Improved Yolov8 for Detection of Intruders Using a Deep Learning Techniques

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Abstract- ***Intrusion detection system (IDS) is an important component of computer vision and cyber security. IDS are installed and configured to protect geographical areas from unwanted intrusion and unauthorized encroachment. conventional means of intruder detection in a farmland are quite expensive, time consuming, labor- intensive, inaccurate giving false alarm and error in their detection. In this research study, various deep learning techniques were explored to identify human intrusion within a farmland. You only look Once (YOLOV8) object detection algorithm was enhanced by adjusting the neck region and optimizing the head region in order to increase its performance. The result generated was compared to the existing YOLOV8, Regional convolution neural network and the single short detector object detection model.The improved YOLOV8 model generates a precision of 93.6%, recall value of 92.7% F-1 score of 93.8% and a mean average precision of 92.9% which shows a better model performance when compared to the other Deep Learning models. This model can be used to detect unwanted and unauthorized human intruder in a real time.***

Index Terms- ***CNN, Improved YOLOV8, R-CNN, SSD, Deep learning, IDS,***

I. INTRODUCTION

Advancement in deep learning has revolutionized various domain of information technology including but not limited to computer vision, cyber security and intrusion detection and cyber security.

(Kathir et al, 2024). Human intrusion detection systems are security systems primarily designed to prevent unauthorized access into an environment. These systems are built using sensors, Microcontrollers, sophiscated cameras, IoT devices and other customized systems for effect intruder detection. These systems can be deployed in a farmland, offices, homes, banks, institutions, security houses and other strategic places to study observe human behavior, recognize pattern, observe movement, to predict and detect unauthorized access within a farmland in real time. (Shetty et al, 2023)

Conventional means of identification of intruder detection in a farmland include the use of close circuit television (CCTV), surveillance system, human observers, forest guards, local detectives etc. although this has achieved a measure of measure of accuracy, it has lots of limitations. It has not been able to detect human intrusion in real time. Some human intruders now adopt technologies, scientific techniques and also disguise as potential farm owners and business men to encroach into farmlands illegally to explore and exploit farms. Despite the huge sum of resources been invested into agriculture in Africa, production is still far from expectation. One of the factors responsible is due to human intrusion. (Fang et al, 2024)

Convolutional Neural Network (CNN) is a type of deep learning model especially well-suited for tasks involving image, video, or spatial data. CNN are the core of most modern computer vision systems — including human intrusion detection, object recognition, face detection.

(Sharma,et al, 2024) The application of CNN can be seen in various aspect of Agriculture which include,

- Crop protection-
- Weed detection and management
- Crop yield prediction
- Soil and nutrient monitoring

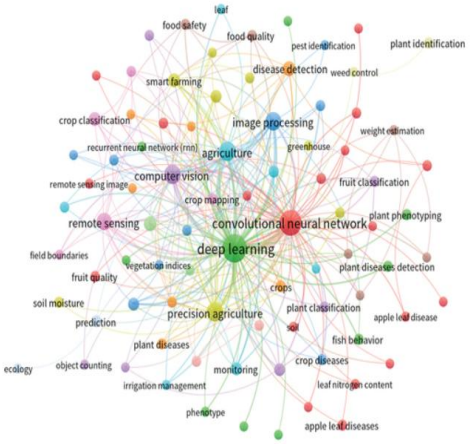

Fig 1.0: Application of CNN in various field

This research study aims to identify human intrusion within a farmland by:

1. Detect unauthorized human presence in a fenced farmland.
2. To develop an artificial intelligent solar powered IDS to detect intrusion.
3. To design cost-effective and affordable IDS system to farmers to capture strange activities in a farmland
4. To train the captured dataset using various Deep Learning techniques for detection of intruder
5. To enhance an existing YOLOV8 Object detection model for the detection of intruder
6. To compare the performance of the improved model with other existing model to evaluate the performance.

Human intrusion on farmland can cause financial losses, theft, reduction in agricultural yield, and death of crops and animals. (FAO, 2024)

The introduction of artificial intelligence has helped to reduce agricultural theft through intruders. It has also aided smart farming, precision agriculture and increase bumper harvest on a regularly basis.
(Ben Ayed et al, 2021)

II. LIMITATIONS OF TRADITIONAL METHOD OF INTRUSION DETECTION

Although, the traditional means of intrusion is generally been in use in Africa including Nigeria, several limitations are still been experienced

1. The conventional means of using security detectives, forest guards and personnel must always be at alert. They must continually be in progressive surveillance throughout the day. Since intrusion into a farmland could take place within a few minutes, hence sleeping, slumbering or discussion could easily distracted them. In Nigeria, where football is a game that unites everyone together irrespective of tribe nor religion, discussion of such could easily distract them while intrusion is taking place.
2. The use of close circuit television (CCTV) is another traditional method that is often used to protect farmland from intruders. This achieved a measure of intrusion detection. However, the CCTV footage is often reviewed post incident to review and check the incident of intrusion. This cannot be deployed in a real time for detection. Internet connectivity and bandwidth is another challenge that is needed to install and progarmme the CCTV. Electrical power supply is another challenge that can hinder the performance of the CCTV.
3. Physical barrier like fence, are often used to create a demarcation to avoid intrusion. This is a primitive way of protecting a farmland from intrusion. Intruders can jump through the barrier, damage or destroy the physical barrier and find their way into the farm.
(Raponi et al, 2019)

III. DEEP LEARNING TECHNIQUES OF DETECTING HUMAN INTRUSION

Deep learning is a subset of machine learning that uses algorithms called artificial neural networks to mimic how the human brain works—allowing machines to learn patterns from large amounts of data. Various deep learning techniques can be deployed to detect farmland invasion in a real time. This includes object detection models (You only look once, single short detector, regional – convolution neural network), Pose Estimation, Semantic Segmentation, Video Surveillances system. Etc

Object detection models are detection algorithms used for identification and detection. Faster R-CNN (Faster Region-based Convolutional Neural Network) is a powerful and widely used deep learning model

for object detection, including human intrusion detection in environments like farmland.

1. Faster R-CNN detects what is in an image (classification) and where it is (bounding box coordinates). It's a two-stage detector, meaning it first proposes regions likely to contain objects, then classifies those regions to detect human intrusion "If a person is detected in a restricted area of the frame (e.g., near crop zones or at night), trigger an alert. While Faster R-CNN is powerful and accurate in detecting human intrusion but, it does have limitations—especially when used in real-world scenarios like farmland human intrusion detection. Faster R-CNN is not real-time: It's accurate but relatively slow because of its two-stage architecture. It requires High Computational Requirements. False Positives in Complex Environments. In open farmland, it might misclassify animals, scarecrows, or farm workers as intruders—especially if not well trained.
2. Single Short Detector (SSD)
   SSD works for human intrusion detection in a farmland setting. SSD is a real-time object detection model, making it faster and more lightweight than models like Faster R-CNN, which is a huge advantage in agricultural surveillance. They Automatically detect if a human enters restricted or unmonitored zones of a farm using camera footage or drone imagery. SSD detects objects (like humans) in a single forward pass, hence the name Single Shot. SSD uses a pre-trained CNN backbone (like VGG16, Mobile Net, or ResNet) to extract feature maps. These maps capture patterns (shapes, edges, textures) useful for recognizing humans and other objects. SSD detects objects at multiple scales by adding extra convolutional layers. This helps detect humans at different distances. SSD is Suitable for Farmland Intrusion Detection because

I. Can work live on security cameras or drones
II. Runs on edge devices (e.g., Jetson Nano, Raspberry Pi)
III. Detects close and faraway intruders
IV. fewer computational resources - Ideal for remote or off-grid farm setups.

3. YOLO is a real-time object detection model that treats object detection as a single regression problem — it detects what objects are in an image and where they are in one pass through the network. YOLO is one of the best choices for real-time detection, especially in outdoor, dynamic environments like farmland. YOLOv8 is helpful for picture classification, object recognition, object tracking, and segmentation. applications. YOLOv8 and its powerful, industry-defining model were developed by Ultralytics. YOLOv8 incorporates numerous changes and improvements to the development experience and architecture over YOLOv5. Ultralytics is currently working on new features and responding to developer community feedback for YOLOv8. It is Ideal for Farmland Human Intrusion because

1. It is a Lightweight module
2. It can detect intruders as they enter
3. Detects intruders from distant cameras with high level of accuracy

IV. RELATED WORKS

The integration of Artificial Intelligence (AI), and deep Learning techniques into farmland has greatly improved real-time monitoring, detection of human and intrusion and aided optimal agricultural production.

Bucketry et al, 2023 provides an Internet of Things (IoT)-based home security system that employs multimodal techniques to identify intruders. Their system uses a Raspberry Pi device, an IP camera, a microphone, and sound and motion sensors to identify unauthorized users and detect intruders by their voice, movement, or knocking on the door. It also uses speaker identification for authorized users and facial recognition to detect intruders with high accuracy and efficiency. Although their work makes use of a YOLO versionV5 and V8 for their research study.

Thai-Nghe et al, 2023 suggest a model for security camera YOLOv8 that can identify human infiltration. Using human identification data, the model's object recognition and tracking accuracy exceeded 80%. The Kaggle dataset was used by the authors to train the model, and it was then evaluated in a variety of

settings, including indoor and outdoor, day and night, and varied weather conditions. Intriguingly, the model showed resilience to occlusions, shadows, and changes in illumination in addition to detecting human intrusions and alerting the security system. The model achieved a mAP of 0.82 at IoU of 0.75 on the test set, surpassing earlier state-of-the-art techniques. In conclusion, it demonstrated a remarkable inference speed of 0.02 seconds per frame.

Appiah, E. O., & Mensah, S-2023 were involved in a research journal titled “Object detection in adverse weather condition for autonomous vehicles”. The study developed a CNN-based object detection system tailored for conditions like fog, rain, and snow, where conventional models often fail. The proposed model showed improved accuracy over baseline models on weather-augmented datasets. They included advanced preprocessing techniques to help the model generalize better under poor visibility. The model was evaluated on synthetic and real-world datasets, supporting its practical viability. However, the model requires significant computational resources, making it challenging for real-time embedded applications in autonomous vehicles Maktoof -2023 conducted a study titled "Crowd counting using YOLOv5 and KCF" (2023). They implemented a YOLOv5 with KCF (Kernelized Correlation Filter) tracking for improved accuracy and speed in real-time people counting, achieving about 98% accuracy. Other work includes YOLOv5 applications such as array-camera-based crowd counting for panoramic surveillance (Zhang et al., 2023), and object counting on Jetson Nano using YOLOv5 variants, exploring TensorRT optimizations and tracker comparisons Alam et al 2022 did research on Artificial intelligent powered firearm detection using Yolov4. They developed a CCTV-based weapon detection system using Scaled-YOLOv4, achieving high accuracy and real-time performance on low-cost edge devices. Their model outperformed previous systems in both speed and accuracy.

Pagano et al, 2022 proposed a model to improve farming conditions and IoT devices in a farmland. This reserach heavily depends on LoRaWAN, which provides animal tracking, irrigation control, and environmental monitoring. Furthermore, its novel method of separating viable from non-viable seeds using X-ray imaging and deep learning achieved an accuracy rate of 86.01%. The use of Weighted Co-occurrence Histograms of Oriented Gradients (W-CoHOG) to detect animal intrusions in agricultural settings was studied in order to improve animal identification. This technique uses in-depth analyses of farm-captured data and incorporates gradient direction and magnitude to improve its detecting capabilities. Using a sliding window technique enhances detection for a range of animal sizes and camera focus lengths.

Kommineni et al, 2022 offers a sophisticated system that uses a Raspberry Pi in combination with passive infrared (PIR) and ultrasonic sensors. With the help of GSM modules, aural alarms, and email, this system effectively detects and categorizes intruders according to their physical characteristics. Additionally, it has a built-in camera to take pictures of potential intruders, giving farmers real-time information about potential dangers. This technique successfully finds a variety of intrusions, such as people and animals.

In order to improve farm security, Yadahalli et al, 2020 outlines a similar agricultural security architecture that uses PIR sensors, ultrasonic sensors, and a Raspberry Pi microprocessor. Four PIR sensors are arranged at different heights in this system to identify motion and classify intruders. When an intrusion is detected, a camera is turned on, and GSM modules and email are used to send out notifications. A cost-effective solution to agricultural security issues, an aural alarm deters the intruder and provides real-time warnings with the least amount of human participation.

Geetha et al, 2019 suggests a system paradigm that uses PIR sensors to track animal movements and auxiliary sensors, such as flame sensors and light-dependent resistors (LDR), to provide features like automatic lighting control and forest fire warning. The device uses an implanted WiFi module to communicate with the agricultural community and forest authorities, activates auditory signals, and illuminates the region when it detects animal movement. Its surveillance capabilities are enhanced by night vision cameras, which provide a powerful

deterrence to protect crops without endangering wildlife.

In order to address agricultural issues as the world's population grows, smart agriculture enabled by IoT and LoRaWAN technologies is thought to be essential. IoT sensors are essential for tracking crop health and resource use, and LoRaWAN offers environmental assessments, irrigation management, and animal monitoring.

V. RESERACH METHODOLOGY

The research methodology adopted in this study is a novel method that uses an integrated Espress if system 32-bit Micro Controller (ESP32) to capture videos, images, pictures of activities taking place in the farmland in real time. The ESP32 is a powerful and affordable microcontroller widely used in IoT, automation, sensor systems, and AI on the edge. It contains Dual-core Xtensa® 32-bit LX6, clock speed of 240 MHz, 320 KB SRAM internal memory, Wi-Fi (802.11 b/g/n) and Bluetooth v4.2, a 2MP OV2640 camera, MicroSD card slot. This is used for real-time image and video capture and data transmission. It was configured using the Arduino IDE interface 2.3.6 was used for configuration of the ESP 32 hardware for image capturing. the ESP32 microcontroller is the central control unit. It serves as the brain of the system, controlling how all other physical parts work. As the primary data transmission interface, the microcontroller ensures a seamless connection between the cloud servers, speaker, motor, and camera module. The camera module and the ESP32 microcontroller are firmly connected. It is essential for facilitating the transfer of live video from the farm to cloud servers. In the event of an anomaly, rapid reaction mechanisms are made possible by AI-driven intrusion detection, which is based on this continuous video stream.

The integration of the ESP 32, Future technology development interface (FTDI1232), jumper cables and a source of power makes up the IDS.

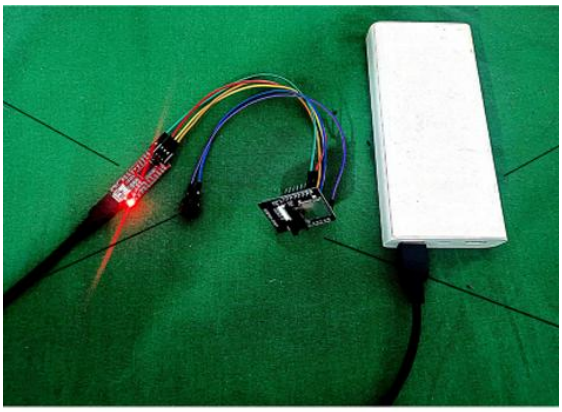

FIG 1.0: A simple IDS connected with a solar powered system.

The IDS powered by a 220V power supply via a universal serial bus (USB) connected to FTDI1232 Module.

Study Area

This was setup in a farmland containing cassava plantation in Oke- Elepe, in Sagamu local government-ogun state Nigeria. Oke- Elepe is a village, along Sagamu- Ogijo expressway. It is located in the southern part of Nigeria. It is loc along the Ibu River and the Eruwuru Stream, between Lagos and Ibadan. The coordinate is approximately 6°50′N latitude and 3°39′E longitude. The people in this community are noted for farming because of the abundant of good soil, rainfall and good climatic condition for the cultivation of cassava. Farm intruders professing to be farmers are also seen around this vicinity. Hence, the IDS was setup in real time to capture image set in this community.

After a period of twelve (12) days, 3986 volumes of data set were captured by the IDS. The dataset went through various stages of data preprocessing, cleaning, stages. It was split into 70:15:15 for data training, testing and validation respectively

Fig 2.0: images captured in a farmland

VI. IMPROVED YOLOV8-OBJECT DETECTION MODELS

Various object detection models were implemented on the dataset for identification of human intruder.
One of the more potent models in the YOLO family, YOLOv8 is well-known for its capacity to do object identification and segmentation tasks concurrently. The YOLOv8 framework is expanded upon and modified for the (LID) system by the LC-YOLOv8 model. Its three primary parts—the neck, head, and backbone—each have specialized roles.

The standard convolutions C2f is substituted with a more efficient and lightweight multi-scale convolution module for efficiency and optimized performance. The YOLOv8n neck structure incorporates an additional tiny object detection layer to help alleviate the loss of small target feature information. These combined together, enhances the YOLOV8 object detection model for detection. One improvement is swapping out the YOLOv8's C3 module with the C2f module, which enhances feature dispersion and dependability. The model was trained using the Improved YOLOV8, existing YOLOV8, SSD and R-CNN. The model training used 25 Epochs for training, and the best result was used for detection and classification of the dataset.

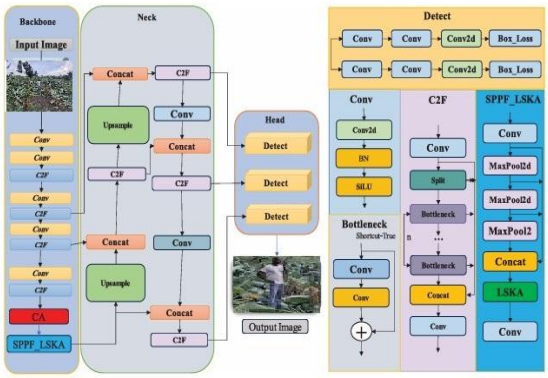

Fig 3.0: Improved yolov8 for detection of intruder in a farmland.

VII. PSEUDOCODE

Start
Import libraries from model files
Read image. ESP 32 Microcontroller
Download video. frame images
Download. imges.jpeg
Import python packages
Break video. Into frames
Add video frames with jpeg images
Download Ip labelling tool
Annotate images
Predict bounding box
Resize frame size= 640
Start P
Initialize
Input X, Y, Z
If X=1 save
else discard
Do same for X1.....X_0
If Y= 1 save
Else discard
Do same for Y1 .....Y_0
If Z=1, save else
Discard
Do same for z1....z0
add (x, y, z) = V
Set threshold value = K
I= Intruder
If v < 0.5= no intruder
If v=0.5. minimal intruder
If v> 0.5 intruder detected

Analysis
The above is a simple analysis of the pseudocode for detecting an intruder in farmland.

The Esp 32-bit Micro controller captures and record all the activities in the farmland. All workers are identified with a unique identity. Others are not permitted to come into the farm space. Every unwanted personality captured by the system are captured by the system. The behaviour pattern, movement, appearance, traits and presence of weapons, bags and gadget are been used as part of the criteria for the detection of intruder in a livestock farmland. All these are integrated into the model. A threshold frequency is set to evaluate the potency of the weapons and equipotent of intrusion.

VIII. RESULT AND DISCUSION

The developed model was evaluated based on the standard metrics of precision, recall, F-1 score,

mAP50, mAP50-90. The improved YOLOV8 model generates a precision of 93.6%, recall value of 92.7% F-1 score of 93.8% and a mean average precision of 92.9%. The traditional Yolov8 has a value of 91.5%, recall 90.5%, F-1 90.8 and mean average precision of 55.7%.

The R-CNN has a precision of 88.7%, recall 86.9% F-1 score 87.5% and mean average precision 85.7%.

The SSD has a precision of 88.7%, recall 86.9% F-1 score 87.5% and mean average precision 85.7%.

Model	Precision	Recall	F-1	mAP50
I-Yolo	93.6	92.7	93.8	92.9
Yolov8	91.5	90.5	90.8	62.7
R-CNN	88.7	86.9	87.5	85.7
SSD	85.3	82.5	82.7	52.6

The improved YOLOV8 has a higher rate of detection of intruders in terms of the standard metrics of precision, recall, F-1, and Map. The higher the value, the better the performance of the system.

CONCLUSION

The Intruder detection system (IDS) developed with the ESP.32 is adopted with the deep learning techniques for detecting intruders. The traditional YOLOV8 was improved, and used alongside other deep learning techniques (SSD, R-CNN, YOLOV8) and were used to train, test and validate the Model. The improved model shows a higher performance in terms of standard metrics. The model reduces loss of data, improves efficiency of the model and optimize accuracy of the model. The improved YOLOV8 can be deployed in a real time to detect intruders, unauthorized access and unwanted personalities in any environment.

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