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Training YOLOv5s under Field-survey Conditions to Detect The Infections of Maize Plants in Real-time

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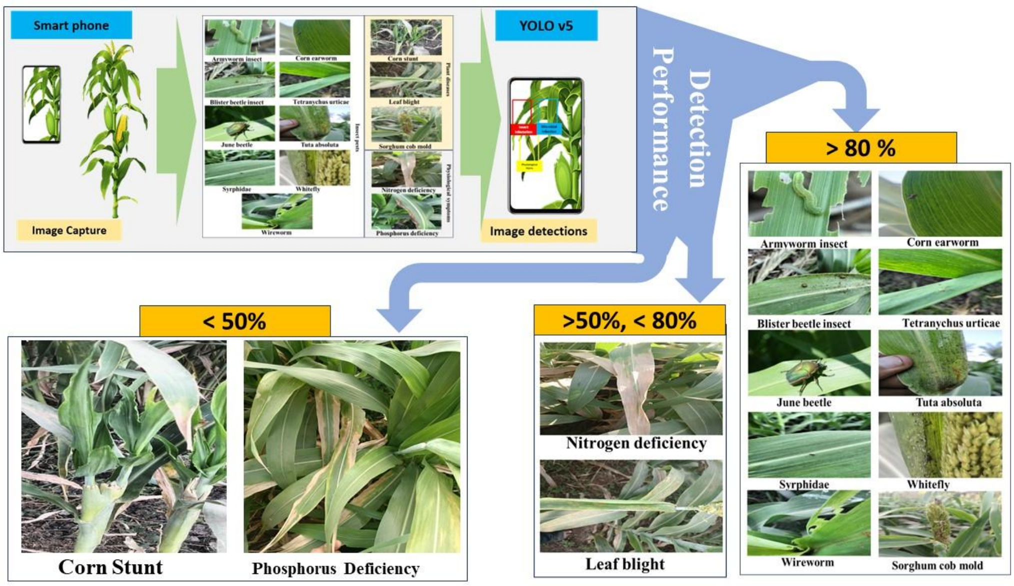
REAL-TIME detection of plant infections by YOLOv5s is important in smart agriculture. Detecting infections in maize poses significant challenges due to the field's complexity. Therefore, YOLOv5s requires multiple training in this aspect. This study aims to explore these obstacles through procedures for training YOLOv5s based on images from field surveying in the real field and evaluate them. It investigated the wide range of infections in maize plants that occurred at the same time, including insect infestations, diseases, and physiological symptoms. A dataset of 938 images was collected from 197 cases (14 infections). YOLOv5s curves were generated using loss and accuracy functions, which rely on metrics such as precision (P), recall (R), mAP@0.5, and mAP@0.5:0.95 to capture detailed model accuracy information. The curves indicate gradual improvement in the model, albeit with some fluctuations attributed to data noise. This fluctuation may be attributed to increased classifications within the dataset. The model shows good R for most object classes, with values over 0.8, indicating accurate identification even for small or difficult-to-see objects. However, it suffers from lower R rates, like corn stunts and phosphorus deficiency, due to its difficulty distinguishing images. The model has strong mAP@0.5:0.95 scores, suggesting its ability to generalize successfully across confidence levels. It works well for most object classes, but its performance for corn stunts and phosphorus deficiency is lower due to visual similarities. To enhance performance, there is a need for further refinement of the detection system, possibly through additional training data or improved algorithms.

Keywords: YOLOv5, Plant infections, Real-time, machine learning, maize.

Graphic abstract



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Introduction

Plant diseases and the pathogens that cause them pose a direct threat to the global economy and food security, as stated by **Sibiya et al., (2019)**. This is identical to what you **mentioned (Javidan et al., 2023)** that plant diseases can cause a decrease in crop yield and quality. Visual crop inspections by humans are time-consuming and can only be done in small areas. In addition, this traditional method of diagnosing plant diseases is not always reliable and is limited by the available expertise of the specialists **(Ramcharan et al., 2019)**. **Khakimov et al., (2022)** found that traditional visual inspection for plant diseases heavily relies on observer expertise and may not be as accurate for early detection. An intelligent machine vision monitoring system can help farmers with automatic inspection **(Javidan et al., 2023).**

According to **Baker et al., (2020)**, early diagnosis of plant diseases is crucial in preventing epidemics and disease outbreaks. Detecting diseases early on enables swift action, such as implementing quarantine measures or targeted treatments, to contain the spread of diseases and prevent significant crop damage on a large scale.

Yadav et al., (2023) used handheld devices with cameras to capture plant images, which depending on computer vision algorithms analyzed the images, in addition to identifying disease symptoms and pathogens. Therefore, other researchers used machine learning and AI to recognize disease patterns in plant images. With more data, the algorithms improved accuracy, becoming valuable tools for automated diagnosis **(Ahmed et al., 2022)**. As so, **Aishwarya et al., (2023)** developed smartphone applications that allowed farmers to capture images of their plants. Instant feedback on potential diseases or nutrient deficiencies was then provided, enhancing accessibility to diagnostic information. In addition, another study conducted by **Zhang et al., (2023)** showed that mobile apps have great potential for farmers and agricultural experts. The uploaded images of affected plants, which are then analyzed using AI algorithms to diagnose potential diseases. A simple method relying on minimal image information is interesting for field conditions **(Javidan et al., 2023)**.

Timely diagnosis of plant infections remains a difficulty for farmers. It takes a lot of time and a lot of human work to discover diseases, especially at an early stage. As a result, **Dmitrijeva et al., (2023)** noted that even though neural networks usually do not solve the problem in general, they have several advantages, for example, they assist us in classifying and grouping. But there are also disadvantages, for example, training big neural networks takes much time, and multiple trials and neural network tweaks must be undertaken to boost the accuracy. **Buja et al., (2021)** noted one of the challenges of real-time monitoring was the conditions of the specifications of the cameras of the smartphones common to farmers. Although almost all cameras now can take such an image, the dataset contains images with different resolutions, lighting, and with different background noises, which will need to improve the recognition of diseases by neural networks. and **Niu et al., (2023)** added that making it challenging to achieve accurate real-time detection. Fruit detection algorithms employing deep learning outperform traditional image recognition methods in terms of speed and accuracy, rendering them the predominant approach in practice. YOLOv5 stands out among single-stage detection models due to its superior detection accuracy and rapid detection speed

YOLOv5 (2020) can categorize the image into a category and detect several items within a image. It is one of the fastest methods that employ CNN for object detection and combines bounding box prediction and object classification into a single end-to-end differentiable network **(Zhu et al., 2021)**. The greatest feature of YOLOv5 is that it features Focus and cross-stage partial connections (CSP) **(Wang et al., 2020)** layer. After comparing to the rest in **Jason et al., (2022)** discovered that the YOLOv5 variations provided the optimum balance between both speed and accuracy while boasting a much higher accuracy-to-speed ratio. **Zhang et al., (2024)** used the YOLOv5s model to build visual detection of tomato bunches from full images, which is a detection task and the recorded dataset. In the other study depending on the YOLOv5s, the results of an experiment demonstrate the effectiveness of the grape detection model in identifying grapes. The model showed high detection accuracy **(Wang et al., 2024).**

Plant detection in unstructured orchard environments remains challenging due to varying illumination conditions and degrees of occlusion. According to **Tang et al., (2023)** and added that despite advancements in object detection technology, detecting fruit with high precision remains challenging. To our knowledge, this is the first time that the problems of training several forms of maize infection detection have been investigated simultaneously to acquire evaluation under field settings

Using YOLOv5s improves the speed and accuracy of object detection, but it requires extensive training to address the challenges in the field and meet our requirements effectively. Some of these challenges arise when employing YOLOv5s for real-time detection of various plant infections at the same time in the same field. This study aims to explore these obstacles through procedures for training YOLOv5s based on images from field surveying to provide concrete examples to support deployment on smartphones for real-time detection and identification. This study investigated the wide range of infections in maize plants that occurred at the same time in the field, including insect infestations, disease outbreaks, and physiological symptoms that field images captured in different ways.

Materials and Methods:

Area Study and plants

The survey was conducted in four Maize fields in Sohag Gov. in the summer of 2023, as illustrated in the following map and each location is represented by a red dot, as depicted in Fig. 1

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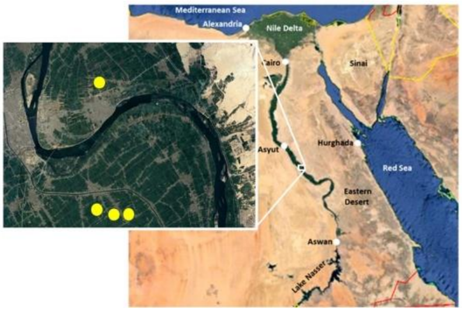

Fig. 1. Map of Area Study

Experimental procedure

The study was done in five steps, as in Fig. 2. Maize as a summer crop to detect insect and plant diseases and physiological symptoms in the actual field, covering four different regions in Upper Egypt fields in this region known for its high temperature. Plant infection detection was done by experts, and images were recorded and numbered through the time of pick-up.

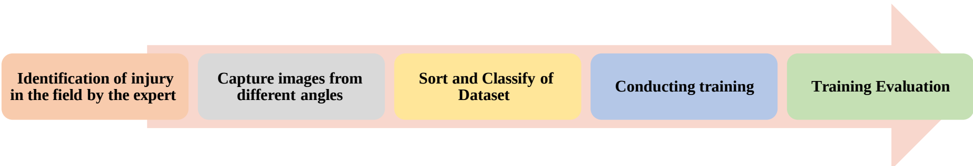

Fig. 2. Experimental procedure stepsInjury identification by the expert

Researchers found 157 maize infection cases in the field which were Distributed. And 14 plant infection types (9 Insect pests, 3 plant diseases, and 2 Physiological symptoms) for each condition (Table 1).

Capture images

Capture images by the camera of the smartphone (Samsung A21s) was used with a resolution of 48 megapixels and an F/2.0 aperture. The images were captured in varying lighting conditions. Documenting the condition of the affected plant by employing a multi-angle photography strategy, including top-down, horizontal, vertical, and lateral angles as shown in Fig. 3.

Multiple images have been taken at variation intervals throughout the day to enhance the diagnostic accuracy of detention. These images, taken at different times during the day, reflect the plant's dynamic response to environmental factors throughout the day. Images in Fig 4 show one example image for every case.

Dataset sort and classify

Images taken have been sorted to exclude unclear and highly noisy images and to classify them by infection. The dataset consists of 197 cases (938 images). The images were classified into main folder maize (Maiz-YOLO) and subfolders for each case of infection and other sub-for each disease, symptom, or insect to facilitate the process of training the model on them, for a better training result. Data have been loaded and prepared as with any deep learning task, the first and most important one is to prepare the dataset. Dataset runs any deep learning model. The dataset for our experiment contains about 938 images of maize for 14 plant infections.

Training

YOLOv5s (small) v7.0 was the model used for training. It is a good option when real-time detection is required, as it balances accuracy and speed (Quick to train). YOLOv5s can forecast category labels to help make better decisions without sacrificing too much accuracy and real-time control on a smartphone screen because of its fast inference speed. Table 2 is showed the

specifications of this model. The network structure of initial YOLOv5s is shown in Fig. 5.
The YOLOv5 network comprises four parts: input, backbone, neck, and detecting head. But in this study depending on the YOLOv5s v7.0 that emerges the neck layer with the head becomes speedy. The detection head performs convolution on three different sizes of feature maps outputted for target category and location regression detection as Fig. 9

TABLE 1. Numbers of cases and images of every Maize infection

	Infection type	Scientific Name	Infections Name	Cases No.	Images No.
1	Insect pests	*Spodoptera frugiperda*	Armyworm	12	70
2		*Epicauta spp.*	Blister Beetle	7	62
3		*Phyllophaga spp.*	June Beetle	3	27
4		*Syrphidae spp.*	Syrphidae	4	35
5		*Helicoverpa zea*	Corn earworm	2	7
6		*Tetranychus urticae*	Tetranychus Urticae	3	26
7		*Tuta absoluta*	Tuta Absoluta	39	231
8		*Bemisia tabaci*	Whitefly	37	238
9		*Agriotes spp.*	Wireworm	2	9
10	plant diseases	*Spiroplasma kunkelii*	Corn stunt	3	19
11		Exserohilum turcicum	Leaf Blight	9	40
12		*Fusarium moniliforme*	Sorghum Cob Mold	2	17
13	Physiological symptoms	Nitrogen Deficiency	Nitrogen Deficiency	28	142
14		Phosphorus Deficiency	Phosphorus Deficiency	6	15
	Total			157	938

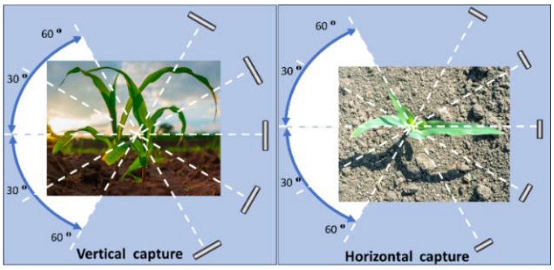

Fig. 3. Angle of captured images

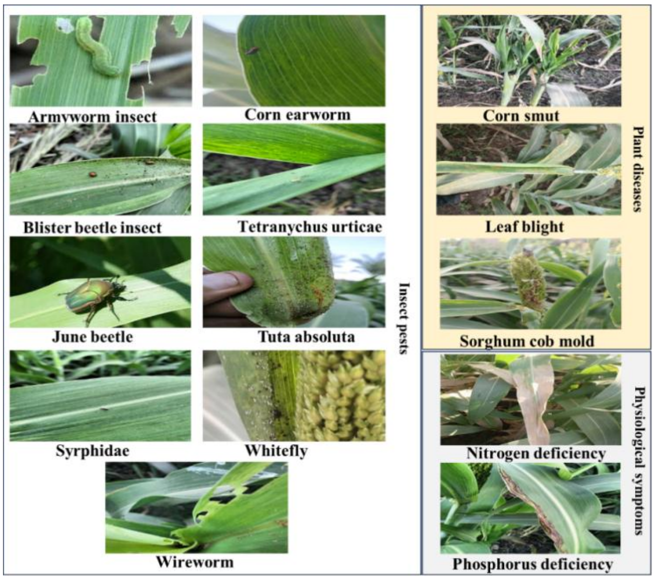

Fig 4. Images of Insect pests, plant diseases, and physiological symptoms

TABLE 2. The specifications of this YOLOv5s v7.0.

Model	Size (pixels)	Mapbox 50-95	mAP mask 50-95	Train time 300 epochs A100 (hours)	Speed ONNX CPU (ms)	Speed TRT A100 (ms)	Params (M)	FLOPs @640 (B)
YOLOv5 s-seg	**640**	**37.6**	**31.7**	**88:16**	**173.3**	**1.4**	**7.6**	**26.4**

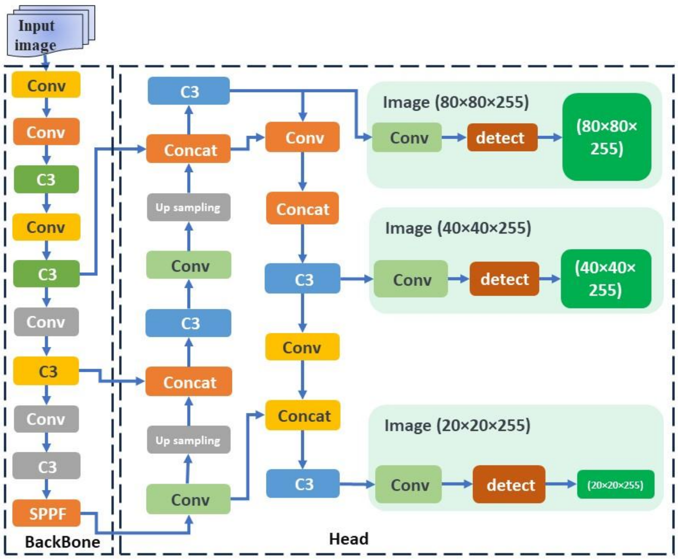

Fig. 5 The network structure of initial YOLOv5s

Dataset was used to train the YOLOv5s neural network. Bounding Box was used as the annotation type, and main folders and subfolders to facilitate the process of training the model on them, for a better training result, the augmented version was increased three times. Once the version was generated, it was exported to YOLOv5 PyTorch format for further use in neural network training. Results and their evaluation of the images were uploaded in one folder to be automatically split into three folders later using the Roboflow tool.

The next stage was to train the YOLOv5 neural network model utilizing the Google Colab environment, applying GPU (Graphics Processing Unit) computing. Kernel YOLOv5s was utilized during training. To train the YOLOv5 neural network, the following procedures were performed: installed YOLOv5s packages (dependencies), imported dataset, defined model setup, and trained YOLOv5.

Performance Evaluation Methods

In this study depending on the YOLOv5s curves during training and the assessment indicators to evaluate the training the different detection of plant infections. YOLOv5s curves during training, Box represents the mean of GIoU Loss, Objectness represents the mean of object detection loss, Classification represents the mean of classification loss, validation (val) Box represents the mean of GIoU loss in the validation set, val objectness represents the mean of object detection loss in the validation set, val Classification represents the mean of classification loss in the validation set

The assessment indicators chosen for this study are frames per second (FPS), floating-point operations (FLOPs), average precision (AP), and mean average precision (mAP). The AP, or mAP, is a metric used to assess the overall accuracy of object detection. The best metrics to gauge the model's the detection accuracy for object detection are AP and mAP. FLOPs are a metric used to quantify the computational effort and model complexity. FPS is a measure of object identification speed that shows how many images the network can identify in a second. The following Eq. (1) – (4) demonstrate the formula:

$$\mathrm{Precision(P)} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{1}$$

$$\mathrm{Recall(R)} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{2}$$

$$\mathrm{AP_i} = \int_0^1 \mathrm{P_i}\,(\mathrm{R_I})\mathrm{dR_i} \tag{3}$$

$$\mathrm{mAP} = \frac{1}{\mathrm{C}}\sum_{\mathrm{I}=1}^{\mathrm{C}} \mathrm{AP_i} \tag{4}$$

Among these, Precision shows how accurate the model is in every box that is discovered. Recall (R) is the detection frame's coverage of all ground facts that the model predicts. AP takes into account the P and R indicators while assessing the model's performance in each area. The area between the coordinate axis and the P-R curve is the value of AP. False positive (FP) is the number of negative cases categorized as positive categories; true positive (TP) is the number of properly predicted positive instances; and false negative (FN) is the number of mistakenly classified positive examples. The accuracy of the ith pest category is represented by C, which is the number of pest species. The recall rate of the ith pest category is represented by Ri.

Results and Discussion:

Identify Metrics, Training, and Validation:

Based on the dataset, Fig. 6 shows different line charts, which are typically used to track changes. Since each chart likely represents a different metric or aspect of a machine learning model's performance. The Maize-YOLO curves indicate the performance of the model in terms of train/box_loss, train/obj_loss, train/cls_loss, and val/cls_loss. Lower values of these metrics suggest that the model is confident and improving as it is trained, which is similar to **(Yang et al., 2023)**. But the val/box_loss curve is not perfectly smooth, which indicates that there is some noise in the data. On the other hand, the val/obj_loss curve shows an inverse trend, which suggests that there is more noise in the validation data than in the training data that different with (**Yang et al., 2023)**. Maybe they used insect pests' images only, but images were used in this study for three types of infections. This means that the model has successfully learned from the training data, but is struggling to perform on the validation data. In addition, the Maize-YOLO curves show the common metrics used to evaluate the model, such as precision, recall, accuracy, F1 score, and mAP. These metrics indicate that the model is improving as it is trained, but the curves are not perfectly smooth, which suggests that there is some variability in the data. This could be due to factors such as an insufficient amount of training data, lack of diversity in the data, or the model being too complex. Overall, the curves suggest that the model is improving, but there is still room for improvement. By addressing the sources of noise and variability in the data, the model can be further optimized to achieve better performance.

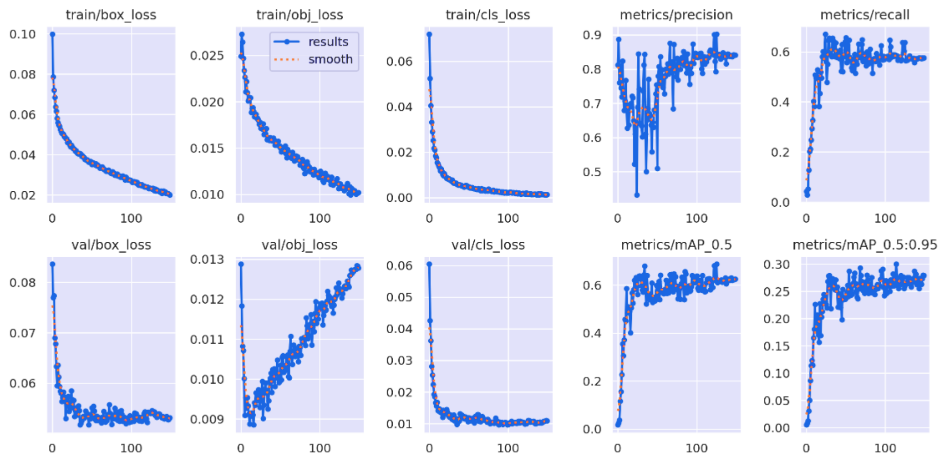

Fig. 6. Maiz-YOLO curves during training

Recall

The recall-confidence Relationship curves in Fig. 7 show the performance of an object detection model on a dataset of imagery. The curves are plotted for each object class in the dataset, with the recall on the y-axis and the confidence threshold on the x-axis. this chart has been presented as a helpful tool for analyzing the effectiveness of a classification model in detecting different plant illnesses and weaknesses in the detection by YOLOv5s.

The curves show that the model has high recall for most object classes, with values greater than 0.8. This means that the model can correctly identify most of the objects in the images, even when the objects are small or difficult to see. However, the curves also show that the model has a lower recall for some object classes, such as corn stunt and phosphorus deficiency. This is likely because these object classes are more difficult to distinguish from other objects in the images. A line that stays high on the graph as confidence grows suggests a class that the model recognizes with high accuracy, even at tighter confidence levels. This threshold is critical for precision agriculture, where the cost of false positives (e.g., wasteful pesticide treatment) and false negatives (e.g., missing infestations) may be high, according to **Wyawahare et al., (2023).** This chart is crucial in fine-tuning the model to ensure it operates effectively for the unique demands of precision agriculture, enabling it to make educated choices based on the model's predictions..

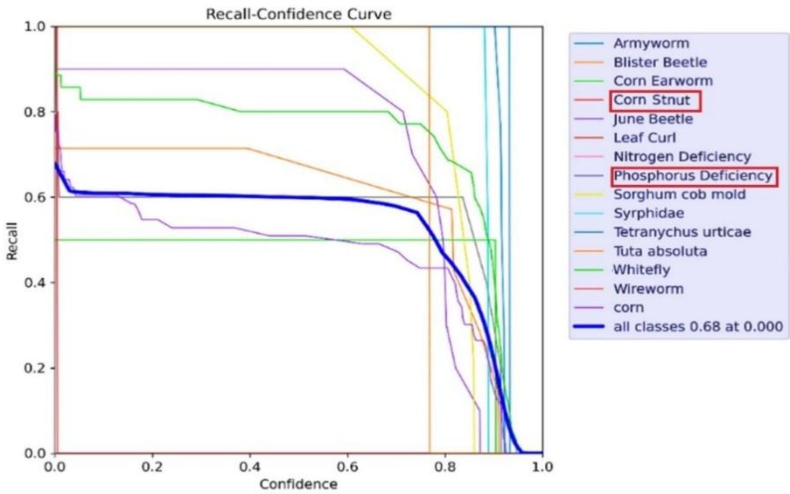

Fig. 7. Recall and confidence curve for Maize infection types

Precision (P), recall (R), mean Average Precision, and images No.

The results in Fig. 8 show that the model is capable of detecting objects in imagery with high accuracy. The effects of armyworm, Syrphidae, Tetranychus urticae, and Tuta absoluta show perfect scores (1.0) for both P and R, indicating that the system accurately identified these types without missing any occurrences or making false identifications. The mAP at both thresholds (0.5 and 0.5:0.95) is also high for these plant infections, suggesting that the system is reliable across different levels of detection difficulty. However, some categories require further work, such as corn stunt and phosphorus deficiency (<50%), nitrogen deficiency, and leaf blight (<75 %). In the same trend, the model performs well, achieving high P and R for most object classes. However, some classes require further work, such as corn stunt and phosphorus deficiency. While mAP@0.5:0.95 scores indicate that the model's performance for corn stunt and phosphorus deficiency is lower than for other classes, this is likely because these two classes are visually similar to other objects in the images. Compared to **Yang et al., (2023)**, these values were the best, with Yang et al. focusing on the insect pests only, but according to **Tang et al., (2023)** under conditions in actual fields with different types of plant infection, that high precision remains challenging. As corn stunt and phosphorus deficiency in this study

Room for Improvement: The corn stunt and phosphorus deficiency have the lowest scores across all metrics, which could indicate that the system struggles to detect these particular plant infections accurately. This might be due to the visual similarity of these plant infections with other benign conditions, or a lack of representative **training** data

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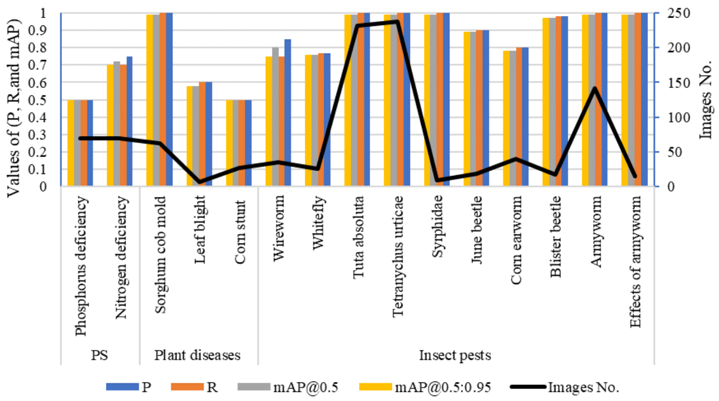

Fig. 8. Detection performance of Maize -YOLO on datasets for various types of plant infections

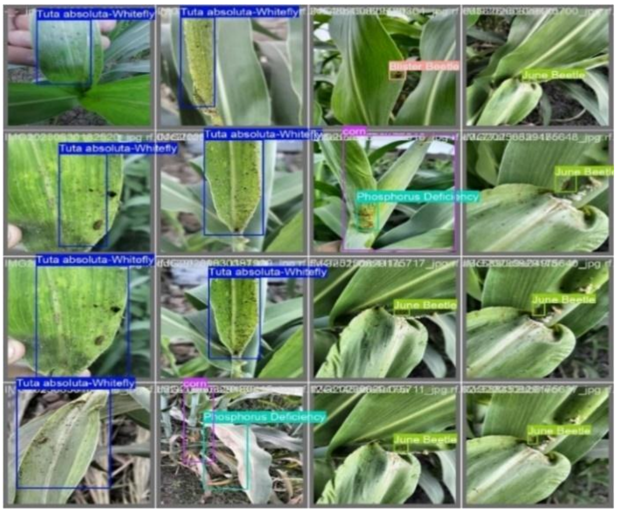

Fig. 9 Example of Maize-YOLO results for pest detection.

Conclusion

Using the Roboflow tool and the Google Colab environment, the YOLOv5s neural network recognizes plant infection species from images. Dataset capture from the survey of the field for 14 plant infections, consisting about of 938 images, was used for training. After training, we received YOLOv5s curves with loss and accuracy functions, and P, R, mAP@0.5, and mAP@0.5:0.95. This value helps to record details of the accuracy of the model.

The Maize-YOLO curves indicate the model's performance in terms of various metrics. Lower values suggest the model is improving and confident, but not all curves are perfectly smooth, indicating noise in the data. The common metrics show improvement as the model is trained, but there is variability, which can be due to insufficient training data, or model complexity. Overall, there is room for improvement by addressing noise and variability in the data. The curves display the model's performance in detecting various plant illnesses and weaknesses. The model has high recall for most object classes, but lower recall for some, such as corn stunt and phosphorus deficiency.

Most plant infections have high P and R, which is promising. However, the lower scores for some plant infections highlight the need for further refinement of the detection system, possibly through additional training data or improved algorithms.

To detect these plant infections, adjusting model complexity can be done, by implementing techniques like dropout or L1/L2 regularization to prevent overfitting, and optimize batch sizes for corn stunt and phosphorus deficiency. This analysis and evaluation can help in understanding the strengths and weaknesses of the detection system under field-survey conditions that are captured randomly, that need guiding further improvements, and ensuring effective pest and deficiency management. Therefore, there is a need for further refinement of the detection system, possibly through additional training data or improved algorithms.

Consent for publication:
All authors declare their consent for publication.

Author contribution:
The manuscript was edited and revised by all authors.

Conflicts of Interest:
The author declares no conflict of interest.

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تدريب YOLOv5s تحت ظروف المسح الحقلي لاكتشاف إصابات نبات الذرة في الوقت الفعلي

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يعد الكشف في الوقت الفعلي عن الإصابات النباتية بواسطة YOLOv5s مجالًا مهمًا في الزراعة الذكية ، يشكل اكتشاف حالات العدوى في الذرة تحديات كبيرة بسبب طبيعة الحقل، لذلك، يتطلب YOLOv5s تدريبًا متعددا في هذا الجانب ، تهدف هذه الدراسة إلى استكشاف هذه العوائق من خلال إجراء تدريب YOLOv5s بناءً على صور جمعت من المسح الميداني في الحقل وتقييمها ، وقد بحثت في مجموعة واسعة من حالات العدوى في نباتات الذرة والتي حدثت في نفس الوقت، بما في ذلك الإصابة بالحشرات، والأمراض، والأعراض الفسيولوجية ، وتم جمع البيانات من 938 صورة لـ 197 حالة (14 إصابة) ، تم إنشاء منحنيات YOLOv5s باستخدام وظائف الفقد والدقة، والتي تعتمد على مقاييس مثل الدقة (P)، والاستدعاء (R)، وmAP@0.5، وmAP@0.5:0.95 لالتقاط معلومات تفصيلية عن دقة النموذج ، وتشير المنحنيات إلى تحسن تدريجي في النموذج، وإن كان ذلك مع بعض التقلبات التي تعزى إلى تشويش البيانات ، قد يعزى هذا التذبذب إلى زيادة التصنيفات ضمن مجموعة البيانات ، يُظهر النموذج قيمة الاستدعاء جيدة لمعظم الفئات ، بقيم تزيد عن 0.8، مما يشير إلى التحديد الدقيق حتى للأشياء الصغيرة أو التي يصعب رؤيتها ، إلا أنها تعاني من انخفاض الاستدعاء في حالتي تقزم الذرة ونقص الفوسفور، وذلك بسبب صعوبة تمييز الصور ، ويحتوي النموذج على درجات mAP@0.5:0.95 قوية، مما يشير إلى قدرته على التعميم بنجاح عبر مستويات الثقة ، وكذلك يعمل بشكل جيد مع معظم فئات الكائنات، ولكن أداءه مع تقزم الذرة ونقص الفوسفور أقل بسبب التشابه البصري ، لتعزيز الأداء هناك حاجة لمزيد من التحسين لنظام الكشف، ربما من خلال بيانات التدريب الإضافية أو الخوارزميات المحسنة.