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Detecting Defect in Central Pivot Irrigation System Using YOLOv5 Algorithms

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Abstract
Global agriculture employs central pivot irrigation system(CPIS) as a highly significant method for intelligent irrigation. Cultivating crucial crops like wheat and other strategically important crops that occupy extensive land areas contributes to global food security. The Central Pivot Irrigation System encounters technical issues that result in malfunctions in its automatic control system. These malfunctions occasionally cause damage to the primary pipes and towers that operate the system, resulting in significant material losses for farmers and agricultural crops. Moreover, the repair process is time-consuming. Therefore, to address this issue, this study employed the YOLOv5 models to accurately identify and detect defects in the CPIS machine by determining whether they are in a safe or dangerous state. The dataset that was used in this study was gathered from agricultural areas in Salah al-Din Governorate. The CPIS detection model yielded the following results: the grayscale color system with Yolov5n achieved a 98 % detection rate with accuracy and F1-score values of 0.866. Similarly, Yolov5m achieved a 98 % detection rate with accuracy and F1-score values of 0.804. In the RGB color system, the maximum results achieved with Yolov5n are 97 % for accuracy and 0.812 for F1-score. On the other hand, Yolov5s6 achieves a result of 95 % for accuracy and 0.82 for both F1-score and accuracy. Based on the aforementioned outcome, we can infer that yolov5s6 accurately detects the CPIS in both its safe and dangerous states. Therefore, they can be deployed in a real-time system for CPIS defect monitoring and control systems.

Keywords
Central Pivot Irrigation System, CPIS, CNN, Defects Detection, Object Detection, Yolov5.

I. Introduction

Smart irrigation is one of the leading technologies for increasing agricultural productivity, improving the yield of most crops by 100 % or more [1]. They use of sensors, such as devices sensitive to humidity and temperature, and attempt to make agricultural conditions suitable for crops as needed for reducing the waste of water sources and improving crop productivity [2]. There are several reasons for using smart irrigation systems, including [3]:

1. Increase crop production.
2. Reducing the waste of water used for irrigation.
3. Reducing the waste of energy used.
4. Reducing labor costs.
5. Increase environmental sustainability.

Types of smart irrigation systems are divided into several types according to the irrigation mechanism, namely, central pivot irrigation, Sprinkler, and drip water [3]. The central pivot irrigation uses a long tube raised above ground level and suspended from several sprinklers to water crops. This center tube rotates in a circular manner. The sprinkler irrigation uses a long tube extended on the surface of the soil with water sprinklers attached to it and it is fixed and immovable, and drip water uses a long, small-diameter tube to which emitters are attached to drip water onto the soil near the roots of crops [4].

Central pivot irrigation, is considered as one of the most important methods used for smart irrigation in agriculture around the world, where crops important for the world's food security are grown, such as wheat and other strategic crops, as these crops cover very large areas [2].

The Central Pivot Irrigation faces some technical problems, these technical problems are due to the weather conditions consisting of high humidity in winter and the occurrence of some dust storms in summer, some dust particles enter the controllers, leading to the formation of carbon on the energy sources of the controllers, resulting in improper functioning of the controller. which lead to a defect in their automatic control system, and sometimes lead to damage to some of the main pipes and towers that drive them, which leads to relatively large material losses for farmers and agricultural crops, as shown in the picture below in Fig. 1, the repair process takes a period of one day. For several days, as every day is important for the farmer.

Fig. 1. Central Pivot Irrigation with damage.

Recently, deep learning-based algorithms have shown superior performance in many engineering applications [5–8], medical applications [9] , and most computer vision tasks, such as image classification [10, 11], subject identification [12, 13], object detection, and segmentation. There have been many successful applications in the field of defects detection [14].

Defects detection technology can classify multiple targets appearing in a single image and obtain their precise positions, which is more widely applicable. Object detection techniques are mainly divided into two categories, one is two-stage networks such as RCNN and Faster R-CNN. The other is one-stage networks such as Single Shot MultiBox Detector (SSD) and YOLO [15].

Deep learning-based defect identification has become a potent tool for visual inspection task automation across multiple industries [16]. Large image datasets can be used to train deep learning algorithms to recognize intricate patterns, which makes it possible for them to precisely detect flaws in materials and products. Safety, quality assurance, and production efficiency have all significantly improved as a result [17].

"You Only Look Once" or YOLO, is the name of a family of object detection algorithms that have become more well-known recently because of their accuracy and speed. In contrast to conventional two-stage object detection algorithms, which carry out classification and region proposal in independent phases, YOLO utilizes a single-stage methodology that derives class probabilities and bounding boxes straight from the input image [18].

Building on the success of YOLOv1 through YOLOv4, YOLOv5 is a cutting-edge object detection method. It is one of the most widely used object identification algorithms available today since it provides notable gains in terms of accuracy, speed, and versatility [19].

Therefore, the goal in this paper is to create a CPIS defect identification model based on Yolov5 to monitor the condition of the CPIS machine. The paper is structured in the following manner: section I. presents the Introduction. Section II. the describes the proposed System. Section III. elaborates the result and discussion. Section IV. presents the conclusions.

II. The proposed system

This section describes the methodological framework for developing the CPIS defect identification model starting from the data collection process and ending with the final model. Fig. 2 depicts the methodological framework for the whole development process. More details described in the following sub section:

A. Data Collection and Preprocessing Phase.

This phase started by collecting CPIS images from the agricultural areas in Salah AL-din. This process is conducted by installing a vision system consist of the following components:

1. Iron pipe Strap with a diameter of 6 inches.

2. An iron pipe 4 meters height to install the camera.

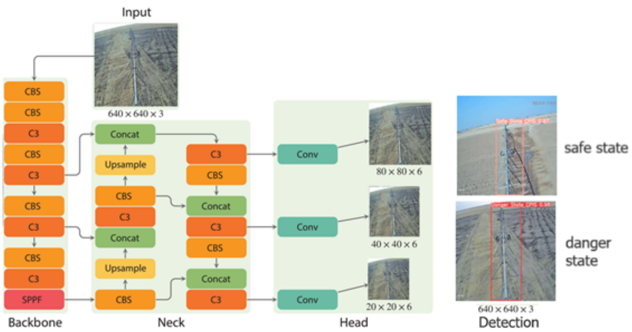

Fig. 2. Methodological framework for CPIS defect identification model.

3. Steel wires to connect the carrier pipe on all four sides to prevent vibration during strong winds.

4. A camera with a resolution 1920 x 1080 pixels.

5. The whole vision system installed on the main pipe at a distance of three meters from the center for center pivot irrigation, as shown in the picture below in Fig. 3.

Fig. 3. Setting up a data collection system.

For the preprocessing stage, the CPIS was visualized in good condition and poor condition, where 1400 images were collected for each condition, 700 images to ensure that no bias will occur during the training phase of the defect detection model. Sample of the collected images presented in Fig. 4. The preprocessing of the collected images as follows:

1. Image size: The image size is 1920 by 1080 is resized to 640 by 640 pixels to match the size of the yolov5 model requirements.

2. Color system: Two systems were used; RGB and grayscale.

Fig. 4. Sample images from the collected dataset; left column (safe state), right column (unsafe state).

B. Training and Testing Phase

The data, consisting of 1400 images, was divided into three groups as shown in Fig. 5: the first group for training consists of 980 images, the second group for validation consists of 280, and the third group for Testing consists of 140 images. The Yolo5 model was used, which consists of 10 different models. Seven models were adopted and trained, these shown in Table I with their parameters. These models consist of three main layers: the first is the input layer, the second which is the hidden layer, consists of several hidden layers, and the third is the output layer as presented in Fig. 6. For training the model on the data, a batch size 16, and 50 epochs utilized.

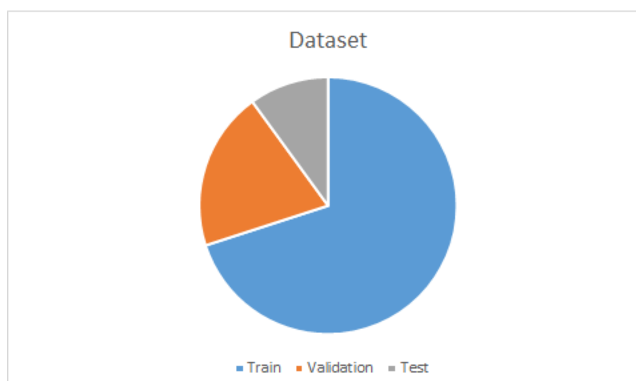

Fig. 5. Yolov5 Models Parameters.

TABLE I. YOLOV5 MODELS PARAMETERS.

Model	Size(pixels)	Mean Average Precision 50-90	Mean Average Precision 50	Params (M)	Hidden layers
YOLOv5n	640	28.0	45.7	1.9	21
YOLOv5s	640	37.4	56.8	7.2	21
YOLOv5m	640	45.4	64.1	21.2	21
YOLOv5l	640	49.0	67.3	46.5	21
YOLOv5x	640	50.7	68.9	86.7	21
YOLOv5n6	1280	36.0	54.4	2.1	21
YOLOv5s6	1280	44.8	63.7	12.6	21

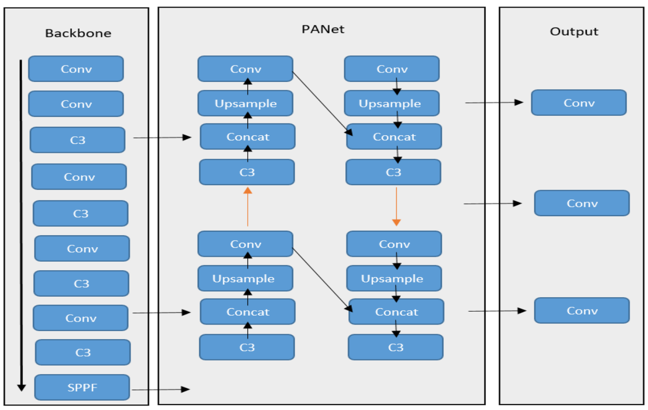

Fig. 6. Overview of YOLOv5.

III. RESULT OF DEFECT DETECTION

This section presents the result of the training and testing phase for the CPIS defect detection using yolov5 models. Basically, there are several models for Yolov5, including Yolov5n, Yolov5s, Yolov5m, Yolov5l, Yolov5x, Yolov5n6, and Yolov5s6. The result of these models described in details in the following sub sections.

A. YOLOV5N

This model showed very good results in terms of speed and accuracy in determining the required conditions for CPIS machine as shown in Figures 7, 8, and 9 and Table II. From the table, we notice the F1-Score value and the Precision value is very good for grayscale, and for RGB color system is Slight decrease in values from the grayscale color system.

B. YOLOV5S

The Yolo5s model showed very good results in terms of speed and accuracy, but less than the Yolo5n model in determining the status of the CPIS machine as shown in Figures 10, 11, and 12 and Table III. From the table we notice that the RGB color system was better in F1-Score, but in Precision the grayscale system was better.

TABLE II. TRAINING AND TESTING RESULT FOR YOLO5N.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5n	0.812	0.975	RGB	97 %
2	Yolov5n	0.866	0.998	Grayscale	98 %

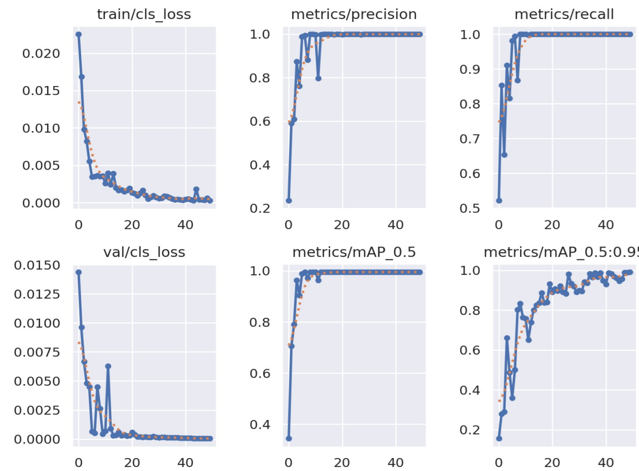

Fig. 7. Curve for training proposed method for Yolov5n with RGB Color System.

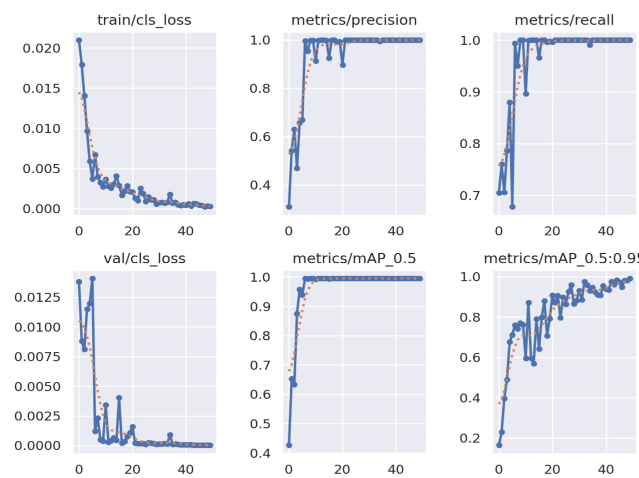

Fig. 8. Curve for training proposed method for Yolov5n with Grayscale Color System.

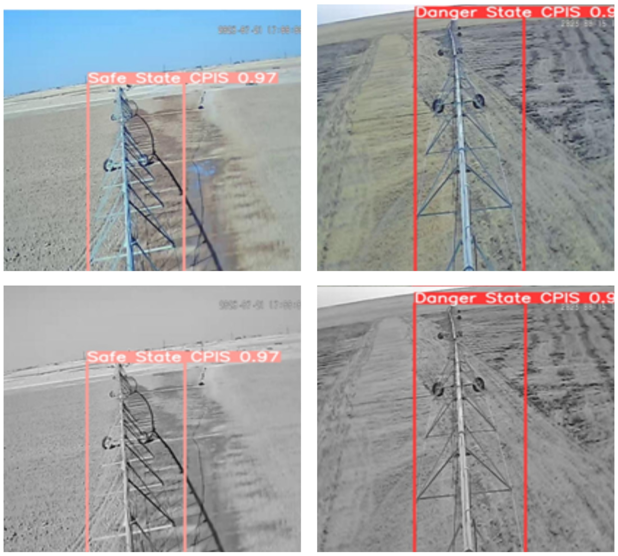

Fig. 9. Results of sample RGB and Gray images with Yolov5n; first row (RGB), second row (Grayscale).

TABLE III. TRAINING AND TESTING RESULT FOR YOLO5S.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5s	0.858	0.939	RGB	94 %
2	Yolov5s	0.714	0.996	Grayscale	97 %

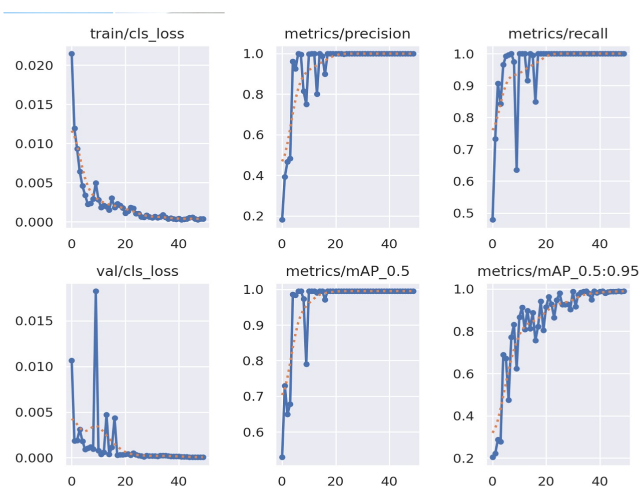

Fig. 10. Curve for training proposed method for Yolov5s with RGB Color System.

C. YOLOV5M

The Yolov5m model showed very good results in terms of speed and accuracy, and the results were better than the

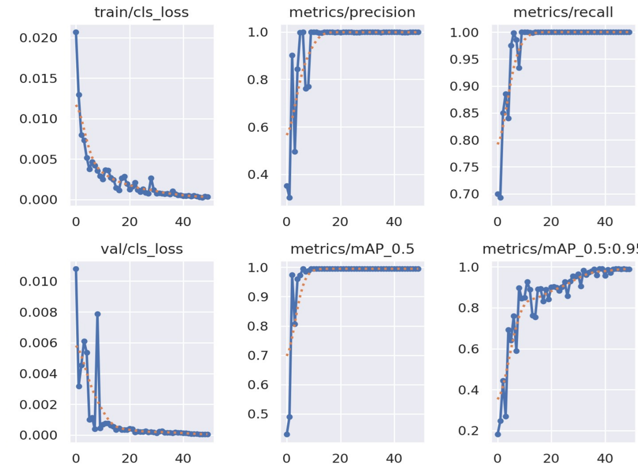

Fig. 11. Curve for training proposed method for Yolov5s with Grayscale Color System.

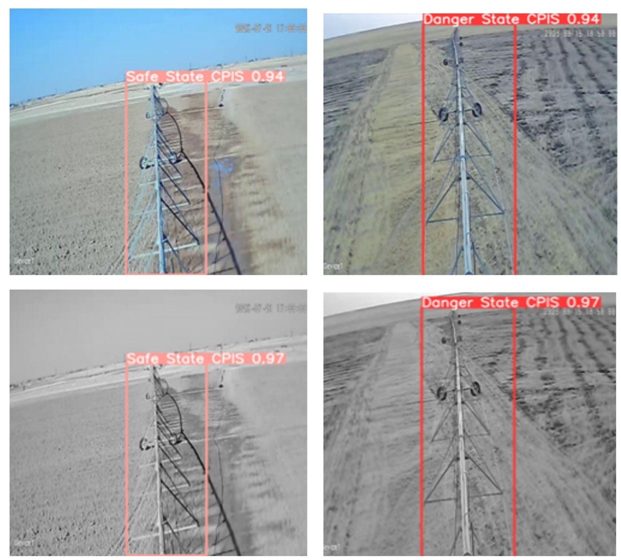

Fig. 12. Results of sample RGB and Gray images with Yolov5s; first row (RGB), second row (Grayscale).

Yolov5s model in determining the status of the CPIS machine as shown in Figures 13, 14, and 15 and Table IV. From the table, we notice that the grayscale values of F1-score were better than the RGB color system.

D. YOLOV5L

The Yolovl5 model showed very good results in terms of speed and accuracy. The results are lower than the Yolov5m model, because, it took more time and the accuracy was less in determining the status of the CPIS machine as shown in Figures 16, 17, and 18 and Table V. From the table, we note

TABLE IV. TRAINING AND TESTING RESULT FOR YOLO5M.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5m	0.793	1	RGB	97 %
2	Yolov5m	0.804	1	Grayscale	98 %

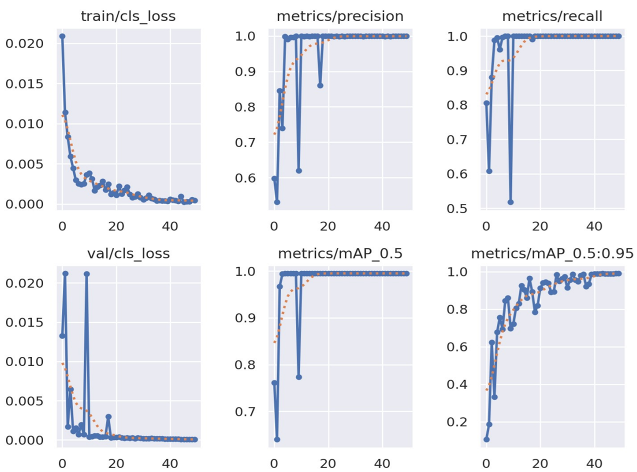

Fig. 13. Curve for training proposed method for Yolov5m with RGB Color System.

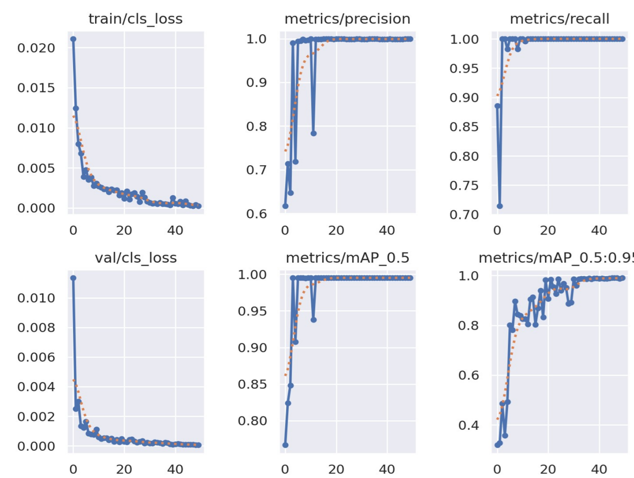

Fig. 14. Curve for training proposed method for Yolov5m with Grayscale Color System.

that the F1Score value in the RGB color system was better than the grayscale, but the grayscale was better in Precision.

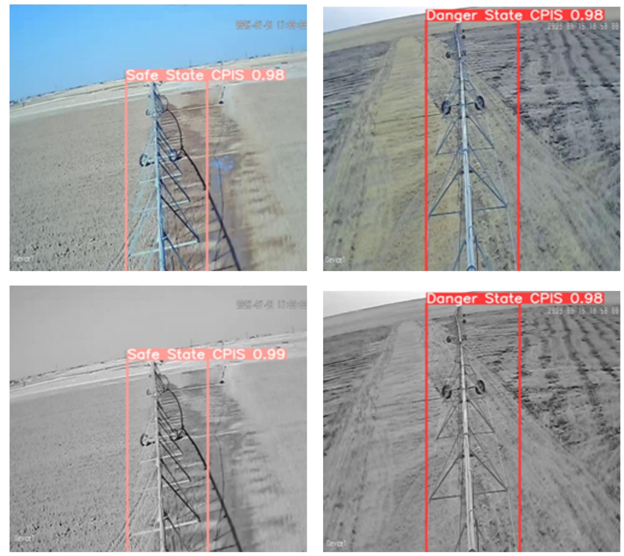

Fig. 15. Results of sample RGB and Gray images with Yolov5m; first row (RGB), second row (Grayscale).

TABLE V. TRAINING AND TESTING Result for YOLO5l.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5l	0.804	0.956	RGB	93 %
2	Yolov5l	0.778	0.97	Grayscale	95 %

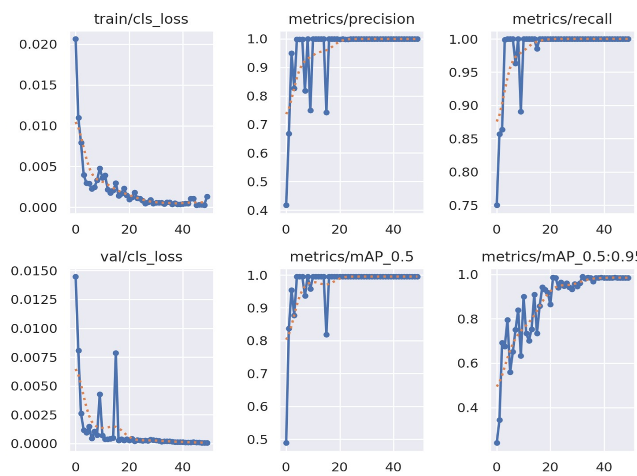

Fig. 16. Curve for training proposed method for Yolov5l with RGB Color System.

E. YOLOV5X

The Yolo 5 model showed very good results in terms of speed and accuracy, and the results were better than the Yolo 5 model

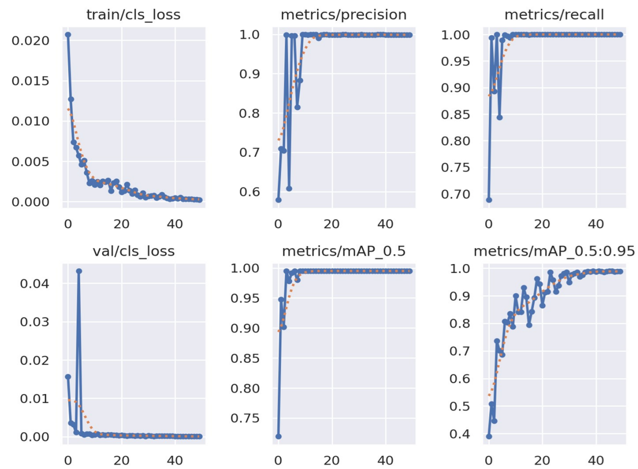

Fig. 17. Curve for training proposed method for Yolov5l with Grayscale Color System.

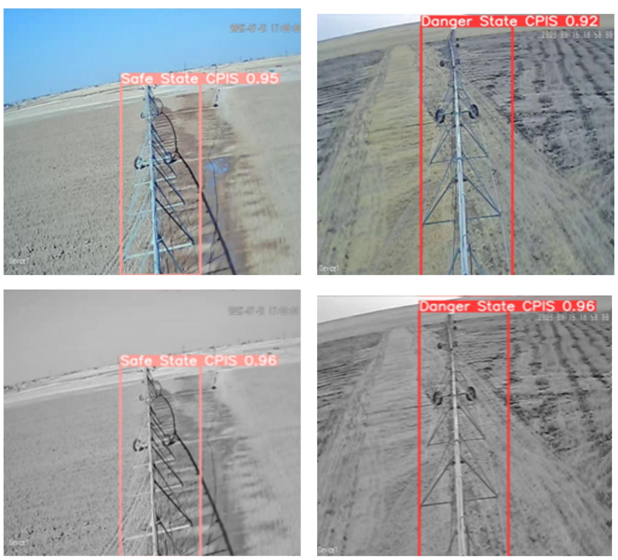

Fig. 18. Results of sample RGB and Gray images with Yolov5l; first row (RGB), second row (Grayscale).

in terms of accuracy, but it took more times to determining the status of the CPIS machine as shown in Figures 19, 20, and 21 and Table VI. From the table, we note that the F1-Score value in the RGB color system was better than the grayscale, but the grayscale was better in Precision.

F. YOLOV5N6

The model showed very good results in terms of speed and accuracy in determining the status of the CPIS machine as shown in Figures 22,23, and 24 and Table VII. From the table we note that the values are equal for the F1-Score for both color systems, as well as for the Precision.

TABLE VI. TRAINING AND TESTING RESULT FOR YOLO5X.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5x	0.722	0.987	RGB	95 %
2	Yolov5x	0.712	0.989	Grayscale	96 %

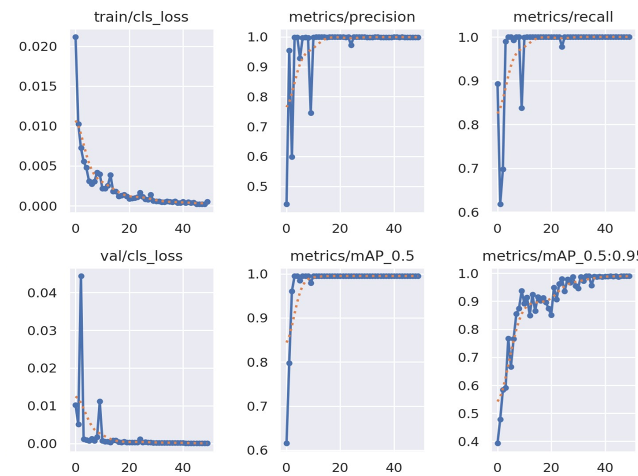

Fig. 19. Curve for training proposed method for Yolov5x with RGB Color System.

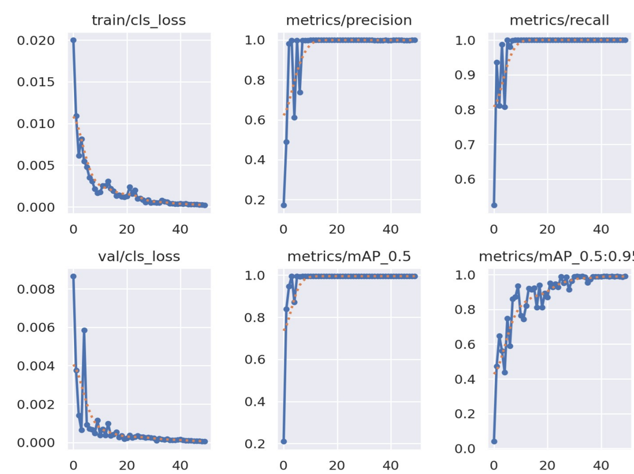

Fig. 20. Curve for training proposed method for Yolov5x with Grayscale Color System.

G. YOLOV5S6

The model showed very good results in terms of speed and accuracy in determining the status of the CPIS machine as

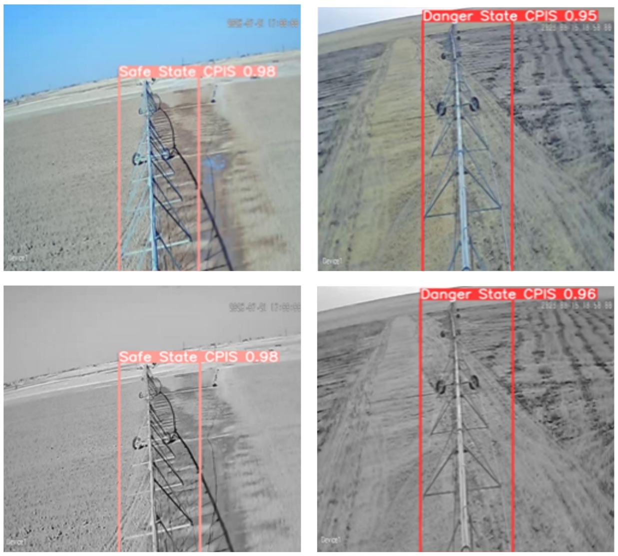

Fig. 21. Results of sample RGB and Gray images with Yolov5x; first row (RGB), second row (Grayscale).

TABLE VII. TRAINING AND TESTING RESULT FOR YOLO5N6.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5n6	0.627	1	RGB	97 %
2	Yolov5n6	0.627	1	Grayscale	97 %

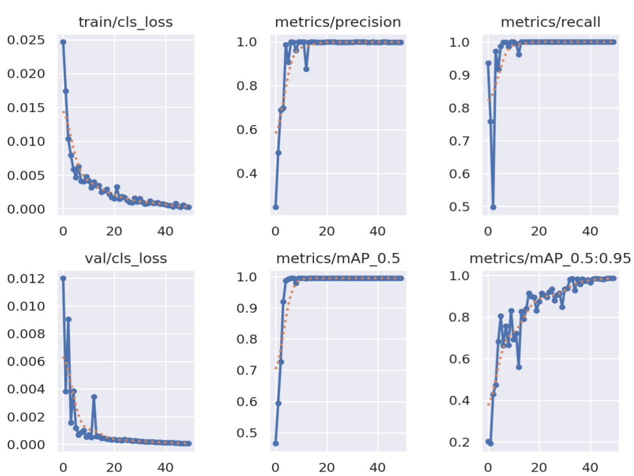

Fig. 22. Curve for training proposed method for Yolov5n6 with RGB Color System.

shown in Figures 25, 26, and 27 and Table VIII. From the table, we note that the F1-Score value in the grayscale color

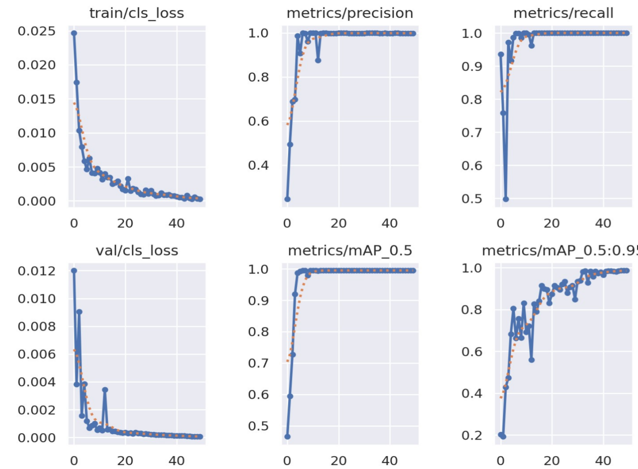

Fig. 23. Curve for training proposed method for Yolov5n6 with Grayscale Color System.

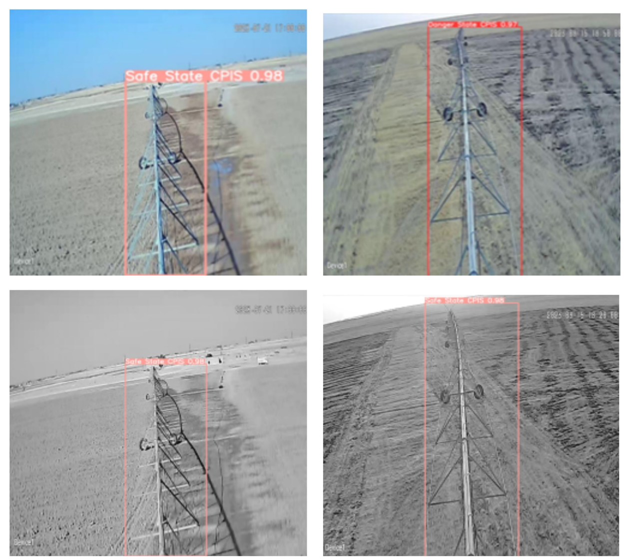

Fig. 24. Results of sample RGB and Gray images with Yolov5n6; first row (RGB), second row (Grayscale).

system was better than the RGB color system, but the RGB color system was better in Precision.

TABLE VIII. TRAINING AND TESTING RESULT FOR YOLO5S6.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5s6	0.82	0.995	RGB	95 %
2	Yolov5s6	0.852	0.961	Grayscale	93 %

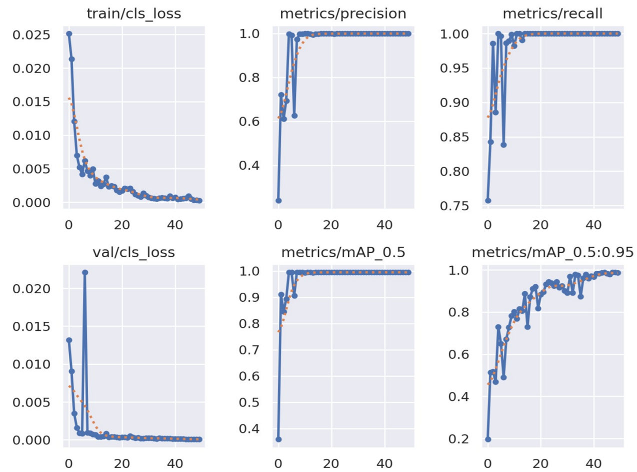

Fig. 25. Curve for training proposed method for Yolov5s6 with RGB Color System.

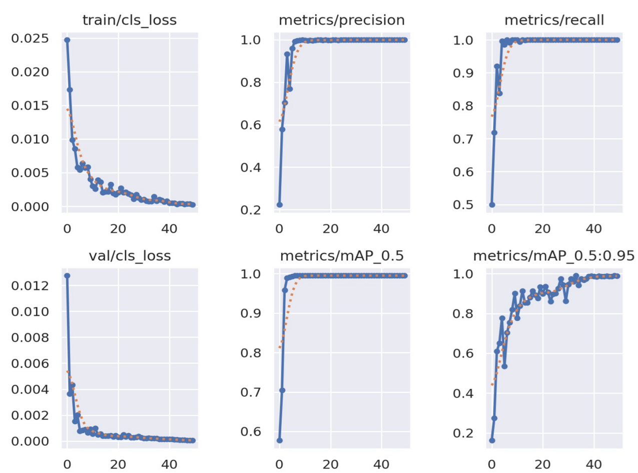

Fig. 26. Curve for training proposed method for Yolov5s6 with Grayscale Color System.

H. Evaluation metrics Phase

These are measurements that are used to assess the effectiveness and performance of the model that is used to validate the results. The process of choosing the best model depends on several main factors, including mAP, F1score, accuracy, and time. Some models were chosen on the basis of three of these factors: mAP, F1score, and time, as in reference [20], and in another reference, the best model was chosen based on the following factors: mAP, F1score, and accuracy [21]. Depending on the reference [21], we will choose the best model according to the previous results of the models that were trained according to the factors mAP, F1score, and accuracy. Recall, commonly referred to as sensitivity, is the first

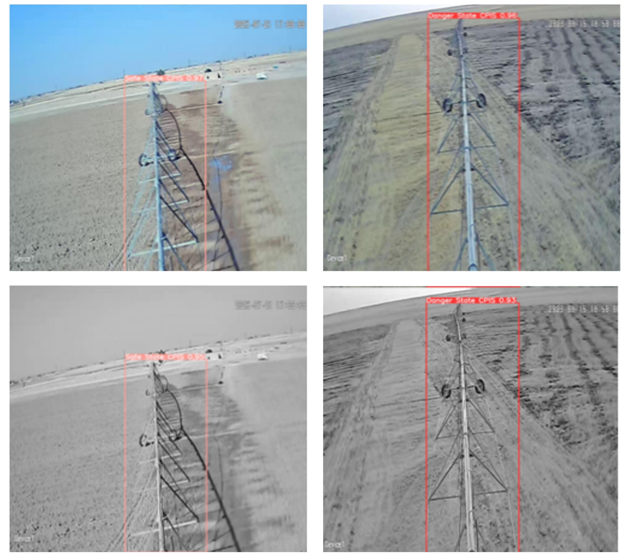

Fig. 27. Results of sample RGB and Gray images with Yolov5s6; first row (RGB), second row (Grayscale).

of these metrics; it measures the amount of true positives. Recall rate is a measure of the probability that an object will be successfully recognized; the higher the recall rate, the fewer false cases there are. It is represented mathematically as:

$$R = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{1}$$

Where TP is True Positives and FN is False Negatives. The mathematical representation of precision can be defined as the proportion of expected positives that turn out to be correct; the smaller the proportion of expected negatives that turn out to be correct, the higher the value:

$$P = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{2}$$

Where FP is False Positives. The F1Score is calculated by averaging recall and precision, as seen below:

$$F1 = 2\frac{PR}{P+R} \tag{3}$$

Whereas mAP is the average of all AP across all classes, AP is the area under the prediction and recall curve. Mathematical representation:

$$\mathrm{mAP} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{AP}i \tag{4}$$

Where n is number of classes.

I. Disscusion

This section discusses the result of the CPIS defect detection using yolov5 models. Practically, the accuracy result of all the developed models ranging from 93 % to 98 % for the color and gray scale images. Basically, using Yolov5n, the evaluation metrics for the RGB images are 97 %, 0.995, and 0.81 for accuracy, mAP, and F1score respectively. While, for the gray scale images are 98 %, 0.995, and 0.866 for accuracy, mAP, and F1score respectively. For the Yolov5s, the evaluation metrics for the RGB images are 94 %, 0.995, and 0.858 for accuracy, mAP, and F1score respectively. While, for the gray scale images are 97 %, 0.995, and 0.714 for accuracy, mAP, and F1score respectively. For the Yolov5m, the evaluation metrics for the RGB images are 97 %, 0.995, and 0.793 for accuracy, mAP, and F1score respectively. While, for the gray scale images are 98 %, 0.995, and 0.804 for accuracy, mAP, and F1score respectively. For the Yolov5l, the evaluation metrics for the RGB images are 93 %, 0.995, and 0.804 for accuracy, mAP, and F1score respectively. While, for the gray scale images are 95 %, 0.995, and 0.778 for accuracy, mAP, and F1score respectively. For the Yolov5x, the evaluation metrics for the RGB images are 95 %, 0.995, and 0.722 for accuracy, mAP, and F1score respectively. While, for the gray scale images are 96 %, 0.995, and 0.712 for accuracy, mAP, and F1score respectively. For the Yolov5n6, the evaluation metrics for the RGB images are 97 %, 0.995, and 0.627 for accuracy, mAP, and F1score respectively. While, for the gray scale images are 97 %, 0.995, and 0.627 for accuracy, mAP, and F1score respectively. For the Yolov5s6, the evaluation metrics for the RGB images are 95 %, 0.995, and 0.82 for accuracy, mAP, and F1score respectively. While, for the gray scale images are 93 %, 0.995, and 0.852 for accuracy, mAP, and F1score respectively. To select the best CPIS Defect detection model, this study, excluded any values for F1score smaller than 0.8 and values for accuracy smaller than 95 %, and since the mAP was 0.995 for all models, the nomination for the best model was based on only two factors namely, the F1score and detection accuracy. According to above, the best model that have been chosen in this study was Yolov5n for grayscale color, where the accuracy was 98 % and the F1score is 0.866, followed by the Yolov5m model with 98 % accuracy and F1score 0.804 for the grayscale system, followed by the Yolov5n model for the RGB color system with 97 % accuracy and F1score 0.812, and finally the Yolov5s6 model for the RGB color system with 95 % accuracy and F1score 0.82.

Based on the above findings, we can conclude that the grayscale model performed better for the YOLOv5n model than the other models in the RGB color scheme in terms of accuracy and F1score. In terms of accuracy and F1score, the RGB color system performed worse than the grayscale model. Also, the single color channel Grayscale color system predicts more quickly than the three-channel RGB color system, which offers high performance speed that benefits real-time systems. The developed CPIS defect detection model has proven its effectiveness in determining the status of center pivot irrigation machine, whether it is in a safe state or in a dangerous state.

TABLE IX. TRAINING AND TESTING RESULT FOR ALL MODELS.

ID	Model	F1-Score @0.50	Precision @0.50	Color	Testing accuracy
1	Yolov5n	0.812	0.975	RGB	97 %
2	Yolov5n	0.866	0.998	Grayscale	98 %
3	Yolov5s	0.858	0.939	RGB	94 %
4	Yolov5s	0.714	0.996	Grayscale	97 %
5	Yolov5m	0.793	1	RGB	97 %
6	Yolov5m	0.804	1	Grayscale	98 %
7	Yolov5l	0.804	0.956	RGB	93 %
8	Yolov5l	0.778	0.97	Grayscale	95 %
9	Yolov5x	0.722	0.987	RGB	95 %
10	Yolov5x	0.712	0.989	Grayscale	96 %
11	Yolov5n6	0.627	1	RGB	97 %
12	Yolov5n6	0.627	1	Grayscale	97 %
13	Yolov5s6	0.82	0.995	RGB	95 %
14	Yolov5s6	0.852	0.961	Grayscale	93 %

IV. CONCLUSIONS

Central pivot irrigation, is considered as one of the most important methods used for smart irrigation in agriculture The Central Pivot Irrigation faces some technical problems, which lead to a defect in their automatic control system, and sometimes lead to damage to some of the main pipes and towers that drive them, which leads to relatively large material losses for farmers and agricultural crops, as the repair process takes long times. Therefore, to solve this problem this study, utilized the YOLOv5 models to detect the defect of the CPIS machine by identifying their status as they are in the safe or dangerous state. In this regard, the dataset that have been used in this study collected from agricultural areas in Salah AL-din Governorate. The result of the CPIS detection model showed that, the highest results for gray scale color system with yolov5n 98 %, and 0.866 for accuracy, and F1score respectively, while, for yolov5m 98 %, and 0.804 for accuracy, and F1score respectively. In the RGB color system the highest results with yolov5n are 97 %, and 0.812 for accuracy, and F1score respectively, while, for Yolov5s6 the result is 95 %, and 0.82 for accuracy, and F1score respectively. From the above result, it can be deduced that the system is able to detect the CPIS in their safe and dangerous state with a high level of detection accuracy, therefore, they can be deployed in a real time system for CPIS defect monitoring and control system.

Conflict of Interest

The authors have declared no conflict of interest.

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