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Enhanced Weed Detection for Sustainable Agriculture: A YOLOv7 and IoT Sensor Approach for Maximizing Crop Quality and Profitability †

J. Lekha and S. Vijayalakshmi *

Department of Data Science, Christ University, Bengaluru, Karnataka, India lekha.ji@christuniversity.in
* Correspondence: s.vijayalakshmi@christuniversity.in
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Abstract: Effective weed detection is essential in modern agriculture to improve crop yield and quality. Farmers can optimize their weed control strategies by applying tailored herbicides based on accurate identification of weed species and the areas they affect. Real-time object detection has been transformed by recent advances in image detection technology, especially the YOLO (You Only Look Once) algorithm, of which YOLOv7 has shown to be more accurate than its predecessors in weed detection. Because of its novel E-ELAN layer, the YOLOv7 model achieves an astonishing 97% accuracy, compared to the estimated 78% accuracy of the YOLOv5 model. This study suggests using Internet of Things (IoT) sensors in conjunction with YOLOv7 to improve weed detection using an integrated strategy. It is advantageous to include a variety of sensors in the proposed work in detecting and managing weeds with greater accuracy and comprehensiveness can be achieved by combining a variety of sensors to improve the data obtained. An enhanced weed detection system can be achieved by utilizing the distinct information that each type of sensor provides. A comprehensive set of environmental data, including soil moisture, temperature and humidity, light intensity, pH, and ultrasonic distance sensors, will be used to correlate with patterns of weed growth. This information will be sent to a central Internet of Things gateway for in-the-moment analysis and merging with video footage taken agricultural fields. Farmers can anticipate weed infestations and optimize their management tactics thanks to predictive analytics made possible by the integration of sensor data withYOLOv7's weed detecting capabilities. The potential for large herbicide application cost savings and improved crop yields, which would increase farmer profits, highlight the economic viability of this strategy. This methodology seeks to revolutionize weed control procedures by utilizing cutting-edge technology and IoT connectivity, making them more effective and efficient.

Keywords: farmers; weed; YOLOV7; image detection; agriculture; crop

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1. Introduction

Weeds are the unwanted plants in the crops that will utilize the nutrients of the crops to grow. Of this, the crop will not get all the sufficient and required nutrients to yield as estimated. Nowadays, as the population is growing rapidly, they are estimated to have 9 billion people in 2050 [1,2], so every government is focusing on double food production to satisfy all the food needs.to achieve this goal, The authors must eliminate all the parasitic plants, insectivorous plants, symbiotic plants, and saprophytic plants. So, to achieve this, the authors are trying to eliminate the weeds so that the actual plant will get the required nutrients.

In ancient times, the identification of weeds used to happen manually, which used to take a lot of time and energy because someone manually must go and check every plant. In that process, sometimes they used to mistake the weeds for the actual crops, so these days, technology is rapidly developing [3]. The most efficient model to identify weeds can be developed using a few techniques. Through this, the authors can help the farmers to ease their work.

On the bases of the statistics which are provided by [4] where the cost of weed in the agricultural fields has highly influenced the growth rate of the yield which got into the hands of the farmers, and the secondary production rate has densely reduced due to the disease which is caused and passed by weeds it also found in studies that the fertility rate of the soil is also decreased due to the unwanted plant species(weeds) is the primary cause of it.

Recent developments in image recognition technology, particularly the YOLO (You Only Look Once) algorithm, have transformed real-time object detection in agriculture and improved current weed detection approaches. Out of all the YOLO versions, YOLOv7 has proven to be more accurate in identifying cannabis species than YOLOv5, with a startling 97% accuracy rate against 78% for YOLOv5. This high degree of precision lessens the likelihood of misidentifying weeds and crops, which is a problem with manual detection techniques.

Furthermore, weed detection can be improved even further by combining IoT (Internet of Things) sensors with the YOLOv7 algorithm. Weed growth patterns are greatly influenced by environmental elements such as soil pH, temperature, humidity, light intensity, and soil wetness. A more thorough picture of the distribution of weeds throughout the field can be attained by utilizing sensors to track these variables in real-time. Predictive weed control is made possible by the real-time examination of this data via an IoT gateway. When IoT sensor data is integrated with video footage, farmers are better able to detect possible weed infestations early on, which lowers costs and allows for more accurate herbicide application.

The integration of ecological and economic sustainability is also emphasized in this approach. Research has indicated that the incorrect or overuse of herbicides has an adverse effect on agricultural production as well as soil health, which can result in long-term degradation. Farmers now have an affordable answer when they combine IoT sensors with sophisticated weed identification systems like YOLOv7. Farmers can save expenses and increase crop yields by lowering the need for blanket herbicide applications. This is particularly important in areas like Vijayawada, where field trials are being carried out to confirm this technique. By using predictive analytics to analyze sensor data, farmers may enhance the profitability and sustainability of their farming methods by making well-informed decisions regarding weed control.

2. Methodology

The proposed system as shown in figure 1 is based on the efficient Object Detection Algorithm. The YOLO itself is one of the effective and efficient object detection algorithms. In that particular algorithm, the proposed framework focuses on the yoloV7 version that is the updated version of the YOLO algorithm.

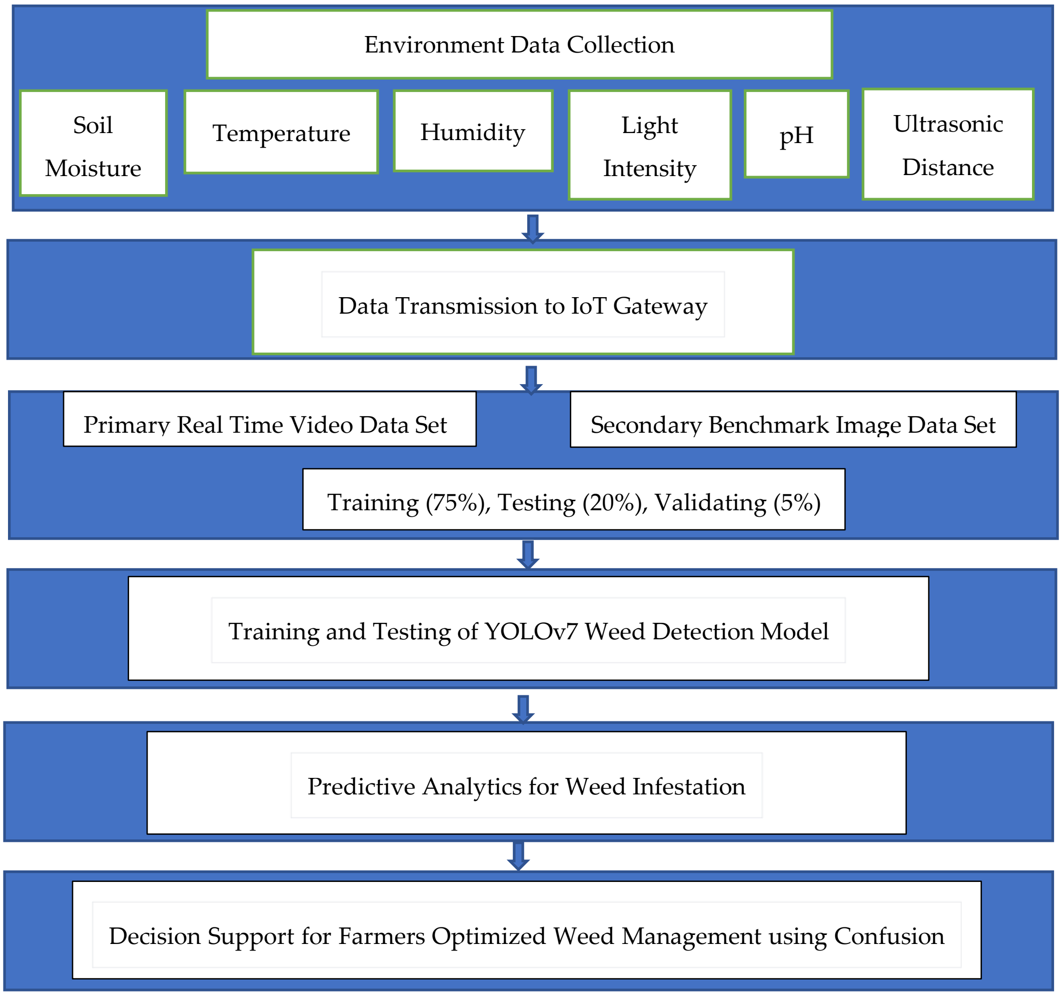

Figure 1. Steps in Proposed Methodology.

2.1. Data Collection from Sensors

In modern agriculture, gathering environmental data from multiple sensors is an essential step, especially to improve weed detection and management techniques. Data collection from many sensor types, including as pH, light intensity, temperature, humidity, soil moisture, and ultrasonic distance sensors, is part of this process. After that, the data is sent to an Internet of Things gateway, which acts as the main hub for data processing, aggregation, and transfer to the cloud for additional analysis.

Soil Moisture Sensors: By measuring the volumetric water content of the soil, these sensors can provide information on the amount of moisture present and whether irrigation is necessary to prevent the growth of weeds. Soil moisture sensors typically measure the dielectric constant of the soil, which changes with the water content.

Temperature sensors: These sensors aid in the study of the environmental factors that promote the growth of weeds by measuring the temperatures of the soil and the surrounding air. Digital temperature sensors like thermistors or thermocouples can be used, which convert temperature readings into an electrical signal.

Humidity sensors: These instruments gauge the amount of moisture in the atmosphere, which can affect the health of crops and the development patterns of weeds.

Capacitive or resistive sensors are commonly used for measuring atmospheric humidityLight intensity sensors measure light levels, which are critical for photosynthesis and have an impact on crop and weed growth. Light sensors use photodiodes or phototransistors that measure the intensity of light and convert it into a readable signal.

pH sensors: The pH of the soil affects both crops and weeds and is essential for the availability of nutrients. These sensors support the monitoring of the alkalinity or acidity of soil. pH sensors typically use an electrode that measures the hydrogen ion concentration in the soil.

Ultrasonic Distance Sensors: These sensors provide information on the physical characteristics of the field by measuring distances to identify plant heights and weed growth. Ultrasonic sensors typically operate at frequencies above 20 kHz and are used in automated systems for weed detection to scan fields.

The sensor's output (analog voltage) can be digitized using an Analog-to-Digital Converter (ADC). The digital data (representing moisture level) can then be transmitted to the gateway using communication protocols like I2C, SPI, or UART.

2.2. Data Collection/Preparation

There are two different datasets used in training and testing the object detection algorithm. The primary dataset which was a real-time dataset and the secondary dataset which is collected from Kaggle and used in this work.

The primary dataset was a video dataset which was collected on our own using the mobile camera with the configuration 12 mp and 30 fps. This video dataset is of 20 s long. For collecting the dataset the authors went to our nearby crop field and used our camera to capture the video. The authors selected a particular area in the crop field and collected the video from that particular area. This crop contains the same crop and weeds as the secondary dataset.

The secondary dataset was a crop_weed_BBox dataset which was collected from Kaggle [5] and contains 1300 images of sesame crops and different types of weeds which were labelled. The images in this detest was 512X512X3-sized colour image. These images were in the Yolo format.

2.3. Synchronized Data Collection and Meta Data in Video and Image Files

The system captures video and images of the field where weeds are to be detected. At the same time, the sensor data is collected via the transmission gateway, which provides environmental context at the time the video/image is captured. The key is to timestamp both video/image data and sensor data so they can be synchronized.You can embed sensor data as metadata within the video file format (e.g., MP4, AVI). This can be done using video processing tools like FFmpeg, where the sensor data is added as metadata at regular intervals corresponding to the video frames.For example, at every frame or specific time intervals (e.g., every second), moisture level, temperature, humidity, etc., are included in the video's metadata.When analyzing the video, the sensor data can be extracted frame by frame to correlate environmental conditions with the visual data.

After video/image capture and sensor data logging, both data sources can be combined into a unified dataset for further analysis or machine learning. This can be done by linking:

Frames of the video (or individual images) with sensor readings as shown in Table 1.

Example of how the dataset could look:

Table 1. Comparison of various Environmental and Soil Conditions for Weed Detection

Frame/Image ID	Moisture Level	Temperature (°C)	Humidity (%)	Light Intensity (lx)	Soil pH	Weed Distance (cm)	Label (Weed/No Weed)
Frame_00001	40%	28	55%	1500	6.5	25	Weed
Frame_00002	42%	29	57%	1600	6.7	22	No Weed

Training/Testing the Model

Training and testing is the basic yet very important test in building any predictive model. For that, the secondary dataset was divided into two parts. 70% of the entire data set is for the training the model and in the remaining 30% also 5% was taken as the validation set, so, for testing 25% was there.

Researchers imported this model's code from the official yolov7 page [6]. Then trained, this model with the training dataset. Then comes the testing dataset part. The testing dataset will help to test the model's performance and accuracy.

3. Modelling

The most recent version of YOLOv7 exceeds all credible object detectors with over 30 FPS on GPU V100 and outperforms them all in terms of speed and accuracy, all falling between 5 and 160 frames per second. When it comes to real-time item detectors, its accuracy of 56.8% AP is the greatest. The transformer-based complete detector SWINL Cascade-Mask R CNN (9.2 FPS A100, 53.9% AP) with 509% speed and 2% accuracy and convolution is inferior to the YOLOv7-E6 Object Detector (56 FPS V100, 55.9% AP), which is 509% quicker. With 8.6 FPS A100 and 55.2% AP, the base detector ConvNeXt-XL Cascade-Mask R-CNN averages 551% tempo and 0.7% AP accuracy [6].

3.1. Model Architecture

A fully connected neural network, or FCNN, is what the YOLO architecture is shown in figure 2. There are three primary parts to the YOLO framework. neck, head, and backbone. One of the initial training datasets for the Backbone will be ImageNet for classification. Generally, recognition is introduced at a lower resolution than the final recognition model because recognition requires finer detail than categorization. Neck predicts probability and bounding box coordinates by utilizing characteristics from the fully connected layers and the convolutional layers of the backbone. The network's last output layer, the header, can be exchanged for transfer learning with other layers that have the same input format. [7].

For real-time application, the YOLO algorithm gives greater frames per second and performs better in all the aspects that have been covered thus far. Rather than picking out interesting regions of the image, the YOLO technique is a regression-based approach that predicts classes and bounding boxes for the entire image in a single run. You must first comprehend what the YOLO algorithm is truly predicting in order to fully comprehend it. Predicting the object's class and the bounding box that indicates its location is the ultimate goal. Four descriptors can be used to characterize each bounding box:

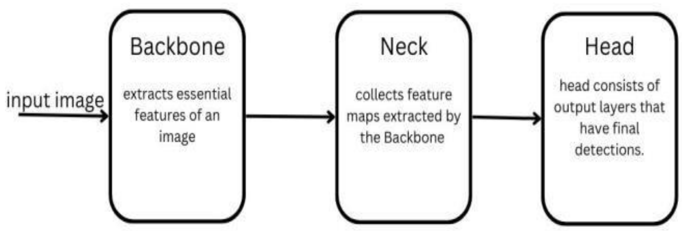

Figure 2. Architecture diagram.

(a) Centre of the box (bx, by)
(b) Width (bw)
(c) Height (bh)
(d) Value c corresponding to the class of an object

There is also a prediction for the real number pc, which is the probability that the object is inside the bounding box.

YOLO divides the image into cells (usually a 19 × 19 grid) rather than looking for interesting regions in the input image that may contain objects. Each cell in this is responsible for predicting the K-bounding boxes [8].

An object is considered to be in a particular cell only if the anchor box's centre coordinates are in that cell. This property causes the centre coordinates to always be calculated relative to the cell, but the height and width are to be calculated relative to the overall image size.

During one pass of forward propagation, YOLO determines the probability that a cell contains a particular class. This formula is:

$$score_{c,} = p_c \times c_i \quad (1)$$

The most likely class is chosen and assigned to that particular grid cell. A similar process is done for all grid cells present in the image.

This shows before and after predicting the class probabilities for each grid cell. After predicting class probabilities, the next step is non-maximal suppression. This helps the algorithm to remove unwanted anchor boxes. The number of anchor boxes is calculated based on class probabilities.

To solve this problem, non-maximal suppression removes bounding boxes very close to each other by performing an IOU (intersection over union) on the highest class probability.

Compute the IOU values for all bounding boxes corresponding to the bounding box with the highest class probability and reject bounding boxes with IOU values greater than a threshold. This means that these two bounding boxes cover the same object, but the other one is unlikely to be the same object, so it is excluded.

Once that is done, the algorithm finds the bounding box with the next highest class probability and performs the same process until all the different bounding boxes are left.

After almost all the work is done, the algorithm finally outputs the required vector detailing the bounding boxes for each class.

And the most important parameter of the algorithm, the loss function, is shown below. YOLO learns all four prediction parameters simultaneously (see above). Here, i, and j are the two input values

The modelling of this yolov7 was mainly focused on the two features as per the main paper of yolov7 [6] Extended efficient layer aggregation networks (E-ELAN) and Model scaling for concatenation-based models.

3.2. Extended Efficient Layer Aggregation Networks (E-ELAN)

A highly efficient layer aggregation network mainly pays attention to the version parameter range and computational density. The VovNet version (CNN tries to make DenseNet more efficient by combining all the features in the final characteristic curve as simply as possible) and the CSPVoVNet version both improve the input-output channel ratio at community inference speed. And the effects of element-sensitive operations. YOLO v7 Extended ELAN, known as E-ELAN. A major benefit of ELAN is that deeper communities can explore and converge more effectively by controlling gradient paths [9].

E-ELAN significantly tweaks the structure within the computational block, leaving the structure of the transition layer completely unchanged. Use augmentation, blending, and merging strategies that complement the learning capacity of the community without destroying your own gradient paths. The method here is to apply a configuration convolution to expand the channels and ranges of computational blocks, thereby applying the same configuration parameters and channel multipliers to all computational blocks in the computational layer. Then the function maps computed in each compute block are shuffled and concatenated. Therefore, the range of channels within each organization of functional mapping is likely to be the same as the range of channels within a unique structure. Finally, merge these companies from the functional map. E-ELAN also performed functions to learn various functions

3.3. Model Scaling for Concatenation-Based Models

The main purpose of version scaling is to adjust some of the version attributes and generate modes consisting of different scales to improve their own inference speed. However, implementing these techniques in a concatenation-based forest and shrinking or increasing the depth can lead to simultaneous translational layer growth and intra-diplomatic shrinkage after concatenation. Mainly based on complete calculation blocks.

Researchers cannot analyse the exceptional scaling factors sequentially but can conclude that they should be considered a largely chain-based holistic version. If the intensity scaling has been considered as an example, such a move can introduce a trade-off between the input and output channels of the transition layer, leading to lower hardware utilization of the version. YOLO v7's Composite Scaling technology preserves the house the version had in its preliminary layout and allows it to continue its first-class form. This is because even if you scale the strength factor of the calculation block, you have to do it without adding it.

Remember to calculate the alternatives for the output channels of this block. Then do the width factor scaling with the same amount of substitution in the transition layer. This continues the house that the preliminary layout version had and resumes the main shape.

3.4. Building the Model

Model building is one of the most important parts to achieve the required results. the model building will primarily take place with the secondary dataset as it was much more convenient to build the model in order to build a good model the training and testing parts to be done very well in any model the training will act as the backbone for the model. The prediction of the model will base on the training only if The authors train the model with not so well labelled data it will not predict so well so training should be done on the well-labelled data.

After training the model the testing will take place. The testing will take place on 30% of the secondary data after testing the validation of the data will come. for validation, The authors divided the part of the data in that part the model will randomly choose the images and will predict that particular/ random image. Every time the authors run the model the images will change automatically to ensure that the model is able to predict all the images equally. So, by this, it will ensure the model is good.

Figure 3. Prediction image with Bounding Boxes.

As in Figure 3, the prediction will happen with bounding boxes, the bounding will have the numbers 0 and 1 on the top of it, so if the bounding box contains 1 on top of it that means it contains the image of weed if it is 0 then it will indicate the image is of crop/the weeds are absent in it. To identify the difference very easily the colours of the bounding boxes were also different the blue bounding box is for the crop and the orange colour is for the weed. this model will even predict the different crops in one image it will not give the bounding box for one whole image it will give the bounding box for both crops and weeds so that if an image contains more than one weed or more than one crop it will identify very easily.

3.5. Predicting the Model

For evaluating this model the primary dataset was used as it will provide a much more accurate prediction. As the primary data set is a video dataset it was a more relevant dataset than the real word dataset. The data that this model should perform in the real world is dynamic data like video data and all. Data that farmers will not only provide image data but they can also provide video data so, this model is evaluated on real-world bases and performs very well and accurately in the real world.

As in Figure 4 the video will be directly predicted in this model. All the pre-prediction part will be done by the model itself in the background. For this model, there is no need to convert the videos into frames and label them individually. As this model was built on the pre-labelled dataset of the same crops and weeds which was in the video the work was much easy.

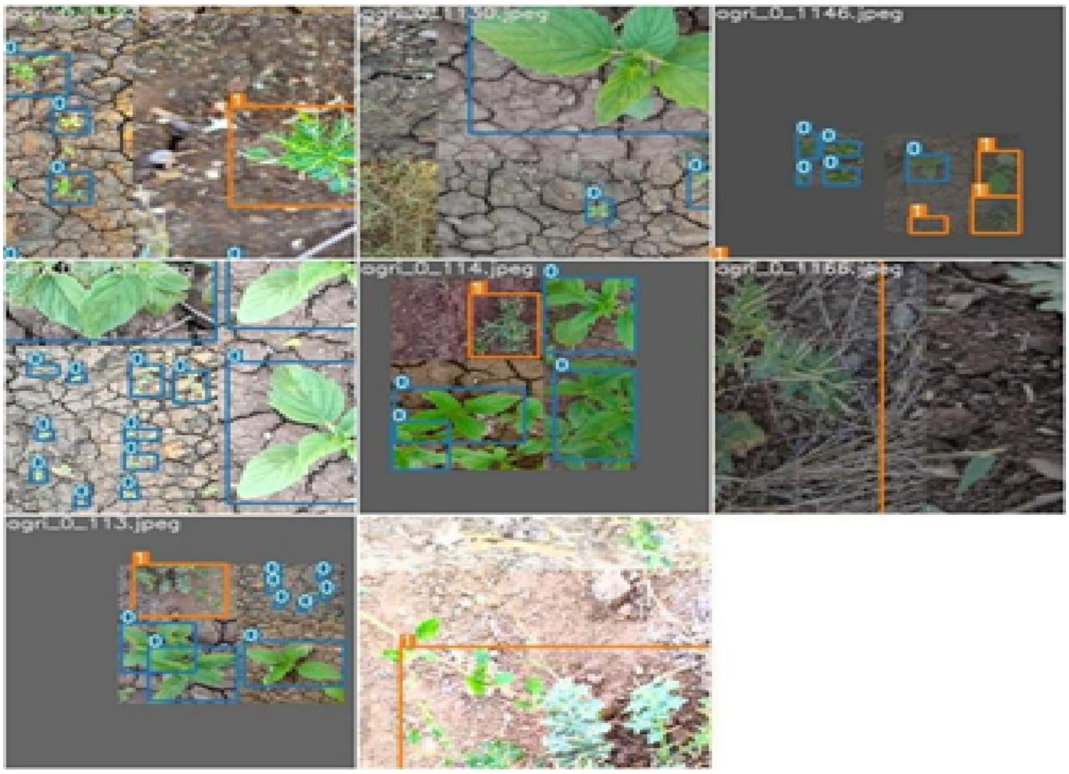

Figure 4. Prediction on the original image

4. Evaluation Metrics

Prediction metrics such as Accuracy, Recall, F1 score, and precision are then calculated to evaluate the model in CCP. True Positive, False Positive, True Negative and False Negative can be calculated from the confusion matrix [10,11] as displayed in Table 2 . The Precision curve represents the degree to which repeated measurements under the same conditions are unchanged [12].

(a) Actual positive: It is a weed.
(b) Actual negative: It is not the weed
(c) Predictive positive: It is showing as a weed
(d) Predictive negative: It is showing as not weed.

Table 2. Confusion matrix.

	Predicted Positives	**Predicted Negative**
Actual positives	True Positives (0.90%)	False Positives (0.02%)
Actual negatives	False Negatives (0.03%)	True Negatives (0.84%)

(a) True Positive (TP): The weed is classified as positive
(b) True Negative (TN): The weed is classified as not weed
(c) False Positive (FP): The crop is classified as a Weed
(d) False Negative (FN): The crop is classified as not weed.

The accuracy of the model was true because, by the confusion matrix, the authors get to know that the true positive and true negative values are greater than the false positive or the false negative.

Accuracy, Recall, and precision can be interpreted from the above measures. F1 score can be construed from Precision and Recall.

5. Results and Discussions

The prediction model has been employed on the above primary dataset. The yolov7 model has been used in the model. The reason for using this model is that this yolov7 was predicting very well on any kind of image and video dataset compared with any other models it's very less time and money-consuming and much easy to implement when compared with previous models. The accuracy for this model was calculated using the f1 score and recall and precision [13].

Finding the f1 score is the last step in finding the correct accuracy of any model. The F1 score is the harmonic mean of accuracy and memory. Combine precision and recall into one number using the following formula: Note that the

F1 score considers both precision and recall. This also means that the authors are considering both FP and FN.

The first step of finding the F1 score is the precision curve. Precision is the amount of information conveyed in digits. This refers to the resolution or limit of the measurement. Figure 5 shows the precision curve of this model. The precision value obtained was 0.932.

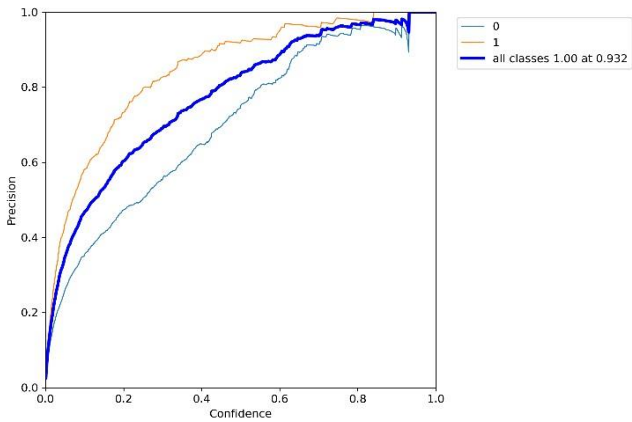

Figure 5. Precision curve.

Precision = True Positives/(True Positives + False Positives)

The second step of finding the F1 score is finding the recall curve. In Figure 6 shows the recall curve of this model. The recall is the measure of our model correctly identifying True Positives. Thus, for all the images which actually have weeds, recall tells us how many the authors correctly identified as having weeds. The recall value obtained in this prediction is 0.99.

Recall = True Positives/(True Positives + False Negative)

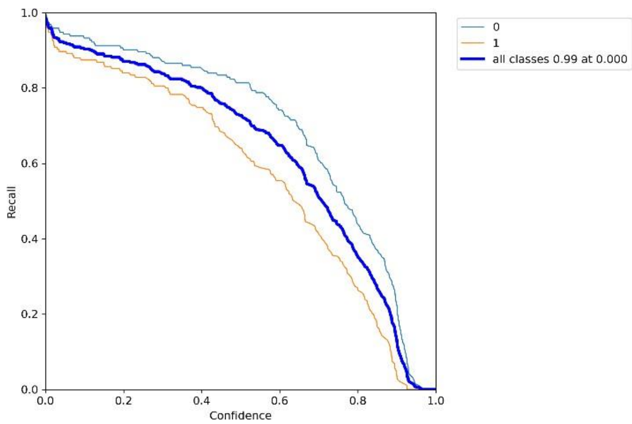

Figure 6. Recall curve.

After the precision and recall curves the precision Vs recall curve should be calculated as shown in figure 7. Precision Vs recall curve is a direct representation of the precision (y-axis) and the recall (x-axis). This happens when you have an imbalanced data set and the number of negative outcomes is much higher than the positive outcomes (or the number of patients without heart disease is much higher than the number of patients with heart disease).in figure 8 the precision Vs recall curve has been shown. The precision Vs recall curve value for this model is 0.845.

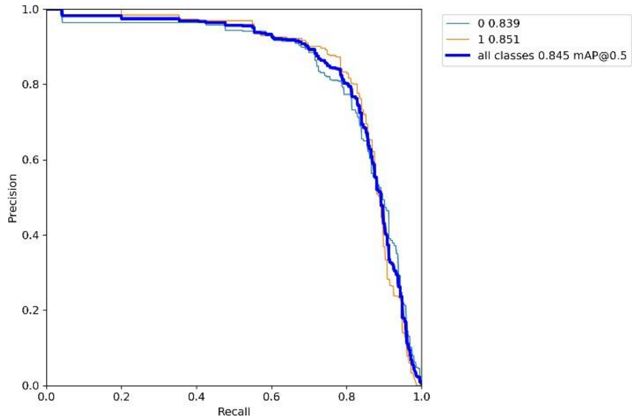

Figure 7. Precision vs recall curve.

Precision and recall are two components of the F1 score. The goal of the F1 score is to combine precision and recall metrics into a single metric. At the same time, the F1 score was designed to perform well even with imbalanced data. In Figure 8, the f1 curve has been given. The F1 score value of this model is 0.78.

F1 = 2 × (precision × recall/(precision + recall))

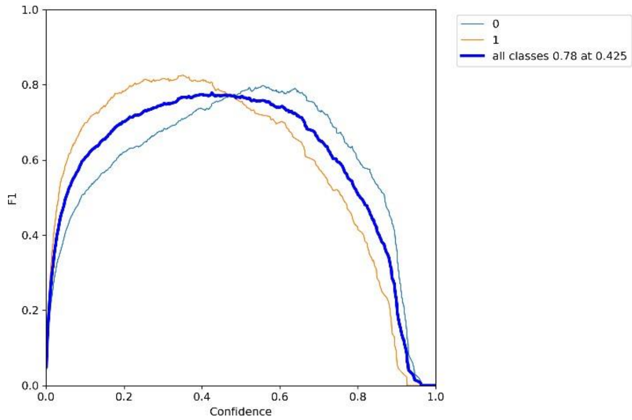

Figure 8 .F1 curve.

A confusion matrix also referred to as an error matrix, is a process that helps to assess and predict the validity of a classification model. Using confusion matrices allows you to see different errors which you could make when you make predictions. The most common representation for a confusion matrix is a grid which is used to figure out the accuracy of classification models. This is shown in the above Table 3 and a comparative chart is shown in figure 9.

Table 3 Score, and accuracy.

	Precision	Recall	Precision/Recall	F1 Score	Accuracy
values	0.932	0.99	0.845	0.78	0.972

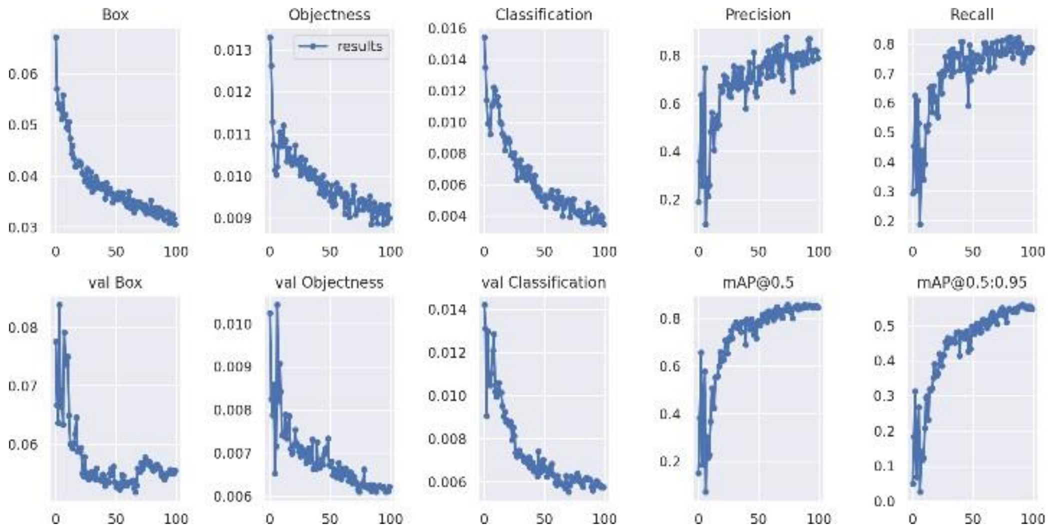

Figure 9. Few other graphs used in this work.

6. Conclusions/Future Works

Today, many farmers are trying to improve the quality and quantity of their crops at the same time every one is becoming conscious enough to protect the environment.so, image and video processing came into play. Models like these will not only help the farmers to achieve their desired production rate but also help them achieve their passive goal of protecting the environment. Here comes the importance of this research work this will provide much more accuracy with a low cost of both time and money when compared with previous models.

This model can also be made as a portable mobile app to make it available for more farmers by that they can actually just scan the crop and can identify the weeds and their types and can find the proper medication for them.

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