Project Report On

Drone based monitoring

Submitted in partial fulfillment of the requirements for the award of the degree of

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in

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CERTIFICATE

This is to certify that the project report entitled ***"Drone Based Monitoring"*** *is a bonafide record of the work done by* ***Neil Sunny (U2003148)***, ***Noel Joe (U2003157)***, ***Salman Sidhik (U2003182)***,***Siddhartha Goutaman(U2003201)***, *submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

The project aims to develop a sophisticated drone based system for comprehensive field management in agriculture. This innovative solution leverages drone technology to autonomously fly along predefined paths within a cultivated field. The primary objectives of the system are to assess fruit ripeness and detect potential animal intrusions, providing timely alerts to the field owner.

To achieve these goals, the project incorporates image processing techniques to analyse real-time drone footage. Fruit ripeness is determined by monitoring the colour of the fruits, and the system sends alerts to the owner when ripe fruits are identified. This assists in optimising harvest timing, reducing crop waste, and enhancing overall yield quality.

In addition to crop monitoring, the drone live streams the footage to a base station equipped with computer vision capabilities to detect and identify potential animal intrusions into the field. When unauthorised access is detected, the system promptly notifies the field owner, allowing for rapid response to mitigate potential damage and enhance field security.

The Smart Agriculture Drone project combines technology with practical agricultural applications, offering an efficient and cost-effective solution for crop management and security. It has the potential to revolutionise the way farms and orchards are managed, increasing productivity and protecting valuable resources.

Contents

List of Abbreviations

GPS- Global Positioning System

IoT- Internet of Things

UAV - Unmanned Aerial Vehicle

RGB - Red, Green and Blue

YOLO - You Only Look Once

ML- Machine Learning

DL- Deep Learning

MS COCO- Microsoft Common Objects in Context

HOG- Histogram of Oriented Gradients

R-CNN- Regional Vonvolutional Nueral Networks

SSD- Single Shot Detector

RPN- Region Proposal Networks

MOS- Mean Opinion Scores AP- Average Precision mAP- Mean Average Precision ESC- Electronic Speed Controllers

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Chapter 1

Introduction

Agriculture, the backbone of our global food supply, continues to face challenges that necessitate innovative solutions for efficient crop management and field security. In this context, the integration of unmanned aerial vehicles, specifically drones, have emerged as a transformative technology in precision agriculture. This project introduces a groundbreaking application of drone technology tailored for smart agriculture – a system designed to autonomously fly through predefined paths in a cultivated field, assessing fruit ripeness and detecting potential animal intrusions. By leveraging advanced image processing techniques, the drone analyzes real-time footage to determine the ripeness of fruits based on their color and promptly alerts the field owner. Simultaneously, the system employs sophisticated computer vision capabilities to identify and notify the owner of any animal intrusion, providing an integrated solution for both crop monitoring and field security.

This report outlines the development, implementation, and outcomes of the Smart Agriculture Drone project, which aims to revolutionize traditional farming practices. By addressing critical aspects of crop management and security, this drone-based solution offers a cost-effective and efficient means of optimizing yields while minimizing losses. As we delve into the technical aspects, methodologies, and results of this innovative system, it becomes evident that the integration of drone technology in agriculture has the potential to redefine how we approach sustainable and intelligent farming practices.

1.1 Background

Agriculture, a cornerstone of human civilization, has undergone transformative changes over the years, adapting to advancements in technology to meet the increasing demands of a growing global population. With the advent of precision agriculture, farmers now have access to a plethora of technologies aimed at optimizing crop yields, reducing resource utilization, and enhancing overall efficiency. In this context, the integration of unmanned aerial vehicles, or drones, has emerged as a revolutionary tool for precision farming.

Current Technologies in Precision Agriculture:

1. Satellite Imagery and GPS Technology: Satellite imaging provides farmers with detailed, high-resolution maps of their fields. Coupled with GPS technology, this enables precise mapping, planning, and monitoring of agricultural activities.

2. IoT and Sensors: The Internet of Things (IoT) has facilitated the deployment of various sensors in the field. These sensors collect real-time data on soil moisture, temperature, and other crucial parameters, providing farmers with valuable insights for data-driven decision-making.

3. Automated Machinery: Farm machinery equipped with automation technology, such as tractors and harvesters, enhances efficiency by optimizing planting, harvesting, and other labor-intensive tasks.

4. Precision Spraying and Fertilization: Drones and specialized equipment enable precision application of pesticides and fertilizers, reducing waste and environmental impact.

5. Machine Learning and AI: Machine learning algorithms and artificial intelligence (AI) applications analyze vast datasets to provide predictive insights, helping farmers anticipate crop diseases, optimize irrigation, and improve overall crop management.

Despite these advancements, challenges persist in the realm of crop monitoring and field security. Traditional methods of assessing fruit ripeness and detecting intrusions rely heavily on manual labor and are often time-consuming. The Smart Agriculture Drone project aims to bridge these gaps by integrating cutting-edge image processing and computer vision technologies into a drone-based system. This innovative approach builds upon existing technologies, enhancing the capabilities of precision agriculture to ensure timely and accurate information for farmers, ultimately contributing to sustainable and efficient farming practices.

1.2 Problem Definition

To develop and implement an autonomous drone system that integrates advanced image processing and computer vision technologies, providing farmers with real-time, automated solutions for efficient crop monitoring, timely fruit ripeness assessment, and prompt detection of animal intrusions to enhance overall field management and productivity.

1.3 Scope and Motivation

1.3.1 Scope

The scope of the Smart Agriculture Drone project encompasses the design, development, and deployment of an autonomous drone system tailored for precision farming. The project will focus on creating a robust drone capable of following predefined paths within a cultivated field. Advanced image processing algorithms will be implemented to analyze drone footage, enabling real-time assessment of fruit ripeness based on color. Additionally, the system will incorporate computer vision capabilities to detect and notify farmers of potential animal intrusions into the field. The project aims to provide a comprehensive solution that integrates seamlessly into existing agricultural practices, offering enhanced crop management and field security for farmers. The scope also involves evaluating the economic and environmental impact of the implemented drone system.

1.3.2 Motivation

1. Precision Agriculture Advancements

    - The project is motivated by the growing need for precision agriculture solutions that leverage cutting-edge technologies to enhance efficiency, reduce resource usage, and optimize crop yields. The integration of autonomous drones presents a promising avenue to achieve these objectives.

2. Timely Crop Monitoring

    - Traditional methods of crop monitoring are often labor-intensive and lack real-time capabilities. The motivation for the project arises from the desire to provide farmers with a technological solution that enables timely and accurate monitoring of fruit ripeness throughout the growing season, thereby optimizing harvest timings.

3. Field Security Enhancement

    - Addressing the challenge of animal intrusions, the project is motivated by the necessity to improve field security measures. By employing computer vision on drone platforms, the system aims to detect and alert farmers promptly, minimizing potential damage and losses due to unauthorized access.

4. Resource Optimization

    - The motivation for the project stems from the need to address resource inefficiencies in agriculture. By integrating advanced technologies, the drone system aims to provide farmers with data-driven insights to optimize resource usage, including water, fertilizers, and pesticides, contributing to sustainable farming practices.

5. Integrated Solution for Agricultural Challenges

    - The project is motivated by the aspiration to provide farmers with a comprehensive, integrated solution that combines crop monitoring and field security. By addressing multiple challenges faced in agriculture, the Smart Agriculture Drone project seeks to enhance overall field management, improve productivity, and contribute to the modernization of farming practices.

1.4 Objectives

1. Precision Agriculture

    - Ripe Fruit Detection: Drones equipped with advanced sensors, such as cameras and infrared imaging, can be used to monitor agricultural fields for the presence of ripe fruits. This enables farmers to identify the optimal time for harvesting, leading to increased yield and better quality produce.

2. Efficiency and cost saving

- Automation: Drone-based monitoring reduces the need for manual labor in inspecting large agricultural fields. This automation can significantly increase the efficiency of farming operations.
- Resource Optimisation: By identifying ripe fruits and areas of concern in the field, farmers can optimise the use of resources such as water, fertilisers, and pesticides, leading to cost savings and environmental sustainability.

3. Security and intrusion detection
   - Surveillance: Drones equipped with cameras and other sensors can be utilised for security purposes. They can monitor agricultural sites for potential intrusions.

1.5 Challenges

1. Accuracy and Reliability
   - False Positives/Negatives: Object detection algorithms, including YOLO, may produce false positives (identifying non-existent ripe fruits) or false negatives (missing actual ripe fruits or animal intrusions).
   - Varying Environmental Conditions: Changes in lighting, weather conditions, and the physical environment can affect the accuracy of the detection system.
2. Technical Limitations
   - Processing Power: Real time processing of high resolution images or video streams from drones may require significant computational power, limiting the deployement options
   - Battery Life: Drones have limited battery life, and continuous moitoring may require efficient power management strategies.
3. Regulatory Compliance
   - Drone Regulations: Depending on the region, there may be strict regulations regarding the use of drones, especially for agricultural monitoring. Compliance with these regulations is crucial.

4. Cost Considerations

    - Initial Investment: Implementing a drone-based monitoring system involves upfront costs for hardware, software, and training. Farmers need to weigh these costs against potential benefits.

1.6 Assumptions

1. Drone Connectivity: It assumes reliable connectivity or data transfer and real-time video streaming from the drone to central server or monitoring station.

2. Adequate Drone Flight Time: The project assumes that the drones have sufficient battery life and operational time to cover the entire agricultural area without frequent recharging.

3. Availability of Quality Training Data: For machine learning-based fruit ripeness detection and animal intrusion detection, the project assumes access to high-quality, labeled training datasets for these specific tasks.

4. Suitable Environmental Conditions: The system assumes that environmental conditions (e.g., weather, lighting, visibility) are within reasonable bounds for effective drone operation and data capture.

5. Farm Layout and Crop Arrangement: The system assumes a reasonably organized farm layout with crops clearly distinguishable and without excessive clutter, which can affect the accuracy of detection algorithms.

1.7 Societal / Industrial Relevance

The Smart Agriculture Drone project holds significant societal and industrial relevance, offering transformative solutions to address pressing challenges in modern agriculture. The project's outcomes directly contribute to the advancement of precision farming practices, fostering sustainable and efficient approaches to food production. Several aspects underscore the societal and industrial relevance of this project:

1. Enhanced Agricultural Productivity: The project's focus on timely crop monitoring and precision field security directly contributes to increased agricultural productivity. By optimizing harvest timings, minimizing crop losses, and improving resource efficiency, the project aids in meeting the growing global demand for food in a sustainable manner.

2. Resource Efficiency and Sustainability: Through the implementation of advanced technologies, the project promotes resource-efficient farming practices. Real-time data on fruit ripeness and potential intrusions allow for precise resource utilization, reducing unnecessary water, fertilizer, and pesticide usage. This contributes to sustainable agriculture by minimizing environmental impact and preserving valuable resources.

3. Economic Benefits for Farmers: The integration of autonomous drones with advanced image processing and computer vision technologies provides farmers with valuable tools for informed decision-making. By optimizing harvests and enhancing field security, the project helps farmers reduce losses, improve yields, and potentially increase their overall income.

4. Technology Adoption and Innovation in Agriculture: The project fosters the adoption of cutting-edge technologies in agriculture, showcasing the potential for drones, image processing, and computer vision to revolutionize traditional farming practices. This technological leap positions agriculture as a dynamic and innovative industry, attracting interest and investment in the development of similar solutions.

5. Rural Development and Skill Enhancement: As the project introduces novel technologies to agriculture, it has the potential to contribute to rural development. Training programs associated with the adoption of drone technology can enhance the skill set of farmers and create new opportunities for employment and entrepreneurship in rural communities.

6. Global Food Security: By optimizing crop management and enhancing field security, the project plays a role in contributing to global food security. Increased agricultural efficiency is essential to meet the nutritional needs of a growing world population, especially in the face of climate change and unpredictable environmental conditions.

7. Industry Collaboration and Growth: The project encourages collaboration between the agricultural and technology sectors. The development and implementation of the Smart Agriculture Drone system may open avenues for partnerships between farmers, drone manufacturers, and technology companies, fostering a collaborative ecosystem for continued innovation in precision agriculture.

1.8 Organization of the Report

The report is organized into several sections, each of which addresses a specific aspect of the project. Chapter 1 provides an introduction which looks into the background of the project as well as defines the problem. This chapter also includes scope, motivation, objectives, challenges, assumptions and discusses the societal relevance of the project. Chapter 2 briefs about the different literature available related to the project for com- prehensive understanding of the current state of knowledge in the field. In chapter 3 we discuss the hardware , software and functional requirements of the project. Chapter 4 looks into the design of the application as well as the work schedule and module division. The system implementation along with dataset is dicussed in chapter 5. Chapter 6 pro- vides a conclusion and outlines the future extensions possible in the project. Finally, this chapter provides a thorough overview and foundation for the project by exploring its historical origins, explaining its applicability, and clarifying the particular issues it seeks to solve. This chapter clarifies the difficulties inherent in the project by highlighting important issues. The aims are stated in a way that prepares the reader for a thorough examination in later chapters. The reader gains the underlying knowledge needed to interact with the project's subtleties and importance through this fundamental investigation, opening the door for a more in-depth examination in the ensuing chapters.

Chapter 2

Literature Survey

2.1 Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV [1]

This investigation introduces a cutting-edge technique for the automated recognition and dimension assessment of citrus fruits using UAV-captured RGB imagery, in conjunction with a neural network algorithm. Undertaken in a 4-hectare citrus plantation in the southwest region of Spain, the study spanned three distinct harvest seasons. Its primary aim was to devise a system capable of accurately determining the count and dimensions of oranges, thereby diminishing the inaccuracies inherent in manual evaluations and aiding citrus farmers in enhancing economic gains and diminishing risk factors.

The methodology encompassed the collection of RGB photographs from a 4-hectare citrus orchard via a UAV. Sampling involved a random selection of 20 trees in sets of five from a total population of 1,654 trees. Subsequently, these images were analyzed through a neural network algorithm tasked with pinpointing and enumerating the citrus fruits. This algorithm was calibrated to provide precise estimates of both fruit quantity and size. Furthermore, an approach was developed that extrapolated the overall yield of the orchard based on the fruit count. The robustness and effectiveness of this automated system for fruit detection and dimension analysis were evaluated, demonstrating promising precision and accuracy in yield estimation.

Moreover, the study highlighted the advantages of adapting production methodologies to configurations that render the majority of fruits externally visible, thereby streamlining automated processes such as detection. The research was conducted without any financial conflicts of interest or personal relationships that could have influenced its outcomes.

Support for the study was provided by the Spanish Ministry of Economy and the University of Seville's research initiative.

2.2 Object detection using YOLO [2]

2.2.1 Evolution of object detectors

The evolution of object detectors in computer vision has seen significant progress over the years. Initially, traditional methods relied on handcrafted features and sliding window approaches. The advent of Haar cascades and Histogram of Oriented Gradients (HOG) marked early milestones. The introduction of two-stage detectors, such as R-CNN, improved accuracy by combining region proposals with deep convolutional networks. Fast R-CNN and Faster R-CNN optimized speed and efficiency by introducing region-based convolutional neural networks (R-CNN) and region proposal networks (RPN).

Single-stage detectors, like YOLO (You Only Look Once), emerged for real-time object detection, processing entire images at once. YOLO's subsequent versions, including YOLOv2 and YOLOv3, refined accuracy and speed. The evolution continued with models like SSD (Single Shot Multibox Detector) and RetinaNet, addressing challenges of multi-scale detection and class imbalance.

2.2.2 Two stage object detection

R-CNN and its successors

Region-based Convolutional Neural Network (R-CNN) and its successors represent signif- icant milestones in the evolution of object detection algorithms:

R-CNN (Region-based Convolutional Neural Network):

• Approach: Introduced by Ross Girshick et al. in 2014, R-CNN was a groundbreaking object detection model. It utilized a two-stage process, first proposing regions of interest (RoIs) using selective search and then classifying these RoIs using a deep convolutional neural network (CNN).

• Strengths: Improved accuracy compared to earlier methods, leveraging the representational power of CNNs for object recognition.

• Challenges: Computationally expensive and slow due to the two-stage approach and independent processing of each proposed region.

Fast R-CNN:

• Improvements: Developed as an enhancement to R-CNN, Fast R-CNN integrated the region proposal step with the CNN, eliminating the need for separate processing for each region. It introduced the Region of Interest Pooling (RoI Pooling) layer for efficient feature extraction.

• Advantages: Faster than R-CNN, as it shared computation for feature extraction among all RoIs, addressing the speed bottleneck.

Faster R-CNN:

• Innovation: Introduced by Shaoqing Ren et al. in 2015, Faster R-CNN further optimized the region proposal process by integrating Region Proposal Networks (RPNs) into the main network. This unified architecture enabled end-to-end training.

• Key Contribution: Achieved a good balance between accuracy and speed, becoming a benchmark in object detection.

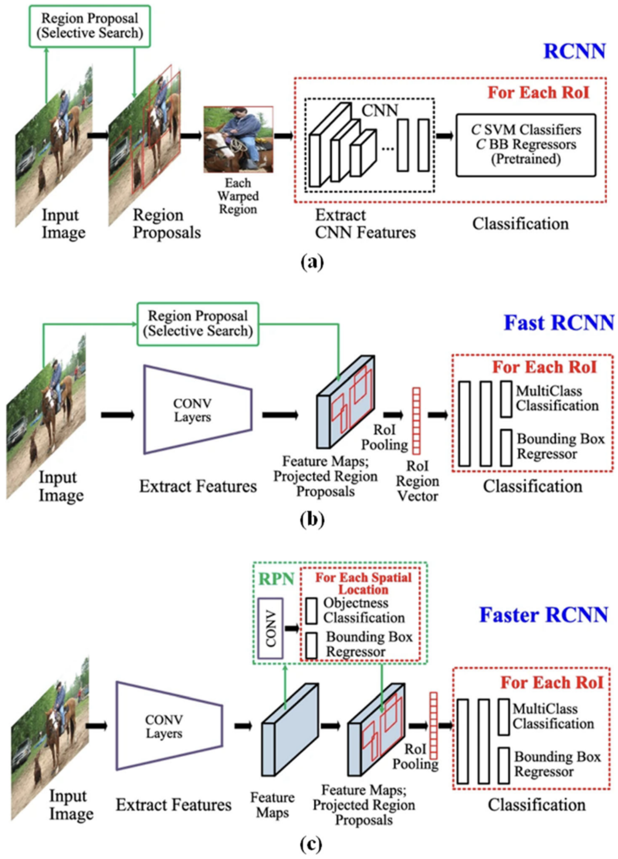


Figure 2.1: Two stage object detectors(a)RCNN(b)Fast-RCNN(c)Faster-RCNN

2.3 Study of Subjective and Objective Quality of High Motion Live Streaming Videos [3]

The study mentioned in the paper involves the assessment of video quality through human perception and subjective evaluations.The study involved human subjects who were tasked with evaluating the quality of the videos. The subjects were selected to represent a diverse cross-section of the general population, ensuring that the evaluations were reflective of a broad range of viewer perceptions. Prior to the study, the subjects received a brief introduction to the study's goals and were provided with detailed instructions on how to operate the system and assign scores.

The subjective mean opinion scores (MOS) were computed based on the scores assigned by the subjects. Subjective scores were converted into Z-scores for each subject, and subject rejection was performed.The subjects used a rating bar to record their subjective opinion scores for each video. The videos were divided into sessions, and each subject participated in two sessions to evaluate the pristine videos and their corresponding distorted versions.The subjective study aimed to capture human perceptions of video quality, providing valuable insights into how viewers subjectively assess the visual experience. The results of the subjective study can be used to validate and calibrate objective video quality assessment models, contributing to the development of more accurate and reliable methods for evaluating video quality.

2.4 Autonomous Navigation of UAV by Using Real-Time Model Based Reinforcement Learning [4]

The proposed methodology for autonomous path planning of UAVs involves a multi-step process that utilizes various techniques to enable drones to navigate autonomously in unknown environments. The first step in this process is to model the environment as a Markov Decision Process (MDP). This involves dividing the state space into a grid of cells, where each cell represents a different position in the environment. The action space consists of four actions: up, down, left, and right. When the UAV takes an action, it moves to the adjacent cell in the corresponding direction.

The second step in the proposed methodology is to use Deep Reinforcement Learning (DRL) to train the path planner to learn the optimal policy for the drone to navigate in the environment. DRL is a type of machine learning that combines reinforcement learning and deep neural networks. The DRL algorithm uses a deep neural network to approximate the Q-function, which is used to determine the optimal action for the drone in a given state. The DRL algorithm learns by trial and error, where the drone takes actions in the environment and receives rewards based on its actions. The algorithm then adjusts the weights of the neural network to improve its performance.

The third step in the proposed methodology is to use explainability methods to interpret the decision-making process of the path planner. Explainability methods are used to enhance the usability and trustworthiness of the path planner, making it suitable for real-world applications. These methods help to interpret the decision-making process of the path planner, which can be useful for understanding and explaining the behavior of the drone. The explainability methods used in the proposed methodology include techniques such as saliency maps, which highlight the regions of the input that are most important for the output, and decision trees, which provide a visual representation of the decision-making process.

Overall, the proposed methodology offers several advantages over existing navigation methods for UAVs. DRL enables UAVs to autonomously navigate, surveil, and avoid obstacles in dynamic environments. The use of MDP and DRL allows the path planner to learn the optimal policy for the drone to navigate in the environment. The explainability methods enhance the usability and trustworthiness of the path planner, making it suitable for real-world applications. The proposed methodology offers a promising approach for autonomous path planning of UAVs in unknown environments.

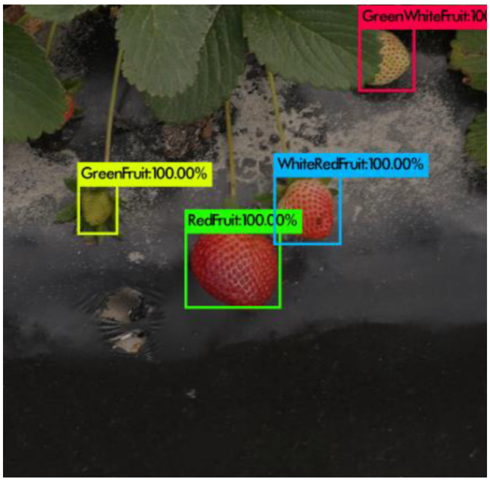
2.5 UAV and Near-Ground Imaging Using Deep Learning [1]

YOLOv3, a renowned algorithm for object detection, has found extensive use across various fields such as image and video analysis, agricultural surveillance, security, and monitoring.

In a particular instance, YOLOv3 was instrumental in automating the process of recognizing and categorizing different stages of strawberry maturity, utilizing both UAV-captured and terrestrial digital camera images. This method utilized YOLOv3's sophisticated object detection capabilities to efficiently identify and sort the stages of strawberry maturity in an agricultural setting. The procedure involved multiple key steps: gathering data, preparing the dataset, training the model, evaluating its performance, detecting and classifying maturity stages, and conducting a thorough examination of the model's accuracy and effectiveness.

The study demonstrated the approach's high level of precision and efficiency in pinpointing and classifying the stages of strawberry maturity from both aerial and ground-level images, as confirmed by the results. Moreover, the approach's capacity for automation, flexibility, and its beneficial impact on crop yield and quality mark it as a significant development for enhancing precision farming and fostering intelligent agricultural practices. This has profound implications for tech-driven innovation and the digital evolution in the agriculture sector.

The outcomes of the research were striking, showing the successful use of the YOLOv3 deep learning model in the detection and classification of strawberry maturity stages from both UAV and ground-based digital camera imagery. The results displayed a high degree of accuracy, as evidenced by metrics like mean average precision (mAP) and average precision (AP) for each maturity stage. The method enabled quick, automated analysis of a large number of images, making it an efficient tool for assessing maturity across vast agricultural areas. YOLOv3's versatility was highlighted by its ability to accurately identify and classify various categories of strawberry maturity stages in different types of images, underscoring its applicability in multiple agricultural contexts. The research also pointed to the potential for automating crop monitoring and maturity assessment, which has direct consequences for improving precision agriculture and maximizing crop yield and quality. Overall, the study emphasized the crucial role of advanced deep learning techniques in agriculture, leading the way in tech innovation and the digital revolution in the farming industry.



(a) YOLOv3 model on near-ground images.

(b) YOLOv3 model on UAV images.

(c) UAV capturing images.

Figure 2.2: YOLOv3 results.

2.6 Summary and Gaps Identified

2.6.1 Summary

Table 2.1: Comparison Table

Paper	Brief	Advantages/Disadvantages
[2]	Implementation of the YOLO algorithm for animal detection and comparison between other models	**Advantages:** Acceptable accuracy levels for the intended project. 300 times faster than FasterCNN classification. **Disadvantages:** Less classification accuracy than other CNN with two step classification
[4]	DRL combines deep learning and reinforcement learning to learn optimal policies in complex environment.	**Advantages:** DRL enables UAVs to autonomously navigate, surveil, and avoid obstacles in dynamic environments. Complex Decision-Making. **Disadvantages:** DRL training can be computationally expensive and time-consuming, depending on the complexity of the task DRL often requires a large number of samples to learn effectively.

[1]	Uses drone based footage and deep learning to predict ripeness of strawberries.	**Advantages:** Uses image collected by UAV make acquisition easy Deep learning and YoloV3 and above are good for small objects **Disadvantages:** Obscured images due to leaves coming into the frame.
[3]	Study in the quality of high motion live streaming videos by subjective and objective scores.	**Advantages:** High motion live streaming videos. Show MOS and DMOS scores. **Disadvantages:** Study is done by getting opinions from different human subjects, human opinions can differ from each other.

2.6.2 Gaps Identified

1. Single fruit: The existing methods only cater to a specific kind of fruit.

2. Real-time processing: Some applications, such as precision agriculture or automated harvesting, require real-time processing. Current methods may face challenges in achieving the speed necessary for these applications.

3. User friendly interface: For widespread adoption, user-friendly interfaces and applications are essential. Ensuring that the technology is accessible to users with varying levels of technical expertise and providing intuitive interfaces for system configuration and operation are important considerations.

4. Changes in lighting: Changes in lighting conditions can affect the appearance of objects, making it difficult for the model to recognize them accurately.

Chapter 3

Requirements

3.1 Hardware and Software Requirements

3.1.1 Hardware

The contains two parts:

1. Drone:
    - Battery
    - Motors
    - Propellers
    - Camera module
    - GPS Module
    - ESC
    - Flight controller
    - Raspberry Pi
    - Drone frame
    - Monitoring Station
    - Computing system
2. Monitoring Stations:
    - A computing system : a. Intel Core i5 b. 8GB RAM c. 256GB SSD

3.1.2 Software

1. Drone control software
2. Image processing and Computer Vision
   - Open CV
3. Data analysis
   - Python or R
4. Operating System
   - Windows or MacOS
5. UI development software
   - HTML or React

3.2 Functional Requirements

1. Real-time Image Processing: Incorporate algorithms for real-time image processing to analyze drone footage, facilitating accurate assessment of fruit ripeness based on color.
2. Computer Vision for Animal Intrusion Detection: Integrate computer vision functionalities to identify and detect potential animal intrusions within the field through the analysis of drone-generated footage.
3. Alert System: Develop a real-time alert system capable of notifying the field owner upon the identification of ripe fruits or the detection of potential animal intrusions.
4. User Interface: Create an intuitive user interface accessible to farmers, providing real-time information on fruit ripeness, potential intrusions, and other pertinent data.
5. Remote Monitoring and Control: Implement remote monitoring and control capabilities, allowing farmers centralized access to the drone system for receiving alerts and managing its operation.

6. Computer Vision for Fruit ripeness detection: Integrate computer vision technologies to accurately distinguish between the various stages of ripening process of fruits through drone generated footage.

Chapter 4

System Architecture

4.1 System Overview

The flowchart shown in fig 4.1 illustrates a sophisticated agricultural surveillance system that begins with a drone equipped with a high-resolution camera capturing aerial footage of a farm.

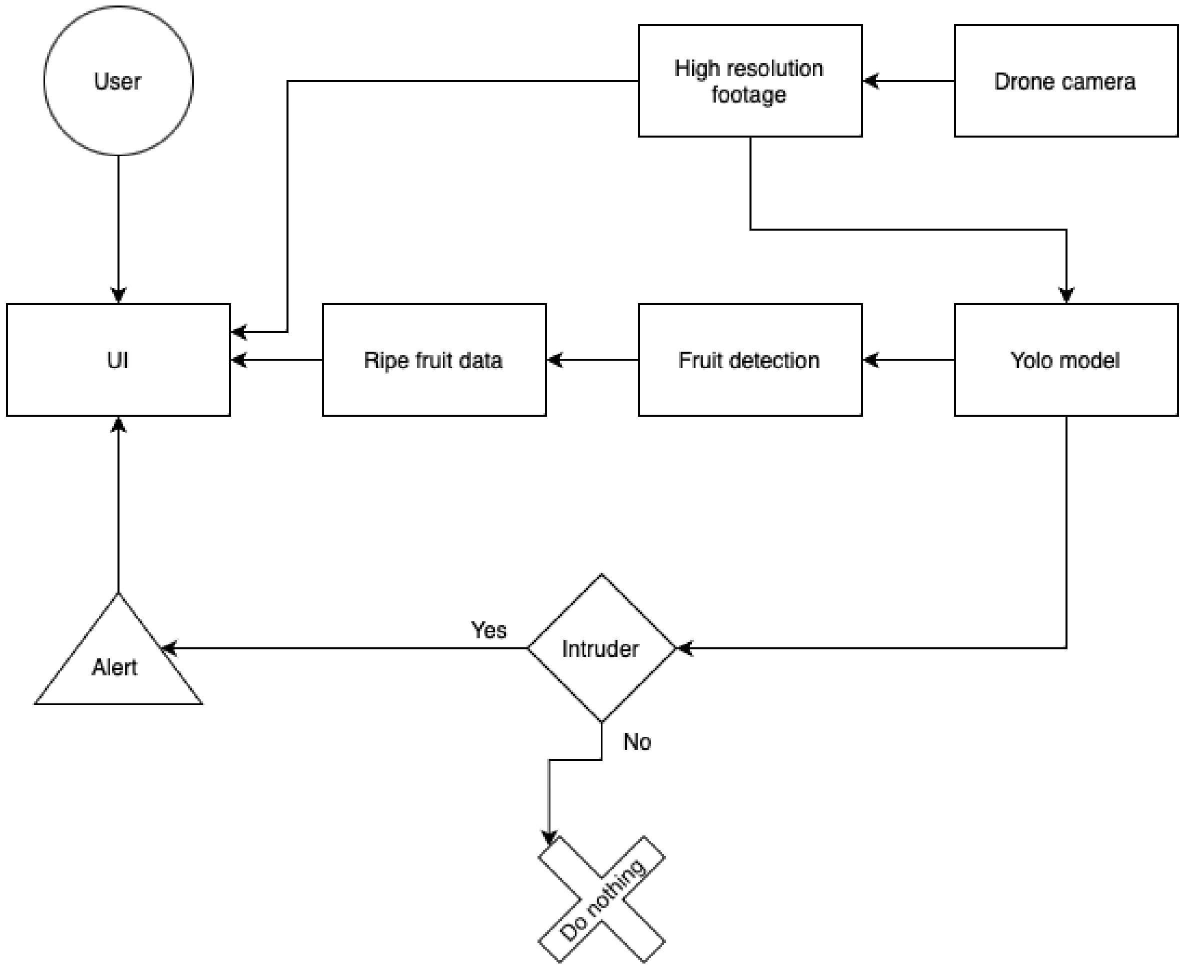


Figure 4.1: Architecture diagram

This footage serves as the primary input for the system, providing detailed images that are crucial for the subsequent analysis. Once the drone captures this high-res footage, it is processed through a fruit detection phase. In this phase, an advanced algorithm utilizing a YOLO model, is used for real-time object detection.

This model is specifically tuned to recognize characteristics indicative of ripe fruits, such as color, size, and texture, which are critical for determining the optimal time for harvest. Concurrently, the system assesses the footage to detect any intruders, a term that could refer to animals, unauthorized personnel, or unexpected objects within the monitored area. This detection triggers an alert if an intruder is present, notifying the user through the system's user interface (UI). If no intruder is detected, the system continues its monitoring without action.

The UI plays a crucial role in this system, serving as the point where the detection data are represented in a form which helps the user to take actions. It is through this interface that the user, such as a farmer or an agricultural technician, receives updates on the ripe fruits and alerts on intruder detection. The interface is designed to be intuitive, presenting the data in a user-friendly format, which might include visual maps or annotated images. Upon receiving an alert, the user can take immediate action to address the intrusion and protect the crops.

In the absence of any alerts, the user can still interact with the UI to make informed decisions regarding crop management. These decisions could involve planning the harvest based on the ripe fruit data or taking precautionary measures to prevent future intrusions. This system thus represents the integration of drone technology, real-time processing, and user-centered design to enhance the efficiency and security of modern agricultural practices. It underscores the potential for technology to streamline farming operations, ensuring that crops are harvested at their peak and that the farmland is kept secure from potential threats.

4.2 Architectural Design

In this section, we take a look at the sequence diagram for the project which gives an idea of how the user interacts with the system, and how the responses are given.

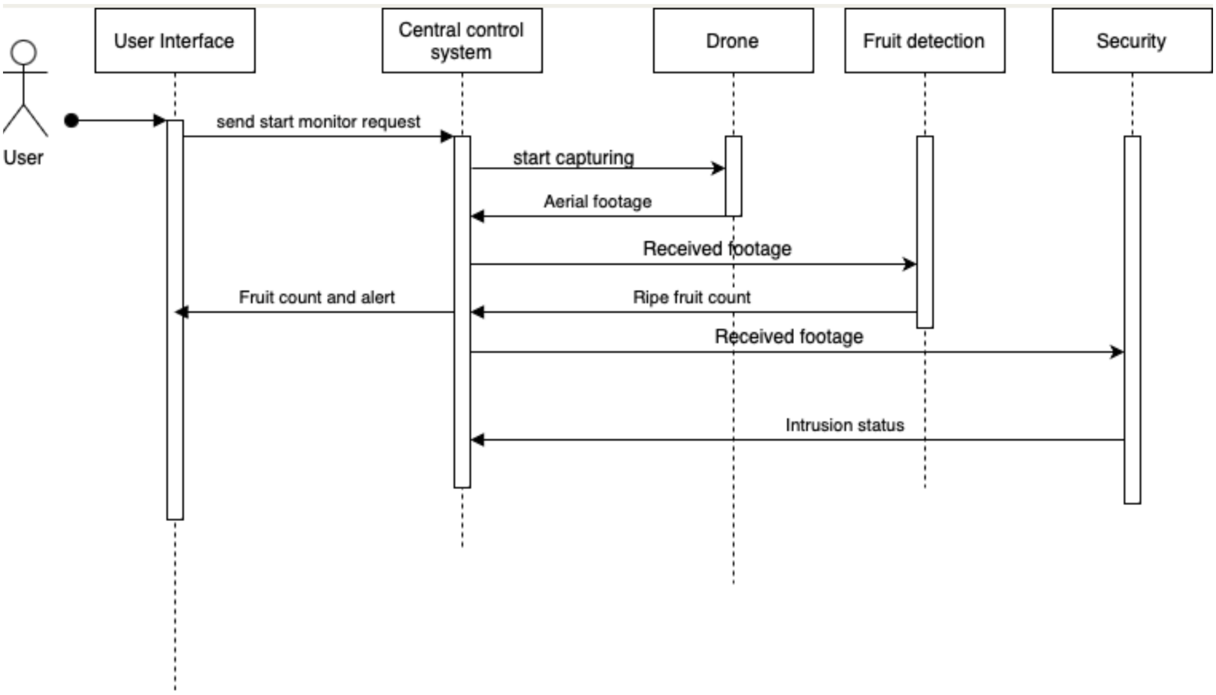


Figure 4.2: Sequence diagram

4.3 Module Division

The architecture of the system is built around six primary segments, each with its distinct set of components and functions with reference to figure 4.3:

1. The initial segment deals with the gathering of data. This involves unmanned aerial vehicles (UAVs) that are outfitted with image-capturing devices and various sensors. Additionally, these UAVs are equipped with modules that facilitate the transfer of the collected information.

2. The second segment encompasses the mechanisms for data communication. It includes the necessary protocols and structures for data exchange as well as systems dedicated to the delivery of the processed information to a centralized hub or the

farm's operational management system, with an emphasis on maintaining the integrity and confidentiality of the data in transit.

3. Moving to the third segment, we encounter the core computing unit. This unit is responsible for receiving the high-definition visual data from the initial data gathering segment and serves as a repository for subsequent extraction and analysis.

4. The fourth segment is dedicated to the identification and classification of objects within the data, employing a YOLO-based approach. It leverages an object recognition framework that has been trained specifically to distinguish ripe produce and potential intrusions by fauna. This system's aim is to ensure accurate detection while concurrently diminishing instances of incorrect identifications.

5. In the fifth segment, we have the data manipulation segment, which boasts robust processing units and specialized GPUs, along with software tailored for image analysis. This segment is tasked with handling the live video feed, assessing fruit maturity, and discerning the presence of animals. It also applies various algorithms to polish and enhance the detection outcomes.

6. The final segment is the user interaction interface, an intuitive visual platform that facilitates real-time data display and interaction. It provides stakeholders with the means to view the monitoring data and to make sense of the findings in an interactive manner.

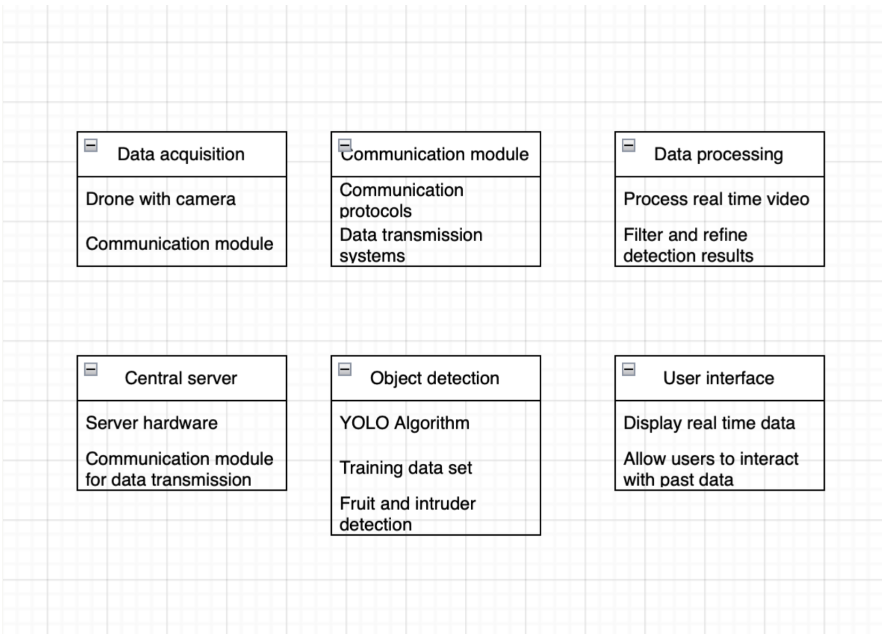


Figure 4.3: Module diagram

4.4 Work Schedule - Gantt Chart

Figure 4.4: Gantt chart

4.5 Chapter conclusion

This chapter discusses the architecture of the system and gives an idea of how the entire process is handled, right from the data acquisition. It explains the various modules that the project is split into and also the expected timeline of each phase of the project.

Chapter 5

System Implementation

5.1 Datasets Identified

The dataset utilized in the project is sourced from Roboflow, a platform that facilitates the creation and management of datasets for machine learning projects. The datasets focus on fruit detection-specifically bananas and strawberries[5], and also on intruder detection where a variety of intruders including cows, dogs, humans, providing images annotated with bounding boxes around the objects This annotation process is crucial for training object detection models like YOLOv8 to accurately identify the objects.

The dataset for strawberry includes 6 classes of ripeness of strawberries, which are as follows:

- Early-Turning
- Green
- Late-Turning
- Red
- Turning
- White

Similarly, the dataset for banana ripeness is split into 6 classes:

- Ripe
- Overripe
- Rotten

- Freshunripe
- Freshripe
- Unripe

As for the intruders dataset, it includes 18 classes, few of which are:

- Raccoon
- Bear
- Buffalo
- Dog
- Cat
- Elephant

5.2 Proposed Methodology/Algorithms

1. Set the waypoints for the drone to follow.
2. Stream live footage from the camera on the drone to the local system via the usage of a TCP server and Python's OpenCV Library.
3. Pass the stream to the trained YOLOv8 model.
4. Get count of the ripe fruits/unripe fruits.
5. On detection of an intruder, send an alert to the user via email for immediate action.

5.3 Description of Implementation Strategies

1. Video Streaming: The project utilizes a TCP(Transmission Control Protocol) stream for streaming video from the Raspberry Pi module. TCP provides a reliable and ordered delivery mechanism, ensuring that video frames are transmitted and received without loss or corruption. By leveraging TCP, a robust communication channel is established between the Raspberry Pi and the receiving end, which ensures seamless

video transmission, essential for timely detection of ripe fruits and intruders by the autonomous drone system. In order to stream the video to the YOLO model, the OpenCV library in Python was used.

2. Object Detection: The project makes use of the YOLOv8 model for object detection. The objects detected as part of the project includes, ripe and unripe fruits, and intruders. YOLOv8 was chosen as the model to be used because of its high precision and fast learning rate.

3. Intruder Alert: An SMTP server was set up in Python, which was facilitated by the smtplib [6] library and MIME (Multipurpose Internet Mail Extensions) standards for sending alerts of intruders detected by our system. This ensures that the users get prompt notifications, facilitating rapid response to a security threat in the farm.

5.4 Chapter Conclusion

In conclusion, the chapter outlines a systematic approach for ripe fruit and intruder detection from footage obtained from a drone. By incorporating client-server protocols, video streaming and object detection, it aims to deliver to the user, relevant information that may be useful in better management of the field.

Chapter 6

Results and Discussions

The Results and Discussions section provides a comprehensive analysis of the system's performance and outcomes. This section begins with an overview of the testing procedures conducted to evaluate the system's efficacy. Subsequently, quantitative results are presented, shedding light on the system's performance metrics such as accuracy, precision and recall Additionally, graphical analysis techniques are employed to visually represent the system's performance trends and comparative analyses across different scenarios or datasets.

6.1 Overview

The drone based agriculture monitoring system has shown remarkable proficiency in identifying a range of ripeness of fruits and intruders within a field. Timely alerts are generated and sent to the users, in the event of an intrusion in the field.

6.2 Testing

Testing the YOLOv8 model generated the following results for animal and fruit detection.

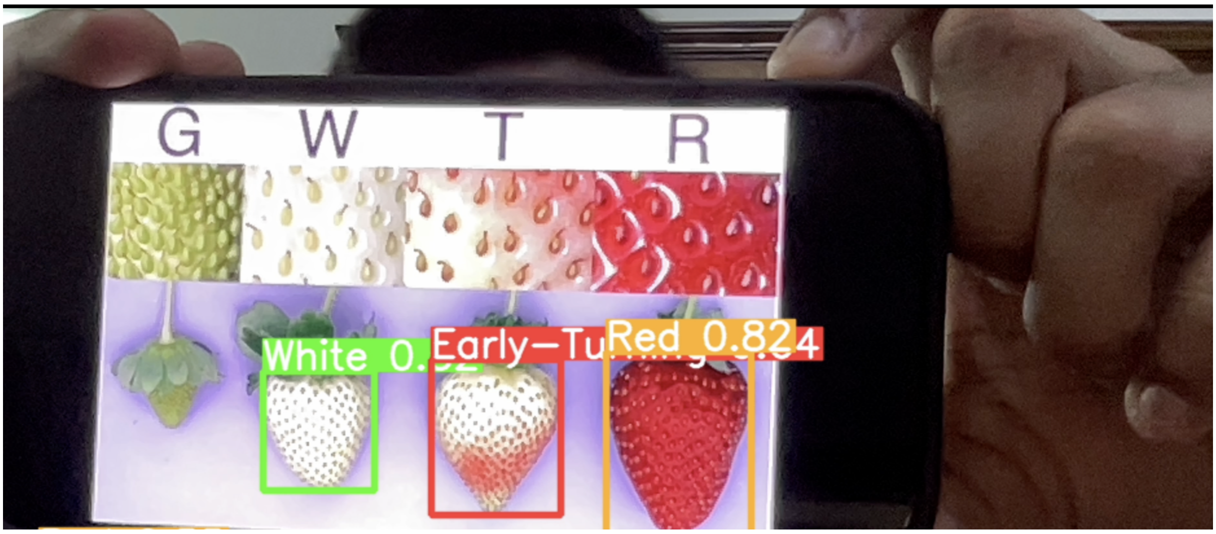


Figure 6.1: Strawberry ripeness detection

Figure 6.2: Strawberry ripeness detection

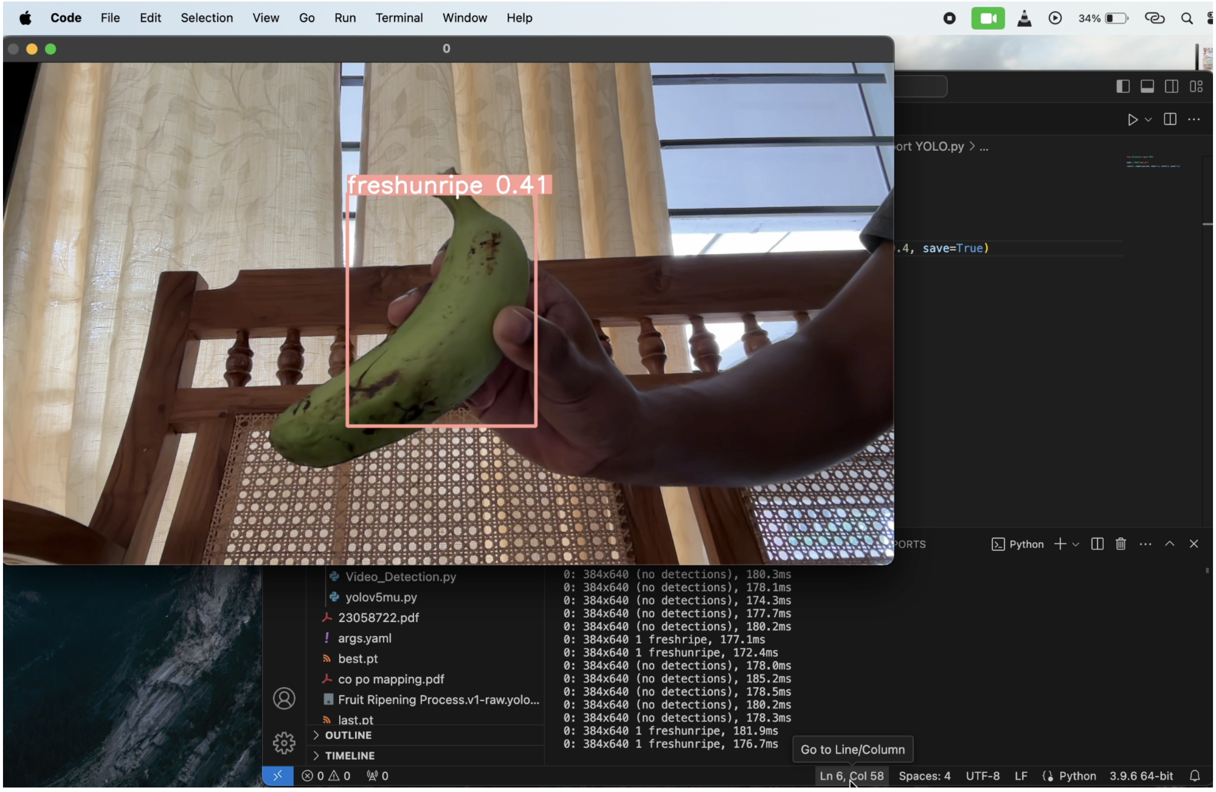


Figure 6.3: Banana ripeness detection

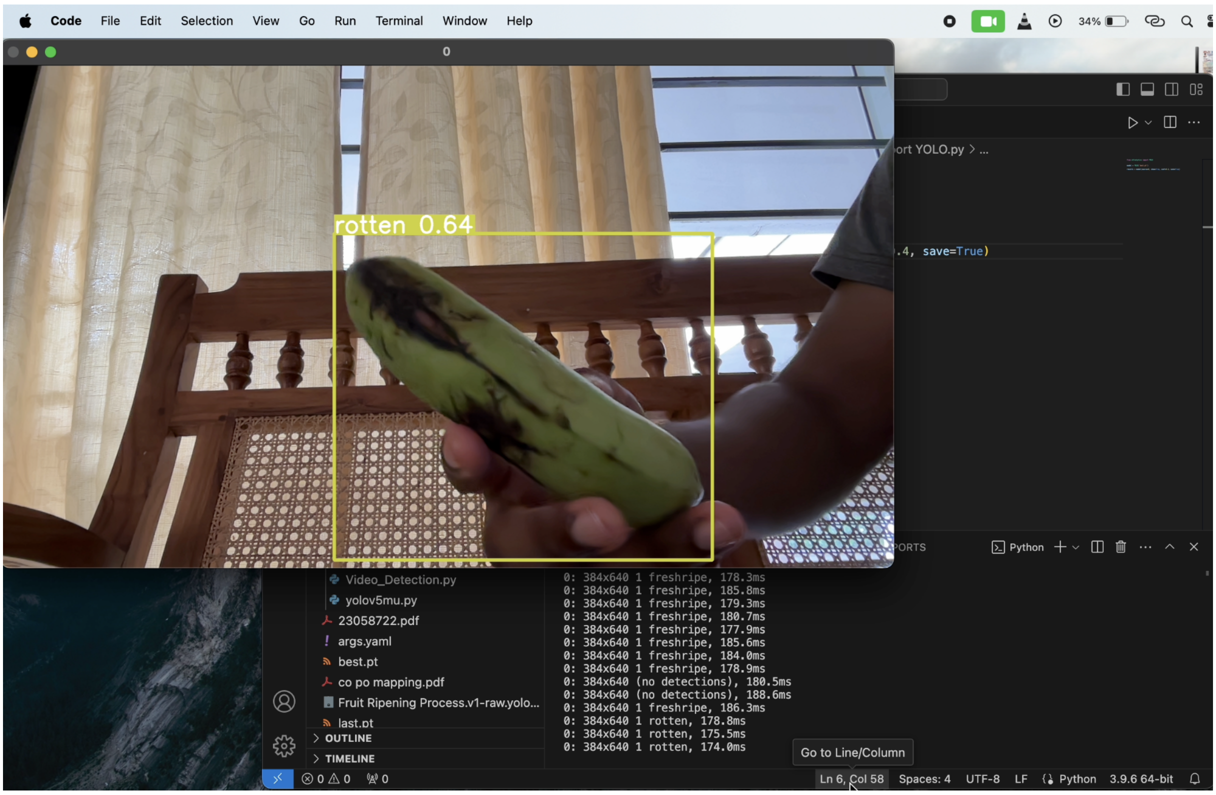


Figure 6.4: Banana ripeness detection

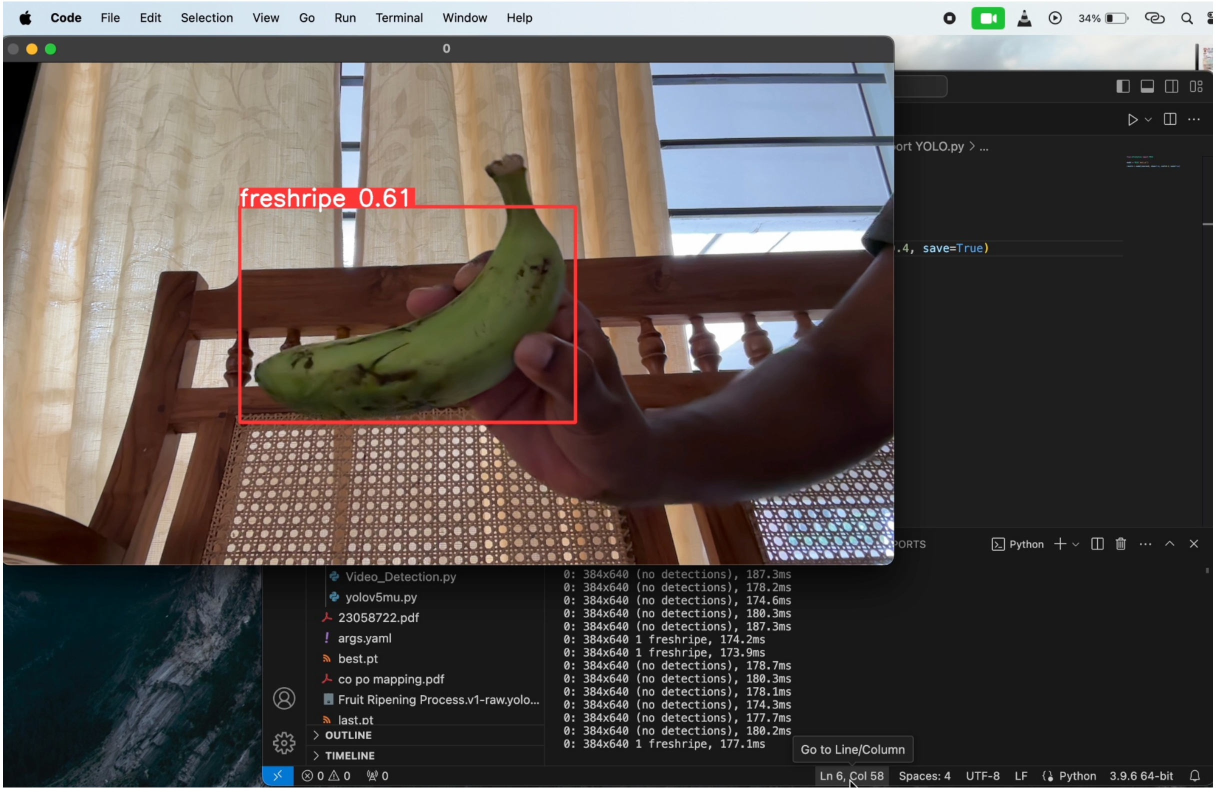


Figure 6.5: Banana ripeness detection

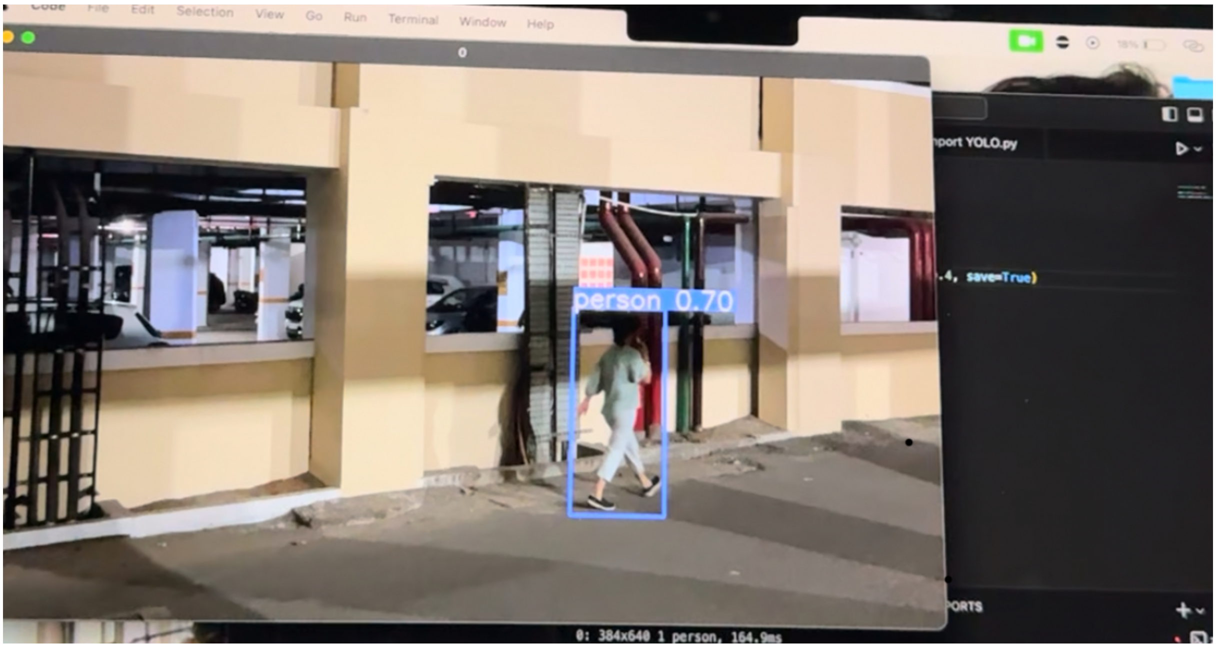


Figure 6.6: Intruder detection

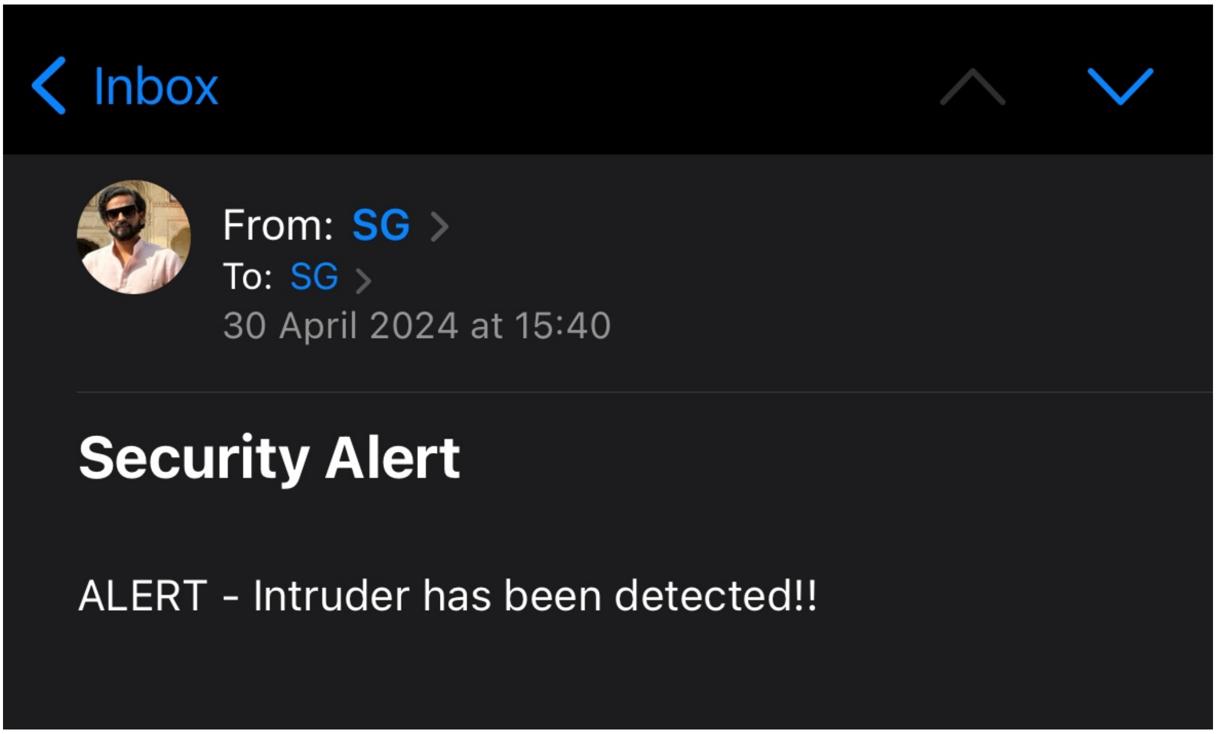


Figure 6.7: Intruder alert email

Figure 6.8: The drone equipped with the camera module

6.3 Quantitative Results

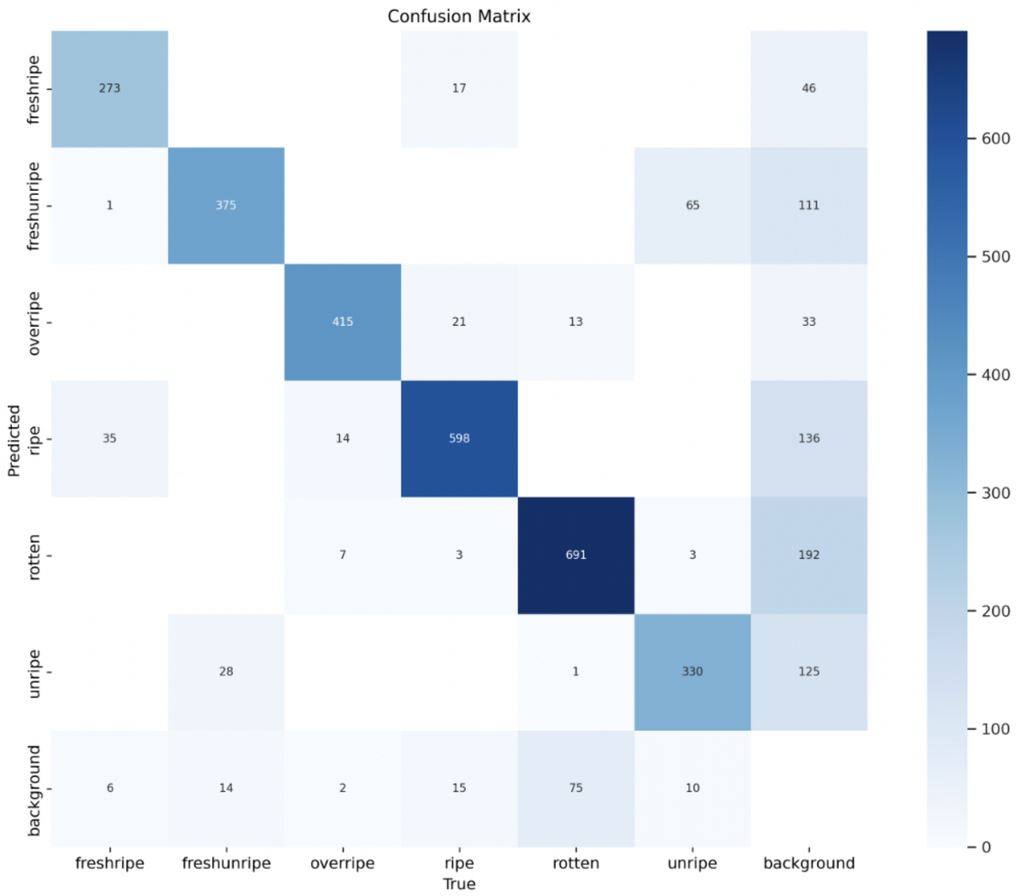


Figure 6.9: Confusion matrix specifying the accuracy of different banana classes

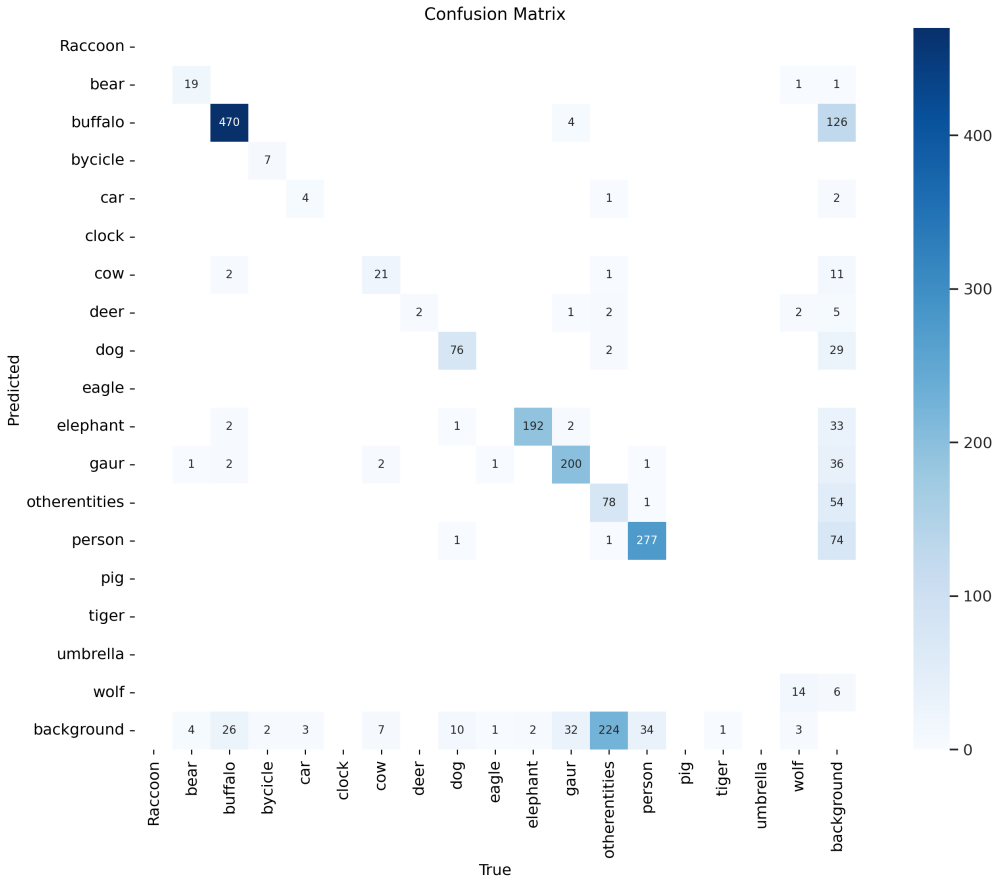


Figure 6.10: Confusion matrix specifying the accuracy of different intruder classes

6.4 Graphical Analysis

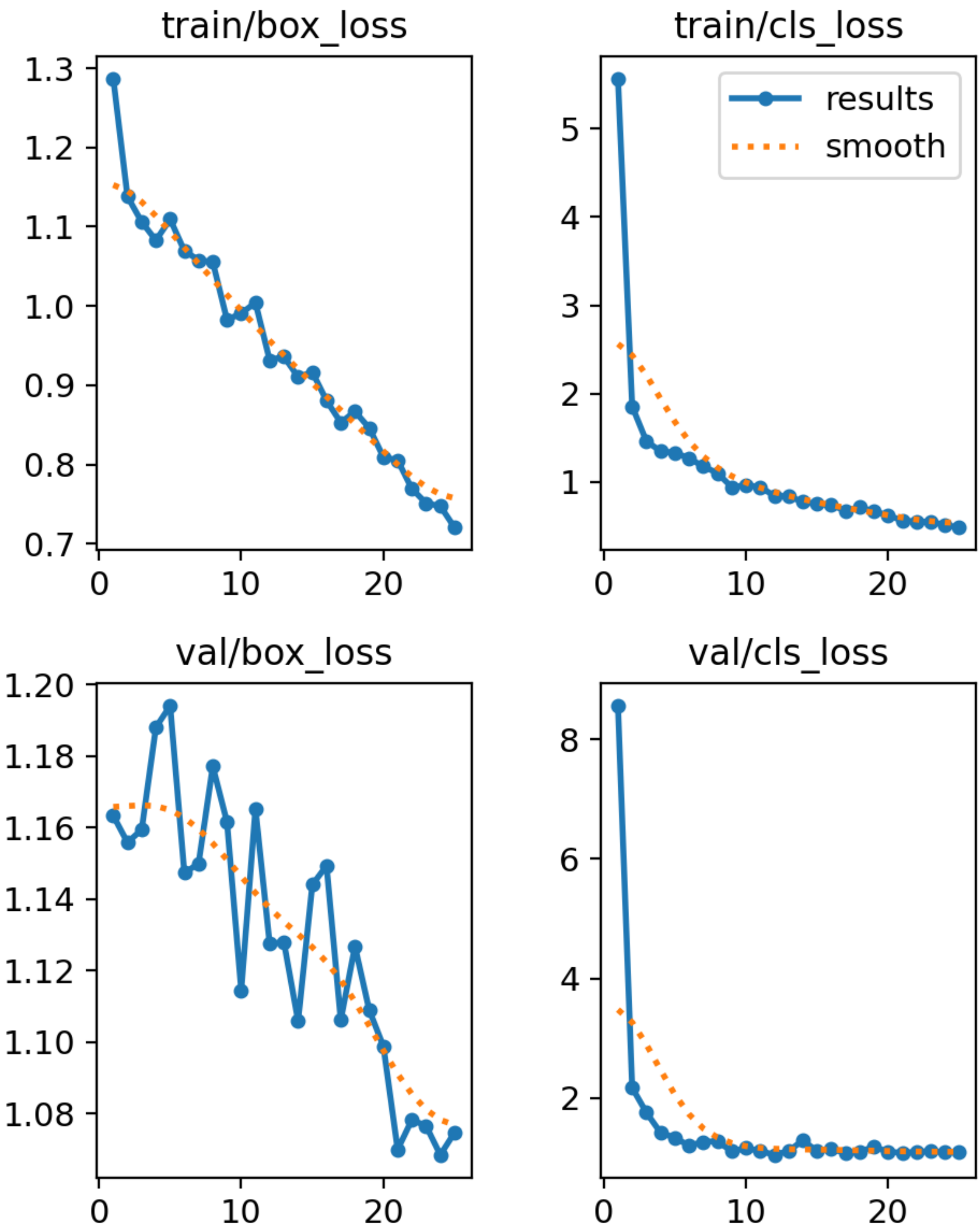


Figure 6.11: Losses during training for Strawberry dataset

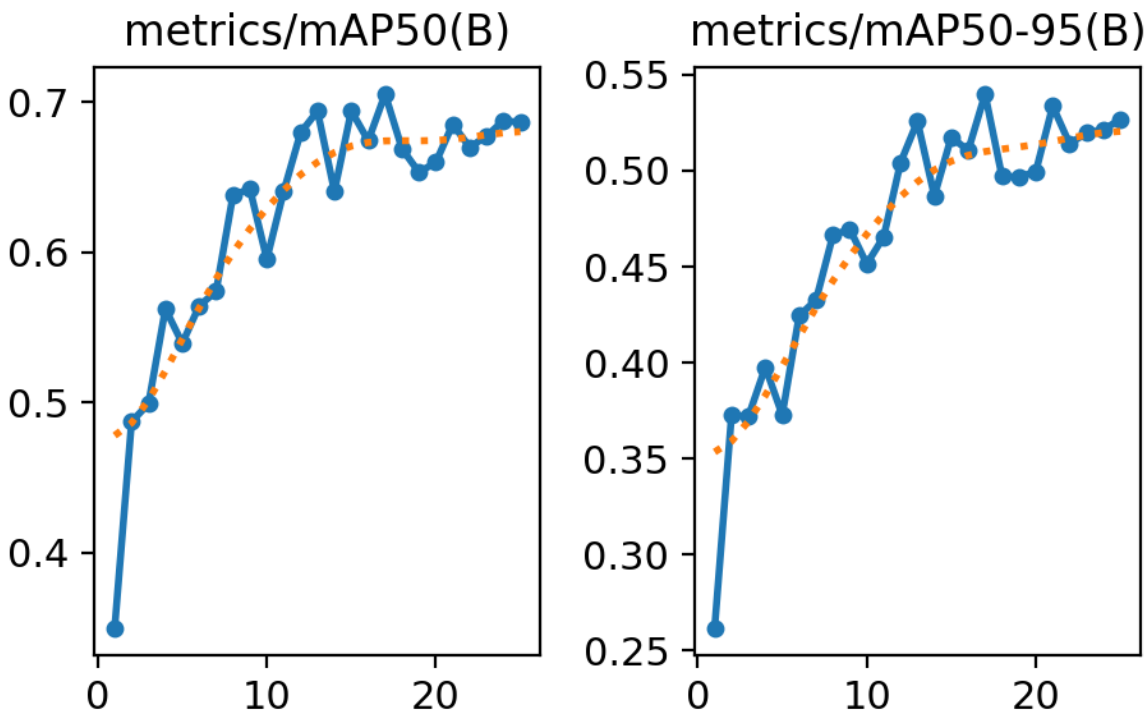


Figure 6.12: Mean Average Precision of Strawberry training

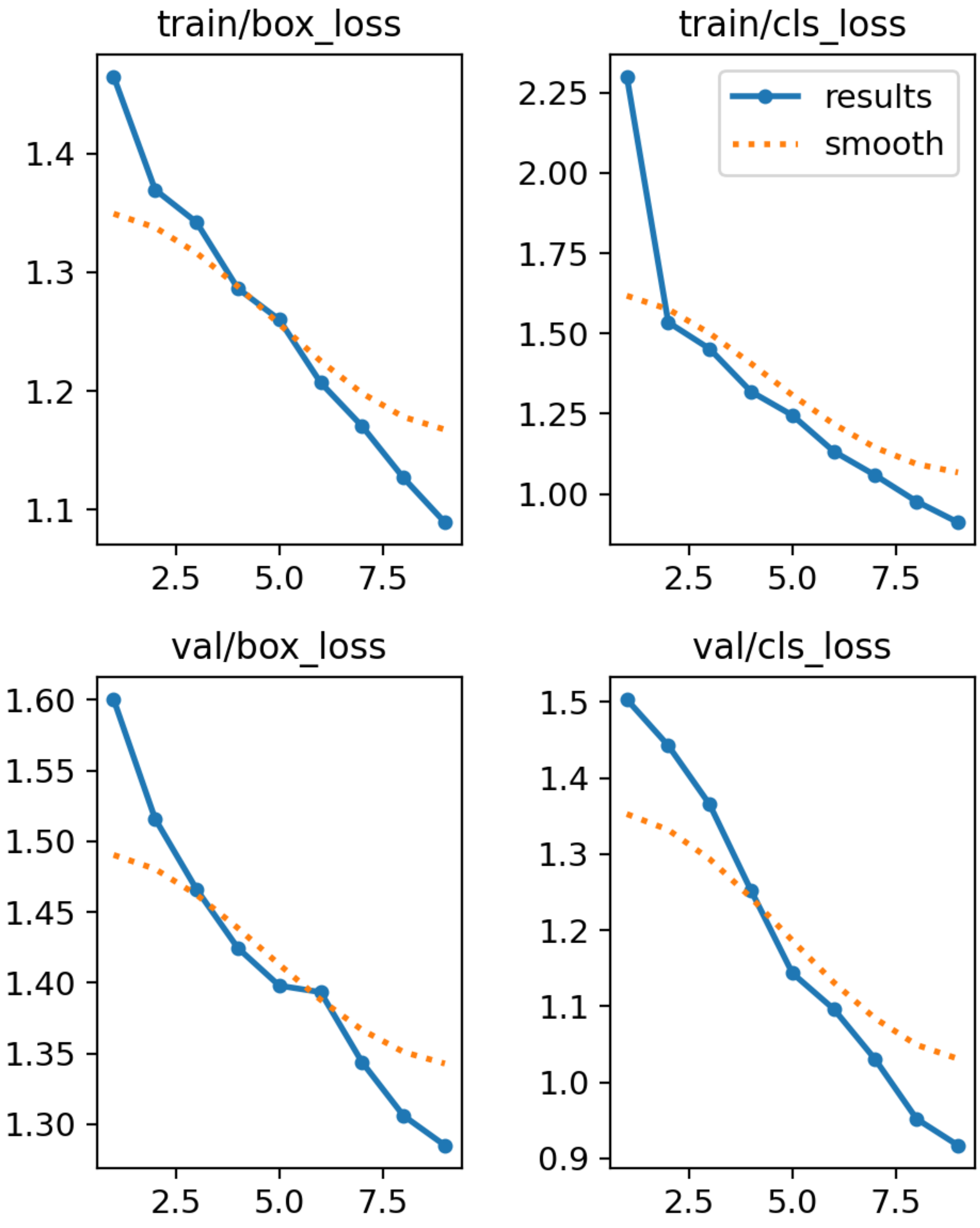


Figure 6.13: Losses during training for Intruder dataset

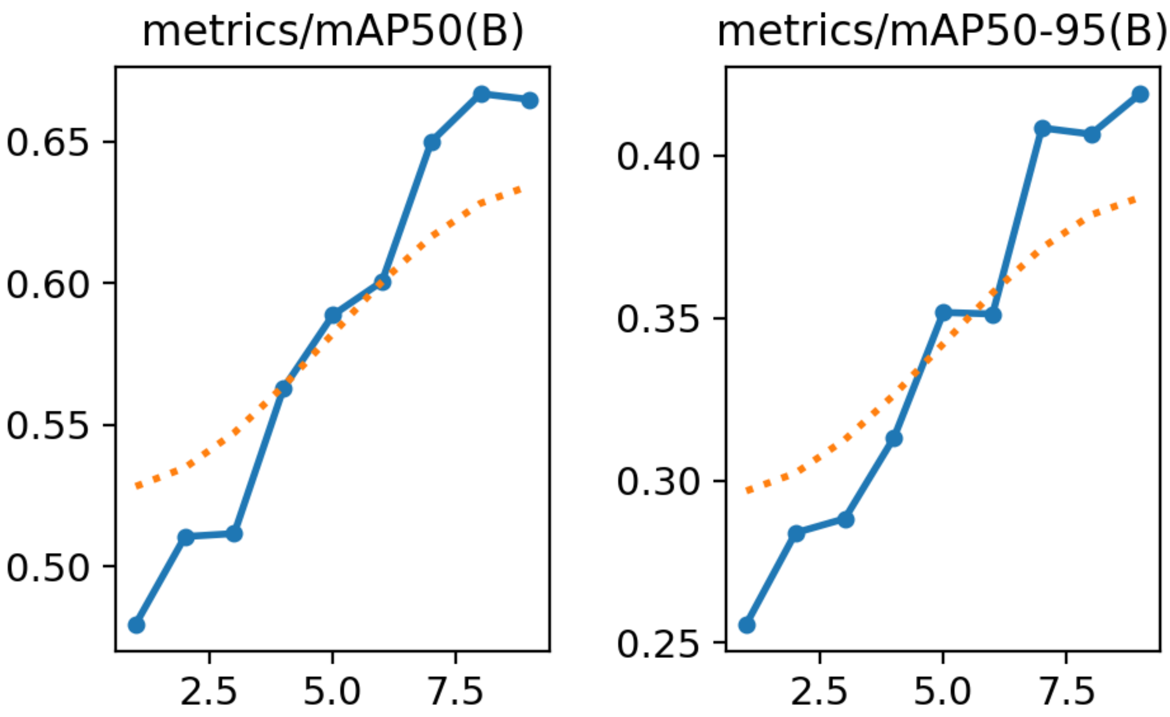


Figure 6.14: Mean Average Precision of Intruder training

6.5 Discussion

The overall system demonstrates commendable performance, boasting a mean average precision of 66.5% across all classes for the intruder detection and an average mAP of 72.8% for fruit detection.

The confusion matrix for the fruits highlights a notable trend. 6.9, shows the confusion matrix for ripeness detection of bananas. It is seen that the 'rotten' class exhibits higher accuracy compared to the other classes. This disparity could stem from the fact that the colour variation in ripe and rotten fruits is easier to identify compared to colour variation in ripe and semi-ripe fruits.

The Results and Discussions section provides a comprehensive evaluation of the ripe fruit detection and intruder detection system. Through rigorous testing and analysis, key insights into the system's performance metrics, quantitative results, and graphical representations have been elucidated. The testing phase has revealed notable trends in the system's accuracy across different classes, with specific challenges identified in smoke detection due to environmental factors. Quantitative assessments, including mean average precision, highlight the system's overall effectiveness in class prediction. Graphical analyses further enhance our understanding of performance dynamics, showcasing trends in loss functions and validation results over epochs

Chapter 7

Conclusions & Future Scope

7.1 Conclusion

In conclusion, the Drone Based Monitoring project represents a significant advancement in precision farming, addressing critical challenges in crop monitoring and field security. Through the integration of autonomous drone technology, advanced image processing algorithms, and computer vision capabilities, the project aims to enhance agricultural efficiency, optimize harvest timings, and mitigate potential losses due to unauthorized animal intrusions. The real-time alert system, intuitive user interface, and emphasis on energy efficiency contribute to the project's practicality and user-friendliness for farmers.

Additionally, the commitment to scalability, compatibility, and a thorough economic and environmental impact analysis underscores the project's holistic approach to sustainable and technologically driven agriculture. The successful implementation of the Smart Agriculture Drone project holds the promise of revolutionizing traditional farming practices, fostering economic benefits for farmers, and contributing to global efforts toward food security and environmental sustainability.

7.2 Future Scope

1. Integration of Artificial Intelligence (AI) for Decision Support:

   Future iterations of the project could explore the incorporation of AI algorithms to provide advanced decision support for farmers. This could involve predictive analytics for crop health, disease forecasting, and personalized recommendations for optimized resource management.

2. Multi-Sensor Fusion for Comprehensive Data Collection:

   The project's future scope could include the integration of multi-sensor systems, such as infrared or hyperspectral sensors, to collect more comprehensive data. This could enhance the system's ability to assess various aspects of crop health and enable more nuanced analysis for precise agricultural management.

3. Drone Swarming Technology for Increased Coverage:

   Exploring drone swarming technology presents an exciting avenue for future development. By coordinating multiple drones to work collaboratively, the project could achieve increased coverage, efficiency, and responsiveness in monitoring larger agricultural areas.

4. Blockchain Integration for Data Security and Traceability:

   Future enhancements may involve integrating blockchain technology to ensure the security and traceability of data generated by the drone system. This could provide a transparent and immutable record of agricultural activities, fostering trust among stakeholders and facilitating compliance with quality standards.

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Appendix A: Presentation

Drone Based Monitoring

Team 5

Neil Sunny
Noel Joe
Salman Sidhik
Siddhartha Goutaman

TEAM 5

Guide: Ms. Anita John

Overview

Problem Definition

TEAM 5

Problem Definition

- To develop an intelligent agriculture drone system that addresses the challenges of crop monitoring through advanced machine learning and computer vision technologies.

TEAM 5

Project objective

TEAM 5

Project objective

1.Precision Agriculture Ripe Fruit Detection: Drones equipped with advanced sensors, such as cameras and infrared imaging, can be used to monitor agricultural fields for the presence of ripe fruits. This enables farmers to identify the optimal time for harvesting.
2. Efficiency and cost saving Automation: Drone-based monitoring reduces the need for manual labor in inspecting large agricultural fields. This automation can significantly increase the efficiency of farming operations.
3. Security and intrusion detection Surveillance: Drones equipped with cameras and other sensors can be utilised for security purposes. They can monitor agricultural sites for potential intrusions.

TEAM 5

Novelty of Idea and Scope of Implementation

TEAM 5

Novelty of Idea and Scope of Implementation I

1. Apple picking drones: Tech companies in Israel have designed fruit-picking drones to make farms more efficient at a time of worker shortages and climate change.

2. Efficiency and cost saving Automation:
Drone-based monitoring reduces the need for manual labor in inspecting large agricultural fields. This automation can significantly increase the efficiency of farming operations. By identifying ripe fruits and areas of concern in the field, farmers can optimise the use of resources such as water, fertilisers, and pesticides, leading to cost savings and environmental sustainability.

TEAM 5

Novelty of Idea and Scope of Implementation II

3. Security and intrusion detection Surveillance: Drones equipped with cameras and other sensors can be utilised for security purposes. They can monitor agricultural sites for potential intrusions.

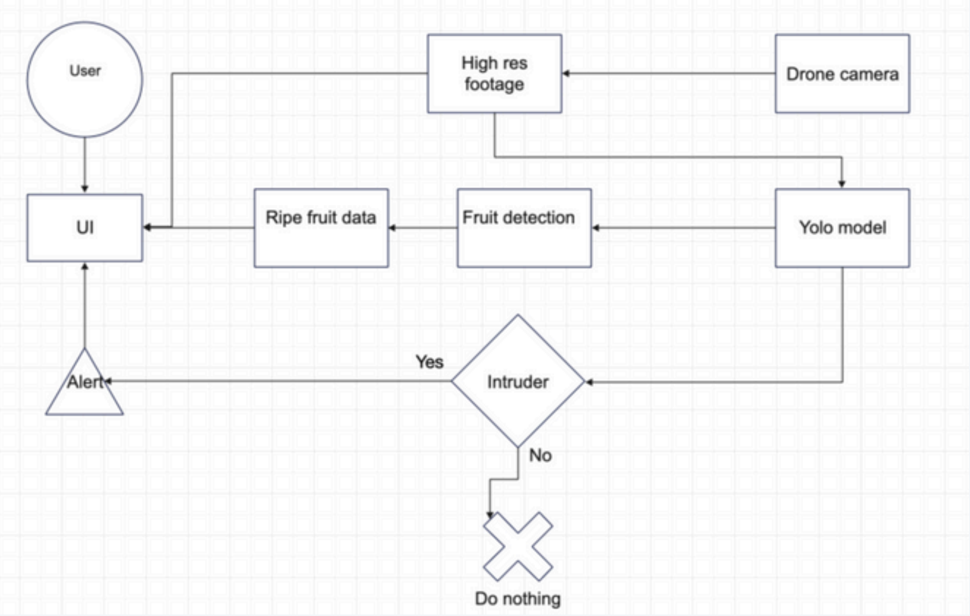
Literature Survey

PAPER	BRIEF	PROS	CONS
YOLO: Challenges, architectural successors, datasets and application	Implementation of the YOLO algorithm for animal detection and comparison between other models	• Acceptable accuracy levels for the intended project • 300 times faster than FasterCNN classification	• Less classification accuracy than other CNN with two step classification
Deep Reinforcement Learning for UAV autonomous path planning	DRL combines deep learning and reinforcement learning to learn optimal policies in complex environment.	• DRL enables UAVs to autonomously navigate, surveil, and avoid obstacles in dynamic environments. • Complex Decision-Making.	• DRL training can be computationally expensive and time-consuming, depending on the complexity of the task • DRL often requires a large number of samples to learn effectively.
Strawberry Maturity Classification from UAV and Near-Ground Imaging using Deep Learning	Uses drone based footage and deep learning to predict ripeness of strawberries	• Uses image collected by UAV make acquisition easy • Deep learning and YoloV3 and above are good for small objects	• Obscured images due to leaves coming into the frame.
Study of the Subjective and Objective Quality of High Motion Live Streaming Videos	Study in the quality of high motion live streaming videos by subjective and objective scores	• High motion live streaming videos (since we are using drone) • show MOS and DMOS scores.	• study is done by getting opinions from different human sunjects ,human opinions can differ from each other.

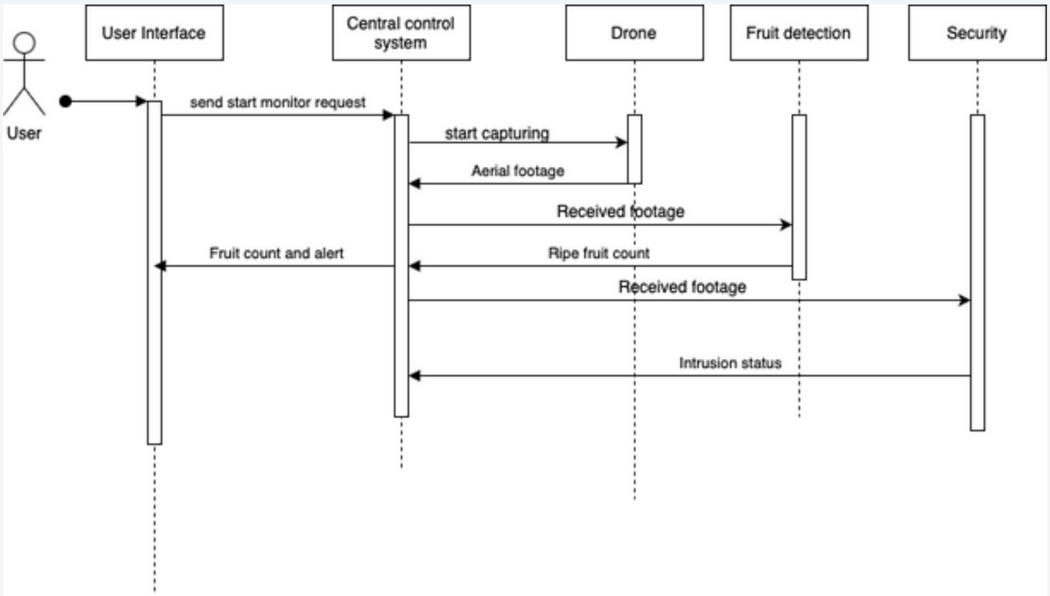
Methodology

- The proposed method for the drone-based field monitoring project involves deploying drones equipped with high-resolution cameras for comprehensive data collection.
- Aerial images of the agricultural field are captured to identify ripe fruits using image processing algorithms and machine learning models.
- These models are trained to recognize ripe fruits based on visual characteristics, while intrusion detection features, object recognition algorithms, are integrated to identify security threats.
- The system enables real-time monitoring and alerts, transmitting data to a central control system for timely decision-making.
- A user-friendly interface is developed for farmers and security personnel to visualize data, receive alerts, and make informed decisions.

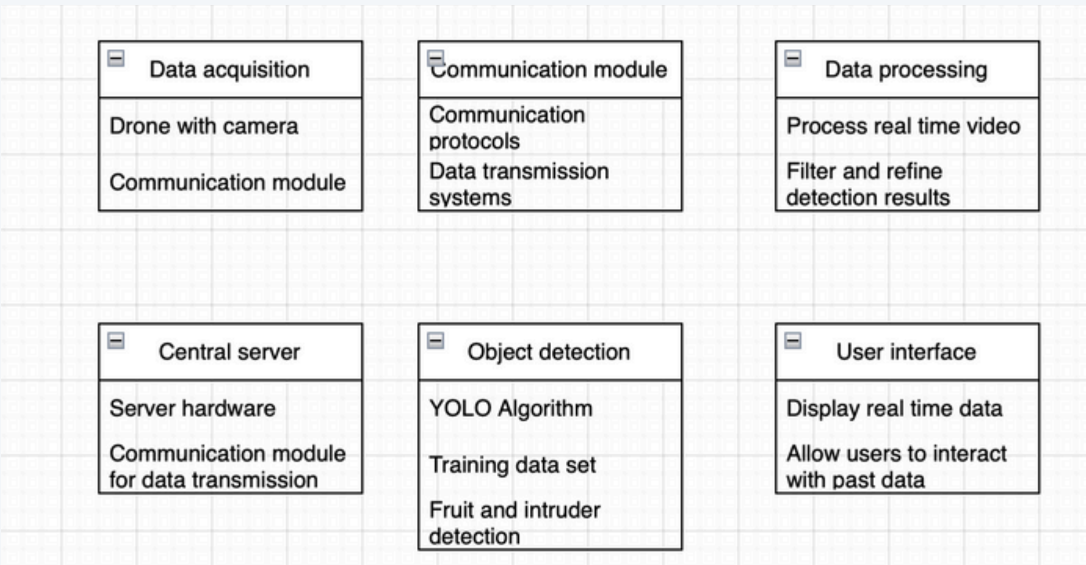
Architecture Diagram



Sequence Diagram



Module Diagram



Module Diagram

Module 1: Data Acquisition Model

Module 2: Communication Module

Module 3: Central Server module

Module 4: Object Detection Module [YOLO Based]

Module 5: Data Processing Module

Module 6: User Interface Module

Module Explanation

Module 1: Data Acquisition Module

- Components:
    1. Drones equipped with cameras and sensors.
    2. Communication modules for transmitting data.
- Responsibilities
    1. Capture high-resolution images or video streams of the farm.

Module 2: Communication Module

- Components:
    1. Communication protocols and infrastructure.
    2. Data transmission systems.
- Responsibilities:
    1. Transmit processed data to a central server or farm management system.
    2. Ensure reliable and secure communication.

Module Explanation

Module 3: Central Server Module

- Components:
    1. Server hardware.
    2. Communication modules for transmitting data.
- Responsibilities
    1. Recieve the high Res video stream from the data acquition module and store it for data extraction.

Module 4: Object Detection Module [YOLO Based]

- Components:
    1. YOLO object detection algorithm.
    2. Training data set for ripe fruit detection and potential animal intrusion.
- Responsibilities:
    1. Detect the ripe fruits accurately and detect the animal intrusion.
    2. Minimize or reduce the number of false positives.

Module Explanation

Module 5: Data Processing Module

- Components:
    1. High performance processors and GPU.
    2. Image processing softwares.
- Responsibilities
    1. Process the real time video for fruit ripeness and animal intrusing detection.
    2. Implement algorithms for filtering and refining detection results.

Module 6: User Interface Module

- Components:
    1. Graphical user interface (GUI).
    2. User interaction components.
- Responsibilities:
    1. Display real-time monitoring results.
    2. Allow the respective authorities to interact with and interpret the data.

30 Percent

1. Collection of dataset of fruits.
2. YOLOv8 model is used for training the dataset.
3. After completion of training, the fruit will be identified as ripe or not.
4. Strawberries and Banana are the fruits that are trained for the model.

30 Percent

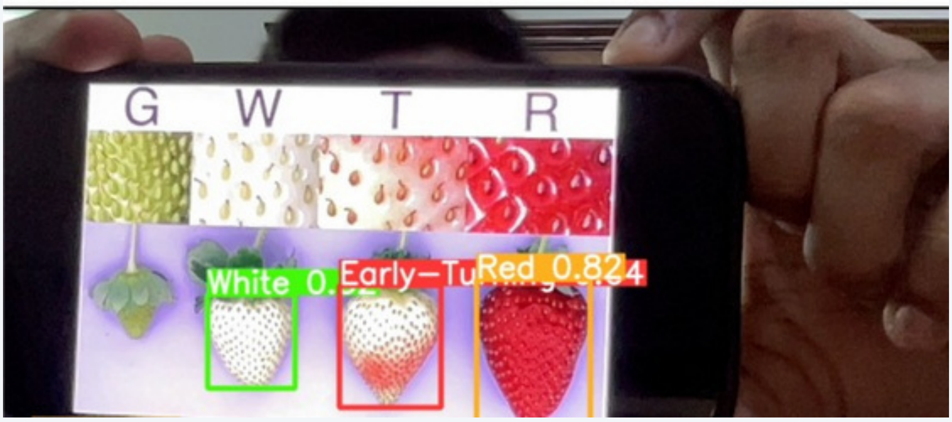
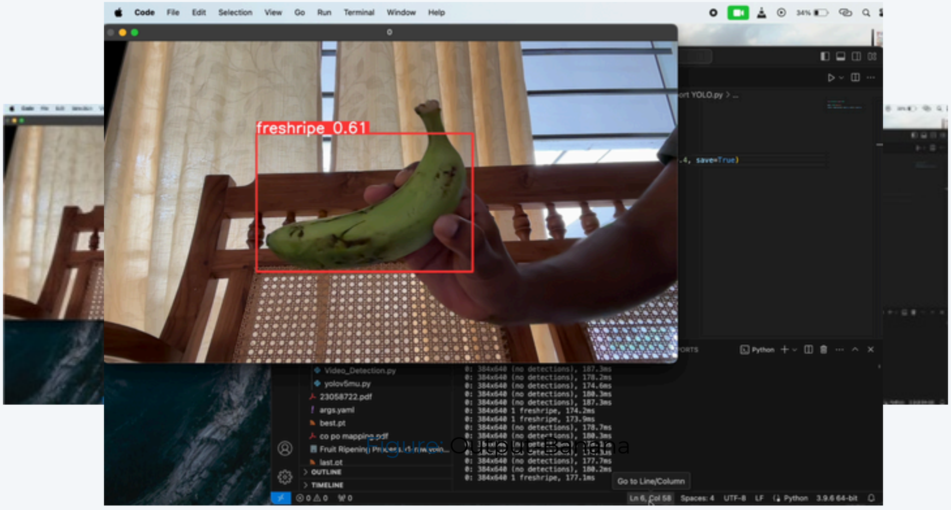


Figure: Output-Strawberry

30 Percent



60 Percent

1. Collection of dataset of animals and other intruders.
2. Compared different models for better accuracy.
3. Finalized on YOLOv8 since maximum accuracy was achieved.
4. After completion of training, the intruder will be classified accordingly.
5. The intruder consists of wide variety of animals like dogs, cows, humans among many others.

60 Percent

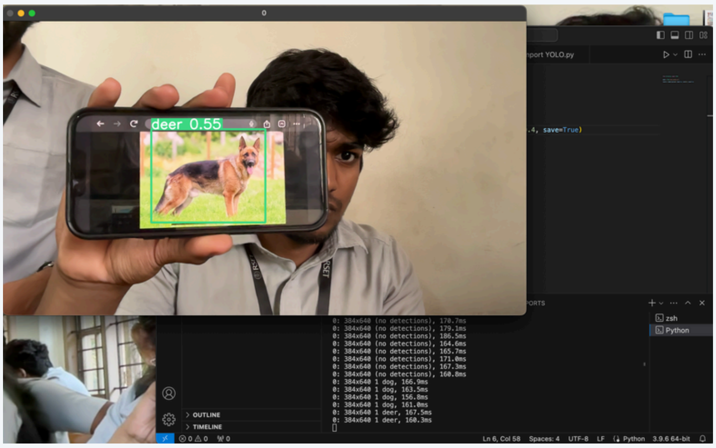


Figure: Output-Animal detection

60 Percent

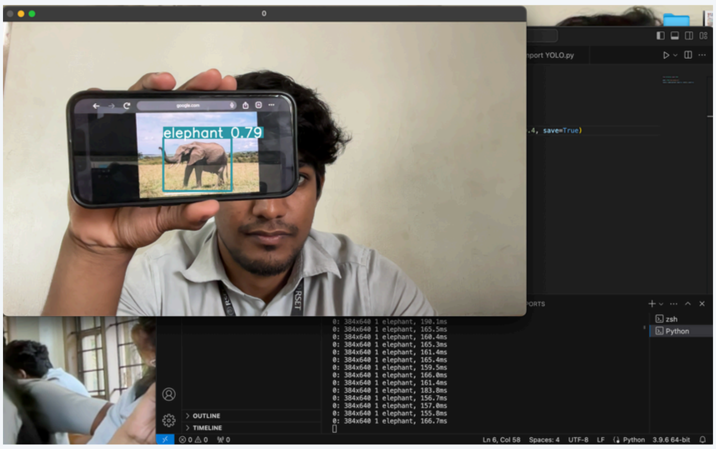


Figure: Output-Animal detection

60 Percent

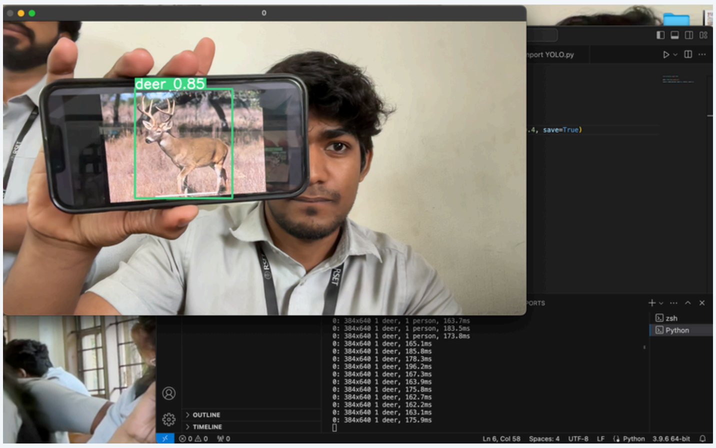


Figure: Output-Animal detection

100 Percent

Task Distribution

1. Neil Sunny- Intrusion Detection
2. Noel Joe- Video Live streaming and optimisation
3. Salman Sidhik- Autonomous Drone
4. Siddhartha Goutaman- Ripe fruit detection

Conclusion

Conclusion

Our project brings together state-of-the-art technology, machine learning, and a dedicated focus on precision agriculture to revolutionize the way farmers monitor and protect their crops. With autonomous systems that provide real-time insights and alerts, farmers can make more informed decisions and take timely actions, ultimately leading to higher crop yields, reduced losses, and enhanced overall farm management.

This project is not just a technological achievement but a game-changer for the agriculture industry, contributing to increased efficiency and sustainability in the face of evolving agricultural challenges.

Future Scope

1. Night vision camera implementation: The implementation of a thermal imaging cam will increase our budgetary constraint singnificantly.
2. With better camera modules the specific disease of the fruits can be detected and a solution can be suggested.

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Status of Paper Publication

- Shortlisted conferences for publication
- Started with paper preparation
  - Cannot finish writing the paper as real life results cannot be concluded without the complete assembly of the drone.

Thank you

Team 5

Neil Sunny
Noel Joe
Salman Sidhik
Siddhartha Goutaman
Guide: Ms. Anita John

February 23, 2024

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. **Engineering Knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. **Problem analysis**: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO - PO Mapping

CO	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12
1	2	2	1	1		2	1					3
2	3	3	2	3		2	1					3
3	3	2			3			1		2		3
4	3				2			1		3		3
5	3	3	3	3	2	2		2		3		3

CO - PSO Mapping

CO	PSO 1	PSO 2	PSO 3
1	1		1
2	1		1
3	1		1
4	1		1
5	1		1

Justification

Mapping	Justification
CO1 - PO1	Reason
CO2 - PO2	Reason