ABSTRACT

- Agriculture is the primary source of income for the majority of Indians. weeds are responsible for agricultural losses.
- To control and prevent weeds, a weed detection method should be implemented.
- In this project, an effective weed detection method using deep learning models that detect weeds in sesame crops is developed .
- In this work, two single stage object detection algorithms namely YOLOV5 and SSD Mobilenet V2 are used to detect the weeds. Both the models are analysed based on their performance. The parameters used to determine the accuracy in detection are MAP, Precision and recall.

INTRODUCTION

- weeds are one of the factors that effects agriculture production. weeds hinder the growth of crops by stealing water, nutrients.
- In traditional methods, farmers will spray the herbicides all over the crops which leads herbicides residue on crops.
- weed detection helps us in providing a means of reducing herbicide use and improving sustainability. It will also improve crop productivity

OBJECT DETECTION

- Object detection is a computer technology related to computer vision and image processing which deals with detecting instances of semantic objects of a certain class (such as humans, buildings, cars) in digital images and videos.

TYPES OF OBJECT DETECTORS:

- One stage Object Detectors
- Two Stage Object Detectors

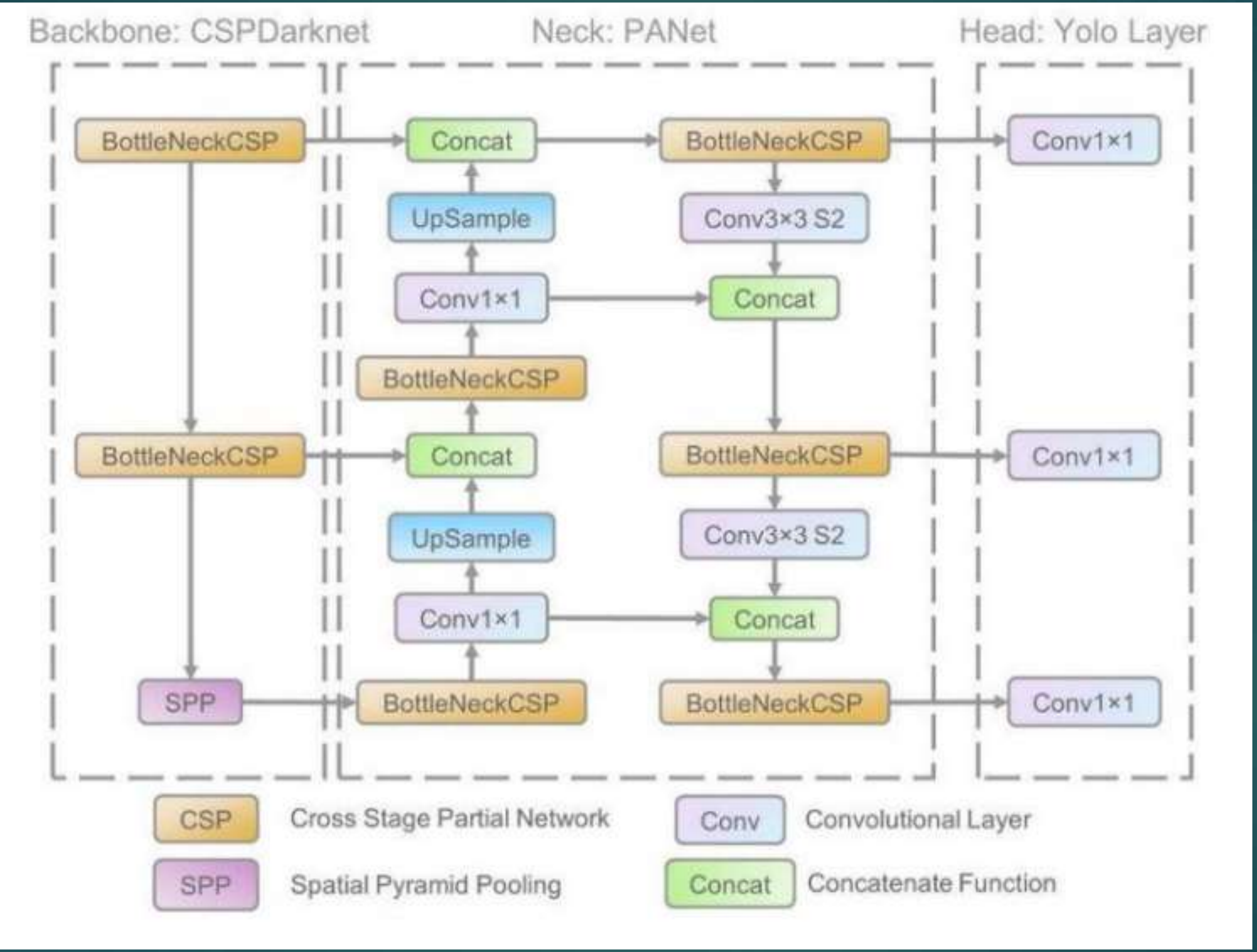
METHODOLOGY

YOLOV5

- YOLO stands for You Only Look Once
- YOLOV5 was launched ultralytics in June 2020 and is now the most advanced object identification algorithm available.
- Object detection in YOLO is done as a regression problem and provides the class probabilities of the detected images.
- The algorithm applies a single neural network to the full image, and then divides the image into regions and predicts bounding boxes and probabilities for each region.

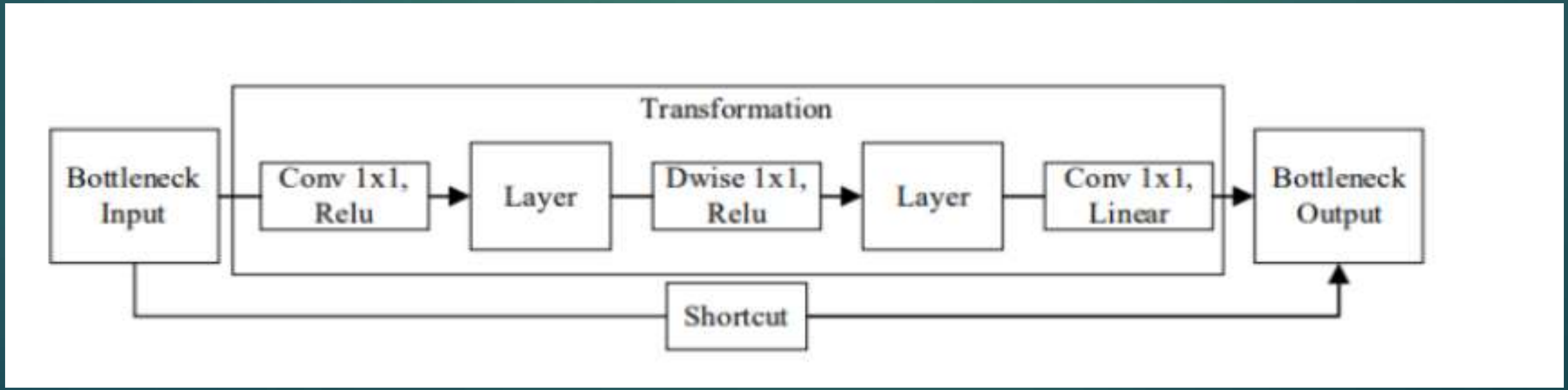
Architecture of YOLOV5

- It consists three parts namely Backbone, neck and head.
- Backbone is mainly used to extract the important features from an image.
- Neck is used to generate feature pyramids
- Head is used to perform the detection


Backbone: CSPDarknet
Neck: PANet
Head: Yolo Layer
BottleNeckCSP
Concat
BottleNeckCSP
Conv1×1
UpSample
Conv3×3 S2
Conv1×1
Concat
BottleNeckCSP
BottleNeckCSP
Concat
BottleNeckCSP
Conv1×1
UpSample
Conv3×3 S2
Conv1×1
Concat
SPP
BottleNeckCSP
BottleNeckCSP
Conv1×1
CSP
Cross Stage Partial Network
Conv
Convolutional Layer
SPP
Spatial Pyramid Pooling
Concat
Concatenate Function

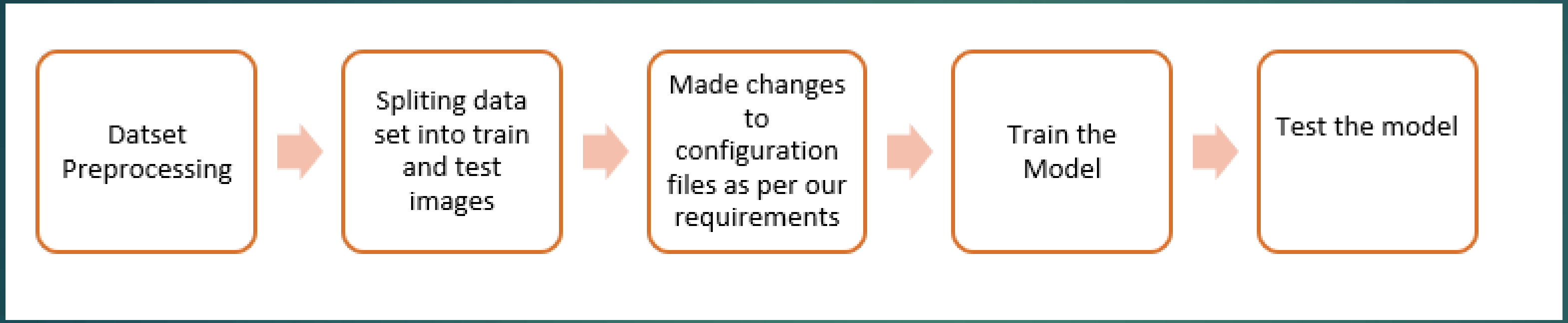
SSD Mobilenet V2

- SSD acronyms Single Shot Detector
- The SSD will generates a fixed-size collection of bounding boxes and scores for the presence of object class instances in those boxes and is followed by a non-maximum suppression step to produce the final detections

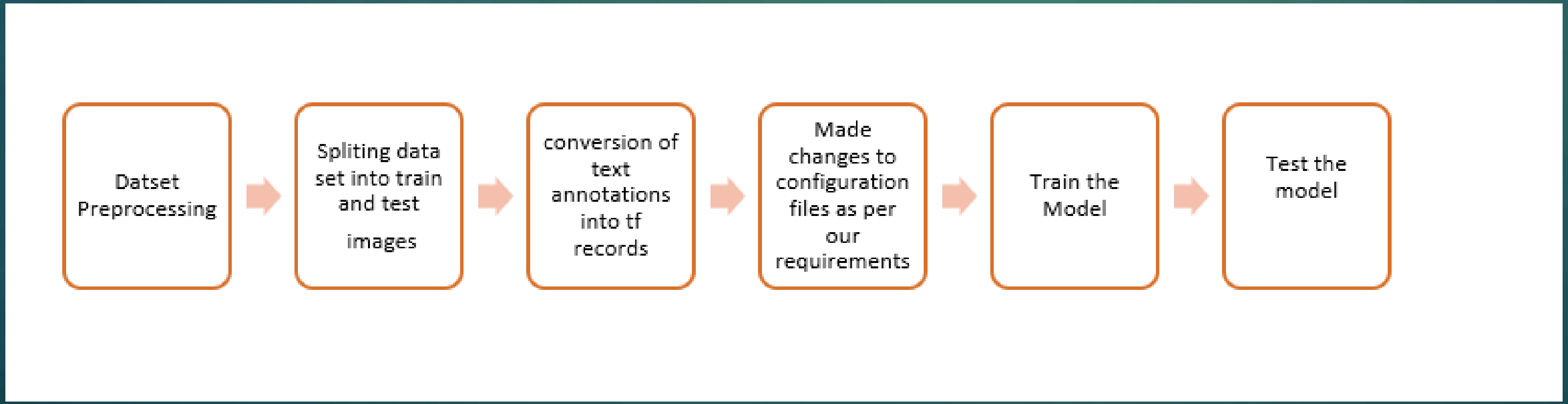


Process flow

- YOLO v5



- SSD MobilenetV2



EXISTING SYSTEM

- Current detection systems repurpose classifiers to perform detection. To detect an object, these systems take a classifier for that object and evaluate it at various locations and scales in a test image.
- After classification, post-processing is used to refine the bounding boxes, eliminate duplicate detections, and rescore the boxes based on other objects in the scene.

DISADVANTAGES

- Complex pipelines
- Slow
- Hard to optimize because each individual component must be trained separately

PROPOSED SYSTEM

- We reframe object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities.

ADVANTAGES:

- Speed
- Accuracy

Experiment Analysis

- Google Colab using inbuilt engine called Python 3 Google Compute Engine Backend.

Dataset

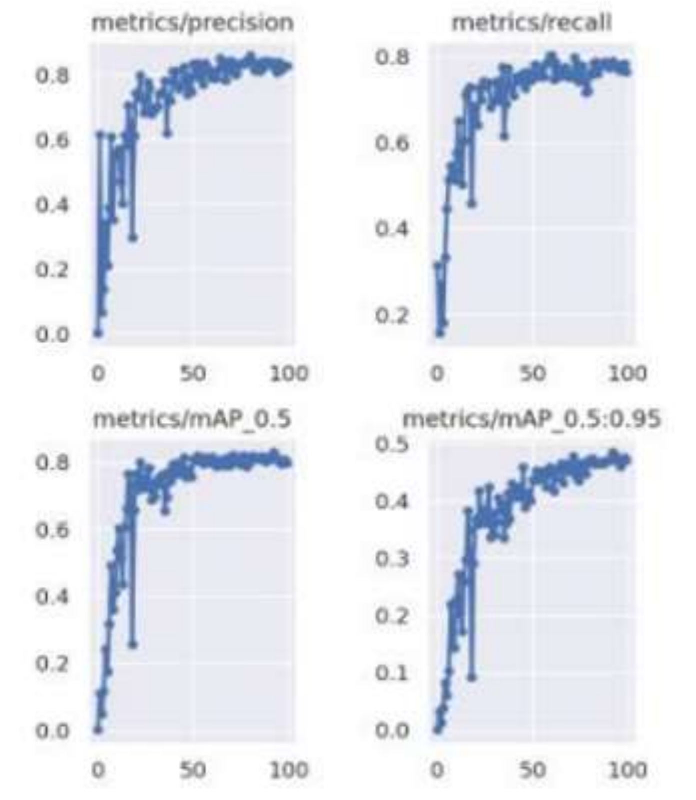
- crop and weed detection data with bounding boxes that is offered on Kaggle website.
- The dataset contains 1300 images of sesame crops and different types of weeds with each image labels

Performance Metrics:

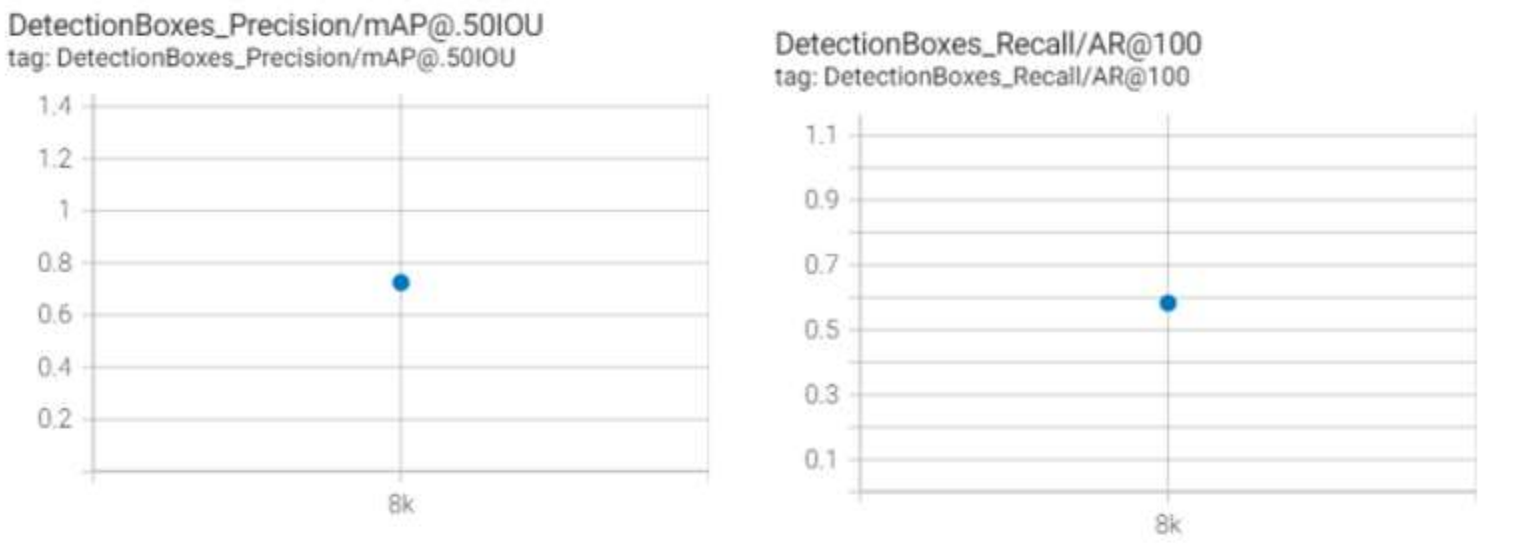
- MeanAveragePrecision
- Precision
- Recall

RESULTS

ALGORITHM	MAP@.5	PRECISON	RECALL
YOLOV5	83%	0.838	0.79
SSD MOBILENET	72.5%	0.725	0.58



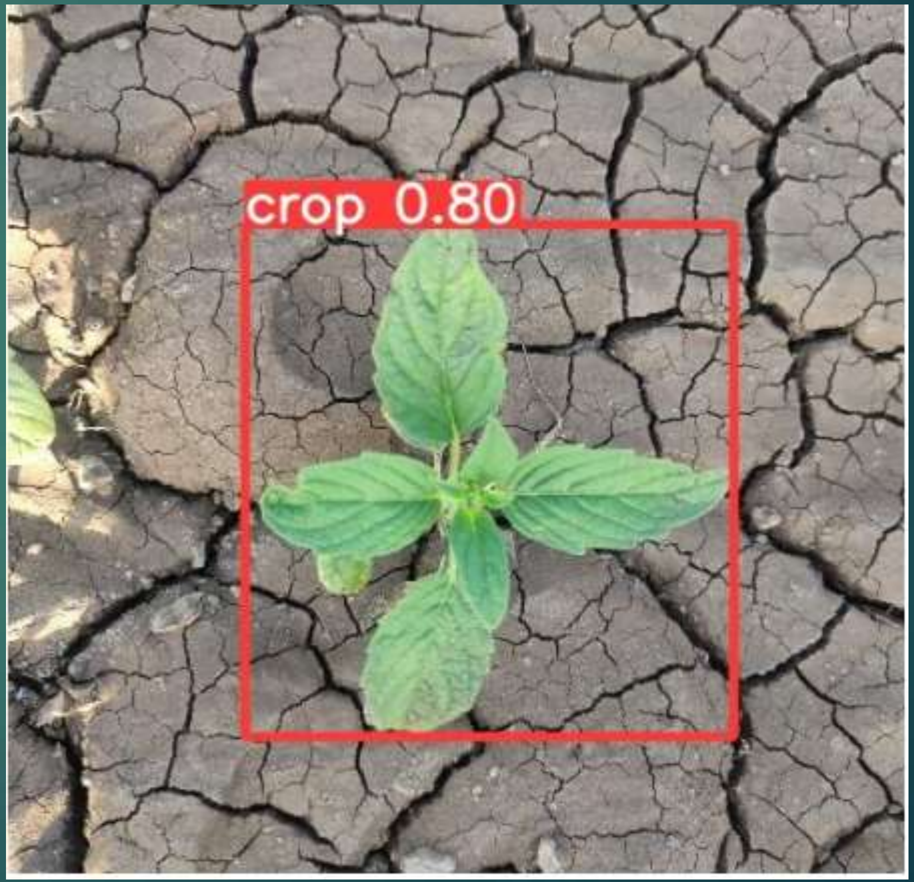
YOLOV5

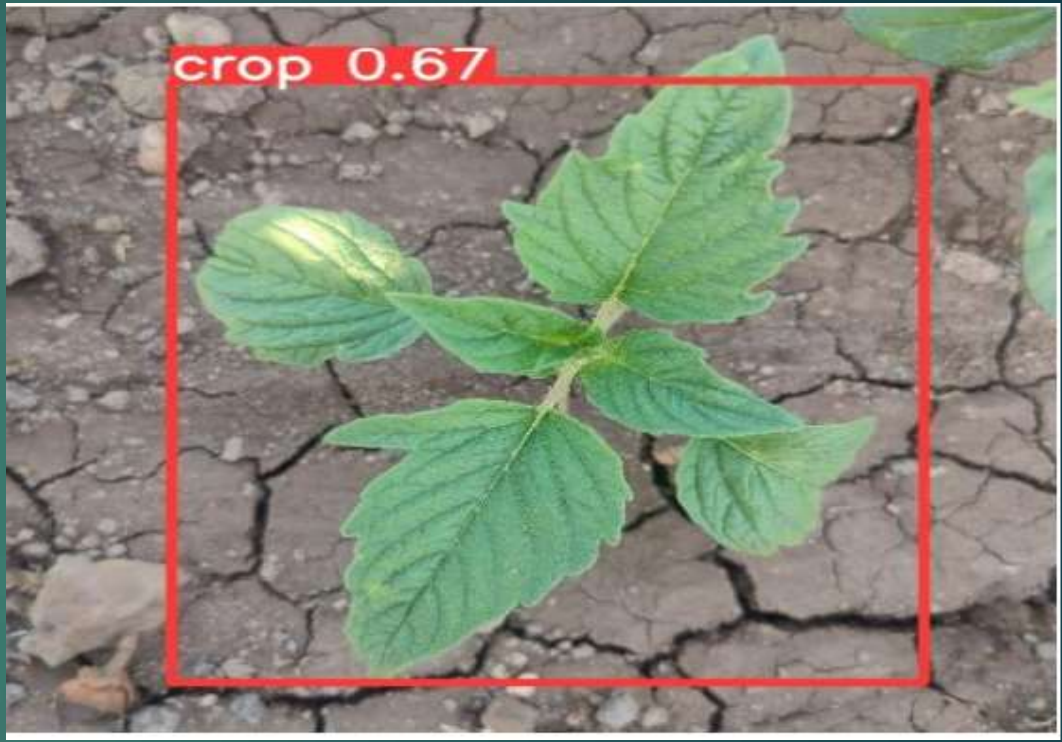


SSD mobilenetV2

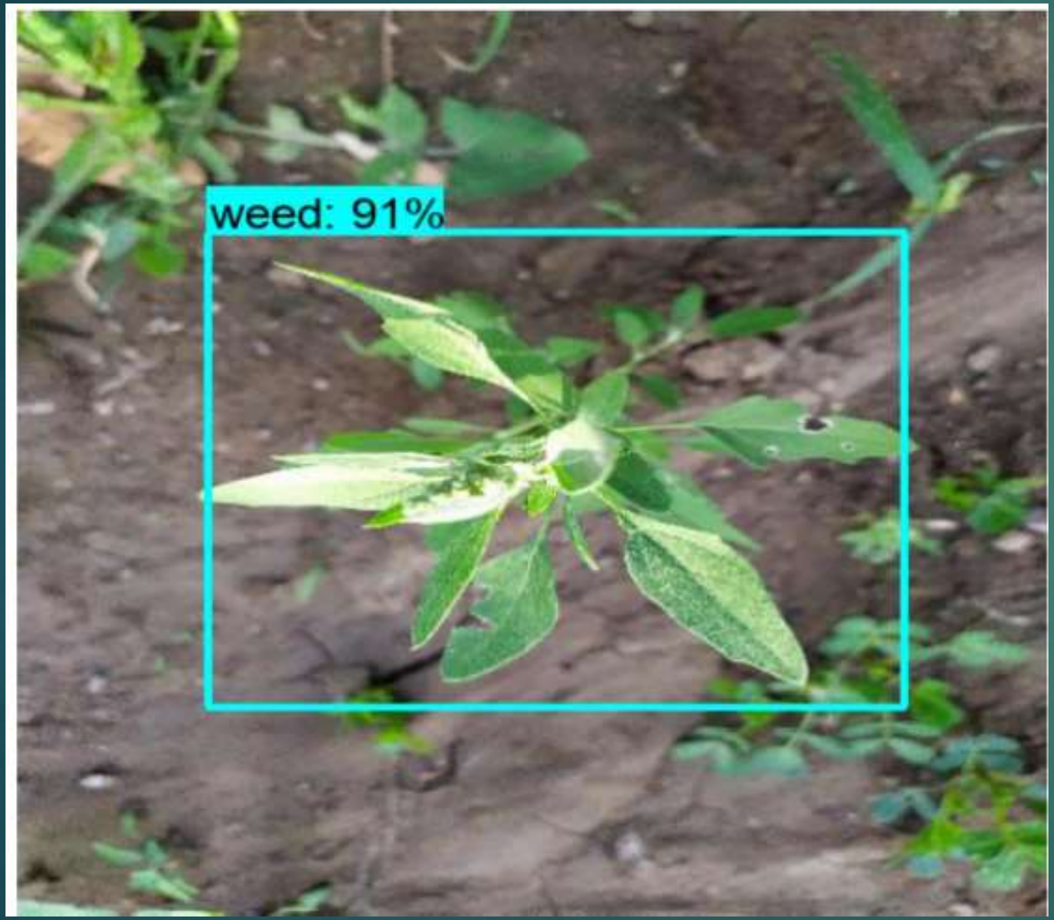
OUTPUT

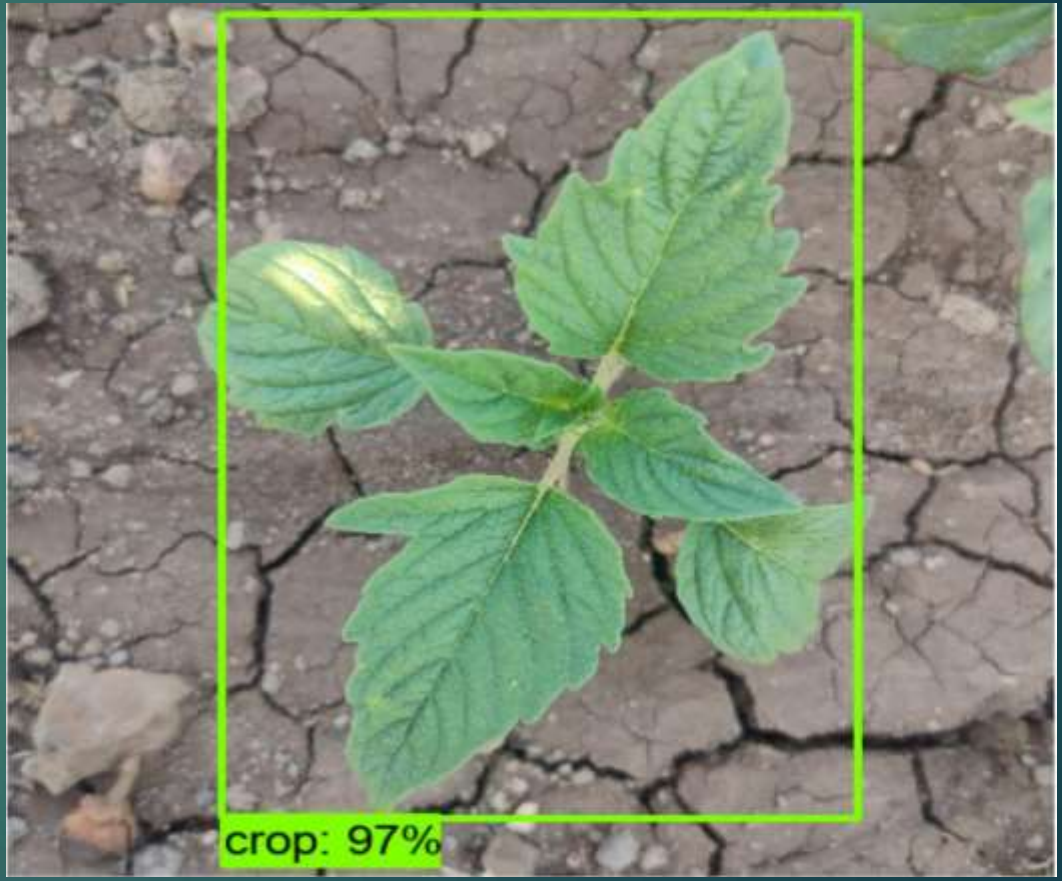
YoloV5




weed 0.69

crop 0.67

SSD MobilenetV2






weed: 84%


crop: 94%

CONCLUSION

- YOLOV5 has map value of 83% and SSD Mobilenet has a map value of 72.5%.
- The time taken to test an image in yolov5 is less when compared with SSD MobilenetV2.
- Yolov5 is better than SSD Mobilenet V2 as it has higher map value and less computation time.
- Yolov5 is more accurate and faster than SSD Mobilenet V2.