

# STARS: Smart Target search using

## Autonomous Reconnaissance Swarms

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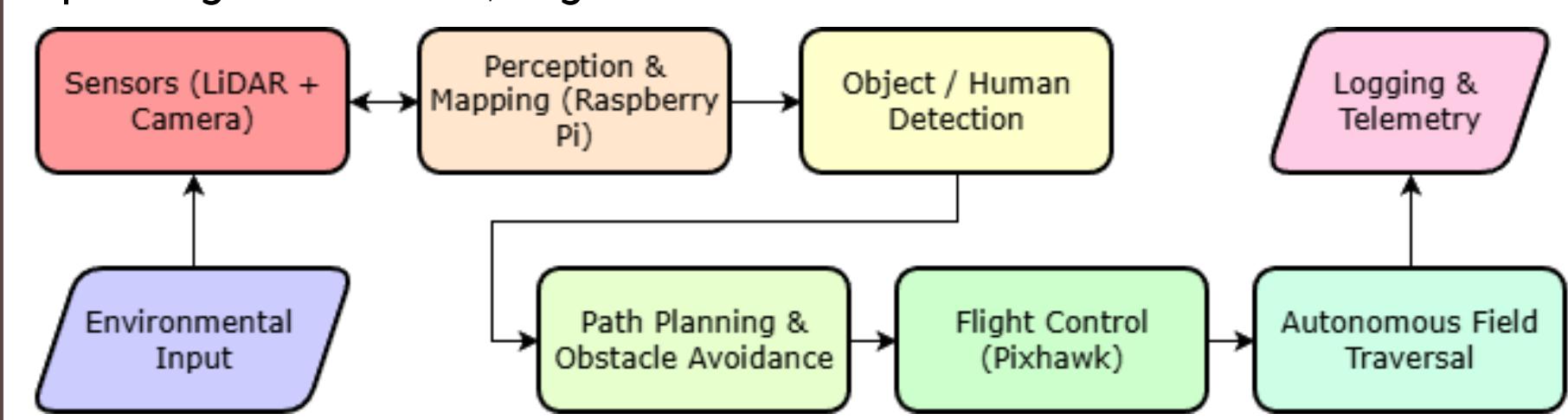
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### Abstract

Traditional drones depend on manual pilots or pre-planned routes, which makes them unreliable in cluttered or dynamically changing environments such as a football field with people, objects, and unexpected obstacles. These limitations highlight the need for smarter autonomous systems that can perceive their surroundings, make decisions in real time, and safely navigate complex spaces without human intervention. With the growing demand for technologies that can assist in search-and-rescue missions, security monitoring, emergency response, and crowd management, autonomous drones equipped with advanced perception and control capabilities have become increasingly important. These systems must not only fly and stabilize themselves but also detect humans, avoid collisions, and cover large areas efficiently.

Table 1: Motivation for Autonomous Drones

This combination of sensing, processing, and decision-making components demonstrates the potential for fully autonomous drone systems capable of operating in real-world, large-scale environments.

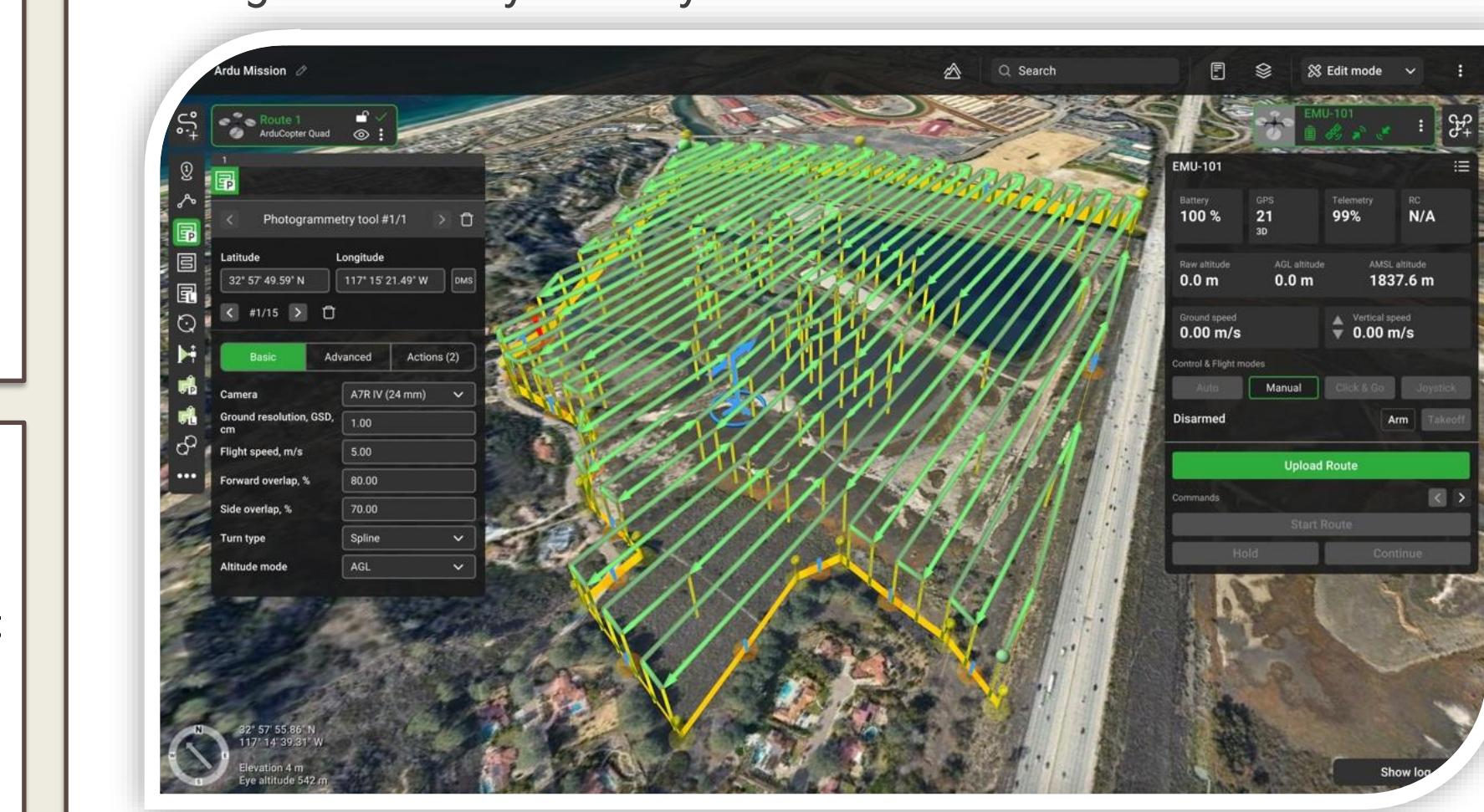
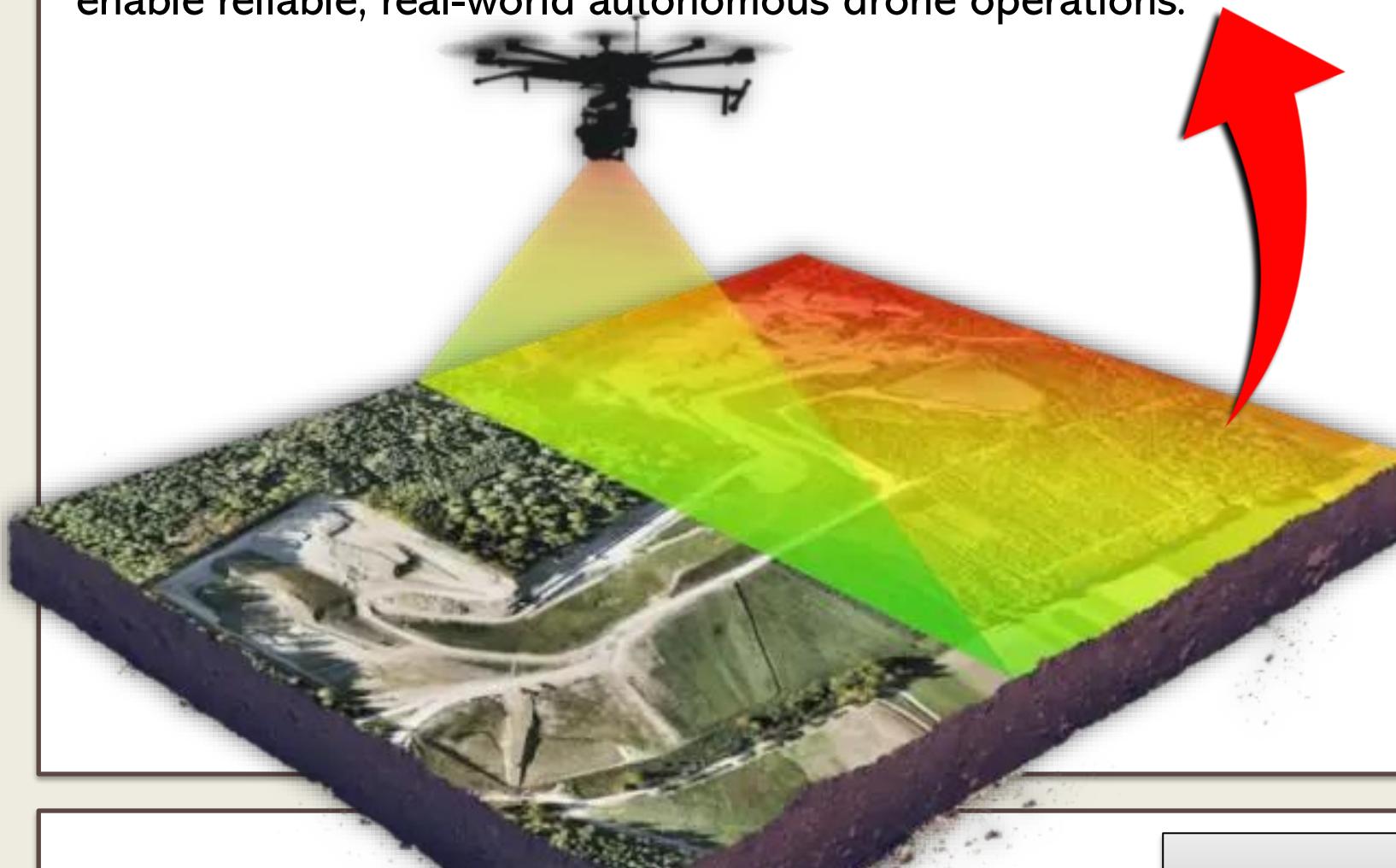


Flowchart 1: Overall Design

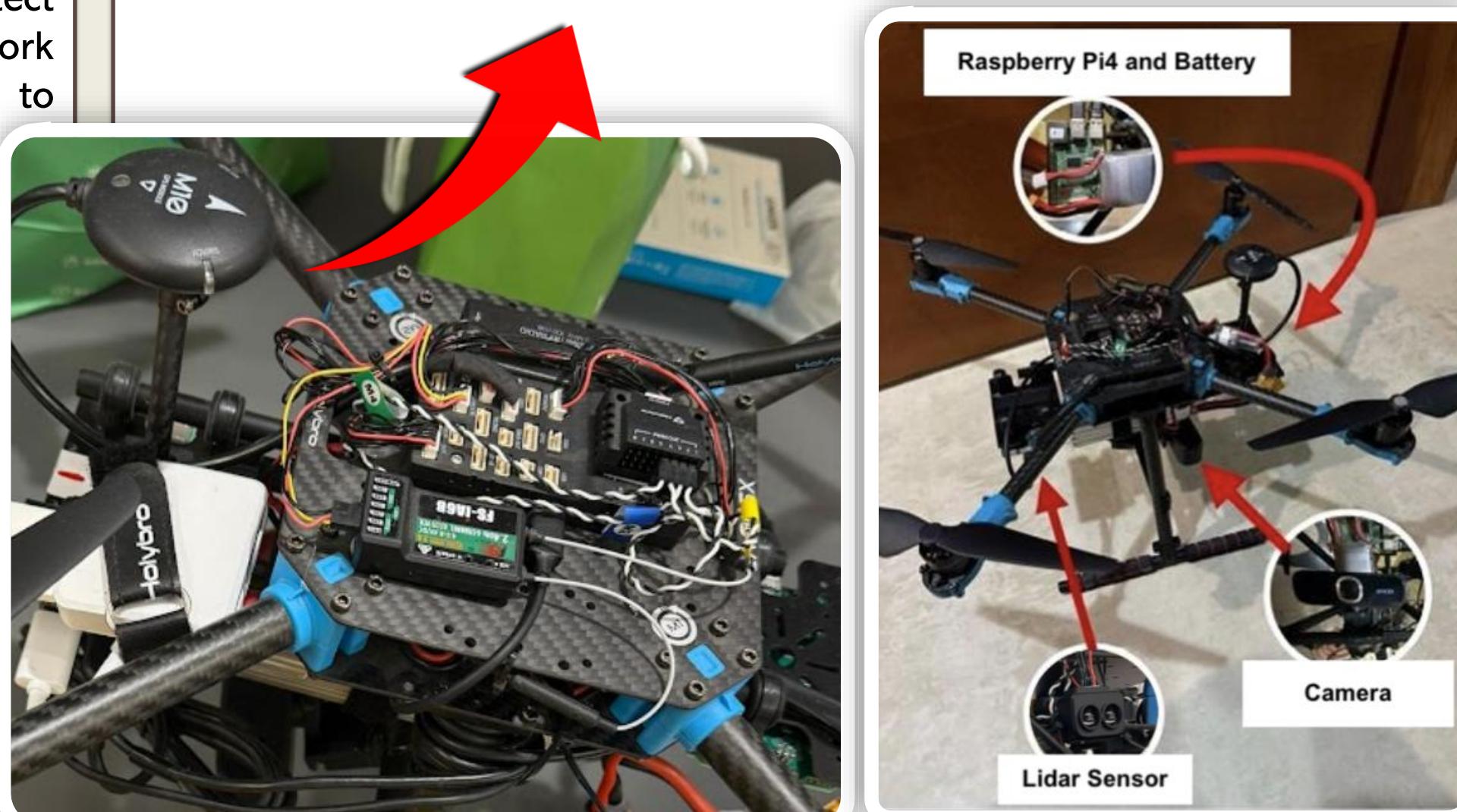
### Introduction

Drones have become an essential tool for modern automation, yet most systems still rely heavily on manual piloting or simple waypoint navigation. These traditional approaches struggle in environments that contain people, obstacles, and unpredictable movements, such as a football field. In such settings, a drone must be able to sense its surroundings, detect humans, and continuously adjust its path to remain safe and effective. The rise of autonomous aerial systems has created a demand for drones that can operate with higher intelligence and independence. Applications like search-and-rescue, security monitoring, field inspection, and emergency response all require platforms capable of real-time mapping, human detection, and collision-free navigation.

This project explores the development of an autonomous drone system that integrates LiDAR for environmental awareness, a camera for visual detection, and onboard computing for decision making. By combining these components with stable flight control through Pixhawk and mission setup through Mission Planner, the system is designed to navigate a football field safely, detect humans accurately, and operate with minimal manual intervention. This work highlights the potential of advanced sensing and control technologies to enable reliable, real-world autonomous drone operations.



Using the processed sensor data, the navigation system estimated obstacle distances, tracked human positions, and calculated safe movement directions. High-level commands, such as yaw adjustments, forward velocity, and altitude corrections, were generated onboard the Raspberry Pi and transmitted to the Pixhawk through MAV Link. This allowed the drone to continuously adjust its path as new LiDAR scans and camera detections were received. Mission Planner was used to define the overall search area, mission boundaries, and initial waypoints before take-off. To support multi-drone operation, both drones shared basic position, coverage progress, and scan information over Wi-Fi, ensuring they avoided overlapping paths and maintained efficient field-wide exploration.

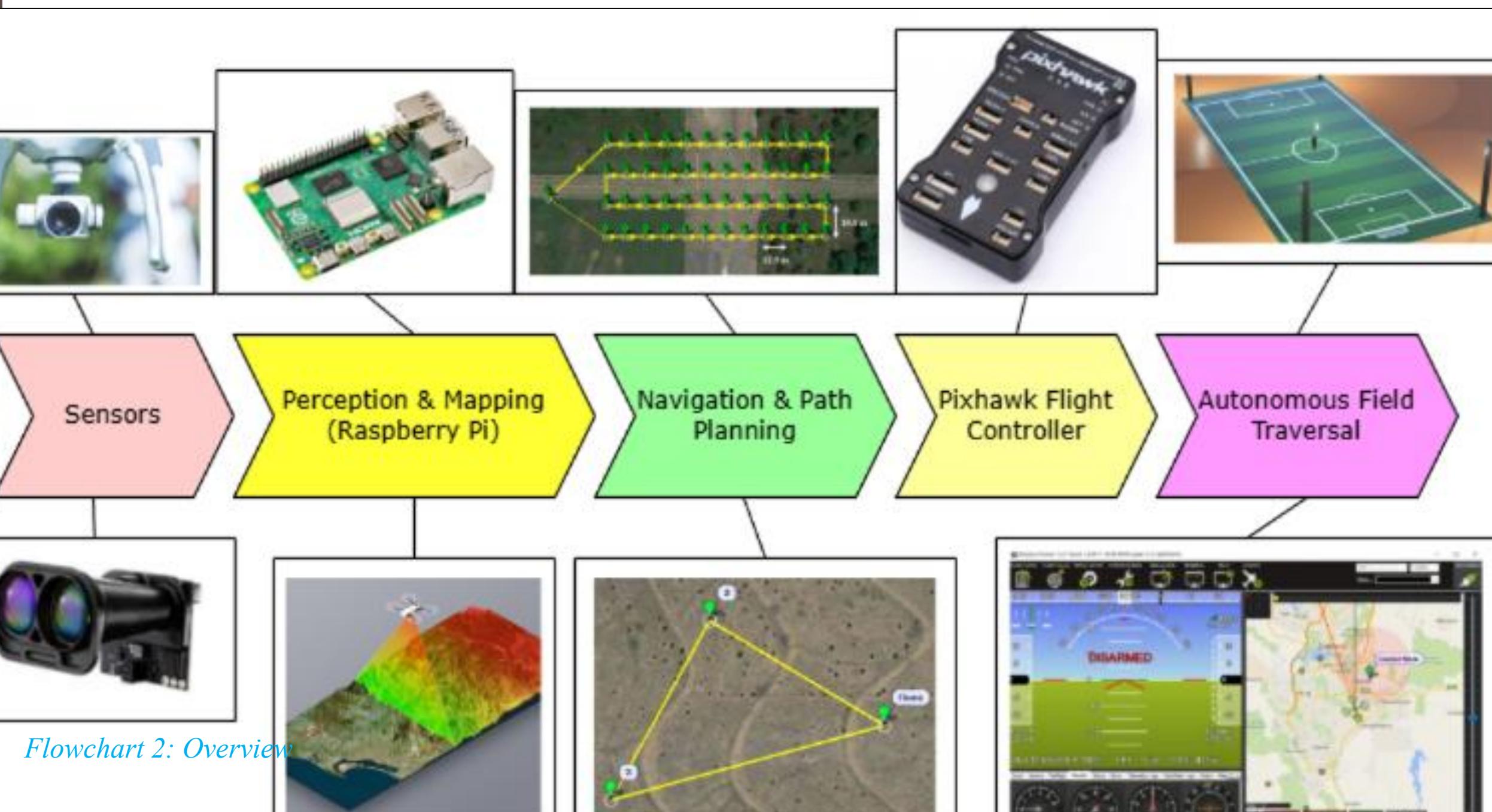


### Project Overview

This project integrates sensing, control, and real-time decision making to create an autonomous drone team capable of scanning a football field, detecting humans, and avoiding obstacles.

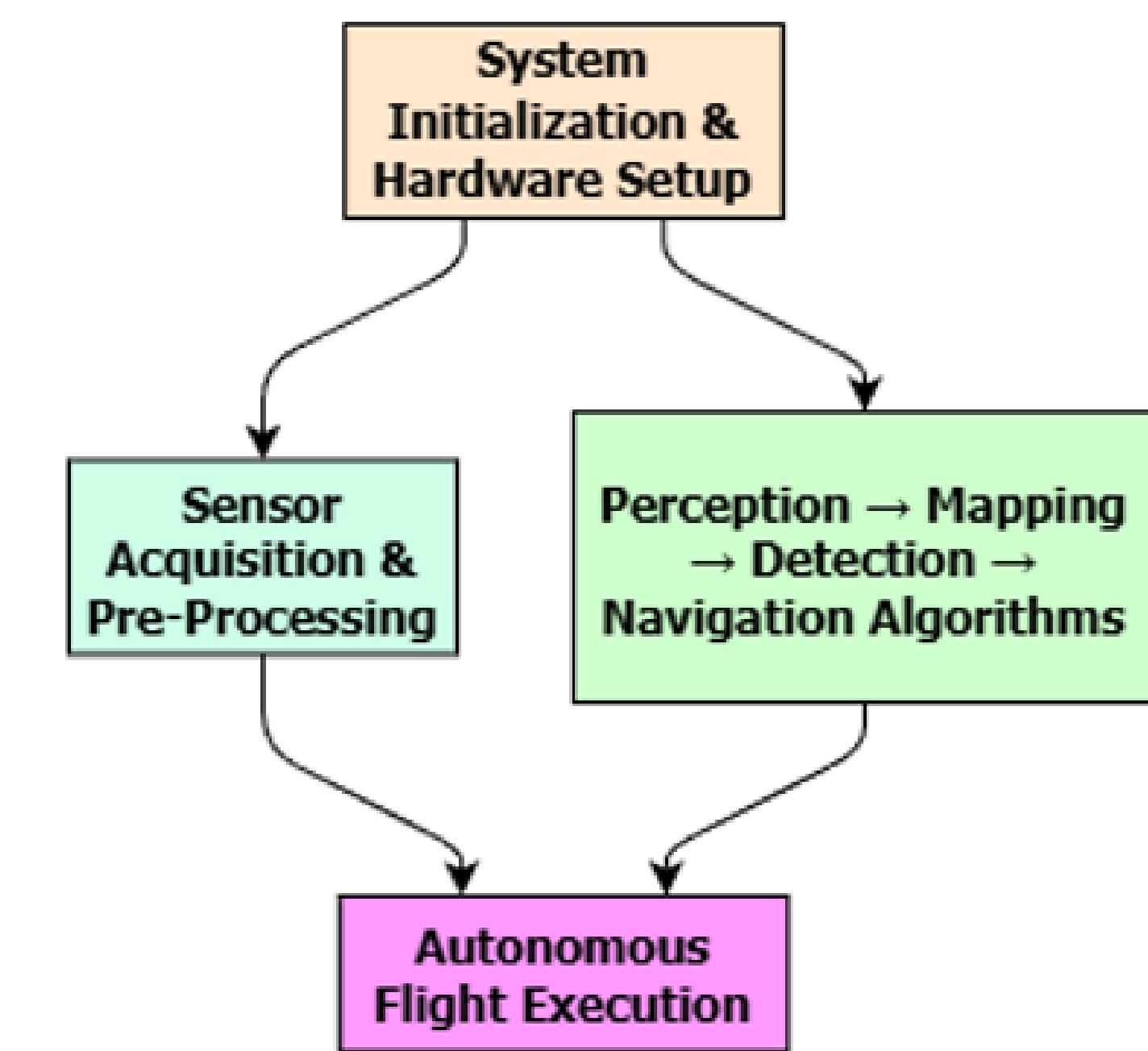
By combining Pixhawk for **flight stabilization**, Mission Planner for field-scale management, **Raspberry Pi** for real-time computation, LiDAR for mapping, and camera-based detection, we present a complete and practical autonomous system.

This platform provides the foundation for **multi-drone intelligence** in larger, more complex environments, enabling reliable performance across diverse conditions and operational requirements.



Flowchart 2: Overview

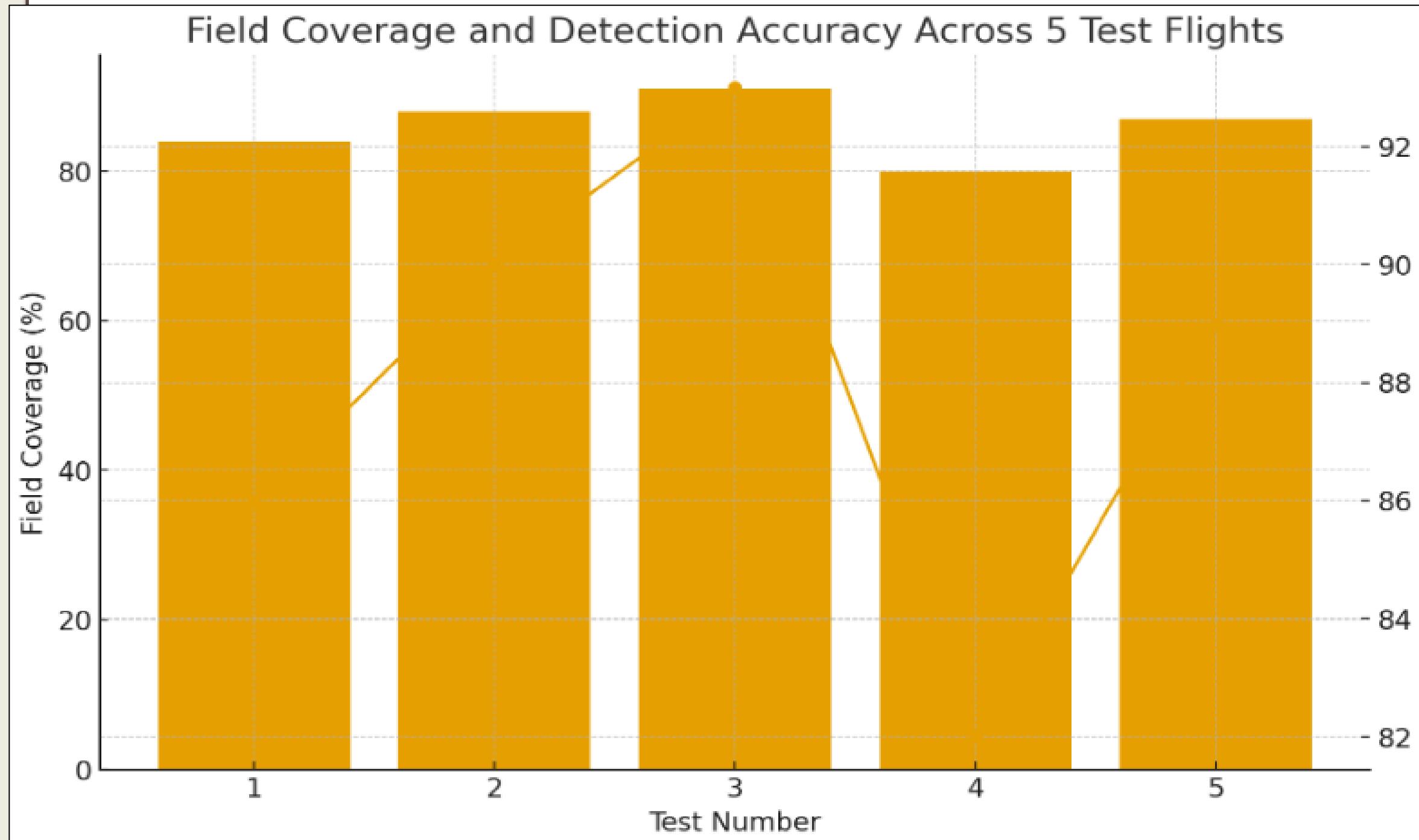
### Methodology



Our system was built on two quadrotor drones equipped with a Pixhawk flight controller, Raspberry Pi, LiDAR sensor, and onboard camera modules. The Pixhawk handled all low-level stabilization, motor control, and flight safety protocols, while the Raspberry Pi served as the high-level onboard computer responsible for perception, mapping, and decision making. LiDAR data was continuously processed to generate 2D and 3D occupancy grids that represented the football field and its obstacles. At the same time, camera frames were analysed using a lightweight human-detection model capable of identifying people in real time. Together, these sensing pipelines provided the drone with an up-to-date view of its environment, allowing it to react dynamically as new data arrived.

### Results

Across the five autonomous missions, the drone consistently achieved **87% field coverage**, demonstrating that the LiDAR-based mapping pipeline could reliably scan most of the football field without leaving major blind spots. The human-detection module performed with an average accuracy of **88%**, even when detection distances varied between 12–18 meters depending on lighting and angle. Obstacle-avoidance performance remained strong throughout testing, with the drone successfully navigating around **100% of both static and dynamic obstacles**, including cones and moving volunteers. Together, these numbers show stable, repeatable performance across multiple independent trial runs.

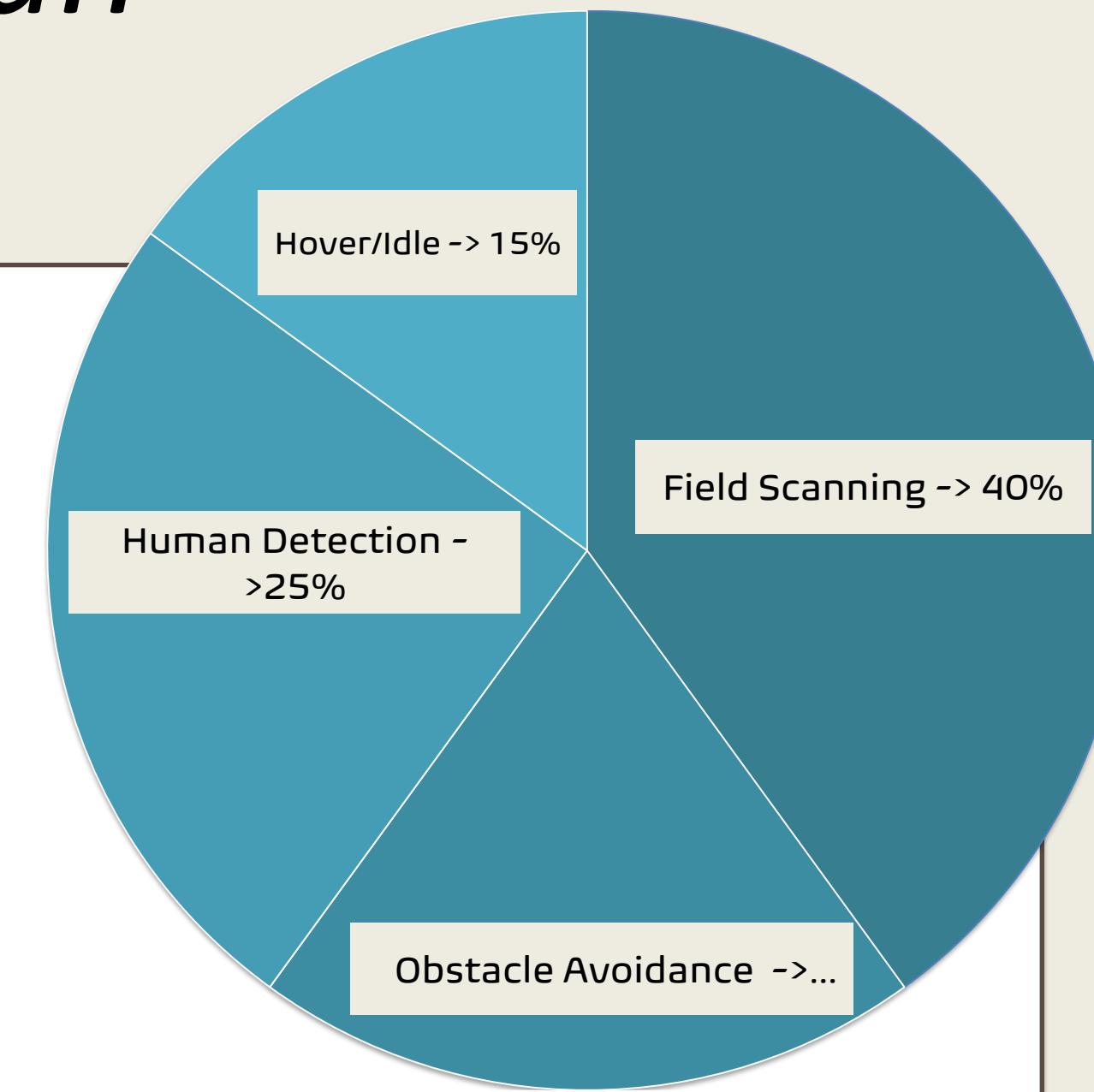


Bar Chart: Field Coverage & Detection Accuracy Across 5 Test Flights

Metric	Value
Camera Processing FPS	13–16 FPS
Human Detection Confidence (Average)	88%
False Detection Rate	6%

Table 2: Camera Performance Results

Across all five test flights, the system showed a clear pattern of stable performance, with field coverage staying within a narrow range of **84%–91%** and detection accuracy remaining between **85%–93%**, depending on lighting and target movement. Obstacle-avoidance behaviour was consistently successful, with every one of the recorded **3–5 static obstacles** and **1–2 dynamic obstacles** per mission being avoided without requiring manual intervention. The tight clustering of these values indicates that the drone's sensing and navigation pipeline performs reliably under repeated trials, suggesting that the system can maintain dependable behaviour even as mission conditions vary slightly between flights. While the results are strong, some limitations became clear during testing. For example, the lower end of detection accuracy (85%) typically occurred during harsh sunlight or when humans were partially occluded.



The average **6–10-minute mission duration**, combined with a LiDAR mapping update rate of **5–10 Hz** and processing latency ranging from **80–120 ms**, indicates that the onboard Raspberry Pi was able to handle real-time perception and decision-making without lag or delays.

### Bar Chart: Field Coverage & Detection Accuracy Across 5 Test Flights

Metric	Result	Explanation
Field Coverage (%)	78–92%	Based on full-field autonomous scans
Human Detection Accuracy (%)	85–93%	Under daylight conditions
Avg. Detection Distance (m)	12–18 m	Varies with lighting & target orientation
Obstacle Avoidance Success (%)	95%	Tested with static cones and dynamic volunteers
Mission Duration (min)	6–10 min	Depends on flight speed & detection events
Mapping Update Rate (Hz)	5–10 Hz	LiDAR frame rate during movement
Processing Latency (ms)	~80–120 ms	Pi-based perception pipeline

Table 3: System Performance

### Conclusion

Our results demonstrate that combining LiDAR-based navigation with vision-driven human detection provides a reliable foundation for fully autonomous drone operation across a football-field-scale environment. The system was able to scan the field, avoid obstacles, and identify humans with consistent performance, showing how tightly integrated sensing and control modules can enable safe and intelligent flight.

Looking ahead, several key improvements can further strengthen the platform:

1. **Reinforcement-learning-based navigation** to allow the drone to adapt its behaviour and make more intelligent decisions in unfamiliar or complex environments.
2. **Enhanced multi-drone coordination**, enabling parallel field coverage and cooperative exploration for larger missions.
3. **Testing in more dynamic and crowded scenarios**, such as moving groups of people or real event settings, to evaluate system robustness under real-world conditions.
4. **Additional sensor fusion**, such as thermal imaging or higher-resolution LiDAR, to improve detection capability in low-light or obscured environments.

Overall, this system shows strong potential for practical use in applications such as search-and-rescue missions, perimeter security, emergency response, and stadium or event monitoring. The project demonstrates how affordable hardware, when combined with **intelligent algorithms**, can create scalable autonomous drone solutions for real-world challenges.

