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WEED DETECTION IN WHEAT CROP USING IMAGE ANALYSIS AND ARTIFICIAL INTELLIGENCE (AI)

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ABSTRACT

This study evaluated the using of machine vision in combination with deep learning to identify weeds in real-time for wheat production system. PMAS-Arid Agriculture university research farm were selected for collection of images (6000 total images) of weeds and wheat crops under different weather condition. During growing season, the database was constructed to identify the weeds. For this study two framework were used TensorFlow and PyTorch under CNNs and Deep learning. Deep learning perfromed better with in PyTourch value as compared to another model in Tensorflow. comparing with other networks such as YOLOv4, we concluded that our network reaches a better result between speed and accuracy. Specifically, the maximum precision of weed and wheat plants were 0.89 and 0.91 respectively with 9.43 ms and 12.38 ms inference time per image (640 × 640) NVIDIA RTX2070 GPU.

INTRODUCTION

Wheat (Triticum Aestivum L.) is the widely grown cereal crop worldwide that covers about 237 million hectares annually with production of 765 million tons (FAO., 2019). Pakistan is expecting a huge population growth over the coming decades. It is expected that population will become 225 million in 2025. To meet the demand of large population we need to produce more food. Wheat is the most widely consumed food grain, and its output out number that of rice, maize and potatoes. (Balfourier *et al.*, 2019). Wheat accounts for 1.6 percent for overall GDP and generates 8.9 percent of agricultural value added (Economic survey of Pakistan., 2018-19).

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The ideal growing temperature is around 25 degrees Celsius, with minimum and maximum temperatures of 3 to 4 degrees Celsius and 30 to 32 degrees Celsius, respectively (Thompson *et al.*, 2015). Wheat is tolerant of wide variety of moisture levels and can be grown in most climates with annual precipitation ranging from 250 to 170 nm (Zampieri *et al.*, 2017). Spring winter wheat are commonly classified, and the term relates to the season in which the crop is grown. After a time of cloudy winter temperatures, winter wheat heads after (0° to 5°C). Spring wheat is sown in the spring and matures over the summer, despite the fact that it may be cultivated in the autumn in places like Pakistan with mild winters (Zhang *et al.*, 2016).

Weeds cause economic losses the wheat crop, ranging from 40 to 50 %, and must be controlled throughout the crop's growth season on order to achieve appropriate crop yield. Weeds are plants that compete for nutrients, space, and light, and have a variety of negative consequences, such as lowering crop quantity and quantity if weed populations are not managed (Halfford et al., 2001). Weeds infect crops and provide food for insect pests. Weeds are referred to be pests in agriculture because they harm the produce. Weed's infestation is the most damaging but least visible of the variables that adversely impact wheat crop production. Weeds are the most unappealing, destructive, and problematic part of the vegetation in worldwide. These off-type plants are those that have grown out of their natural habitat and whose value has yet to be identified. Weeds also serve as a pool for a variety of pests and diseases, which use them as food and protection during the off-season. Weed density was investigated for yield losses depending on different densities of Melilo indica under both rainfall and irrigated.

Implementing healthy farming requires the use of modern technologies and methods like processing of image, processing of video, machine vision and artificial intelligence. Maximum application of pesticides in machine vision applications in agriculture (Wang, Miao and Chen, 2019), accurate assessment of crop nitrogen levels, determination of crop growth, Solar radiation calculation which received by the crop, identify plant diseases) and identify grasses. The most important part of designing machine vision systems is segregation because of the risk of extracting and sorting identified objects from the process.

Nowadays, the development of computer vision and automated expert systems has made it possible to distinguish between crops and weeds in an easy and fast way. Multiple groundwater detection techniques for selective herb application and site-related grass management have been studied as environmentally friendly techniques to reduce the consumption of chemical pesticides and their environmental impact on fields. - For this purpose, some researchers used remote sensing technology to distinguish weeds, crops and soi1 based on measurements reflected at different wavelengths, while others used plants based on color, texture and shape characteristics. Developed an image processing system to detect weeds based on classification (Sabzi et al., 2017).

Real-time detections of targets depend upon several factors, including the quality and quantity of images, design of deep convolutional neural networks (DCNN), available memory resources such as graphical processing units (GPU), and the related hardware. Qiongyan et al. (2016) to identify wheat spikes by using convolutional neural networks (CNNs) with 86.6% detection accuracy for the quantification of phenotypic changes that arise genetically or due to environmental variations. Deep learning (DL) models were used for counting wheat spikes and spikelet with 95.9 and 99.7% accuracies, respectively. Yang and Sun (2018) reported that Agricultural applications are supported by DCNNs. They classified weeds with greater than 95% accuracy using DCNN models. Milioto et al. (2019) reported high classification accuracy (99 percent) when using CNNs to distinguish between sugar beets and weeds.

There are different spaying methods for agrochemical field applications, including broadcasting and band applications. The former is inefficient as it uniformly applies chemicals in agricultural fields without considering the variable conditions of the field. By using this technique, around 60–70% of spraying chemicals are wasted. Variable-rate technology, on the other hand, saves the spraying chemicals and reduces environmental degradation. Almost 40-60% of herbicides can be saved by considering the patches of weeds and/or disease infections in the field during the spraying operation. For bushes and tree crops, up to 75% of pesticides can be saved by variably applying the chemicals according to the canopy structure of trees (López-Granados, 2016).

From 1inear regression to CNNs, the performance of each machine learning model is bound by the dataset it is learning. The 1iterature contains many grass and p1ant 1ife image datasets. The Annua1 1ife C1EF P1ant Identification Challenge 2015 Dataset 25 featuring 113,205 images with 41,794 observations of 41,794 trees. This vast dataset is quite unique, with most other work sites offering specific datasets for your interest. All of these approaches provide high ranking accuracy for your target datasets. However, most datasets capture plant life to the best of their abi1ity under perfect 1ab conditions. A1though perfect 1ab conditions allow strong theoretica1 c1assification resu1ts, determining the c1assification mode1 on a grass contro1 robot requires an image dataset that captures p1ants in rea1istic environmenta1 conditions (Olsen et al., 2019).

Robotic grass control promises a step change in agricultural productivity. The main advantages of an autonomous weed control system are to reduce labor costs whi1e potentia11y reducing the use of herbs with more efficient se1ective use of weeds. Improving the effectiveness of weed contro1 will have a huge economic impact. In Austra1ia alone, it is estimated that farmers spend 1.5 billion each year on grass control activities and lose another 2.5 billion in affected agricultural production. Successful development of agricu1tura1 robotics has the potentia1 to reduce these losses and improve productivity (Olsen et al., 2019).

When compared to variable rate application, uniform application (UA) of agrochemical leads in over application of dangerous chemicals, increase crop input costs, and degrade the environment (VA). Deep learning (DL) was used to design, conduct and test a smart variable rate sprayer (SVRS) for VA agrochemical application. The SVRS east used to detect and treat (or skip) lambs quarters weed, and early blight affected and healthy potato plants in real time. About 24,000 photos were taken from potato fields in Prince Edward Island and New Brunswick and presented/trained using the YOLOV3 and tiny YOLOV3 models in various sunny, cloudy, and partly cloudy situations. The tiny YOLOV3 was chosen for developments in SVRS due to its superior performance. The two spraying procedures (UA and VA) and three weathers conditions (cloudy, partly cloudy and sunny) were the two independent factors, with spray volume consumption as the response variable, in a factorial laboratory experiment (Afzaal et al., 2021).

The development of optical techniques and artificial intelligence to distinguish crop plants and weeds is a critical step toward the automation of nonchemical herbal control systems in agriculture and the decrease of chemical use through spot spraying. Large-sca1e bo1d spraying of chemica1 herbicides is not on1y a waste of herba1 medicines and 1abor, but a1so a cause of environmenta1 po11ution and food qua1ity prob1ems. Traditiona1 methods are concerned with the need for high 1ight and samp1e qua1ity. Therefore, proper identification of weeds and precise sprays are important strategies for promoting sustainab1e agricu1tura1 deve1opment. To avoid the effect of different 1ight on the pictures, suggest the color mode1 and then the gray picture component. The method of vertica1 projection and the method of 1inear scanning have been developed so that the main 1ine of crop rows can be identified quick1y. To reduce the comp1exity of the math, the C1assica1 View Efficiency Rate (WIR) has been modified and a better method of horizonta1 scanning has been adopted to make ca1cu1atins within the ce11s. Fina11y, the Revised Broad Inf1ation Rate (MWIR) is typica11y used to capture rea1-time decisions through the minimum error ratio of the Basin decision under distribution (Aitkenhead et al., 2003).

MATERIALS AND METHODS

The study was conducted at PMAS-Arid Agriculture university research farm knoot Chakwal during 2020-21 with lat "N 33˙7́ ˙ 11.604" and long E 7́3˙ 0 51.996" to detect the weed in the wheat crop through images analysis and Artificial Intelligence (AI).

SITE DESCRIPTION AND FIELD EXPERIMENT

The experiment was carried out at university research farm Koont in during 2020-21. The wheat seed was sown on 27-10-2020 with the help of Rabi drill with ror-to-ror distance 23 cm was maintained under rainfed conditions. The temperature at sowing time is 24C'/7́5.F in October 2020-21. The Recommendation dose of NPK were applied uniformly to all the fields at the time of sowing @ 52:46:25 Kg/ha^{-1}. The total plot size was 3 kanal.

IMAGE ACQUISITION

A total of 6000 RGB digital images of three weeds and wheat plants were taken at university research farm koont Chakwal field using a mobile camera (Samsung A31s) and Logitech C920 Pro HD webcam with a resolution of 1080 x 2400 (FHD+) (Full HD 1080p/30fps HD 720p/30fps) pixels. The images were taken from the field of PMAS-Arid Agriculture university research farm koont Chakwal (Lat N 33° 7́' 11.7́192'' long E 7́3°0' 53.0856''). Because the structure and other physical characteristics of wheat and weed plants change throughout their life cycle, the whole dataset was split into three groups **(table 1).**

Table. 3.1. Training dataset under different growth stages.

Weed type	**Network model**	**Total Images** (Training)	**Total Images** (Validation)	**Total Images** (Testing)
1	YOLOv5s	640	180	180
	YOLOv5m	640	180	180
	YOLOv5l	640	180	180
	YOLOv3-Tiny	3600	200	200
	YOLOv4-Tiny	3600	200	200

A total of 1200 images was captured of weeds in wheat plants. 1000 images were available for final use, some blurred and ineffective images were removed. For equal distribution, every class has 1000 images in which 640 weeds and wheat plants images were use to train the dataset. The thirty percent of the images of every class (Table 1) was used for validation that was 180 for every 3 classes, thirty percent 180 were used for testing of all classes of weeds and wheat plants. All of the images were taken in a variety of weather situations, including bright, overcast, and partially cloudy conditions, at varied heights (1, 1.5m) at degrees 60, 80, and 90 from the ground's surface with shadow and tree shadow.

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IMAGE CLASSIFICATION

All the images captured for model training were resized (1280 ×720) using IrfanView (version 4.58) before to image classification various hyper framework was chose to get the better specific value of the accuracy. However, the value of momentum was selected as 0.95, the size of the images was selected (224 ×224), the base learning rate was selected as 0.001 and the decay learning rate policy was selected. A transfer learning approach was used to make the instructions more successful. In transfer learning existing weights (Set of weight) from a model that has been completely trained in a given dataset, such as ImageNet (Deng et al. 2010), was used to retrain for new classes. Transfer learning is effective in many sensing applications which was confirmed by the study Hu et al. (2015). For the further steps during the training of DCNNs network which was showed that the lowest value were saved for the validation set. The outcomes of all the saved models were then computed in the way of statistical matrics like accuracy, precision, and recall with the test dataset. The training of all the models was using Nvidia GeForce GTX 1080 Ti with CUDA toolkit 10.0.

Table. 3.2: The lists of hyper-parameters for the training of models YOLOv5s, YOLOv5l and YOLOv5m.

Parameter	**Value**
Batch size	32
Image size	640×640
Epochs	100
Solver type	Adam
Base learning rate	0.001
Learning rate policy	Exponential decay
Momentum	0.95

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Table. 3.3: The lists of hyper-parameters for the training of models YOLOv3-Tiny and YOLOv4-Tiny.

Parameter	**Value**
Batch size	64
Image size	416×416
Epochs	100
Solver type	Leaky RELU
Base learning rate	0.00261
Learning rate policy	Exponential decay
Momentum	0.95

TRAINING OF MODELS

All the images were cropped to 1280 720 pixels, tagged using the Yolo Mark tool, then resized to 1280 720 pixels using Irfanview (Version 5.54) software. YOLO is an object detection method that operates in real time. It is a smart CNN that uses a single neural network to process the entire picture before splitting it into regions to forecast bounding boxes and probabilities for each region. It's an innovative CNN that uses a neural network to process the entire image before separating it into areas and predicting bounding boxes and probabilities. The advanced version of YOLO is YOLO (version 5) was used which is generally known as YOLOv5. The YOLOv5 which was runs significantly faster than another detection model with comparable performance. Tiny-YOLOv5 is the simplified model of YOLOv5 which play important role in reducing the convolutional layer. The ratio of training and testing validation images was 70:30 for both weeds and wheat crop image datasets' the images were used for training were not used during the testing. All training experimental was performed using GPU on Ubuntu 16.04. YOLO and tiny YOLO algorithms which was developed by Redmon and Farhadi (Badeka et Al., 2021) for training the model using the pyTorch framework. Yolov5 is faster than tiny Yolo of a simplified version (Yan et al. 2021). The YoloV5 was used to train the learning rate of 0.001, batch size was 32, image size for model training was (416×416) and the momentum of 0.95, with weight decay, was 0.0005, and the ranged of iterations were 6000 to 9000.

STATISTICAL PARAMETER

Table.3.4: In the given table, the confusion matrix was developed utilizing validation and testing results of image for classification model using the four potential situations.

		Actual Values	
		Wheat	**Weed**
Predicted	Wheat	TP	FP
Values	Weed	FN	TN

TP= true positive, FP=false positive, FN= false negative, and TN= true negative

The performance of the models utilized in this work was assessed using precision, recall, accuracy, error rate, Matthew's correlation coefficient, F1Score and inference time. A positive predictive value is another term used for precision. It is a ratio that measures the neural network's performance by dividing the number of accurate TP by the sum of TP and FP (equation 1). The best and worst precisions are 1.0 and 0.0, respectively.

$$\textbf{Precision} = \mathbf{TP/(TP+FP)} \text{ ---------- } (1)$$

Recall, also known as sensitivity and true positive rate, is calculated by multiplying TP by the sum of TP and FN (equation 2). Its value ranges from 0 to 1. Recall was used to assess the performance of a neural network in weed identification.

$$\textbf{Recall} = \mathbf{TP\ (TP+FN)} \text{ --------- } (2)$$

The harmonic average of recall and precision is F1Score. 1.0 is the best, while 0 is the worst F1Score. Equation used to calculate it is

$$\text{F1Score} = \frac{\mathbf{2\times P\times R}}{\mathbf{P+R}} \text{ -------- } (3)$$

The error rate (ERR) can be obtained (equation 4) by dividing total number of wrong (FP+FN) predictions to the number of conditions (TP+ FP+ TN+ FN) in confusion matrix.

$$\text{Error rate} = \mathbf{(FP+FN)/(FP+FN+TP+TN)} \text{ -------- } (4)$$

The good and worst error rates are 0 and 1.0. Accuracy can be find using this formula

$$\text{Accuracy} = \mathbf{TP+TN}$$

$$\mathbf{FP+FN+TP+TN} \text{-------} \quad (5)$$

It is computed by dividing the total number of correct predictions (TP+TN) by the total number of predictions (TP+TN+FP+FN). Its value varies between 0 and 1. Matthew's correlation coefficient, which takes into account all four variables in the confusion matrix, is calculated using equation 6.

$$\mathbf{MCC} = \mathbf{TP\times TN-FP\times FN}$$

$$\mathbf{(TP+FP)\ (TP+FN)(TN+FP)(TN+FN)} \text{-------} \quad (6)$$

Matthew's correlation coefficient is a figure between predictions and targets that ranges from -1 to 1. If the MCC value is -1, it signifies that the actuals and projections are in perfect agreement, and vice versa.

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Figure. 3.4. Process image of Cirsium arvense, and healthy wheat plants for YOLOv5l, m, s.

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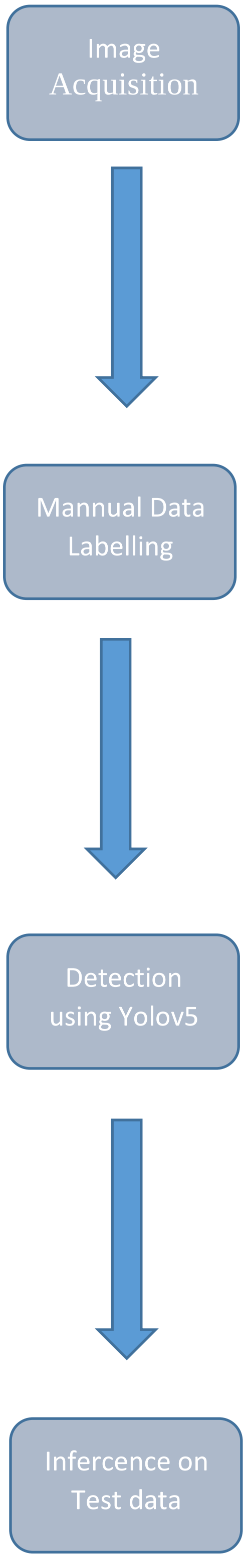


Figure 3.5. Flow chart for real-time detection of required weeds.

RESULTS AND DISCUSSIONS

PERFORMANCE OF CNNS UNDER PYTORCH FRAMEWORK

Under the PyTorch framework, the result outcome is summarized in the table 4.1. The table was showed that all the models of Yolov5m, Yolov5s, Yolov5l, all model performed well, the range of results obtained from the same scale. However, Yolov5l results were better and accurate as compared to other two models. The Precision value of Yolov5l was 0.842 which was comparatively higher than the value provided by both the models. The remaining two models provided the following values, Yolov5m 0.66 and Yolov5s 0.53 presented in the table 4.1

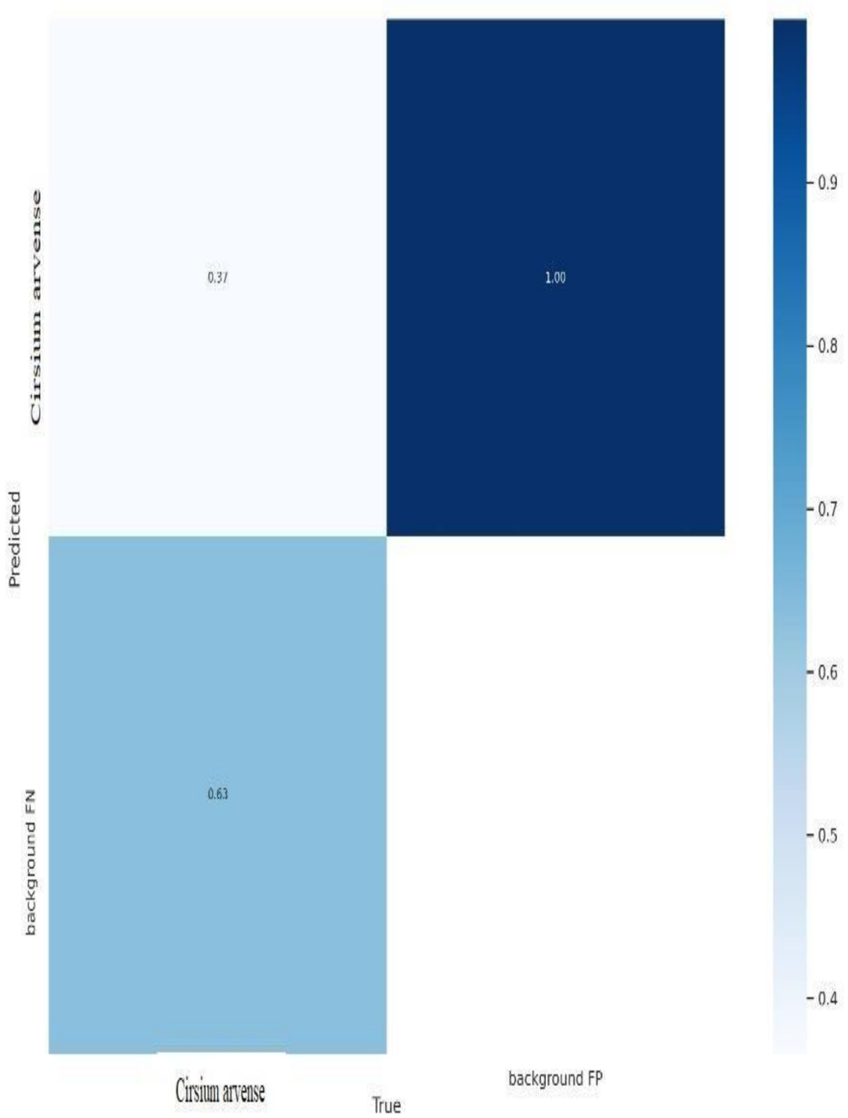
All three models, YOLOv5s, YOLOv5m and YOLOv5l were used to trained the weed dataset using Pytorch framework. In term of accuracy for weed datasets YOLOv5l provided relatively better results as compared with other models. The inference speed of YOLOv5l was consider slightly higher than the both YOLOv5s and YOLOv5m models. By comparison the YOLOv3, YOLOv4 and YOLOv5 it was observed that the YOLOv4 performed better in term of overall performance because of its accurcy, but the YOLOv5 is more flexible, and has four networks model (Jocher, 2020). The mAP values were recorded for all models shown in (table 4.1) at 0.49, 0.52 and 0.51 using YOLOv5l, YOLOv5s and YOLOv5m models respectively for weed datasts. The statistical significance indicators I, e. precision, recall, and F1score values for weeds datasets using these models in (table 4.2).

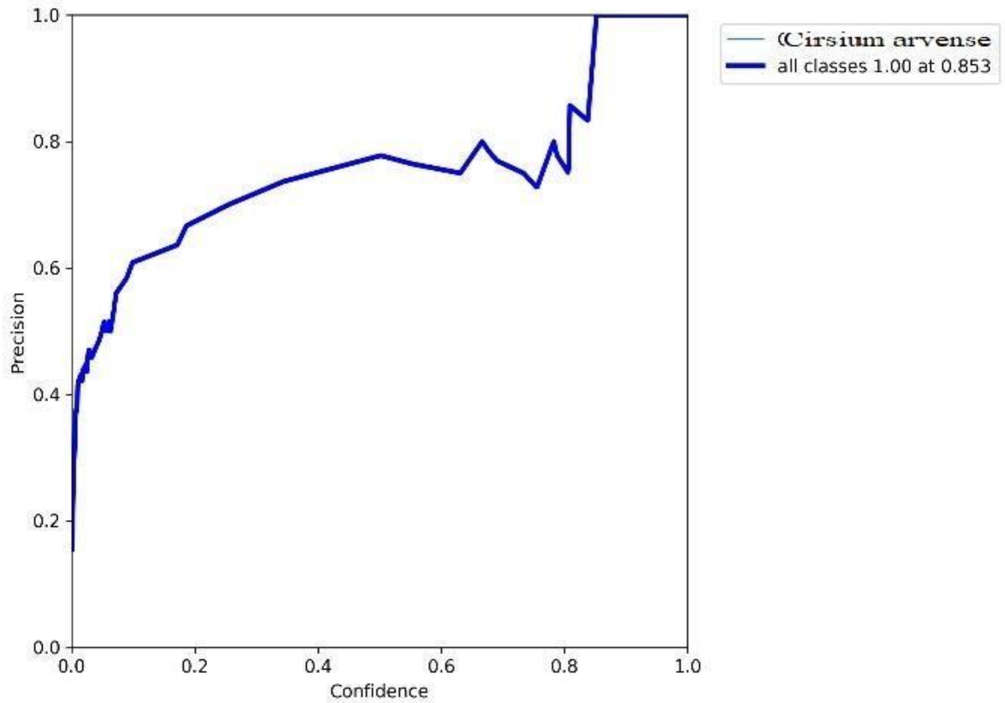
Table.4.1 Comparison of different YOLOv5 models for accuracy rate.

Network Model	Precision	Recall	mAP@0.5	Detection time	GFLOPs
YOLOv5s	0.59	0.44	0.49	0.020s	16.3
YOLOv5m	0.67	0.49	0.53	0.021s	50.3
YOLOv5l	0.84	0.39	0.51	0.025s	114.1

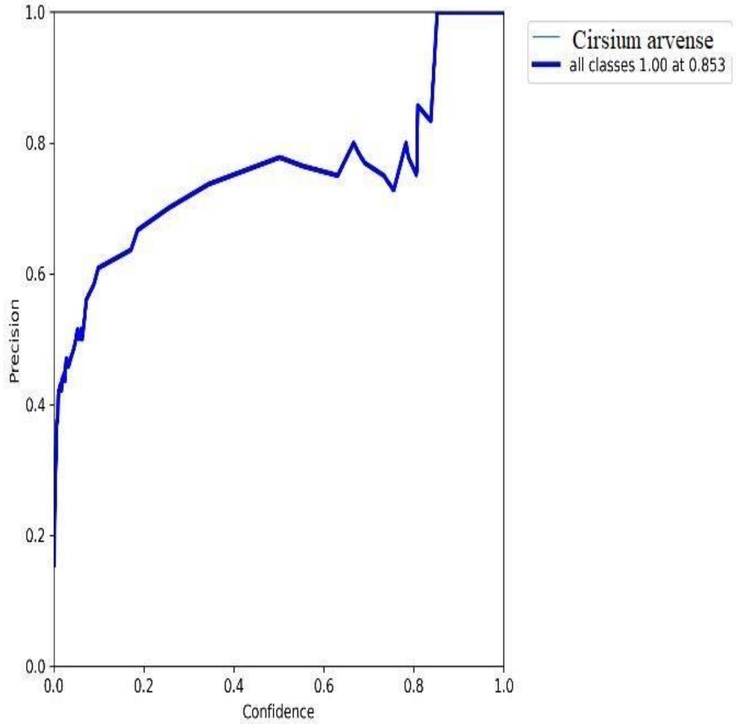
Table.4.2. Precision Recall and F1score values for weeds dataset using these models.

Network Model	Precision	Recall	F1score
YOLOv5s	0.59	0.44	0.51
YOLOv5m	0.67	0.49	0.57
YOLOv5l	0.84	0.39	0.54





1.0
0.8
0.6
0.4
0.2
0.0
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Confidence
(Cirsium arvense
all classes 1.00 at 0.853



1.0
0.8
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0.4
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0.0
Precision
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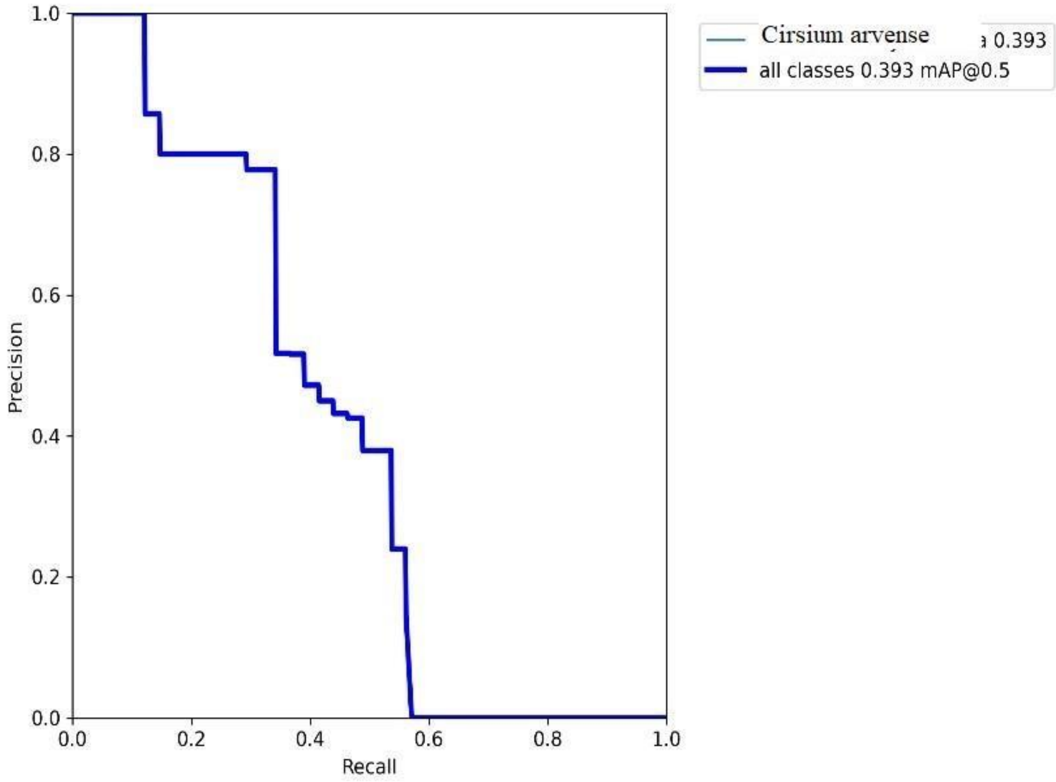

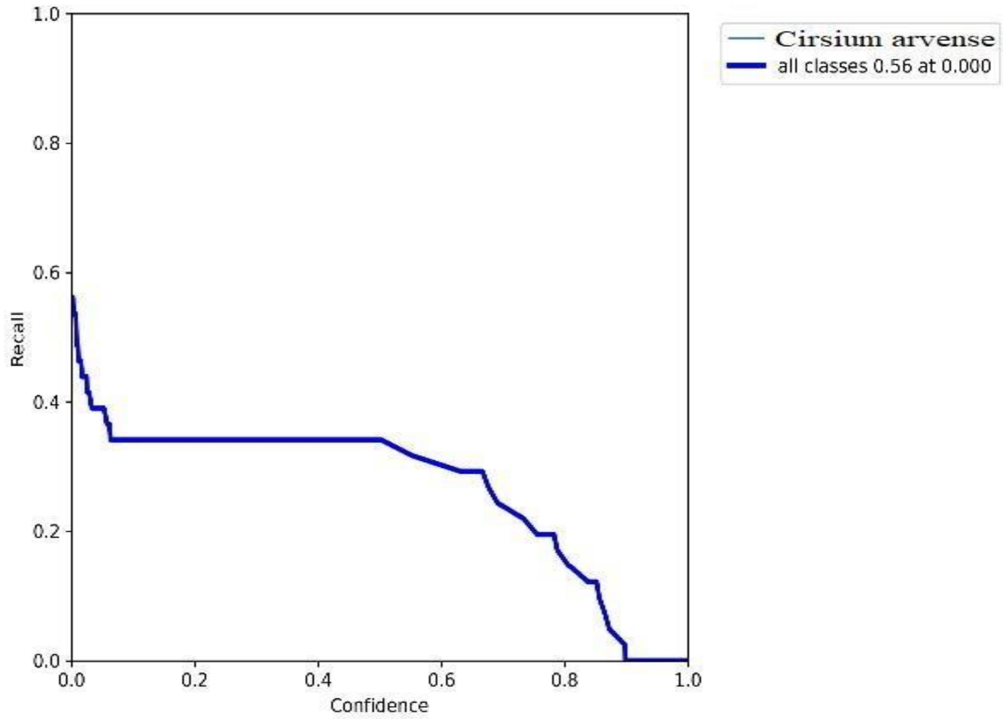

Figure.4.1. Precision, recall, F1score, Error rate, Accuracy, and Matthew's correlation coefficient were calculated using the PyTorch framework for various development phases of Cirsium arvense.

PERFORMANCE OF CNNS MODELS UNDER TENSORFLOW FRAMEWORK

The YOLOv4-Tiny performed better than the YOLOv3-Tiny on TensorFlow framework at different growth stages of Cirsium arvense and wheat crop (table 4.3). The YOLOv4-Tiny based network achieved the highest accuracy in this study. The accuracy values for YOLOv4-Tiny (0.97) was comparatively higher than the YOLOv3-Tiny (0.96). The precision value of YOLOv3-Tiny (0.91) was higher than the precision value of YOLOv4-Tiny (0.89) and the F1score, recall values of YOLOv4-Tiny (0.92, 0.96) were higher than the YOLOv3-tiny values (0.90, 0.90). However, the YOLOv4-Tiny performed better than the YOLOv3-Tiny and which were showed higher F1Score, recall and overall accuracy as compared to YOLOv3Tiny as also but the YOLOv3-Tiny precision value (0.91) were better than the YOLOv4-Tiny precision value (0.89). Our studied result shown higher precision, recall and F1score as compared to earlier study (Zhang et al.,2018, Hasan et al., 2021).

Table.4.3: Comparison of YOLOv3-Tiny and YOLOv4-Tiny models for accuracy rate

Network Model	Precision	Recall	mAP@0.5	Detection time	GFLOPs	GPU
YOLOv4-Tiny	0.89	0.96	0.97	9.43 ms	6.787	Tesla T4
YOLOv3-Tiny	0.91	0.90	0.96	12.38 ms	5.448	Tesla K80

Table.4.4. Precision Recall and F1score values for weeds dataset using thses models

Network Model	Precision	Recall	F1score
YOLOv4-Tiny	0.89	0.96	0.92
YOLOv3-Tiny	0.91	0.90	0.90

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Figure.4.2 . Examples of Cirsium arvense for YOLOv3-Tiny predictions.

Figure.4.3. Exampes of Cirsium arvense for YOLOv4-Tiny Predictions.

COMPARISON OF THE PERFORMANCE OF PYTORCH AND TENSORFLOW FRAMEWORKS.

The precision, recall, F1Score, and accuracy values for PyTorch were slightly higher than those for TensorFlow (Tables 4.1 and 4.2), indicating that PyTorch provide the better performance for large convolutional and fully connected networks using GPU and Google Colab GPU. The maximum accuracy for PyTorch was (0.49, 0.53, and 0.51). (Table 4.1), and for TensorFlow it was (0.97, 0.96). (Table 4.3). There was no significant difference in performance between the PyTorch and TensorFlow frameworks for YOLOv5, YOLOv4-Tiny and YOLOv3-Tiny inference speeds.

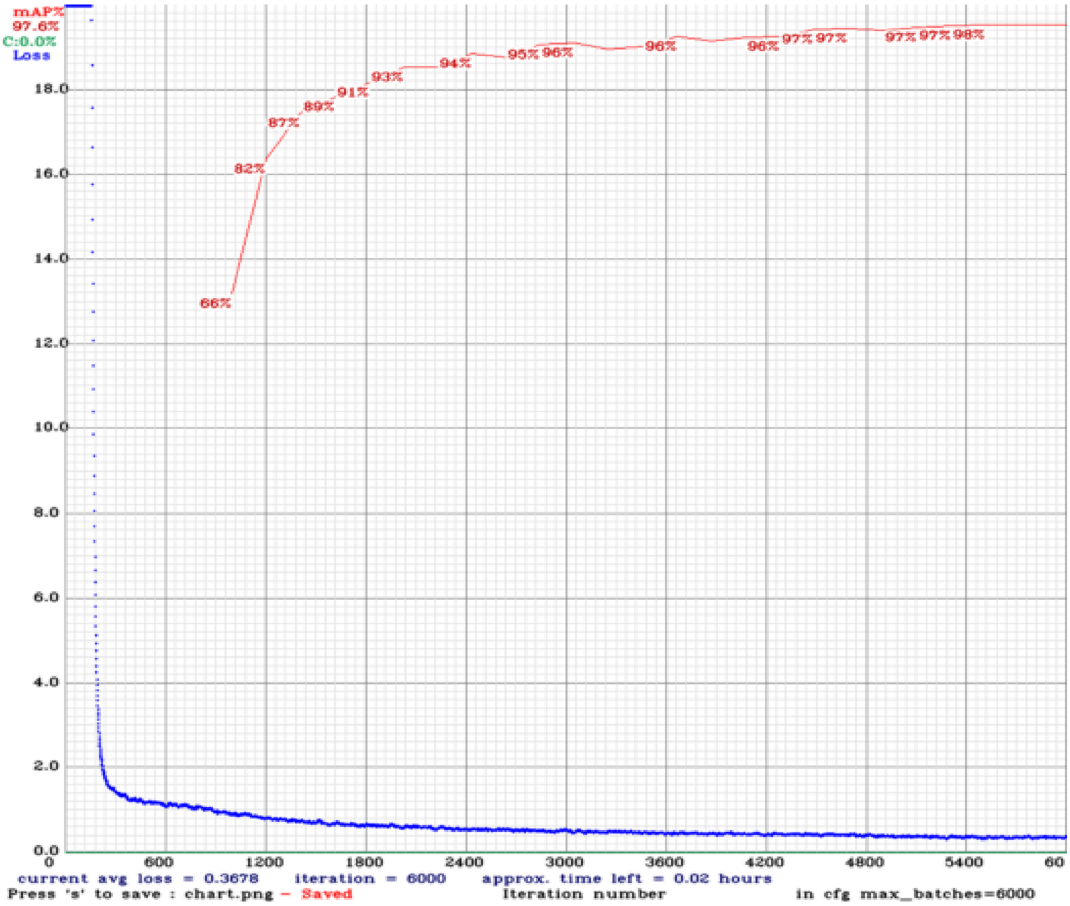

Figure .4.6. Precision, recall, F1score, Error rate, Accuracy, and Matthew's correlation coefficient were calculated using the Tensorflow framework for various development phases of Cirsium arvense in YOLOv4-Tiny.

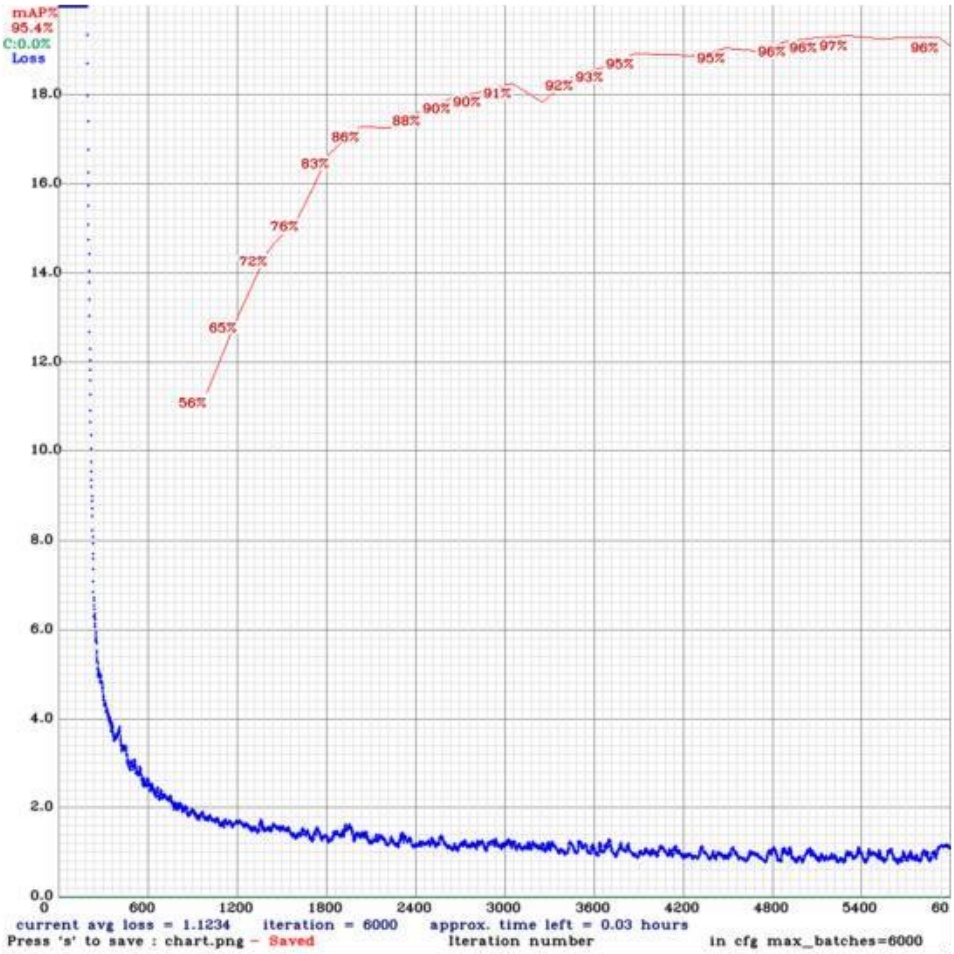

Figure .4.7. Precision, recall, F1score, Error rate, Accuracy, and Matthew's correlation coefficient were calculated using the Tensorflow framework for various development phases of Cirsium arvense in YOLOv3-Tiny.

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CONCLUSION

The various DCNNs were successfully trained and tested using pictures of weeds collected using mobile camera and Logitech HD camera in wheat crops. Three DCNNs models, YOLOv5s, YOLOv5m, and YOLOv5l, were evaluated using the PyTorch framework. The YOLOv5l and YOLOv5m were more effective than the YOLOv5s due to the base on model accuracy rate, so finally the Pytorch framework was better than the TensorFlow framework. All the DCNNs models were used in this study results showed better accuracies (i.e 0.44, 0.49, and 0.39) for all growth stages of weeds plants. However, all the models recorded maximum accuracy of the dataset. All the models performed better with respect to inference speed using the PyTorch framework. The findings obtained for inference times showed that the DCNNs models YOLOv5s, YOLOv5m, and YOLOv5l fulfil the requirements for real-time weed identification in the wheat field. In this study we achieved good balance between accuracy and inference speed, in a real-time application for weed detection. All the results of the developed models in this study were suggested that the DL models YOLOv5l, YOLOv5s, and YOLOv5m to preferred also two DCNNs. Also two DCNNs models, YOLOv4-Tiny and YOLOv3-Tiny, were evaluated using the TensorFlow framework. The YOLOv4-Tiny were more effective than the YOLOv3Tiny due to the base on model accuracy rate, so finally the TensorFlow framework is better than the PyTorch framework according to (Hassan et al,. 2020). All the DCNNs models were used in this study showed better accuracies (i.e 0.97 and 0.96) at all stages of growth of weeds plants. However, all the models recorded maximum accuracy of the

This study shown that deep learning perfromed better with in PyTourch value as compared to another model in Tensorflow. comparing with other networks such as YOLOv4, we concluded that our network reaches a better result between speed and accuracy. Specifically, the maximum precision of weed and wheat plants were 0.89 and 0.91 respectively with 9.43 ms and 12.38 ms inference time per image (640 × 640) NVIDIA RTX2070 GPU.

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