Smart Farm Security System Using Edge AI for Animal Detection

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***Abstract*—Animal entry into livestock areas can put sheep and other farm animals at risk, especially on farms located close to forest edges or areas where wild animals are common. This paper describes a prototype security system that uses a camera and an AI-based detection model to monitor a sheep enclosure. This model will identify six different animal classes from the camera feed. The area being watched was divided up into two regions; the buffer region and the sheep enclosure to tell when a new animal was coming into the area. When an intruder is detected an audio deterrent will be played depending on what animal class they have been identified as. This will then send an alert to the farmer using a web dashboard and telegram. All information for events will be recorded for future reference. We have built a 3ft x 2ft physical model to represent our enclosure and monitoring area. This paper outlines how we designed our system and implemented them. Our testing requirements are also described.**

***Index Terms*—animal intrusion detection, smart farming, deterrent system, object detection, IoT, livestock protection, real-time alerting.**

I. INTRODUCTION

Sheep and other livestock may be exposed to danger when wild or stray animals enter farm premises. This risk is difficult to manage in locations near forests or open land, where an enclosure cannot always be watched by a person. Fences and regular patrols are useful, but they require maintenance and attention, and they may not provide an immediate warning when an animal
approaches. A camera-based monitoring arrangement can help by observing the enclosure continuously and identifying activity that needs attention.

The project described in this paper uses a webcam and a locally connected processing unit to monitor a model sheep enclosure.
Its purpose is not simply to detect an animal in the camera view; it also considers where the animal appears. The monitored space has a buffer region around the sheep enclosure and a separate protected region. This distinction allows the system to treat an animal approaching the enclosure differently from one that has crossed into the protected area. For a confirmed entry, the system is designed to play a suitable non-harmful sound and notify the farmer. The prototype provides a small-scale platform for demonstrating these functions and considering how the arrangement could be extended to a farm.

II. LITERATURE SURVEY

Farmers use several methods to reduce the risk of animal intrusion, including fences, human observation, sound-based scare devices, and electronic sensors. These methods can provide a warning or act as a barrier, but their usefulness may be limited when the monitored area is large or when regular human supervision is unavailable. Motion and infrared sensors can indicate that movement has occurred; on their own, however, they do not necessarily identify which animal caused it. Environmental movement may also lead to unwanted alerts. These limitations have encouraged the use of camera-based systems that can provide information about the object as well as its presence. [7,3]
Computer-vision methods offer a way to examine images and identify animals within them. Deep-learning detectors can locate an animal in a frame and

assign it a class, rather than reporting movement alone. The studies considered in this work describe the use of YOLO-family models for applications were detection speed matters alongside recognition performance. Smaller model configurations, including YOLOv8 variants, are relevant when the processing hardware has limited resources.

Camera-based detection still depends on image quality: poor lighting, objects blocking one another, busy backgrounds, and weather can affect what the model recognizes. [7,1]

Processing the camera feed close to the farm is another consideration for practical deployment. In an edge-based arrangement, images are analysed on a nearby device instead of sending every frame to a remote server. This can reduce the amount of data that must travel over the network and can help the system continue to operate where internet access is unreliable. The AP2 study describes a farm-protection approach that brings together laser boundary sensing, YOLOv8m detection, Raspberry Pi processing, and IoT notifications. The wider body of work also discusses edge processing as a way to support timely responses and reduce reliance on continuous cloud connectivity. [2,7,1]

Detection is only one part of an intrusion-management system; the response after detection also matters. Research has considered several non-lethal options, including warning sounds, lights, animal-related audio, and electronic repellents. The AP13 work draws attention to the problem of habituation: an animal may become less responsive if the same deterrent is repeated. This makes the choice and variation of a response an important design consideration. Across the reviewed approaches, detection and remote monitoring are common features, while the combination of animal-aware responses, zone information, and direct farmer notifications is less consistently addressed. [13,7]

Communication design has also been examined in wildlife-monitoring applications. In an event-driven system, information is sent when an activity of interest occurs rather than continuously transmitting every observation. This approach can reduce unnecessary network traffic. Secure communication is another concern because monitoring systems may transmit event details and images over a network. The work cited in [3] considers secure, event-driven communication, although its main emphasis is not the full combination of animal classification, zone assessment, and deterrent control considered in this project. [3]

The literature therefore provides useful individual approaches to animal recognition, edge processing, IoT communication, and deterrence. A practical farm installation, however, needs these functions to work together. An animal's presence alone does not indicate whether it is still outside the enclosure or has entered the area where livestock are kept. Likewise, a warning system that uses the same response for every animal does not make use of the class information provided by a detector. These observations motivate the proposed arrangement, which links animal identification with zone assessment, a class-dependent sound response, farmer alerts, and a record of each event. [7,11,13

III. SYSTEM ARCHITECTURE OF THE PROPOSED MODEL

The webcam is positioned centrally within the model to provide coverage over the sheep area and buffer zone. The webcam feeds into a local processor unit which takes each frame of the recorded video feed. This data is processed using the animal detection model. The animal detection model will identify what type of animal is present within the area being monitored and provide a rough estimate of where the animal is located within the area. This information is used to determine whether the animal is located within the buffer zone or protected area. The primary data processing will occur on the local processor unit. Therefore, there is no need to continually upload the webcam footage to an external server. Once an animal has been identified, the processor unit will check to see if it is within the specified areas. This data will then be sent to the response and monitoring aspects of the system. If there has been an intrusion, this will trigger the chosen deterrent sound. This information will also be sent to the dashboard and notification service.

Overall, this provides a connection between the webcam, detection model, zone logic, response system and recording of events. This can be seen as 5 stages of the process. Firstly, the webcam will record footage of the area. Secondly, the detection model will identify the animals present within the frames. Finally, the zone logic will check to see if the identified animal is within the buffer zone or protected area.

The main analysis is carried out on the local processing unit. In this arrangement, the camera feed does not need to be continuously uploaded to an external server for the basic detection and zone decision. After an animal is identified, the processing unit checks its position against the configured regions. The result is passed to the response and monitoring functions: an intrusion can lead to the selected deterrent sound, while the dashboard and notification service receive the event details. The architecture therefore connects the camera, detection model, zone logic, response mechanism, and event record as parts of one monitoring process.

The operation can be viewed as five connected stages. First, the webcam acquires video of the enclosure and its surroundings. Next, the detection model identifies and classifies animals in the frames. The zone logic then checks whether a detected animal is in the buffer region or the protected sheep area. If the conditions for an intrusion are met, the system activates the relevant animal-specific sound and sends an alert. Finally, the event information is saved so that it can be viewed later in the dashboard.

Stage	Function
Sensing	Central webcam captures continuous live video of the enclosure and buffer zone
Detection	AI model identifies and classifies the animal with a bounding box and confidence score
Zone Logic	System checks the animal's position against buffer-zone and sheep-area boundaries
Response	Deterrent sound plays automatically; Telegram and dashboard alerts are sent
Logging	Event details are stored for the dashboard's intrusion history

Table 1. Five-stage system architecture

The five stages operate sequentially to establish a continuous intrusion-monitoring and response cycle. The system begins with visual sensing and AI-based animal identification, followed by zone-based assessment to determine the intrusion status. When an animal enters the protected zone, the corresponding deterrent and notification mechanisms are activated, while the event is simultaneously recorded in the monitoring dashboard. This integrated workflow enables the proposed system to perform detection, decision-making, response, and monitoring within a unified architecture.

IV. METHODOLOGY

A. Data Preparation and Model Development

The detection dataset contains images for the six animal classes selected for the project. Images were gathered and annotated so that the animals of interest were marked for model training. The annotated data was used to train the object-detection model, and the trained model was then evaluated for its intended use. After this stage, the model was connected to the webcam stream so that it could process incoming frames during operation. The quality and variety of the collected images are important because the model can only learn from the examples represented in its dataset.

B. Real-Time Animal Detection and Classification

The webcam remains focused on the enclosure and sends its live stream to the local computer. The detection model looks at the incoming frames and identifies any animal. This will give the class name, confidence and bounding box of an object. This information will be sent to the zone checker function which determines if the animal has been detected in the buffer region or the protected sheep area based on its position.

C. Zone Based Intrusion Decision

The camera feed has been split into two zones. The outer zone will be considered the buffer zone. The inner zone will be considered the protected zone as it represents the sheep enclosure. The position of the animal will then be checked against these zones. If the animal is detected within the buffer zone, this can be considered as an early warning to the farmer. If the animal was detected in the protected zone, then this can be considered a critical intrusion.

D. Intrusion Response and Animal-Specific Deterrence

The animal class reported by the detection model is used to select the sound assigned to that class. Each of the six target classes have their own individual audio file. When the zone logic identifies that the protected area has been entered, the corresponding audio file will play on the laptop or external speaker. The intrusion details will also be passed through to the notification function.

E. Notification & Event Management

Once the system identifies an intrusion, an event will be created. This event will include information on what class of animal

was detected, confidence value, zone and time. This information will be used to update the dashboard and send a Telegram message. If an image can be captured by the camera, this will be attached to the event/notification to give the farmer more information on what was detected. It will also show if the audio response and notification were triggered. Keeping these details makes it possible to review earlier events rather than relying only on the live alert.

F. Prototype Implementation and System Testing

A physical prototype measuring 3 ft × 2 ft was used to represent the monitored farm area. It includes a marked enclosure for the sheep and a surrounding buffer region. Entry paths allow animal models to be placed at different positions during testing. The webcam is mounted centrally to view both regions, and a laptop or connected speaker provides the audio output. The prototype was used to show the integrated functionality of the system; detecting and identifying the animal, testing if they are within the zone, triggering the sound, sending the alert and recording the event.

V. RESULT AND DISCUSSION

The system was designed to process real-time webcam footage. The dashboard displays information about the detected objects in the webcam feed, which will include the predicted class, confidence level and bounding box of the animal. A zone was created that separated the outside buffer zone and the area where the sheep are protected. This helped to determine whether an animal had intruded based on their position. The system responds by playing the corresponding sound to the detected class, and sending an alert via Telegram. The dashboard also records information about the event, including images, times and how many animals were detected. There are options to change the detection threshold, zone area, manually play the sound and see the status of the camera

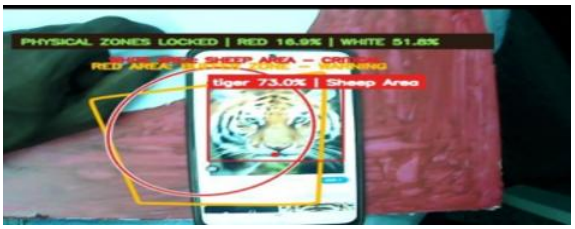


Fig 1: Animal intrusion detection

More testing would be required to give quantitative insight into the performance of the system. This could include testing that the model can identify each of the target animals accurately, thata detections have been correctly assigned to zones using the logic, and whether it works as intended with the audio and alert features. This could be measured by looking at the accuracy of each class of detection, frame rate, and latency.

VI. CONCLUSION

The following work presents an example of how a camera-based farm security system could be used to monitor a livestock enclosure and respond when an animal enters the protected space. This was achieved using real-time webcams, an animal detection model, two monitoring zones, animal specific sounds, alerts to the farmer, and record events. The video was processed on a local computer so that the detection and zone determination could happen close to the camera. The buffer zone and sheep enclosure split helps ensure that there is a clear distinction between the animal approaching the camera and entering the protected area. The system was designed to detect 6 potential animal types. The type and location of the animal will then decide what actions are taken. When an animal intrudes the aim is to play the relevant animal safe sound. It will also provide information to the dashboard and Telegram. Information such as animal type, confidence, zone, time, image and response can be recorded. A physical model 3ft x 2ft was created to allow the full process to be implemented and tested. More testing is needed to ensure that the detection, zone determination, response time, alerts and event recording are working correctly. Testing under various lighting, angle and background conditions would help to see how well the method could be applied to a real farm.

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