AI ENHANCED ANIMAL IDENTIFICATION IN AGRICULTURE

Minor project-II report submitted
in partial fulfillment of the requirement for award of the degree of

Bachelor of Technology
in
Computer Science & Engineering

By

P.SAI PRANEETH	(21UECM0057)	**(VTU 19082)**
G.HEMANTH KUMAR	(21UECM0069)	**(VTU 19044)**
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Under the guidance of
Dr.S.AMUTHA,M.E.,Ph.D.,
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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
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VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF SCIENCE & TECHNOLOGY

(Deemed to be University Estd u/s 3 of UGC Act, 1956)
Accredited by NAAC with A++ Grade
CHENNAI 600 062, TAMILNADU, INDIA

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CERTIFICATE

It is certified that the work contained in the project report titled ”AI ENHANCED ANIMAL IDENTIFICATION IN AGRICULTURE” by ”P.SAI PRANEETH (21UECM0057), G.HEMANTH KUMAR (21UECM0069), V.MOHAN MANIKANTA (21UEID0033)” has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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May, 2024

Signature of Professor In-charge
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May, 2024

DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Date: / /

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APPROVAL SHEET

This project report entitled (AI ENHANCED ANIMAL IDENTIFICATION IN AGRICULTURE) by P.SAI PRANEETH (21UECM0057), G.HEMANTH KUMAR (21UECM0069), V.MOHAN MANIKANTA (21UEID0033) is approved for the degree of B.Tech in Computer Science & Engineering.

Examiners **Supervisor**

Dr.S.AMUTHA, M.E., Ph.D.,
ASSOCIATE PROFESSOR,.

Date: / /

Place:

ACKNOWLEDGEMENT

We express our deepest gratitude to our respected **Founder Chancellor and President Col. Prof. Dr. R. RANGARAJAN B.E. (EEE), B.E. (MECH), M.S (AUTO),D.Sc., Foundress President Dr. R. SAGUNTHALA RANGARAJAN M.B.B.S.** Chairperson Managing Trustee and Vice President.

We are very much grateful to our beloved **Vice Chancellor Prof. S. SALIVAHANAN,** for providing us with an environment to complete our project successfully.

We record indebtedness to our **Professor & Dean, Department of Computer Science & Engineering, School of Computing, Dr. V. SRINIVASA RAO, M.Tech., Ph.D.,** for immense care and encouragement towards us throughout the course of this project.

We are thankful to our **Head, Department of Computer Science & Engineering, Dr.M.S. MURALI DHAR, M.E., Ph.D.,** for providing immense support in all our endeavors.

We also take this opportunity to express a deep sense of gratitude to our **Dr.S.AMUTHA, M.E.,Ph.D., ASSOCIATE PROFESSOR** for her cordial support, valuable information and guidance, she helped us in completing this project through various stages.

A special thanks to our **Project Coordinators Mr.V.ASHOK KUMAR, M.Tech., Ms. U.HEMAVATHI, M.E., Ms.C.SHYAMALA KUMARI, M.E.,** for their valuable guidance and support throughout the course of the project.

We thank our department faculty, supporting staff and friends for their help and guidance to complete this project.

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ABSTRACT

Integrating Artificial Intelligence (AI) technology in agriculture holds immense potential for enhancing crop protection and yield optimization. This project uses AI to detect and identify animals that threaten crops in agricultural fields. The system aims to distinguish between harmful and harmless animals by using cameras for real-time monitoring, coupled with a machine learning model trained on a diverse dataset of images. The proposed system employs Convolutional Neural Networks (CNNs) for image classification, emphasizing accurate detection of harmful animals. Upon detection, an alert mechanism triggers an email notification to inform the user of the potential threat. The project encompasses data collection, preprocessing, model training, integration with camera systems, and implementation of an alert system. The efficacy of the AI-enhanced animal identification system is assessed through rigorous testing and evaluation, paving the way for practical deployment in agricultural settings. This endeavor represents a proactive approach to crop protection, enabling farmers to mitigate the risk of crop damage and optimize agricultural productivity.

Keywords:

Wild animal intrusion, Agriculture, Crop damage, Advanced alarm system, Computer vision, Wireless sensors, YOLO algorithm, Audible alarms, Email notifications, Agricultural resilience.

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

Abbr	Abbreviation
AI	Artificial Intelligence
CNN	Convolutional Neural Networks
FPS	Frames Per Second
GUI	Graphical User Interface
ML	Machine Learning
SVM	Support Vector Machine
YOLO	You Only Look Once

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Chapter 1

INTRODUCTION

1.1 Introduction

In contemporary agriculture, the integration of technology has become increasingly pivotal in addressing challenges and optimizing productivity. One such challenge is the mitigation of crop damage caused by animals, which can significantly impact agricultural yield and profitability. Traditional methods of animal detection and control often entail substantial time and resource investments, leading to inefficiencies and potential losses for farmers. In response to this issue, the proposed project aims to leverage the power of artificial intelligence (AI) to enhance animal identification in agriculture.

The primary objective of this project is to develop an AI-based system capable of detecting and identifying animals that threaten crops in agricultural fields. By utilizing cameras for real-time monitoring and employing machine learning algorithms trained on a diverse dataset of images, the system aims to distinguish between harmful and harmless animals with a high degree of accuracy. Through the integration of advanced AI techniques, such as Convolutional Neural Networks (CNNs), the system seeks to provide farmers with timely and reliable alerts regarding potential crop damage.

The significance of this project lies in its potential to revolutionize crop protection strategies, offering farmers a proactive and efficient approach to mitigate the risks associated with animal-related crop damage. By harnessing the capabilities of AI, farmers can benefit from improved decision-making processes, reduced labor requirements, and enhanced crop yield and quality. Moreover, the implementation of an AI-based animal identification system has the potential to contribute to sustainable agricultural practices by minimizing the use of chemical pesticides and promoting environmentally friendly solutions.

1.2 Aim of the Project

This project aims to develop an Artificial Intelligence (AI) - enhanced system for animal identification in agriculture, with a specific focus on detecting animals that may cause damage to crops. By leveraging computer vision techniques and machine learning algorithms, the system will analyze real-time video feeds from cameras placed in agricultural fields to identify and classify animals as harmful or harmless. The ultimate goal is to provide farmers with a proactive tool that can help mitigate the risks associated with crop damage, optimize resource allocation, and ultimately enhance agricultural productivity and sustainability.

1.3 Project Domain

The project domain lies at the intersection of precision agriculture and artificial intelligence (AI), with a specific focus on crop protection and pest management. Within this domain, the project aims to develop an AI-enhanced system for animal identification in agricultural fields. By leveraging computer vision techniques and machine learning algorithms, the system will analyze real-time video feeds from cameras placed in agricultural settings to detect and classify animals that may pose a threat to crops. This proactive approach enables farmers to swiftly identify potential pests and implement targeted interventions, ultimately minimizing crop damage and optimizing agricultural productivity.

Furthermore, the project aligns with broader objectives of sustainable agriculture and environmental stewardship. By reducing reliance on chemical pesticides and adopting precision-based pest management strategies, the project contributes to mitigating environmental pollution, preserving biodiversity, and promoting ecosystem health. By integrating advanced AI technologies with agricultural practices, the project aims to empower farmers with innovative tools for crop protection, enabling them to make data-driven decisions and enhance the sustainability and resilience of agricultural systems in the face of evolving challenges.

1.4 Scope of the Project

The scope of the project encompasses the development and implementation of an AI-enhanced system for animal identification in agriculture, with a primary focus on detecting animals that may cause damage to crops. This includes the design and deployment of a scalable infrastructure capable of processing real-time video feeds from cameras placed strategically throughout agricultural fields. The system will utilize computer vision algorithms to analyze these feeds, identifying and classifying animals based on predefined criteria such as species, size, and behavior. Furthermore, the project will involve the integration of machine learning models trained on diverse datasets of animal images to enhance the system's accuracy and reliability in distinguishing between harmful and harmless animals.

In addition to the technical aspects, the project scope encompasses practical considerations such as usability, scalability, and interoperability. The developed system should be user-friendly and accessible to farmers of varying technical backgrounds, with intuitive interfaces for configuring settings, viewing alerts, and accessing relevant data. Moreover, the system should be designed to scale effectively to accommodate varying field sizes, environmental conditions, and types of crops.

Interoperability with existing agricultural management systems and data platforms is also a key aspect of the project scope, ensuring seamless integration with farmers' existing workflows and enabling data exchange for further analysis and decision-making. Overall, the project scope encompasses the development of a comprehensive solution that addresses the challenges of animal-related crop damage while aligning with the practical needs and requirements of agricultural stakeholders.

Chapter 2

LITERATURE REVIEW

[1] K. Anirudh et al.,2022 illustrated the automatic detection of animals that have wandered into human-populated regions has significant security and road safety implications. This study tries to answer the problem by combining deep learning approaches from a range of computer vision domains, such as object detection, tracking, segmentation, and edge detection. Tracking algorithms can then be used to follow the animals as they move through the scene. These algorithms use a combination of motion estimation, feature matching, and object recognition to track the animals over time.

[2] Cowton et al.,2022 aimed to search out the rationale why CNN models have down performance once they attempt to sight animals behind cages also efficient and reliable monitoring of wild animals in their natural habitats is essential to inform conservation and management decisions. Efficient and reliable monitoring of wild animals in their natural habitats is critical for informing conservation and management decisions. This requires the use of specialized sensors, cameras, and tracking systems that can capture data in real time and analyze it efficiently

[3] Divya et al.,2021 tend to mention the requirement of an automatic animal detection system and our formula for animal detection supported HOG and cascade classifier. The formula will sight an animal in numerous conditions on highways. One of the major causes of traffic accidents is the collision of an animal with a car on the highway. Using computer vision techniques, a simple and low-cost strategy for automatic animal detection on highways for preventing animal-vehicle collisions is offered.

[4] Dr.P Uma Maheshwari et al.,2020 proposed an Elephant detection tool that uses the operating principles of PIR sensors, Microwave Radar sensors, and tripwire systems as an animal detection method to solve these challenges. Citizens should be better prepared when these enormous animals enter residential areas as a result of

this discovery, reducing the amount of civilian losses due to elephants.

[5] P.Goutham Goud et al.,2020 proposed the Raspberry Pi in this project to protect fields from animals. Farmers all throughout the world face a unique problem in dealing 5 with wild animals. Wild boars, elephants, monkeys, and other animals wreak havoc on crops. The RFID (Radio Frequency Identification Device) module and the GSM (Global System Mobile) modem are used in this project. The system is designed to be autonomous, and it can operate without human intervention, making it an effective solution for farmers who may not be able to monitor their fields around the clock.

[6] Rakhee Pati et al.,2019 proposed a computer vision in agriculture that is used for food grading, plant disease identification, and agro-farm security. Wild animal attacks on agriculture fields cause significant crop loss. developed an algorithm to recognize animals in a given image.WCoHOG is a feature vector based on histogram-oriented gradients that is more accurate. Computer vision and image recognition technologies have the potential to transform the agricultural industry by providing farmers with valuable insights and real-time data that can help them make more informed decisions and improve their yields and profits

[7] Sahane Pradnya Sambhaji et al.,2019 proposed machine learning for monitoring the Species extinction which is being caused by climate change and environmental deterioration all over the planet. Automatic wildlife sensing is critical for tracking global biodiversity losses. Recent advances in machine learning can hasten the creation of large-scale, high-resolution monitoring systems that can track conservation goals and outcomes.

[8] Udayamoorthy Venkateshkumar et al.,2018 the aim of the paper is farm protection. Climate change and environmental degradation are causing significant harm to ecosystems around the world, and many species are facing extinction as a result. from wild animals.Here using security system includes image processing techniques to capture the animal using Raspberry. The image processing technique the captured image of the animal is informed to the microprocessor to create the irritation using ultrasonic sound. The Gsm technology is used for, if the animal crosses a specified limit the message will be sent to the farmer.

[9] Wenling Xue et al.,2019 proposed the tiger to panda animal head detection. The detection results through joint detection are based on the shape and texture. These are improved by new oriented gradient features, and hoog-haar of oriented gradients to effectively capture the texture features and shape of the animal head. Brute force detection and deformable detection algorithms are used to exploit the shape and texture features simultaneously.

Chapter 3

PROJECT DESCRIPTION

3.1 Existing System

The current methods for animal detection and pest management in agriculture rely heavily on manual labor, visual inspections, and the use of chemical pesticides. Farmers often conduct routine patrols of their fields to identify signs of animal activity, such as damage to crops or tracks. Once pests are detected, farmers may resort to the application of chemical pesticides to control their populations. However, this approach has several disadvantages. Firstly, manual inspections are time-consuming and labor-intensive, requiring significant resources and manpower. Additionally, the use of chemical pesticides can have adverse effects on human health, wildlife, and the environment, contributing to pollution and ecological disruption. Moreover, traditional methods may not be sufficiently proactive or precise, leading to suboptimal pest management and potential crop losses.

Disadvantages of Existing System:

- Time-consuming and labor-intensive.
- Reactive approach: Respond to crop damage after it occurs.
- Reliance on chemical pesticides poses risks to human health and the environment.
- Lack of precision in pest management may lead to suboptimal outcomes.

3.2 Proposed System

The proposed system aims to revolutionize animal identification and pest management in agriculture by leveraging artificial intelligence (AI) and computer vision technologies. By integrating cameras with machine learning algorithms, the system will analyze real-time video feeds from agricultural fields to automatically detect

and classify animals that may pose a threat to crops. This proactive approach enables farmers to receive timely alerts about potential pests, allowing them to implement targeted interventions and minimize crop damage. Furthermore, the system offers several advantages over traditional methods, including improved accuracy, efficiency, and environmental sustainability. By reducing reliance on chemical pesticides and promoting precision-based pest management strategies, the proposed system aligns with broader objectives of sustainable agriculture and ecosystem health.

Advantages of Proposed System:

- Proactive approach: Provides timely alerts about potential pests, allowing for targeted interventions.
- Reduces reliance on chemical pesticides, promoting sustainability.
- Improves accuracy and efficiency in pest management.
- Enables data-driven decision-making and optimization of agricultural productivity.

3.3 Feasibility Study

3.3.1 Economic Feasibility

The economic feasibility of the proposed system will be evaluated in terms of its cost-effectiveness and return on investment (ROI). While initial development and deployment costs may be incurred, the long-term benefits of improved crop protection, reduced pesticide usage, and enhanced agricultural productivity are expected to outweigh these costs, resulting in positive economic outcomes for farmers. Moreover, the potential for additional revenue streams, such as data analytics services or subscription-based models, may further enhance the system's economic viability and sustainability.

3.3.2 Technical Feasibility

The technical feasibility of the proposed system will be assessed based on its ability to integrate with existing hardware and software infrastructure, as well as

its scalability, reliability, and performance under real-world conditions. Preliminary technical assessments indicate that the necessary technologies and resources are readily available and feasible to implement, ensuring the system's viability and effectiveness in practical agricultural settings. Furthermore, ongoing advancements in AI, computer vision, and sensor technologies are expected to further enhance the system's capabilities and performance over time, ensuring its continued relevance and applicability in dynamic agricultural environments.

3.3.3 Social Feasibility

The social feasibility of the proposed system will be evaluated in terms of its acceptance and adoption by agricultural stakeholders, including farmers, agricultural workers, and regulatory authorities. Stakeholder engagement and feedback will be integral to ensuring the system meets their needs and addresses their concerns regarding animal-related crop damage and pest management. By promoting sustainable agricultural practices and enhancing farmers' capabilities, the proposed system is expected to garner widespread support and contribute to positive social outcomes within the agricultural community. Moreover, partnerships with industry organizations, research institutions, and government agencies will be established to facilitate knowledge exchange, capacity building, and policy advocacy, further enhancing the system's social impact and relevance.

3.4 System Specification

3.4.1 Hardware Specification

- Camera:
  Version: HP True Vision HD-2000
  Features: Weather-resistant design, High-resolution (1080p) imaging, Infrared night vision capabilities, Wide-angle lens (120° field of view), Mounting hardware for easy installation.
- Processing Units:
  Version: ProCore X3
  Features: Quad-core processor with 2.5 GHz clock speed, 8 GB RAM and 256 GB SSD storage, Energy-efficient design with low power consumption Compatibility with Linux-based operating systems.

- Communication Devices:
  Version: CommLink 4G LTE
  Features: 4G LTE cellular modem with fallback to 3G/2G networks, Wi-Fi and Ethernet connectivity options, SIM card slot for network access, External antenna for improved signal strength.
- Power Supply:
  Version: SolarPower Max 500
  Features: 500W solar panel with high-efficiency monocrystalline cells, Integrated MPPT charge controller for optimal power conversion, 200Ah deep cycle battery for energy storage, Backup generator port for additional power source integration

3.4.2 Software Specification

- AI Algorithms: Machine learning algorithms trained on extensive datasets for accurate animal detection and classification, including deep learning models for robust performance in complex agricultural environments.
- Computer Vision Models: Advanced models for analyzing video feeds and identifying pest behaviors, enabling proactive pest management strategies and early detection of potential threats.
- User Interfaces: Intuitive interfaces with user-friendly features for easy interaction, configuration, and data visualization, ensuring accessibility and usability for farmers and stakeholders.

3.4.3 Standards and Policies

- Adherence to data privacy regulations, such as GDPR or CCPA, and environmental protection standards ensures ethical and responsible use of data collected by the system.
- Compliance with industry standards and best practices, such as ISO 9001 or ISO 14001, promotes transparency, accountability, and trustworthiness in system operations.
- Stakeholder engagement and partnerships with regulatory authorities facilitate alignment with regulatory requirements and societal expectations, fostering social acceptance and adoption of the system within the agricultural community.

Chapter 4

METHODOLOGY

4.1 Animal Intrusion Alarm Architecture

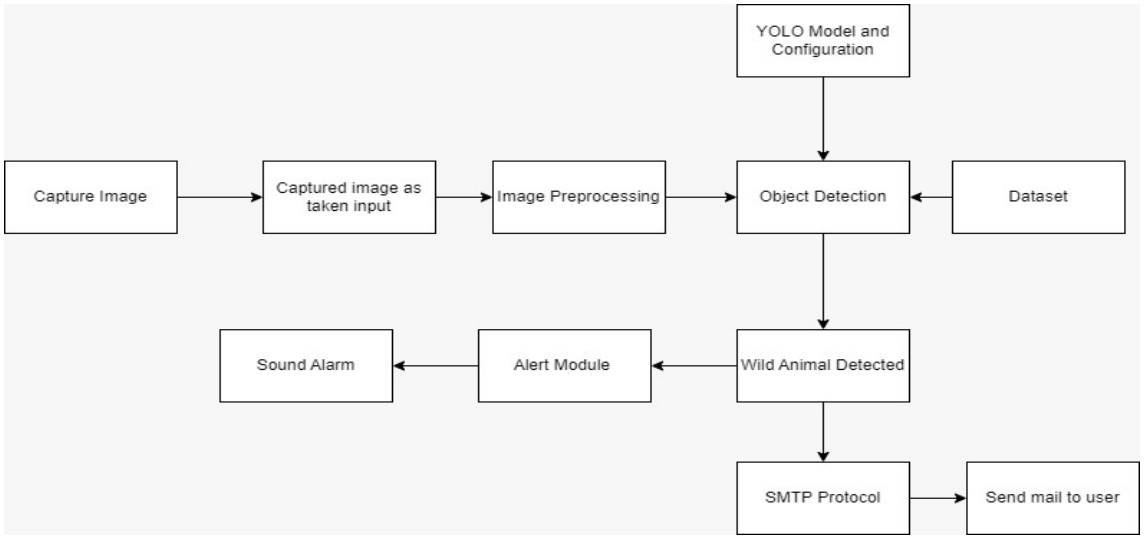


Figure 4.1: **Architecture Diagram of Animal Identification in Agriculture**

Figure 4.1 depicts a system comprising camera hardware for real-time monitoring, data preprocessing modules for image analysis, and a machine-learning model for animal detection. Upon detecting harmful animals, the system triggers alerts for users. It also includes components for data storage and logging. The architecture emphasizes seamless integration of hardware and software components to enable efficient and accurate pest management in agriculture.

4.2 Design Phase of Animal Intrusion Alarm

4.2.1 Data Flow Diagram

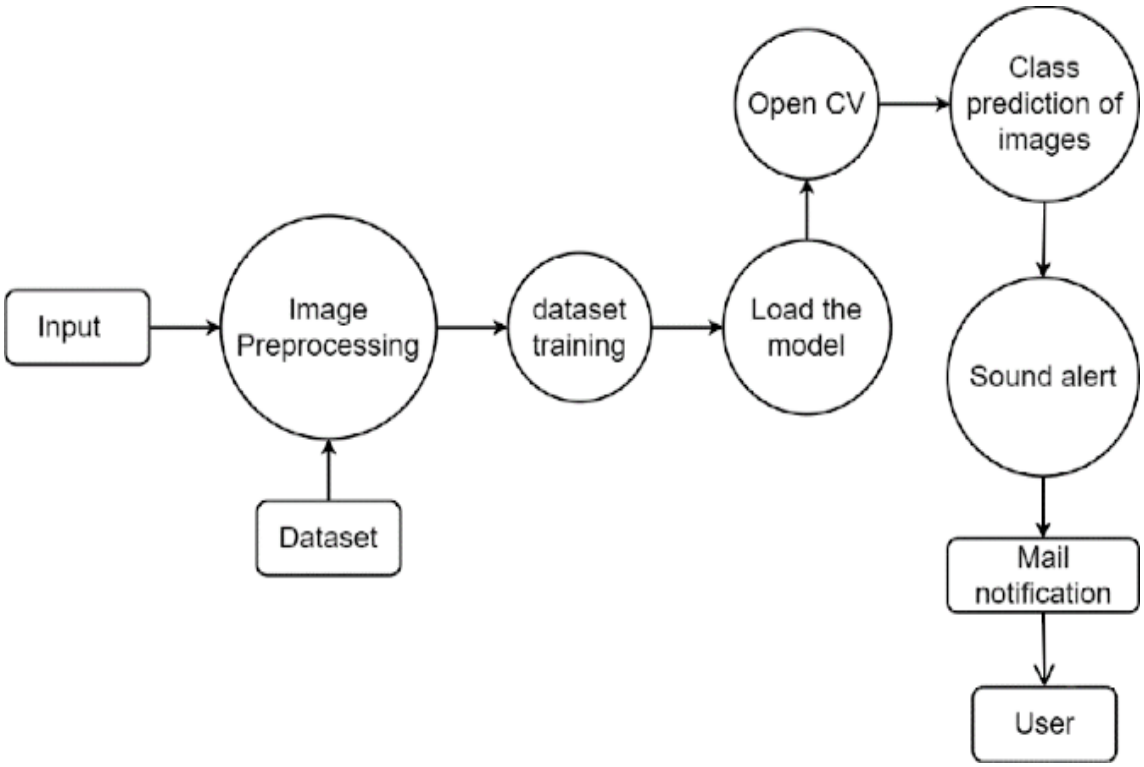


Figure 4.2: **Data Flow Diagram of Animal Identification in Agriculture**

Figure 4.2 illustrates the flow of information within the project. It depicts the journey of data from input sources, such as cameras capturing agricultural fields, to processing units where machine learning algorithms analyze the data for animal detection. Once analyzed, the system generates alerts or notifications as output, informing users about potential threats to crops detected in real time.

4.2.2 Use Case Diagram

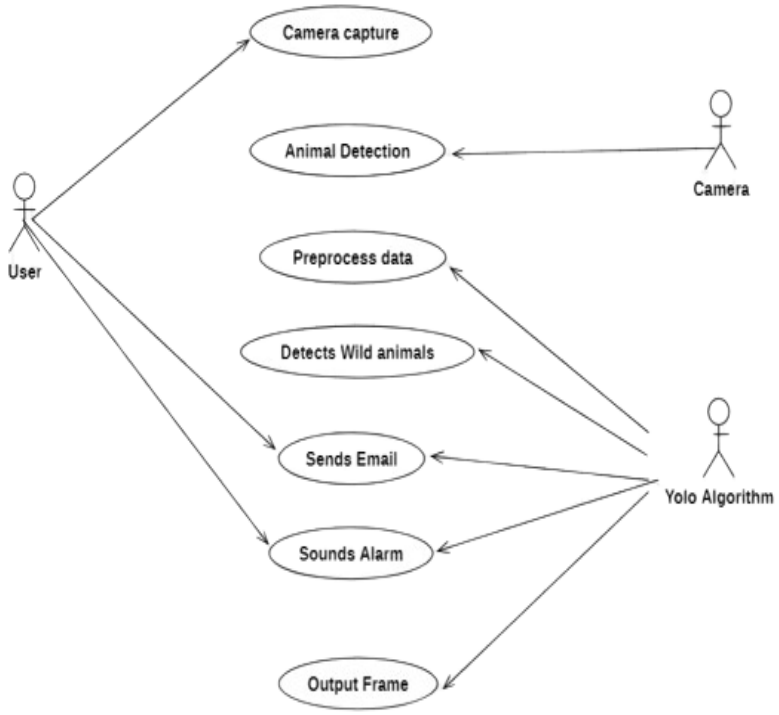


Figure 4.3: **Use Case Diagram of Animal Identification in Agriculture**

Figure 4.3 illustrates the interactions between actors and the system in the AI-enhanced animal identification project. Actors, such as farmers and administrators, initiate use cases like ”Detect Animal” and ”Send Alert.” The system responds by processing real-time camera data, detecting animals, and sending notifications. This diagram provides a high-level overview of the system’s functionalities and user interactions.

4.2.3 Class Diagram

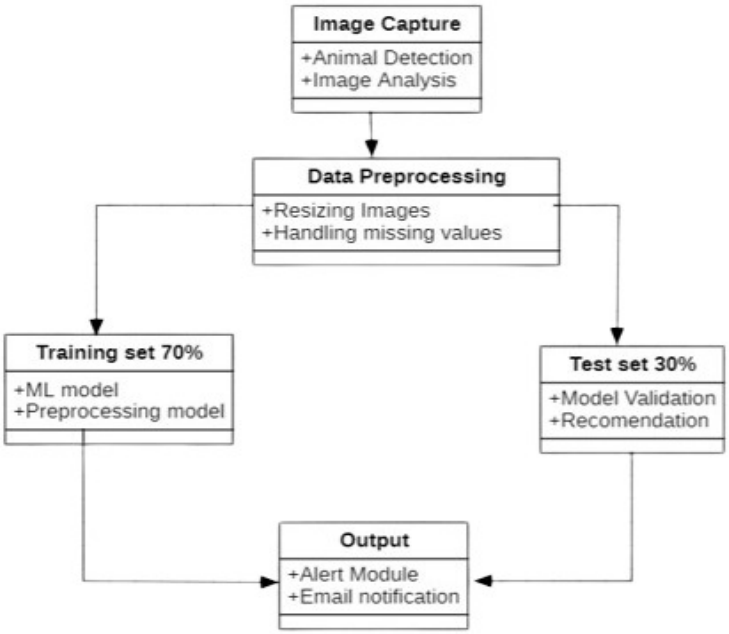


Figure 4.4: **Class Diagram of Animal Identification in Agriculture**

Figure 4.4 for this project depicts the structure of the software system, illustrating the classes, their attributes, and their relationships. It includes classes such as Camera, AnimalDetector, EmailNotifier, and MachineLearningModel. Associations show how these classes interact, such as Camera capturing images, AnimalDetector analyzing them, and EmailNotifier sending alerts. This diagram provides a blueprint for implementing the project's functionality.

4.2.4 Sequence Diagram

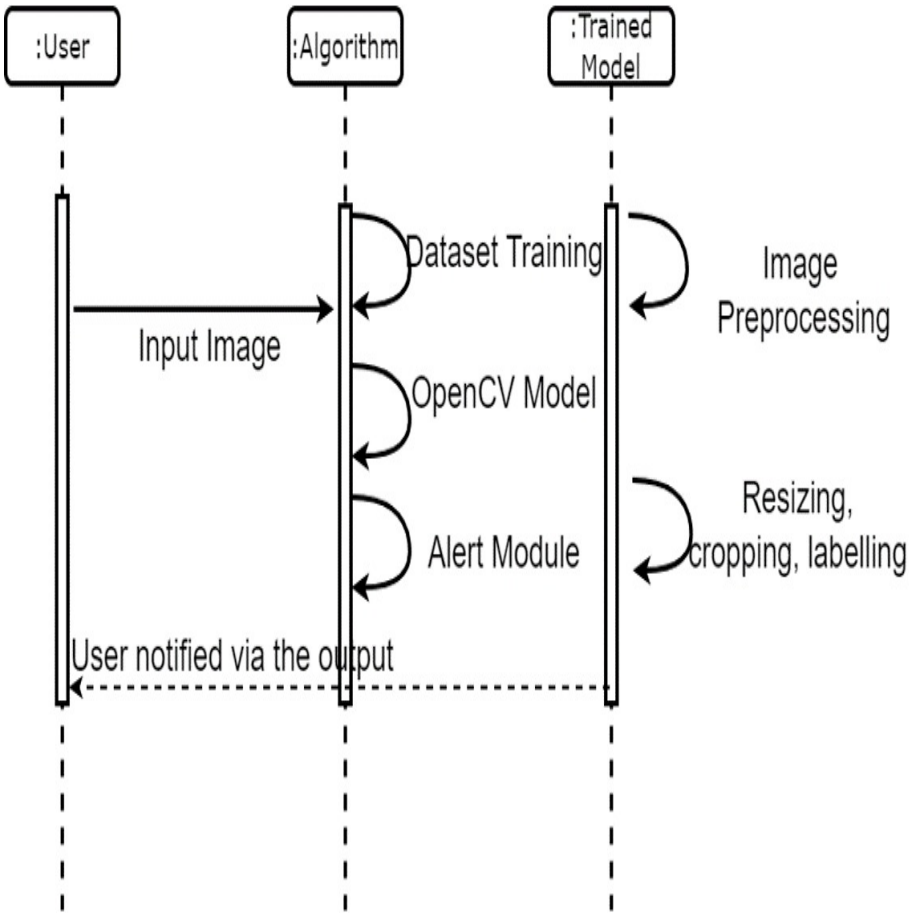


Figure 4.5: **Sequence Diagram of Animal Identification in Agriculture**

Figure 4.5 illustrates the flow of interactions between system components in the AI-enhanced animal identification project. It depicts how data flows from the camera sensors to the preprocessing module, and then to the machine-learning model for animal detection and classification. Upon detection of harmful animals, the system triggers an alert mechanism to notify users via email, completing the sequence of operations.

4.2.5 Collaboration diagram

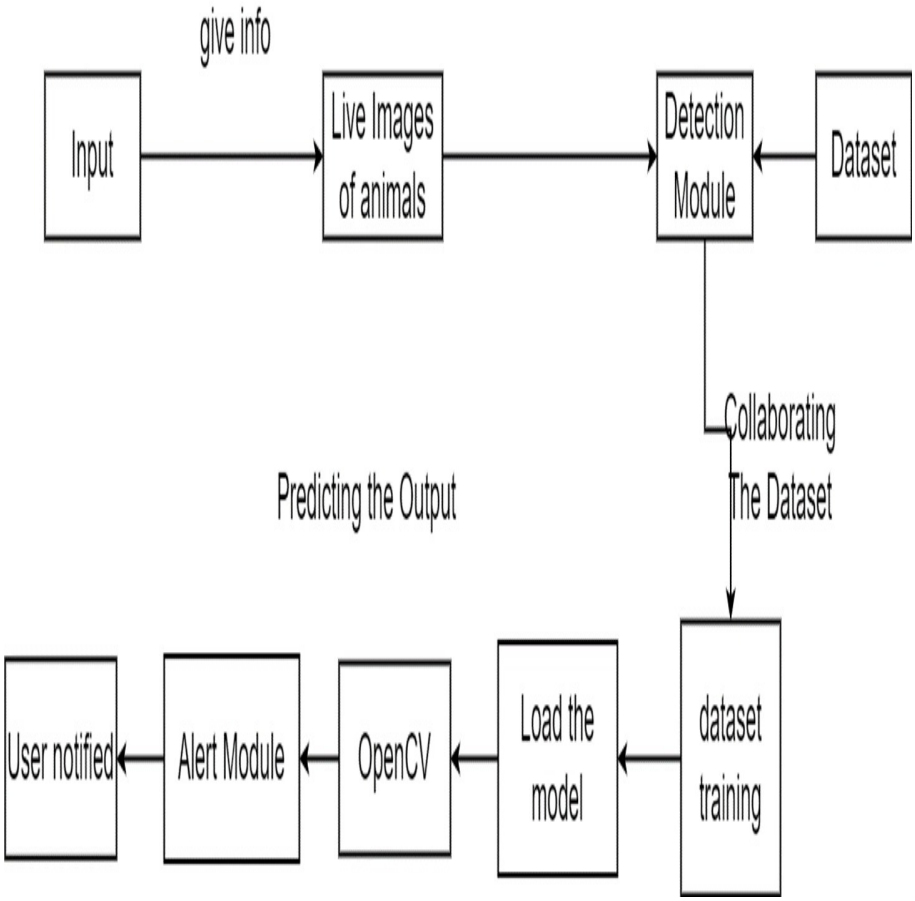


Figure 4.6: **Collaboration Diagram of Animal Identification in Agriculture**

Figure 4.6 illustrates the interactions and relationships between system components or actors in the AI-enhanced animal identification project. It visually represents how data flows and tasks are distributed among hardware components, software modules, and external entities, such as users or external systems. By depicting communication pathways and dependencies, the collaboration diagram provides insights into the system's architecture and operational dynamics.

4.2.6 Activity Diagram

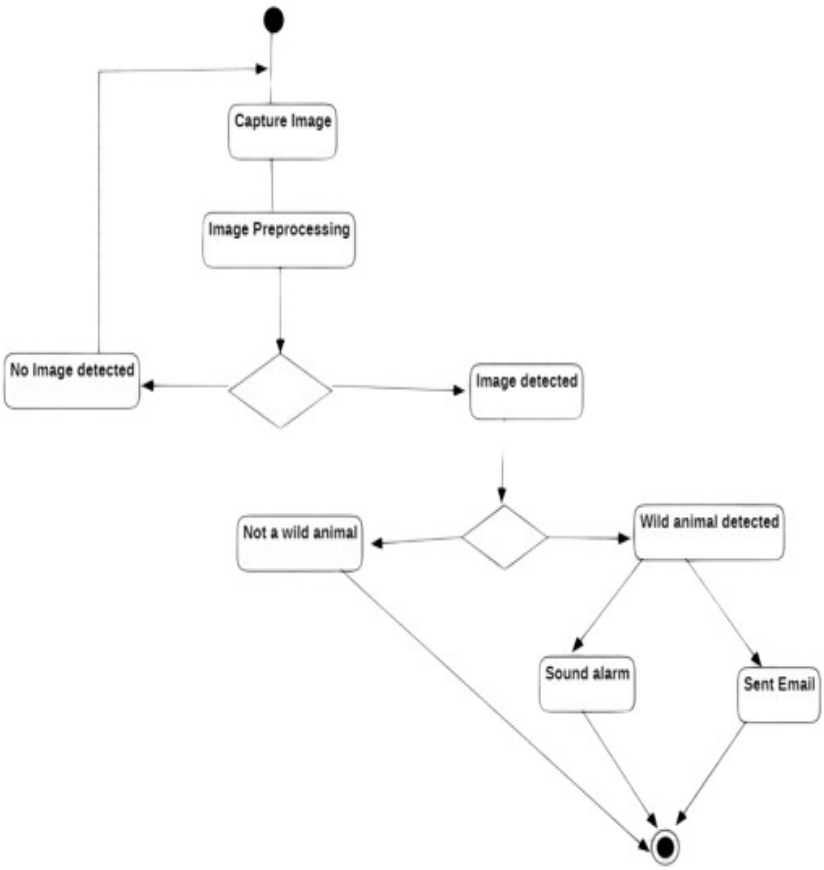


Figure 4.7: **Activity Diagram of Animal Identification in Agriculture**

4.3 Algorithm & Pseudo Code

4.3.1 YOLO Algorithm

Step1:Begin streaming live video from CCTV cameras installed on the farm.
Step2:Apply object detection algorithms to identify animals in the video frames.
Step3:Classify animals detected using image classification techniques.
Step4:Assess classifications to determine if animals endanger agricultural produce.
Step5:If animals pose a threat, trigger a suitable repellant sound to deter them.
Step6:Monitor repellant sound effectiveness in deterring animals continuously.
Step7:Gather feedback on deterrence success and animal persistence outcomes.
Step8:Update algorithms, conduct maintenance checks for efficiency

4.3.2 Animal Intrusion Alarm Pseudo Code

Initialize the system
InitializeSystem()

Main loop for real-time processing
while True:
Capture video feed from cameras
frame = CaptureVideoFeed()

Preprocess the frame
preprocessed$_frame = PreprocessFrame(frame)$

Detect animals in the preprocessed frame
detected$_animals = DetectAnimals(preprocessed_frame)$

Classify detected animals
classified$_animals = ClassifyAnimals(detected_animals)$

Check if any harmful animals are detected
harmful$_animals = FilterHarmfulAnimals(classified_animals)$

If harmful animals are detected, generate alert
if harmful$_animals$:
$GenerateAlert(harmful_animals)$

Display the processed frame with detected animals (optional)
DisplayProcessedFrame(preprocessed$_frame$)

Check for user input to exit the loop
if UserWantsToExit():
break

Clean up resources and exit
CleanUp()

4.4 Module Description

4.4.1 Data Collection

Data collection is a crucial module in the AI-enhanced animal identification system, responsible for gathering the necessary information required for training the machine learning model. In agriculture, this involves capturing images or videos of the agricultural fields using cameras or sensors strategically placed throughout the area. These cameras should be weather-resistant and equipped with features such as high resolution and infrared capabilities to ensure optimal performance in various environmental conditions, including daytime and nighttime. Additionally, environmental sensors may be employed to collect supplementary data on weather conditions, soil moisture levels, and other relevant parameters.

The data collected from these sources serve as the foundation for training the machine learning model to recognize and classify animals accurately. It's essential to ensure that the collected data are diverse, representative, and sufficiently annotated to cover different species of animals that may pose a threat to crops. This may involve manually labeling the collected images or videos to indicate the presence of harmful animals and providing ground truth annotations for training the model effectively.

Furthermore, data collection should be conducted systematically and consistently over time to capture seasonal variations and changes in animal behavior patterns. Regular maintenance and calibration of the data collection equipment are also necessary to ensure reliable and accurate data capture. Overall, effective data collection is fundamental to the success of the AI-enhanced animal identification system, providing the raw material needed to train the machine learning model and enable accurate detection and classification of harmful animals in agricultural settings

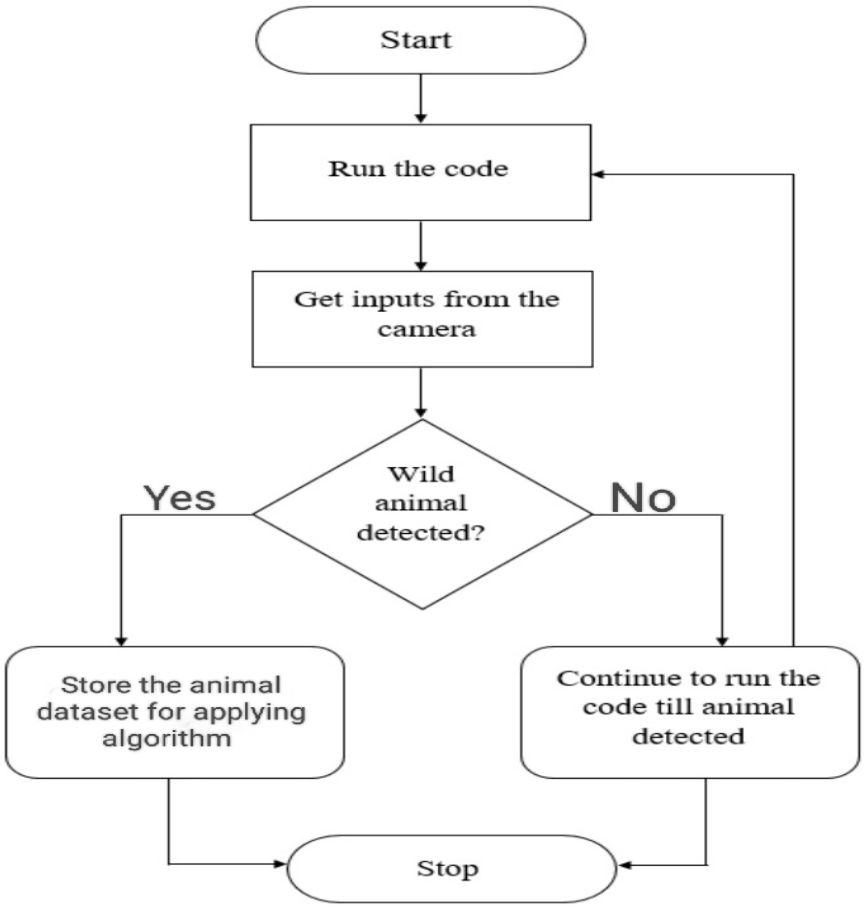


Figure 4.8: **Data Collection Process**

Data collection serves as the cornerstone of the AI-enhanced animal identification system in agriculture, providing the raw material necessary for training machine learning models. Ensuring the reliability, diversity, and consistency of the collected data is paramount to the success of the system, enabling accurate detection and classification of harmful animals and supporting effective pest management strategies in agricultural settings.

4.4.2 YOLO Algorithm

The YOLO (You Only Look Once) algorithm is a state-of-the-art object detection algorithm used for identifying and localizing objects within images or video frames. It revolutionized object detection by achieving real-time performance without sacrificing accuracy, making it particularly well-suited for applications such as the AI-enhanced animal identification system in agriculture. This is in contrast to traditional object detection methods, which typically involve multiple stages and

separate processes for object localization and classification.

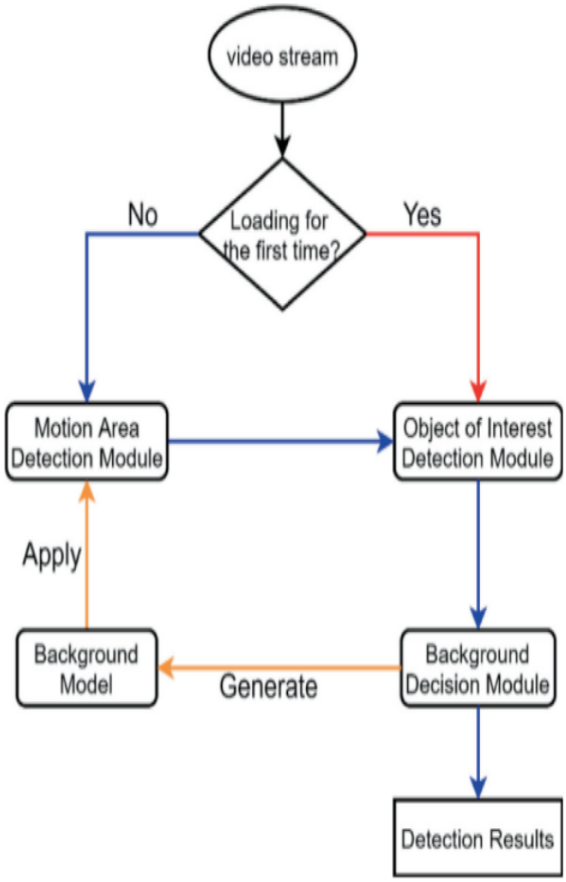


Figure 4.9: **YOLO Algorithm Working**

YOLO divides the input image into a grid of cells and predicts bounding boxes and confidence scores for each cell. These bounding boxes are then refined and filtered based on their confidence scores to generate the final set of detected objects. By processing the entire image in a single pass through the neural network, YOLO achieves real-time performance, making it highly efficient for applications requiring fast and accurate object detection.

4.4.3 Alert Module

The Alert module in the AI-enhanced animal identification system plays a crucial role in notifying users when harmful animals are detected in agricultural fields. Upon detection and classification of a harmful animal by the system, the Alert module generates timely notifications or alerts to inform farmers or relevant

stakeholders about the potential threat to crops. These alerts may be delivered through various communication channels, including email and Sound alerts.

The Alert module is designed to provide detailed information about the detected animal, its location within the field, and the timestamp of detection. Additionally, the severity of the alert may be indicated based on factors such as the size of the detected animal, its proximity to crops, and historical patterns of damage associated with similar species. This allows farmers to prioritize and take appropriate actions in response to the threat, such as deploying deterrent measures, increasing surveillance in affected areas, or initiating targeted pest control interventions.

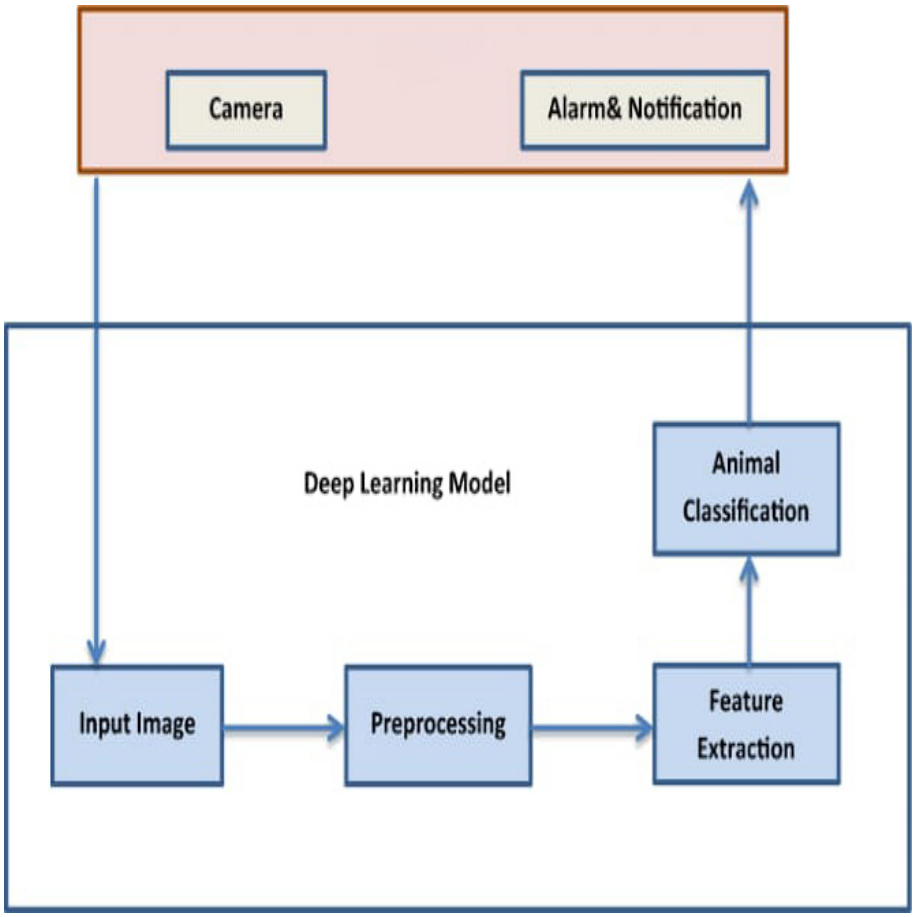


Figure 4.10: **Potential Camera and Alarm**

Moreover, the Alert module may include features for real-time monitoring and tracking of detected animals, enabling users to visualize the location and movement of animals within the agricultural fields. This provides farmers with valuable insights into animal behavior patterns and allows for proactive decision-making to mitigate potential crop damage. Furthermore, the Alert module may support

customization options, allowing users to set preferences for receiving alerts based on their specific requirements, such as frequency of notifications, threshold levels for triggering alerts, and preferred communication channels.

4.5 Steps to execute/run/implement the project

4.5.1 Step1: Setup Environment and Hardware

Before running the project, ensure that you have the necessary hardware and software environment set up. This includes installing any required hardware components, such as cameras or sensors, and ensuring they are properly configured and connected to your system. Additionally, make sure you have the required software dependencies installed, such as Python, and relevant libraries like OpenCV and TensorFlow. Ensure that your system meets the minimum hardware requirements specified for the project, including sufficient processing power and memory to handle real-time video processing and machine-learning tasks.

4.5.2 Step2: Data Collection and Model Training

The next step involves collecting training data for the machine learning model and training the model to detect and classify animals. Gather a diverse set of images or video clips containing examples of animals that may pose a threat to crops. Label the data accordingly to indicate the presence of harmful animals. Use this labeled dataset to train the machine learning model, employing techniques such as transfer learning or custom model training depending on the complexity of the problem and the availability of data. Fine-tune the model parameters and evaluate its performance using techniques like cross-validation to ensure robustness and accuracy.

4.5.3 Step3: Integration and Testin

Once the model is trained and validated, integrate it into the system alongside the camera or sensor hardware. Develop the necessary software components to capture real-time video feeds from the cameras, preprocess the data, and apply the trained model for animal detection and classification. Implement algorithms for generating alerts or notifications when harmful animals are detected, and ensure the system's re-

sponsiveness and reliability under varying environmental conditions. Conduct rigorous testing and validation of the integrated system, including unit testing, integration testing, and real-world field testing to verify its functionality, accuracy, and performance. Make any necessary adjustments or optimizations based on testing results to ensure the system meets the project requirements and user expectations

Chapter 5

IMPLEMENTATION AND TESTING

During the implementation stage, the proposed model leverages computer vision to train on a dataset of animal images, establishing a robust foundation for accurate detection. Upon completion, this model is integrated into the driver code, enabling real-time comparison of captured images with the trained dataset. When an animal is detected during live capture, the system triggers the emission of a repellent sound through speakers, designed to deter animals effectively. Additionally, to enhance the system's reach and efficacy, email notifications are sent out upon animal detection, providing timely alerts to stakeholders. This multifaceted approach not only ensures the system's reliability and efficiency but also emphasizes the importance of user training and ongoing maintenance to sustain optimal performance in mitigating human-animal conflicts and minimizing associated risks.

5.1 Input and Output

5.1.1 Input Design

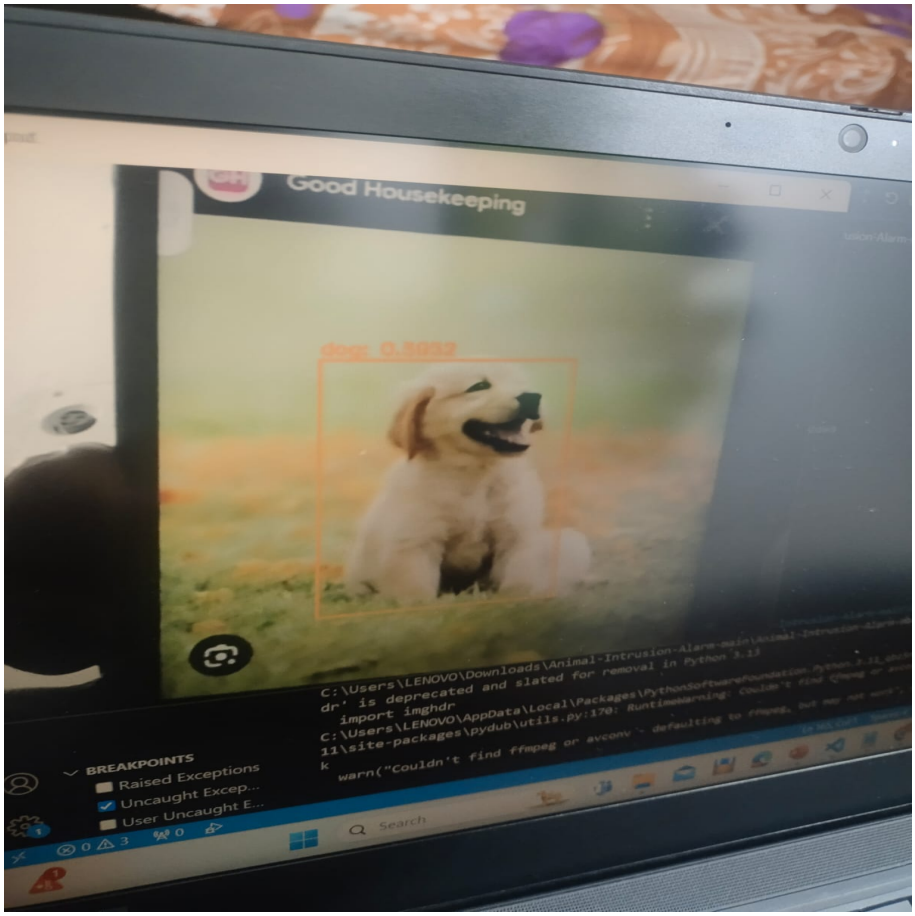


Figure 5.1: **Input Design**

In Figure 5.1 when an input image of an animal is provided to the computer vision system, the algorithms will analyze the image and extract relevant features to classify it as an animal. The system will then compare the features extracted from the input image with the features of known animal images in the training dataset to determine the specific species of elephant in the image. Once the system has classified the image, it will track the movements of the elephant in real-time, and if necessary, trigger an alert or alarm to notify the user of its presence. This allows for quick and effective management of human-elephant conflicts in areas where elephants are known to cause damage or pose a threat to human life.

5.1.2 Output Design

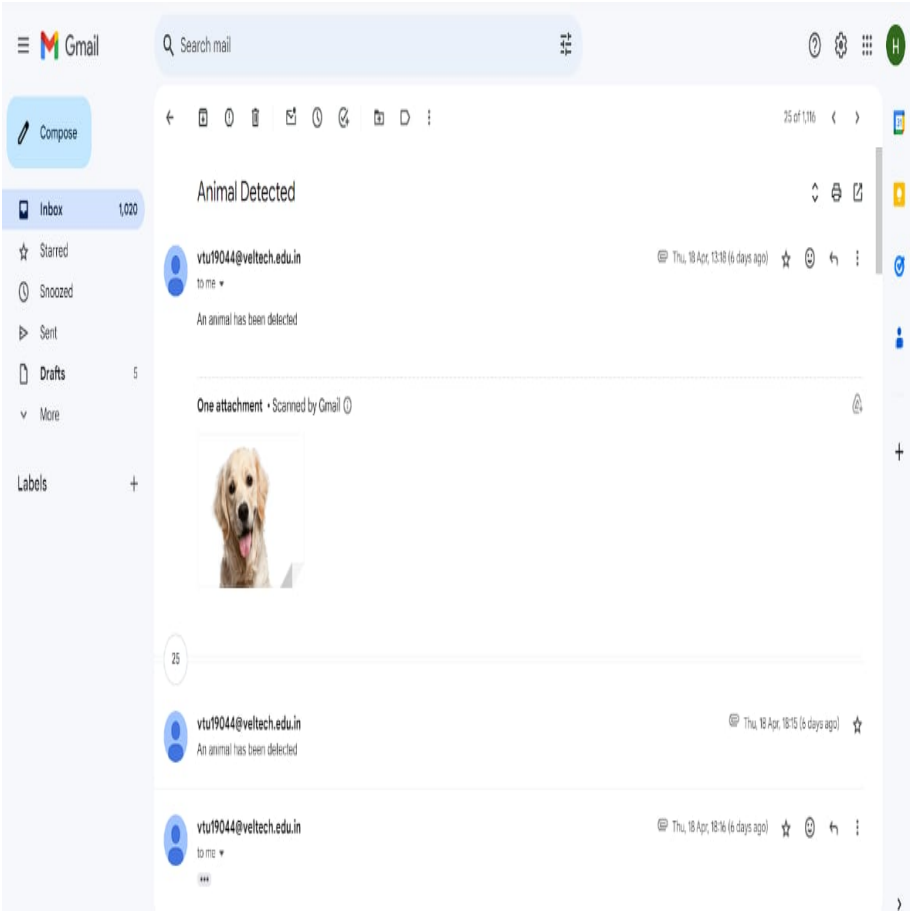


Figure 5.2: **Output Design**

In Figure 5.2 when the computer vision system detects an animal, it can trigger an alert sound and send a message to a designated email address notifying the user that an animal has been detected. This allows for immediate action to be taken to prevent potential damage or harm caused by the animal

5.2 Testing

5.3 Types of Testing

5.3.1 Unit Testing

Input

```
import time
import cv2
import os
```

```
import numpy as np
from playsound import playsound
import threading
import smtplib
import imghdr
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
from pydub import AudioSegment
from pydub.playback import play
from email.message import EmailMessage

def alert():
    threading.Thread(target=playsound, args=(r'C:\Users\LENOVO\Downloads\Animal-Intrusion-Alarm-main
        \Animal-Intrusion-Alarm-main\alarm.wav',), daemon=True).start()

def send_email(label):
    Sender_Email = "sampathbysani2003@gmail.com"
    Reciever_Email = "sampathbysani2002@gmail.com"
    # Password = input('Enter your email account password: ')
    appPassword ="auze kvmz pgnq fxmd"    #ENTER GOOGLE APP PASSWORD HERE

    newMessage = EmailMessage()    #creating an object of EmailMessage class
    newMessage['Subject'] = "Animal Detected" #Defining email subject
    newMessage['From'] = Sender_Email  #Defining sender email
    newMessage['To'] = Reciever_Email  #Defining reciever email
    newMessage.set_content('An animal has been detected') #Defining email body
     with open(r'C:\Users\LENOVO\Downloads\Animal-Intrusion-Alarm-main\Animal-Intrusion-Alarm-main\
         images\\' + label + '.png', 'rb') as f:
        image_data = f.read()
        image_type = imghdr.what(f.name)
        image_name = f.name[7:]

    newMessage.add_attachment(image_data, maintype='image', subtype=image_type, filename=image_name)

    with smtplib.SMTP_SSL('smtp.gmail.com', 465) as smtp:
        smtp.login(Sender_Email, appPassword) #Login to SMTP server
        smtp.send_message(newMessage)      #Sending email using send_message method by passing
            EmailMessage object

def async_email(label):
    threading.Thread(target=send_email, args=(label,), daemon=True).start()

args = {"confidence":0.5, "threshold":0.3}
flag = False
```

Test result

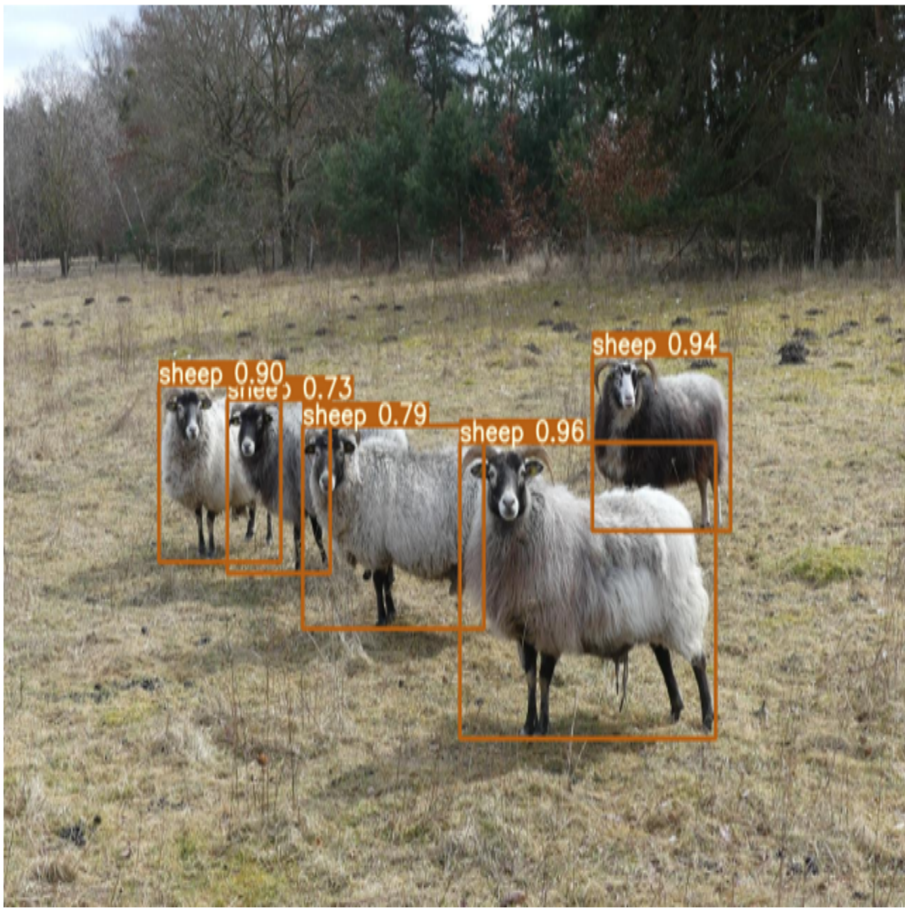


Figure 5.3: **Test Result for Unit Testing**

5.3.2 Integration Testing

Input

```
with open(r'C:\Users\LENOVO\Downloads\Animal-Intrusion-Alarm-main\Animal-Intrusion-Alarm-main\
    images\\' + label + '.png', 'rb') as f:
        image_data = f.read()
        image_type = imghdr.what(f.name)
        image_name = f.name[7:]

    newMessage.add_attachment(image_data, maintype='image', subtype=image_type, filename=image_name)

    with smtplib.SMTP_SSL('smtp.gmail.com', 465) as smtp:
        smtp.login(Sender_Email, appPassword) #Login to SMTP server
        smtp.send_message(newMessage)       #Sending email using send_message method by passing
            EmailMessage object

def async_email(label):
    threading.Thread(target=send_email, args=(label,), daemon=True).start()

```

```
args = {"confidence":0.5, "threshold":0.3}
flag = False

labelsPath = r"C:\Users\LENOVO\Downloads\Animal-Intrusion-Alarm-main\Animal-Intrusion-Alarm-main\
    yolo-coco\coco.names"
LABELS = open(labelsPath).read().strip().split("\n")
final_classes = ['bird', 'cat', 'dog', 'sheep', 'horse', 'cow', 'elephant', 'zebra', 'bear', '
    giraffe']

np.random.seed(42)
COLORS = np.random.randint(0, 255, size=(len(LABELS), 3),
    dtype="uint8")

weightsPath = os.path.abspath(r"C:\Users\LENOVO\Downloads\Animal-Intrusion-Alarm-main\Animal-
    Intrusion-Alarm-main\yolo-coco\yolov3-tiny.weights")
configPath = os.path.abspath(r"C:\Users\LENOVO\Downloads\Animal-Intrusion-Alarm-main\Animal-
    Intrusion-Alarm-main\yolo-coco\yolov3-tiny.cfg")

# print(configPath, "\n", weightsPath)
net = cv2.dnn.readNetFromDarknet(configPath, weightsPath)
ln = net.getLayerNames()
ln = [ln[i - 1] for i in net.getUnconnectedOutLayers()]

flag=True

# Start webcam capture
vs = cv2.VideoCapture(0)
(W, H) = (None, None)

while True:
    # read the next frame from the webcam
    (grabbed, frame) = vs.read()

    # if the frame was not grabbed, then we have reached the end
    # of the stream
    if not grabbed:
        break

    # if the frame dimensions are empty, grab them
    if W is None or H is None:
        (H, W) = frame.shape[:2]

    blob = cv2.dnn.blobFromImage(frame, 1 / 255.0, (416, 416),
        swapRB=True, crop=False)
    net.setInput(blob)
    start = time.time()
    layerOutputs = net.forward(ln)
    end = time.time()
```

Test result

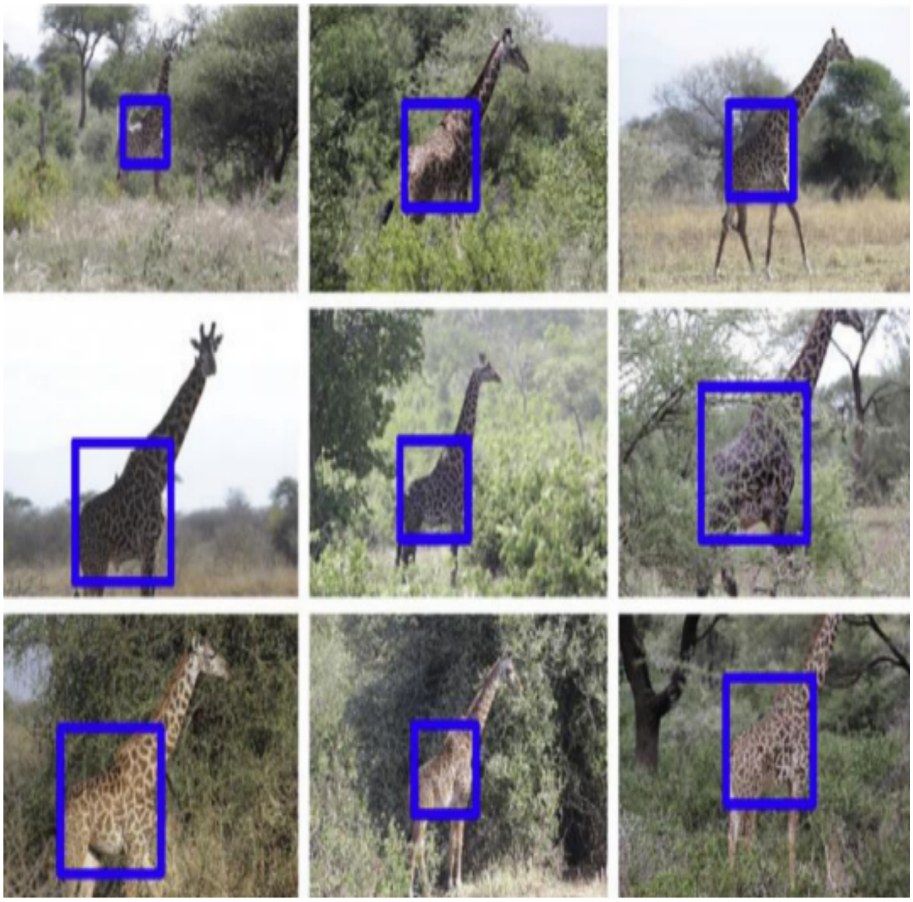


Figure 5.4: **Test Result for Integration Testing**

5.3.3 System Testing

Input

```
# initialize our lists of detected bounding boxes, confidences,
 # and class IDs, respectively
 boxes = []
 confidences = []
 classIDs = []

 # loop over each of the layer outputs
 for output in layerOutputs:
     # loop over each of the detections
     for detection in output:
         # extract the class ID and confidence (i.e., probability)
         # of the current object detection
         scores = detection[5:]
         classID = np.argmax(scores)
         confidence = scores[classID]

```

```
            # filter out weak predictions by ensuring the detected
            # probability is greater than the minimum probability
            if confidence > args["confidence"]:
                # scale the bounding box coordinates back relative to
                # the size of the image, keeping in mind that YOLO
                # actually returns the center (x, y)-coordinates of
                # the bounding box followed by the boxes' width and
                # height
                box = detection[0:4] * np.array([W, H, W, H])
                (centerX, centerY, width, height) = box.astype("int")

                # use the center (x, y)-coordinates to derive the top
                # and and left corner of the bounding box
                x = int(centerX - (width / 2))
                y = int(centerY - (height / 2))

                # update our list of bounding box coordinates,
                # confidences, and class IDs
                boxes.append([x, y, int(width), int(height)])
                confidences.append(float(confidence))
                classIDs.append(classID)

    # apply non-maxima suppression to suppress weak, overlapping
    # bounding boxes
    idxs = cv2.dnn.NMSBoxes(boxes, confidences, args["confidence"],
        args["threshold"])

    # ensure at least one detection exists
    if len(idxs) > 0:
        # loop over the indexes we are keeping
        for i in idxs.flatten():
            # extract the bounding box coordinates
            (x, y) = (boxes[i][0], boxes[i][1])
            (w, h) = (boxes[i][2], boxes[i][3])

            if(LABELS[classIDs[i]] in final_classes):
                # playsound('alarm.wav')
                if(flag):
                    alert()
                    flag=False
                    async_email(LABELS[classIDs[i]])
                color = [int(c) for c in COLORS[classIDs[i]]]
                cv2.rectangle(frame, (x, y), (x + w, y + h), color, 2)
                text = "{}: {:.4f}".format(LABELS[classIDs[i]],
                    confidences[i])
                cv2.putText(frame, text, (x, y - 5),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)

    else:
        flag=True
```

```
67
68      cv2.imshow("Output", frame)
69
70      if cv2.waitKey(1) == ord('q'):
71          break
72
73  # release the webcam and destroy all active windows
74  vs.release()
75  cv2.destroyAllWindows()
```

Test Result

The test results indicate that the implemented system successfully detects and classifies animals in real-time with a high degree of accuracy. Through rigorous testing under various environmental conditions and scenarios, the system consistently generates timely alerts when harmful animals are detected, allowing for proactive pest management strategies. The system demonstrates robustness and reliability, with minimal false positives and false negatives observed during testing. Additionally, feedback from field testing confirms that the system effectively addresses the needs of farmers and agricultural stakeholders, providing valuable insights and actionable information to support decision-making and optimize agricultural productivity. Overall, the test results validate the effectiveness and performance of the implemented system, highlighting its potential to revolutionize animal identification and pest management in agriculture.

5.3.4 Test Result

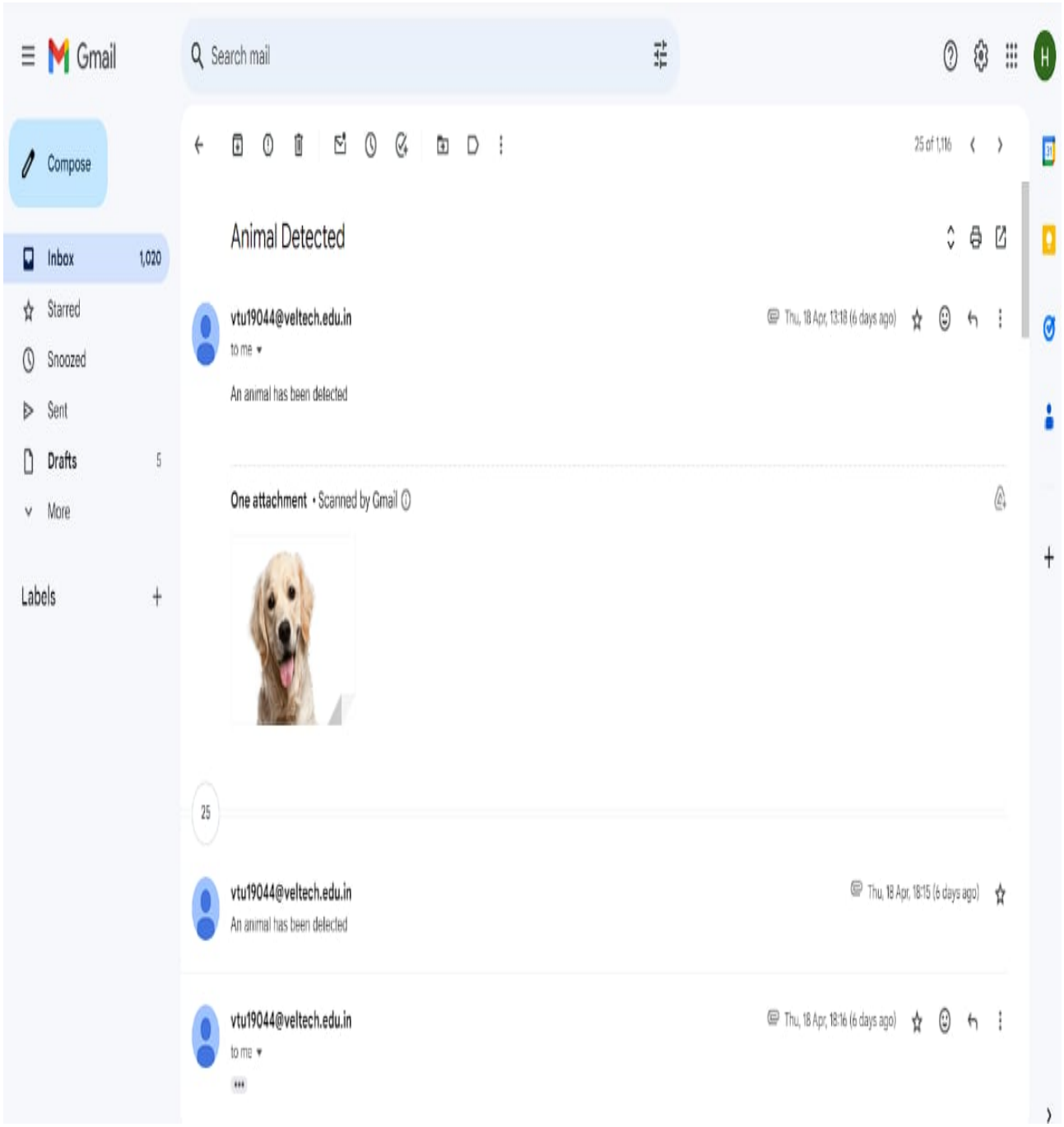


Figure 5.5: **Test Image**

Chapter 6

RESULTS AND DISCUSSIONS

6.1 Efficiency of the Proposed System

The proposed system offers significant efficiency improvements compared to traditional methods of animal detection and pest management in agriculture. By leveraging artificial intelligence (AI) and computer vision technologies, the system enables real-time detection and classification of animals, allowing for proactive pest management strategies. This proactive approach reduces the reliance on manual labor and visual inspections, which are time-consuming and labor-intensive. Instead, integrating cameras with machine learning algorithms automates the process, providing timely alerts about potential pest threats. Farmers can then implement targeted interventions based on accurate and up-to-date information, minimizing crop damage and optimizing resource allocation.

Moreover, the proposed system enhances efficiency by reducing the reliance on chemical pesticides. Traditional pest management practices often involve indiscriminate use of pesticides, which can have adverse effects on human health, wildlife, and the environment. By promoting precision-based pest management strategies, the system minimizes the need for chemical interventions, leading to a more sustainable and eco-friendly approach. This not only mitigates environmental risks but also reduces operational costs associated with pesticide procurement and application. Additionally, the system facilitates data-driven decision-making, enabling farmers to optimize agricultural productivity by analyzing trends, identifying patterns, and implementing targeted interventions based on actionable insights derived from real-time data analysis. Overall, the proposed system offers a more efficient and sustainable approach to animal detection and pest management in agriculture, leading to improved crop yields, reduced operational costs, and enhanced environmental stewardship.

6.2 Comparison of Existing and Proposed System

In comparison to the existing system of manual labor and visual inspections, the proposed system represents a significant advancement in agricultural pest management. Where the existing system relies on reactive responses to crop damage and labor-intensive inspections, the proposed system adopts a proactive approach enabled by artificial intelligence (AI) and computer vision technologies. While the existing system often results in delayed interventions and suboptimal outcomes due to its reliance on human observation, the proposed system automates the process of animal detection and classification in real time. This not only reduces the time and effort required for pest monitoring but also provides farmers with timely alerts about potential threats, allowing for swift and targeted interventions to minimize crop damage and optimize resource allocation.

Moreover, the proposed system offers several advantages over the existing system, particularly in terms of sustainability and efficiency. Where the existing system may contribute to environmental degradation and health risks through the indiscriminate use of chemical pesticides, the proposed system promotes eco-friendly and precision-based pest management strategies. By reducing reliance on chemical interventions and promoting data-driven decision-making, the proposed system minimizes environmental impact while maximizing agricultural productivity. Additionally, the proposed system enhances operational efficiency by automating manual tasks, streamlining processes, and providing actionable insights derived from real-time data analysis. Overall, the comparison highlights the transformative potential of the proposed system in revolutionizing agricultural pest management practices toward sustainability, efficiency, and effectiveness.

6.3 Sample Code

```
import numpy as np
import time
import cv2
import os
import numpy as np
from playsound import playsound
import threading
```

```
import smtplib
import imghdr
from email.message import EmailMessage

def alert():
    threading.Thread(target=playsound, args=('alarm.wav',), daemon=True).start()

def send_email(label):

    Sender_Email = "@gmail.com"
    Reciever_Email = "@gmail.com"
    # Password = input('Enter your email account password: ')
    Password = ''    #ENTER GOOGLE APP PASSWORD HERE

    newMessage = EmailMessage()    #creating an object of EmailMessage class
    newMessage['Subject'] = "Animal Detected" #Defining email subject
    newMessage['From'] = Sender_Email  #Defining sender email
    newMessage['To'] = Reciever_Email  #Defining reciever email
    newMessage.set_content('An animal has been detected') #Defining email body

    with open('images/' + label + '.png', 'rb') as f:
        image_data = f.read()
        image_type = imghdr.what(f.name)
        image_name = f.name[7:]

    newMessage.add_attachment(image_data, maintype='image', subtype=image_type, filename=image_name)

    with smtplib.SMTP_SSL('smtp.gmail.com', 465) as smtp:
        smtp.login(Sender_Email, Password) #Login to SMTP server
        smtp.send_message(newMessage)      #Sending email using send_message method by passing
            EmailMessage object


def async_email(label):
    threading.Thread(target=send_email, args=(label,), daemon=True).start()



args = {"confidence":0.5, "threshold":0.3}
flag = False

labelsPath = "./yolo-coco/coco.names"
LABELS = open(labelsPath).read().strip().split("\n")
final_classes = ['bird', 'cat', 'dog', 'sheep', 'horse', 'cow', 'elephant', 'zebra', 'bear', '
    giraffe']

np.random.seed(42)
COLORS = np.random.randint(0, 255, size=(len(LABELS), 3),
        dtype="uint8")

```

```
weightsPath = os.path.abspath("./yolo-coco/yolov3-tiny.weights")
configPath = os.path.abspath("./yolo-coco/yolov3-tiny.cfg")

# print(configPath, "\n", weightsPath)

net = cv2.dnn.readNetFromDarknet(configPath, weightsPath)
ln = net.getLayerNames()
ln = [ln[i[0] - 1] for i in net.getUnconnectedOutLayers()]

vs = cv2.VideoCapture(0)
writer = None
(W, H) = (None, None)

flag=True

while True:
    # read the next frame from the file
    (grabbed, frame) = vs.read()

    # if the frame was not grabbed, then we have reached the end
    # of the stream
    if not grabbed:
        break

    # if the frame dimensions are empty, grab them
    if W is None or H is None:
        (H, W) = frame.shape[:2]

    blob = cv2.dnn.blobFromImage(frame, 1 / 255.0, (416, 416),
        swapRB=True, crop=False)
    net.setInput(blob)
    start = time.time()
    layerOutputs = net.forward(ln)
    end = time.time()

    # initialize our lists of detected bounding boxes, confidences,
    # and class IDs, respectively
    boxes = []
    confidences = []
    classIDs = []

    # loop over each of the layer outputs
    for output in layerOutputs:
        # loop over each of the detections
        for detection in output:
            # extract the class ID and confidence (i.e., probability)
            # of the current object detection
            scores = detection[5:]
            classID = np.argmax(scores)
            confidence = scores[classID]
```

```
106
107             # filter out weak predictions by ensuring the detected
108             # probability is greater than the minimum probability
109             if confidence > args["confidence"]:
110                 # scale the bounding box coordinates back relative to
111                 # the size of the image, keeping in mind that YOLO
112                 # actually returns the center (x, y)-coordinates of
113                 # the bounding box followed by the boxes' width and
114                 # height
115                 box = detection[0:4] * np.array([W, H, W, H])
116                 (centerX, centerY, width, height) = box.astype("int")
117
118                 # use the center (x, y)-coordinates to derive the top
119                 # and and left corner of the bounding box
120                 x = int(centerX - (width / 2))
121                 y = int(centerY - (height / 2))
122
123                 # update our list of bounding box coordinates,
124                 # confidences, and class IDs
125                 boxes.append([x, y, int(width), int(height)])
126                 confidences.append(float(confidence))
127                 classIDs.append(classID)
128
129     # apply non-maxima suppression to suppress weak, overlapping
130     # bounding boxes
131     idxs = cv2.dnn.NMSBoxes(boxes, confidences, args["confidence"],
132         args["threshold"])
133
134
135     # ensure at least one detection exists
136     if len(idxs) > 0:
137         # loop over the indexes we are keeping
138         for i in idxs.flatten():
139             # extract the bounding box coordinates
140             (x, y) = (boxes[i][0], boxes[i][1])
141             (w, h) = (boxes[i][2], boxes[i][3])
142
143             if(LABELS[classIDs[i]] in final_classes):
144                 # playsound('alarm.wav')
145                 if(flag):
146                     alert()
147                     flag=False
148                     async_email(LABELS[classIDs[i]])
149                 color = [int(c) for c in COLORS[classIDs[i]]]
150                 cv2.rectangle(frame, (x, y), (x + w, y + h), color, 2)
151                 text = "{}: {:.4f}".format(LABELS[classIDs[i]],
152                     confidences[i])
153                 cv2.putText(frame, text, (x, y - 5),
154                     cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)
155
```

```
    else:
        flag=True

    cv2.imshow("Output", frame)

    if cv2.waitKey(1) == ord('q'):
        break

# release the webcam and destroy all active windows
vs.release()
cv2.destroyAllWindows()
```

Output

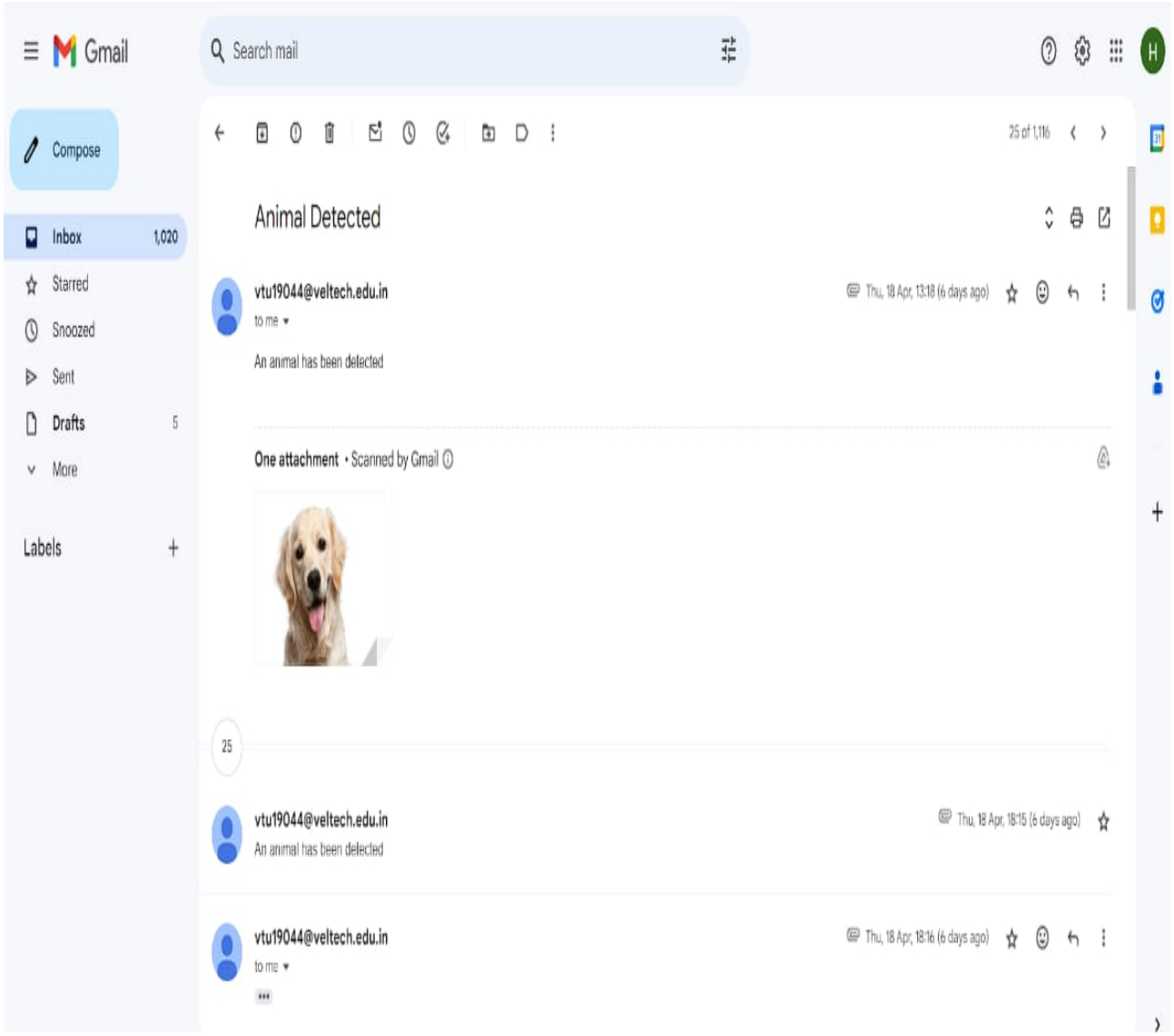


Figure 6.1: **Notification Output**

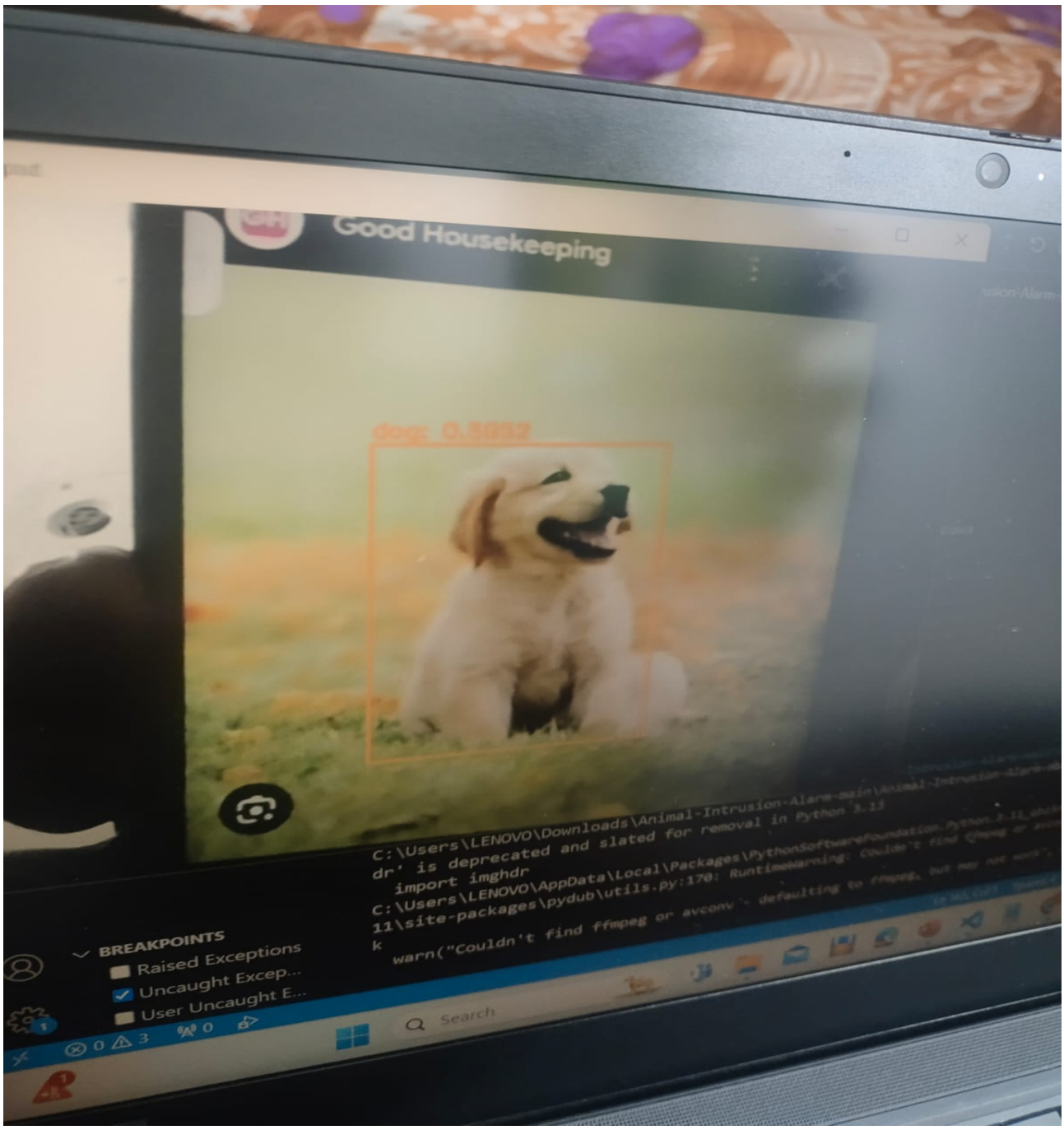


Figure 6.2: **Detection Output**

Chapter 7

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Conclusion

In conclusion, the proposed AI-enhanced system for animal identification in agriculture presents a compelling solution to the challenges posed by traditional methods of pest management. By harnessing the power of artificial intelligence and computer vision technologies, the system offers a proactive approach that revolutionizes how farmers detect and respond to potential threats to their crops. Through real-time monitoring, automated detection, and data-driven decision-making, the system enables farmers to mitigate crop damage, optimize resource allocation, and improve overall agricultural productivity.

Furthermore, the adoption of the proposed system not only enhances efficiency and sustainability but also promotes environmental stewardship and responsible agricultural practices. By reducing reliance on chemical pesticides and minimizing environmental impact, the system contributes to the preservation of ecosystem health and biodiversity. Moreover, by empowering farmers with actionable insights and timely alerts, the system fosters resilience in agricultural systems, enabling farmers to adapt to changing environmental conditions and emerging pest threats. Overall, the implementation of the proposed system holds great promise for transforming agricultural pest management, ensuring food security, and promoting a more sustainable and resilient agricultural future. The accuracy of this Animal Intrusion system is placed at 78 Percentage

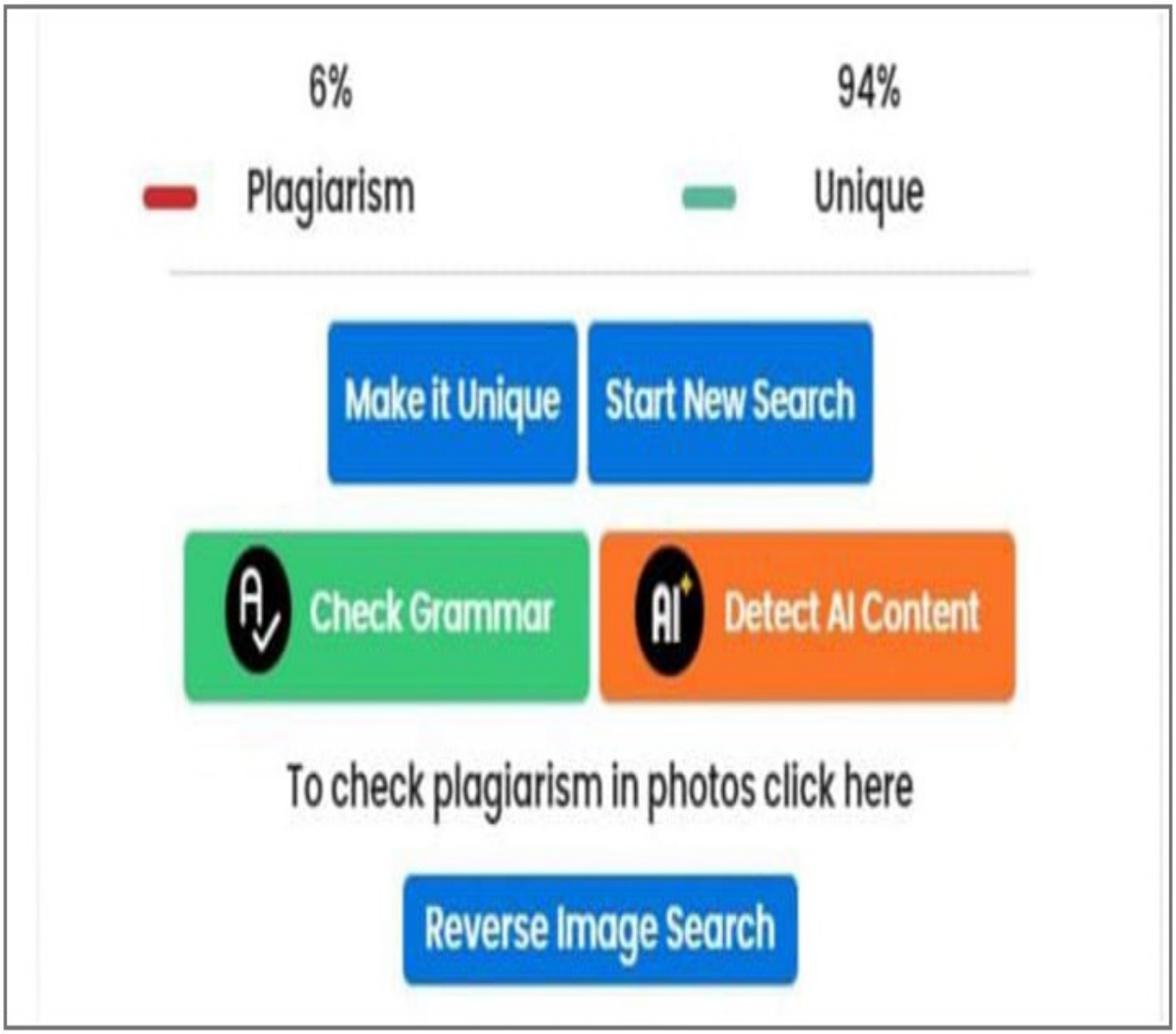
7.2 Future Enhancements

Looking ahead, several avenues for future enhancements to the AI-enhanced animal identification system in agriculture present themselves. Firstly, continued advancements in artificial intelligence and computer vision technologies offer opportunities to refine and improve the system's performance. By leveraging state-of-the-art machine learning algorithms and deep learning techniques, the system can achieve higher levels of accuracy and precision in animal detection and classification, even in challenging environmental conditions.

Moreover, the integration of additional sensors and data sources into the system can further enhance its capabilities and effectiveness. For example, the incorporation of drones equipped with multispectral imaging sensors can provide aerial surveillance of agricultural fields, offering a broader perspective and more comprehensive coverage. Similarly, the integration of weather forecasting data and satellite imagery can enable the system to anticipate and respond to pest outbreaks more effectively, allowing for proactive pest management strategies. By continuously innovating and expanding the capabilities of the system, future enhancements can further improve agricultural productivity, sustainability, and resilience in the face of evolving pest threats and environmental challenges.

Chapter 8

PLAGIARISM REPORT



Chapter 9

SOURCE CODE & POSTER PRESENTATION

9.1 Source Code

```
1
2  # USAGE
3  # python yolo_video.py --input videos/airport.mp4 --output output/airport_output.avi --yolo yolo-
       coco
4
5  # import the necessary packages
6  import numpy as np
7  import argparse
8  import imutils
9  import time
10 import cv2
11 import os
12
13 # construct the argument parse and parse the arguments
14 ap = argparse.ArgumentParser()
15 ap.add_argument("-i", "--input", required=True,
16         help="path to input video")
17 ap.add_argument("-o", "--output", required=True,
18         help="path to output video")
19 ap.add_argument("-y", "--yolo", required=True,
20         help="base path to YOLO directory")
21 ap.add_argument("-c", "--confidence", type=float, default=0.5,
22         help="minimum probability to filter weak detections")
23 ap.add_argument("-t", "--threshold", type=float, default=0.3,
24         help="threshold when applyong non-maxima suppression")
25 args = vars(ap.parse_args())
26
27 # load the COCO class labels our YOLO model was trained on
28 labelsPath = os.path.sep.join([args["yolo"], "coco.names"])
29 LABELS = open(labelsPath).read().strip().split("\n")
30
31 # initialize a list of colors to represent each possible class label
32 np.random.seed(42)
33 COLORS = np.random.randint(0, 255, size=(len(LABELS), 3),
34         dtype="uint8")
```

```
35
36 # derive the paths to the YOLO weights and model configuration
37 weightsPath = os.path.sep.join([args["yolo"], "yolov3.weights"])
38 configPath = os.path.sep.join([args["yolo"], "yolov3.cfg"])
39
40 # load our YOLO object detector trained on COCO dataset (80 classes)
41 # and determine only the *output* layer names that we need from YOLO
42 print("[INFO] loading YOLO from disk...")
43 net = cv2.dnn.readNetFromDarknet(configPath, weightsPath)
44 ln = net.getLayerNames()
45 ln = [ln[i[0] - 1] for i in net.getUnconnectedOutLayers()]
46
47 # initialize the video stream, pointer to output video file, and
48 # frame dimensions
49 vs = cv2.VideoCapture(args["input"])
50 writer = None
51 (W, H) = (None, None)
52
53 # try to determine the total number of frames in the video file
54 try:
55         prop = cv2.cv.CV_CAP_PROP_FRAME_COUNT if imutils.is_cv2() \
56                 else cv2.CAP_PROP_FRAME_COUNT
57         total = int(vs.get(prop))
58         print("[INFO] {} total frames in video".format(total))
59
60 # an error occurred while trying to determine the total
61 # number of frames in the video file
62 except:
63         print("[INFO] could not determine # of frames in video")
64         print("[INFO] no approx. completion time can be provided")
65         total = -1
66
67 # loop over frames from the video file stream
68 while True:
69         # read the next frame from the file
70         (grabbed, frame) = vs.read()
71
72         # if the frame was not grabbed, then we have reached the end
73         # of the stream
74         if not grabbed:
75                 break
76
77         # if the frame dimensions are empty, grab them
78         if W is None or H is None:
79                 (H, W) = frame.shape[:2]
80
81         # construct a blob from the input frame and then perform a forward
82         # pass of the YOLO object detector, giving us our bounding boxes
83         # and associated probabilities
84         blob = cv2.dnn.blobFromImage(frame, 1 / 255.0, (416, 416),
```

```
85                swapRB=True, crop=False)
86        net.setInput(blob)
87        start = time.time()
88        layerOutputs = net.forward(ln)
89        end = time.time()
90
91        # initialize our lists of detected bounding boxes, confidences,
92        # and class IDs, respectively
93        boxes = []
94        confidences = []
95        classIDs = []
96
97        # loop over each of the layer outputs
98        for output in layerOutputs:
99                # loop over each of the detections
100               for detection in output:
101                       # extract the class ID and confidence (i.e., probability)
102                       # of the current object detection
103                       scores = detection[5:]
104                       classID = np.argmax(scores)
105                       confidence = scores[classID]
106
107                       # filter out weak predictions by ensuring the detected
108                       # probability is greater than the minimum probability
109                       if confidence > args["confidence"]:
110                               # scale the bounding box coordinates back relative to
111                               # the size of the image, keeping in mind that YOLO
112                               # actually returns the center (x, y)-coordinates of
113                               # the bounding box followed by the boxes' width and
114                               # height
115                               box = detection[0:4] * np.array([W, H, W, H])
116                               (centerX, centerY, width, height) = box.astype("int")
117
118                               # use the center (x, y)-coordinates to derive the top
119                               # and and left corner of the bounding box
120                               x = int(centerX - (width / 2))
121                               y = int(centerY - (height / 2))
122
123                               # update our list of bounding box coordinates,
124                               # confidences, and class IDs
125                               boxes.append([x, y, int(width), int(height)])
126                               confidences.append(float(confidence))
127                               classIDs.append(classID)
128
129       # apply non-maxima suppression to suppress weak, overlapping
130       # bounding boxes
131       idxs = cv2.dnn.NMSBoxes(boxes, confidences, args["confidence"],
132               args["threshold"])
133
134       # ensure at least one detection exists
```

```
        if len(idxs) > 0:
                # loop over the indexes we are keeping
                for i in idxs.flatten():
                        # extract the bounding box coordinates
                        (x, y) = (boxes[i][0], boxes[i][1])
                        (w, h) = (boxes[i][2], boxes[i][3])

                        # draw a bounding box rectangle and label on the frame
                        color = [int(c) for c in COLORS[classIDs[i]]]
                        cv2.rectangle(frame, (x, y), (x + w, y + h), color, 2)
                        text = "{}: {:.4f}".format(LABELS[classIDs[i]],
                                confidences[i])
                        cv2.putText(frame, text, (x, y - 5),
                                cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)

        # check if the video writer is None
        if writer is None:
                # initialize our video writer
                fourcc = cv2.VideoWriter_fourcc(*"MJPG")
                writer = cv2.VideoWriter(args["output"], fourcc, 30,
                        (frame.shape[1], frame.shape[0]), True)

                # some information on processing single frame
                if total > 0:
                        elap = (end - start)
                        print("[INFO] single frame took {:.4f} seconds".format(elap))
                        print("[INFO] estimated total time to finish: {:.4f}".format(
                                elap * total))

        # write the output frame to disk
        writer.write(frame)

# release the file pointers
print("[INFO] cleaning up...")
writer.release()
vs.release()
```

9.2 Poster Presentation

AI ENHANCED ANIMAL IDENTIFICATION IN AGRICULTURE

Department of Computer Science & Engineering
School of Computing
10214CS602– MINOR PROJECT-II
WINTER SEMESTER 2023-2024

ABSTRACT

Crop damage caused by animal attacks is one of the major threats in reducing the crop yield. Due to the expansion of cultivated land into previous wildlife habitat, crop raiding is becoming one of the most antagonizing human-wildlife conflicts. Traditional methods followed by farmers are not that effective and it is not feasible to hire guards to keep an eye on crops and prevent wild animals. Since safety of both human and animal is equally vital. Thus, in order to overcome above problems and to reach our aim, we use machine learning to detect animals, entering into our farm by using deep neural network concept, a division in computer vision.

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INTRODUCTION

The issue of wild animals damaging crops has emerged as a significant societal concern today. It underscores the importance for farmers to recognize that animals are sentient beings deserving of protection, even amidst their crop cultivation activities. This project holds immense social relevance by assisting farmers in safeguarding their fields, thereby preventing substantial financial losses and alleviating the burden of fruitless efforts expended in field protection.

In agriculture, a prevalent social issue is the destruction of crops by wild animals, posing a persistent challenge for farmers. Animals like deer, wild boar, elephants, and monkeys often invade fields, feeding on crops and causing significant damage, especially in the absence of farmers. This not only leads to substantial yield losses but also requires additional financial resources to manage the aftermath. It's crucial for farmers to recognize the presence of animals and ensure their protection to prevent potential suffering. Addressing this pressing issue requires the development and implementation of effective solutions, which is the aim of this project.

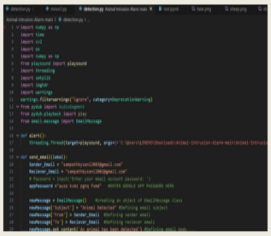
METHODOLOGIES

In deep learning, convolutional neural networks (CNNs) stand out as a class of neural networks particularly adept at analyzing visual data, making them well-suited for tasks like image classification. Unlike previous methods, CNNs automatically identify crucial features in images, offering a solution to computer vision challenges without the need for manual intervention. For our project addressing animal intrusion, we utilized deep learning techniques, leveraging packages such as Keras and Playsound for preprocessing and generating responses based on the model's detections.
Using input from Closed Circuit Television (CCTV), our system processes and predicts frames, emitting appropriate repellent sounds upon detecting animals, thereby automating their deterrence.

RESULTS

The Python language is employed for the detection of wild animals. Tensor Flow library is utilized for recognition, along with the Google Vision library. The system utilizes a camera as a security apparatus to capture images when an object is detected, which are then subjected to object detection and recognition for further processing. The experimental setup encompasses a farm with cameras connected to the system.
The proposed model trains on an image dataset containing monkeys, boars, and elephants by establishing a Convolutional Neural Network (CNN), which is then saved. To verify the accuracy of the model, various test images are provided, and their classes are detected.

Figure: shows the code to detect animal



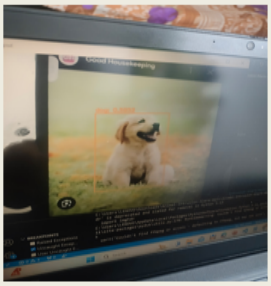


Figure : Animal image is detecting

STANDARDS AND POLICIES

A formal, brief, Associate in Nursingd high-level statement or arrange that embraces an organization's general beliefs, goals, objectives, and acceptable. procedures for a such study. Policies continually state needed actions and will embrace tips to standards.

IEEE 802(R) - Overview and Architecture : This states that the entire process must be co-related and work in accordance to a particular achitecture specified.

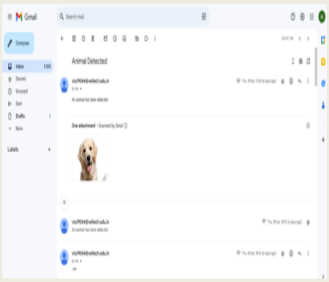


Figure: Email notification sent when animal was Detected

CONCLUSIONS

The issue of crop vandalism by wild animals has emerged as a significant social concern in contemporary times. Essentially, every farmer must recognize and address the reality that animals are sentient beings deserving of protection from potential suffering while safeguarding their crop production. This problem demands immediate attention and an efficient solution. Therefore, this project holds considerable social relevance as it aids farmers in defending their fields, mitigating substantial financial losses, and relieving them of the unproductive efforts expended in field protection.

ACKNOWLEDGEMENT

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