Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766169

POWER LINES AND LANE DETECTION USING DEEP LEARNING BASED YOLO V5 ALGORITHM FOR SMART AGRICULTURE

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Abstract: In this manuscript, the real-time detection of power lines and lanes in agricultural fields is discussed. This proposed method will make a significant improvement in smart agriculture. Real-time scene parsing through object identification in embedded systems is extremely challenging due to processing resource constraints the accuracy is less. The detection is performed using the YOLO v5 (You Only Look Once) algorithm based on deep learning. The YOLO v5 algorithm and the deep neural network algorithm are trained by feeding image datasets of power lines and different types of lanes in agricultural fields. Transmission lines and lanes are detected in real-time using a system consisting of a Raspberry Pi 3, a Pi camera, and a single-channel relay that connects to a DC motor. The proposed deep learning approach for power line and lane detection can increase the accuracy to 99.3% and improve the robustness of the system compared to traditional methods.
Keywords: YOLO v5, Deep neural network, Object identification, Smart agriculture, Raspberry Pi.

1.INTRODUCTION:

Information and communication technologies (ICT) must revolutionize agriculture in order to satisfy the growing demand for food from the growing population. In order to produce food in a sustainable and healthy manner, smart agriculture employs the most advanced ICT techniques (**Garg et al.,** 2020). Precision agriculture is a methodical, scientific approach to farming with the goal of increasing yield in both quantity and quality, while assuring profitability, sustainability, and environmental preservation through the efficient use of resources (**Mohapatra et al.,** 2022). The Internet of Things (IoT), remote sensing, and unmanned aerial vehicles (UAV) (**Garg et al.,** 2019) are examples of ICT technologies that can be used to successfully use sensors for a variety of smart agriculture applications. UAVs are used in smart agriculture due to their ability to fly in a variety of weather conditions and can take high-resolution pictures at a range of altitudes (typically 50 to 100 meters) (**Pham et al.,** 2020,**Jubair et al.,** 2018 **and Jannoura et al.,** 2015)

Deep learning has advanced significantly in computer vision over the past few years (Jothy et al., **2022**, Logisvary et al., **2022 and** Zhang et al., 2016). The convolutional neural network (CNN) has advanced object classification and object recognition due to the large datasets in numerous areas and high-performance computing hardware like GPU (Deng et al., **2009** and Lin et al., **2014**). In numerous areas of industrial examination, neural networks have proven their effectiveness and adaptability (Zhu et al., **2019**,Liao et al., **2018** and Zhu et al., **2020**).

However, only a few studies have been done using CNN in detecting foreign objects to monitor transmission lines due to the uniqueness of the application situation (Sampedro et al., **2014**). Applying the generic CNN to find foreign items near transmission lines presents some challenges (Zhang et al., **2019**). Because the majority of the collected datasets do not contain foreign objects, the CNN model cannot be trained with features that are helpful to it. This detection is more challenging and tough because there are insufficient image samples (Nguyen et al., **2018**). A significant challenge still exists in how to rapidly generalize a CNN-based model to carry out the task of foreign body detection from small datasets(Zhu et al., **2020**).

Son, Kim et al 2022., proposed the detection of power lines with bounding boxes and tiny-YOLOv3 model was served as the training model. The limitation of this technology is that the proposed algorithm can incorrectly detect ridges as power lines. Hui Li et al.,2022 proposed the inspection of detecting the transmission line based on YOLO v3. The limitation of this technology is that the improved YOLO v3 has low FPS (Frames Per Second) compared with YOLO v5 technology. Hasan et al.,2020 proposed agricultural drone can spray pesticides over the crops' field of any desired trajectory programmed from the GCS(Ground Control Station). Since it is an autonomous drone, any obstacle in its path has not been considered which may lead to damage of drone. Zhu et al.,2020 proposed *DFB-NN* (Deep-Learning Feedforward-Backpropagation Neural Network) to detect invading foreign objects for inspecting power transmission lines. However the model still has a small number of detection errors. Nguyen et al., 2018 proposed a systematic algorithm that integrates a fully convolutional network (FCN) for lane detection and a probabilistic graphical model for lane tracking. But it is not real-time and cannot be used for embedded system. This manuscript proposes detecting power lines and lanes in agricultural fields using a deep learning-based YOLO v5 algorithm. The YOLO v5 algorithm has fast speed and high accuracy.

The rest of the paper is organized as follows. Section 2 presents a detailed overview on the power lines and lane detection using deep learning based YOLO v5 algorithm. Section 3 discusses a detailed experimental analysis of the proposed manuscript. Section 4 concludes the paper.

2. POWER LINE AND LANE DETECTION

To achieve better accuracy, the YOLO v5-based method is proposed to detect power lines and agricultural lanes. YOLO is a well-known object identification algorithm with multiple iterations.

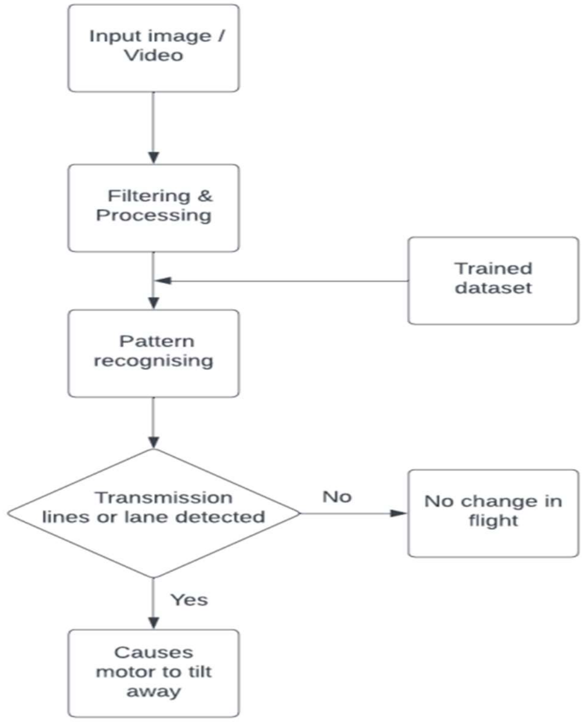


Fig.1 Block diagram of proposed method

The training data is fed into the system and trained using YOLO v5. Deep learning for power line and agricultural lane detection is a system that loads an image, preprocesses, filters and scales the image to find the power lines and agricultural lanes. Fig.1 shows the flow of the proposed method.

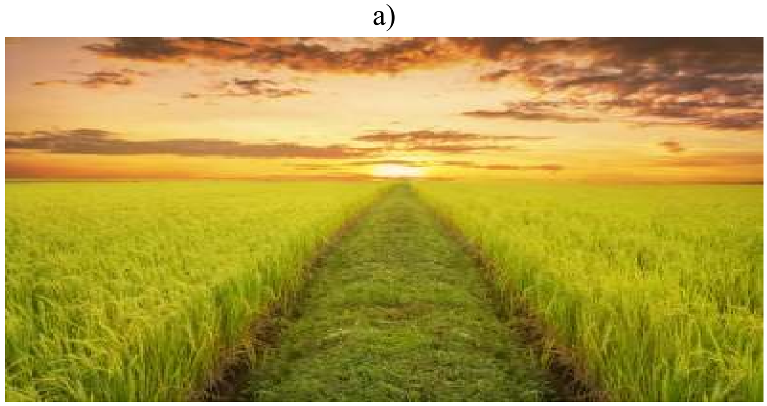
DATA ACQUISITION

With the exception of rainy days, pesticides are usually sprayed on sunny or cloudy days. Therefore, images of power lines are taken on sunny or cloudy days, as shown in Fig. 2. Also, images of different types of lanes in agricultural fields are taken to train the model.

Fig.2 Images of power lines

Datasets were obtained from a website called Kaggle. The sample dataset for agricultural lanes are shown in Fig.3.

a)



b)

c)

Fig.3 Images of lanes in agricultural fields: (a) water passage in field (b) lane covered in green grass (c) a dry passage

FILTERING AND PROCESSING

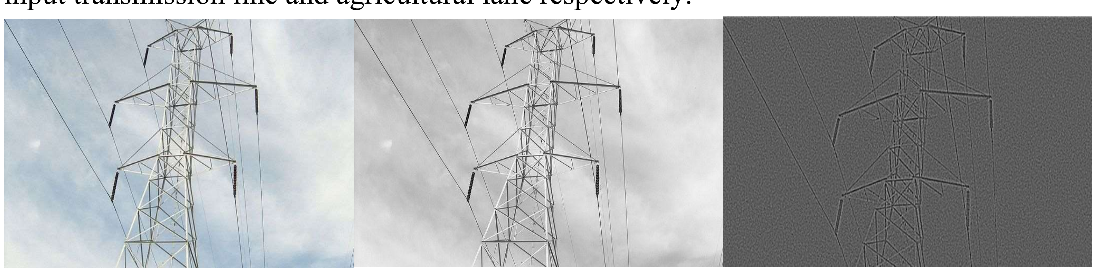
The process of filtering and processing is used to extract and magnify image features for better object recognition.

a) Laplacian of Gaussian (LoG) operation

In order to locate regions of rapid change (edges) in images, laplacian filters are used. Since derivative filters are noise-sensitive, it is typical to first apply a Gaussian filter to the image before using the Laplacian filter. This process is performed according to the formula (1)

$$LoG(x,y) = -\frac{1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

The process of Laplacian of Gaussian operation is performed by inputting an RGB image (red-blue-green). The input image is converted to a grayscale image for further processing. The LoG operation is performed on the grayscale image to make the edges of the original image sharper and more contrasty. Figs. 4 and 5 show the process of Laplacian of Gaussian operation for the input transmission line and agricultural lane respectively.



(a) (b) (c)

Fig.4 (a) Input Transmission line image (b) Gray scale conversion image (c) edge detected image

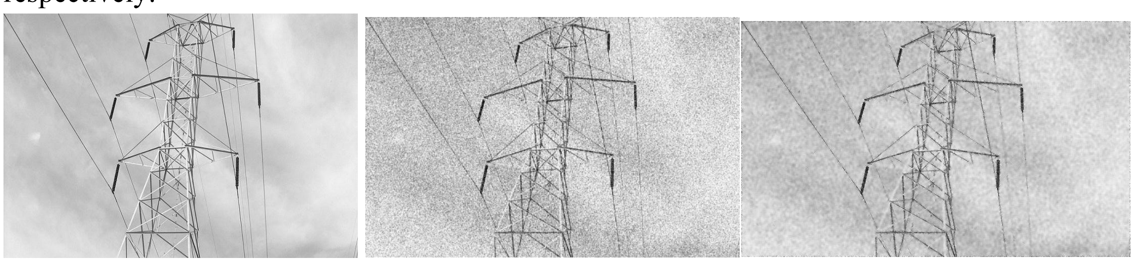
(a) (b) (c)

Fig.5 (a) Input agricultural lane image (b) Gray scale conversion image (c) edge detected image

b) Weinner filtering

Inverse filtering or generalized inverse filtering, a recovery method for deconvolution, can be used to restore blurred images. Weinner filtering is extremely susceptible to additive noise, though. Wiener filtering performs an optimal tradeoff between inverse filtering and noise smoothing. Thus, it removes additive noise and inverts the blurring simultaneously.

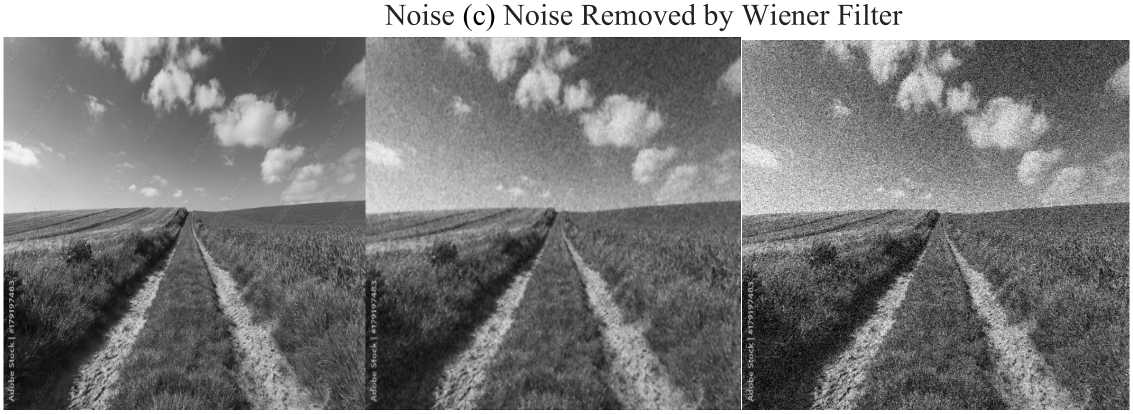
The input image is converted to a grayscale image for processing. Weinner filtering is performed on the grayscale image to which Gaussian noise has been added. Figs. 6 and 7 show the process of Weinner filtering for the input transmission line and agricultural lane respectively.



(a) (b)

(c)

Fig.6 (a) Transmission line Gray scale image (b) Image with Added Gaussian Noise (c) Noise Removed by Wiener Filter



(a) (b) (c)

Fig.7 (a) Agricultural lane gray scale image (b) Image with Added Gaussian Noise (c) Noise Removed by Wiener Filter

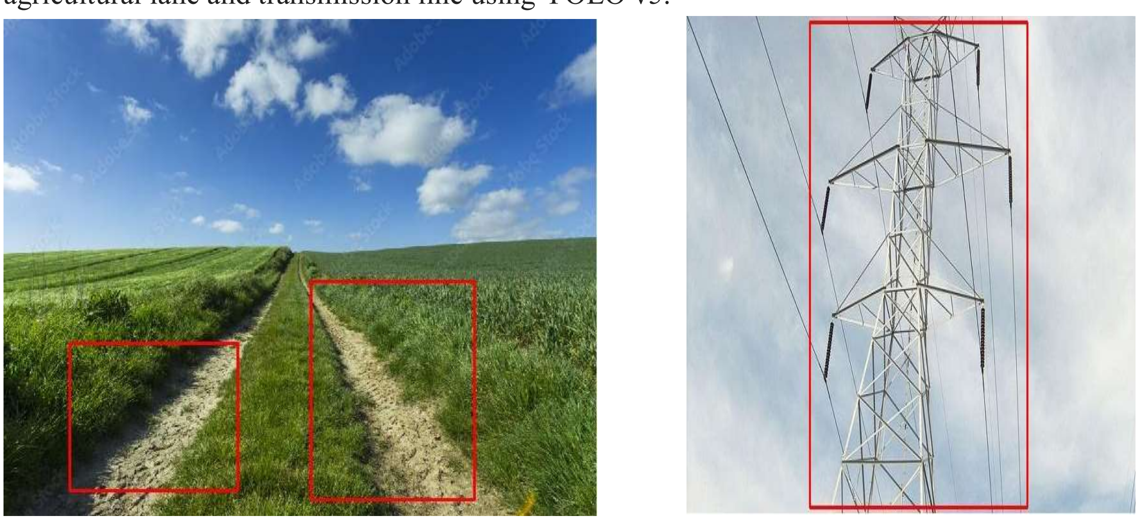
YOLO v5 MODEL

YOLO v5 has the improved performance in precision, recall, and average precision compared to Faster R-CNN (Regions with CNN features), YOLO v3, and YOLO v4. In 2020, the fifth iteration of YOLO was made available. YOLO v5 models are composed of 3 components, which consist of CSP-Darknet53 (Cross Stage Partial Network) as the backbone, SPP (Spatial Pyramid Pooling) and PANet (Path Aggregation Network) as the model neck and the head. YOLO v5 uses the same head as YOLO v3 and YOLO v4. The backbone is a convolutional neural network created by combining image characteristics in different sizes. Neck is a collection of layers that mix and combine image features to deliver before the prediction. Head takes data from Neck (PANet) and performs box and class prediction stages.

Table 1 Hardware specifications for the power line and lane detection system

HARDWARE SPECIFICATION	
Memory Card	64 Gigabyte
Program IDE	Python
Pi-Camera	3280x2464 Pixel
Raspberry Pi	Version 3

Real-time detection of transmission lines and lanes is accomplished with a system consisting of a Raspberry Pi 3, a Pi camera, and a single-channel relay connected to a DC motor that acts as a drone engine. The Raspberry Pi 3 has a quad-core 64-bit Broadcom BCM2837 ARM Cortex-A53 SoC processor running at 1.2 GHz. The specification of the proposed model is given in Table 1. The single-channel relay is used here to convert the 5 V power supply from the Raspberry Pi to a 12 V supply to run the DC motor. In the Raspberry Pi, YOLO v5 is employed using the python ide. Thus, when the Pi camera detects a power line or lane, the system causes the drone motor to slow down and tilt away. Fig. 8 shows the detection of the agricultural lane and transmission line using YOLO v5.



(a) (b)

Fig.8 Detection of (a) agricultural lane (b) transmission line using YOLO v5

3. EXPERIMENTAL RESULTS AND DISCUSSION

The YOLO v5 algorithm is used to detect power lines and lanes in agricultural fields. The datasets used to train the YOLO v5 model consist of 1200 images of power lines and 950 images of different types of lanes in agricultural fields.

In this paper, the performance of the YOLO v5 model is evaluated based on Precision (2) and Recall (3).

Precision:

$$\text{Precision} = \alpha / (\alpha + \beta) \tag{2}$$

Recall:

$$\text{Recall} = \alpha / (\alpha + \gamma) \tag{3}$$

Where,

α = True Positive

β = False Positive

γ= False Negative

Precision refers to the percentage of all recognition results that are correctly recognized. The recall is used to indicate how well a positive prediction is made given a positive input. Simply put, it means how well the model recognizes it. α (True Positive) is a number that was recognized for an object. β (False Positive) means that the object is recognized as an object of a different class. In other words, it is a false detection. γ (False Negative) means that an object that should have been detected was not detected. Table 2 shows the calculation of precision and recall value for different datasets of agricultural lanes.

Table 2 Recall and precision calculation for Lane

	100 DATASET SAMPLE	**200 DATASET SAMPLE**	**300 DATASET SAMPLE**	**400 DATASET SAMPLE**	**500 DATASET SAMPLE**
TRUE POSITIVE(α)	60	130	230	350	430
FALSE POSITIVE(β)	20	30	20	20	20
TRUE NEGATIVE	0	0	10	10	10
FALSE NEGATIVE(γ)	20	40	30	40	20
RECALL	0.778	0.764	0.884	0.897	0.956
PRECISION	0.778	0.813	0.920	0.945	0.956

Fig.9 shows the graphical representation of the calculated precision and recall values of agricultural lane detection. It also compares the performance of various methods. The YOLO v5 method has the highest precision vs recall value of 0.956 for 500 sample datasets compared to RCNN and YOLO v3 methods.

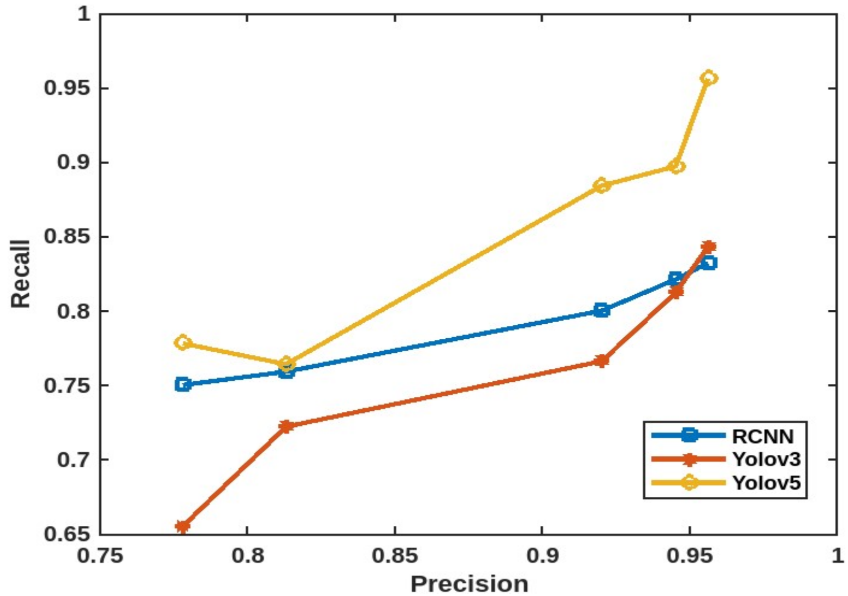


Fig.9 Precision vs Recall graph for Lane

Table 3 shows the calculation of precision and recall value for different sets of transmission line datasets. Fig.10 shows the graphical representation of the calculated precision and recall values of transmission line detection. The YOLO v5 method has the highest precision vs recall value of 0.978 and 0.957 respectively for 500 sample datasets compared to RCNN and YOLO v3 methods.

Table 3 Recall and precision calculation for Transmission Line

	100 DATASET SAMPLE	200 DATASET SAMPLE	300 DATASET SAMPLE	400 DATASET SAMPLE	500 DATASET SAMPLE
TRUE POSITIVE(α)	70	150	240	330	450
FALSE POSITIVE(β)	10	20	20	20	10
TRUE NEGATIVE	0	0	10	10	20
FALSE NEGATIVE(γ)	20	30	30	40	20
RECALL	0.778	0.833	0.889	0.892	0.957
PRECISION	0.875	0.882	0.923	0.943	0.978

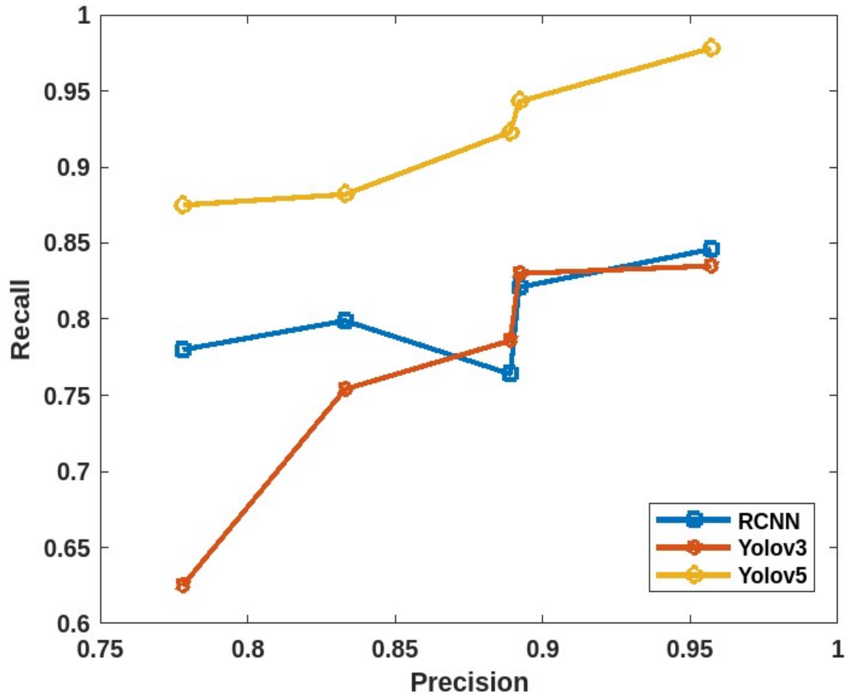


Fig.10 Precision vs Recall graph for Transmission line

The accuracy based on epochs for the trained datasets is shown in the below graph Fig.11. The graphical representation shows the accuracy based on the training and testing datasets.

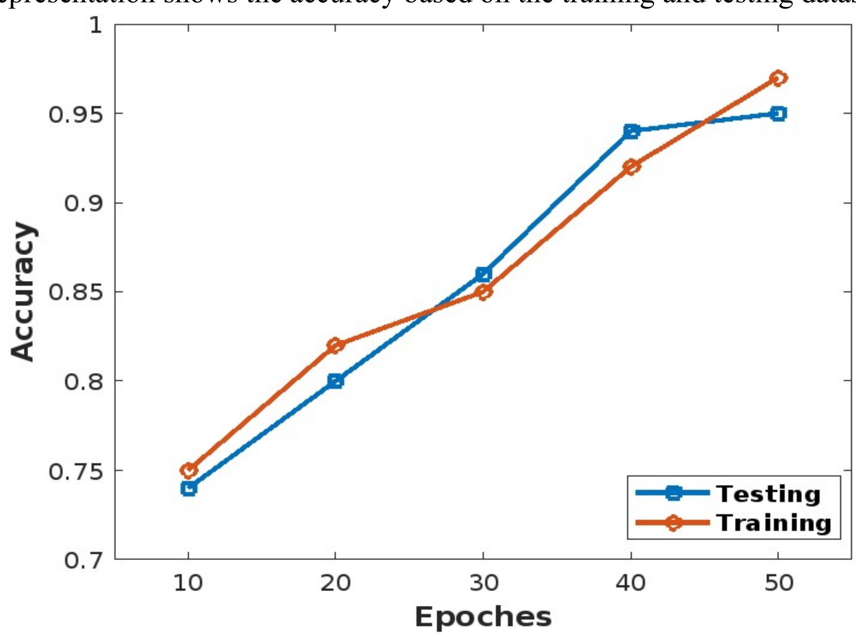


Fig 11. Comparison graph of accuracy and epochs

The performance of previous works and proposed work are discussed in a tabulation manner which is shown in Table 4. In the previous study, the accuracy of power line detection was 94%, and the method proposed in this paper showed that the accuracy of power line detection was 99.3%. In the previous study, the processing time was between 0.15 seconds. This paper obtained a processing time of 0.5 seconds. This shows an above-average result than previous studies.

Table 4 Performance and detection techniques comparison with related work

Author Name	Detection technique	Processing time	Accuracy
X. Luo et al., (2014)	Joint linear- time line segment detector	2 s	88%
Q. Ma et al., (2011)	Hough transform +SVM	0.1 s	98%
L. Baker et al., (2016)	Hough Transform + line tracking algorithm	5.55 s	85.71%
H. -S. Son et al., (2022)	Deep learning (Tiny YOLO v3)	0.15s	94%
Proposed	Deep learning (YOLO v5)	0.5s	99.3%

4. CONCLUSION

In this paper, the deep-learning method to locate power lines and lanes in agricultural fields was done using YOLO v5. The usual object detection technique for a single thing, such as animals and cars, is not appropriate for power line detection because they are continuous objects. It is anticipated that by using it with agricultural spray drones, it will be profitably monetized. The drones have high sustainability in the case of object detection. By reducing health risks, the agricultural drone can save time and money. The proposed work described in this research will undoubtedly be useful economically and contribute significantly to the automation of the agricultural industry. The method proposed showed that the accuracy of power line detection was 99.3% and a processing time of 0.5 seconds.

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