DRONE BASED AGRICULTURE DETECTION & SURVEILLANCE

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INTRODUCTION

In the modern world of agriculture, there is an increasing need for innovative technologies that can enhance efficiency and yield in orchard management. The advent of autonomous drones and machine learning algorithms has opened up exciting possibilities in precision agriculture, enabling farmers to monitor and optimise their operations like never before. Our project aims to harness this technological potential by developing an Autonomous Orchard Monitoring Drone that employs cutting-edge machine learning techniques to revolutionize orchard management.

PROBLEM STATEMENT

Modern agriculture faces the challenge of efficient crop monitoring and protection against potential threats. The primary objective of this project is to develop an intelligent agriculture drone system that addresses these challenges through advanced machine learning and computer vision technologies.

OBJECTIVES

Ripe Fruit Detection

The system must be capable of autonomously identifying and categorizing ripe fruits within the orchard using machine learning algorithms applied to drone-captured footage.

Animal Intrusion Detection

Implement the YOLOv5 algorithm to detect and track potential animal intruders within the agricultural area. This includes the ability to classify detected animals to determine if they pose a threat to the crops.

Alert and Notification

Upon detecting ripe fruit or animal intrusion, the system should be able to send real-time notifications to the owner or designated personnel. These notifications should include the location of the event and relevant details for immediate action.

Real-Time Video Streaming

Establish a reliable real-time video streaming system from the drone to provide farmers with live visual access to their crops. This includes addressing challenges related to bandwidth, latency, and video quality to ensure an effective monitoring experience.

Drone Building & Path Planning

Create a drone from scratch with the components, calibrate it and make the drone traverse through a designated path at regular intervals for the detection and surveillance

ASSUMPTIONS

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

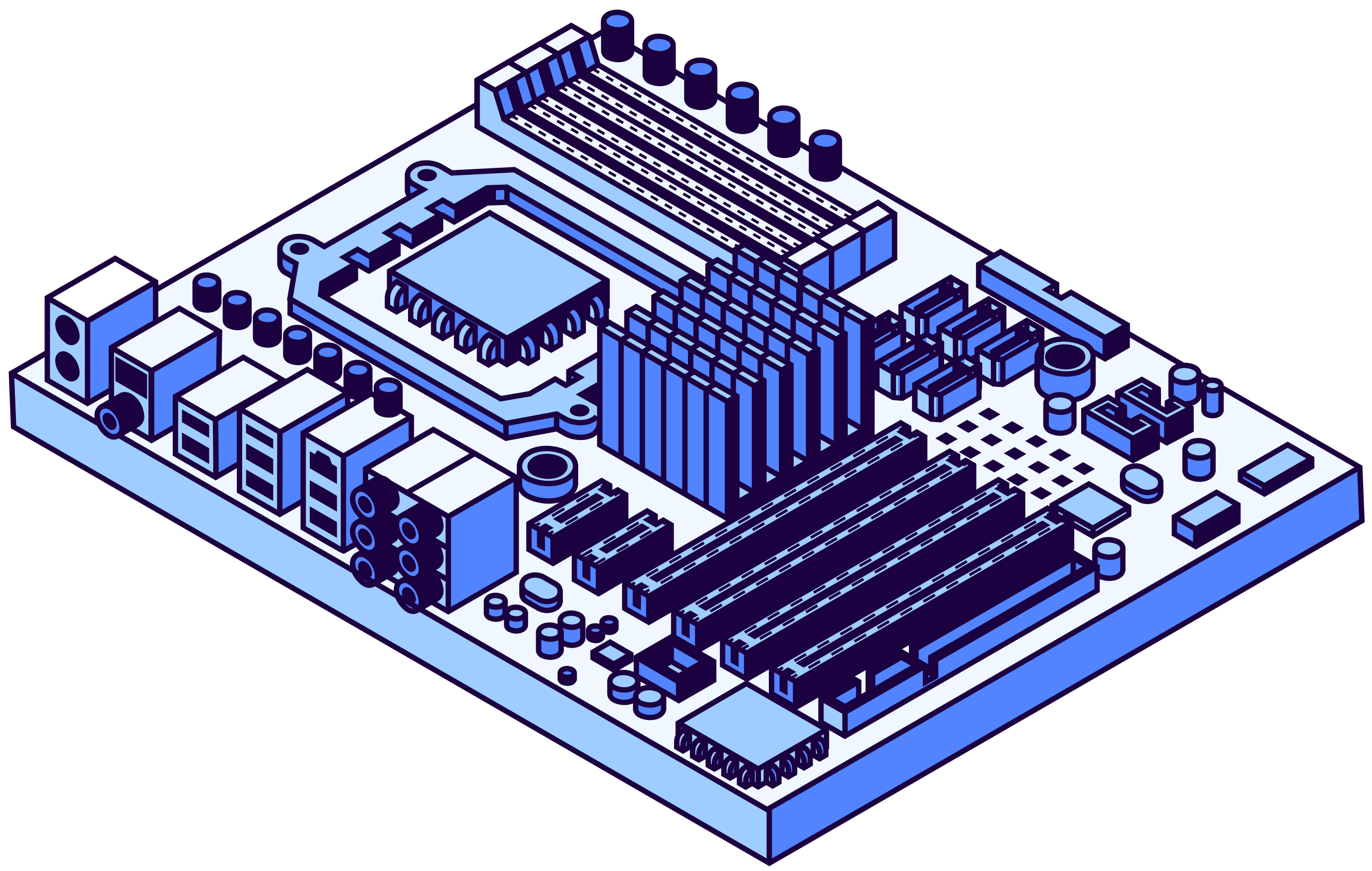
HARDWARE REQUIREMENTS

- **DRONE**

1. Battery
2. Motors
3. Propellers
4. Camera module
5. Antenna
6. ESC
7. Flight controller
8. Transmitter & Reciever
9. Frame

- **MONITORING STATION**

1. Computing system
   a. Intel Core i5
   b. 8GB RAM
   c. 256GB SSD



SOFTWARE REQUIREMENTS

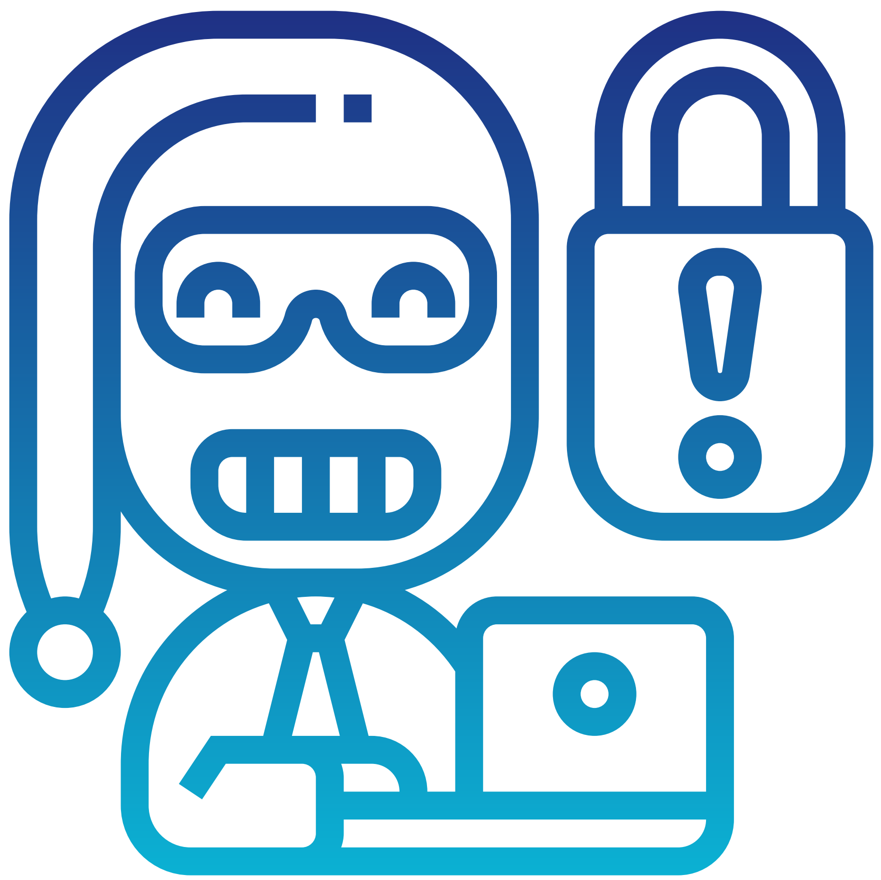
- **Drone control software**
- **Image processing and Computer Vision**
  - OpenCV
- **Data analysis**
  - Python/R
- **Operating System**
  - macOS
  - Windows
- **UI development software**
  - HTML/React

EXPECTED OUTPUT

- **Fruit Detection**
  - **Ripe Fruit Count**: The drone should be able to detect and count the number of ripe fruits in the field.
  - **Fruit Location Data**: The project should provide information about the location of the ripe fruits within the field.

- **Intruder Detection**

- **Intruder Alert**: When an intruder is detected, the system should send an alert or notification to a concerned person or authority.
- **Intruder Location**: The system should provide information about the location of the intruder within the field, which can be crucial for responding to the intrusion.



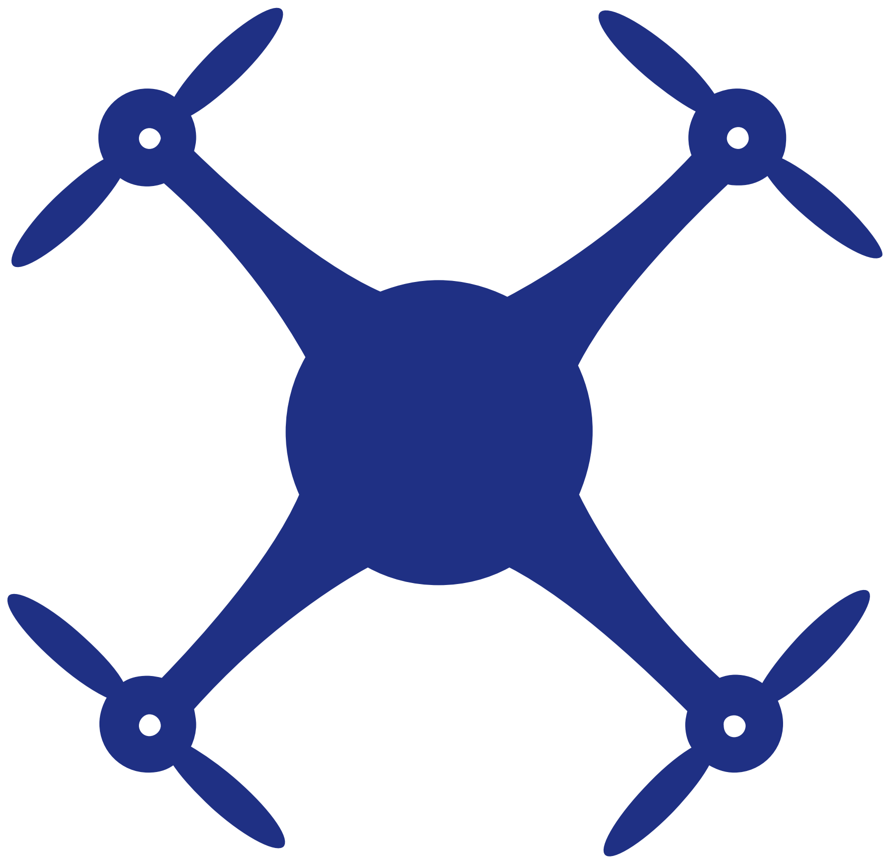
- **Data Dashboard**
  - Provide visual real time data about fruits and intruders.

MOOC COURSE

- Introduction to Machine Learning - by Prof. Balaraman Ravindran, IITM
- Machine Learning For Soil And Crop Management - by Prof. Somsubhra Chakraborty, IITKG

CONCLUSION

Our project brings together state-of-the-art technology, artificial intelligence, 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.



LITERATURE SURVEY

PAPER	**BRIEF**	**PROS**	**CONS**
YOLO: Challenges, architectural successors, datasets and application [Main][1]	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
Animal Detection and Classification from Camera Trap Images Using Different Mainstream Object Detection Architectures [2]	Animal detection using trap cameras and classification of these animals according to the yolov5m algorithm	• Implements yolov5m which combines yolov5 and R-CNN for under feature extraction • Achieves accuracy levels of 88%	• Takes more time for classification since it combines both one step and two step classification for better accuracy • Does not discuss about classification from data extracted from live footage
Improved YOLOv5: Efficient Object Detection Using Drone Images under Various Conditions [3]	Efficient object detection from pictures taken from drones use of yolov5_oursmodel for better results	• High altitude object detection accuracy on various weather conditions was close to 87%	• Night time object detection accuracy was only 57% • Does not talk about animal detection
Real-Time Target Detection System for Animals Based on Self-Attention Improvement and Feature Extraction Optimization [4]	Wildlife detection algorithm yolov5m which combines the dataset of six different animals of various sizes and shape	• Faster and better animal detection than other CNN • Average increase of 4% better efficiency in classification accross all animal datasets	• Requires high FPS video footage to implement structural reparameterization (concept of separating the subject from the background)

PAPER	BRIEF	PROS	CONS
Deep Reinforcement Learning for UAV autonomous path planning (chosen)[5]	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.
Machine Learning Approach to Real-Time 3D Path Planning for Autonomous Navigation of Unmanned Aerial Vehicle [6]	Traditional machine learning techniques such as object detection using ml and yolo is used.	• Many ML algorithms are interpretable, which can be advantageous for understanding and explaining decision-making processes in UAVs.	• ML algorithms often rely on strong assumptions, which may not hold in complex and dynamic environments. • ML algorithms may struggle when applied to high-dimensional or unstructured data.
Q learning algorithm based UAV path learning and obstacle avoidence approach[7]	Q-learning algorithm uses tabular method to estimate action values and find an optimal policies	• Q-learning is a straightforward and easy-to-understand algorithm, making it suitable for simple reinforcement learning problems.	• Q-learning can struggle in high-dimensional state spaces, where the state-action space becomes too large to explore exhaustively. • Q-learning lacks the generalization capabilities of DRL.

Paper	Brief	Pros	Cons
Strawberry Maturity Classification from UAV and Near-Ground Imaging using Deep Learning(chosen)[8]	• 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.
Deep learning techniques to classify agricultural crops through UAV imagery: a review[9]	• Compares various methods of RSTs • Compares different algorithms for classification	• Drones are low cost and allow high spatial resolution • Satellites are expensive, although they cover large area. • CNN has higher precision	• Low endurance of drones • Drones require more time than satellites. • Satellite data not available always
Immature green citrus fruit detection using color and thermal images[10]	• Uses colour difference in fruits and thermal imaging to predict ripeness.	• High recall rate - 96.8% • Colour difference alone is accurate	• Depends on time of day • Have to include color images specifically.
Ripe Fruit Detection and Classification using Machine Learning[11]	• Uses WMRD to detect ripeness , which evaluates the amount of ethylene emitted.	• High accuracy - 91.76%	• Requirement of additional components for WMRD- PEN. • Less availability of datasets

Paper	Brief	Pros	Cons
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 subjective and objective scores	• study is done by getting opinions from different human sunjects ,human opinions can differ from each other
Implementation and analysis of Real time streaming protocols	• Implementation of Real time streaming protocol • sents real time video and audio packets to the user.	• Shows different factors such as QOS and QOE • High efficency and low latency	• implementation is complex • It has limited error handling and recovery protocols
RTP: A Transport system Protocol for Real Time Applications			

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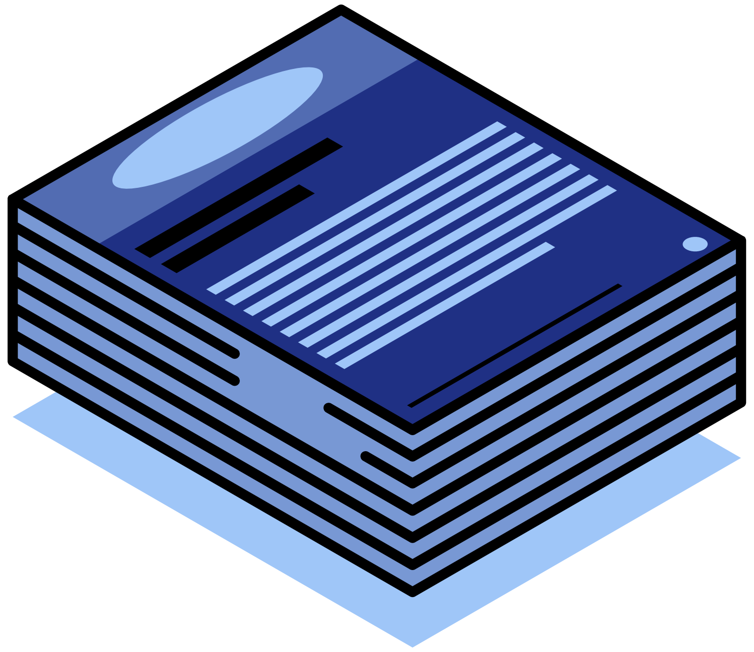

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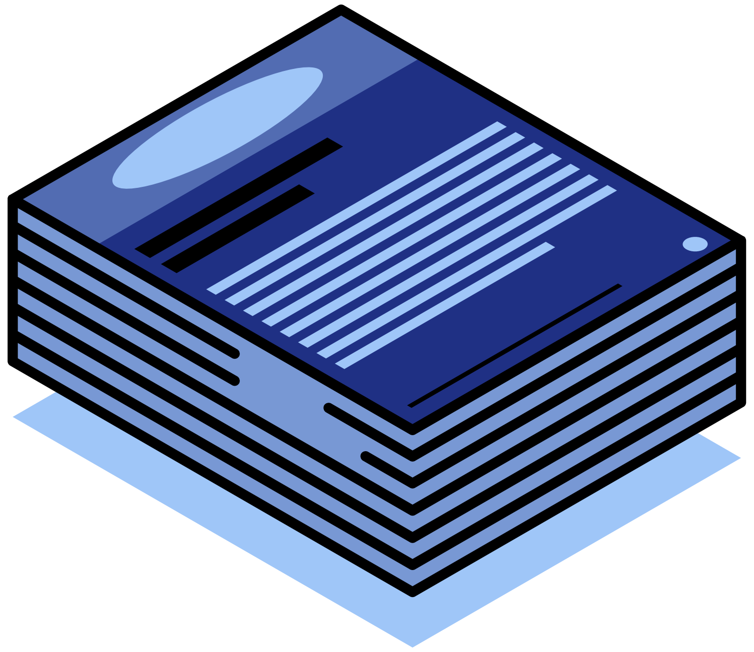

Thank you!