Animal Intrusion Detection in Farm Lands Using CCTV

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***Abstract*—Timely prevention of unexpected animal incursions into agricultural fields can be a significant challenge. Overall crop damage and threats to livestock often result from unexpected animal incursions into these types of fields, requiring the use of traditional prevention methods (manual surveillance, fencing, basic alarm systems, etc.), which can be ineffective, time-consuming and unreliable depending on the environmental conditions. The purpose of this paper is to present a new artificial intelligence-based system designed specifically for detecting animal incursions in agricultural fields by using cutting-edge computer vision and deep learning technologies. These technologies will be used to enable real-time surveillance of agricultural land through the use of CCTV or webcam video feeds and state-of the-art object detection models, such as YOLO and Faster R-CNN, which will provide a way to accurately detect, identify and track animals. The proposed solution is expected to provide users with an intuitive web-based interface that will allow them to upload video feeds, define regions of interests (ROIs) and view detected animal incursions in real-time. The system will notify users (through real-time alerts) when an animal incurs into a defined ROI so that timely action can be taken by users to prevent any future damages to crops/livestock. The proposed solution will also provide additional functionalities through use of computer vision-based preprocessing techniques, data logging and analytics facilitating better detection of animal incursions and enabling longer-term surveillance of the agricultural site. Based on the results of the experimental studies, the proposed solution has demonstrated a relatively high level of detection accuracy and a relatively low level of false alarms and, therefore, is deemed appropriate for deployment on agricultural properties. The proposed solution additionally offers users with a scalable, cost-effective, automated approach to securing their agricultural properties while contributing to sustainable agriculture and reducing incidences of conflict between humans and wildlife on farm properties.**

Index Terms—Animal Intrusion Detection, Computer Vision, Deep Learning, YOLO, Faster R-CNN, Object Detection, Smart Agriculture, CCTV Surveillance, Real-Time Monitoring, Image Processing, Precision Farming, Artificial Intelligence.

I. INTRODUCTION

Sustaining both human life and economic prosperity relies heavily on the agriculture industry, which faces many obstacles; one of which is the presence of wild and feral animals invading agricultural land. Wild and feral animals (such as elephants or feral boars (such as deer, or monkeys)) frequently invade agriculture fields, damaging crops, causing financial losses to farmers, and endangering the farmers' crops, and ultimately threatening the safety of farmers and their livestock. The traditional method of guarding or fencing off an area or using a scarecrow does not work very well, requires a great deal of labour, and is often unreliable to large scale or remote farming operations. The use of artificial intelligence (AI) and computer vision technology have created a number of new possibilities for automated monitoring systems as a means of addressing this problem. YOLO and Faster R-CNN are examples of deep learning object detection model architectures that have very high accuracies and efficiencies for these types of real-time detection tasks. By providing the capability to continuously monitor areas via the use of video from CCTV/surveillance cameras or webcams, these models are able to identify and classify animals with almost no human involvement required.

Instead of using conventional means, this proposed system provides an intelligent and automated means of protecting farmland through the use of these technologies. The proposed Animal Intrusion Detection System will be capable of receiving both live and recorded videos; analysing those videos and automatically determining the presence of an animal and the path the animal took through specific user-defined areas; allowing a farmer via user-friendly web interface to upload videos, define areas of interest and view detection results in real-time; when an animal is detected to trigger an immediate alert to allow a farmer to take timely proactive action to both minimize crop loss and increase farm security.

The proposed system will provide farmers with the ability to both determine (real-time) whether or not an animal has entered their field (agricultural) by using video technology and provide additional capabilities through the inclusion of various video preprocessing techniques (e.g., to account for changing light, weather conditions, etc.) to achieve a higher level of confidence that the information is accurate. The data logging and analytic component provides long-term monitoring and better decision-making support through better tracking of animal intrusion patterns and trends. The combination of artificial intelligence (AI), machine learning and web-based applications will provide a cost-efficient, scalable and effective solution as compared to traditional methods used in agriculture.

Overall, the proposed solution will effectively advance precision farming by automating the surveillance of farmland, reducing the amount of human effort required to monitor invasive species and improving the time it takes to respond to potential threats to farming operations. The proposed solution also promotes the use of sustainable agricultural practices by reducing the number of crops that are lost and fostering co-existence between farming and wildlife. In short, the research demonstrates how 21st century AI applications can be successfully applied to solve real-world problems related to agriculture security and management.

II. PROBLEM DEFINITION

Frequent intrusions by wild animals such as elephants, boars, deer, and monkeys into agricultural fields have led to significant levels of damage to agriculture, lost economic productivity, and risks to human and livestock safety. In search of food, wild animals frequently enter farming areas, destroy crops and disrupt agriculture productivity. Losses due to these events can often be significant (depending on the region), having a severe impact on the livelihoods of farmers, most notably those relying on small-scale agriculture.

Current methods of deterring animal intrusion (such as manual monitoring systems, fencing, and traditional animal deterrents) have proven to be ineffective in providing an adequate level of protection. Checking/monitoring manually is a very labour-intensive task, which is subject to human error, and is not practical for continuous monitoring, particularly during times of darkness or extreme weather. Likewise, alarm systems and motion detectors commonly used for alarming or detecting animals provide a lot of false alarms (due to non-threatening environmental disturbances, or due to minor animal movements) which decreases their reliability.

Despite the recent progress made within the area of surveillance monitoring technologies through advances in actual Camera based systems there still many gaps in their overall functionality due mostly to their inability to perform real time detection or intelligent analysis; thus, requiring human intervention to access recorded footage prior to initiating a response resulting in delays and greater risk of loss for the farmer. Additionally, most currently available systems do not accurately classify each anima/ by species thereby limiting the ability or opportunity for the farmer to take preventative measures.

Therefore, there exists the need for an entirely automated - intelligent - real - time monitoring system that provides both accurate detection / identification of animal intrusions as well as significantly reduce false positives / negatives and/or human intervention; and therefore, maintain a consistently high level of service and reliability regardless of the environmental condition being monitored. Furthermore, to improve the effectiveness of this system towards supporting farmers and agribusinesses alike through providing timely alerts of unauthorized animal intrusions , and an easy interface for interaction with their operational systems, it is critically important to achieve these objectives in order to improve the security of farms, reduce economic loss to all parties involved and support the continued sustainable growth of global agricultural production through the utilization artificial intelligence (AI) and computer vision technologies.

III. LITERATURE SURVEY

Animal intrusion detection systems are much more effective today as a result of developments in both AI and Computer Vision. There have been a number of studies on using deep learning and image processing methods to help build automated surveillance systems for agriculture.

Sharma and his co-authors [1] proposed a system that uses convolutional neural network (CNN)-based real-time animal detection and alerting technology. This system achieved an accuracy of over 90%, and created alerts in real time. However, the study used a relatively small dataset, limiting the generalizability of its results to various environments.

Kumar and his co-authors [2] developed object detection algorithms (YOLO) for monitoring wildlife on agricultural land. Their area of application was primarily focused upon speed and ease of access through the rapid detection of the animal or wildlife in question, which had a precision of 88% or better. However, their model experienced difficulties detecting small or partially obscured animals, a drawback that became evident with complex conditions in the field.

Gupta and Bansal [3] proposed a hybrid deep learning architecture comprised of CNNs and RNNs that combined both spatial and temporal information when identifying animals in video. The system achieved over 93% accuracy in identifying animals and required twice the computing resources than available on most low powered edge devices used in rural areas.

In the work by Li et al. (2016), a Computer Vision-based method was developed using feature extraction methods and multi object tracking methods to track and recognize animals. The systems that were developed were good capable of tracking a variety of animals in variable environments and with multiple animals, but the computational cost of the solution limited the ability to deploy the system in real-time in resource-constrained environments.

Ahmed et al. (2016) used traditional image processing techniques such as background subtraction and edge detection to develop an animal intrusion detection system. The systems developed by Ahmed et al. were computationally inexpensive and effective but were not capable of effectively distinguishing between species of animals. In addition, the systems were also sensitive to noise and therefore had fairly high false alarm rates.

Nair and Thomas (2021) developed a YOLOv5 based detection system to enable real-time surveillance of farms. Their model achieved 92% accuracy while increasing the speed and robustness of the model. However, the performance of their model was dependent on the availability of high-quality labelled datasets, and the models developed by Nair and Thomas struggled with scenarios involving small and/or camouflaged animals.

Rajan and Suresh (2020) developed an AI-based surveillance solution that used sensor data and predictive analytics to produce an early warning system for wildlife intrusion. Although the system improved the reliability of detecting wildlife, it also increased the complexity and the cost of deploying the system due to the use of multiple sensors.

A deep learning animal detection monitoring system developed by Chen et al. [8] utilized deep convolutional neural networks (CNNs) to achieve high accuracy, precision, and recall for detecting animals in multiple environments. This showed improvement when comparing accuracy, precision, and recall for such tasks; however, an additional limitation was the requirement of excessive computational resources to attain this high level of performance (i.e., low resource scaling).

Joshi and Mehta [9] proposed an Internet of Things (IoT)-based animal intrusion detection platform that uses sensor networks and machine-learning models to provide alerts of animal intrusion. While this provided real-time alert functionality and scalable monitoring capabilities, a major limitation of the system was its reliance on stable network connectivity for optimal system operation. Additionally, the cost-to-installation required for this solution was also a limitation.

Prasad and George [10] researched the use of a combination of machine learning algorithms and computer vision techniques for detecting wildlife in smart farming applications. The results of their work demonstrated that classifying these animals is achievable with real-time response, but there were limitations to using this system (i.e., needing large labelled data sets and high-performance computing capabilities for the best solution).

In summary, the prior studies indicate the effectiveness of both deep learning-based solutions to detection of animals through the use of both YOLO (you only look once) algorithms and CNNs, but also indicate that computational complexity, the need for large-sized labelled data sets, false positives, and poor adaptability to real-life applications produce significant limitations for their respective solutions. Thus, the proposed work should produce a scalable, efficient, and easy-to-implement solution that provides a balance of accuracy, speed, and practical implementation.

IV. METHADOLOGY

This proposal describes its design approach for an Animal Intrusion Detection System based around a systematic approach to integration of Computer Vision, Deep Learning and Web based Technology to provide real-time and exact measurement of farmland use by animals (i.e., intrusions). This will be accomplished by breaking the modelling down into the following major areas:

A. DATA ACQUISITION

The detection system begins with recording of video data from CCTV and Web Cameras (User Video). These recorded video streams will then serve as the basis for detecting animal intrusions on farmland. The system accommodates real-time video feeds as well as pre-recorded video to optimize the deployment of the solution to farmland.

B. FRAME EXTRACTION AND PREPROCESSING

The video data is separated into a set of frames using video processing techniques. Each frame is thus pre-processed by performing operations such as height/width resizing, normalization, noise reduction, contrast enhancement and similar operations to enhance the quality of images within a frame or set of frames. The overall objective of these operations is to make the input data as consistent as possible resulting in an "accurate" animal intrusion detection system under a variety of environmental conditions (low light, rain, fog etc).

C. ANNOTATION/ DATA SET PREPARATION

After the (above) extracted frames have been processed, they need to be annotated with bounding boxes related to each of the animal classes. After all of the frames have been annotated (with bounding boxes) they can then be divided into Training and Test data sets typically at an 80:20 ratio, and, then augmented using data augmentation techniques such as rotation, flipping, increasing brightness and so forth.

D. Development and training of the selected model

YOLOv5 is chosen for implementation as the object detection model because of its fast-processing speed and accuracy in detecting objects in a given area, specifically animals, in real-time. The model is trained using annotated datasets to identify distinguishing characteristics of each species of animal being studied. Once trained, the YOLOv5 model will utilize performance metrics (precision, recall, and mean Average Precision (mAP)) to evaluate the success of the training process.

E. Detection and Classification of Objects

After training of the YOLOv5 model has been completed, the object detection model is applied to video frames to identify animals that would be captured in these video frames. The model will first detect objects (i.e., animals) then classify (label) the object, generate a bounding box with the level of certainty that the object is identified correctly for each animal detected in the video frame, and will apply (i.e., implement) Non-Maximum Suppression (NMS) to remove duplicate detections and keep the most accurate bounding box.

F. Intrusion Detection and Boundary Definition

A unique feature of the system is to define areas of interest (AOIs) on the agricultural land in which the animals will be detected by the YOLOv5 model. The defined AOIs will provide the user with the ability to draw virtual boundaries on the web interface to define the area of interest. The system will, therefore, be able to continuously monitor the defined AOIs for any detected animals that cross into or out of the user's defined area, and generate intrusion alerts if an animal crosses over the user's defined boundary.

G. Alert Generation and Notification

When any intrusion is detected, the system generates alerts in real-time. The alerts can be presented via the web dashboard, an internet-based pop-up notification or by using other external mechanisms like SMS or email, allowing farmers to quickly respond to an incident and take appropriate preventive measures to limit potential damage.

H. Visualization and User Interface

The system offers an easy-to-use web interface that was designed using Flask to allow for visual inspection of intrusion detection in real-time; an image of each detected animal with a bounding box and its associated label is shown on each frame of the video showing any detected animal. Users are also able to upload their video and configure fencing boundaries before monitoring the results in real-time.

I. Data Logging and Analysis

All intrusions will be logged in a database to record important information about the intrusion including data points such as date/time of the intrusion, type of animal detected/recorded and the geographical location of the detected animal. The historical data created can then be analysed to determine if there are any unique patterns of intrusion and inform future decisions made by the farmer in managing their farm.

J. System Optimization

The method of optimizing the system for improved overall performance is to reduce redundant frames or irrelevant data and also to tune hyperparameters such as the confidence threshold and the Intersection over Union (IoU) to ensure optimal detection accuracies and the reduction of the number of false positives as well as computational overhead.

In general, the methodology provides for a robust, scalable, and efficient animal detection and alerting system that will provide farmers with the ability to detect and respond to animal intrusions in real time. The integration of deep learning algorithms and appropriate implementation methodologies effectively address the limitations inherent in the traditional methods used to monitor and detect intrusions on farmland.

V. SYSTEM ARCHITECTURE

The proposed Animal Intrusion System design is called an integrated pipeline system and includes video input, smart detection, and real-time alerting to a user via a user interface and the many parts of the system are connected to one another as depicted in the system diagram.

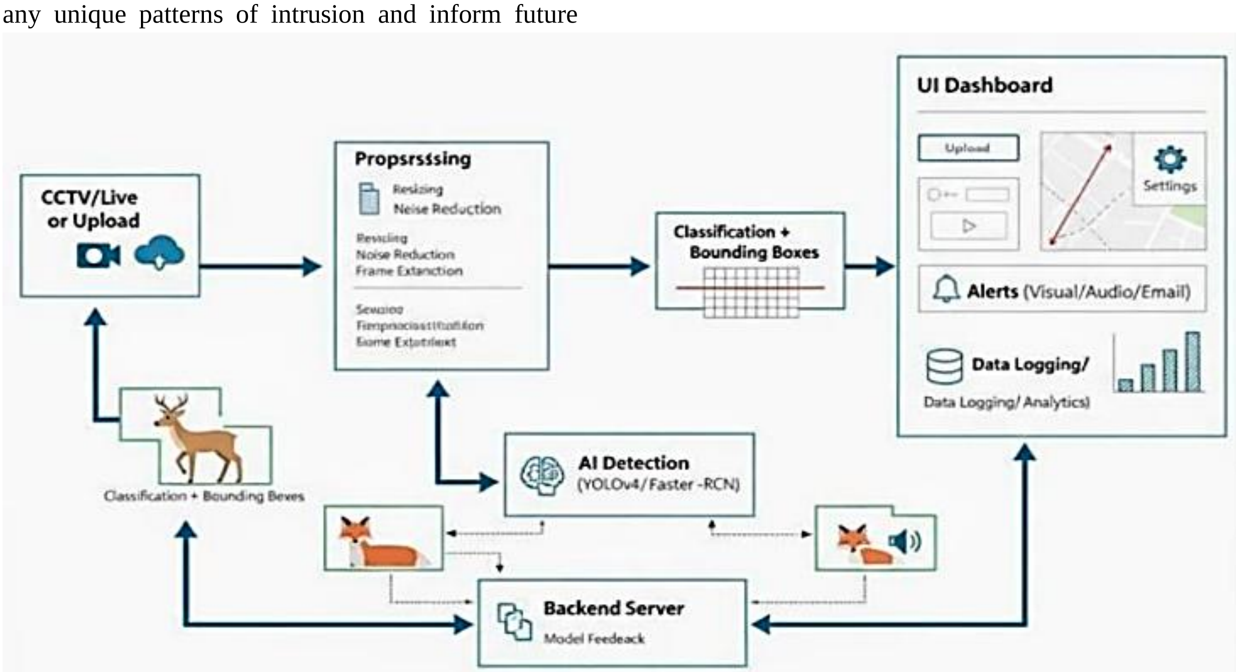

Fig. 1. System Architecture of The Animal Intrusion Detection System

The initial phase in the animal intrusion system is the Data Input Module, which receives and retrieves video data in two different ways, (1) through CCTVs/live camera feeds or (2) through uploading video(s) by users and will therefore be considered the main source of information that is used for monitoring activities on a farmer's land.

Once video has been captured, it is then forwarded to the Preprocessing Module where pre-processing happens, including resizing, plurality noise removal, frame extraction, etc. By performing these operations to an input frame of video, the data that has been input before is processed in order to enhance its quality when further processed and to maintain consistency during ongoing processing. As part of the pre-processing, segmentation and feature extraction techniques are also used to extract the relevant features of the captured video frame to allow for better object identification.

At the end of the pre-processing stage the pre-processed video frame is then forwarded to the AI Detection Module, which forms the main component of the overall system. Within this module is a method for implementing deep learning models, (i.e., YOLO and Faster R-CNN), to detect and classify animals present in the pre-processed video frame and create bounding boxes with confidence scores on objects present in the pre-processed video frame.

Once an initial detection has been made and the animals have been detected and labelled, resulting in a Bounding Box being drawn around each animal, it is easy to determine which animals belong where based on how they are displayed in the images.

These detected animals will then be sent into the Backend Server where they will be processed and the animals will be allocated to their respective databases. The backend then provides data back to the User Interface (UI) Dashboard via the Data Flow Module.

On the User Interface (UI) Dashboard, the user can interact with the entire functionality of the system through various forms. For instance, the user can upload new videos, change system parameters and view current detections in real time.

In addition, the system also has built-in Alert Generation. If an animal is detected, the system will generate an alert and send it as a Visual Alert, Audible Alert or Email Alert. This enables the user to respond quickly to an incursion into their farm.

Furthermore, there is a Data Logging and Analytics Module within the system to capture and retain the details of every animal intrusion, the time the event took place, the type of animal detected and where the animal was located on the user's farm. This data can be processed to provide trends that the user can use to improve farm management.

VI. RESULTS AND DISCUSSION

In order to assess the performance of the proposed system for detecting animal intrusion into farmland by monitoring real-time video and recorded video from virtual camera sources, numerous test cases were created by analysing video recordings of actual agricultural environments. The various conditions were modelled with various illuminations, difficulties in scenery backgrounds, and different animal movements.

The deep learning model primarily based on YOLO demonstrates capable of accurately detecting and classifying different types of animals, such as wild animals and domesticated animals. Each detected object was produced with both a bounding box outline and confidence score, meaning that animal detection was capable of real-time processing. Preprocessing techniques for model performance improvement and parameters tuning assisted with improving detection performance and reducing false alarm rates.

Fig. 2. Home page of the system.

The experimental results indicate that a detection system in operational mode within agricultural environments is capable of producing reliable detection results and providing timely alerts.

The system we established contained a user friendly, interactive website for monitoring animal intrusions. The first image shows the dashboard through which users can upload images, upload videos, or start an active camera to monitor their property in the way they choose.

The site's interactive interface has a detection legend that separates domestic animal detections from wild animal detections using colour codes; this creates an easier to understand and visually identifiable detector system, so that users may interpret the results without necessarily the need to have a technical background; the ease of uploading video footage into the monitoring system is enhanced by the drag-and-drop features of the upload window.

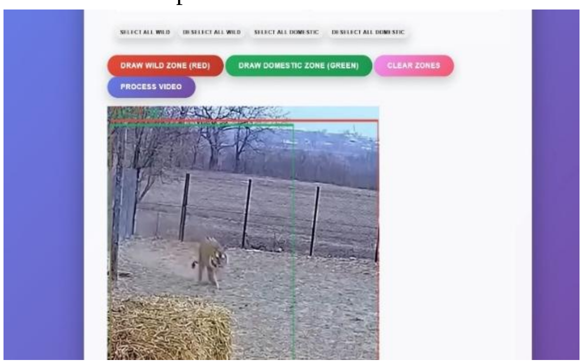

Fig. 3. Result preview container ui.

The second image shows how the monitoring system is able to detect the presence of a wild animal by placing it inside a box as well as the predetermined areas in which domestic animals will be inside of the monitoring project marked with different colours for easy identification. The area inside the red boxed region represents the wild animal monitoring area, and the green boxed region denotes the domestic region.

The system continues to monitor and track the movement of animals in the monitoring region, and sends alerts to the user when an intrusion has occurred. The boundary monitoring system operates under a principle of accurate location based on the location of the designated area as opposed to unnecessary alert areas to increase accuracy and decrease the number of false alarms. The visual results produced from the monitoring system allows for intuitive and effective real time decision making regarding to animal intrusion monitoring.

The Animal Intrusion Detection System has been identified as providing a high level of accuracy for the real-time detection and classification of animals due to its use of deep learning models, preprocessing methods, and area-based observation of animals. As a result, the system can deliver high reliability and accuracy across a variety of different environmental scenarios.

The simple and easy to use interface of the system will allow the farmer to easily observe their crops and take immediate action against intrusion-based events. The combination of real-time notifications, video feedback to the user, and historical data recording provides a practical and efficient method of securing their crops from intrusions in modern agriculture.

In conclusion, the results demonstrate that this system aids in decreasing the amount of manual monitoring needed by farmers, thereby decreasing the amount of damage to crops and enhancing the ability of the farmer to make data-driven decisions which may improve their ability to adopt intelligent farming techniques.

VII. CONCLUSION

The proposed solution, the Animal Intrusion Detection System (AIDS) provides a smart effective method of discussing a continuing problem of wildlife intrusion in agriculture by using computer vision advanced learning techniques, specifically employing models like YOLO and Faster-RCNN for accurate detection/classification of animals from real-time video feeds collected by surveillance cameras.

The overall improvement to the system's performance through the use of pre-processing, boundary-based monitoring and automated alert systems will greatly improve reliability and responsiveness. Providing users (farmers) with an easy-to-use web interface built into the system will allow them to easily monitor their field(s) using the system's alerting functionality based upon established monitoring zones, ultimately decreasing reliance on manual surveillance. In addition, the inclusion of data logs and analysis provides the farmer with relevant insight into intrusion patterns, increasing the farmer's ability to make informed decisions regarding long-term management strategy.

Research results indicate that the system provides a very high degree of accuracy in detecting objects along with a high degree of reliability; furthermore, the ability to operate efficiently indicates its suitability for real-world applications. The modular framework allows for scalability and flexibility and for future integration of IoT devices, edge computing, and fully automated deterrents.

The proposed system contributes to the development of precision agriculture by developing automated, scalable, and affordable methods for securing agricultural land. In addition to minimizing the impact of crop damage and economic loss from crop damage and theft, there is significant potential for encouraging sustainable coexistence between agricultural practices and wildlife through utilisation of non-invasive methods of monitoring agricultural properties via the use of artificial intelligence in the transition of conventional farming processes to smart, efficient systems like agriculture.

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