SMART CROP GUARDIAN:WILD ANIMALS INTRUSION DETECTION AND ALERT SYSTEM

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report titled **"SMART CROP GUARDIAN:WILD ANIMALS INTRUSION DETECTION AND ALERT SYSTEM"** Is the bonafide work of **SANGEETHA S (REG NO: 811721243047) UDHAYAMALATHI N (REG NO: 811721243059) VASANTHAPRIYA M (REG NO:811721243060)** who carried out the project under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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DECLARATION

We jointly declare that the project report on **“SMART CROP GUARDIAN: WILD ANIMALS INTRUSION DETECTION AND ALERT SYSTEM”** is the result of original work done by us and best of our knowledge, similar work has not been submitted to **“ANNA UNIVERSITY CHENNAI”** for the requirement of Degree of **BACHELOR OF TECHNOLOGY**. This design project report is submitted on the partial fulfillment of the requirement of the award of Degree of **BACHELOR OF TECHNOLOGY**.

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ABSTRACT

In modern agricultural practices, managing and protecting crops from animal intrusions is a significant challenge for farmers. The emergence of intelligent surveillance systems powered by artificial intelligence (AI) and machine learning has presented a promising solution to this issue. This paper proposes a comprehensive real-time animal detection and surveillance system designed to aid farmers in identifying and managing intruding animals using the YOLO (You Only Look Once) object detection algorithm.The core functionality of the proposed system relies on the YOLO V8 algorithm for real-time animal detection. YOLO V8 is an advanced deep learning framework capable of identifying objects in images quickly and efficiently. In this system, a camera continuously captures images of the environment, and YOLO V8 detects and recognizes the presence of animals in these images. Once an animal is detected, the camera system captures an image and uploads it to a remote server for further processing. This process not only helps identify the animal but also ensures minimal storage usage as the images are deleted after being processed. Before being fed into the YOLO V8 model, each captured image undergoes a series of pre-processing steps using OpenCV. These steps include noise reduction, resizing, and normalization to enhance the image quality for better detection accuracy. These techniques help in reducing computational load while maintaining the quality of the input data, ensuring fast and reliable detection in real-world conditions. Once the image is processed and analyzed, the system automatically triggers a set of actions. First, a notification is sent via email to the farmer, alerting them of the intrusion. This email contains vital information such as the timestamp of detection and the type of animal detected.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
CNN	-	Convolution Neural Network
PCA	-	Principal Component Analysis
SVD	-	Singular Value Decomposition
ML	-	Machine Learning
YOLO	-	You Only Look Once

CHAPTER 1

INTRODUCTION

In recent years, the advancement of technology in agriculture has led to the development of various intelligent systems aimed at improving efficiency, security, and management. One significant challenge faced by farmers, especially those in rural or remote areas, is the protection of crops from intruding animals. These animals can cause substantial damage to crops, leading to significant financial losses for farmers. The traditional methods of animal control, such as physical barriers, fencing, and manual monitoring, are often time- consuming, expensive, and not always effective.

1.1 BACKGROUND

In modern a agriculcuture with the increasing size and complexity of modern farms, manual surveillance becomes impractical, making it essential to explore more efficient and automated solutions. This has given rise to the concept of intelligent surveillance systems, which leverage the power of machine learning, artificial intelligence (AI), and image processing techniques to detect, recognize, and respond to animal intrusions in real-time.The proposed system aims to address this challenge by developing a robust and efficient solution for real-time animal detection using the YOLO V11 (You Only Look Once) object detection framework.

YOLO V11 is a deep learning-based model that has gained widespread popularity for its ability to detect objects in images with high accuracy and speed. YOLO V11 works by processing an entire image in one go, making it highly efficient and suitable for real-time applications. The system integrates YOLO V11 with a camera-based monitoring system.

1.2 PROBLEM STATEMENT

In modern agriculture, protecting crops from animal intrusions is a critical challenge. Traditional methods, such as physical barriers or manual patrols, are often inefficient and labor-intensive. With the advancement of artificial intelligence (AI) and machine learning (ML), there is a growing potential to integrate intelligent surveillance systems into farming practices. AI-powered systems can detect, identify, and respond to animal intrusions in real time, offering a more efficient solution for crop protection.

One such AI technology is the YOLO (You Only Look Once) object detection algorithm, known for its speed and accuracy in real-time image processing. YOLO V8, the latest version, is particularly suitable for outdoor applications like animal detection in farming environments. By using cameras for continuous monitoring, YOLO V8 can identify animals as they approach crops and trigger automated actions. The system processes captured images using OpenCV for pre-processing, such as noise reduction and resizing, ensuring that the data fed into YOLO V8 is of high quality for accurate detection. Once an animal is detected, the system notifies the farmer via email and activates a buzzer for immediate response. This technology helps farmers manage intrusions effectively, reduce crop damage, and streamline farm operations.

The significance of this project lies in its potential to revolutionize how farmers protect their crops from animal intrusions. With the global demand for food growing, ensuring crop yield is critical for maintaining food security. Animal damage can lead to significant financial losses, especially in large-scale farming operations. Traditional methods of protection are losses, especially in large-scale farming operations. Traditional methods of protection are often costly, inefficient, and labor-intensive.

The proposed AI-driven surveillance system provides an automated, real-time solution that reduces the dependency on manual intervention, enhances the speed and accuracy of detection, and ensures timely responses to intrusions. By utilizing the YOLO V8 object detection algorithm, the system can efficiently identify animal sand trigger alerts, helping farmers act swiftly to prevent damage. This technology can not only save costs but also improve overall farm productivity, supporting sustainable agricultural practices.

Fig. 1.1 Significance

1.3 AIM AND OBJECTIVE

1.3.1 Aim

Aims to address a common problem in modern agriculture: protecting crops from intruding animals. In many regions, animals such as deer, cows, pigs, and wild boars can cause significant damage to crops, leading to losses in both yield and profit for farmers. Traditional methods like fencing or manual monitoring are often expensive and inefficient. As agricultural lands expand, manually controlling these intrusions becomes impractical. Hence, there's a growing need for automated systems that can detect and respond to animal intrusions in real time with minimal human intervention. This system combines artificial intelligence (AI), machine learning, and image processing technologies with hardware components like LCD display, buzzer, LED, and Arduino Uno to provide an efficient and smart solution.

1.3.2 Objective

- Develop a real-time animal detection system using YOLO V8 to prevent animal intrusion and protect agricultural fields, ensuring continuous farm surveillance and safety for improved yield and productivity.
- Enhance image quality through OpenCV pre-processing techniques such as noise reduction, resizing, and normalization to improve YOLO V8 model accuracy and facilitate efficient real-time animal detection.
- Implement automatic notification systems to alert farmers via email with crucial information, including detection timestamps and identified animal types, enabling timely decision-making and rapid response.
- Incorporate a buzzer alert system to provide immediate auditory warnings, deterring intruding animals and notifying farm personnel, ensuring immediate action and increased farm security.
- Enable remote control of the buzzer system through web and mobile interfaces, allowing farmers to manage system functionality flexibly from any location with internet access.
- Utilize advanced image compression techniques, including dimensionality reduction and feature extraction, to minimize computational load while preserving image quality, ensuring fast, reliable, and real-time animal detection.
- Train the YOLO V8 model on a diverse labeled dataset of animal images to improve classification accuracy, adapting to different environmental conditions and enhancing overall system robustness.
- Reduce false positive rates through continuous refinement of the YOLO V8 model by incorporating feature fusion techniques, ensuring accurate detection and minimizing unnecessary alerts for farmers.

CHAPTER 2
LITERATURE SURVEY

2.1 IOT-BASED SYSTEM OF PREVENTION AND CONTROL FOR CROP DISEASES AND INSECT PESTS.

Zhibin Wang, Xiaojun Qiao, Ying Wang, Hao Yu, Cuixia Mu

An IoT-Based System for the Prevention and Control of Crop Diseases and Insect Pests utilizes advanced technologies to monitor and manage agricultural health. This system integrates sensors, cameras, and smart devices across agricultural fields to detect early signs of diseases and pest infestations. Using real-time data from the IoT sensors, it can identify environmental conditions conducive to disease spread, monitor pest movement, and assess crop health. The data collected is analyzed using machine learning algorithms to predict potential outbreaks and recommend preventive measures. Automated responses, such as the activation of pest control mechanisms or environmental adjustments, can be triggered to reduce the need for chemical pesticides, promoting sustainable farming practices. Additionally, the system ensures energy efficiency by using solar-powered IoT devices, thus reducing operational costs. By enabling timely interventions, this IoT-based approach significantly improves crop protection, minimizes yield loss, and supports eco-friendly agricultural practices.

Merits:

- Early detection of crop diseases and pests using real-time IoT sensor data.
- Integration of machine learning for predictive analysis and decision-making.

Demerits:

- High initial setup cost for sensors, cameras, and infrastructure.
- Dependency on stable internet connectivity for real-time monitoring.

2.2 CROP PROTECTION AND MONITORING FROM ANIMAL ATTACKS USING IOT SOLUTIONS.

Nandhini G S, Kaviyarasu M, Saminathan K, Aakash A

The project "Crop Protection and Monitoring from Animal Attacks Using IoT Solutions" focuses on the development of an innovative system that integrates Internet of Things (IoT) technology to protect agricultural crops from animal intrusions. The system employs sensors such as motion detectors, infrared cameras, and ultrasonic sound emitters to monitor and detect the presence of animals in and around crop fields. IoT-enabled devices are used to continuously track and report real-time data, which is then analyzed to identify any potential threats from animals like wild boars, deer, or rodents. Once an animal is detected, the system triggers deterrents such as sound alarms or ultrasonic waves, ensuring minimal harm to the crops. The integration of IoT ensures that farmers can remotely monitor their fields, receive alerts, and take immediate action, ultimately reducing the need for manual surveillance. This solution improves crop yield while ensuring sustainability and reducing energy consumption in pest control.

Merits:

- Remote monitoring allows farmers to oversee fields anytime, anywhere.
- Minimally invasive solution that avoids harming animals.

Demerits:

- System may require regular maintenance in harsh weather conditions.
- Initial cost of deployment for IoT devices and setup.

2.3 SUSFL:ENERGY-AWARE FEDERATED LEARNING-BASED MONITORING FOR SUSTAINABLE SMART FARMS.

Dian Chen, Paul Yang, Ing-Ray Chen, Dong Sam Ha, Jin-Hee Cho

SusFL: Energy-Aware Federated Learning-based Monitoring for Sustainable Smart Farms" presents an innovative solution to monitor and manage the sustainability of smart farms using federated learning (FL) and energy-aware techniques. The paper proposes SusFL, a system designed to optimize the use of energy in agricultural monitoring by leveraging edge devices and federated learning algorithms. The primary goal of this approach is to reduce energy consumption while maintaining the efficiency of real-time monitoring of farm operations. By using FL, the system allows for decentralized data processing, minimizing the need for frequent data transfers to central servers, thus saving bandwidth and energy. Additionally, the system employs energy- efficient protocols that adapt the learning process based on available resources, ensuring that farm operations such as irrigation, pest control, and crop monitoring can be optimized in a sustainable manner. SusFL aims to empower smart farms to make informed decisions, ultimately enhancing productivity and minimizing the ecological footprint.

Merits:

- Energy-efficient monitoring through the use of federated learning (FL).
- Decentralized data processing reduces bandwidth and energy usage.

Demerits:

- Complex implementation due to federated learning integration.
- Edge devices may have limited computational power affecting performance.

2.4 SCARECROW MONITORING SYSTEM: EMPLOYING MOBILENET SSD FOR ENHANCED ANIMAL SUPERVISION.

Balaji VS, Mahi AR, Anirudh Ganapathy PS, Manju M

The "Scarecrow Monitoring System: Employing MobileNet SSD for Enhanced Animal Supervision" is an innovative solution aimed at protecting crops from animal intrusions using advanced IoT and machine learning technologies. This system integrates MobileNet SSD (Single Shot MultiBox Detector), a lightweight convolutional neural network (CNN), to detect animals in agricultural fields in real-time. MobileNet SSD is designed for efficient computation and accurate object detection with minimal computational resources, making it ideal for deployment in resource-constrained environments such as farms. The scarecrow monitoring system uses cameras equipped with this technology to identify animals like deer, wild boars, and other pests that could damage crops. Once detected, the system triggers a deterrent response, such as activating a scarecrow or emitting sounds to drive the animals away. This system not only improves crop protection but also minimizes the need for pesticides, reducing environmental impact and promoting sustainable farming practices.

Merits:

- Environmentally friendly by minimizing pesticide use.
- Supports sustainable farming and promotes ecological balance.

Demerits:

- May struggle with low-light or poor weather conditions.
- Limited to known animal types unless retrained for others.

2.5 THRESHOLD-BASED AUTOMATED PEST DETECTION SYSTEM FOR SUSTAINABLE AGRICULTURE.

Tianle Li, Jia Shu, Qinghong Chen, Murad Mehrab Abrar, John Raiti

The "Threshold-Based Automated Pest Detection System for Sustainable Agriculture" leverages advanced technologies such as Internet of Things (IoT), image processing, and machine learning to detect and manage pest infestations in agricultural fields. The system works by using IoT sensors and cameras deployed across the field to monitor real-time environmental data, including humidity, temperature, and soil conditions, which are key factors affecting pest activity. When the system detects pest activity surpassing a pre-set threshold level, it triggers automatic alerts and intervention measures, such as activating pest repellents or notifying farmers via mobile applications. This threshold-based approach ensures that pest control is applied only when necessary, thus preventing overuse of chemicals and minimizing environmental impact. Additionally, the system helps farmers achieve sustainable crop protection by providing timely and data-driven insights, optimizing resource usage, and reducing the overall cost of pest management. By integrating automation and precision agriculture, this system enhances productivity while promoting eco-friendly farming practices.

Merits:

- Minimizes chemical use, reducing environmental impact.
- Real-time alerts and interventions enhance responsiveness.

Demerits:

- Initial setup and calibration can be complex.
- False triggers may occur if conditions fluctuate rapidly.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

In the current agricultural landscape, crop protection from wildlife is a critical issue. Existing animal detection and deterrent systems use a mix of traditional and advanced technologies to safeguard crops. Motion sensors are commonly used to detect movement in fields and trigger alarms. Infrared cameras are employed to capture heat signatures, enabling detection in low light or nighttime. Automated deterrents, such as noise-making devices or sprinklers, are activated by sensors to scare off animals. Physical barriers like fences are also used to prevent animal intrusion. Advanced systems integrate these technologies into a network, often using IoT-based solutions for real-time monitoring and automated responses. While these systems offer increased control, they still face several limitations. Despite these innovations, current systems face challenges such as high costs, the need for technical maintenance, human monitoring, and limited analytical capabilities. Privacy concerns also arise with the use of surveillance devices connected to cloud networks.In conclusion, while current wildlife detection systems help safeguard crops, improvements are needed in cost, accuracy, automation, and data insights. The future of crop protection lies in smart systems powered by artificial intelligence, real-time analytics, and adaptive learning algorithms.

3.1.1 Demerits

- **False Positives:** Motion sensors often trigger false alarms from non-animal movements like wind or debris.
- **High Costs:** Infrared cameras, advanced sensors, and automated deterrents can be expensive, especially for small-scale farmers**.**
- **Maintenance Requirements:** Regular monitoring and technical expertise are needed to maintain these systems, which is labor-intensive.
- **Limited Data Insights:** Current systems often lack real-time analytics or long-term data tracking for better decision-making.

- **Ineffectiveness for Certain Animals:** Physical barriers and some deterrents are not effective against agile animals like deer or wild boars.

3.2 PROPOSED SYSTEM

The proposed system aims to address a common problem in modern agriculture: protecting crops from intruding animals. In many regions, animals such as deer, cows, pigs, and wild boars can cause significant damage to crops, leading to losses in both yield and profit for farmers. Traditional methods like fencing or manual monitoring are often expensive and inefficient. As agricultural lands expand, manually controlling these intrusions becomes impractical. Hence, there's a growing need for automated systems that can detect and respond to animal intrusions in real time with minimal human intervention. This system combines artificial intelligence (AI), machine learning, and image processing technologies with hardware components like LCD display, buzzer, LED, and Arduino Uno to provide an efficient and smart solution. At the core of the image-based detection lies the YOLOv8 (You Only Look Once Version 8) algorithm, a cutting-edge object detection model known for its real-time performance and high accuracy. System Overview Cameras installed around the farm continuously monitor the area, capturing images that are sent to a server where the YOLOv8 algorithm analyzes them. YOLOv8 processes these images in a single pass, efficiently detecting animals by drawing bounding boxes and labeling them according to the type of intrusion. Before analysis, the images are preprocessed using OpenCV, involving resizing, noise removal, normalization, and contrast enhancement. This ensures better accuracy and reduces false detections. Additionally, image compression techniques are used to lower data transmission loads, which is useful in remote areas with limited bandwidth. Hardware Integration with Arduino Uno Once an animal is detected, a series of hardware responses is triggered using Arduino Uno, a microcontroller that acts as the bridge between the software and physical components: LCD Display: The type of detected animal and time of detection are shown on an LCD module connected to the Arduino. This provides instant local feedback even without internet access. Buzzer Activation: A buzzer is turned on immediately to scare the animal away. The loud noise acts as a deterrent and also alerts nearby workers or the farmer about the intrusion.

LED Indicator: An LED is lit to show that an animal has been detected. Different colors of LEDs can be used to indicate different animals or levels of threat. Remote Notification: Simultaneously, the system sends an automated email notification to the farmer.

3.2.1 Merits

- **Real-Time Detection and Response:**

  Uses YOLOv8, a highly accurate and fast object detection algorithm, ensuring quick identification of animals.

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- **Remote Monitoring and Control:**

  Farmers can receive automated notifications (email) and remotely control hardware (buzzer, LED) via mobile or web interfaces.

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CHAPTER 4

SYSTEM SPECIFICATIONS

4.1 HARDWARE SPECIFICATION

- **Processor(CPU):**Intel Core i5 (or equivalent) or higher
- **RAM:**8GB or more
- **Storage:**256GB SSD(Solid State Drive) or higher for faster data access
- **Graphics:** Integrated graphics or dedicated GPU for handling app rendering during development
- **Operating System:**Windows10or11(64-bit),macOS(Mojave or later),or Linux (Ubuntu 20.04 or later)
- **Display:**1080p resolution, at least 13-inch screen for comfortable development
- **Network:** High-speed internet (minimum 10 Mbps)

4.2 SOFTWARE SPECIFICATION

- **Operating System:** Windows, macOS, or Linux platforms
- **Development Tool:** Python IDLE
- **Object Detection Algorithm :** YOLO

4.2.1 Python Idle

A Python Integrated Development Environment (IDE) serves as a centralized platform that simplifies and enhances the entire software development lifecycle for Python programmers. It combines a variety of essential tools into a single user-friendly interface, significantly increasing productivity and reducing the need to switch between multiple applications. At the heart of every Python IDE is a sophisticated code editor equipped with features like syntax highlighting, code folding, and intelligent autocompletion, which help developers write cleaner code faster while minimizing syntax errors. These editors often include real-time linting and error detection, which flag issues as code is written, encouraging immediate corrections and improved code quality. Another core strength of Python IDEs lies in their powerful debugging capabilities. Developers can set breakpoints, inspect variables, evaluate expressions, and step through code execution line by line to better understand program behavior and locate bugs. This process is far more efficient and intuitive within an IDE than using standalone debugging tools. Moreover, Python IDEs support integrated terminal consoles that allow direct interaction with the Python interpreter, enabling immediate code execution and testing of snippets without running the entire script.

4.2.2 YOLO

YOLO (You Only Look Once) is a cutting-edge object detection algorithm designed for high-speed, real-time image analysis. Unlike traditional methods such as R-CNN or Fast R-CNN, which involve multiple stages like region proposals and classification, YOLO processes the entire image in a single forward pass using a convolutional neural network (CNN). This single-shot approach drastically reduces computation time while retaining high accuracy, making it ideal for applications such as surveillance, autonomous driving, and industrial automation.

The YOLO architecture divides the input image into an S × S grid, where each grid cell predicts multiple bounding boxes, confidence scores, and class probabilities. A key principle of YOLO is treating detection as a regression problem: it directly predicts bounding box coordinates and class probabilities from the entire image. This architecture ensures fast inference, capable of reaching up to 45 frames per second (fps) in earlier versions.

YOLO’s architecture consists of convolutional layers for feature extraction and fully connected layers for final predictions. Each grid cell is responsible for detecting objects whose centers fall within it. To avoid duplicate detections, YOLO uses non-max suppression (NMS), keeping only the boxes with the highest confidence scores.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

A Wild Animals Detection System using the YOLO (You Only Look Once) detector is an advanced AI-based solution designed to identify wild animals in real time. It employs surveillance cameras placed in strategic outdoor locations, such as forest edges or farmlands. The YOLO algorithm processes the video feed instantly to detect animals like elephants, leopards, or wild boars with high accuracy. This real-time object detection model classifies and localizes animals in a single pass, making it ideal for speed and efficiency.

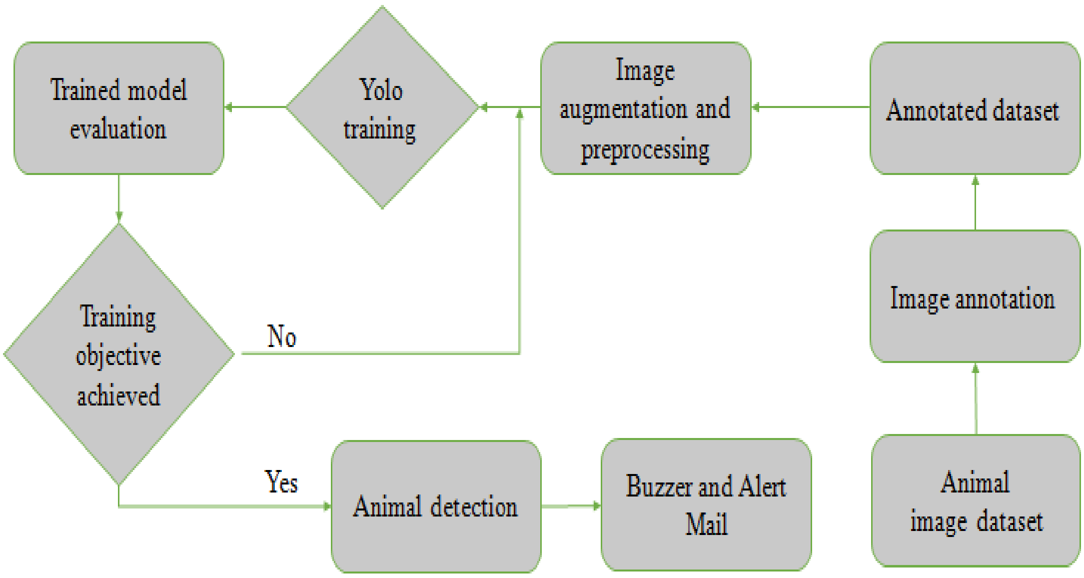

Fig 5.1 System Architecture

5.2 DATA FLOW DIAGRAM

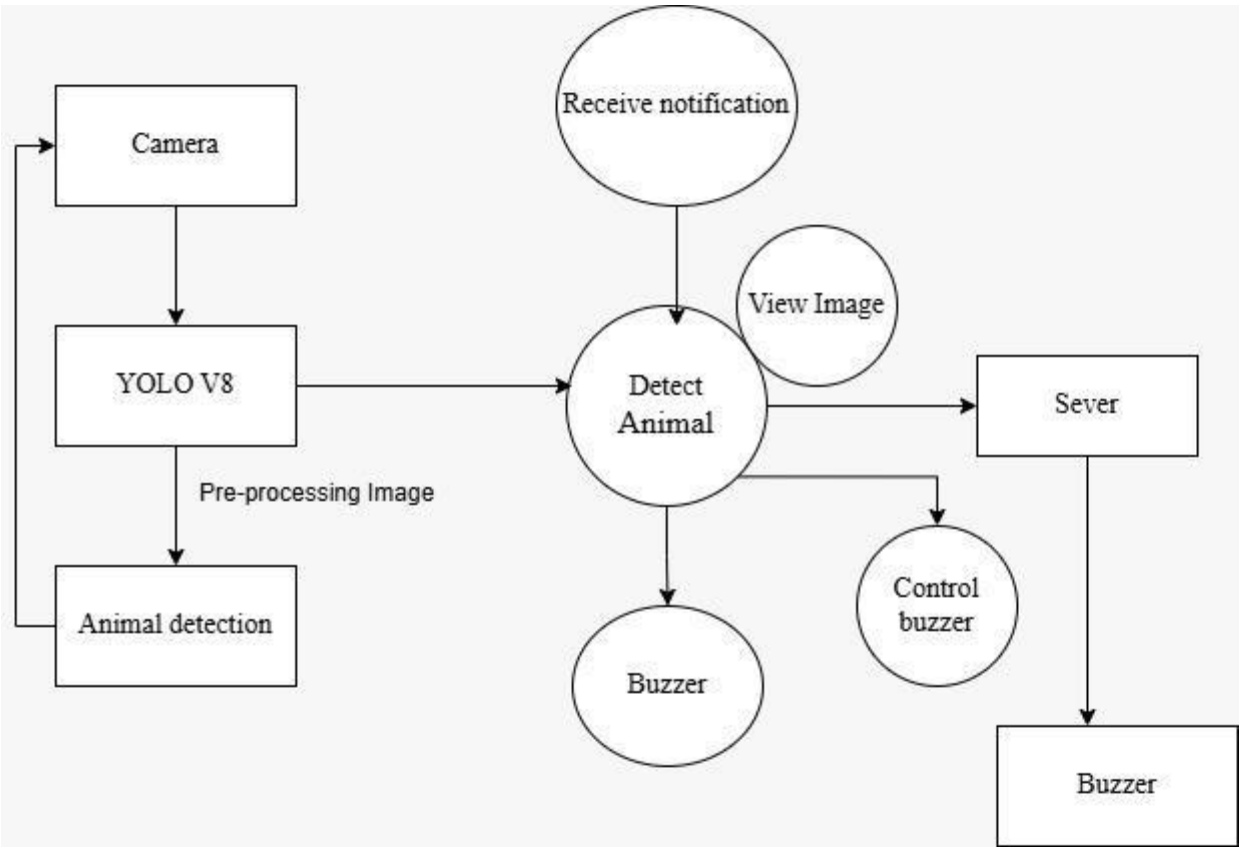

Fig 5.2 Data Flow Diagram

5.3 SEQUENCE DIAGRAM

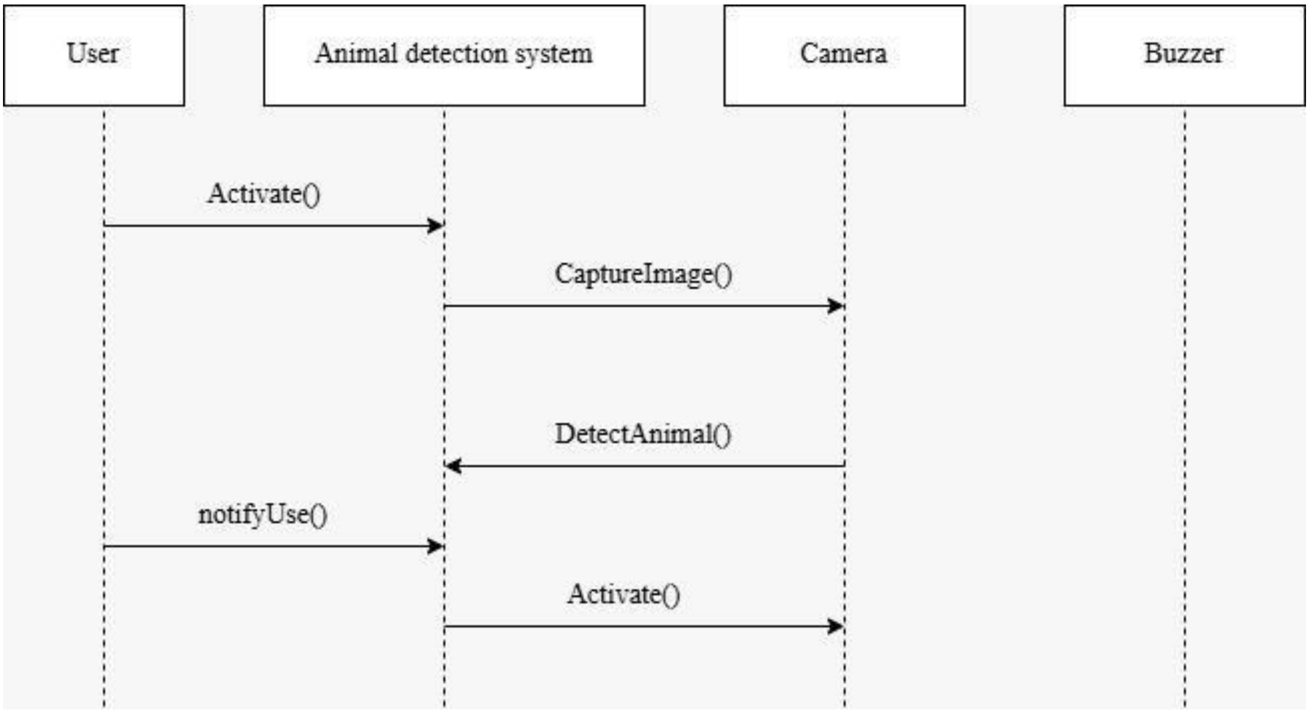

Fig 5.3 Sequence Diagram

5.4 USE CASE DIAGRAM

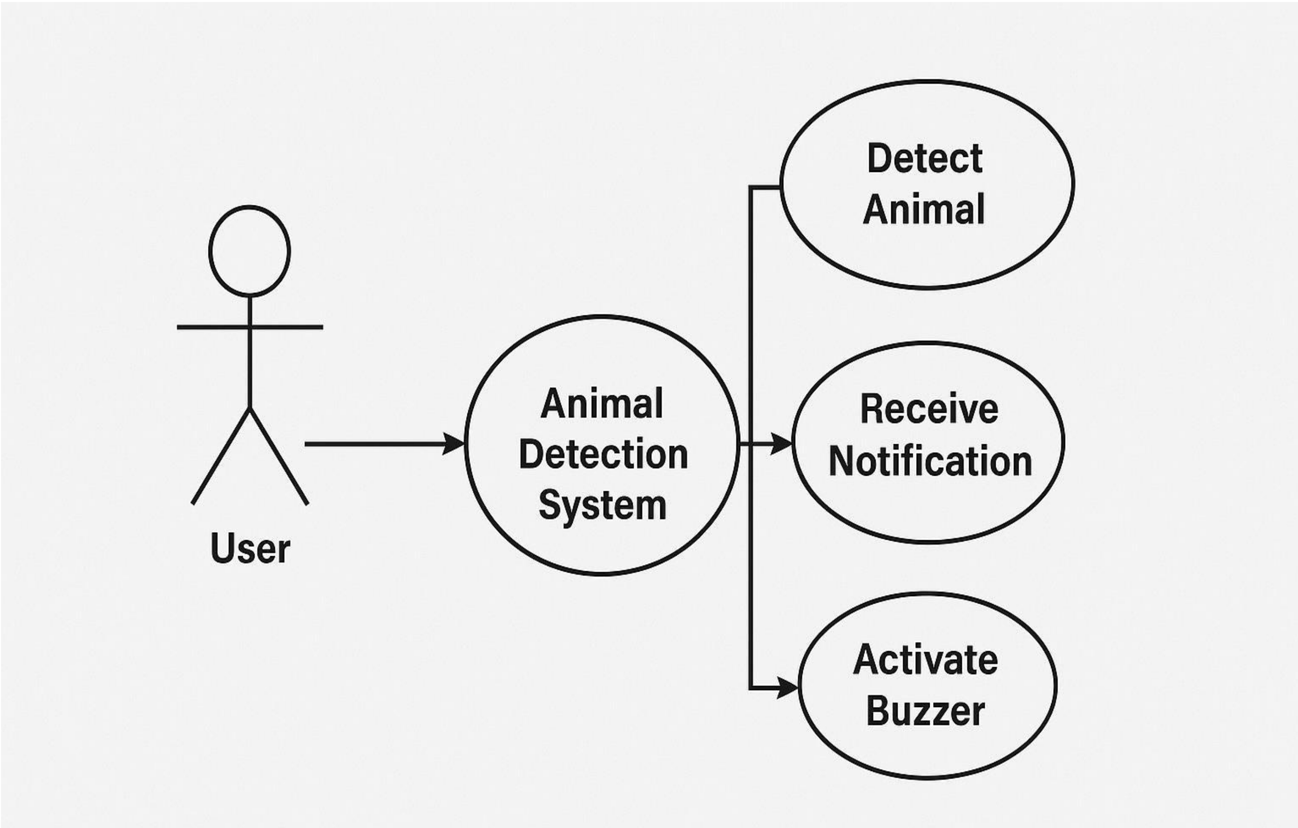

Fig 5.4 Use Case Diagram

5.5 FLOW DIAGRAM

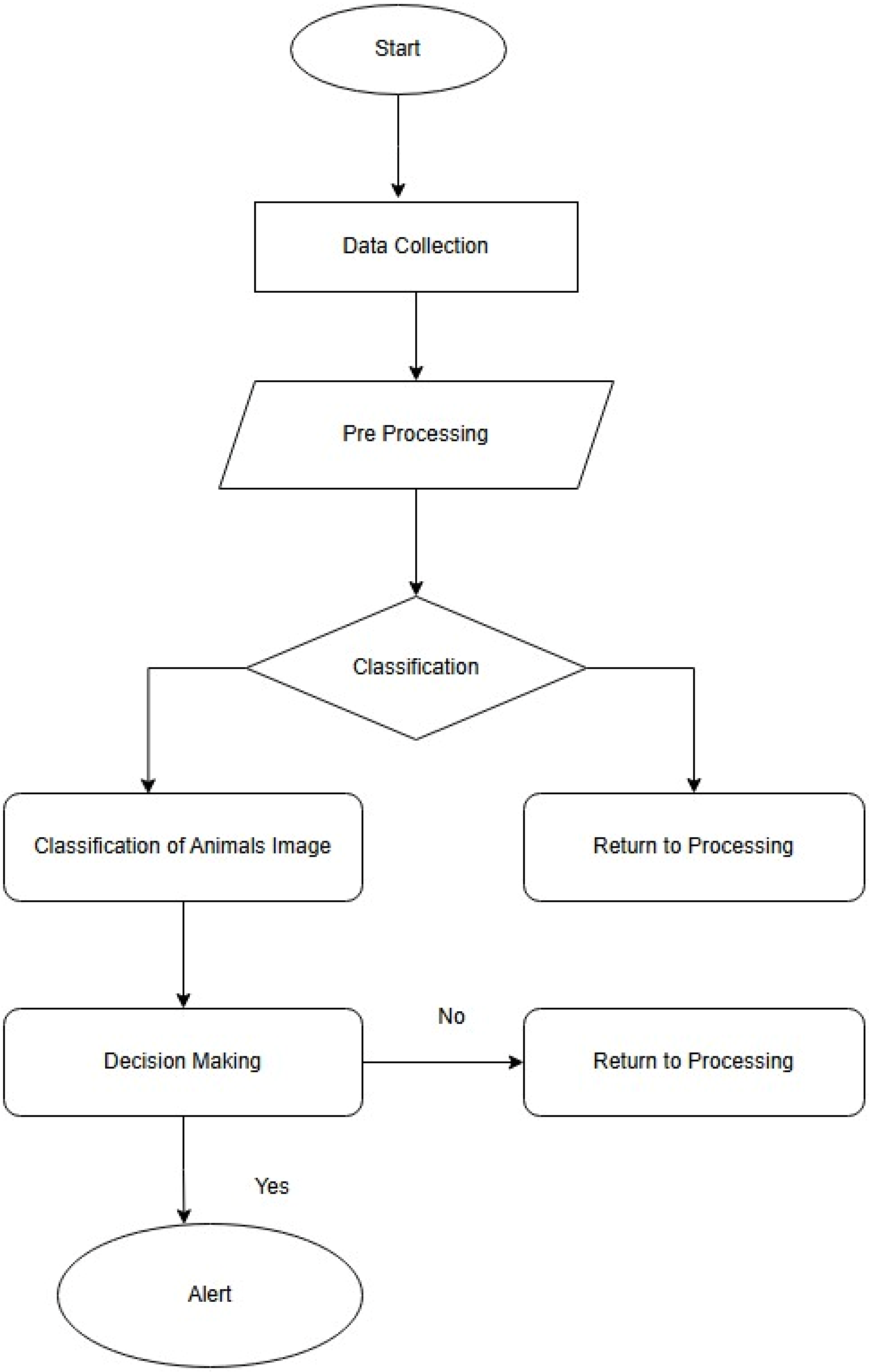

Fig 5.5 Flow Diagram

CHAPTER 6
MODULE DESCRIPTION

6.1 IMAGE ACQUISITION AND PRE-PROCESSING

The system initiates with a high-resolution camera strategically placed across the farm, continuously capturing images of the surrounding environment. These images are acquired in real-time and serve as the primary input for detecting animal intrusions. To ensure that the captured images are suitable for analysis, a series of pre-processing techniques are applied using OpenCV. Pre-processing begins with noise reduction using Gaussian blur, which eliminates unnecessary distortions and enhances image clarity. The images are then resized to a fixed resolution to standardize input dimensions, ensuring consistency across all captured data. Normalization is applied to adjust pixel values within a specific range, typically between 0 and 1, which facilitates smoother processing by the YOLO model. Additionally, edge detection techniques, such as Canny edge detection, are implemented to highlight object boundaries, enabling the YOLO model to better identify potential animals in the image. Contrast adjustments and brightness corrections may also be performed to further enhance image visibility. These pre-processing steps improve the accuracy of the YOLO detection model by enhancing key visual features while eliminating unnecessary noise. By preparing high-quality input data, the system reduces the likelihood of false positives and ensures that animal detection is both accurate and efficient. The processed images are then ready for input into the YOLO object detection framework, where further analysis and classification occur. This rigorous pre-processing phase is critical for maintaining the reliability of the overall system and ensuring that accurate detection is performed under various lighting conditions and environmental challenges. The optimized image quality obtained through pre-processing leads to improved detection results, enabling real-time operation and enhanced surveillance accuracy across agricultural fields.

6.2 YOLO-BASED ANIMAL DETECTION AND CLASSIFICATION

After the pre-processing stage, the processed images are forwarded to the YOLO (You Only Look Once) object detection algorithm, which performs real-time animal detection and classification. YOLO is a deep learning-based algorithm known for its speed and accuracy in object detection. The model divides the input image into an S x S grid and predicts bounding boxes along with confidence scores for each detected object. YOLO processes the image in a single pass, making it exceptionally fast compared to other object detection models that involve region proposals and multiple passes. The YOLO model is trained on a diverse dataset of labeled animal images captured in various environmental conditions, ensuring the system's robustness in detecting multiple types of animals commonly found near agricultural fields. During training, YOLO learns to identify critical features such as animal shape, size, texture, and movement patterns. The extracted features are then mapped to specific classes representing different animal species, enabling precise classification. When a potential intrusion is detected, the YOLO model generates bounding boxes around the detected animal, highlighting its position within the image. The classification confidence score is also included, helping the system determine the reliability of the detection. The model's high-speed processing capability ensures near-instantaneous detection, which is crucial for providing timely alerts to farmers. The system continuously improves the YOLO model by retraining it with new images collected during real-time operation, adapting to evolving environmental conditions and increasing classification accuracy. The incorporation of transfer learning techniques allows the system to refine its detection capabilities, minimizing false positives and ensuring that the system operates effectively under various scenarios. This real-time detection and classification mechanism forms the core of the system, ensuring that animal intrusions are identified promptly and accurately.

6.3 IMAGE COMPRESSION AND FEATURE EXTRACTION

To optimize system performance and minimize computational overhead, the detected images undergo compression and feature extraction after detection. Once YOLO identifies an animal, the image is processed to reduce its dimensionality without losing critical information. Dimensionality reduction techniques such as Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) are used to reduce image complexity while retaining key features. These techniques analyze the image's pixel structure and discard redundant data, ensuring that only relevant information is preserved. Additionally, feature extraction techniques such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) are applied to identify distinctive patterns and textures associated with the detected animal. These extracted features enhance the model's ability to differentiate between similar objects, improving classification accuracy. Image fusion techniques may also be employed, where information from multiple frames is combined to create a more comprehensive representation of the detected object. This fusion enhances detection robustness and helps maintain consistency in varying environmental conditions. By reducing the size of the processed image, computational load is minimized, enabling faster processing and real-time analysis. The compressed images are stored temporarily on the remote server for logging and future analysis, after which they are deleted to optimize storage. The combination of image compression and feature extraction ensures that the system operates efficiently without compromising detection accuracy. This approach not only accelerates the processing time but also reduces memory usage, making the system suitable for deployment in resource-constrained environments. The integration of these techniques enhances overall system performance, ensuring reliable and consistent animal detection in real-world conditions.

6.4 AUTOMATED NOTIFICATION AND ALERT SYSTEM

Upon successful detection and classification of an animal, the system initiates an automated notification process designed to alert farmers immediately. The notification system operates in real-time, ensuring that the farmer receives timely updates regarding potential intrusions. Once the YOLO model detects an animal, an email notification is generated containing essential information such as the type of animal detected, the timestamp of detection, and an image of the detected animal. The email is sent via an SMTP (Simple Mail Transfer Protocol) server, ensuring reliable and secure delivery. Alongside the email notification, the system activates a buzzer to provide an immediate auditory alert at the site of intrusion. The buzzer serves as a deterrent to scare off the intruding animal and simultaneously informs nearby farm workers about the detected intrusion. The auditory alert is designed to be loud and distinct, ensuring that it can be heard over large agricultural fields. For added flexibility, the system allows the farmer to configure notification settings and alert preferences through a web or mobile interface. The interface provides the option to modify alert sensitivity, change notification intervals, and enable or disable specific alert modes. The automated notification and alert system ensures that farmers are immediately informed of any animal intrusion, enabling them to take timely action to prevent potential crop damage. This system enhances farm security by combining visual, auditory, and remote notifications, offering a multi-layered defense mechanism against animal intrusions.

6.5 MANUAL AND REMOTE-CONTROL MECHANISMS

To provide enhanced operational flexibility, the system integrates manual and remote control mechanisms that empower the farmer to manage system functions efficiently. Through a web-based or mobile interface, the farmer gains complete control over the system’s core functionalities, including activating or deactivating the buzzer and modifying alert settings. The web interface is built using responsive design principles, ensuring compatibility across various devices, including desktops, tablets, and smartphones. It allows the farmer to monitor real-time detection logs, review past alerts, and control system settings from any location with internet connectivity. The mobile application, synchronized with the system's backend server, provides push notifications and allows remote control of system components, ensuring uninterrupted access to system controls. The interface also includes override functionalities that enable the farmer to silence false alarms or reactivate the buzzer manually if needed. Additionally, the system incorporates user authentication and role-based access control to prevent unauthorized access, ensuring secure management of system settings. Manual control is particularly useful in scenarios where the farmer needs to intervene directly, while remote control offers convenience and flexibility for managing farm security remotely. By integrating manual and remote control mechanisms, the system empowers farmers to maintain continuous oversight and control over the surveillance system, ensuring proactive management of farm security.

6.6 MODEL TRAINING AND PERFORMANCE REFINEMENT

The YOLO model used in the system undergoes continuous training and refinement to ensure high detection accuracy and adaptability to changing environmental conditions. The initial training phase involves using a large and diverse dataset of labeled animal images collected from various agricultural environments. This dataset includes images captured under different lighting conditions, angles, and weather variations to improve the model's robustness. Transfer learning is employed to fine-tune the pre-trained YOLO model, leveraging its existing feature extraction capabilities and reducing the time required for retraining. During real-time operation, new images captured by the system are periodically added to the training dataset, allowing the model to continuously learn and adapt to evolving scenarios. Cross-validation techniques are used to evaluate model performance, ensuring that the model generalizes well to unseen data. Hyperparameter tuning is conducted to optimize parameters such as learning rate, batch size, and the number of training epochs, minimizing overfitting and improving overall model performance. The system also incorporates feedback loops that analyze detection accuracy and refine model weights accordingly.

CHAPTER 7

RESULTS AND PERFORMANCE COMPARISON

7.1 RESULT

The Smart Crop Guardian: Real-Time Animal Detection and Surveillance System developed in this project successfully addressed the challenge of managing animal intrusions in agricultural fields. Using the advanced YOLO V8 object detection algorithm, the system demonstrated high efficiency and accuracy in real-time animal detection. The camera continuously captured images of the field, with the YOLO V8 model performing the task of detecting and classifying animals in these images. This approach enabled quick identification, even in diverse and complex environmental conditions, without overwhelming the system with unnecessary data.

The image pre-processing steps using OpenCV—such as noise reduction, resizing, and normalization—significantly contributed to enhancing the system's performance. These steps reduced computational load, allowing the system to process images faster while maintaining high detection accuracy. The pre-processed images were then fed into the YOLO V8 algorithm, ensuring minimal delay in detecting animal intrusions. As a result, the system was able to identify animals in real-time with impressive precision, facilitating rapid decision-making for farmers.

Once an animal was detected, the system triggered a multi-layered response. An immediate email notification was sent to the farmer, providing details like the timestamp and the type of animal detected, enabling timely intervention. In addition, an auditory alert was activated through a buzzer, creating an immediate deterrent to the animal. These notifications ensured that farmers could take quick action to safeguard their crops.

The system's minimal storage usage was another key benefit, as the captured images were automatically deleted after being processed, preventing unnecessary storage demands. Overall, the project achieved its objective of developing an automated, real-time animal detection and alert system that reduced the need for manual surveillance and increased the efficiency of crop protection.

In terms of performance, the YOLO V8-based detection system achieved high detection accuracy and low-latency responses, ensuring effective management of animal threats in the agricultural environment. The real-time notification mechanism and auditory alerts proved to be effective in minimizing damage from wild animals, providing a cost-efficient, scalable solution for modern farm management.

7.2 PERFORMANCE COMPARISON

Table 7.1 Performance Comparison of Algorithms

Aspect	**YOLOv8**	**SSD (Single Shot Detector)**	**Faster R-CNN**
Detection Speed (FPS)	Very High (Real-time)	High (Real-time)	Low (Slow inference)
Accuracy (Precision & Recall)	High Precision & Recall	Moderate to High	Very High
Model Complexity	Moderate	Low (Lightweight)	High
Small Object Detection	Good	Can miss small/camouflaged objects	Excellent
Resource Requirements	Moderate (GPU preferred)	Low (runs on edge devices)	High (requires powerful hardware)
Ease of Deployment	Suitable for drones,	Easy on low-power devices	Difficult to deploy in field

	cameras, IoT devices		environments
Real-time Suitability	Best choice	Good	Not suitable
Training Time	Moderate	Fast	Slow
Use Case Fit	Wildlife monitoring, drone surveillance	Edge-based animal detection systems	Detailed analysis post-capture

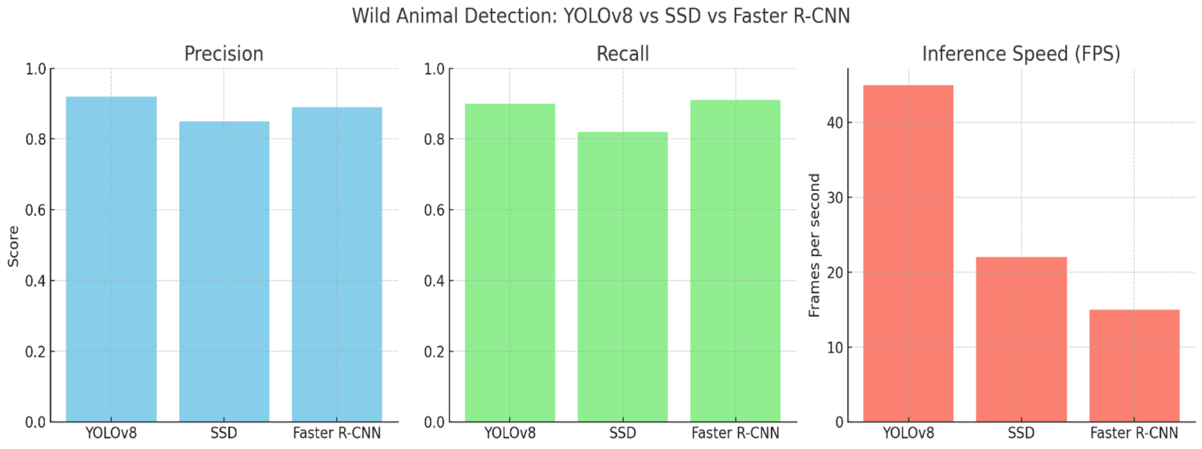

Fig 7.1 Comparison Graph

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

In conclusion, the proposed animal detection and surveillance system represents a significant advancement in farm security and animal management. By integrating cutting- edge technologies such as artificial intelligence (AI), machine learning, computer vision, and cloud computing, the system offers a highly effective solution for real-time detection and response to animal intrusions.At the core of the system lies the YOLOv8 (You Only Look Once) algorithm, which ensures fast and accurate identification of animals. The OpenCV library is employed for essential image preprocessing tasks, improving detection accuracy even under challenging environmental conditions such as low light, glare, or motion blur.

Together, these tools enable the system to automatically process images, detect animals, and generate real-time alerts.An LCD display is used to provide immediate, local information such as the detected animal's type and the time of detection, even without internet connectivity.A buzzer is automatically activated when an animal is detected, serving as an immediate deterrent to scare away the intruding animal and alert nearby farmers.An LED indicator lights up during a detection event to visually notify anyone nearby of the intrusion. Different colored LEDs can be configured to represent various animals or alert levels.

Ultimately, this innovative system empowers farmers with a smarter and more proactive approach to managing animal intrusions—allowing them to focus on other critical aspects of farm management while relying on this intelligent system to safeguard their property and ensure crop security.

8.2 FUTURE ENHANCEMENT

The proposed real-time animal detection and surveillance system can be further enhanced through several advanced features and improvements to increase efficiency, accuracy, and adaptability. One key enhancement involves integrating thermal imaging cameras alongside standard vision cameras. Thermal imaging can detect animal presence based on heat signatures, making the system functional even during nighttime or low-visibility conditions, thereby extending its operational capability. This dual-mode vision system can further reduce false positives by cross-verifying animal detection across both visible and thermal spectrums.Another future enhancement includes the implementation of deep reinforcement learning (DRL) to improve model accuracy dynamically. By incorporating DRL, the system can autonomously learn from its environment and adjust detection thresholds, alert mechanisms, and response actions based on real-time conditions. This self-learning capability can enhance long-term system efficiency and reduce the need for manual model retraining.Integration with IoT-based smart fencing systems is another enhancement that can improve real-time response to animal intrusions. When an animal is detected, the system can trigger automated responses such as activating electric fencing or emitting ultrasonic sound waves to deter the animal. This proactive response mechanism can minimize potential damage without requiring direct human intervention.

APPENDIX A

SOURCE CODE

```
import cv2

import numpy as np

import matplotlib.pyplot as plt import serial

from mail import report_send_mail import time

from mail import *

from pygame import mixer

 net = cv2.dnn.readNetFromDarknet("yolov8_custom.cfg",
"yolov8_custom_last.weights")

class_ = None

classes = ['bear', 'lion', 'peacock', 'Tiger', 'Elephant', 'Chinkara'] def
classifer(label):

print(label)

cap = cv2.VideoCapture(0) while True:

_, img = cap.read()

img = cv2.resize(img, (1280, 720)) height, width, _ = img.shape

 blob = cv2.dnn.blobFromImage(img, 1/255, (416, 416), (0, 0, 0),
swapRB=True, crop=False)

net.setInput(blob)

output_layers_name = net.getUnconnectedOutLayersNames()

layerOutputs = net.forward(output_layers_name) boxes = []

confidences = [] class_ids = []

for output in layerOutputs:

for detection in output:
```

score = detection[5:] class_id = np.argmax(score) confidence =score[class_id] if confidence > 0.7:

center_x = int(detection[0] * width) center_y = int(detection[1] * height) w = int(detection[2] * width)

h = int(detection[3] * height) x = int(center_x - w / 2)

y = int(center_y - h / 2) boxes.append([x, y, w, h]) confidences.append(float(confidence)) class_ids.append(class_id)

indexes = cv2.dnn.NMSBoxes(boxes, confidences, 0.5, 0.4) font = cv2.FONT_HERSHEY_PLAIN

colors = np.random.uniform(0, 255, size=(len(boxes), 3)) if len(indexes) > 0:

for i in indexes.flatten(): x, y, w, h = boxes[i]

label = str(classes[class_ids[i]])
cv2.imwrite('image.jpg', img) classifer(label)

if label == 'bear': print('bear') time.sleep(2)

report_send_mail(label, 'image.jpg') elif label == 'lion':

print('lion')
report_send_mail(label, 'image.jpg') elif label == 'peacock': print('peacock')

time.sleep(2) report_send_mail(label, 'image.jpg') elif label == 'Tiger': print('Tiger') time.sleep(2) report_send_mail(label, 'image.jpg') elif label == 'Elephant': print('Elephant')

time.sleep(2) report_send_mail(label, 'image.jpg') elif label == 'Chinkara': print('Chinkara') report_send_mail(label, 'image.jpg') try:

mixer.init() mixer.music.load("sound.mp3")

mixer.music.set_volume(0.7) mixer.music.play()

```
except:
print('Issues in Speaker')
confidence =str(round(confidences[i], 2)) color = colors[i]
cv2.rectangle(img, (x, y), (x + w, y + h), color, 2)
cv2.putText(img, label + " " + confidence, (x, y + 400), font, 2, color, 2)
cv2.imshow('img', img)
if cv2.waitKey(1) == ord('q'):
break cap.release()
 cv2.destroyAllWindows() ## import packages  import os
import time import smtplib
from email.mime.multipart import MIMEMultipart from email.mime.text import
MIMEText
from email.mime.base import MIMEBase from email.mime.image import
MIMEImage from email import encoders
import imghdr
## define function
def report_send_mail(label, image_path): '''
This function sends mail '''
with open(image_path, rb') as f:
img_data = f.read()
fromaddr = "sangeethasiva2804@gmail.com" toaddr =
"sangeethasiva2804@gmail.com" msg = MIMEMultipart()
msg['From'] = fromaddr msg['To'] = toaddr msg['Subject'] = "Alert" body = label
msg.attach(MIMEText(body, 'plain'))  # attach plain text
```

```
image = MIMEImage(img_data, name=os.path.basename(image_path))
msg.attach(image) # attach image

s = smtplib.SMTP('smtp.gmail.com', 587) s.starttls()

s.login(fromaddr, "iedsixgnppwiucud") text = msg.as_string()
s.sendmail(fromaddr, toaddr, text) s.quit()
```

APPENDIX B

SCREENSHOTS

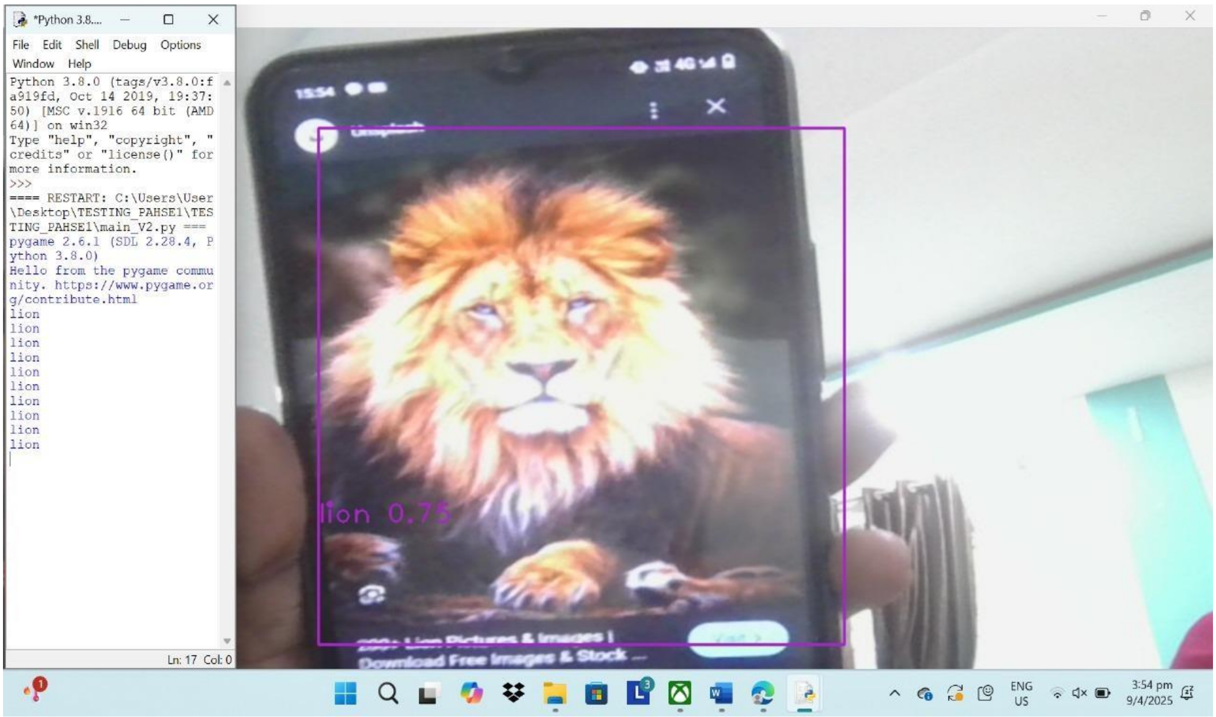

Fig B.1 Realtime Image Detection

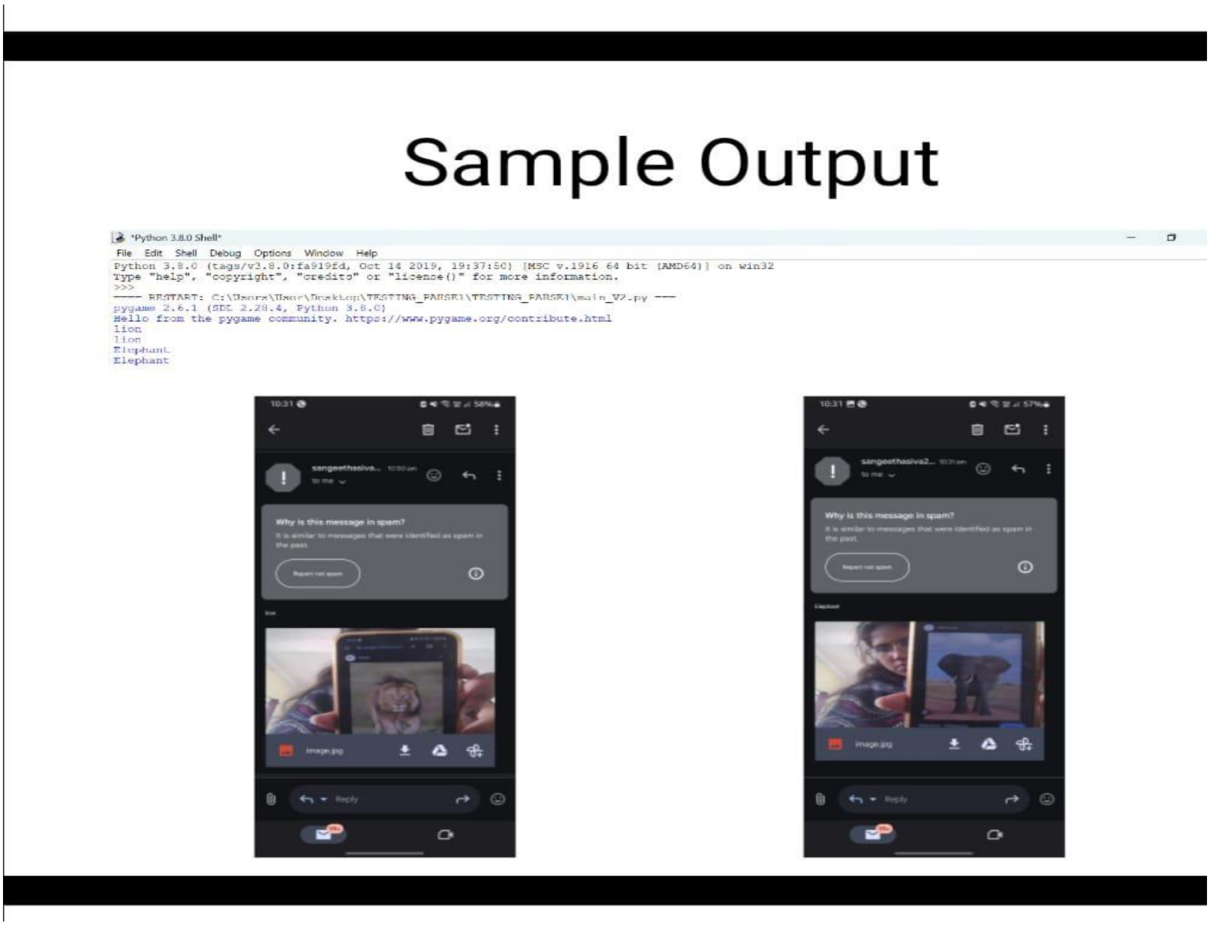

Fig B.2 Mail Notification

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IEEE VELAMMALITECH STUDENT BRANCH

VELAMMAL INSTITUTE OF TECHNOLOGY

CERTIFICATE OF PARTICIPATION

This is to certify that Prof./Dr./Mr./Ms. Ms.S.Sangeetha of K.Ramakrishnan College of Technology has presented a paper titled Smart Crop Guardian : Wild Animals Intrusion Detection and Alert System in 2nd International Conference on Data Analytics and Intelligence Computing organized by the Department of Artificial Intelligence and Data Science, Velammal Institute of Technology, Chennai, TamilNadu, India on April 09, 2025.

COORDINATORS	HOD		VICE PRINCIPAL	PRINCIPAL
Ms.K.Sudha Mr.K.Dinesh Kumar	Dr.S.PadmaPriya	POORVIKA	Dr.S.Soundararajan	Dr.N.Balaji

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