Performance of deep learning algorithms for automatic crop type and weed classification

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Presentation Outline

- Introduction and Study background
- Materials and methods
- Research findings
- Concluding remarks

Introduction

- Agricultural management and monitoring are crucial aspects of modern-day farming.
- With the increasing demand for food and a growing global population, the need for efficient and effective agricultural practices has become more pressing than ever.

Introduction

- The idea of precision agriculture (PA), also known as smart farming, has been discussed in the agricultural sector as a management method since the middle of the 1980s.
- Precision Agriculture is a systematic technique and also a management system of using the proper quantity of input at just the appropriate time and place to increase productivity and minimize chemical use in order to protect the environment from pollution (Zhang & Kovacs, 2012; Huang & Thomson, 2015).

Introduction

- It refers to the use of advanced technologies such as sensors, GPS, and drones to optimize agricultural practices, increase efficiency, and reduce waste.
- It involves collecting and analyzing data to make informed decisions about planting, fertilizing, and harvesting crops, as well as managing soil and water resources.
- The ultimate goal is to increase productivity and profitability while minimizing environmental impact.

Introduction

- Unmanned Aerial Vehicles (UAVs) have emerged as an important tool for agricultural monitoring and management.
- UAVs can capture high-resolution images of agricultural fields, which can be used to identify crop types and detect weeds.
- Therefore, UAV imaging technologies can be employed for many precision agriculture operations such as plant health tracking (McCabe *et al*., 2015), weeds control (Hassanein & El-sheimy, 2017), and plant row identification (Slaughter *et al*., 2008).

Introduction

- However, manually analyzing UAV images for agricultural applications can be time-consuming and prone to errors.
- Deep learning (DL) algorithms, which are a subset of machine learning techniques, have shown great promise in the field of image classification (Rodriguez-Galiano et al., 2012).
- DL algorithms can automatically learn and extract features from images, which can be used to classify objects in the image.

Introduction

- In recent years, various deep learning algorithms have been used for automatic crop type and weed classification on UAV images.
- However, the performance of these DL algorithms can vary depending on the specific algorithm used, the dataset used for training, and the preprocessing techniques applied.

Introduction

- While DL has proven to be a powerful tool for a wide range of applications, it also has some limitations and potential drawbacks. Some of which includes the data requirements and overfitting.
- Deep learning algorithms require a large amount of data to be trained effectively, and this can be challenging and expensive to acquire, especially for small organizations or individuals.
- This can make utilizing DL algorithms quite difficult for smallholder farmers in precision agriculture because of their small farmlands

Introduction

- The goal of this study is to evaluate the performance of two popular deep learning algorithms, YOLOv5 and faster RCNN, for automatic crop and weed classification on UAV images.
- YOLOv5 is a state-of-the-art object detection algorithm that can detect objects in real-time, while RCNN is a more traditional object detection algorithm that has been used extensively in the past.
- We will be comparing the performance of these algorithms based on various metrics, including accuracy, precision, and recall.

Introduction

- Faster RCNN is built on the original region-based methodological framework called the Region Based Convolutional Neural Network (RCNN) (Girshick *et al*., 2015).
- The RCNN required a lot of computing work because each suggested location required a CNN-based feature extraction.
- YOLO version 5 is one of the versions of the You Only Look Once class algorithm, which is an advanced object detector that does exceptional real time object identification (Francies *et al*., 2022).

Introduction

- These two CNN architectures were implemented on the drone images of a mixed cropping farm for an automated identification and classification of weeds from four (4) different crop classes.
- The significant influence of various training iterations or epochs on the overall performance of the algorithms weed identification and classification scheme was also investigated.
- Five varying epochs were experimented to determine the optimal point of the training phase before the model begins to flatten out.
- For FRCNN, 10,000, 20,000, 100,000, 200,000, and 242,000 epochs were tested while 100, 300, 500, 600, 700 and 1000 epochs were tested for YOLOv5.

Study area

- The study area is about 2.2 Ha in area and it is a mixed crop farmland located in Lapan Gwari.
- Lapan Gwari, Minna, Niger State is located within geographical coordinates (9°31'33"N 6°30'02"E), and (9°31'37"N 6°30'05"E), under Bosso LGA area is situated at about 7km away from F.U.T Minna permanent site.
- The natives are Gwaris and they depend solely on agricultural practices such as crop cultivation and fish farming. The natives mostly practice mixed cropping such as, pepper, vegetables, sugarcane, rice maize and yams.

Study Area

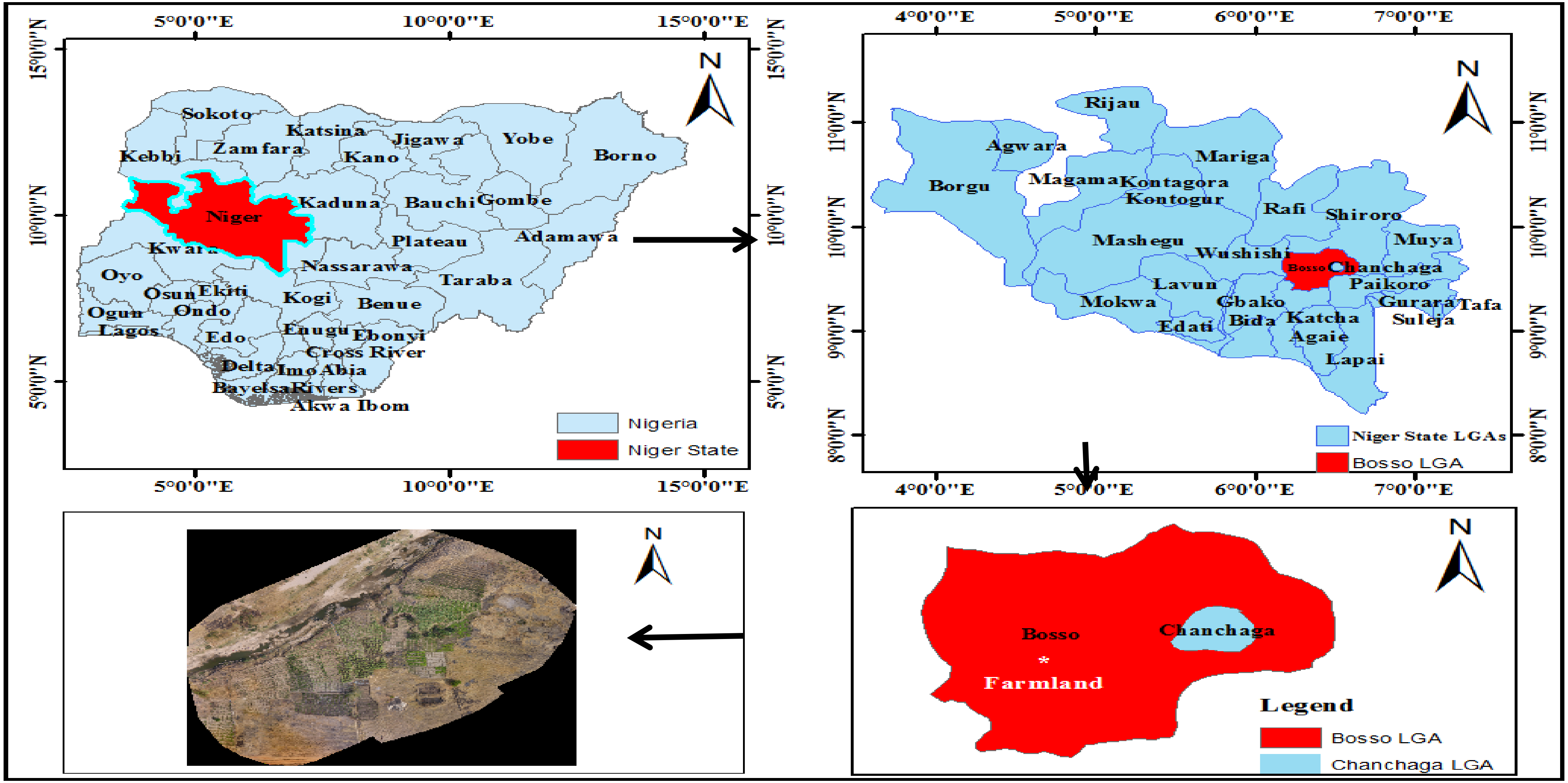

Figure 1: The geographical location of the study area

Dataset

- Using DJI Phantom 4 done, about 254 nadir photographs were captured at a flying height of 30 m, mapping speed of 7 mph having a side and front overlap of 75%, correspondingly.

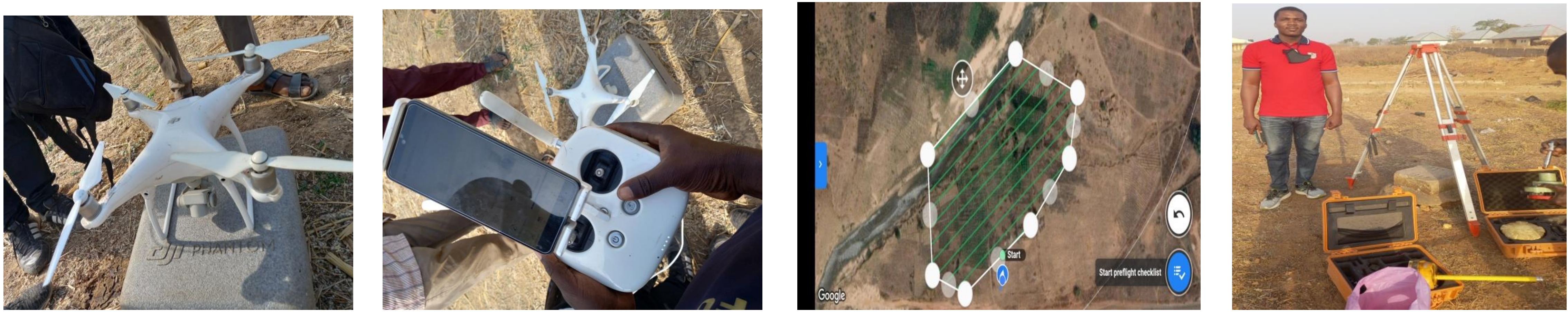

Figure 2: Unmanned aerial system design for field data collection

Image pre-processing and preparation

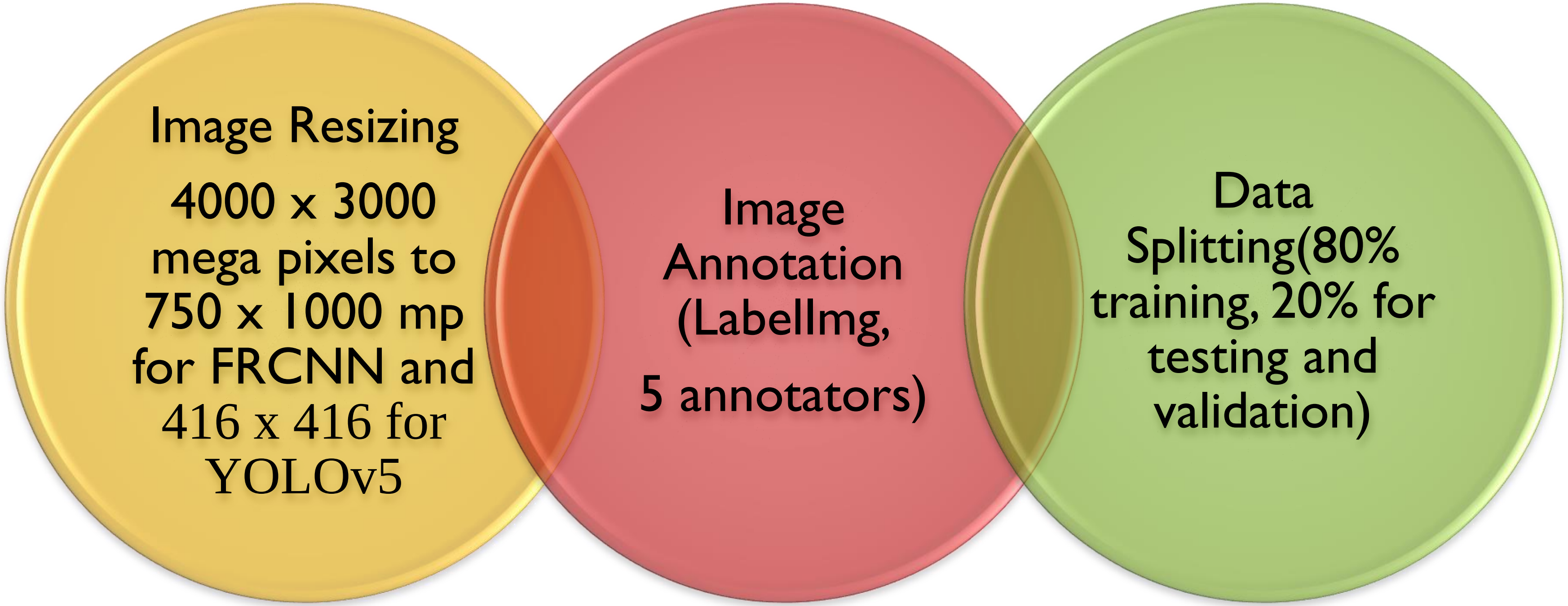

Figure 3: Pre-processing workflow

Model training

- The models were trained on Google Colab having a GPU (NVIDIA GeForce GTX TITAN X (Linux)) employing Google Colaboratory Free with a GPU R-80 and RAM 16GB and Google ColabPro with GPU K80,T4,P100 and RAM 32GB.
- Tensorflow and CUDA/CuDNN were implemented to parallelize computations on the GPU.
- Five (5) classes (sugarcane, spinach, pepper, banana, and weed) were defined, having a learning rate of 0.0002, a batch size of 32, for FRCNN and a batch size of 16 images for YOLOv5 was used due to the higher complexity of the model.

Implementation workflow for FRCNN

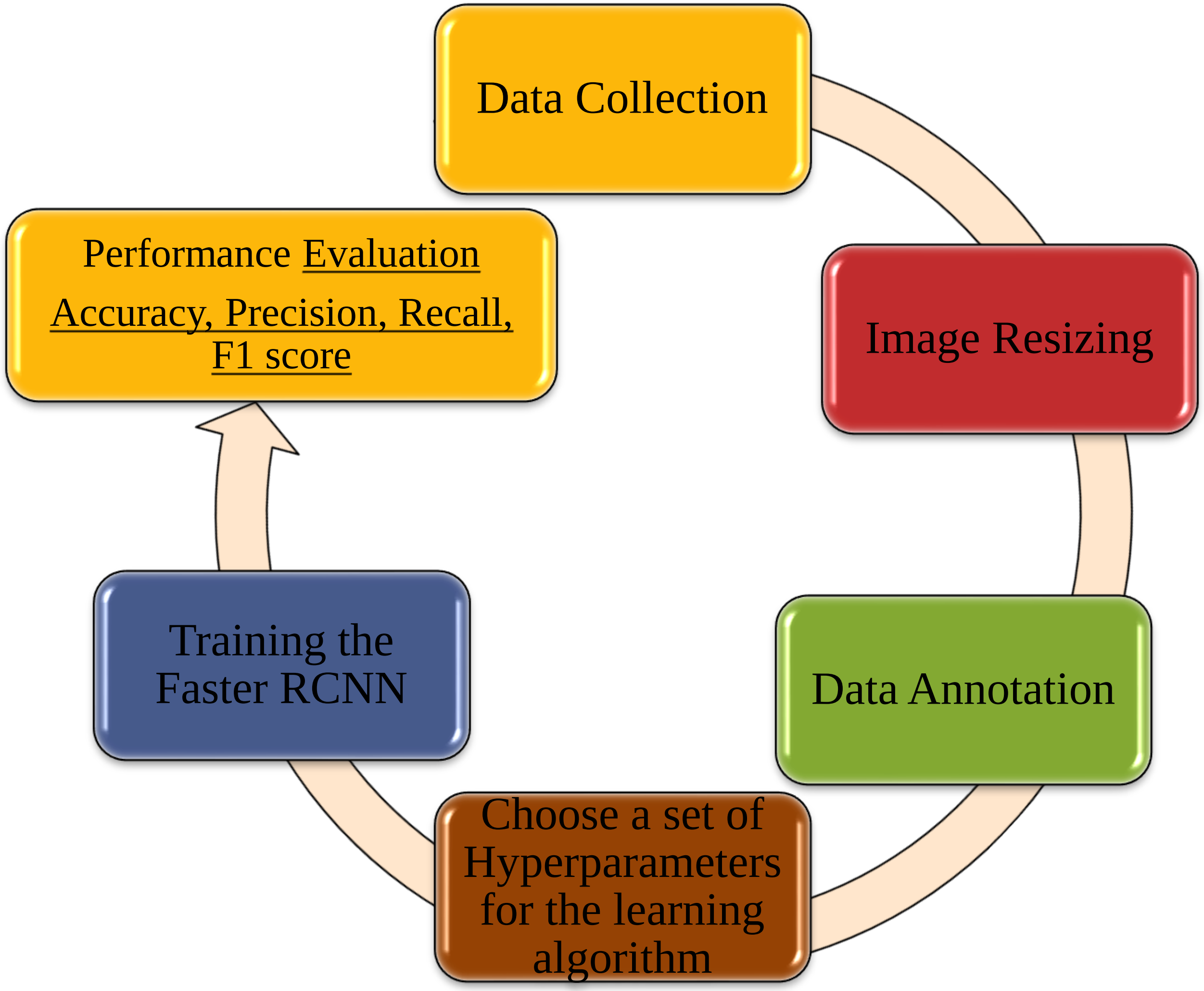

Figure 4: The workflow-FRCNN

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Implementation workflow of YOLOv5

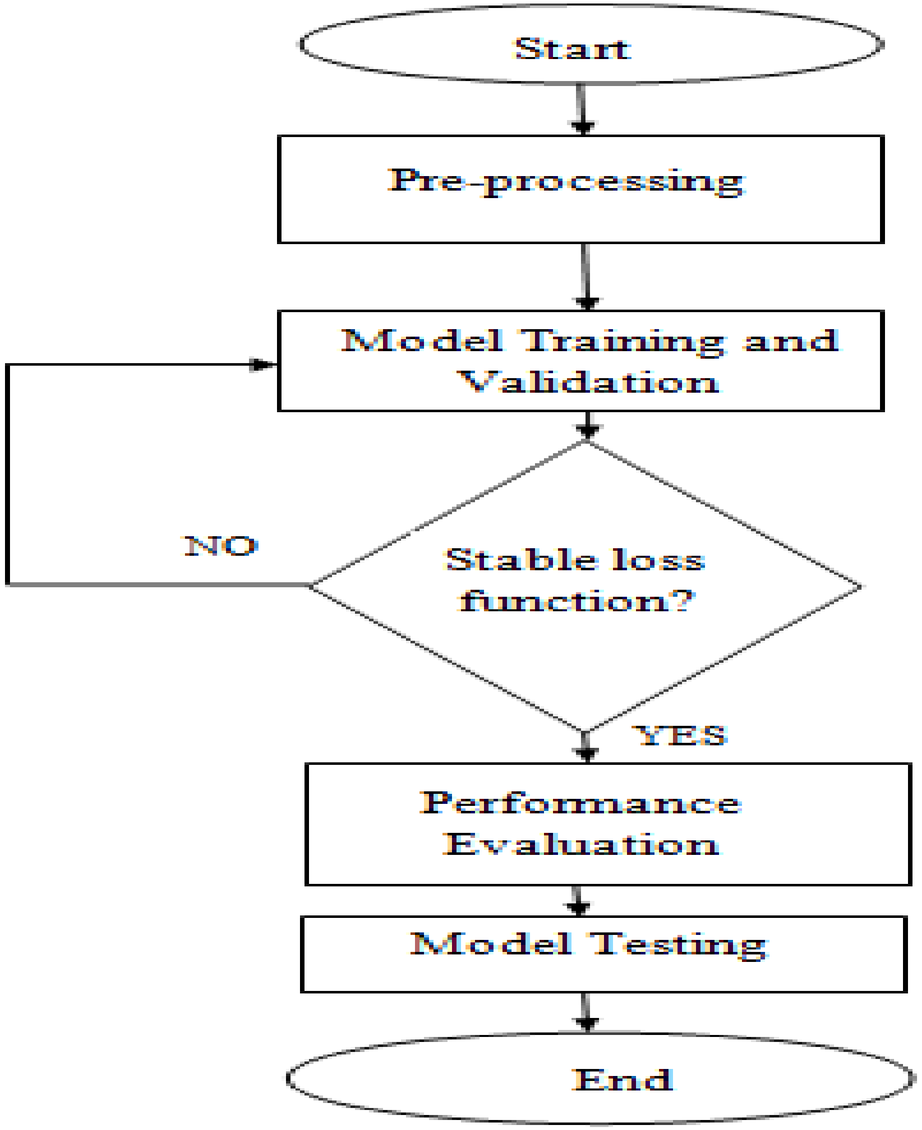

Figure 5: Process workflow for implementing YOLOv5

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FINDINGS AND DISCUSIONS

Performance Evaluation of FRCNN

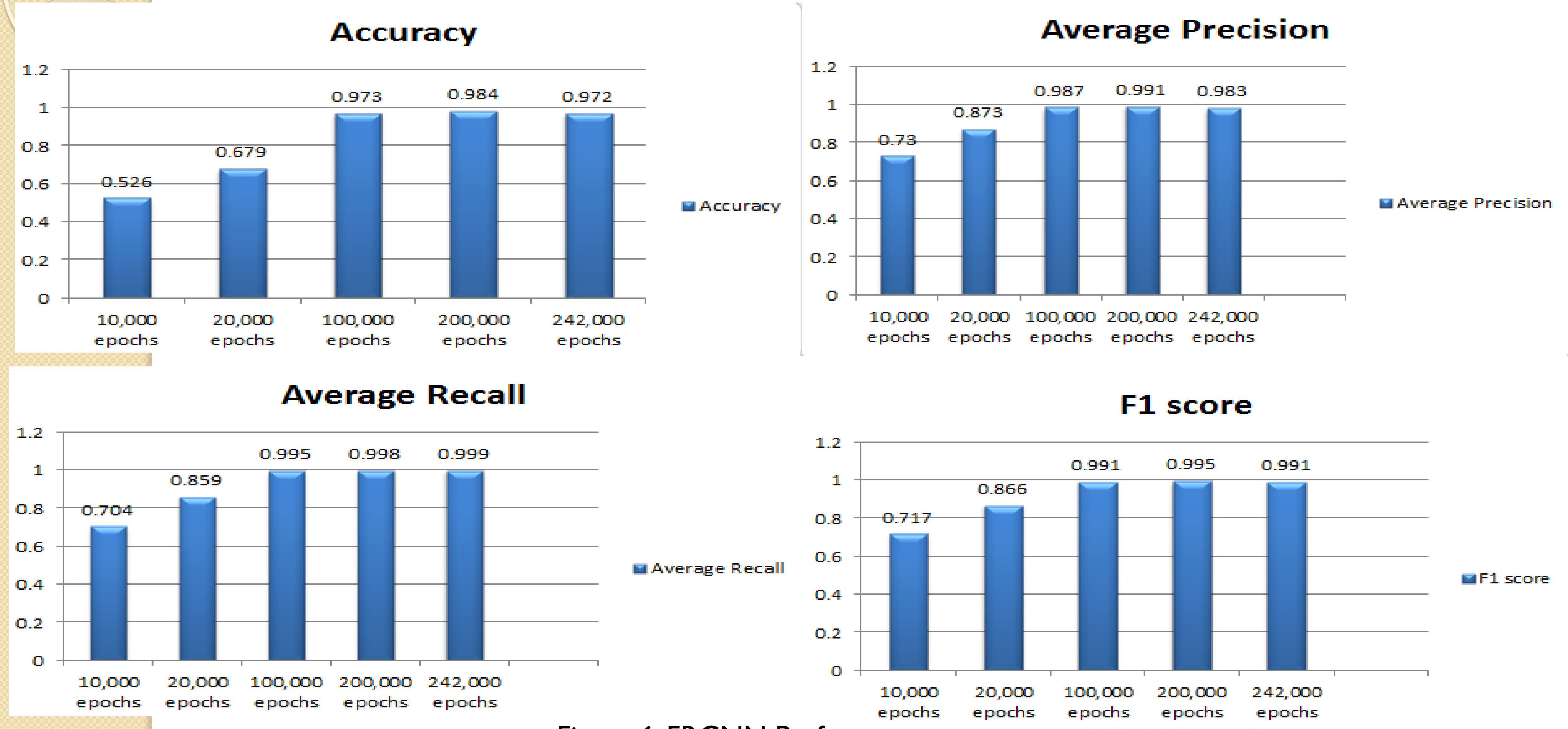

Figure 6: FRCNN Performance

Model classification using bounding box-FRCNN

Figure 7(a): FRCNN at 10,000 epochs

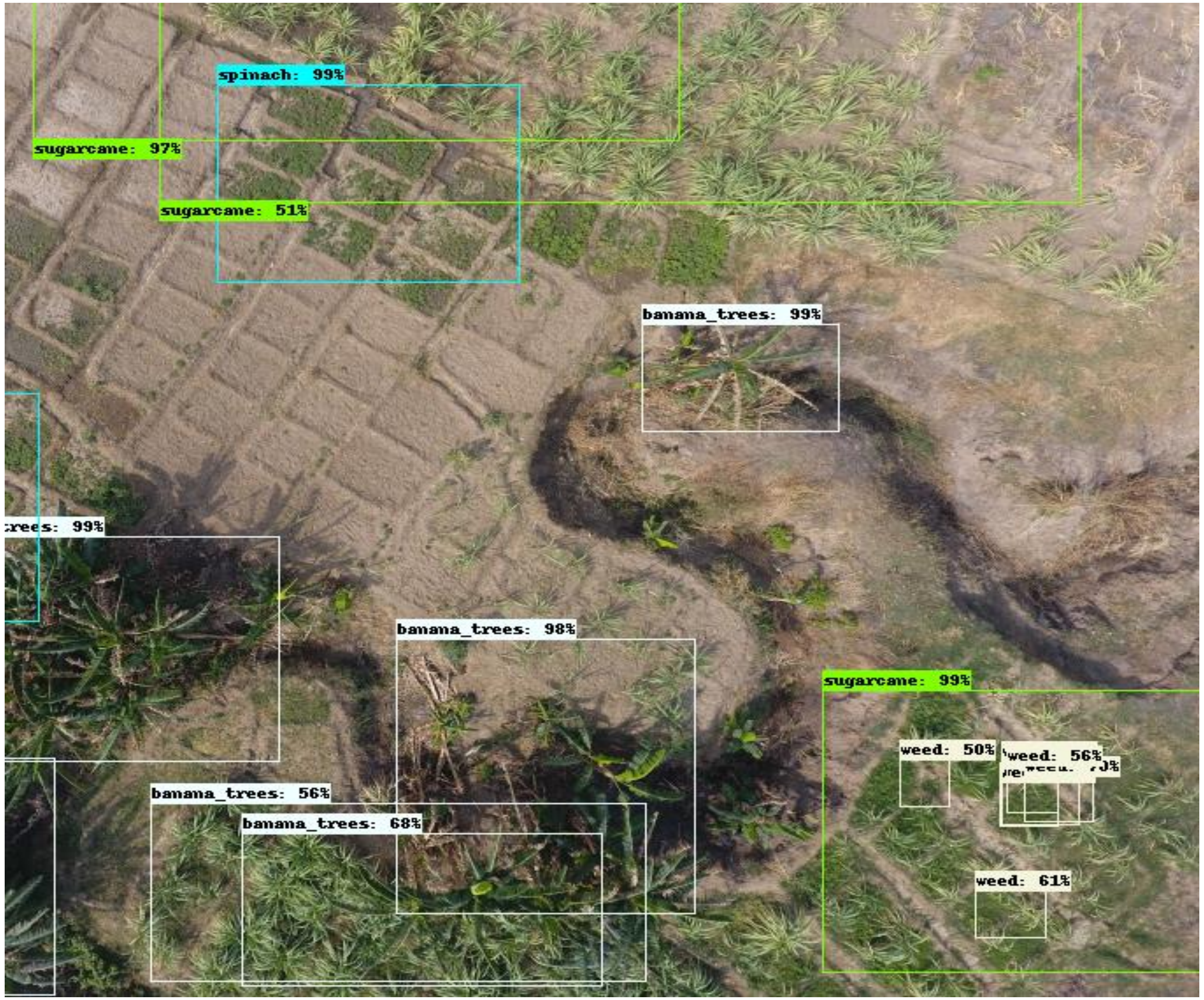

Figure 7(b) FRCNN at 20,000 epochs

Model classification using bounding box-FRCNN

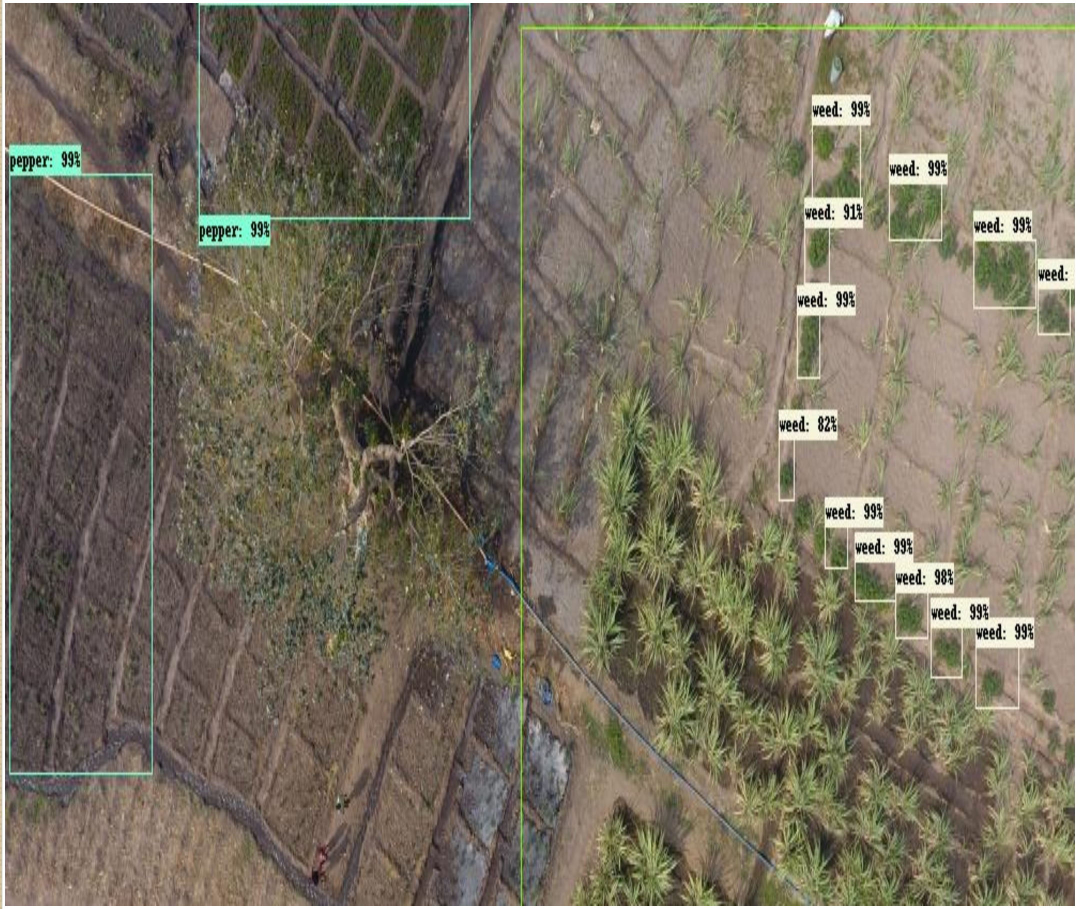

Figure 7(c): FRCNN at 100,000 epochs

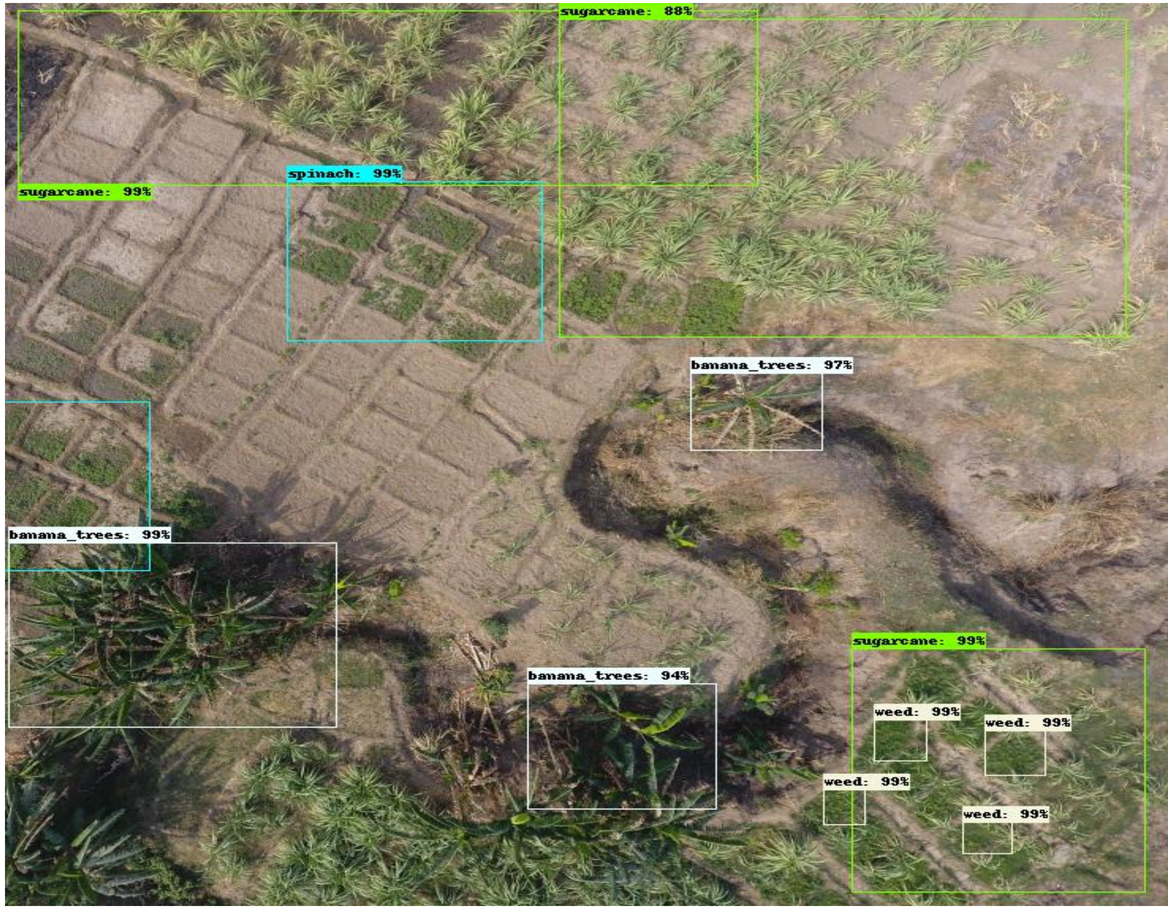

Figure 7(d): FRCNN at 200,000 epochs

Model classification using bounding box-FRCNN

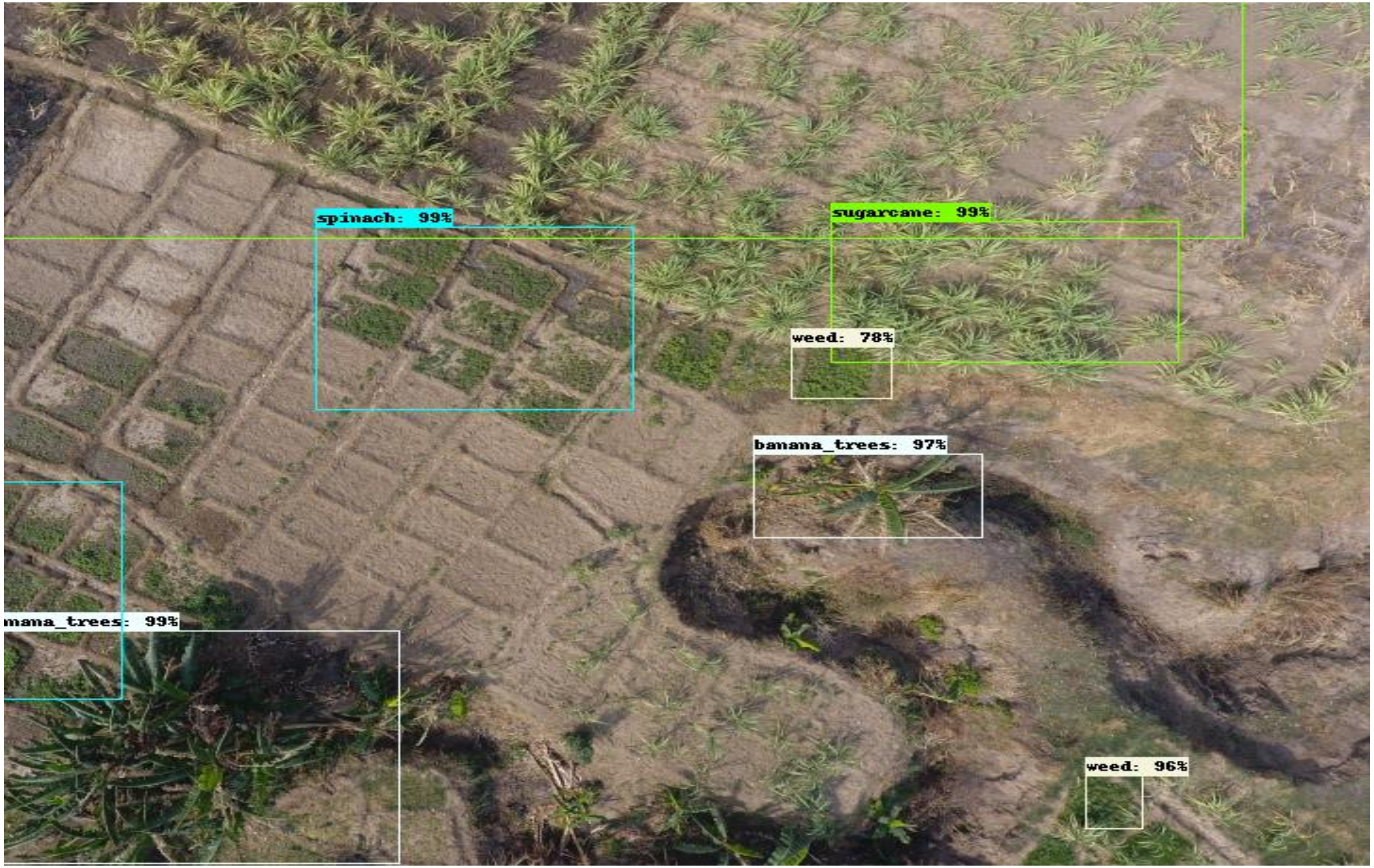

Figure 7(e); FRCNN at 242,000 epochs

Graphical illustrations of the YOLO metrics from 100 to 1000 epochs

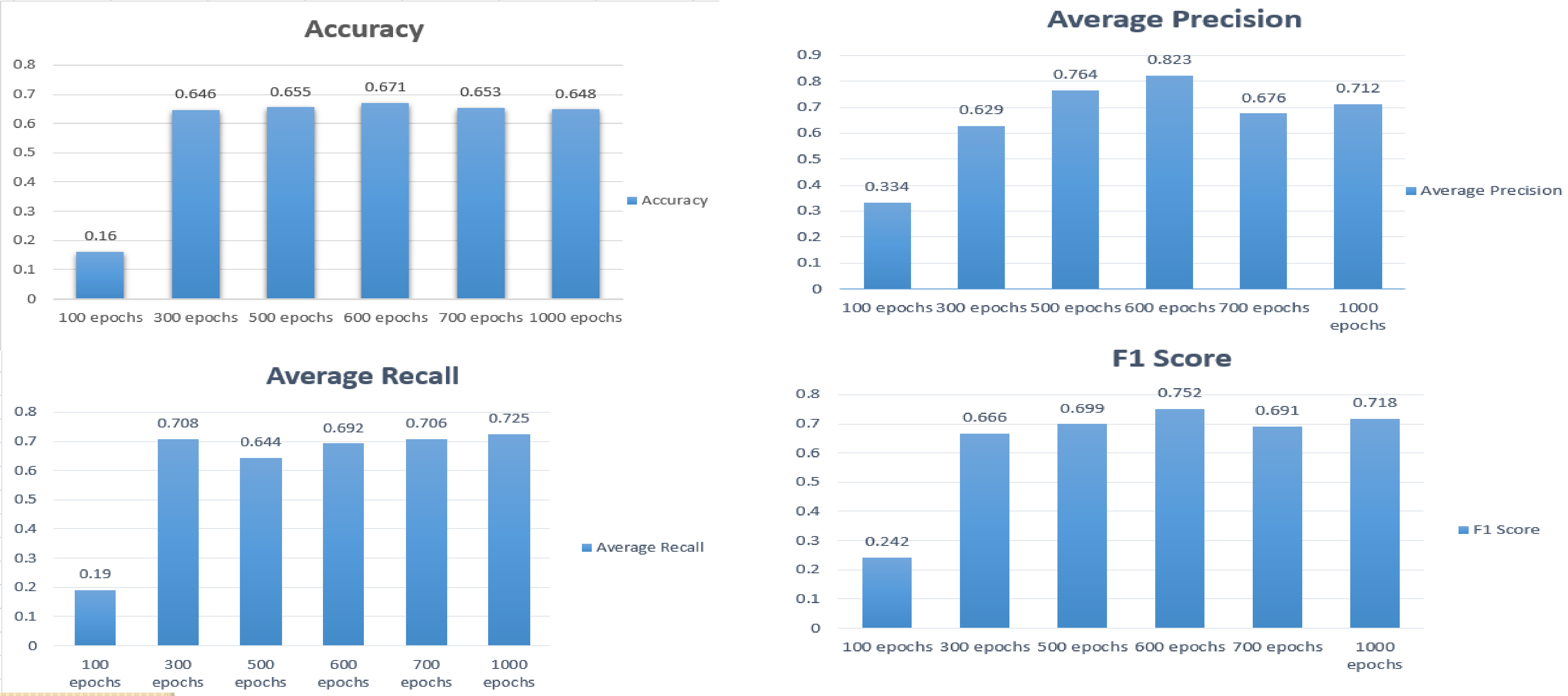

Figure 8: FRCNN Performance

Weed and crop type model visualization of YOLOv5

Figure 9 (a):YOLOv5 at 100 epochs

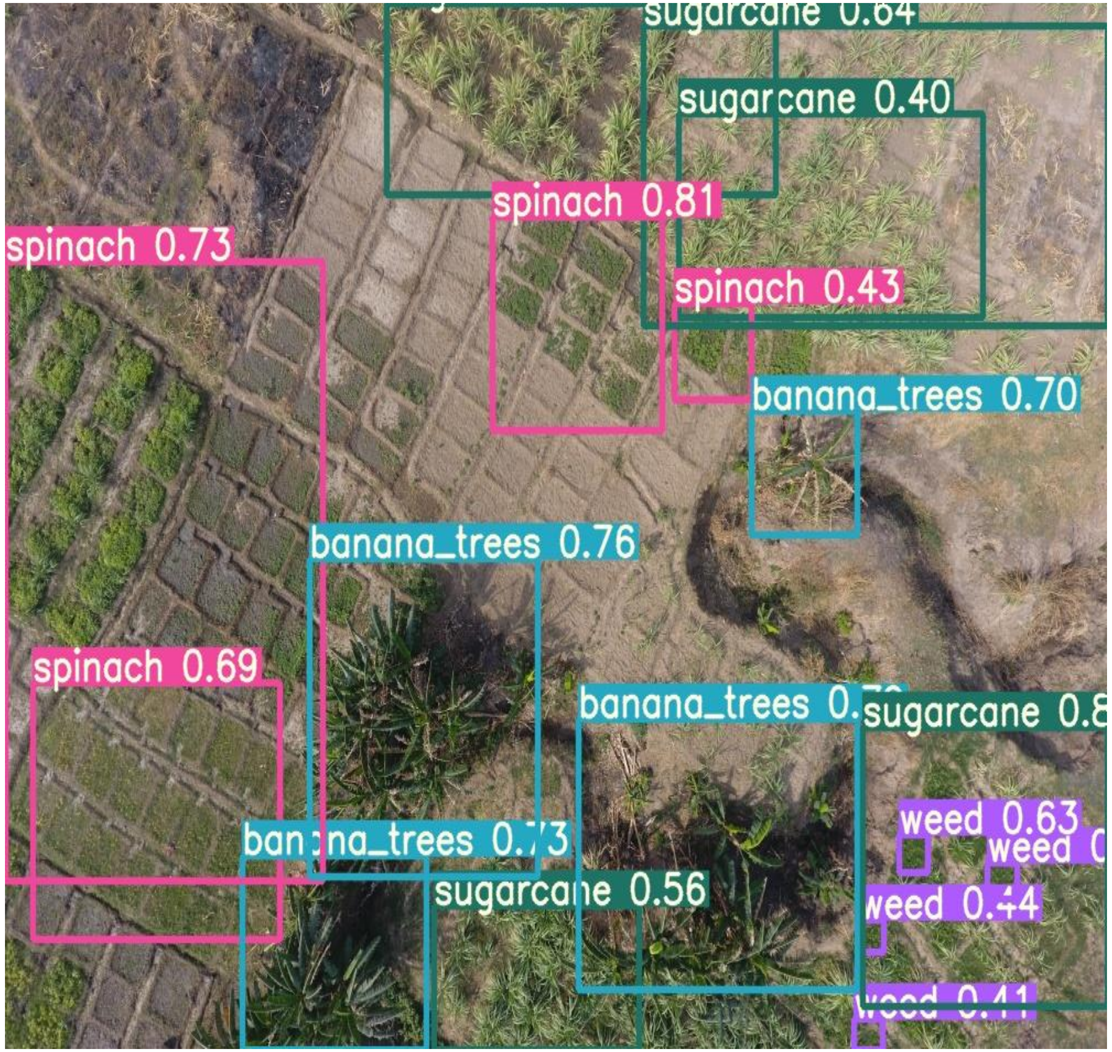

Figure9 (b): YOLOv5 at 300 epochs

Weed and crop type model visualization of YOLOv5

Figure 9(c): YOLOv5 at 500 epochs

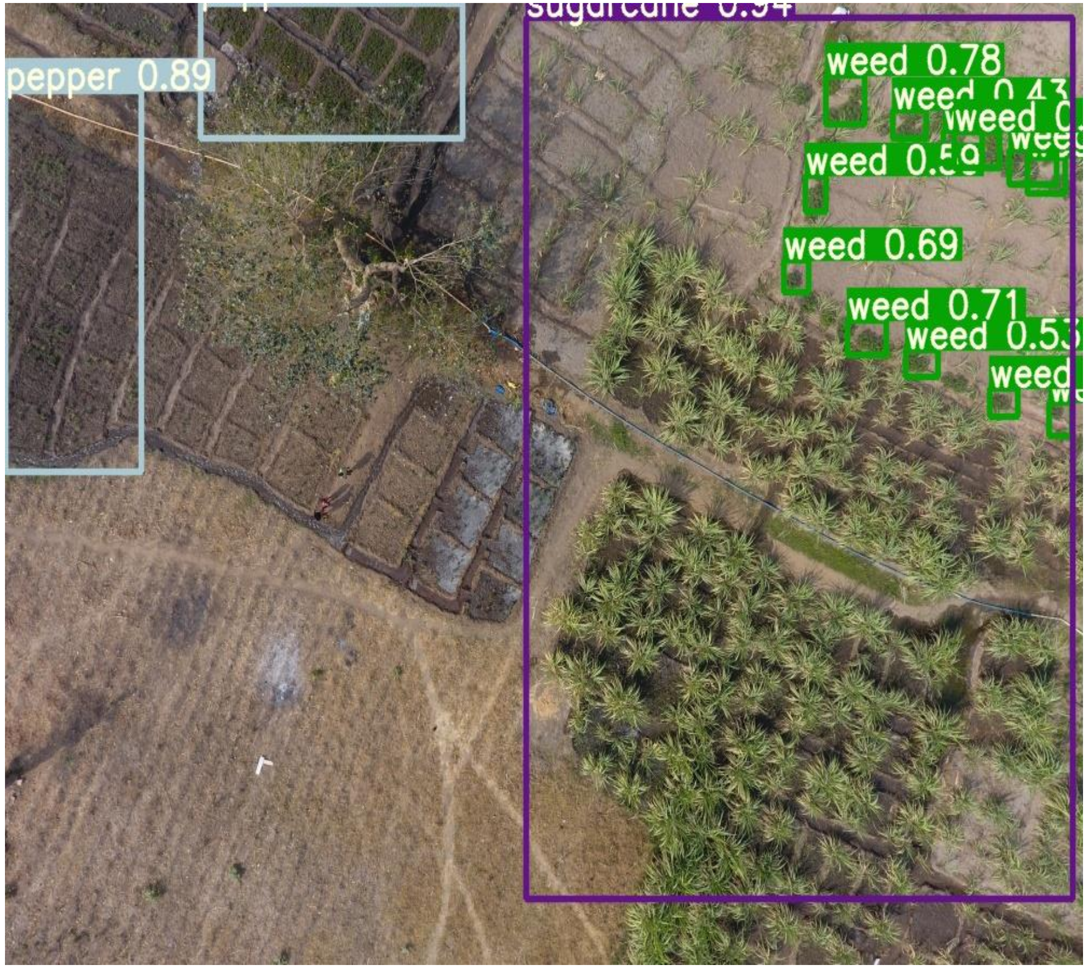

Figure 9(d): YOLOv5 at 600 epochs

Weed and crop type model visualization of YOLOv5

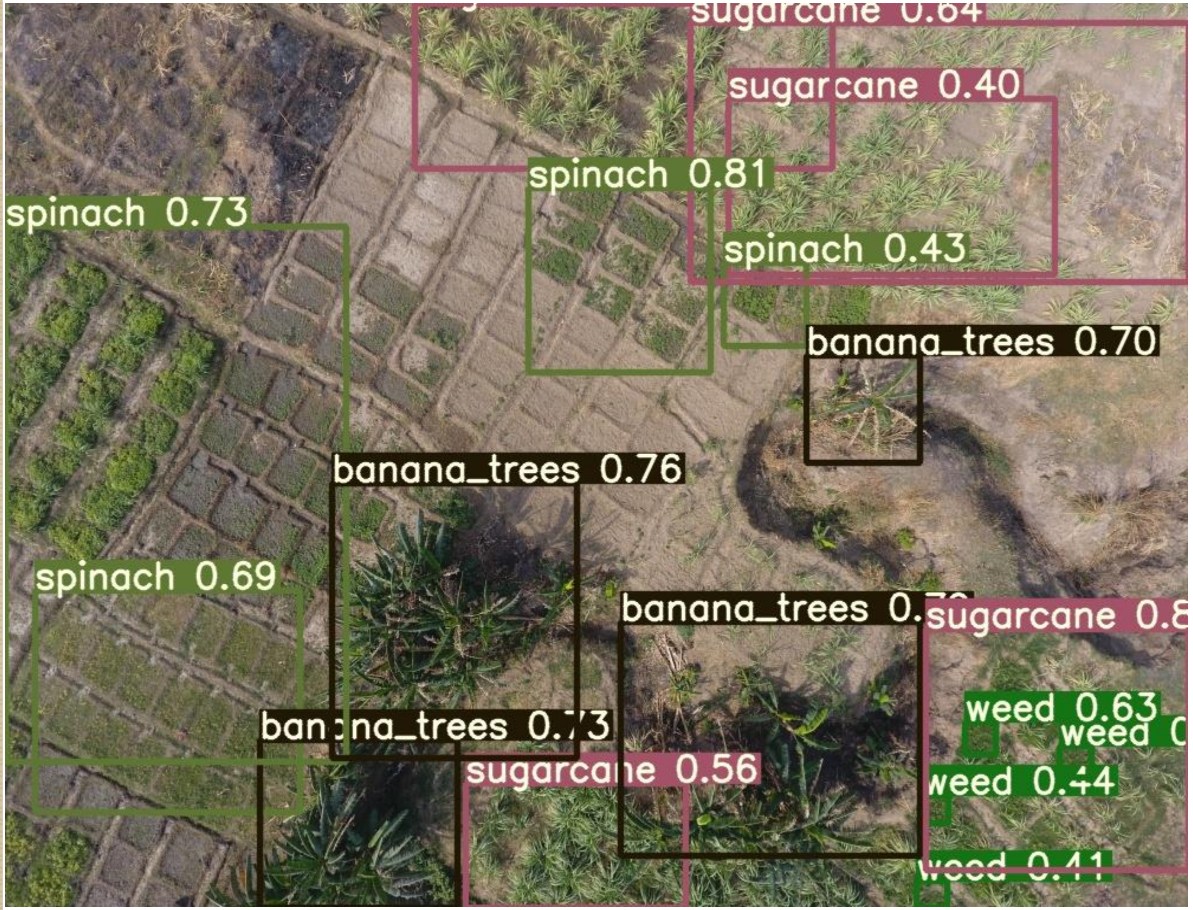

Figure 9(e): YOLOv5 at 700 epochs

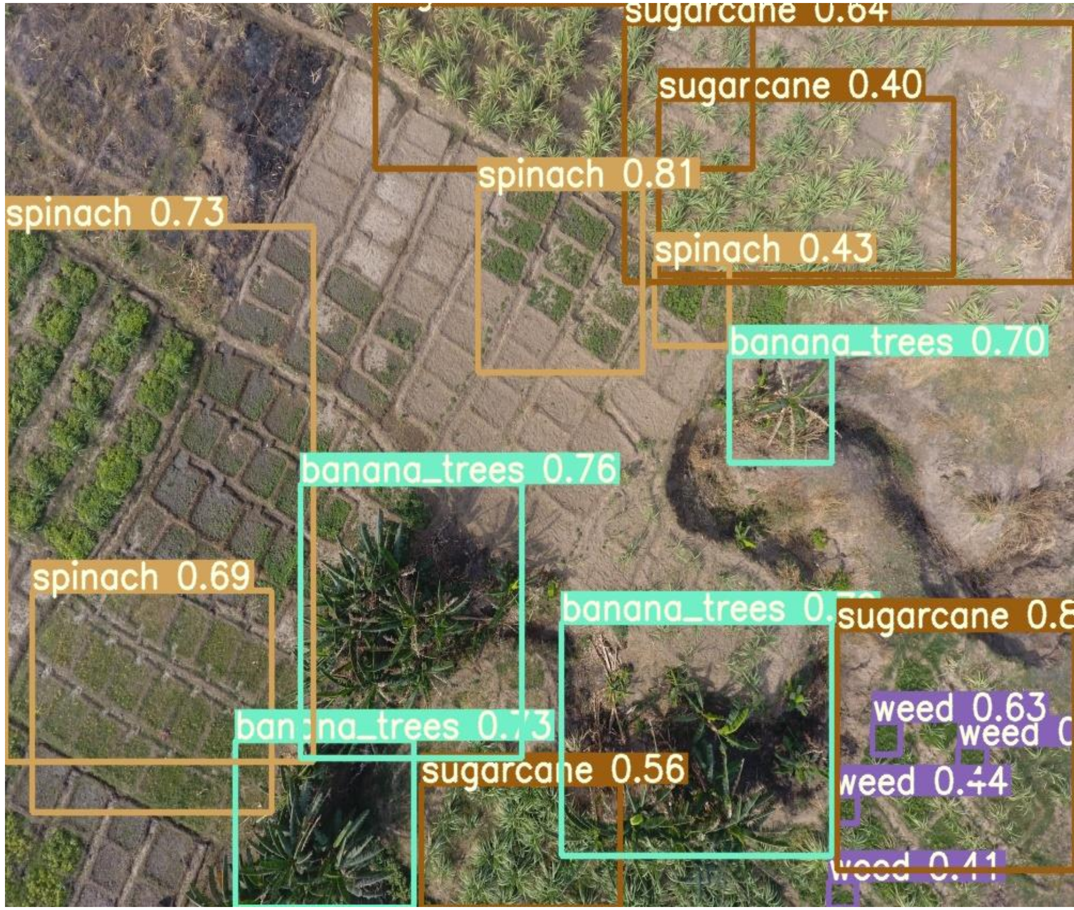

Figure 9(f): YOLOv5 at 1000 epochs

Processing Time

Table 1: Average processing time for training two distinct models.

Classifier	Epochs	Training time per classification
Faster RCNN	10,000	27 minutes
	20,000	54 minutes
	100,000	3 hours 6 minutes
	200,000	7 hours 9minutes
	242,000	9 hours 6 minutes
YOLO v5s	100	4 minutes 62 seconds
	300	11 minutes 88 seconds
	500	18 minutes 48 seconds
	600	22 minutes 92 seconds
	700	25 minutes 86 seconds
	1000	38 minutes 22 seconds

Concluding remarks

- This research integrated two methods which are the Faster RCNN inception v2 model and YOLOv5s architecture making use of UAV imagery for weed detection
- The model improved significantly with increase in the numbers of epochs.
- Faster RCNN out-performed the YOLO v5 model in terms of performance accuracy.
- Faster RCNN attained its optimal result when trained at 200,000 epochs while Yolov5 attained its optimal result when trained at 600 epochs. Both models began to flatten out after this epochs

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Thank you for listening