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Detecting Defect in Central Pivot Irrigation System using YOLOv7 Algorithms

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ABSTRACT: Central Pivot Irrigation System (CPIS) is a significant method for intelligent irrigation used in global agriculture. It is used to cultivate important crops like wheat, which contribute to global food security. However, the CPIS encounters technical issues that result in malfunctions in its automatic control system, leading to damage to the primary pipes and towers. This can result in significant material losses for farmers and their crops. Repairing the system is also a time-consuming process. To address this issue, a study was conducted using YOLO algorithm which contains several models, and this study used the Yolov7 models to detect defects in the CPIS machine accurately. The study used a dataset gathered from agricultural areas in Salah al-Din Governorate. The models were used to determine whether the CPIS was in a safe or dangerous state. The RGB color system with Yolov7x achieved a 95% detection rate with an accuracy, F1-score, and precision values of 0.798 and 0.954. Similarly, Yolov7x achieved a 93% detection rate with accuracy, F1-score, and precision values of 0.77 and 0.932 in the Grayscale color system. Based on the outcome, this study can conclude that the yolov7x model with RGB Color System accurately detects the CPIS in both its safe and dangerous states. This makes them useful in real-time systems for CPIS defect monitoring and control.

Keywords: Central pivot irrigation system, CPIS, CNN, Defects detection, Yolov7

1. INTRODUCTION

Smart irrigation is a new method in the use of technology such as sensors, basics, and algorithms in irrigation to control the usage of water in the fields, and gardens. The means of watering can be done correctly right quantity at right time by smart irrigation systems hence encouraging better farming and avoiding wastage of water[1]. This technology though is effective at saving water it is also efficient in increasing crop production and minimizing cases of over or under watering the plants. As more and more people realize the need for food production all over the globe and as water becomes a scarce resource in most parts of the world, smart irrigation is the answer to lack of water and productivity in agriculture[2]. Depending on the mechanism of irrigation, smart irrigation systems have the following main classifications. There are various types of irrigation like Central pivot Irrigation, Sprinkler irrigation, and Drip water irrigation. In central pivot irrigation, there is a long tube that is hoisted and supported lightly from a number of sprinklers to irrigate crops[3]. The center tube moves around or in circles. Ways of irrigation also vary and two of the most common methods include drip irrigation, and sprinkler irrigation in which a long tube is fitted on the surface of the soil with sprinklers on the outer side. It is fixed and cannot be moved from one place to the other as the case is with the mobile perennial systems. The last method of drip water irrigation involves the use of a long pipe with a small diameter with emitters fixed on it. The emitters dispense water on the ground close to the root zones of crops[4].

Central pivot irrigation is one of the modern techniques and efficient methods of supplying crops with water. They entail pipes and sprinklers that rotate 360 degrees that ensure that the water to the crops is controlled and evenly distributed over the field [5]. This technique is commonly used in agriculture most especially in the driest regions of the world. The following are the advantages of central pivot irrigation. It enables the farmer to well regulate water application whereby water wastage is limited, and the crops receive their expected amounts of moisture [6]. It also reduces the rates of soil erosion and nutrient run off hence resulting to healthier soil and enhanced yields. Besides, central pivot irrigation

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technique is also easily made automatic hence reduces on time and labor for farmers. But it is also pertinent to look at the drawbacks of central pivot irrigation[7]. The equipment and surface setting up costs a lot of cash in the beginning, and the expenses such as maintenance, energy usage add up in the long run. Also, the pattern of circles for the irrigated fields will be incompatible with certain crops or the land gradient[8].

The Central Pivot Irrigation system is facing technical issues due to weather conditions, such as high humidity in winter and dust storms in summer. These conditions cause dust particles to enter the controllers, resulting in the formation of carbon on the energy sources. This leads to improper functioning of the controllers and defects in their automatic control system. Sometimes, it even damages the main pipes and towers that drive the controllers, as following Figure 1, resulting in significant material losses for farmers and crops. The repair process takes one day or more, which is crucial for farmers.

FIGURE 1. - Central Pivot Irrigation with damage

2. Deep Learning

Deep learning is a subset of machine learning, and focuses on using artificial neural networks to model systems[9]. It is a tool that has achieved great results, more or less, in almost all areas and has drastically altered many fields in the past few years ranging from computer vision, natural language processing and speech recognition [10]. The following is a key characteristic of deep learning: In this method, many layers of connected neurons are able to learn representations on their own. These neural networks imitate the human brain where each neuron feeds the result of their calculation to the next neuron above in a process that only involves simple arithmetic[11]. Having multiple layers of neurons enable deep learning models to analyze data and find the relationships between the sets of data so that to give precise estimations and evaluations[12]. Basically, while deep learning has brought joy with several successes the area is still faced with a number of challenges[13]. In particular, one of the main problems of deep learning is data requirements for training: the need for significant amounts of labeled data, which often can be rather time-consuming and expensive, especially when it is concentrated in rather narrow thin expert sectors[14]. Furthermore, deep learning models are often the black-box models which are hard to understand and explain how the model came about the decision[15]. Deep learning is an effective and universal technology that has dominated a lot of domains such as computer vision, natural language processing, voice recognition and so on[16]. The ability to learn and represent the data automatically through neural networks has given a big boost to the AI system and new advancements are possible because of it, and things that were otherwise impossible are becoming an reality now[17]. However, deep learning still has some challenges that limit its development; however, its ability to create change and propel innovation cannot be questioned; deep learning will remain a key player in the definition of the years to come[18].

3. Convolutional Neural Networks (CNN)

CNN technology referred to as convolutional neural networks is a sub discipline of artificial intelligence that was comparatively presented a few years back but has since stormed the field[19]. This superior advancement has been widely used in various fields; as those of image recognition, speech recognition[20]. CNNs have demonstrated their absolute efficiency in dealing with multiple input data while generating accurate predictions, which is why they are beneficial for AI engineers[21]. The CNN technology also has some advantages where on its own, it can extract the features from the raw data. It does it through convolution in which the network scans through the input data to extract interesting patterns and features. Complex convolutional features occurring in the object can be obtained by merging the results of more complex tasks learned with the help of several layers of various convolutions; this makes CNNs truly capable of recognizing objects, faces, and other similar items[21]. CNN technology has been very ideal especially when it comes to image recognition and it has been applied often with a lot of success. That is, it is possible to train the net on the preparation of the photograph's introduction and their division into recognizing classes of objects. Which has relatively many uses; for instance in a self-driving car: an object recognition technique is used to detect traffic signs and people or in the medical field to detect and locate cancers and tumors, in the agricultural sector, for instance, to detect pests in crops and plants among others [22]. CNN technology has had a significant impact on the field of artificial intelligence. It has enabled researchers and developers to create advanced models that can learn from data and make accurate predictions[23]. CNNs are proven to be safer and highly efficient structures for creating solutions to such challenging issues as picture identification and language translation. Subsequently, one can predict that the additional improvement of the technology a priori would enrich the AI with the assistance of CNN technologies[24].

4. 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.

4.1 PHASE 1: DATA COLLECTION AND PREPROCESSING

This phase involved the collection of CPIS images from agricultural areas in Salah AL-din. This was done by installing a vision system consisting 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.

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 of center pivot irrigation, as shown in the picture below in Figure 2 and Figure 3 .

FIGURE 2. - **Setting up a data collection system**

FIGURE 3. - **Setting up a Monitoring system**

During the preprocessing stage, the CPIS was examined in both good and poor conditions, and a total of 1400 images were collected for each condition. The goal was to ensure that there was no bias during the training phase of the defect detection model, which is why 700 images were taken for each condition. A sample of the collected images is provided in Figure 4.

Safe State UnSafe State

FIGURE 4. - Sample images from the collected dataset

4.2 PHASE 2: TRAINING AND TESTING

The dataset containing 1400 images was divided into three sets as illustrated in Figure 5. The first set, comprising 980 images, was used for training the model. The second set, containing 280 images, was used for validation, and the third set, with 140 images, was used for testing. The Yolo7 models, were used. These models are characterized by their fast performance, and high accuracy. The figures below depict the models architecture that was utilized to train the data., as shown in Figure 6. During the training process, the batch size was set to 16, and 50 epochs were used.

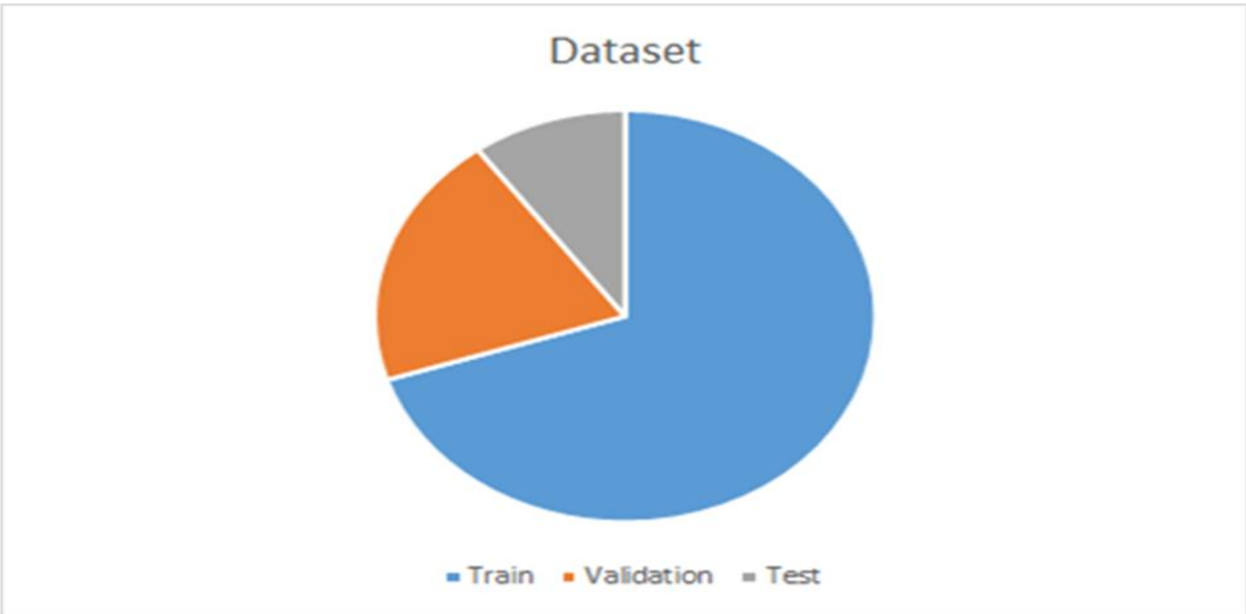

FIGURE 5. - The splitting of the dataset

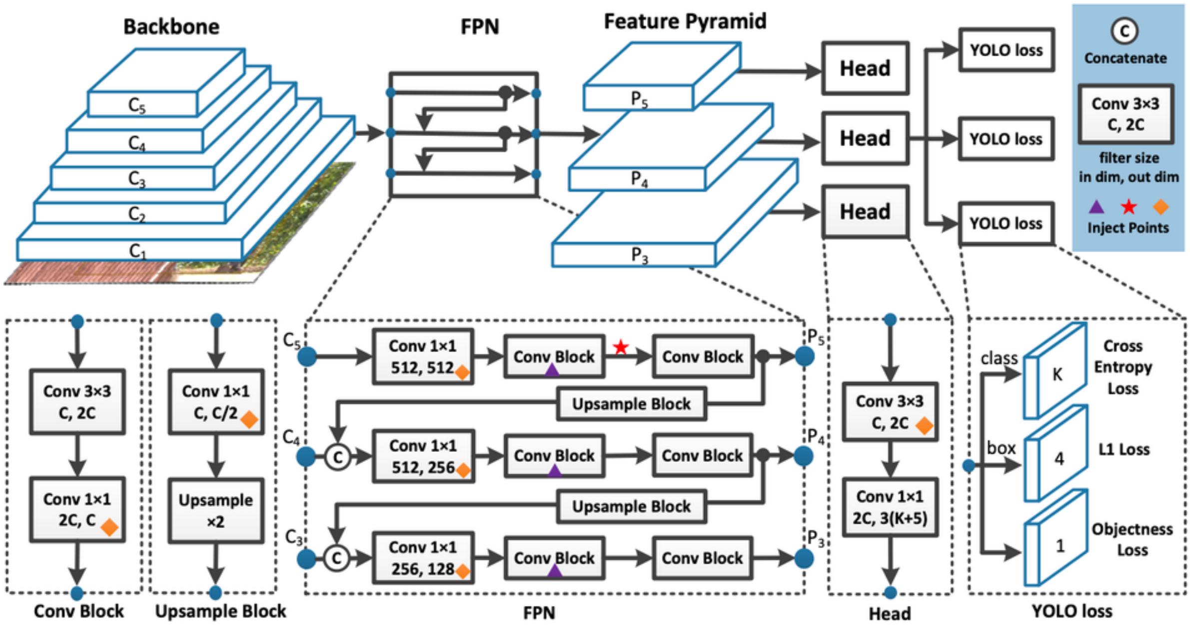

FIGURE 6. - Yolov7 architecture[25]

4.3 PHASE 2: Evaluation metrics

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[26], and in another reference, the best model was chosen based on the following factors: mAP, F1score, and accuracy[27]. Depending on the reference[26], this study 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 of these metrics; it measures the number 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 [28].

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

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 [29].

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

Where FP is False Positives.

The F1-Score is calculated by averaging recall and precision, as seen below[30].

$$F-1 = 2 * \frac{\text{P*R}}{P+R} \tag{3}$$

Whereas mAP is the average of all AP across all classes, AP is the area under the prediction and recall curve. Mathematical representation [31].

$$mAP = \frac{1}{n}\sum_{i=1}^{n}\text{APi} \tag{4}$$

Where n is number of classes.

5. RESULT OF DEFECT DETECTION

The outcomes of the training and testing stages for CPIS defect detection using YOLOv7 models are presented in this section. Two scenarios were considered: the first one involved YOLOv7 models with an RGB color system, while the second one utilized YOLOv7 models with a grayscale color system. The detailed descriptions of the results of these models can be found in the subsequent subsections.

5.1 PHASE 1: SCENARIO ONE (YOLOV7 WITH RGB IMAGE)

Table 1.- Yolov7 result with RGB color system

Models	Evaluation metrics					
	F1-score	mAP 0.5	Recall	Precision	Testing Accuracy	Color System
YOLO V 7	0.91	0.995	0.77	0.937	92%	RGB
YOLO V 7 E6	0.36	0.995	0.178	0.662	85%	RGB
YOLO V 7 W6	0.564	0.995	0.09	0.69	85%	RGB
YOLO V 7 X	0.798	0.995	0.57	0.954	95%	RGB

In these tests, the models were trained with 50 epochs, and the subsequent testing shows the outcomes with boxing annotation around the CPIS. From the Table 2, we observe that the highest F1-score value was for the model Yolov7, Yolov7x, and Yolov7w6 respectively 0.91, 0.798,0.564, while for Precision that the highest value was for model Yolov7x, Yolov7, and Yolov7w6 respectively 0.954, 0.937, 0.69, while for Accuracy that the highest value was for model Yolov7x, Yolov7, Yolov7e6, and Yolov7w6 respectively 95%, 92%, 85%, 85%. From these results, we can analyze and reach the best model by considering the best Accuracy, F1-score, and Precision, we can determine that the best model was Yolov7x in this experiment as the following Figure 7 and Figure 8.

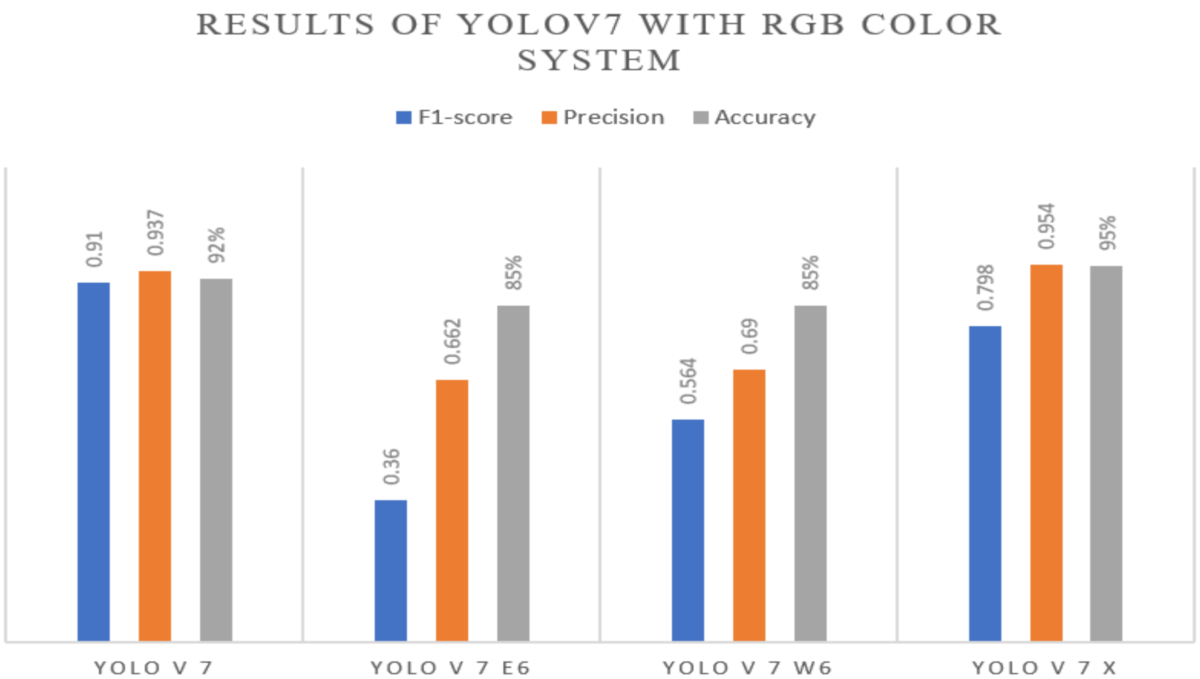

FIGURE 7.- Statistic Images for Yolov7 with RGB color system

Safe State Danger State

RGB

FIGURE 8. - Result of Testing Yolov7x with RGB Color System

5.2 Scenario Two (Yolov7 with grayscale Image)

Table 2. - Yolov7 result with RGB color system

Models	Evaluation metrics					
	F1-score	**mAP 0.5**	**Recall**	**Precision**	**Testing Accuracy**	**Color System**
YOLO V 7	0.718	0.995	0.39	0.887	88%	Grayscale
YOLO V 7 E6	0.731	0.995	0.35	0.758	85%	Grayscale
YOLO V 7 W6	0.07 at 0.012	0.168	0	0.016	15%	Grayscale
YOLO V 7 X	0.77	0.995	0.5	0.932	93%	Grayscale

In these tests, the models were trained with 50 epochs, and the subsequent testing shows the outcomes with boxing annotation around the CPIS. From the Table 3, we observe that the highest F1-score value was for the model Yolov7x, Yolov7e6, and Yolov7 respectively 0.77, 0.731,0.718, while for Precision that the highest value was for model Yolov7x, Yolov7, and Yolov7e6 respectively 0.932, 0.887, 0.758, while for Accuracy that the highest value was for model Yolov7x, Yolov7, Yolov7e6, and Yolov7w6 respectively 93%, 88%, 85%. From these results, we can analyze and reach the best model by considering the best Accuracy, F1-score, and Precision, we can determine that the best model was Yolov7x in this experiment as the following Figure 9 and Figure 10.

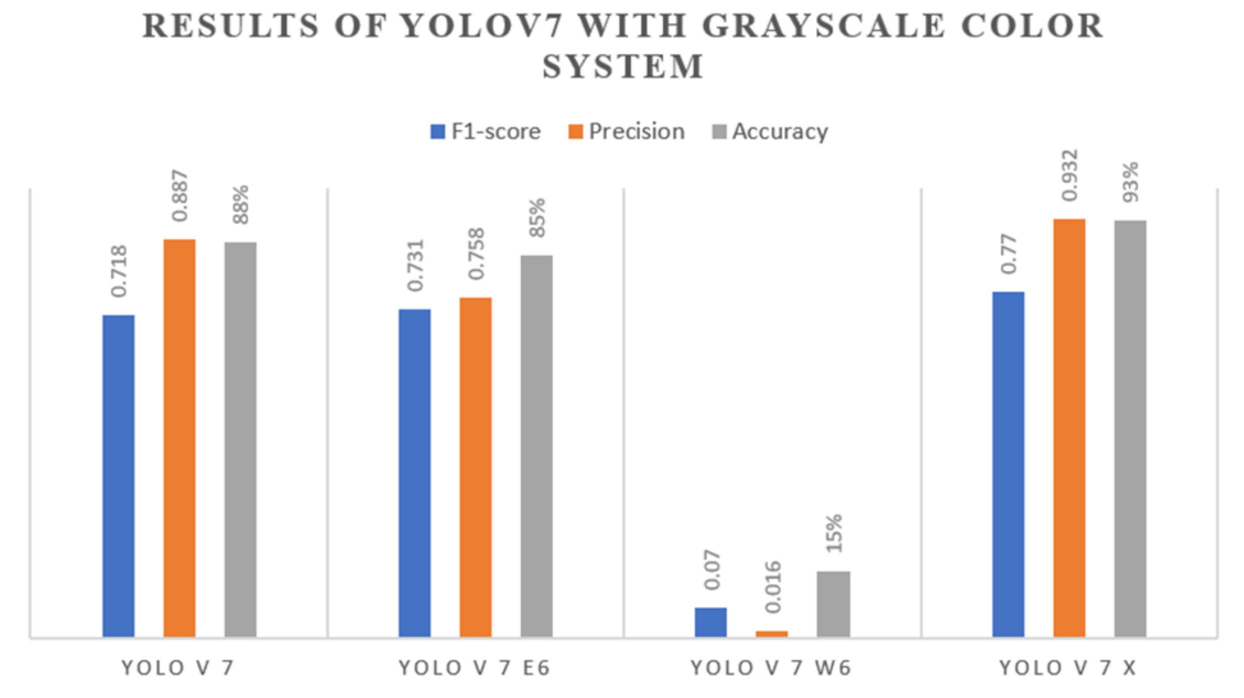

FIGURE 9. - **Statistic Images for Yolov7 with grayscale color system**

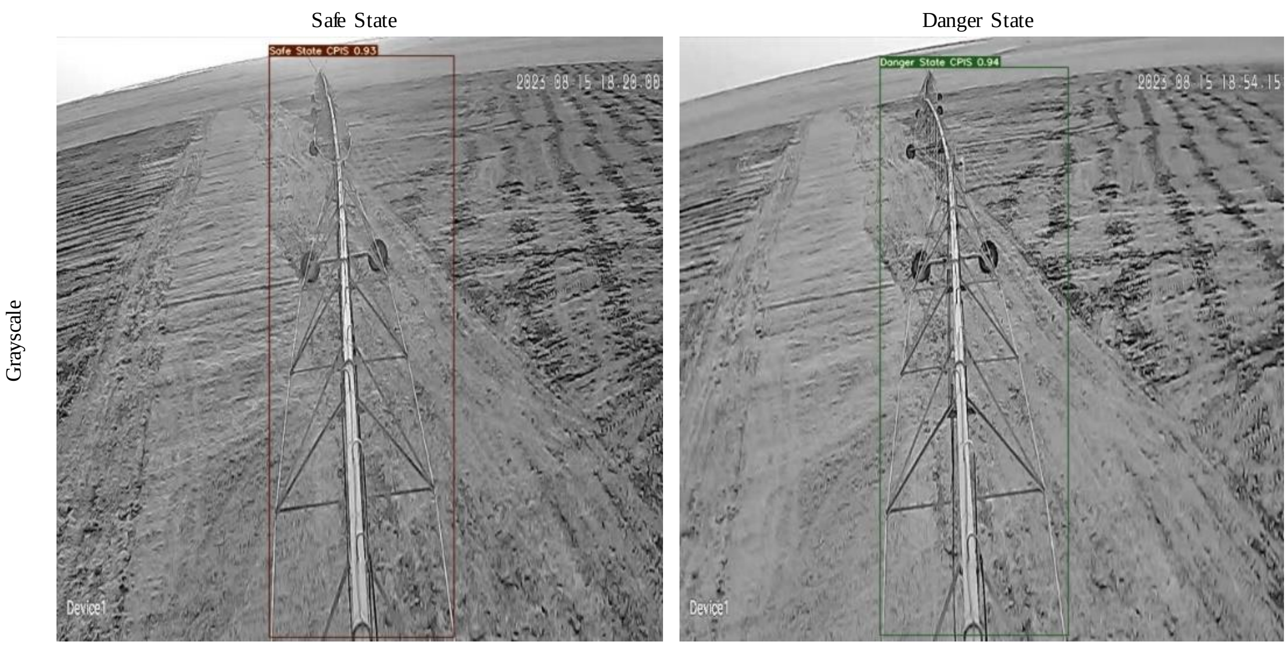

FIGURE 10. - **Result of Testing Yolov7x with Grayscale color system**

6. Results and Discussion

Table 3. - **Yolov7 result with RGB color system**

ID scenario	Best Models Result					
	Models	**F1-score**	**Recall**	**Precision**	**Testing Accuracy**	**Color System**
One	Yolov7x	0.798	0.57	0.954	95%	RGB
two	Yolov7x	0.77	0.5	0.932	93%	Grayscale

Based on the Table 3, it is evident that the yolov7x model performed best in the first and second scenarios. In the first scenario, it provided an accuracy of 95% and a precision value of 0.954 using the RGB color system. Similarly, the model exhibited the highest accuracy of 93% and a precision value of 0.932 in grayscale for the second scenario. Therefore, yolov7x was chosen as the best model for both scenarios. Comparing the performance of the best model in both scenarios, the values achieved in the first scenario were higher than those in the second scenario. The Figure 11 also supports this conclusion. Therefore, yolov7x with the RGB system and the dataset for CPIS is considered as the best model in terms of accuracy and precision.

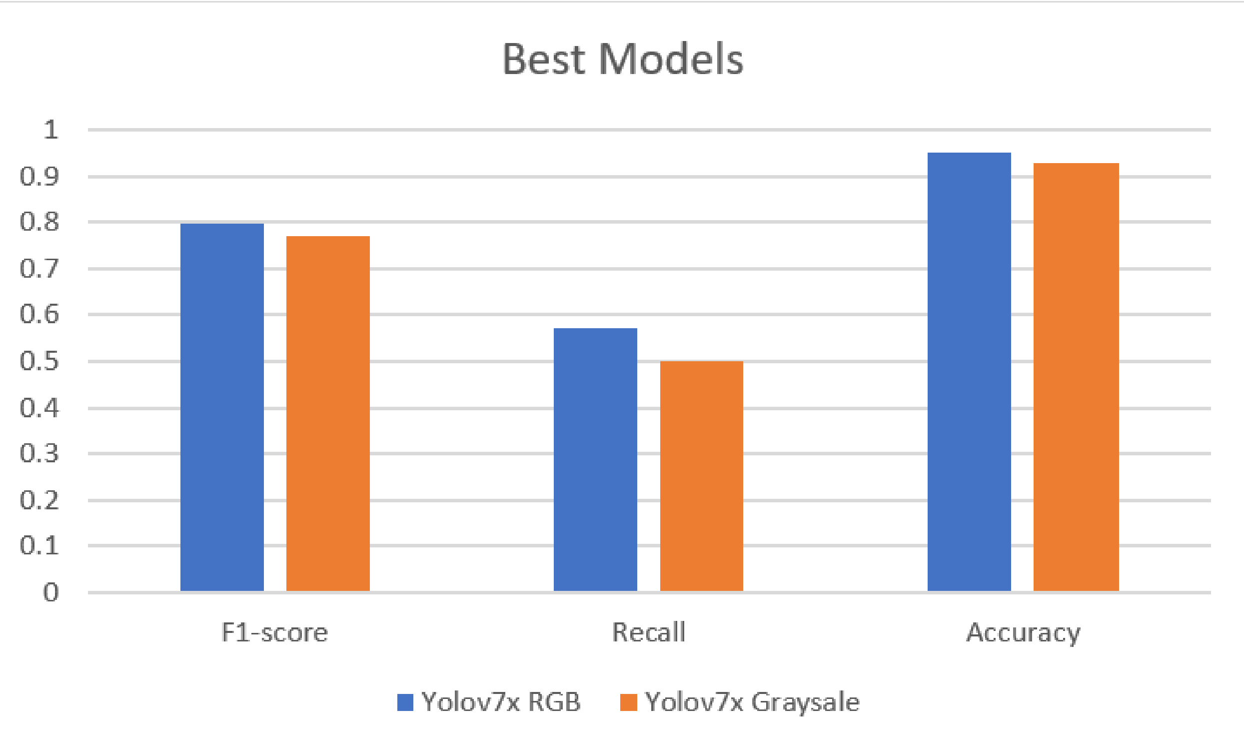

FIGURE 11. - Best models for two scenarios

7. FUTURE WORK

The primary objective of implementing a monitoring system for central pivot irrigation is to mitigate potential material damage resulting from the movement of the irrigation system and to proactively prevent the occurrence of cracks in the main pipelines. In the near future, we aim to build an integrated system to enable remote control and monitoring of the irrigation system, facilitating the transmission of real-time data on humidity and temperature conditions for the crops. This comprehensive approach equips farmers with detailed information essential for maximizing crop productivity and streamlining their agricultural operations.

8. CONCLUSIONS

Central pivot irrigation is considered one of the most important methods used for smart irrigation in agriculture 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 YOLOv7 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 has been used in this study was collected from agricultural areas in Salah AL-din Governorate. The result of the CPIS detection model showed that the highest results for the RGB color system with yolov7x were 95%, 0.798, and 0.954 for accuracy, F1score, and precision respectively, while, yolov7x for the Grayscale color system showed results 93%, 0.77, and 0.932 for accuracy, F1score, and precision respectively. From the above result, it can be deduced that the system can 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.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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