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Early diagnosis system to detect phosphorus deficiency in barley fields Based on an Improved YOLO-v8 Network

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Abstract

This study presents a diagnostic method for early and rapid detection of phosphorus (P) deficiency in barley fields in the natural environment, stemming from computer vision and based on a deep learning approach. This is done by creating a training model based on the YOLOv8 network. A phenotyping method is used to identify the plant, and then based on the color of the leaves and stems to detect phosphorus (P) deficiency. Some improvements have been made to the basic algorithm, using image processing techniques such as flipping, rotating, deep convolution, and resizing for feature enrichment. In our approach, images were classified using polygonal bounding boxes in collaboration with agricultural experts to identify areas of interest for the model. The dataset was divided into validation, training, and testing. In the experimental phase, we analyzed the model's performance using a set of video clips captured with a mobile phone camera as a first stage, and our model achieved a detection accuracy of up to 80%. In the second stage, we tested the model using images and video clips taken from a group of cameras installed on top of the pivot irrigation machine to take advantage of the machine's movement to scan the entire field. The model achieved a detection accuracy of up to 65%. Therefore, the proposed

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method can provide an early prediction system for plant needs, helping farmers maintain crop health and choose appropriate fertilizers.

Keywords: Phosphorus (P), deep learning, YOLOv8, computer vision, image processing.

نظام التشخيص المبكر للكشف عن نقص الفوسفور في حقول الشعير بناءً على شبكة YOLO-v8 المحسنة

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الملخص

تقدم هذه الدراسة طريقة تشخيصية للكشف المبكر والسريع عن نقص الفسفور (P) في حقول الشعير في البيئة الطبيعية، وذلك من خلال الرؤية الحاسوبية وعلى أساس نهج التعلم العميق. ويتم ذلك عن طريق إنشاء نموذج تدريب يعتمد على شبكة .YOLOv8 يتم استخدام طريقة التنميط الظاهري للتعرف على النبات، ومن ثم اعتماداً على لون الأوراق والسيقان للكشف عن نقص الفوسفور (P).تم إجراء بعض التحسينات على الخوارزمية الأساسية، باستخدام تقنيات معالجة الصور مثل التقليب والتدوير والالتفاف العميق وتغيير الحجم لإثراء الميزات. في نهجنا، تم تصنيف الصور باستخدام مربعات محيطة متعددة الأضلاع بالتعاون مع خبراء زراعيين لتحديد مجالات الاهتمام للنموذج. تم تقسيم مجموعة البيانات إلى التحقق والتدريب والاختبار. وفي المرحلة التجريبية، قمنا بتحليل أداء النموذج باستخدام مجموعة من مقاطع الفيديو الملتقطة بكاميرا الهاتف المحمول كمرحلة أولى، وحقق نموذجنا دقة كشف تصل إلى 80%. وفي المرحلة الثانية

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قمنا باختبار النموذج باستخدام الصور ومقاطع الفيديو المأخوذة من مجموعة كاميرات مثبتة أعلى آلة الري المحوري للاستفادة من حركة الآلة في مسح الحقل بالكامل. حقق النموذج دقة كشف تصل إلى 65%. ولذلك، فإن الطريقة المقترحة يمكن أن توفر نظام التنبؤ المبكر لاحتياجات النبات، مما يساعد المزارعين على الحفاظ على صحة المحاصيل واختيار الأسمدة المناسبة.

الكلمات المفتاحية: الفوسفور (P) ، التعلم العميق، YOLOv8، الرؤية الحاسوبية، معالجة الصور.

1. Introduction

Barley plants are considered an important grain crop, especially in third-world countries (أحمد محمد أشتيوي, 2010). Cereals and their derivatives are considered the main food of these peoples, and they still occupy a prominent place in the diet of humans and animals. Barley is considered one of the most important crops grown in Libya. It tops the list of agricultural crops. Some studies concluded a set of results, the most important of which is that grain production in Libya ranged between a minimum of 23.00 thousand tons in 1995 and a maximum of about 129 thousand tons in 1991, while the average annual grain production in Libya reached 60.6 thousand tons during the year 2010. Grain production decreased in Libya at a rate of about 4.07 thousand tons annually (إلهام جمعة بلعيد البقي, 2019). This is due to several reasons, the most important of which are: lack of water supplies, deterioration of agricultural lands from year to year, and the spread of agricultural pests. And the use of traditional methods in agriculture, as farmers face difficulties in determining the lack of nutrients in their crops, which wastes time, effort, and money(المحبسّ, 2020).Many researchers have tried to document modern practices and build predictive models based on machine learning to solve some of the problems faced by farmers. Remote sensing techniques(Roy & Bhaduri, 2021) and machine learning (Goyal et al., 2021).

In this regard, precision agriculture has developed using many techniques and tools. The leaves of the plant are used to detect

nutritional deficiencies in crops and can also be seen in the stems, flowers, fruits and other parts of the plant. A plant typically needs approximately a dozen nutrients for effective growth. These needs vary from one stage of a plant's life to another. As for the element phosphorus, it encourages and forms a good root system that serves the plant for better vegetative growth. As for the rest of the elements, it is preferable to increase them during the development and growth of the plant (Sudhakar & Swarna Priya, 2023). Paper is used detection of nutritional deficiency in crops. Due to phosphorus deficiency, the leaves turn reddish-purple(Adesanya & Yinka-Banjo, 2022). A phenotyping kit was used for plants collected from the field or cultivated. For example, an automated plant phenotyping system using a digital camera and robotic platform can automatically collect and analyze serial images of soybean plants (Qiu et al., 2019).
Deep learning has shown promising results for agricultural image processing such as plant disease detection, pesticide detection, plant species classification, etc. For example, the study (Lin et al., 2019) proposed the detection of Fusarium head blight in wheat crops. With the development of deep learning and digital image processing technology, target detection technology has been applied to crop canopies, major organs, diseases, and insect pests, such as phenotypic detection of soybean (He et al., 2022), strawberry (Chen et al., 2021), and tomato (Zhang et al., 2022). They have recently relied on classification techniques to identify crop diseases such as K-nearest neighbor (KNN) (Bian et al., 2022) and Fisher's linear discriminator (FLD) (Zou et al., 2013), (Mukhopadhyay et al., 2021). Several studies on HEB-23 have revealed wide-ranging variations in important agronomic traits, such as grain nutrient concentration ratios, plant growth resistance to nitrogen deficiency, pathogens, salinity stress, and drought (Herzig et al., 2021; Maurer et al., 2015; Merchuk-Ovnat et al., 2018; Pham et al., 2019), (Atila et al., 2021). The EfficientNet deep learning model was used to detect diseases using leaves, and it outperformed other state-of-the-art deep learning models in terms of accuracy (Selvaraj et al., 2019). Using data collected from different regions in Africa and India, they

worked on banana disease detection using DCNN (Chen et al., 2020). Developed a new model for weeds and crops in which the system combines pre-trained neural networks with classical machines (Xiao et al., 2021). Use transfer learning on deep convolutional neural networks to quickly identify and diagnose disease and integrate VGGNet with the starting module. Spectroscopy and imaging techniques have been used, such as hyperspectral imaging (HSI) (Y. Li et al., 2017). It has already been combined with deep learning schemes to enhance automatic disease detection. For example, Li et al.'s “You Only Look Once” (YOLO) algorithm (Redmon et al., 2016) which has been used in agriculture for target detection, can meet the real-time requirement but has relatively lower detection accuracy. Deep learning-based target detection algorithms can be divided into two sections, two-stage detection algorithms (such as Faster R-CNN). Detection algorithms of this type are single-stage (such as the YOLO series), as this type is characterized by faster processing speeds than the first, which makes it more suitable for detecting plants and diseases that affect them in field environments in real-time (R. Li & Wu, 2022) proposed an improved YOLO-v5 algorithm based on a shallow feature layer to overcome the noise of the field environment to meet the practical requirements for detecting and counting Wheat spikes. Although previous algorithms were optimized according to the physical and ecological characteristics of the plant, To the best of our knowledge, YOLO network-based deep learning methods have not yet been used in barley plants to detect nutrient deficiencies and pest patterns. Furthermore, no dataset is available for plant images.

Table 1. Summary of the literature review.

Article	Plant	Dataset	Model used	Accurac
(Qiu et al., 2019)	Wheat	Shandong Province, China	Deep convolutional neuralnetwork	92%
(He et al., 2022)	Wheat	Real Field	AlexNet, VGG-16	90.01%
(Khaki & Wang, 2019)	Maize	Crop Genotype, Environmental,	DNN	81.91%

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		Yield data (2001 – 2015)		
(Boulent et al., 2019)	Unspecified	Minnesota, USA	CNN	83.02%
(D. Li et al., 2020)	Rice	Anhui, Jiangxi, HunanProvince, China	ResNet-101, VGG-16, ResNet-50	85%
(Kaur et al., 2019)	Fruits and vegetables	Support vector machine,fuzzy classifier,neural network	PlantVillage	Not given

Through our review of the literature, we found that barley plants are affected by a lack of nutrients. However, the patterns of pests have not been studied and researched much. They are considered insufficient to detect target landmarks in complex field environments, especially in the early stages of plant life. Therefore, this study focuses on making an autonomous system for the dynamic detection of (P) deficiency in barley crops. In real-time conditions based on the improved YOLO-v8 network, our method takes advantage of the benefits of deep learning, such as its ability to automatically learn features and use augmented data techniques to improve model performance.
This research study makes the following main contributions:

- Development of a YOLO-based deep learning model to diagnose phosphorus deficiency in barley crops.
- Develop a dataset of images collected from multiple sources of early stages of plant life with hand-tagged images, providing more comprehensive training examples.
- Demonstrate the potential of the proposed model to assist the farmer in making appropriate diagnoses, leading to improved results, saving time, and reducing fertilizer costs.
- Our work also highlights the importance of image processing and computer vision.

The rest of this article is organized as follows: In Section 2, we provide a summary, the original YOLOv8 model is revised, and an

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improved YOLOv8 model is proposed. In Section 3, we list experimental materials and methods, and experiment results, and analyses are covered in Section 4. Finally, conclusions are summarized in Section 5.

2. Detection Object Algorithm

Object detection algorithms can be classified into different groups based on labeling methods and linking frames. Regarding the approaches based on the algorithms, YOLO and SSD adopt a single-stage approach, while R-CNN, Fast R-CNN(Noureldeen et al., 2023), and Faster R-CNN adopt a two-stage approach. Where link boxes are used to define a set of objects and pre-defined boxes that enable object detection using information scale and aspect ratio(Haider et al., 2021). In our detection method, we slightly modify the original YOLOv8 model with a more lightweight method. This change helps balance accuracy and efficiency, allowing the system to work well even on devices with limited processing power. We also modified the YOLOv8 output layer to focus solely on detecting 'barley plants', instead of predicting probabilities for many object categories.

2.1. The YOLO-v8 Network Model

Through research and analysis of the YOLO-v8 network model, which was released by Ultralytics on January 10, 2023. To improve detection and the ability to deal with small targets in complex environments, the YOLO network has achieved success in the field of computer vision; The YOLOv8 model is an advanced and sophisticated model that provides the highest accuracy and speed of detection. has three components: head, neck, and backbone (Wang et al., 2023), which is shown in Figure 1

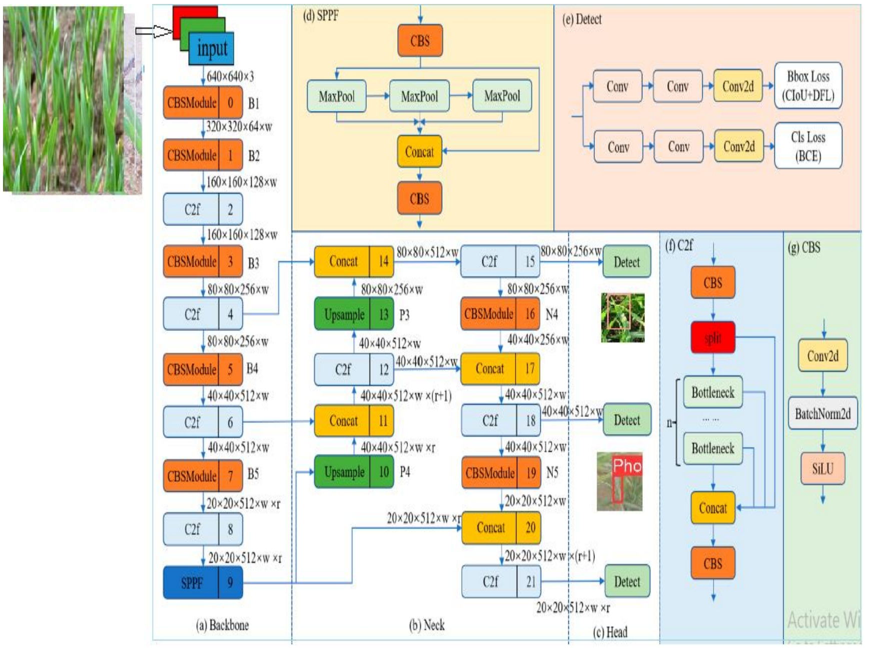

Figure 1. Architecture diagram for YOLOv8, adapted from (Wang et al., 2023).

3. Materials and Methods

3.1. Overview of phosphorus deficiency detection system(PDDS)

This section explains the use of the deep learning model used to detect phosphorus deficiency in barley fields. Additionally, the dataset used for training purposes is explained. Before starting the task, necessary measures are taken, including: Navigation, model and algorithm selection, and system implementation must be completed successfully. As depicted in Figure 2, the system consists of three cameras installed on top of the pivot irrigation system at a height of (2 m) and connected via Wi-Fi to a computer. These cameras send images or video clips while the pivot irrigation system is moving, so that the focus of the cameras is in the direction of the machine's movement before the water arrives. of the plant in order to obtain low-noise images, which in turn undergo a series of processes that include pre-processing, feature extraction, discovering areas of the field that contain plants with a phosphorus deficiency, and then issuing an alarm sound as the supervisor turns on the phosphorus fertilizer pump, which reaches its peak. The ultimate in generating predictive results.

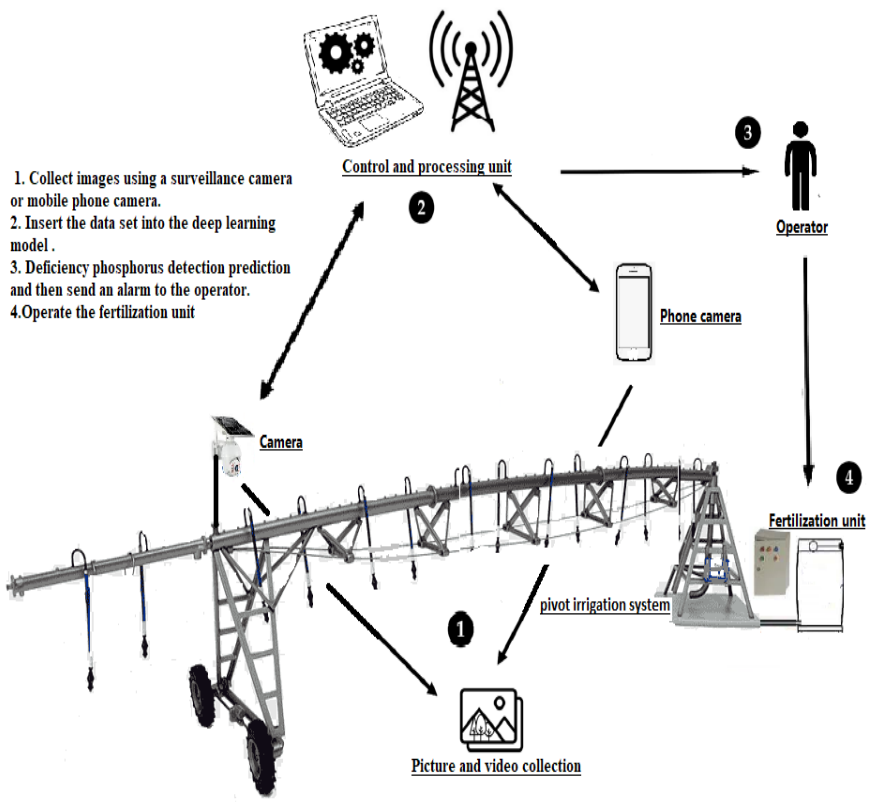

Figure 2. Shows the proposed idea of the Phosphorus Deficiency Detection System (PDDS).

3.2. Experimental materials

In general, the data set contains a variety of collected images of barley leaves in the early stages of the plant's life, during the 2022-2023 season, from several farms in the beach area located at a latitude of 27°30′ north, 14°29′ east, so these images were named into 2069 continuous images of phosphorus deficiency and 3600 healthy images of plants, in cooperation with agricultural and pest resistance experts in the municipality of Brak Al-Shati. The average temperature during the sample collection phase was 23 degrees Celsius, and the group of images was taken at different times of the day to represent all natural conditions scenarios on different days, under natural lighting conditions in different weather conditions, such as sunny and cloudy weather conditions, using a mobile phone camera and a 4-megapixel surveillance camera, at different angles to ensure diversity in the representation of the image set while taking into account all weather conditions. With an image resolution of 459 x 720 pixels. A picture of phosphorus deficiency is shown in Figure 3.

Figure 3. Pictures of barley plants. Taken from the farms of the Brak Agricultural Project under the supervision of the Agriculture Office of the Municipality of Brak Al-Shati (a) Plant affected by phosphorus deficiency, (b) The plant is healthy.

3.3. Experimental Process

In this study, an experimental data processing process was conducted in which we comprehensively scanned the images before training the model, classified the sample data with the help of expert knowledge, to identify the key points of interest to the model, and used image processing techniques such as re-measurement, zooming, and flipping. Horizontal, width, and height offset. We then created new image models to enrich and augment the dataset. After that, the sample data was classified with the help of the knowledge of plant pathology experts, and we carried out a labeling process on the dataset. The images were labeled with polygonal bounding boxes to identify areas of interest in the deep learning model. We created a class for the set of images classified as suffering from phosphorus deficiency and another class for images of healthy plants. Then we divided the data set into 70% of it for training, 20% for validation, and 8% of the total set for selection. We then used the classified sample data for the training phase of the algorithm and then A method using a neural network based on a deep learning model was developed using YOLOv8. The stochastic gradient descent algorithm was used to optimize the network model during the course training process, and the optimal weight of the network was obtained after training. The preprocessing results are shown in Figure 4.

Figure 4. The result of processing images obtained from the field**.**

3.4. Experimental equipment

A laptop computer was used as the processing platform, and it was the operating system WINDOWS 10, PyTorch Framework, and YOLOv8 We ran our tests on Colab GPU with YOLOv8 version 7.0114-g3c0a6e6, Python version 3.11.3, Torch version 2.00 + cu118 and it was 10.1. As for the hardware, the processor was Intel

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Core i7-3612QM, the main frequency was 2.10 GHz, the memory was 3G and the graphics card was GeForce GTX 1060 6G. The specific configurations are provided in Table 2.

Table2. Test environment.

Parameter	Configuration
Operating system	WINDOWS 10
Programing language	Python version 3.11.3
Algorithm framework	Torch version 2.00
GPU	GeForce GTX 1060 6G
CPU	Intel Core i7-3612QM

4. Results and discussion

4.1. Experimental Results

We trained the model to recognize phosphorus deficiency in barley fields based on the YOLOv8 model using the following hyperparameters: learning rate (lr0) 0.01, momentum 0.937, decrease 0.0005, and batch size 18. We used a stochastic gradient descent (SGD) optimizer for 300 episodes with patience tuning. We tested the model in two stages, first testing it using photographs and video clips taken with a mobile phone from several different areas in the field to confirm the efficiency of the model. In the second stage, the model was tested using a group of video clips taken using cameras mounted on the pivot irrigation system. During the work period to survey the entire field, according to the YOLOv8 s model we trained, we achieved good results in terms of overall map and individual class performance. The model achieved an overall mAP50 of 0.769 and a mAP 50-95 of 0.398 in the validation set. This means that the model was able to detect the deficiency with high accuracy. Figure 3 shows the loss values for box loss, object loss, and separation loss at each period during the training process. Box loss represents the difference between the truth and expected bounding box coordinates, object loss represents the confidence score for each detected object in an image, and class loss represents the probability that each detected object belongs to a certain class. The primary goal of training an object detection model is to minimize the overall loss, which is a combination of bin loss, item loss, and class loss. Loss values should appear. A decreasing trend as training progresses indicates an improvement in the efficiency of the model in detecting phosphorus deficiency in field crops.

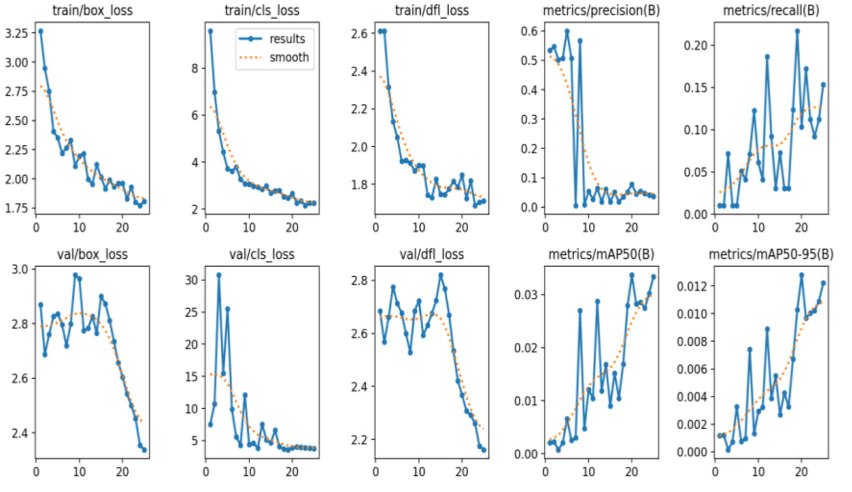

Figure 5. The training results

We also created additional evaluation metrics to analyze the performance of our YOLOv8 model further. The accuracy confidence curve, retrieval confidence curve, exact retrieval (PR) curves, and confusion matrices can be found in Fig. 6, Fig. 7, Fig. 8, and Fig. 9, respectively. These evaluation scales provide a more detailed understanding of the model's ability to detect and classify phosphorus deficiency in images. Confusion matrices show information on the number of true positives, true negatives, false positives, and false negatives for each class.

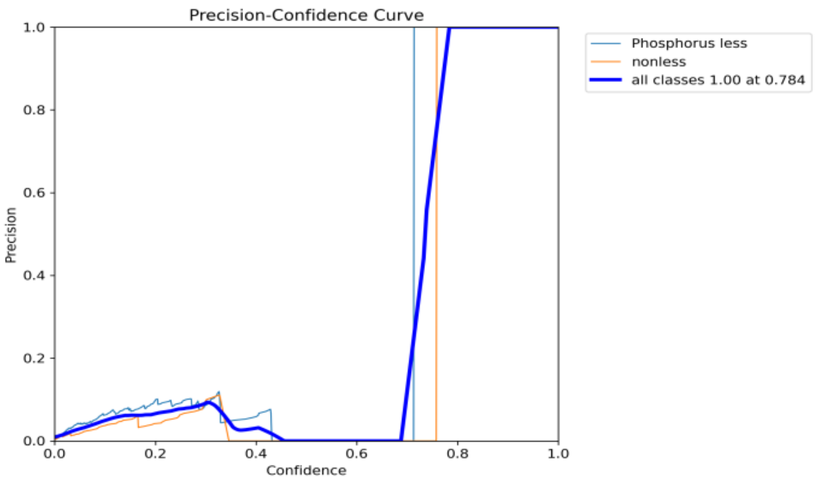

Figure 6. Precision confidence curve

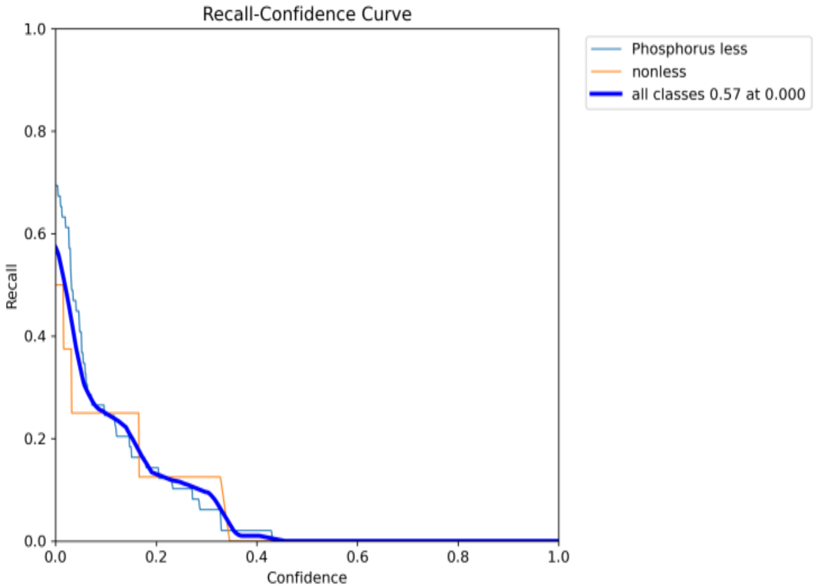

Figure 7. Recall confidence curve

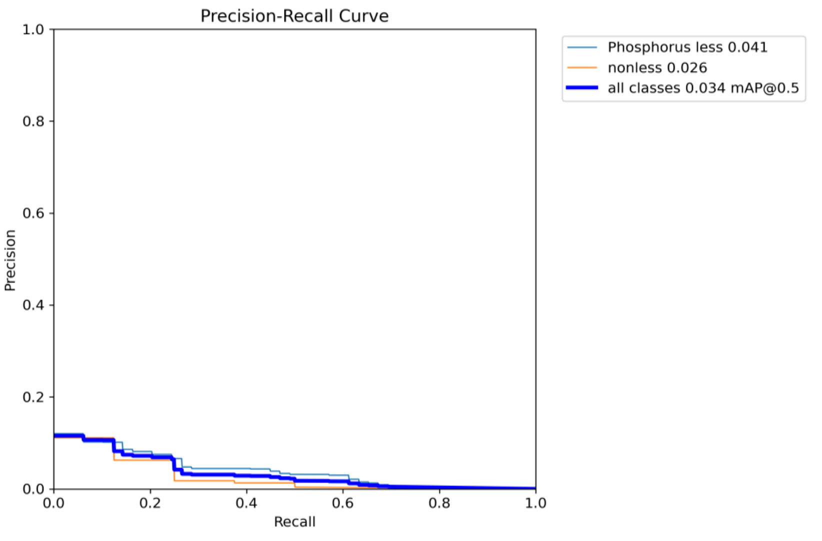

Figure 8. Precision–recall (PR) curves

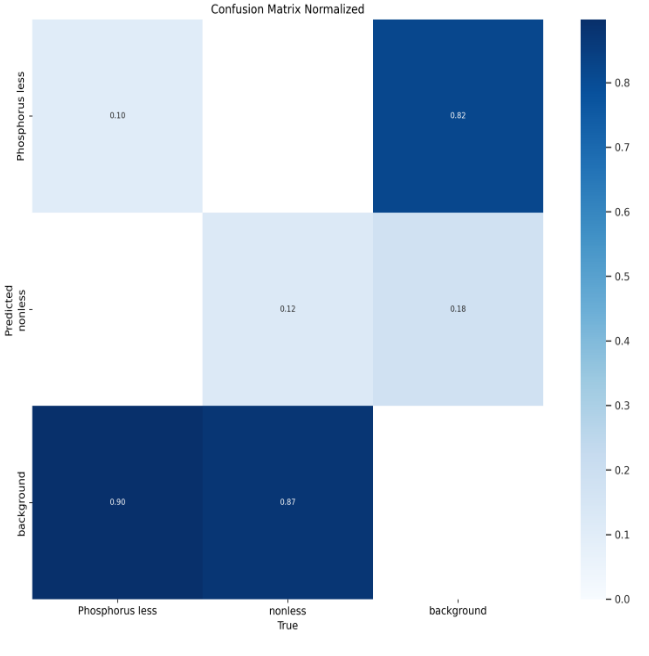

Figure 9. Confusion matrices

4.2. Verification of the Model

In this study, an evaluation of the effectiveness of the proposed approach based on the YOLOv8 network is performed Using evaluation scales. The accuracy and efficiency of the output are determined by generally accepted rules in the sensitivity of diagnostic systems. Average precision and average precision were used as evaluation metrics, and They are respectively defined as follows.

$$P_r = \frac{TP}{TP+Fp} \quad (1)$$

$$R_e = \frac{TP}{TP+FN} \quad (2)$$

$$AP=\int_0^1 P_r(P_e)d(R_e) \quad (3)$$

$$mAP=\frac{1}{N}\sum_{i=1}^{N} AP_i \quad (4)$$

Where: TP stands for True Positive, FP stands for False Positive, TN stands for True Negative, and FN stands for False Negative. Overall, the improved YOLOV8 network achieved accuracy levels of 86.5% and 86.8% for phosphorus deficiency detection. Figure 10 shows the result of applying the improved YOLOV8 networks to several images.

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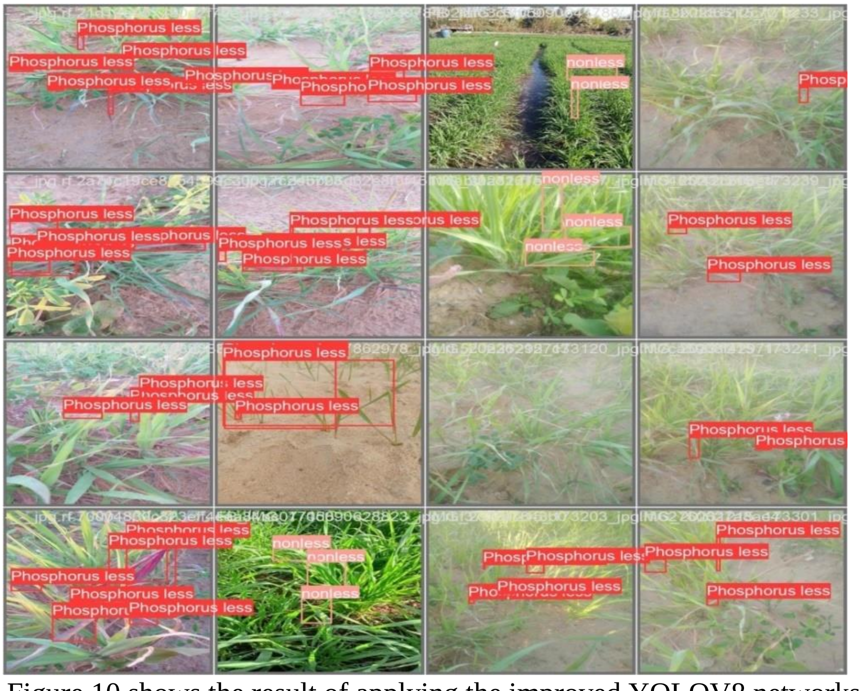

Figure 10 shows the result of applying the improved YOLOV8 networks to several images.

5. Conclusion

This study aims to solve the problem of detecting phosphorus deficiency in barley plants growing in their natural field environment. We propose a deep-learning approach that utilizes the phenotypic characteristics of barley leaves. Our system builds on the improved YOLOv8 network and is implemented in a Python development environment, which has yielded promising results. The key findings of our study are as follows:

1. High accuracy for Close-up Images: The verification model showed an impressive accuracy of up to 80% in detecting phosphorus deficiency in detailed plant photos captured using a mobile phone camera.

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2. Surveillance camera challenges: The detection accuracy for images taken by surveillance cameras mounted on pivot irrigation machines was 65%. However, the complex natural environment significantly impacted the detection process, resulting in a mean relative error between predicted and actual numbers of deficient plants that was still within a manageable range of 2-3%.

We have promising results regarding the benefits and overall performance of our model, despite the challenges that come with working with surveillance camera images. Our model has successfully detected phosphorus deficiency in barley by analyzing phenotypic patterns collected directly from the field. This technology has the potential to offer significant benefits to farmers, allowing for early intervention and potentially reducing production costs. However, we recognize the need for further improvements in accuracy. To address this, we plan to combine our framework with Advanced Color-Based algorithms. This approach will enable us to extract more color and information from pre-processed images. We will also define target hue ranges specific to healthy and phosphorus-deficient leaves, which will provide additional decision-making support alongside the object detections from the YOLOv8 network.

By combining color analysis with deep-learning object detection, we hope to achieve a more robust and reliable classification of phosphorus deficiency. To achieve this, we plan to expand our dataset by including a wider variety of images captured under different environmental conditions and with varying degrees of phosphorus deficiency. Our research will also broaden its scope to encompass the detection of nutrient deficiencies beyond phosphorus. We may potentially explore the applicability of our research to other crop varieties.

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