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Performance Analysis of YOLO Models for Beetroot Crop Disease Detection

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***Abstract*—In agriculture, technological advancements are essential to meeting the growing global food demand, particularly in the early detection and control of crop diseases. This work presents an automated disease detection system for Cercospora leaf spot in beetroot crops, utilizing the YOLO object detection model. Deep learning models YOLOv5s and YOLOv8x are used for processing. Cercospora beticola, a fungal pathogen, significantly reduces beetroot yield and quality, with its impact worsened by environmental conditions. A detailed comparative analysis of YOLOv5s and YOLOv8x is conducted, demonstrating YOLOv8x's superior performance for cercospora disease detection in beetroots. The experimental results indicate that YOLOv8x outperforms YOLOv5s, achieving a precision of 0.924, recall of 0.821, F1-score of 0.869, and mAP50 of 0.944, compared to YOLOv5s, which attained a precision of 0.814, recall of 0.857, F1-score of 0.834, and mAP50 of 0.884. The improved detection accuracy of YOLOv8x demonstrates its effectiveness in disease detection. By automating disease detection using a deep learning approach, this system enhances agricultural productivity, minimizes crop losses, and promotes sustainable beetroot farming through precise and timely intervention.**

***Keywords*— Deep learning, YOLO, disease detection, Cercospora leaf spot, precision agriculture.**

I. INTRODUCTION

The incorporation of deep learning in agriculture has transformed conventional farming into advanced, data-driven processes, greatly enhancing disease detection, crop monitoring, and yield forecasting. By leveraging machine learning and deep learning algorithms, extensive agricultural data—encompassing crop health, soil conditions, and pest activity—can be analyzed to generate predictive insights for precision farming. These innovations improve resource efficiency, reduce waste, and promote sustainability, fostering more effective and environmentally conscious agricultural practices.

Among various agricultural challenges, disease detection in crops remains a critical concern, as plant diseases can significantly impact yield and quality. Root crops such as beetroot are vital for global agriculture due to their nutritional and economic value. However, fungal diseases like Cercospora leaf spot, caused by Cercospora beticola [1-5], pose a serious threat to beetroot cultivation. The various factors affecting crops are classified into infectious and non-infectious types.

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Infectious diseases are caused by viral, bacterial, and fungal pathogens, leading to conditions like leaf curl, rust, spot, blight, and albication. Non-infectious diseases arise from environmental factors such as rainfall, humidity, nutrient deficiency, and temperature changes. On the leaves, there are tiny asymmetrical round dots with dark borders and brown or gray centers. These patches may combine as the illness worsens, resulting in more extensive necrosis. A yellow halo is frequently observed around the spots, and under severe conditions, leaves may wither and fall off, reducing the plant's ability to photosynthesize and develop healthy roots. Environmental conditions like high humidity, inadequate air circulation, and extended leaf wetness facilitate the rapid spread of this disease through wind, irrigation water, and rain splash. [6-10].

To address these challenges, automated disease detection systems leveraging deep learning models [16-20] and robotics have gained prominence. This work proposes a real-time, automated detection system for Cercospora leaf spot in beetroot crops, employing a robotic vehicle equipped with a mobile phone camera and YOLO object detection models [21-24]. The robotic vehicle, using the IP Webcam application, captures real-time images of beetroot leaves and streams them to Google Colab for analysis with YOLOv5 and YOLOv8. This cloud-based processing eliminates the need for onboard computation while ensuring high-accuracy disease detection. By removing the dependency on manual inspection, this approach enables timely intervention and effective disease management, ultimately improving crop health and productivity.

II. Related Work

Moussa El Jarroudi et al. developed a weather-based model to predict Cercospora leaf spot (CLS) infection in Belgian sugar beet fields using temperature, humidity, and rainfall thresholds. Three top-performing models demonstrated high accuracy, supporting timely fungicide application for effective disease management [1]. With an emphasis on the cmdA, Varucha Misra et al. examined Cercospora beticola, a significant disease that affects up to 63% of agricultural regions. gene's role in pathogenicity. Phylogenetic analysis of 56 sequences identified two clades and seven haplotypes, revealing high genetic diversity (haplotype diversity: 0.83745, Tajima's D: 6.48675), offering valuable insights for crop management strategies [2]. Yingxi Li et al. conducted high-throughput sequencing of 139 Cercospora beticola isolates from China, identifying 93 contigs representing eight novel mycoviruses from three families and unclassified RNA viruses. This first report of highly diverse mycoviruses in C. beticola offers new potential biocontrol agents for managing Cercospora leaf spot [3]. Sebastian Liebe et al. evaluated fungicide application timing for Cercospora beticola control in sugar beet. While spore flight-based application slowed disease progression, it did not surpass the traditional 5% disease incidence (DI) threshold. Under high disease pressure, a second application was necessary for effective control [4]. M. F. A. Ahmed et al. investigated the efficacy of four commercial biocides and biocontrol agents against Cercospora beticola in organic sugar beet fields in Egypt. All treatments effectively reduced disease severity and enhanced crop quality, with Blight Stop (Trichoderma harzianum) showing the highest efficacy, while Bacillus megaterium was the least effective [5]. For accurate plant disease identification and severity classification, Arunangshu Pal et al. provide the Agriculture identification framework, which combines the INC-VGGN model with Kohonen-based deep learning. The framework tackles occlusion, illumination, and overfitting challenges using a multi-variate grabcut algorithm and dropout layers, achieving improved accuracy over existing methods [6].

Fan Xijian and associates, this work proposes a deep learning system for identifying plant diseases, integrating transfer learning with handcrafted features for enhanced classification. By incorporating center loss, the method improves feature discrimination, achieving high accuracy (99.79%, 92.59%, and 97.12%) across three public datasets [7]. Mukhopadhyay Somnath et al. With the use of multi-class SVM for classification, PCA for feature reduction, and NSGA-II clustering for segmentation, this work presents an image processing-based approach for early tea leaf disease identification. The method reduces losses in tea yield by identifying five illnesses with an average accuracy of 83% [8]. Zhencun Jiang et al, This work presents an improved VGG16 model with multi-task transfer learning for recognizing rice and wheat leaf diseases. The method achieves 97.22% accuracy for rice and 98.75% for wheat, outperforming ResNet50, DenseNet121, and other models in comparative experiments [9]. Seyed Mohammed Javidan et al. This work proposes an image processing-based technique for grape leaf disease diagnosis, including multi-class SVM for classification and K-means clustering for segmentation. Feature extraction in RGB, HSV, and lab color spaces, combined with PCA for dimensionality reduction, achieved 98.97% accuracy. The approach outperformed CNN (86.82%) and GoogleNet (94.05%) while ensuring faster processing times [10]. Junde Chen et al. propose a deep learning-based approach for rice disease identification, leveraging MobileNet-V2 with an attention mechanism and optimized loss function. By applying dual transfer learning, the model achieves 99.67% accuracy on a public dataset and 98.48% in complex conditions, demonstrating its effectiveness in precise rice disease classification [11]. Aditya Karlekar et al. present a computer vision-based approach for soybean plant disease identification using a two-stage model: background subtraction for leaf segmentation and the deep learning-based SoyNet for classification. Evaluated on their work, the proposed method achieves high accuracy, surpassing nine state-of-the-art models, including VGG19, ResNet50, and XceptionNet [12]. Amreen Abbas et al. describe a deep learning-based method for detecting tomato illness that uses a DenseNet121 model for classification and a Conditional Generative Adversarial Network (C-GAN) to create synthetic images. The PlantVillage dataset was used to train the model, which outperforms current techniques in a variety of categorization settings with high accuracy.[13].

Zeng Weihui et al. This work addresses issues like scale variations and complex backgrounds by introducing a lightweight mdoel for corn leaf disease diagnosis. An enhanced dense dilated convolution block is incorporated into the model to improve feature extraction and flexibility. With a high accuracy, LDSNet outperforms both lightweight models like MobileNet and ShuffleNetV2 and heavyweight models like VGG16 and ResNet50, all while guaranteeing effective deployment on mobile devices. [14]. Ruirou Ding et al, this work presents two enhanced ResNet18-based models, ResNet-CBAM and ResNet18-RC, for apple leaf disease classification, achieving 95.2% and 97.2% accuracy, respectively. These improvements enhance disease identification, supporting effective prevention and control strategies [15]. Mohit Agarwal et al. propose a lightweight CNN model with hidden layers for tomato disease identification, achieving high accuracy on the PlantVillage dataset and on other datasets. The model surpasses traditional ML methods and pretrained CNNs by incorporating image preprocessing techniques for improved performance [16]. S. Nandhini et al., This work presents an 8-layer CNN technique with different layers for classifying tomato, maize, and apple leaf diseases. Achieving an accuracy of 96–98%, the model demonstrates the efficiency of neural networks in plant disease detection [17]. B.V. Nikith et al. examine the effectiveness of SVM, KNN, and CNN in detecting various leaf diseases, highlighting the importance of smart farming in disease prevention. Their work shows that the CNN model, trained on a soybean leaf disease dataset, outperforms KNN and SVM, demonstrating its superior accuracy in agricultural disease detection.[18]. Lawrence C. Ngugi et al, This work introduces an algorithm for generating lesion-based datasets to improve leaf disease recognition. The proposed model achieves performance with an mIoU of 0.8448 for leaves and 0.6257 for lesions. Additionally, a fully automatic algorithm integrating semantic segmentation with a GoogLeNet classifier enhances disease recognition accuracy by over 15% compared to whole-leaf classification [19]. Vimal Singh et al., This work explores deep learning-based pre-trained models for bean plant disease detection using transfer learning. EfficientNetB6 outperforms others with 91.74% accuracy on the Beans Leaf image dataset. The work highlights the role of optimization techniques in enhancing CNN performance, enabling real-time disease diagnosis for effective crop management [20].

Weiwei Gao et al., This work introduces the YOLO V5-technique for rice leaf disease detection, optimizing both accuracy and speed. Enhancements include improved K-Means anchor generation, attention mechanisms for refined feature extraction, and an optimized loss function for occluded targets. The model outperforms YOLO V5 with a 9.90% mAP increase, ensuring high precision and robustness in detecting small lesion features [21]. Jiawei Li et al., This work presents an enhanced YOLOv5s-based algorithm for vegetable disease detection, improving feature extraction and minimizing environmental interference. The proposed model achieves a 93.1% mAP, surpassing YOLOv5s, YOLOv4-tiny, and other benchmarks in accuracy and localization. With a compact 17.1 MB size and a fast detection speed of 0.03s per image, it provides a highly efficient solution for real-time vegetable disease identification [22]. Jiangtao Qi et al., This work presents an enhanced YOLOv5 technique for detecting tomato virus diseases by incorporating a squeeze-and-excitation module to refine feature extraction. The model achieves 91.07% accuracy and 94.10% mAP@0.5, surpassing Faster R-CNN, SSD, and YOLOv5, providing a robust solution for precise disease identification in greenhouse environments [23]. Hua Yang et al. proposed the yolo-SDW algorithm to enhance corn leaf disease detection by integrating spatial depth conversion convolution (SPD-Conv) and a deformable attention Transformer (DAT) into YOLOv5. The adoption of the Wise-IOU V3 loss function further improves accuracy, achieving an 83.5% mAP—6.4% higher than YOLOv5—while increasing detection speed by 3.2% [24].

In our work, A comparative analysis of YOLOv5s and YOLOv8x demonstrates YOLOv8x's superior performance in detecting Cercospora leaf spot in beetroot crops. This approach enhances precision agriculture by enabling cost-effective, automated, and high-accuracy disease detection in real-world field conditions.

III. METHODOLOGY

The improved object detection system YOLOv5 expands on the achievements of its predecessors. Because of its reputation for speed and accuracy, YOLOv5 is a great option for real-time object detection applications. With just one neural network, the effective object detection model YOLOv5 can predict bounding boxes and class probabilities in a single assessment. Its architecture consists of a backbone (CSPDarknet53) for feature extraction, a neck (PANet) for multi-scale feature aggregation, and a head for final detection. CSPNet optimizes computational efficiency by evenly distributing operations across convolutional layers, reducing memory usage and processing time. The neck enhances object scale generalization using feature pyramids, while the head generates bounding boxes, object scores, and class probabilities at three different scales. The model is trained with a robust loss function, incorporating localization, confidence, and classification losses, along with augmentation techniques like mosaic augmentation. During inference, it processes images in a single pass, eliminating redundant detections using Non-Maximum Suppression (NMS). Activation functions include Leaky ReLU in hidden layers and Sigmoid in the final detection layer for precise and efficient object detection.

The most recent addition to the YOLO family is YOLOv8, adds several advances to its forebears. While YOLOv8 retains the core components of YOLOv5, it also includes new features and performance-boosting adjustments. YOLOv8n the lightest model, while the heaviest is YOLOv8x. The convolutional kernel and the feature extraction number are the two main differences that cause one version to weigh more than the other. It is critical to keep in mind where Ultralytics, the company responsible for YOLOv8, is also creator of YOLOv5. Main reason why both architectures are similar. YOLOv8x is being used to investigate the weed and disease identification problem in this research because it satisfies our goals for accuracy, interference speed and lightness. This section, including the steps used for data gathering, preprocessing, model building, training, assessment, and deployment. The goal is to develop an efficient deep learning model using YOLOv5 and YOLOv8 for detecting crop diseases in beetroot The proposed system methodology is illustrated in Fig. 1, and each section is described as follows:

A. Data Collection

The dataset was collected from local farms in and around Mysuru, Karnataka, India, focusing on beetroot crops affected by Cercospora leaf spot. Around 500 plus high-resolution images were captured using digital cameras in various lighting conditions to ensure dataset diversity. Manual annotation was performed using Roboflow, where bounding boxes were drawn around infected regions.

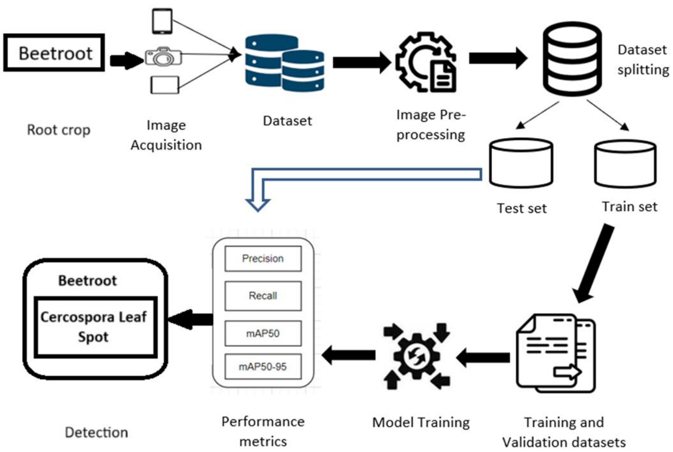

Fig. 1. Proposed System Methodology

B. Data Preprocessing

Images were resized to a standard dimension to maintain uniformity and compatibility with YOLO model input requirements. To enhance dataset variability and improve model generalization, multiple augmentation techniques were applied. Rotation was used to randomly alter angles, flipping was applied horizontally and vertically, and scaling was adjusted to change crop sizes within images. Additionally, brightness, contrast, and saturation modifications were applied to simulate real-world conditions. Pixel values were normalized between 0 and 1 to facilitate faster model convergence and improve training efficiency.

C. Model Development

YOLOv5 was chosen for its balance between speed and accuracy, while YOLOv8 was selected for its enhanced architectural improvements, providing better precision and efficiency. The YOLOv5 model consists of

CSPDarknet53 as the backbone, PANet as the neck, and a YOLO head for multi-scale detection. YOLOv8 features an improved backbone and neck structure for superior feature extraction and enhanced detection accuracy. By varying the learning rate, batch size, and number of epochs, hyperparameter tuning was done to maximize model performance. To minimize the loss function, stochastic gradient descent (SGD) with momentum and weight decay was employed as the optimizer.

D. Model Training and Evaluation

Ten percent of the dataset was used for testing, ten percent for validation, and eighty percent for training. Google Colab with GPU acceleration was used for training. In order to avoid overfitting, early stopping was used to end training when validation loss did not decrease over a predetermined number of epochs. A number of important metrics were used to evaluate performance. Recall (R) evaluated the completeness of positive predictions, whereas Precision (P) gauged how well the model predicted actual positives. Precision at different IoU thresholds was assessed using the Mean Average Precision (mAP), which included mAP50 (50% IoU threshold) and mAP50-95 (mean precision across IoU thresholds from 50% to 95%). Accuracy, recall, F1-score, and mAP scores were measured for models using validation and test sets.

To ascertain each model's advantages and disadvantages across various datasets, performance indicators were evaluated. To find common misclassification errors, an analysis of false positives and false negatives was conducted. To evaluate categorization performance across several crop groups and identify areas for development, a confusion matrix was employed. By contrasting actual and expected classifications, the confusion matrix assesses the effectiveness of a deep learning model. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are its four measures. Whereas FP and FN denote incorrect classifications, TP and TN reflect successfully categorized samples. Figures 9 and 10 provide an example of the confusion matrix. It is used to calculate key performance measures that measure model correctness, including precision, recall, and F1-score. The ratio of TP to the entire quantity of anticipated positive data is known as precision. The variable FP is the divisor in the denominator. Equation 1 can be used to write this.

$$precision = \frac{TP}{TP+FP} \times 100\% \qquad (1)$$

The ratio of TP to the total number of truly good occurrences is known as recall. Equation 2 can be used to write the denominator, which contains FN as the divisor.

$$recall = \frac{TP}{TP+FN} \times 100\% \qquad (2)$$

Precision will be very low while recall is very high, and vice versa. Precision and memory have a trade-off relationship. According to this trade-off relationship, these two variables add up to one. The F1-score is the average of precision and recall that has been harmonized. Equation 3 indicates that the F1-score's highest value is 1.0 and its worst value is 0.0.

$$F1 - score = 2 \times \frac{precision \times recall}{precision + recall} \qquad (3)$$

IV. RESULTS AND DISCUSSION

For the Beetroot crop, which is private gathered dataset focusing on the Cercospora leaf spot class, both YOLOv5s and YOLOv8x were evaluated. In YOLOv5s, trained totally with 416 images in batch 16 for 150 epochs achieved a precision of 81.4%, recall of 85.7%, F1-score of 83.4%, mAP50 of 88.4%. In contrast, YOLOv8x trained for 30 epochs with 224 images, significantly improved precision to 92.4%, F1-score of 86.9% and mAP50 to 94.4% through slightly less recall of 82.1%. The mAP50-95 also showed a substantial increase from 0.366 to 0.424. These results indicate that while YOLOv8x achieves higher precision and mAP values, it might miss some instances that YOLOv5s detects, reflected in its lower recall.

TABLE I: PERFORMANCE METRICS COMPARISON IN DETECTING CERCOSPORA LEAF SPOT

Model	Epochs	Class	Precision (P)	Recall (R)	F1-Score	mAP50	mAP50-95
YOLOv5s	150	Cercospora leaf spot	0.814	0.857	0.834	0.884	0.366
YOLOv8x	30	Cercospora leaf spot	0.924	0.821	0.869	0.944	0.424

According to table1, the metrics analysis for both YOLOv5s and YOLOv8x is compared in the bar graph which as depicted in the Fig. 2.

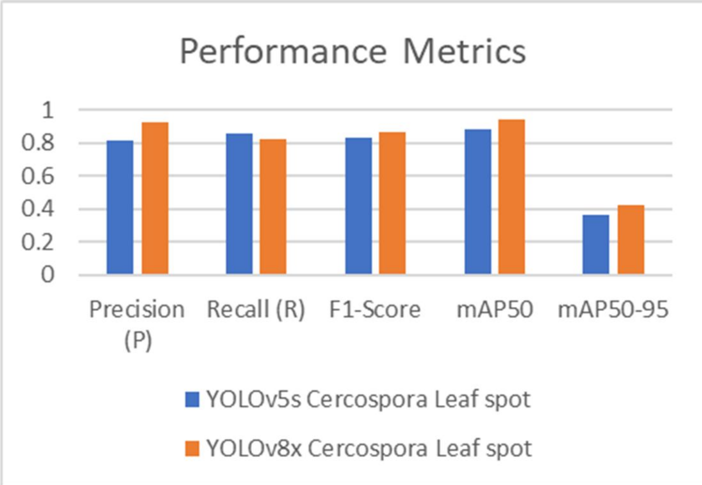

Fig. 2. Performance metrics analysis with YOLOv5s and YOLOv8x

According to metrics analysis metrics analysis curve plotted with different variants to depict the model performance for both YOLOv5s and YOLOv8x. F1-Confidence Curve: The F1 score is plotted against various confidence criteria. It is the precision and recall harmonic mean. Better performance is shown by a higher F1 score, which is plotted in Fig. 3 & 4. The confidence level at which the F1 score is maximum is frequently regarded as the ideal threshold for making predictions.

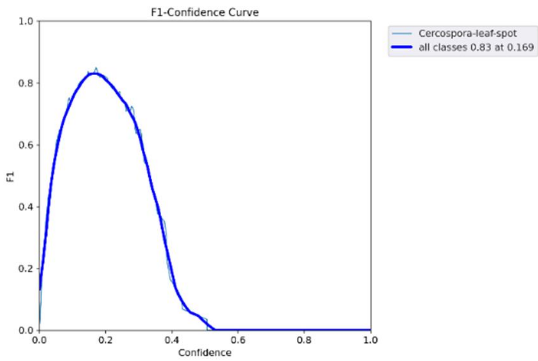

Fig. 3. F1: YOLOv5s model confidence curve

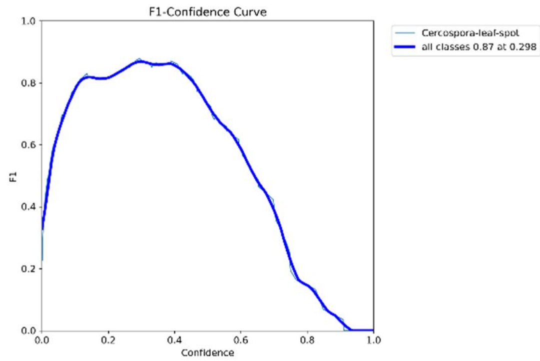

Fig. 4. F1: YOLOv8x model confidence curve

Precision-recall (PR) Curve: It is depicted in Fig. 5 & 6, is a plot that assesses the effectiveness of deep learning models by utilizing precision and recall, two performance parameters that assess a classification model's quality.

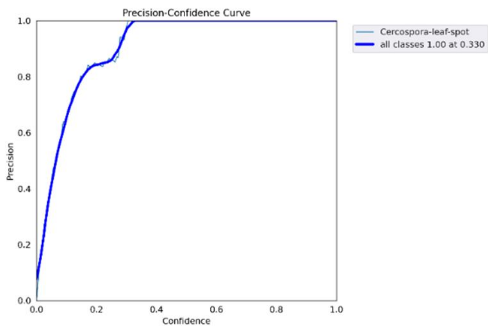

Fig. 5: YOLOv5s Precision-Confidence curve

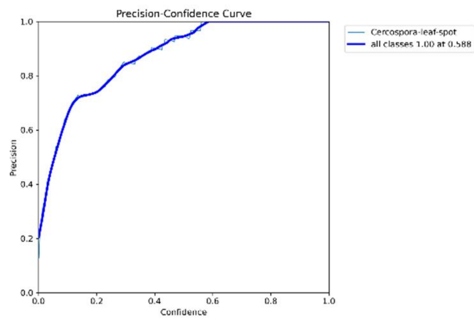

Fig. 6: YOLOv8x model precision-confidence curve

Recall-confidence: The curve shows how the confidence threshold affects the recall measure. More predictions, including probable false positives as well as real positives, are deemed valid when the confidence level drops. As seen in Fig. 7 & 8, these predictions are shown for both models.

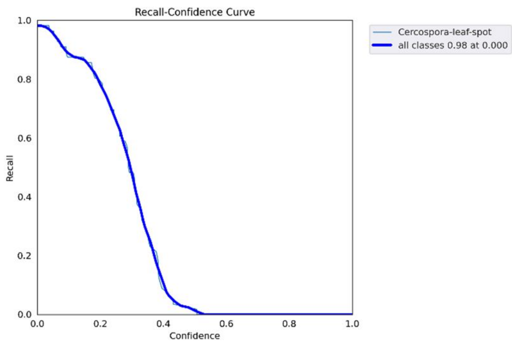

Fig. 7: YOLOv5s model recall-confidence curve

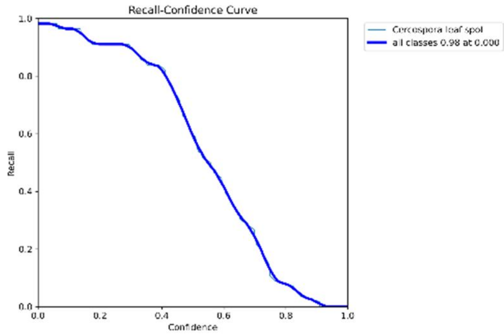

Fig.8: YOLOv8x model recall-confidence curve

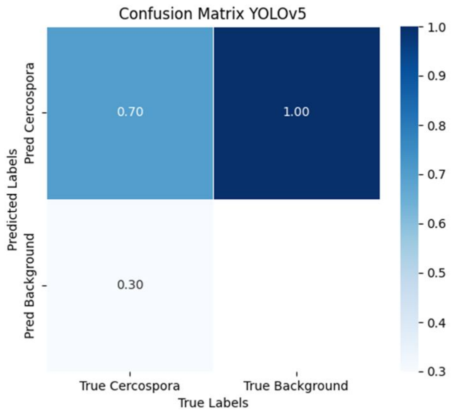

Fig. 9. The YOLOv5s model's visual confusion matrix

When evaluating the effectiveness of a classification model, a confusion matrix is commonly employed. It utilizes the test photos for Cercospora leaf spot disease identification and compares the real class label with the expected class label. A multitude of performance indicators, including as F1 score, accuracy, precision, and recall, can be calculated using confusion matrices. Fig. 9 shows the confusion matrix for the YOLOv5x model. TP 0.70, FP 1.00, and FN 0.30 for the YOLOv5 model. The values obtained from the validation stage's detection of the Cercospora leaf spot image were as follows: 81.4% precision, 85.7% recall, 83.4% F1-score, 88.4% mAP50, and mAP 50-95 of 0.366. A summary of these performance outcomes is provided in Table 1.

Fig. 10 displays the YOLOv8x confusion matrix, the TP values are 0.89, FP 1.00, and FN 0.11. The values obtained from the validation stage's detection of the Cercospora leaf spot picture were as follows: mAP50 of 94.4%, Map50-95 of 0.424, Precision of 92.4%, Recall of 82.1%, and F1-score of 86.9%. A summary of these performance outcomes is provided in Table 1.

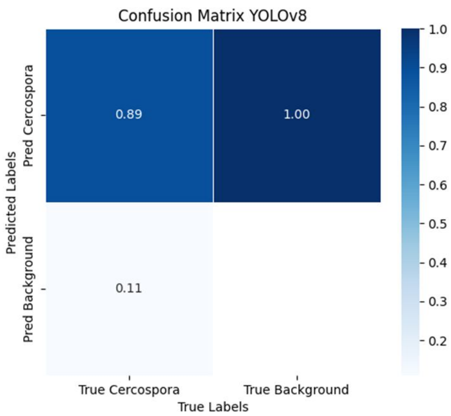

Fig. 10. Confusion Matrix of YOLOv8x model for images

The below fig. 11, 12 and 13 depicts the training batch image, valid batch label and valid batch prediction for the Cercospora leaf spot disease for beetroot crop for YOLOv5s model.

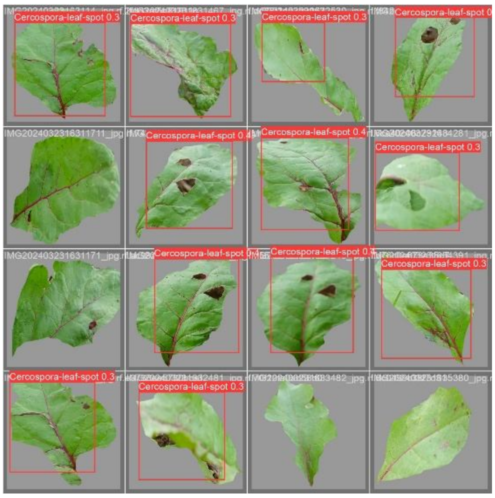

Fig. 11. Sample train batch image and valid batch label

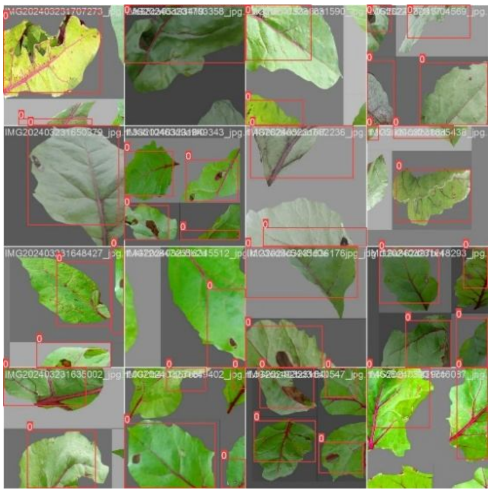

Fig. 12. Valid batch prediction

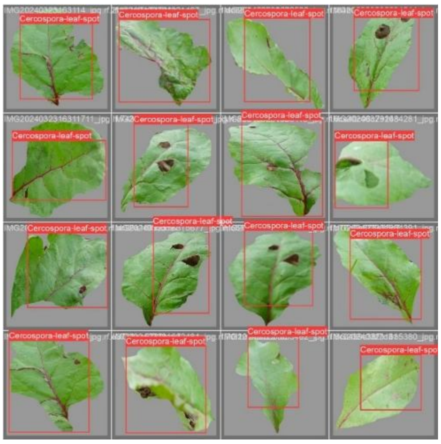

Fig. 13. Sample train batch image and Valid batch label

The below fig. 14, 15, 16 and 17 depicts the training batch image, valid batch label, valid batch prediction and detection result for the Cercospora leaf spot disease for beetroot crop for YOLOv8x model.

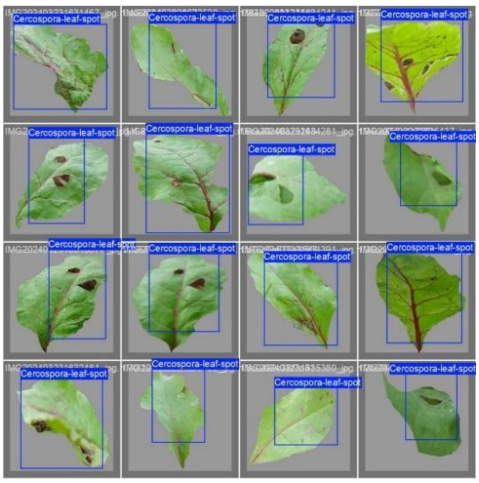

Fig. 14. Sample train batch image and valid batch label

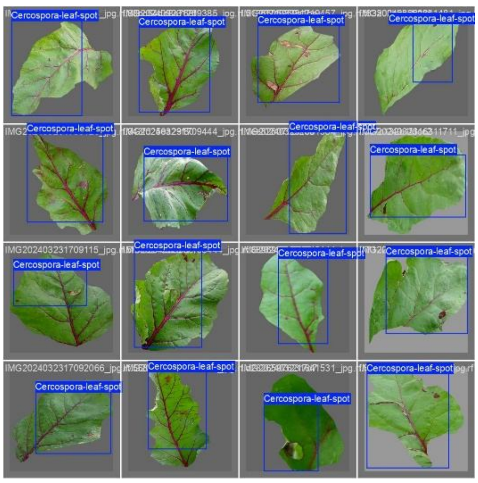

Fig. 15. Valid batch prediction

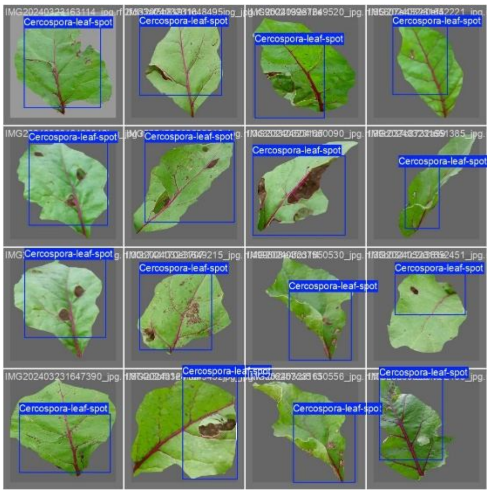

Fig. 16. Sample train batch image and Valid batch label

Fig. 17. Valid batch prediction and output image with bounding box

V. CONCLUSION

A significant advancement in agricultural technology is the application of YOLO models for disease detection in beetroot crops. This research effectively tackles the challenge of identifying Cercospora Leaf Spot in beetroot leaves by utilizing the robust object detection capabilities of YOLOv5 and YOLOv8. By employing advanced computational processing, the system ensures accurate and timely detection of the fungal disease, enabling targeted treatment that reduces crop losses and minimizes excessive pesticide use, ultimately improving yield quality. A comprehensive evaluation of model performance, including precision, recall, and accuracy, highlights YOLOv8's superior detection accuracy and efficiency over YOLOv5 in disease detection. This AI-powered detection system enhances precision agriculture by enabling efficient crop monitoring and management, promoting sustainable farming practices. Ultimately, the proposed approach contributes to increased agricultural productivity and improved beetroot yield quality.

FUTURE SCOPE

Future advancements in this disease detection system could focus on integrating edge computing for real-time field processing, expanding the model to detect multiple crop diseases, and optimizing deep learning techniques for higher accuracy. Incorporating automated treatment mechanisms, such as precision spraying, can further enhance efficiency while reducing pesticide use. Scaling the system through large-scale field trials and industry collaborations could drive its commercialization, making AI-powered disease detection more accessible and impactful in modern agriculture.

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