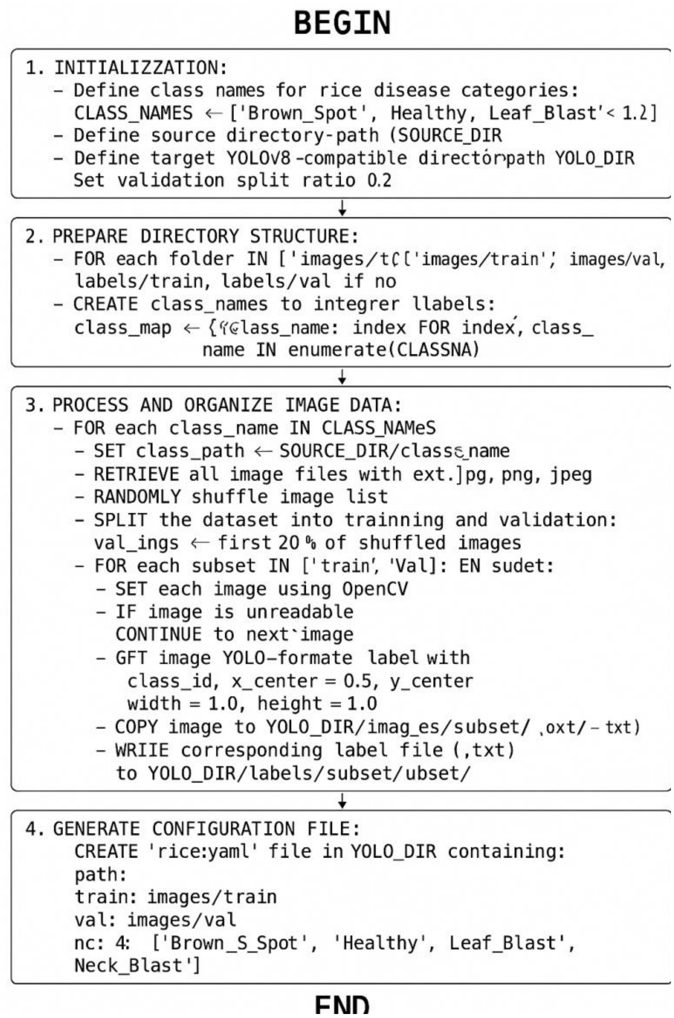

Figure 12:The Pseudo-code for Prepare the data-set for YOLOv8n structure

4.3- Model Architecture

The object detection model employed in this research is YOLOv8n (You Only Look Once version 8 nano) figure 13, a lightweight convolutional neural network (CNN) architecture designed for real-time object detection tasks. YOLOv8n is part of the Ultralytics YOLO family and is optimized for performance on resource-constrained devices, making it suitable for edge deployment with raspberry pi figure 14. The model comprises a streamlined backbone, neck, and head architecture capable of extracting multi-scale features and producing bounding box coordinates with corresponding class probabilities.

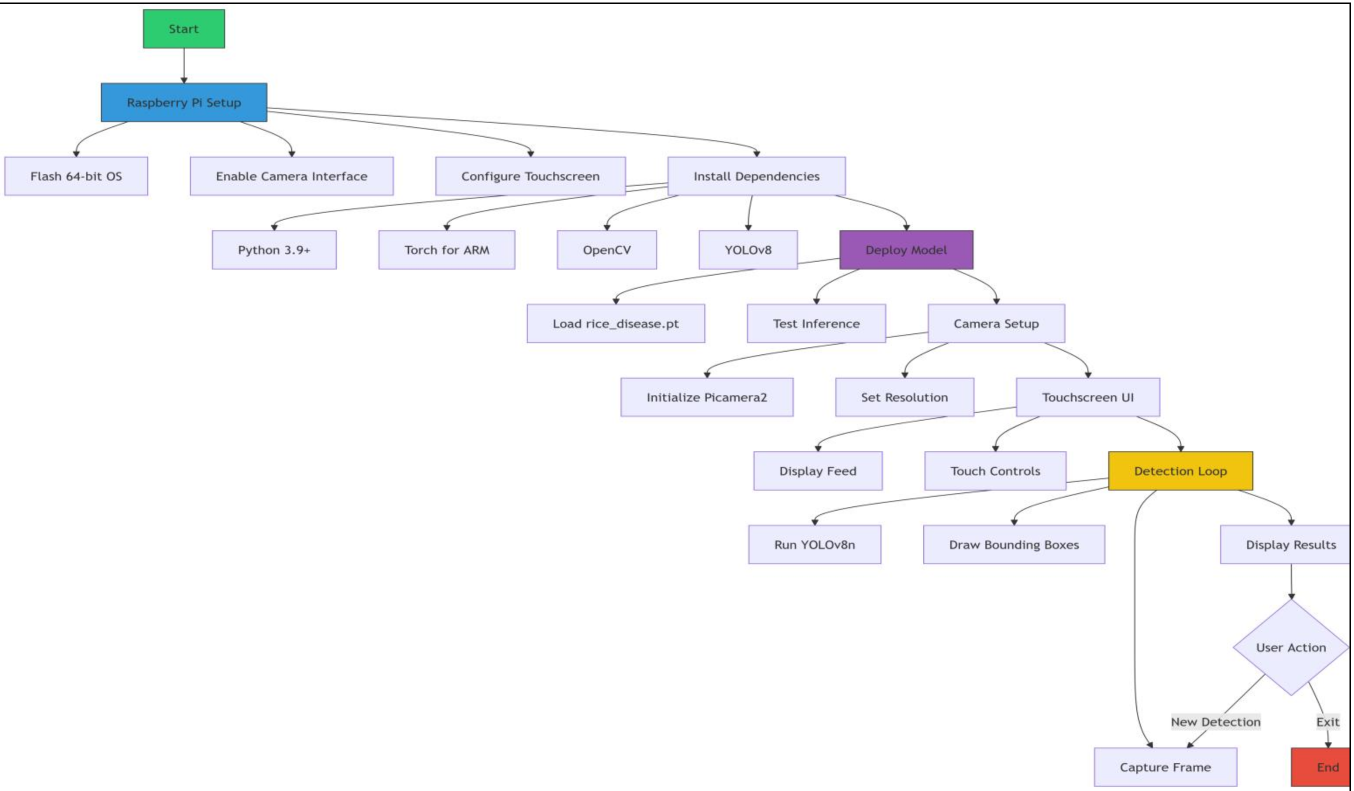

Figure 13: YOLOv8n deployment with raspberry pi 4

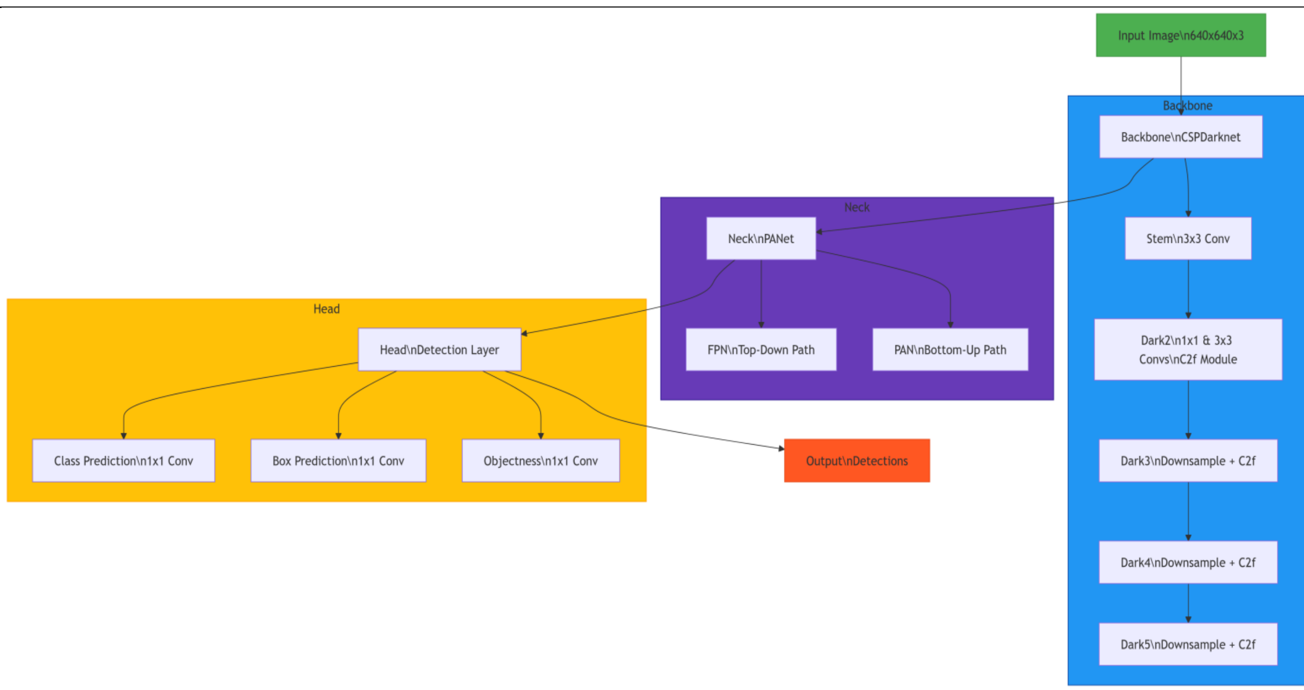

Figure 14: YOLOv8n pipeline architecture

5- Training Configuration

Model training was conducted using a GPU-enabled workstation to accelerate computation. The training configuration was fine-tuned to optimize detection accuracy while maintaining computational efficiency Figure 13,14. Key parameters included a batch size of 16, an input image resolution of 320 × 320 pixels, and a training duration of 30 epochs. The choice of image size balanced the trade-off between detection resolution and training speed, while the batch size was selected based on the available GPU memory. The Adam optimizer was used with a cosine learning rate scheduler, and data augmentation was applied dynamically during training to prevent overfitting.

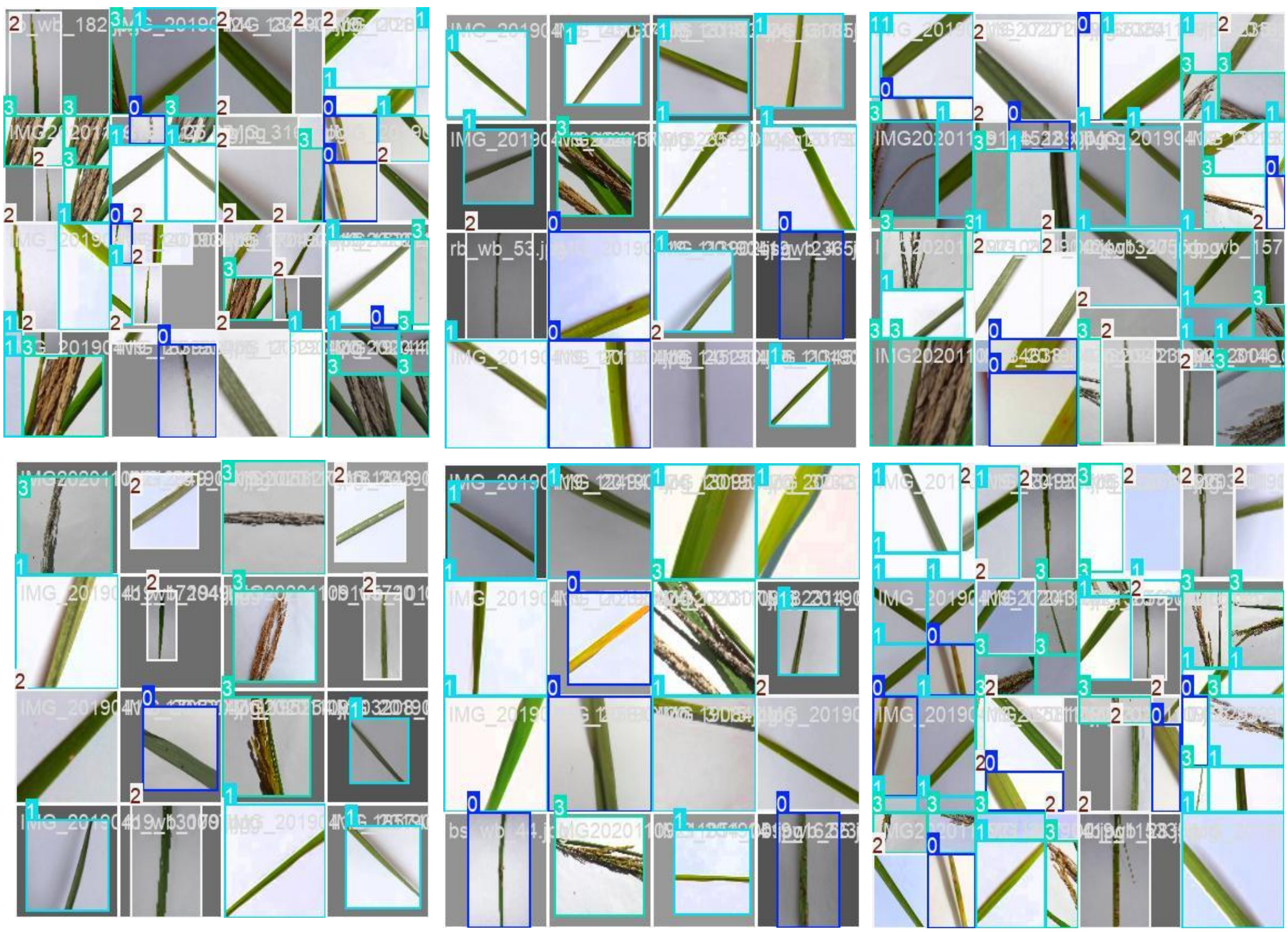

Figure 15 :this figure showing the rice image after training and before validating.

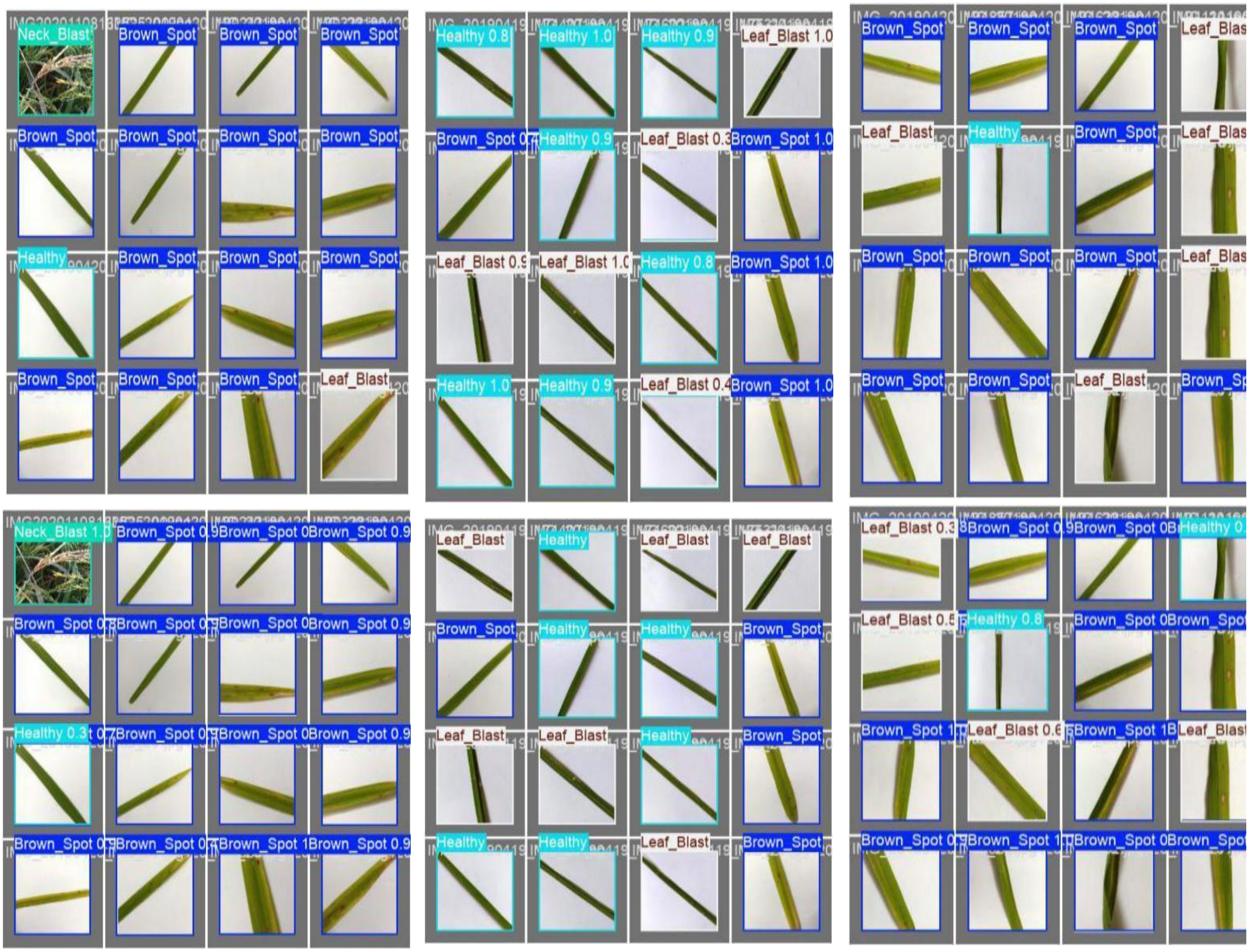

Figure 16:this figure showing the rice image after validating.

6- Deployment Hardware and Environment

To enable real-time field deployment, the trained YOLOv8n model was ported to a Raspberry Pi 4—a low-cost, compact, and energy-efficient single-board computer. The Raspberry Pi was equipped with an integrated camera module for image acquisition and a 7-inch touchscreen interface for user interaction and output display. This embedded setup allows the system to function autonomously in field conditions, providing farmers with on-device diagnostic capabilities without requiring continuous internet access. The model inference pipeline was optimized using TensorRT and OpenCV to ensure low-latency processing on the Raspberry Pi's ARM-based architecture figure 17.

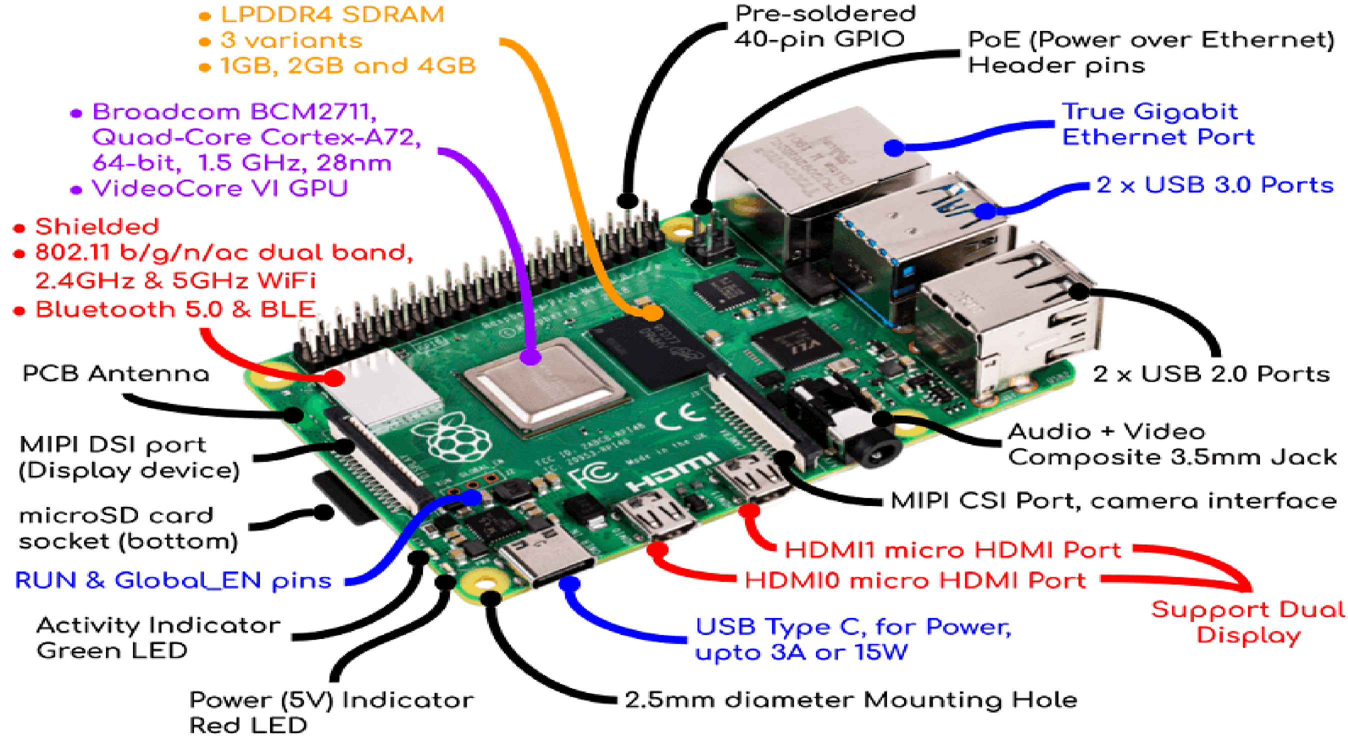

Figure 17:this figure showing the architecture of raspberry pi 4 model B

7- Model Equations and Evaluation Metrics

7.1- YOLOv8 Loss Function

The overall loss function used to train the YOLOv8 object detection model is composed of three primary components:

Total Loss=Classification Loss+Localization Loss+ Objectness Loss

7.2- Classification Loss:

Measures the error in predicting the correct class label for each detected object.

7.3- Localization Loss:

Quantifies the difference between the predicted bounding box and the ground truth bounding box.

7.3- Objectness Loss:

Evaluates the confidence score associated with whether an object exists in the proposed bounding box.

This multi-part loss function ensures that the model not only classifies diseases correctly but also accurately localizes them within the image.

7.3.1- **Accuracy**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where

TP (True Positive): Number of correctly identified positive cases (e.g., diseased leaves correctly detected).

TN (True Negative): Number of correctly identified negative cases (e.g., healthy leaves correctly ignored).

FP (False Positive): Number of incorrect positive predictions (e.g., healthy leaves incorrectly labeled as diseased).

FN (False Negative): Number of missed positive cases (e.g., diseased leaves not detected).

Accuracy provides a general measure of the model's performance across all classes.

7.3.2-F1 Score

$$Accuracy = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (2)$$

Where:

Precision = $\frac{TP}{TP + FP}$: Proportion of true positive detections among all positive predictions.

Recall = $\frac{TP}{TP + FN}$: Proportion of true positive detections among all actual positives.

The **F1 Score** is the harmonic mean of precision and recall. It balances the trade-off between them, especially useful when class distribution is imbalanced.

7.3.3-Coefficient of Determination (R² Score)

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \qquad (3)$$

Where:

$\boldsymbol{y_i}$: Actual value for the i^{th} data point.

$\boldsymbol{\hat{y}_i}$: Predicted value for the i^{th} data point.

$\boldsymbol{\bar{y}_i}$: Mean of all actual values.

The **R² Score** measures how well the predicted values approximate the actual data. An R² value of indicates perfect prediction, while a value closer to 0 suggests poor model performance. Here we are showing the hyperparameters of our model in table 1

Table 1: showing the hyperparameters of our yolov8n model

Hyperparameter	Description	Typical Value (YOLOv8n)
imgsz	Input image size (height and width)	320
epochs	Number of training epochs	30
batch	Batch size (based on GPU/CPU capacity)	16
learning_rate	Learning rate	0.001
optimizer	Regularization parameter to prevent overfitting	AdamW
weight_decay	Momentum for the optimizer	0.0005
momentum	Learning rate for model biases during warmup	0.937
warmup_epochs	Learning rate for model biases during warmup	3.0

warmup_bias_lr	Learning rate for model biases during warmup	0.1
box	Box loss gain	0.05
cls	Class loss gain	0.5
dfl	Distribution focal loss gain (used in YOLOv8)	1.5
hsv_h, hsv_s, hsv_v	HSV augmentation values for hue, saturation, value changes	0.015, 0.7, 0.4
degrees, translate, scale, shear	Data augmentation for rotation, translation, etc.	0.0–0.5 range
fliplr	Probability of horizontal flip	0.5
mosaic, mixup	Image augmentation techniques	1.0 (on/off)
patience	Early stopping if no improvement after n epochs	20

8- Benefits of the Proposed Approach

This research introduces a number of notable benefits that support the development of efficient and practical plant disease detection systems suitable for agricultural use:

8.1- Efficient Model Designed for Resource-Constrained Devices

By utilizing the YOLOv8n architecture—a streamlined and efficient variant within the YOLO object detection family—the system ensures low computational demand. This makes it well-suited for edge devices with limited processing capabilities, such as the Raspberry Pi 4. The model achieves a favorable balance between speed and accuracy, eliminating the need for high-performance computing resources during deployment.

8.2- High-Performance Real-Time Detection

The model offers rapid and accurate detection of rice diseases directly in the field. Real-time inference capabilities are crucial for prompt decision-making in agricultural management. The system ensures immediate feedback, helping farmers take timely action to control and mitigate disease spread.

8.3- Low-Cost and Easily Deployable Hardware Solution

The implementation utilizes affordable hardware components, including the Raspberry Pi 4, camera, and touchscreen display, making the system accessible and economically feasible for widespread agricultural deployment. This cost-effective design also supports scalability, enabling the system to be extended to additional crops or regions with minimal additional investment.

8.4- Customization for Rice Disease Classification

The system has been specifically trained to identify four key rice conditions—Healthy, Brown Spot, Leaf Blast, and Neck Blast. This focused design enhances detection precision for rice-specific applications, making it more effective than general-purpose models. Tailoring the system to a single crop improves reliability and practical utility in real farming environments.

8.4- comparison between our model and some baseline models

Table 2: showing the comparison between our model YOLOv8n and some baseline models

Model	Architecture Type	Model Size (MB)	Inference Speed (FPS)	Accuracy (mAP@0.5)	Edge Deployment Suitability	Notes
Our model YOLOv8n	Anchor-free, CNN-based	~6.2 MB	50+	~91%	Excellent	Best balance of accuracy and speed
YOLOv5n	Anchor-based, CNN	~7.5 MB	45+	~88%	Very Good	Accurate, but slightly slower and larger
YOLOv4-tiny	Two-stage CNN	~23 MB	60+	~85%	Good	Fast but lower accuracy
MobileNetV2	Depthwise Separable CNN	~14 MB	35+	~82%	Good	Lightweight, but less precise for detection tasks
SSD-Lite	Single-stage CNN	~17 MB	30–40	~80%	Moderate	Slower and less accurate in small object detection

In essence, the proposed solution offers an accurate, efficient, and affordable tool for rice disease monitoring, supporting the broader goal of precision agriculture and sustainable crop management.

9- Conclusion

This research confirms the practicality and effectiveness of using the YOLOv8n object detection model for real-time identification of rice plant diseases, even when operating on low-cost, resource-limited hardware. By adopting a compact and efficient neural network architecture, we successfully trained and deployed the model on a Raspberry Pi 4 with an integrated camera and touchscreen interface, achieving reliable detection results across key rice disease categories.The study highlights how deep learning techniques can be translated from experimental models into usable tools for agricultural practitioners. The custom-labeled dataset supported precise training outcomes, enabling the model to perform well under real-world conditions without requiring powerful computational infrastructure. Moreover, the deployment on an accessible and portable device underscores the system's potential to assist farmers in disease diagnosis and monitoring, particularly in regions with limited technological access. The intuitive interface further supports ease of use, making it suitable for field-level application by non-expert users.

10- Future Directions

The YOLOv8n-based rice disease detection system has proven effective in delivering fast and accurate results; however, it faces certain limitations. The Raspberry Pi 4 Model B's limited processing power restricts performance, especially when working with high-resolution images. Moreover, the model may produce false positives or negatives in challenging field environments, such as poor lighting, occluded plant parts, or cluttered backgrounds. Variations in camera positioning, image clarity, and disease development stages also influence detection accuracy. These issues highlight the need for system enhancements, including more efficient hardware utilization, better post-processing, and training tailored to real-world agricultural conditions.

To advance the system's effectiveness and adaptability, several improvements are planned. Increasing the diversity of the dataset by incorporating images from different climates, rice types, and regions would help the model perform more reliably across various scenarios. Enhancing the model's ability to detect early and subtle disease symptoms—through image enhancement, attention mechanisms, or combining traditional and deep learning techniques—would improve diagnostic precision. Integrating drone-based aerial imaging could scale the system for broader field coverage, while adding IoT features would support real-time monitoring, data sharing, and automated alerts. Together, these developments aim to create a smarter, more responsive solution for precision agriculture and large-scale disease management.

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