

STARS: Smart Target search using Autonomous Reconnaissance Swarms

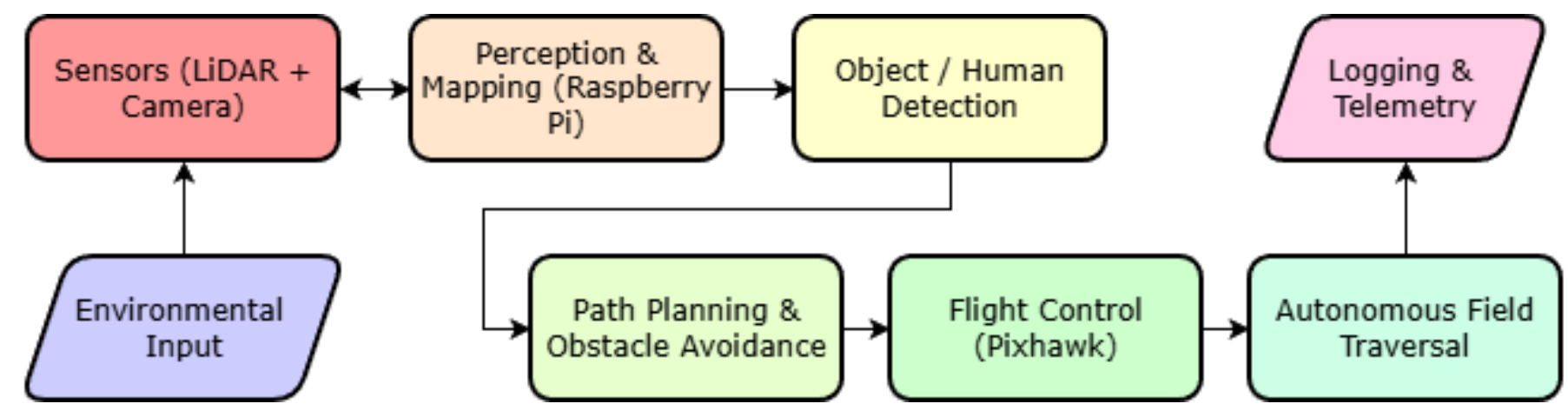
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Abstract

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.

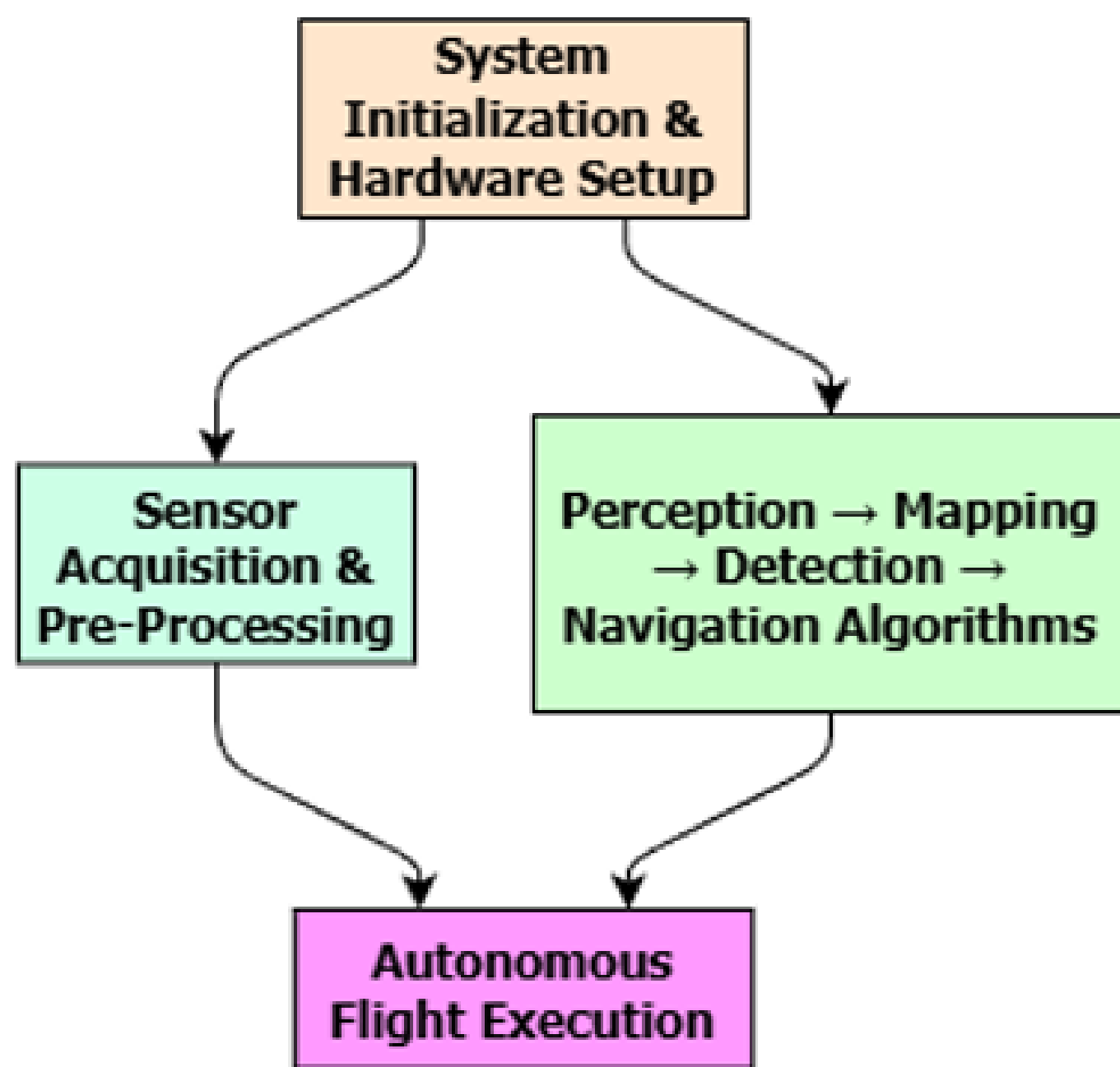
This combination of sensing, processing, and decision-making components demonstrates the potential for fully autonomous drone systems capable of operating in real-world, large-scale environments.



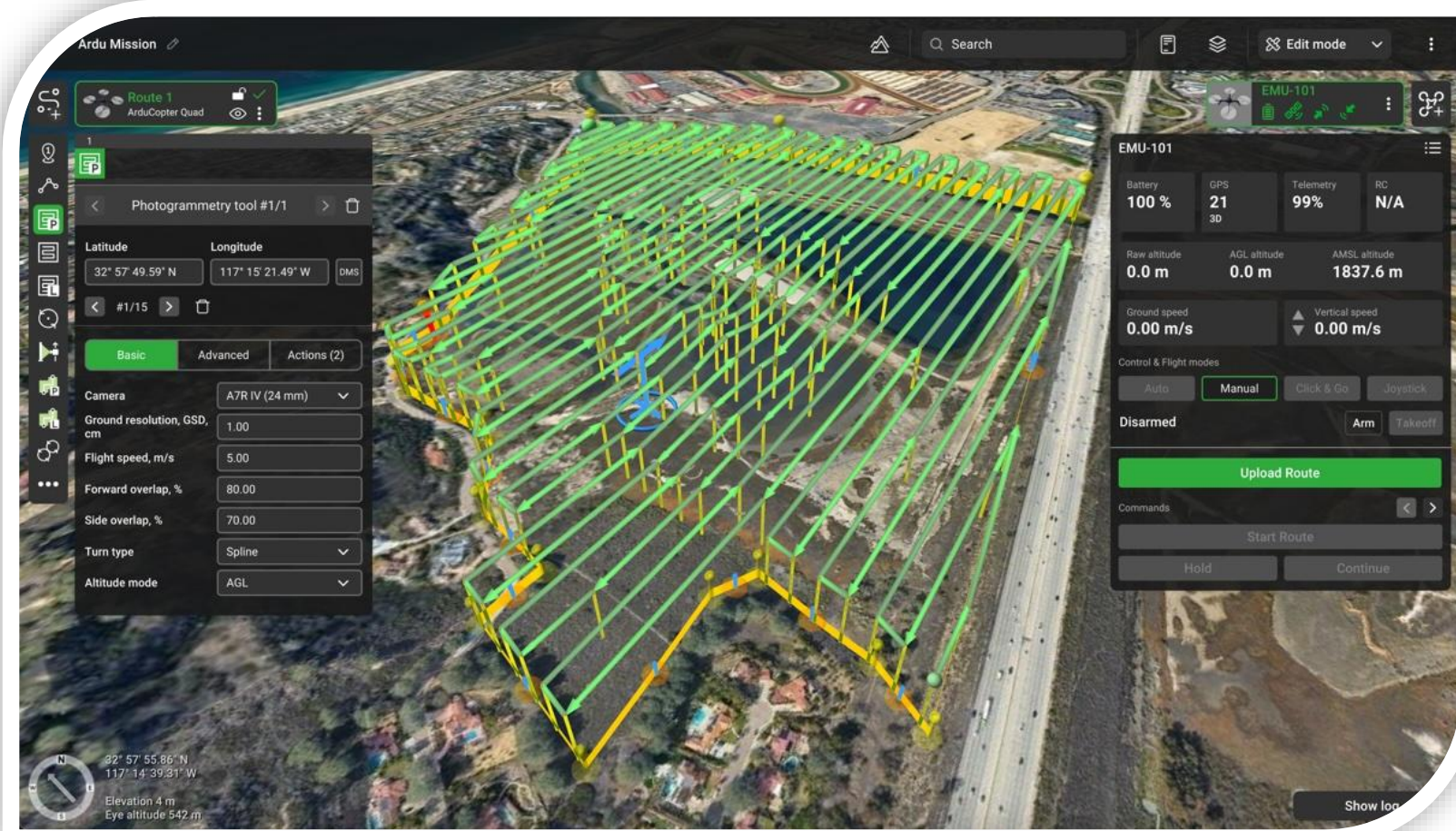
Challenge	Explanation
Manual Control Limitations	Human pilots struggle with accuracy, consistency, and long missions.
Unpredictable Environments	Football fields can have people, obstacles, and moving targets.
Need for Real-Time Awareness	Drones must sense surroundings to avoid collisions and detect humans.
Large Area Coverage	Manual scanning is slow; autonomous drones cover fields faster.
Safety & Reliability	Automation reduces human error in search, monitoring, and security.

Table 1: Motivation for Autonomous Drones

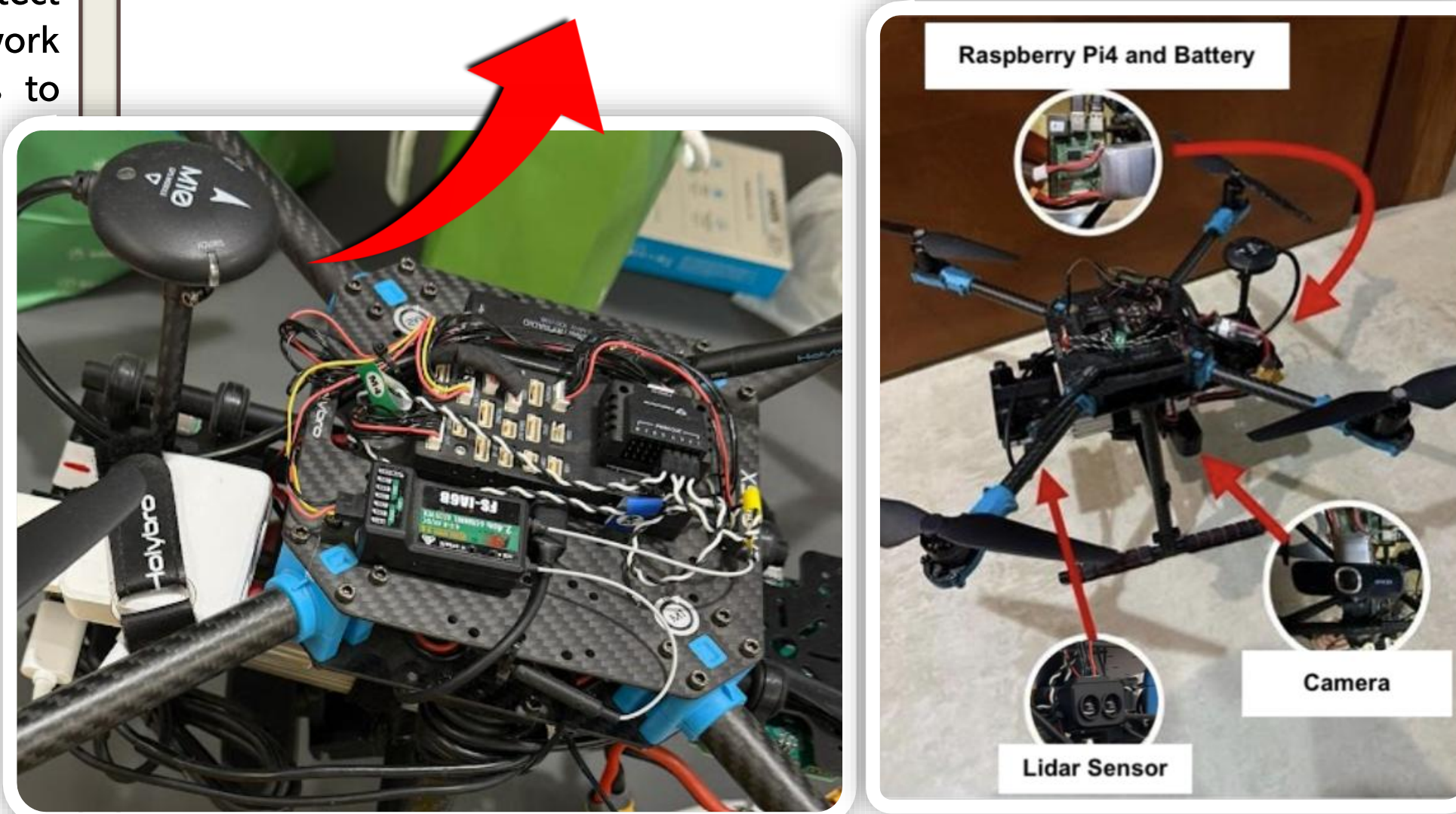
Methodology



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.

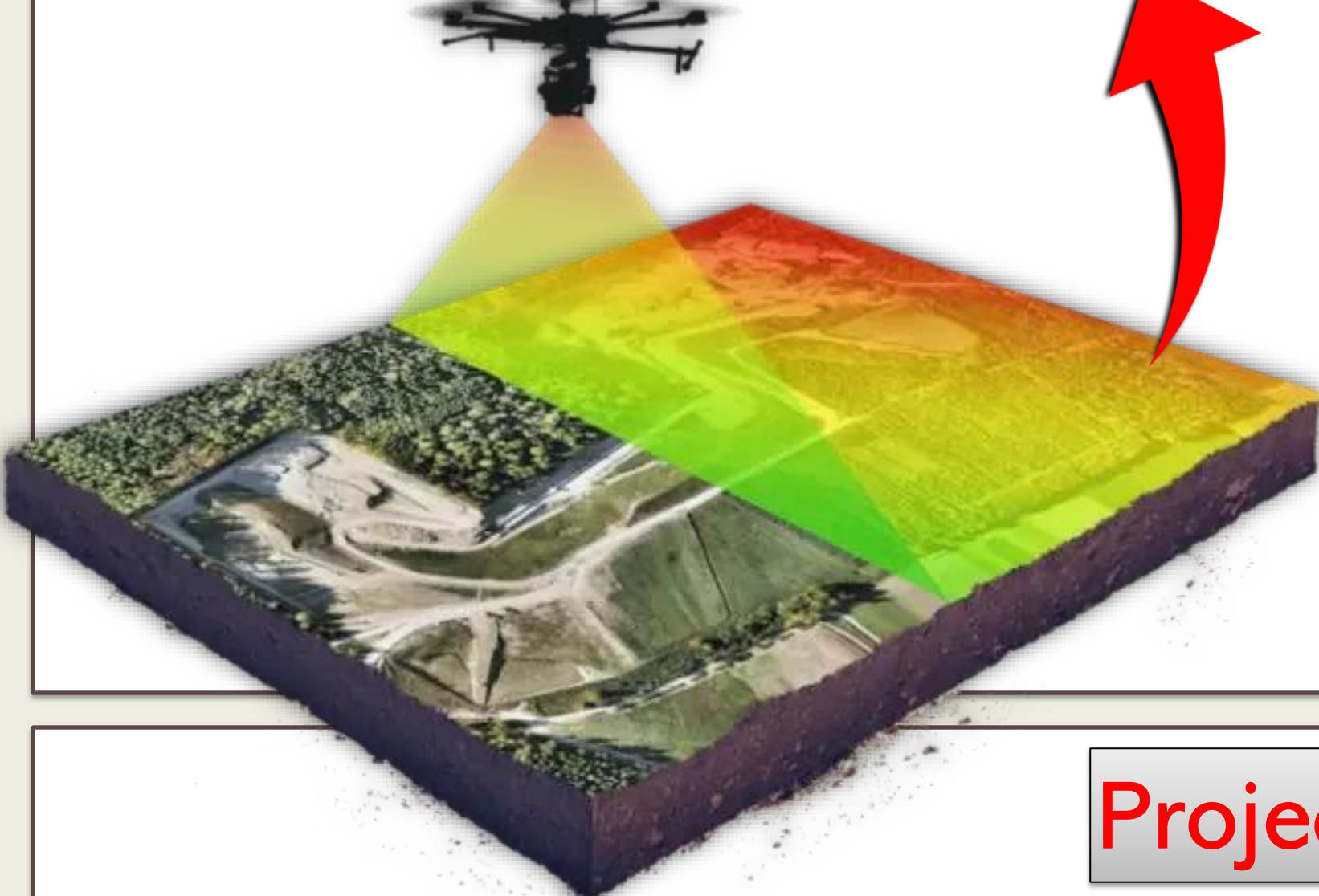


Using the processed sensor data, the navigation system estimated obstacle distances, tracked human positions, and calculated safe movement directions. High-level commands, such as yaw adjustments, forward velocity, and altitude corrections, were generated onboard the Raspberry Pi and transmitted to the 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.



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.



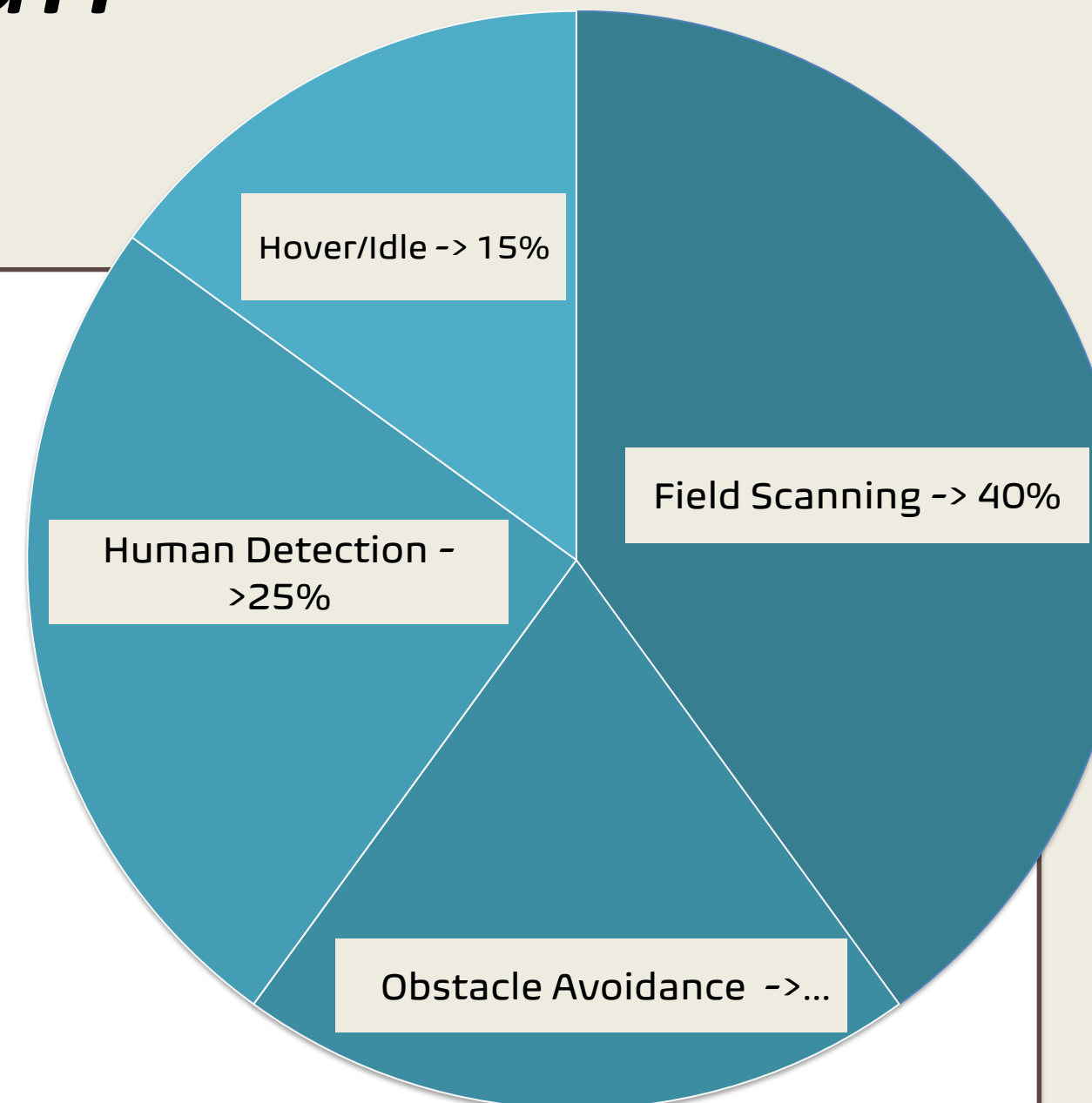
Project Overview

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.

Category	Summary
Goal	Autonomous drone system for football-field traversal, human detection, and obstacle avoidance.
Key Hardware	Pixhawk, Raspberry Pi, LiDAR sensor, Camera module, Wi-Fi for communication.
Core Functions	Real-time mapping, human detection, safe navigation, field coverage.
Mission Flow	Take-off -> Scan -> Detect -> Replan -> Approach -> Resume Coverage -> Land
End Outcome	Reliable autonomous system capable of large-area exploration and detection.
Applications	Search-and-rescue, stadium monitoring, and multi-drone exploration.

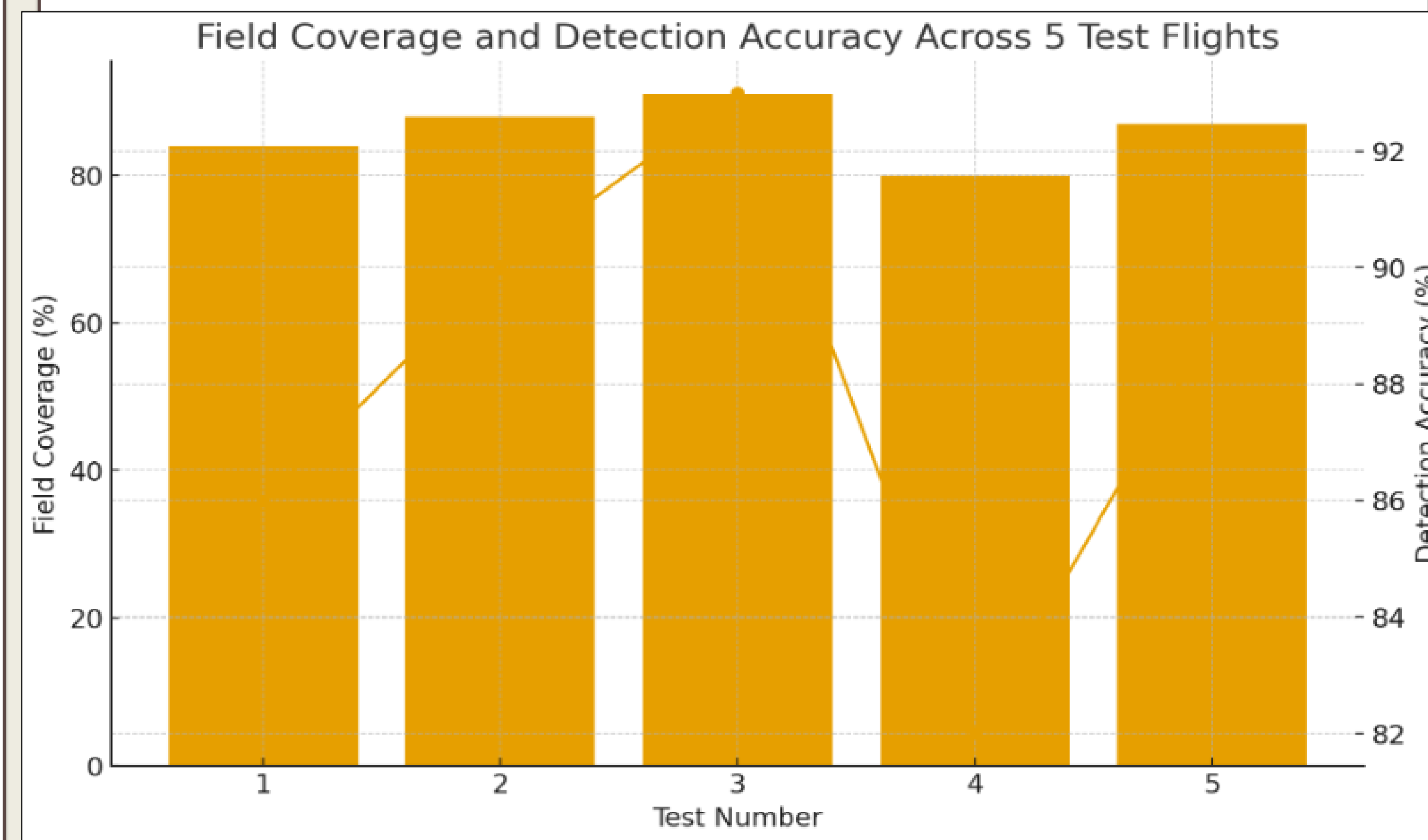
Results

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.



Pie Chart: Time Spent in Total Mission Flight

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	Value	Metric	Result	Explanation
Camera Processing FPS	13–16 FPS	Field Coverage (%)	78–92%	Based on full-field autonomous scans
Human Detection Confidence (Average)	88%	Human Detection Accuracy (%)	85–93%	Under daylight conditions
False Detection Rate	6%	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 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.

Table 3: System Performance

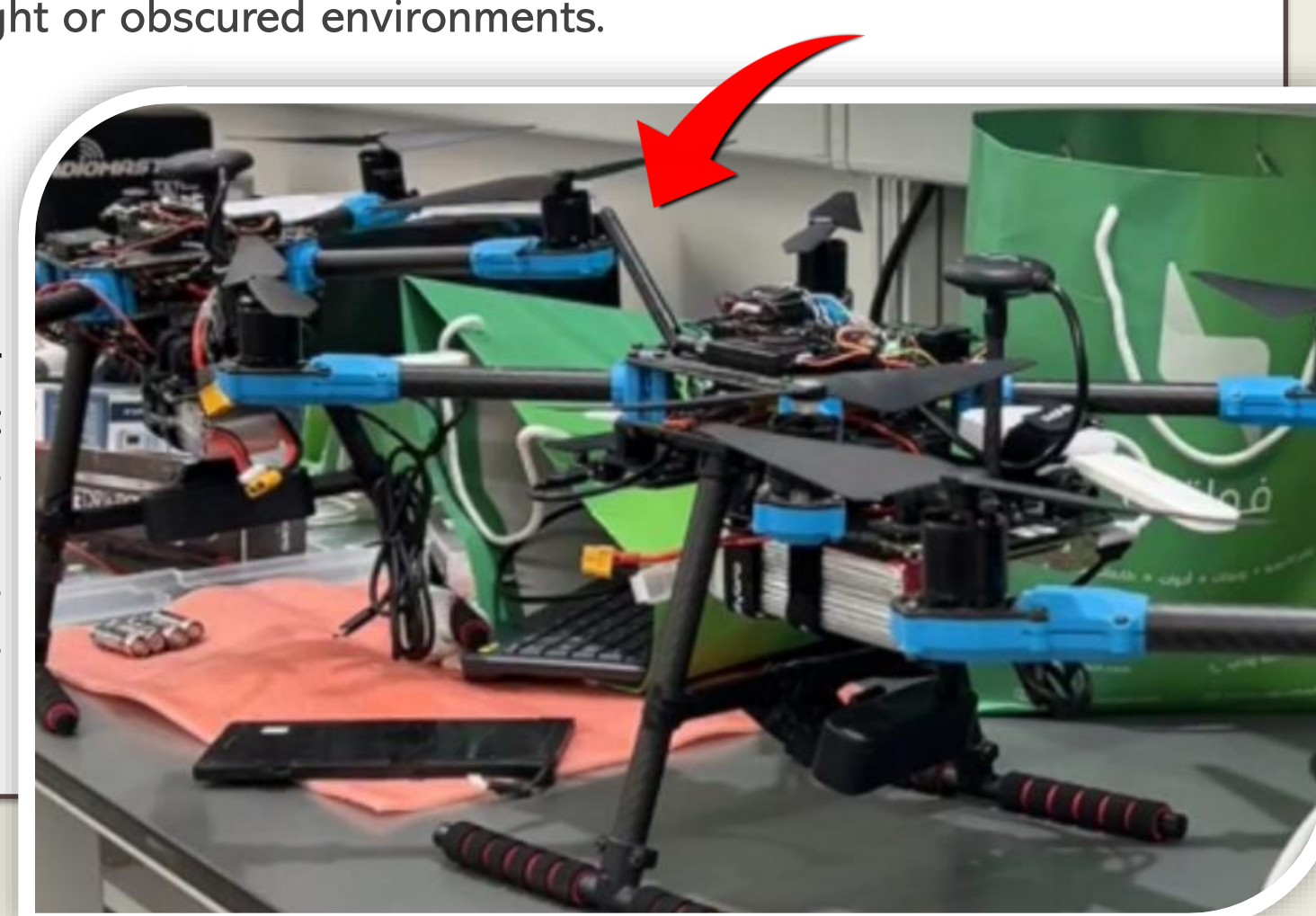
Conclusion

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.



Flowchart 2: Overview

