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AI-Guided Drone-GPS Detection of Fall Armyworm Pest and Symptoms in Maize Farm

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Abstract **- The invasion of the fall armyworm into African farms has posed a significant threat to maize production, resulting in huge economic losses for farmers and threatening food security on the continent. Most farmers have tackled this menace using chemical methods, but excessive use of insecticides carries environmental and health risks. Early detection of this pest will facilitate control and limit pesticide use through precision spraying. This study exploits all the features of the pest and its symptoms to train a robust deep learning model that can identify the presence and symptoms of this pest on maize plants. Images of fall armyworm and its symptoms on maize farms were gathered across three locations in Nigeria. The YOLO (You Only Look Once) algorithm was used to train the deep learning model until consistent and fair performance metrics were obtained. From the developed model, a mobile app was created in Android Studio, while another version of the model was deployed on a laptop in a Python environment. A demonstration farm was set up for maize plantation. The mobile app showed excellent performance in detecting the pest and its symptoms. To further automate the detection process, a drone (DJI technology) was used to scan the farm in waypoint mode, and its recordings were linked to the model on the laptop with satisfactory detection and even counting of the number of detections obtained. GPS locations of the detection spots were collated in real time. This development enables capacity for on-the-spot precision spraying as a more economical approach to pest eradication.**
Keywords: **Fall Armyworm, Drone, AI, Maize, Precision, App**

I. INTRODUCTION

Fall armyworm (FAW) is a highly polyphagous pest with wide-ranging effects on scores of plant families (Montezano *et al.,*[35]). The pest has a particularly alarming rate of spread across different parts of the world. Though native to the Americas, its detection in West Africa in 2016 signalled its rapid spread to other parts of the world in just a few years (Goergen *et al.,* [16]; Cock *et al.,* [7]). It has reportedly been found in more than 30 sub-Saharan countries (FAO 2018; Prasanna *et al.,* 2018). Since its invasion of West Africa, it has caused significant losses to farmers and negatively affected household food security. In the Benin Republic, 93.9% of the maize surveyed was infested by the pest, amounting to yield losses of 797.2 kg of maize per hectare, representing 49% of the average maize yield commonly obtained by farmers (Houngbo *et al.,* [20]). On maize alone, damage caused by FAW is estimated at between 8.3–20.6 million tonnes across Africa if no plant protection strategy is employed Day *et al.,* [10].

Control methods have primarily involved the use of synthetic chemicals as pesticides as well as genetically modified crop varieties (Abrahams *et al.,*[2]). However, there are health and environmental implications associated with excessive use of synthetic chemicals. Generally, smallholder farmers in developing economies rely on manual applications of these synthetic chemicals for pest control. This usually happens after physical observation of symptoms on the field, since physical observation of pests or their symptoms is the most common means of detecting their presence on farms. This method may be ineffective for pests such as the fall armyworm, whose spread is very rapid and whose havoc on crops can occur within a short period of time.

At the current age, automating the detection of pests and their symptoms is key to the monitoring and control of pests such as FAW, thus reducing their effects on crop health and yield. Applying computer vision, IoT and UAVs are veritable means to automate agricultural practices, prevent, and control crop pests. Myriads of physico-chemical sensors and deep learning algorithms have become cheaply and easily accessible for farming processes. Using these technologies will return maximum productivity on farm produce to farmers while also assuring nations of food sufficiency. Future deployment of IoT in the downstream parts of agriculture, such as storage, sales, and conversion, will boost its application in broader parts of the economy. IoT is currently well applied in monitoring crop storage conditions like humidity, temperature, and so on. It can also be used to remotely safeguard against toxic preservatives by checking air concentrations of chemicals. Computer vision can be introduced to monitor pest invasions of silos, including minute pests in storage. It can also be used to perform accounting of crop inputs and outputs from agricultural warehouses. Future directions also include monitoring farms with computer vision to guard against theft, rodent invasions, and crop growth regimes.

Kiki *et al.*,[26] proposed a sensor–metal oxide semiconductor (MOSFET) transducer for early detection of fall armyworm before invasion. The sensor was developed based on the physiological secretions of the pests. Similar early-warning pest-detection systems were proposed by others (Selvaraj *et al.,* [48]; Emera *et al.,* [14]; Kim and Kim, [27]). At the current age, automating the detection of pests and their symptoms is key to monitoring, controlling, and eventually eradicating or reducing their effects on production and crop health. In addition, automatic spraying of pesticides using UAVs and other tools is germane to the complete control of pests in agriculture.

The process of automated pest detection and pesticide application can be implemented using artificial intelligence (AI). AI offers the tools and means to automate the detection of pests and their symptoms on leaves, stems, crops, and farm environments through a deep learning algorithm technique called Convolutional Neural Network (CNN). Thus, AI technology developed through deep learning techniques like CNN (He *et al.,* [18]) offers an easy solution to the challenges farmers face regarding pests and pesticide application. Mobile applications, for example, can facilitate accurate pest detection and diagnosis using the symptoms of pests on the field (Akinyemi *et al.,* [4]). AI detection of pests will also help to reduce the quantity of insecticide applied through early detection and precision spraying. It will bring about rapid measures to tackle invasions before they spread.

With respect to the fall armyworm, the use of deep learning and artificial intelligence has been reported. However, the majority of deep learning investigations in the literature rely on images of the pest rather than its symptoms. Meanwhile, the symptoms of the pest on leaves, stems, and crops are much more pronounced than the pest itself. Therefore, comprehensive study is needed to address these shortfalls in scientific investigations. For example, many computer-vision studies on fall armyworm rely only on images of the pest without the symptoms on leaves, stems, and cobs. Oyege *et al*.,[41] applied computer vision technology to detect the larvae and adult fall armyworm without recourse to the symptoms of the pest.

Conversely, Kaiiru [24] utilized only the symptoms of the pest on maize leaves to develop an AI-based detection system. Also, Obasekore *et al.*,[37] used deep learning on the larvae of fall armyworm to develop a robot system that tackles the pest in maize farms. All of these reports did not comprehensively address both the pest and its symptoms. Furthermore, apart from Obasekore *et al*.,[37] none of the authors combined detection with control using AI-guided technology. To achieve complete eradication of the pest in maize plantations, computer vision technology is germane for rapid and comprehensive detection of the pest and symptoms together with AI-guided technology for instant control.

Furthermore, the commercial agricultural drone is very costly and may not be affordable for the average farmer in developing countries. Meanwhile, the major component present in agricultural drones is the spraying tank, and in most cases, it is not guided or sensitive to the presence of the pests or their symptoms, as it is mostly unconnected to an AI model. Thus, these expensive agricultural drones conduct blanket spraying of the farm, using excessive pesticide in both necessary and unnecessary parts of the farm. This often impacts the environment negatively and raises the farmer's production costs.

The above analyses point to the need for a comprehensive automated detection system for fall armyworm pests and symptoms. The proposed system in this study will provide cost-effective AI-guided, location-specific information about the pests and symptoms in order to achieve precision spraying in future development. This will go a long way toward cutting farmers' costs on pest eradication and safeguarding the environment from indiscriminate pesticide application. The aim of this study is to create a pest detection system based on computer vision and develop a cost-effective AI-guided, location-specific pest/symptom identification system for fall armyworm using drone technology.

II. METHODOLOGY

A. Data Gathering

Image data of fall armyworms as pests, and symptoms on leaves, stems, and crops of maize farms were gathered across the northern and southern parts of Nigeria. These include Osogbo and Ogbomoso (Southwestern Nigeria) and Ilorin (North Central Nigeria). In total, 1,637 images were selected (70%, 20%, and 10% for training, validation, and testing, respectively). The images were gathered using mobile phones.

B. Data Preprocessing

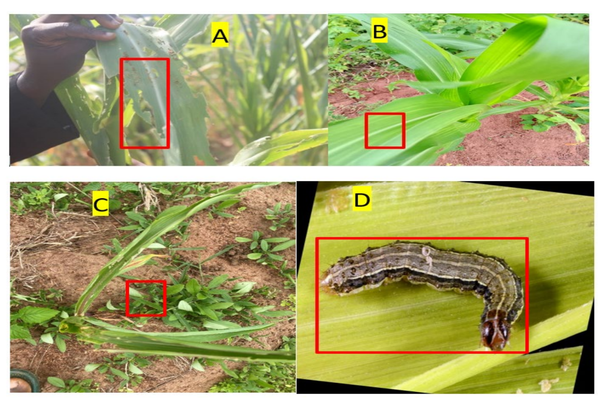

Fig.1 Samples Images with Bounding Boxes Representing Classes (A) Infected (B) Healthy (C) None (D) Infected

Data were preprocessed in the project workspace of Roboflo (Roboflo.com). Roboflo offers annotation tools and other features for deep learning studies. Images were uploaded to the workspace, and the classes annotated were "Infected," "None," and "Healthy," under the Object Detection Model. The "Infected" class represents images where symptoms of fall armyworm infestation were found on the leaves, stems, cobs, and so on, or where the armyworm itself was present. The "Healthy" class is for maize plants with no symptoms or images of the pest. "None" represents non-maize images found in the farm areas. The images were manually annotated with rectangular bounding boxes using the Roboflo software. A dataset was created with the annotated images. From the dataset, train, validation, and test subsets were created at a ratio of 7:2:1, respectively.

C. Computer Vision and Model

Computer vision is one of the recent and versatile developments that can be implemented in agriculture to utilize feature-sensing devices with IoTs for visual analysis of farms, crops, pests, and others (Oliveira-Jr *et al.,*[40]). It is an advanced technique for image processing and automated feature identification in heterogeneous domains (digital images, videos, and visual inputs, etc.) (Tripathi and Maktedar, [51]). Computer vision relies on many algorithms to interpret and understand visual data. These algorithms include Convolutional Neural Networks (CNNs), Region-Based Convolutional Neural Networks (R-CNNs), YOLO (You Only Look Once), SSD (Single Shot Detector), Mask R-CNN, Generative Adversarial Networks (GANs), Optical Character Recognition (OCR), SIFT (Scale-Invariant Feature Transform), Eigenfaces and Fisherfaces, DeepFace, and so on. These deep learning algorithms extract features from an input image by assigning weights and biases to prominent attributes of different objects or their aspects, and differentiate one from another. YOLO is a one-stage detector that detects objects in a single pass through its network, offering higher speed and efficiency. It detects objects by predicting bounding boxes and class probabilities. It was adjudged the best compared to many deep learning algorithms for pest detection and classification tasks (Oyege *et al.,*[41]). The model has shown excellent performance across diverse domains of application, including medical imaging analysis and agricultural pest detection (Xiao *et al.,* [53]).

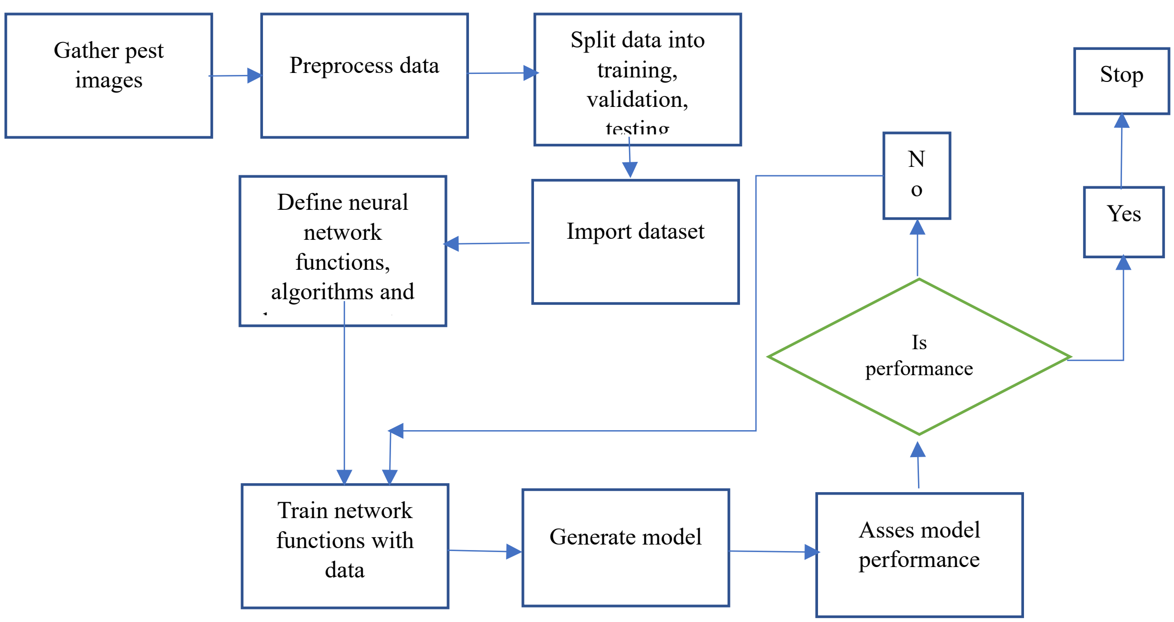

Fig.2 Procedure for Generating AI Model for Pest Detection

In this work, the YOLO11 model, the latest version of the YOLO algorithm, was used for training the images and developing the custom model. After image preprocessing in the Roboflow software, training, validation, and testing were performed in Google Collaboratory. Image sizes of 640 × 640 pixels were used for 100 epochs and a batch size of 20. A schematic of the training, validation, and testing processes is shown in Figure 2. The data were segmented into 70%, 20%, and 10% proportions for training, validation, and testing.

D. Training and Validation

Training and validation were performed in Google Collaboratory using the YOLO11 model. The model requires the Ultralytics package (www.ultralytics.com), with core dependencies such as PyTorch, which is one of the major machine learning frameworks currently used in the research and deployment of machine learning networks. The YOLO11 model is a computationally efficient deep learning algorithm built with improved architectural design over YOLO9 and YOLO10. This version of the model possesses higher feature-extraction power and training efficiency than earlier models.

Google Collaboratory (Colab) was used as the computing platform to run the simulation. Colab hosts free Jupyter Notebook resources. The model (YOLO11) was installed via

Ultralytics. YOLO11-L (large version) was used because of its higher accuracy. The training progress provides outputs such as training loss, validation loss, confusion matrix, and so on. A total of 100 epochs were used for the training. Inference was performed on new images using the best model generated during the training phase of the simulation. Results were produced with various confidence levels. Still images, videos, and websites were used to test the custom model. The performance metrics used to assess the model include box loss, classification loss, distribution focal loss (DFL), precision, recall, and mean Average Precision (mAP). The best of the trained models was selected for prediction purposes.

E. Deployment of Model on Android Mobile and Drone

To convert the custom YOLO11 model into a mobile phone app, the trained model was converted into TensorFlow Lite format (TFLite), which is the Android-compatible format for mobile applications. This conversion was achieved using the 'export' code in Google Colab. The trained model in TFLite format was further tested for accuracy. After successful TFLite model performance, the model was uploaded into the Android Studio Integrated Development Environment (IDE), to which the mobile phone was connected. This loaded the model onto the mobile phone as an APK file. The mobile app was tested for accuracy using new images. To implement the model with a drone system, a DJI Mini 4 drone was used (DJI Technology, China). The drone was operated in Waypoint flight mode to perform image acquisition at the research farm. The waypoints were selected around the center of operation, and the drone was electronically tethered to the center point. The drone navigated around the selected locations and captured essential pictures and GPS data. These pictures and GPS coordinates were analyzed by the model on a laptop for detection and location identification.

F. Tracking/Counter for Objects from Drone Video

To test-run the efficacy of the model in diagnosing objects recorded with the drone camera, the DJI Mini 4 Pro drone was flown over the demonstration maize farm at a low height. The recorded video from the drone was loaded onto a laptop computer in the PyCharm environment, where the model was preloaded. This required the installation of several software packages, including cvzone, pandas, ultralytics, numpy, and cv2. The programming also used a tracker code to count the number of detections. The best version of the model was used. For counting purposes, a Mouse Event was used to obtain the X and Y coordinates to make the counting easier. The main code runs as follows:

Detect object from video frame:

results=model.predict(frame)

Save the bounding box of the detected object:

For index, row in px.iterrows():
x1=int (row [0])
y1=int (row [1])
x2=int (row [2])
y2=int (row [3])
d=int (row [5])
c=class_list[d]

if 'Infected' in c:

Create list for the coordinates*:*
list.append([x1,y1,x2,y2])
The list of detected object was sent to tracker code:
bbox_id=tracker.update(list)

Tracker code assigns new coordinates and 'id' to the object as follows:
for bbox in bbox_id:
x3, y3, x4, y4,
id=bbox
To get centrepoint of each rectangle,
cx=int(x3+x4)//2
cy=int(y3+y4)//2

The line method for counting the object centre point (*cv2.line* method) was used to draw the line. This enables the counting of each object as the video frame passes the set line. Code was inserted to avoid counting same 'id' more than once.

III. RESULTS AND DISCUSSION

The following are the results and discussions of the above investigations. These were presented under various headings.

A. Training and Validation Performances of the Custom Model

Figure 1 shows the performance of the model during the training and validation. It can be seen that the model learns very well during the training as shown in the box loss value reducing with epoch. The box loss indicates the difference between the predicted bounding box and real bounding the box of the model. As shown in the figure, this difference reduces with epoch during the training and the validation stages. The reduction in losses indicated that the model learns very well the patterns of the objects and that the model's predictions matches correctly the object positions. The classification loss (cls_loss) also shows good quality of the model in learning the classes of the objects.

The difference or loss in predicted classes and actual ones dimmish with epochs. Similarly, the distribution focal loss(dfl) reduces with epochs. 'dfl' is used to deal with class imbalance that arises when dealing with datasets having very rare objects. The accuracy metrics shows good performance of the model in all cases where 'precision' and 'recall' values are rising with epochs.

1. Inference on Test Images: It is to be noted that the classes of objects that make up the dataset of this study are difficult to extricate, as they involve various dissimilar patterns of the pest (fall armyworm) and its symptoms, which pose challenges for the neural network to learn. However, based on the above performance metrics, the current study can be commended for the learning level attained by the model. The work of Roosjen *et al.*,[46] reported difficulties in model learning patterns owing to the complex details embedded in pest samples from various backgrounds. However, the results compare well with the reports of Obasekore *et al.* [37] and Oyege *et al.*,[41].

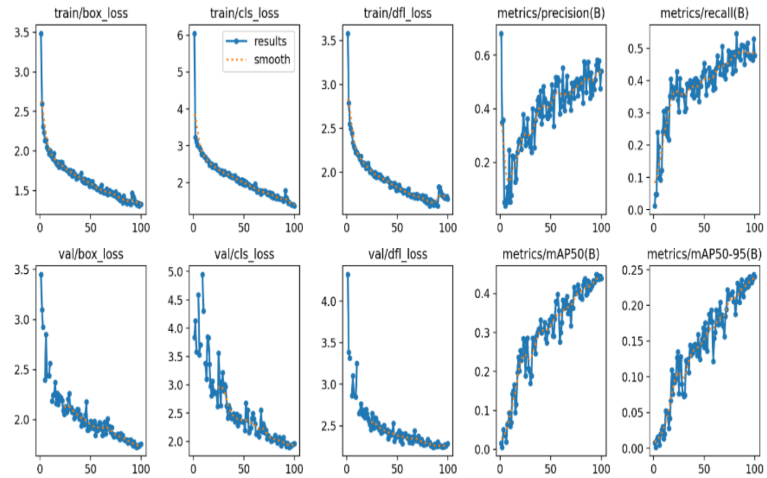

Fig.3 Metrics of Performances During Training and Validations

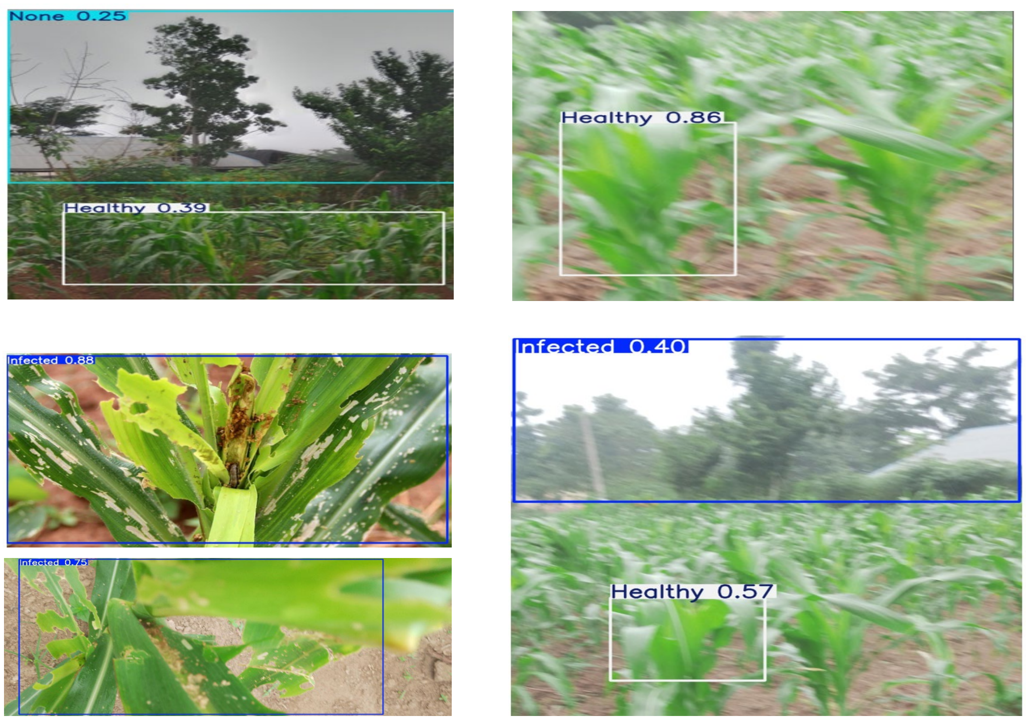

Fig.4 Interferences on Test Images

2. Performance of custom model on android mobile app: Figure 5 shows the performance of the mobile app model on different images. Figs. 5(A) and 2(B) show “None” as the app output. This indicates that the model found no patterns of the pests or their symptoms in the image. However, in Figs. 5(B) and 5(C), the model showed “Infected,” indicating the presence of the pest and/or its symptoms on leaves, stems, cobs, and so on. It can also be noted that the detection time was fairly short. The detection speed ranged between 482 and 593 milliseconds, implying that, on average, it takes the mobile app around half a second to detect objects. The performance of the mobile app was comparable to that demonstrated in the work of Zhao *et al.*,[54] who also used a mobile app for target detection and demonstrated its effectiveness. The mobile app was able to detect both the pest and its symptoms. However, this involves manual operation of the app, whereby users must physically move around the farm to acquire images of pests and symptoms. This represents only a slight improvement over visual inspection. Therefore, a more automated and effective technique is needed to achieve higher efficiency.

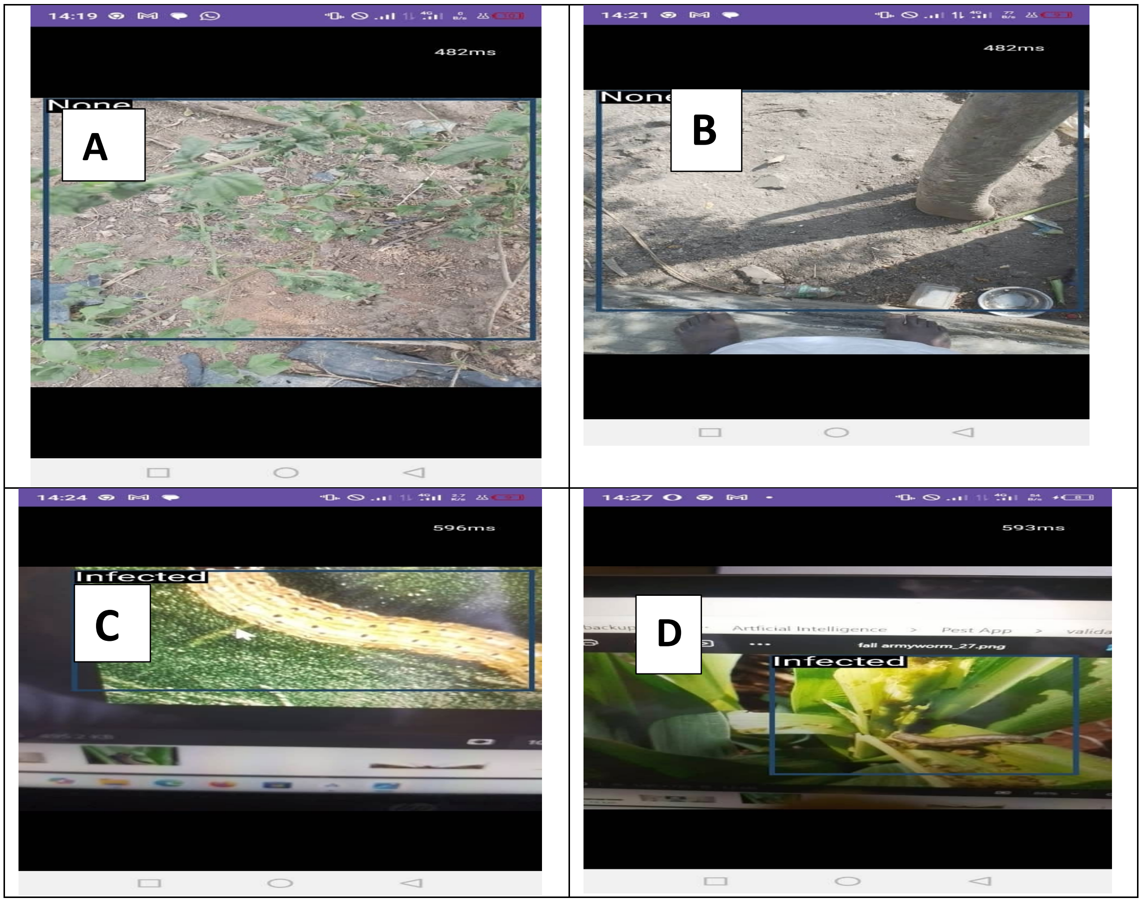

Fig.5 (A- D) Mobile App Model Detection of Different Objects

3. Drone Scanning of the Demonstration Farm:

Fig.6 Drone Traversing the Demonstration Farm in Waypoints Mode for Video Recording Purpose

Figure 6 shows the field demonstration of the drone traversing the farm in waypoint mode. The drone was used to collect video images of the farm, plants, pests, and symptoms. The waypoint mode enabled the drone to travel through the rows and columns of the farm to ensure thorough scanning. In the semi-automatic mode of drone scanning, the video recording was stored on a memory card for later use in model diagnostics in Python. Model diagnostics of the drone recording are shown in Figure 4.

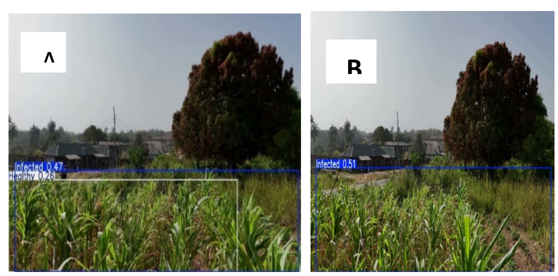

Fig.7 Model Inference on the Video Record of the Drone

Figure 7 shows the model inferencing of the video recording from the drone scanning. The model can be seen detecting some of the symptoms, classifying them as “Healthy” and “Infected.” This performance of the model demonstrates its reliability in identifying areas of the farm with symptoms.

4. Model Counting Symptoms and Location of Detection: Counting procedure of the detected pest and symptoms were also implemented in python programming language. Figure 8 shows the counting and tracking system for the model detection system. The system was implemented in the Python environment. The model detects the pests and/or symptoms and passes the index to the tracker code, which is then used to count the number of detections in the farm. Figure 8A shows 131 detections for “Infected” after a longer period of tracking the video recording from the drone. A shorter tracking time gives up to 112 counts of the symptoms, as shown in Figure 8B. These results demonstrate the reliability of the model developed in this work. This semi-automatic mode is particularly useful for farmers or users without internet access, or for those who prefer to work offline.

Fig.8 (A, B) Counting the Model Objection Detection

Fig.9 Sample Information About Location (Longitude/Latitude) for Detected Pests/Symptom by the Drone

Figure 9 shows a sample of detection locations recorded by the drone. The figure displays the latitude and longitude of the exact detection spots. This information can be used to guide the spraying process for the affected parts of the farm. Thus, the current work will serve as a prelude to the development of an effective AI-guided precision spraying system. It will lead to reduced pesticide consumption, safeguard the environment, and increase farmers' profit. The work of Roosjen *et al*.,[46] found deep learning to be effective in spotting fruit pests, but their use of UAV images reduced the efficacy of model detection. This was attributed to the lower image quality caused by instability of the UAV during image collection. Compared to that work, image detection in the current study improved with the use of UAVs for image collection.

Moreover, the communication between the UAV and the model in this work was highly efficient, demonstrating the efficacy of the current approaches. One can also infer that the specifications of the UAV may be a significant factor in performance. Roosjen *et al.,*[46] used the RKM4x UAV, unlike the DJI Mini 4 Pro used in this work, which is known to be among the latest technologies.

Li *et al*.,[30] demonstrated a drone-deep learning system using a reverse approach. They used a drone, radar, and mobile client to gather information from the farm and transmit it to the control center. This approach created some time lapses between detection and control. The current work shortens this process by live transmission of drone information and location to the model. Thus, this work represents an improvement and a more cost-effective alternative to some of the current approaches reported in the literature.

IV. CONCLUSION

Fall armyworm is an invasive pest species that has threatened maize production and has resulted in huge economic losses for farmers, thus threatening food security. Literature reports show no comprehensive solution to tackle this menace in Nigeria, as most approaches are limited to insecticide application with little information on exploring AI as a monitoring and management strategy. This study addresses the challenge comprehensively by exploiting all the features of the pest and its symptoms to train a robust deep learning model. The YOLO (You Only Look Once) algorithm was used for its computational efficiency and higher feature-extraction power to identify the presence and effects of the pests on plants, cobs, soil, and so on. Images of fall armyworm and its symptoms on maize farms were gathered across Northern and Southern Nigeria to create a truly representative dataset of the local effects of the pest.

The model training and validation showed robust performance. The developed AI model was deployed in multiple ways: as a mobile application created in Android Studio and also on a laptop in a Python environment. The mobile app developed from the model demonstrated excellent detection ability during field investigations. Integration of the model with a drone system and demonstration on the research farm showed reliability with instant detection and counting. A DJI drone was used to scan the farm in waypoint mode.

Furthermore, GPS locations of the detection spots were collected from the drone system. Thus, this work develops an AI-guided, UAV-enabled system to automate instant detection of fall armyworm pests and symptoms, with a view to potentially enabling precision pesticide spraying, protecting the environment, and improving farmers' operations.

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Declaration of Conflicting

The authors declare no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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Use of Artificial Intelligence (AI) - Assisted Technology for Manuscript Preparation

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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