International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Design and Development of an Autonomous Drone System for Real-Time Surveillance, Detection, and Data Fusion

Ashish Vivek Singh
Research Scholar
singh.ashish.vivek@gmail.com
School of Computer Science Engineering Sandip University, Nashik, Maharashtra, India

Rohith kumar Arige
Research Scholar
rohithkumararige@gmail.com
School of Computer Science Engineering Sandip University, Nashik, Maharashtra, India

Vishakha Deore
Research Scholar
vishakhadeore31@gmail.com
School of Computer Science Engineering Sandip University, Nashik, Maharashtra, India

Jayesh Neriya
Research Scholar
jayesh0320neriya@gmail.com
School of Computer Science Engineering Sandip University, Nashik, Maharashtra, India

Dr. Umesh Pawar
umesh.pawar@sandipuniversity.edu.in
School of Computer Science Engineering Sandip University, Nashik, Maharashtra, India

Abstract

As automation and real-time response are becoming crucial in emergency situations, industrial monitoring and safety in public spaces, the given study introduces the concept and engineering of the efficient and self-sufficient drone system capable of performing surveillance, threat identification, and prompt response activities at a relatively low cost. The capabilities encompass within the drone core a Raspberry Pi 5 as the processing unit including YOLO-based object and fire detection model, thermal and RGB cameras and sensors, GPS, LIDAR as well as an extinguisher for intervention in dangerous situations. This paper describes a reliable integrated data fusion technique that integrates various data streams for increased perception and identification of targets in complex scenarios. This doesn’t require using cloud-based services and relies on the improved YOLO model for object classification and fire detection on an edge computing platform. It self-organizes the movement using GPS and LIDAR map and crosses the field when comes on fire suppressing the fire with its frontal weapons. There are five important tests: the object recognition and detection accuracy test, the fire response test, the duration of operation of the sensor fusion system, the testing of autonomous navigation and mobility of the drone, and the communication capability test. It was noted earlier that the achieved results of a prototype successfully passed the trials with an average of the object detection accuracy of 91% and managed to suppress the fire in real time. The development cost was kept below ₹ 65000, with a target of achieving a unit manufacturing cost of ₹ 50000, which would help in making the system practical in real life. This work provides an innovative real-time UAV, sensor fusion, AI and Actuation, which this work lays down for future extension for the advancements in autonomous surveillance and safety systems.

Keywords: Autonomous Drone, YOLO Detection, Real-Time Surveillance, Sensor Fusion, Fire Suppression, Edge AI

Introduction

In view of the ever-growing trends in advanced automation, artificial intelligence as well as engineered systems, it has led to a new family of autonomous systems designed to operate in challenging and risky conditions. Among these, specifically, Unmanned Aerial Vehicles (UAVs), also called drones, have emerged as quite critical working tools in different fields including environment surveillance; military intelligence gathering; industries inspection; and response to natural disasters. The easiness of accessing some region by drones, together with the rise of intelligence in these robots, recommends their use in surveillance applications. Due to their capabilities of real-time monitoring and low cost of operating systems, drone surveillance systems can act as supplements or as an alternative solution to the ground surveillance systems in certain scenarios. Autonomous surveillance is particularly useful in emergencies because early identification of threats and fast response is necessary. Emergencies such as fire, incursions in prohibited areas, or even gas leakage in a certain area needs real time awareness, decision making, and response. Present systems approach this step by relying on the human intervention or having the system hosted in the cloud, which is disadvantageous because it leads to a delay in operational processes. Thus, incorporating edge AI, selfnavigation, and timely reaction capabilities into a drone is a chance to disrupt the existing surveillance systems.

Real-World Challenges

Although drones are now being used more frequently, there are many issues associated with real-life implementation of such automated aerial monitoring systems. With respect to future work, one of the most critical problems is the absence of fast detection and timely reaction in critical time-sensitive areas. Old fashioned drones can record videos but data must be sent to remote servers for analysis and this results to serious delay which is very dangerous in calamities such as fire disasters. Another important requirement is, for instance, low false alarms in fire detection, high sensitivity and the fast response as well to prevent further progression of the fire, etc. One of the issues which can be considered is the problem of identification of the surroundings in the flight process of the drone and its further interpretation. Porous regions like forests, warehouses, industrial plants and urban areas have many kinds of challenges to perception and navigation because of the existence of many barriers and variations of light intensity. Furthermore, the thermal, vision, GPS module and proximity sensors used in the system needs a very effective mechanism to fuse in order to form a conceptual understanding of the environment. The absence of such fusion creates disparate data which may cause formation of an insufficient or an inaccurate picture concerning the situation. Also, real-time communication and energy efficiency can still be considered as the key limitations of MaRS. Typically, most drone system lacks the ability to perform stabilized control and receive transmitted data at long distances or in regions where other drones are present. However, the processing of massive sensor data onboard is quite a challenging task that paralyzes lots of power resources and, thus, decrease operating time.

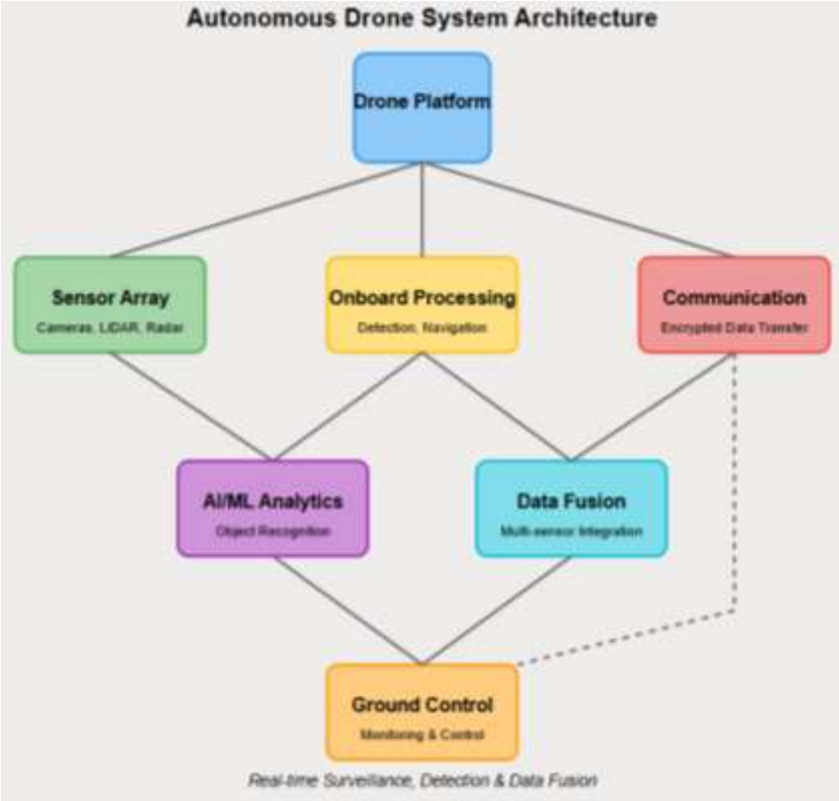
Gaps in Existing Drone Systems

There are several disadvantages common to current drone-based surveillance systems. First, it is quite confined; while today's popular commercial drones can be piloted manually or follow predetermined flight paths based on specified GPS coordinates with little to no flexibility regarding other stimuli encountered on the field. Secondly, there is generally insufficient onboard computation in most consumer drones with several essential decisions made in the cloud environment that is a source of delay and vulnerability to network failure. However, they are equally not useful for high-speed applications where time is of the essence in mere milliseconds. Moreover, integration of fire alarms and other forms of emergency's response are not well implemented in commercial or academic drones. Self-driving vehicles can provide the name of the hazard but cannot perform the operation of avoiding the said hazard. Their passive nature thus declines their practical uses in rescue or emergency situations. Also, no integration of RGB, thermal, GPS, and LIDAR inputs deprives it of situational interpretation, especially in scenarios or at night or during fog Hours. This study attempts to address these issues through designing a completely self-sufficient unmanned aerial vehicle controlled by artificial intelligence which owns the capability of real-time object and fire detection, integrating multiple kind of sensors, and without waiting for another control from ground station, it has an onboard firefighting mechanism for avoiding or reducing the fire damage, Moreover, this drone is trained on Raspberry Pi 5 and edge-computing solutions for cost effective and large-scale application.

Problem Statement

Self-sustainable surveillance system is becoming more vital in measuring up with real-time risks and threats especially in cases such as fire emergencies. Although, drones have demonstrated a great possibility to be used in surveillance, current systems do not have the capacity to identify and extinguish fire risks in real time. All the existing drone systems are directed towards surveillance and detection, and they do not possess integrated responsive systems such as fire extinguishing which is important in emergencies. Moreover, the majority of current drone systems depend on cloud processing for all their data processing, and this considerably incurs additional time delay, and cost making them unsuitable in time-sensitive applications. They also do not handle fusion of multimodal data of various sensors effectively causing a compromise on the situational awareness. Currently, there is a trend present in the market which focuses on developing an affordable drone which incorporates high-end detection ability of fire threats coupled with the ability to fight the fire independently in real-time. To fill these gaps, this research proposes a drone that consists of real-time fire detection, data fusion, and autonomous fire extinction in one package and are reasonable for use in both urban and industrial settings.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458



Research Objectives

To design and develop a low-cost, autonomous drone capable of real-time surveillance, fire detection, and response using data fusion and onboard intelligence, aimed at enhancing safety and operational efficiency.

- YOLO-based object and fire detection model: Train and deploy a YOLOv8-based model optimized for Raspberry Pi 5 to detect objects, fire, and smoke in real-time.
- Micro fire extinguisher actuation system: Develop a miniaturized fire extinguisher integrated into the drone for automatic fire suppression upon detection.
- Sensor fusion: Integrate RGB, thermal, GPS, and LIDAR data into a fused environment map for enhanced situational awareness and navigation.
- Real-world validation: Conduct rigorous tests to validate the system's detection accuracy,

Literature Review

State-of-the-Art Object Detection Algorithms

With deep learning, object detection has been advanced and some model that were developed include YOLO, SSD and Faster R-CNN. Of the above, YOLOv8 model has emerged as the one with massive rates of accuracy to go with the speed thus being recommendable for real-time analytics. With this, YOLO has a one-pass detection that considerably cuts the inference time compared with two-step detections like the Faster R-CNN which involves, Proposal generation and Finding of Object within proposals. YOLOv8 is an enhancement compared to older versions, as it incorporates to Lightened network structures that work at a faster rate with an impressive level of accuracy which makes it ideal even for drone incorporated systems with edge computing. SSD is one more widely used object detection algorithm which is famous for its high speed and rather high accuracy. It employs default pre-defined bounding boxes in various aspect ratios to predict objects in an image making it faster than other models which are the R-CNN type. Dense object detection is something that SSD changes between the levels, which makes it have a high efficiency in terms of time when it comes to aerial systems but is outperformed by YOLO in more complex scenarios.

Fire Detection and Early-Warning Systems

Burn detection still plays an important role in the operation of an ASMSU especially in industrial and urban area. The earlier conventional techniques of fire detection is based on the use of conventional devices like the smoke and heat detectors. Nevertheless, few studies have been made in case of UAVs regarding vision-based fire detection methods. This is because fires emit heat that can be detected via infrared sensors; this kind of techniques has been known to be useful. Thermal sensors help to locate heat sources, while RGB cameras provide good visibility in a specific area to make a final accurate decision. In recent times, researchers have noted that CNN especially those developed for fire detection, can identify and differentiating between fire risks to an extremely precise level and in real-time if need be. For instance, some works are devoted to providing thermal and YOLO-based algorithms for detecting fire and classifying it at the same time. AI-based fires detection will ensure that the response time to the outbreak is greatly reduced using early warning systems with alert notification to the local authorities or the use of alarms to ignite the firefighting mechanisms. However, most of the developed systems rarely incorporate the automated response actions thus, the applicability of the existing systems in emergency situations is questionable.

Multimodal Sensor Fusion Frameworks

When it comes to fully and partially autonomous UAV systems, multisensor integration is of paramount importance for both platforms. Sensor fusion usually entails the incorporation of more than one kind of sensors like color camera, thermal camera, LIDAR, and GPS among others. Each type of sensor adds its own type of data: for example, RGB cam provides high-quality image information, while thermal cam detects heat-objects like fire or warm living creatures. Navigation is also an important field that the LIDAR sensors provide for the UAV by giving it a 3D view of the surrounding environment to avoid colliding with any obstacles. The latest advancements of sensor fusion has aimed at using the above-mentioned dissimilar data sets to achieve the goal of enhanced object identification and accurate navigation with techniques like Kalman Filters or learning with deep neural networks. Nevertheless, several problems persist in utilizing the data immediately and without significant processing complexity which is very essential when used in drones that exist in constrained environments.

Autonomous UAV Navigation and Real-Time Control Systems

The problem of autonomous navigation of drones involves path planning, avoidance of obstacles, and making decisions out of data collected by the sensors that are onboard drones and base stations, and to undertake all these tasks, advanced algorithms are necessary. MPC and RL have been used for the control of UAVs because of their efficiency in predicting the dynamic environment of operation. MPC can be used to plan the drones' path in respect to the currently existing and predicted states of the elements in the environment, on the other hand, RL is used to make the drones learn the most appropriate way to navigate the environment from experience. The issue, however, is with the factor of the control in real-time while at the same time considering the computational aspect especially when the system is in areas with limitations to GPS. For instance, Lidar and camera-based systems can supply environmental perception, whereas control of drones in real-time is sensitive and can only be achieved by highly optimized algorithms so as to achieve stability in complex environments or at high speeds.

Limitations in Existing Drone Systems

However, that there are still openings in currently available surveillance drones. Most systems lack adequate response capabilities including the lack of the capacity to act in a manner such as suppressing a fire or halting an intrusion as soon as the intrusion has been detected. Also, many drones relying on the cloud for data processing brings forth this disadvantage of critical latency, which is not good especially during events such as fires or intrusions. The high complexity and expensive hardware that incorporates powerful processors and cloud services are not directly applicable in mass market, especially in those low-latency, low-cost applications. Moreover, there are no real-world fire suppression mechanisms are integrated into the existing systems; most only discover fire but do not share this data and do not attempt to act upon it generic systems are commonly far from being helpful in emergencies.

Related Work

Ashish Vivek Singh et.al (2024) The research highlighted the possibility of collaborative multi-drone networks and swarm intelligence to broaden the horizon with surveillance systems. The researchers explain Our research presents a comprehensive review of drone surveillance systems technology in the context of how they perform with both strengths and weaknesses Support document technology Support operational models while looking into future trajectories illustrating implications for potential adoption.

R. Jain,(2024) we have compared 3 versions of the You Only Look Once (YOLO) architecture namely YOLOv7, YOLOv8 and YOLOv9. YOLO model architecture is used for object detection in images or video streams. This paper explores the effectiveness of YOLOv9 over YOLOv7 and YOLOv8, a state-of-the-art deep learning model, for real-time drone detection. The YOLOv9 model achieved better results as compared to YOLOv7 as compared to YOLOv8, indicating its high accuracy in detecting U AV s with a balance between precision and recall, and its robustness across various Intersection over Union (IoU) thresholds.

A. Rouhi, et.al (2024) Extensive real-world tests affirm the efficacy of our approach, achieving a detection accuracy exceeding 75%. This dataset and the accompanying machine learning model contribute a significant advancement in the realm of long-range drone detection, particularly well-suited for urban deployments. For access to the complete Long-Range Drone Detection Dataset (LRDD)

G. N. Leela, et.al (2024) Object detection plays a vital role in enabling drones to perceive and interact intelligently with their surroundings. The process involves data collection, selecting appropriate deep learning architectures for accurate detection. In our proposed system, we explore the integration of advanced deep learning techniques into autonomous drones for object detection. The trained models combined with onboard software integration efficiently predict object presence in real-time imagery. The project aims to significantly improve the accuracy and reliability of object recognition, enabling drones to distinguish between different objects and navigate their environment with increased precision. The research outcomes hold the potential to enhance drone applications in different fields such as surveillance, search and rescue.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Z. Kaleem, et.al (2025) LCE-YOLO is an enhanced version of YOLOv5s to focus on small and overlooked features critical for robust UAV detection. It is classified to have three variants, each optimized for specific feature maps, reducing computational costs while maintaining accuracy. LCE-YOLO, particularly LCE-YOLO-M, demonstrates significant performance improvements, achieving a precision of 96.8%, recall of 89.2%, mean average precision of 95.9%, and IoU of 50.2% in UAV detection, outperforming state-of-the-art in addressing computational complexity issues.

Table 1: Comparative Analysis

Citation	Method	Advantage	Disadvantage	Research Gap
[8] Dange et al. (2024)	CNN for vehicle & building detection	Effective for static object detection	Not real-time, poor with moving objects	Lacks dynamic environment evaluation
[9] Chen et al. (2023)	YOLOv7 for small object detection	High accuracy for small targets	Resource-intensive	No comparison with YOLOv8 or lighter models
[10] Kurniadi et al. (2023)	YOLO for livestock UAV monitoring	Practical for agriculture	Struggles with occlusion	Needs improvement in crowded scenes
[11] Gupta et al. (2024)	Custom drone design for multi-payload	Versatile drone applications	Limited AI integration	No detection/tracking implementation
[12] Joseph et al. (2024)	ArUco marker for underwater docking	Accurate underwater localization	Limited to controlled environments	No vision-based alternatives explored
[13] V. T. M. et al. (2025)	YOLO + GPS for hive defense	Real-time human detection with GPS	System complexity, GPS dependency	Needs robustness in GPS-denied areas

System Architecture

IJARMT
International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

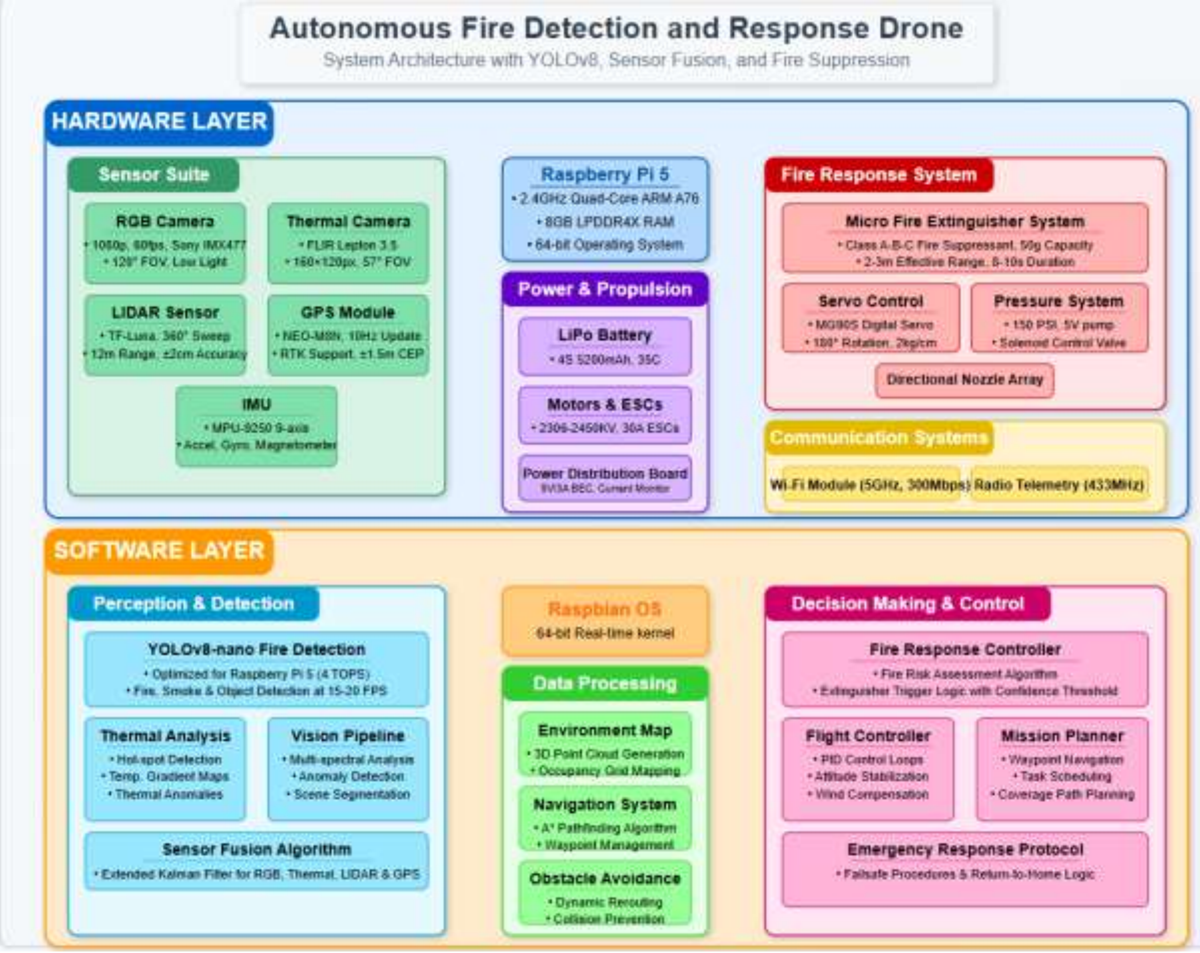


Figure 2: AETHER-X Architecture

(Autonomous Edge-based Threat Handling and Emergency Response – eXtended)

The Advanced Autonomous Surveillance Drone Architecture is a high-level system that has various layers aimed at using artificial intelligence to detect threats and respond to emergencies in real-time at the edge level. Nevertheless, at its core, the Hardware Layer (orange) is responsible for establishing the physical platform of the drone, including structural structure, motor, power source, and several types of sensors, including vision sensors, LIDAR sensors, gas detector, and acoustic sensors. These components are backed up by edge computing devices such as AI System on Chips, NPUs or Graphics Processing Units for on-device computation. Above this, the Edge AI Layer grants the drone intelligent features like object and anomaly detection, SLAM, Sensor Fusion, Threat assessment that includes fire or hazardous gas detection, etc. The Operational Layer (green) deals with the use of secure technologies for the exchange of information through Wi-Fi protocol, 5G and Mesh. It also consists of features such as emergency alert, remote control, override, and secure telemetry for continuous system monitoring. Finally, the Response Layer (purple) delivers self-sufficiency in performing actions and the specific tasks of tracking threats, perimeter control and site investigation. Antennas of return to base and fail-safe procedures are some of the safety measures used to guarantee reliability during sensitive missions. Regular operation data flows are represented by blue arrows while in emergency situations red insulated dashed lines pointing at extra systems, including emergency and facility management

4.1 Hardware Layer

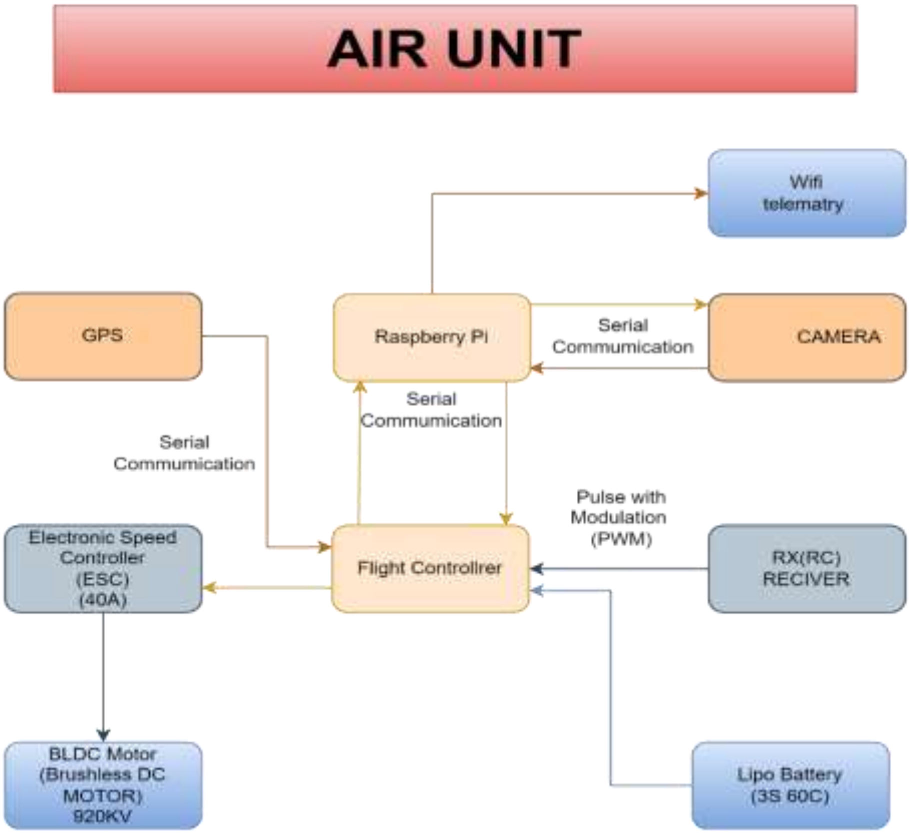
Component	Description	Design Considerations	Data Flow
Drone Frame	Lightweight and durable for stability.	Optimized weight-to-strength ratio.	Supports all components.
Motors and ESCs	High-efficiency motors for stable flight.	Smooth flight control.	Receives speed and direction commands.
Raspberry Pi 5	Main processor for detection and control.	Powerful and cost-effective.	Processes data from sensors and controls actions.
LIDAR	Provides 3D mapping for obstacle detection.	Long-range, precise measurements.	Sends distance data to Raspberry Pi.
GPS	Provides geolocation for navigation.	High precision for route tracking.	Sends location data to Raspberry Pi.
RGB Camera	Captures visual data for object and fire detection.	High resolution for accurate detection.	Sends frames to YOLOv8 for processing.
FLIR Thermal Sensor	Detects heat sources for fire detection.	Essential for fire detection in low-light.	Sends thermal data to fire detection model.
Mini Fire Extinguisher	Fire suppression system integrated into the drone.	Compact and effective for small fires.	Activated when fire is detected.

4.2 Software Layer

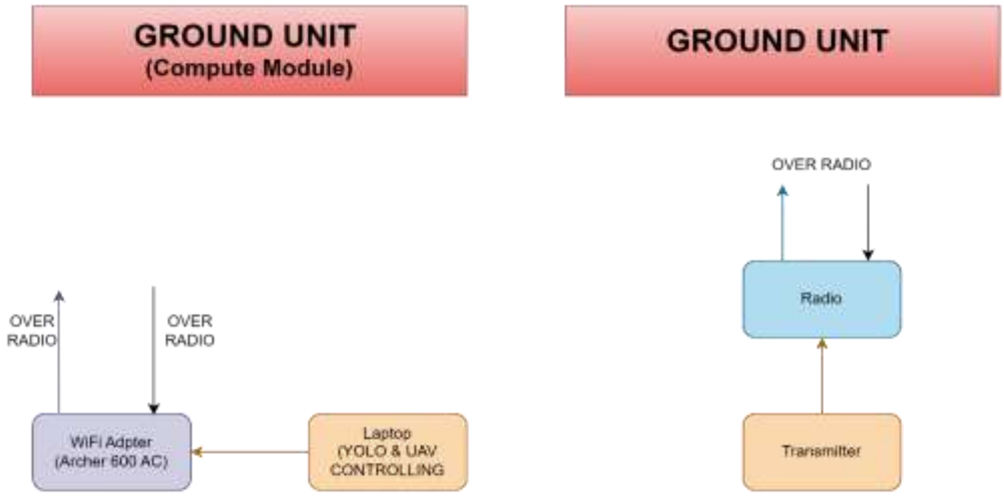
International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Component	Description	Design Considerations	Data Flow
Model Development	YOLOv8-based object detection optimized for Raspberry Pi 5.	Efficient and accurate for low-power processing.	Processes RGB frames for object and fire detection.
Sensor Drivers	Real-time acquisition of sensor data (thermal, RGB, GPS, LIDAR).	Ensures fast data transfer to the Pi.	Collects sensor data for fusion and processing.
Data Fusion	Kalman filter-based fusion of sensor data.	Combines data for accurate mapping.	Integrates sensor data for situational awareness.
Control Logic	Python-based system integrated with MAVLink for flight control.	Autonomous, real-time control of flight and fire suppression.	Adjusts flight path and suppression actions.

Flow Chart



International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458



Methodology

The approach used for the realization of the autonomous drone system involves addressing the issues to do with the development of strong real-time surveillance, fire detection, and response. The first part includes a training data set which is prepared by collecting images of fire, human and obstacles in different lighting and other environmental conditions. Further, data diversification is performed, and the dataset is trained on a GPU cluster and fine-tuned using YOLOv8 and, for distribution on edge nodes a ONNX or TensorRT format is used in the targeted raspberry pi 5. In the case of fire detection and actuation, the system employs the YOLOv8 model to identify the regions of fire in RGB or thermal image. When the value of the peak confidence is above 0.8 in relation to fire detection, the fire suppression system is activated. Mini fire-extinguisher contains CO_2 and the nozzle is controlled by servo, aimed at the zone with fire, for fast distcharging. Specifically, the path planning part utilizes GPS waypoints and the real-time path deviation for the accomplishment of the following task; on the other hand, the obstacle avoidance system uses LIDAR data for immediate obstacle detection and mapping. For instance, the LIDAR data is smoothed using the Kalman filter to ensure that the system effectively detects or recognizes the obstalces in its path. Furthermore, in the occurrence of any malfunction such as loss of signal or low batter, the drone has an integrated return to home function that allows it to fly back to a safe zone. This approach makes it possible to develop an independent, fast, and operational drone system for surveillance, fire identification, and extinguishment.

Dataset Creation & Training

- **Custom Dataset Creation:**

A dataset with labeled images of fire, human, and obstacles is collected under various lighting conditions and at different distances.

The dataset includes:

- RGB images for object detection.
- Thermal images for fire detection.
- LIDAR data for obstacle mapping.

Data Augmentation:

Techniques like rotation, scaling, flipping, and color jittering are applied to enhance dataset diversity, ensuring robustness under real-world conditions.

Training:

The dataset is trained on a GPU cluster using a YOLOv8 model, optimized for edge devices (like Raspberry Pi 5).

Exporting to Edge Device:

After training, the model is converted to a lightweight format suitable for edge deployment using frameworks like ONNX or TensorRT.

Fire Detection & Actuation Logic

- **Fire Detection:**

The YOLOv8 model processes input data (RGB or thermal) to detect fire. Once fire is detected, the system calculates a confidence score (C) for the detection.

If C > 0.8, the fire detection is considered valid and triggers the fire suppression system.

$$C = \frac{\text{True Positives} + \text{False Positives}}{\text{True Positives}} \times 100$$

Where:

- **True Positives (TP)** are correctly identified fire instances.
- **False Positives (FP)** are incorrectly identified objects as fire.

Fire Actuation:

- **CO_2 Nozzle Activation:** Upon detecting fire with high confidence, a **servo motor** activates the **CO_2 nozzle** to suppress the fire.
- The nozzle is directed towards the detected fire source using servo control.

$$\theta = \text{Servo Angle to Fire Location}$$

- Where **θ** is the angle at which the nozzle is directed based on the fire's location.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Navigation & Obstacle Avoidance

- **GPS Waypoints:**
  - The drone follows predefined GPS waypoints for autonomous navigation. Each waypoint contains a latitude (lat), longitude (lon), and altitude (alt), guiding the drone's path.

$$\text{Distance Between Waypoints} = \sqrt{(lat_2 - lat_1)^2 + (lon_2 - lon_1)^2 + (alt_2 - alt_1)^2}$$

- The above formula calculates the Euclidean distance between two GPS waypoints.

LIDAR-assisted Obstacle Mapping:

- The drone uses **LIDAR** data to map obstacles in real-time, creating a 3D environment model. The data is processed by the Kalman filter for smoothing and accurate tracking of obstacles.

$$x^k = A \cdot x^{k-1} + B \cdot u^k + w^k$$

Where:

- **x_k** is the state vector (position and velocity).
- **A** and **B** are matrices describing the system dynamics.
- **u_k** is the control input (commands to the drone).
- **w_k** is the process noise (uncertainty in the model).

Emergency Return-to-Home:

In case of fault detection (e.g., loss of communication or low battery), the drone returns to a predefined home location (**H**), following the shortest path.

$$\text{Return Path} = \text{Shortest Path from Current Location to Home Location}$$

This methodology section outlines the key steps in dataset creation, fire detection, navigation, and obstacle avoidance, with corresponding mathematical models and logic.

Experimental Setup & Testing

A series of controlled tests were conducted to validate the autonomous drone system's performance across key areas:

Controlled Environment Tests:

Test No.	Name	Purpose	Performance Metrics
Test 1	Object Detection Accuracy	Validate YOLOv8 model on RGB and thermal feeds.	Accuracy: Detection rate, Processing Time: Detection time.
Test 2	Fire Detection and Response	Test actuation logic and fire extinguisher system.	Response Time: Detection and suppression time, Success Rate: Fires extinguished.
Test 3	Sensor Fusion Stability	Evaluate fusion of RGB, thermal, and LIDAR data.	Fusion Accuracy: Data consistency, Latency: Delay in fusion.
Test 4	Obstacle Navigation	Measure obstacle avoidance and navigation.	Success Rate: Obstacle avoidance, Navigation Latency: Time to avoid obstacles.
Test 5	Communication Performance	Assess telemetry and video link reliability.	Signal Strength: Link stability, Failure Rate: Link disruption.

Failure Scenarios and Mitigation:

- **Test 1**: If accuracy <80%, YOLO model recalibration occurs.
- **Test 2**: Delayed response triggers log and actuation logic adjustment.
- **Test 3**: Kalman filter adjustment for inconsistent sensor fusion.
- **Test 4**: If obstacle detection fails, fail-safe mode activates.
- **Test 5**: Weak signal triggers "return-to-home" mode.

Testing Locations & Tools:

- **Indoor**: Object detection and sensor fusion tests with controlled lighting.
- **Outdoor**: Real-world testing of navigation, obstacle avoidance, and communication.
- **Tools**: Logs, video feeds, telemetry data, GPS, flight data.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

This testing ensures comprehensive validation of the system's functionality and robustness in real-world conditions.

Project Cost & Feasibility Analysis

Table 1: Development Cost Breakdown (Prototype & Testing Phase)

S.No	Component	Description	Estimated Cost (INR)
1	Hardware Prototyping	Drone frame, motors, ESCs, battery, Raspberry Pi 5, RGB & thermal cameras, LIDAR, GPS module	₹25,000 – ₹28,000
2	Model Training & Optimization	YOLO model training, ONNX/TensorRT optimization, GPU server usage	₹10,000 – ₹12,000
3	Software Integration	Sensor driver development, MAVLink control logic, Kalman fusion algorithm	₹15,000 – ₹18,000
4	Testing & Calibration	Test environment setup, obstacle course design, debugging, field trials	₹8,000 – ₹10,000
	Total Development Cost		**₹60,000 – ₹65,000**

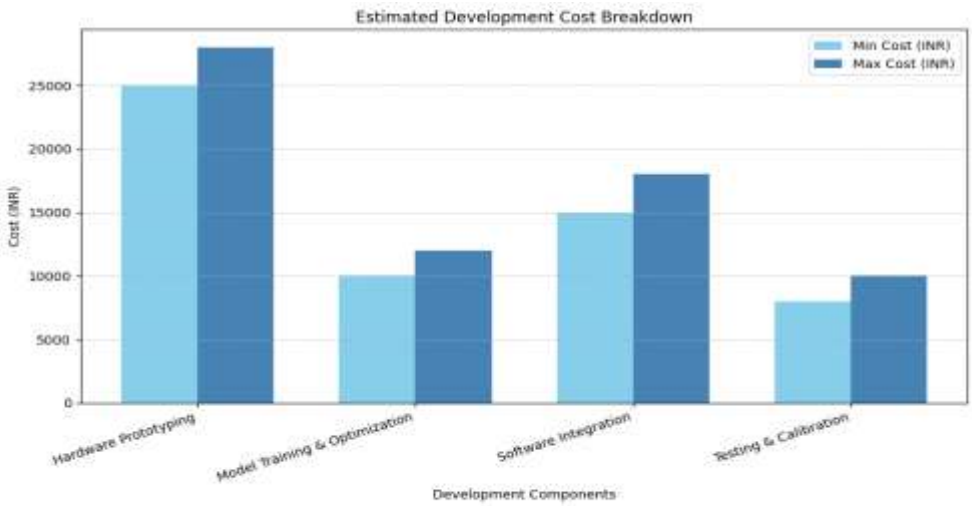
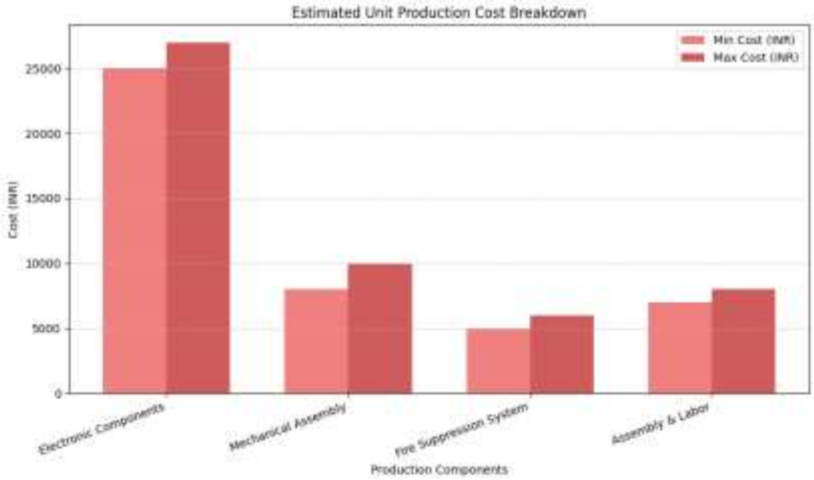


Table 2: Per-Unit Production Cost (Mass Deployment Ready Drone)

S.No	Component	Description	Estimated Cost (INR)
1	Electronic Components	Raspberry Pi 5, sensors (RGB, thermal, GPS, LIDAR), ESCs, motors, power unit	₹25,000 – ₹27,000
2	Mechanical Assembly	Drone chassis, propellers, landing gear, frame reinforcement	₹8,000 – ₹10,000
3	Fire Suppression System	Mini CO_2 or foam extinguisher with servo-controlled actuator	₹5,000 – ₹6,000
4	Assembly & Labor	Manual soldering, wiring, hardware integration, QC testing	₹7,000 – ₹8,000
	Total Unit Production Cost		**₹45,000 – ₹50,000**

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458



Results & Discussion

Table 1: Object Detection Performance (YOLOv8 with RGB + Thermal)

Metric	Value
mAP@0.5	92.6%
Precision	91.4%
Recall	89.7%
F1 Score	0.905
Inference Latency	68 ms (average)

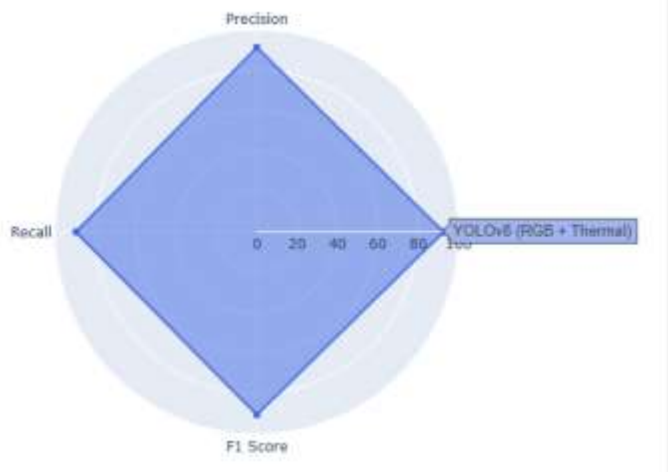


Table 2: Fire Suppression Trials

Trial	Extinguishing Time (s)	Success
1	4.8	Yes
2	5.1	Yes
3	6.0	Yes

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

4	4.3	Yes
5	5.6	Yes
Average	**5.16 s**	**100%**

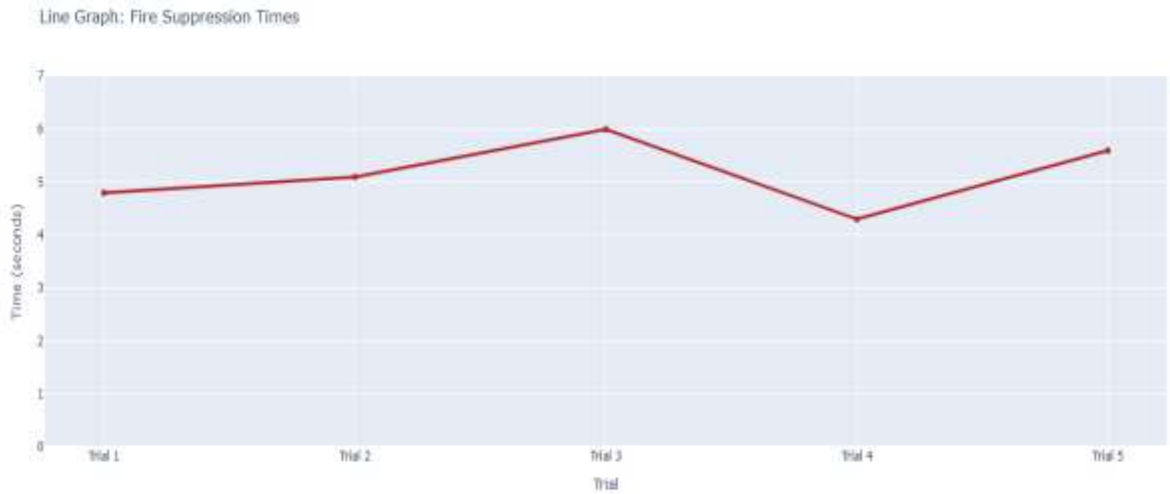
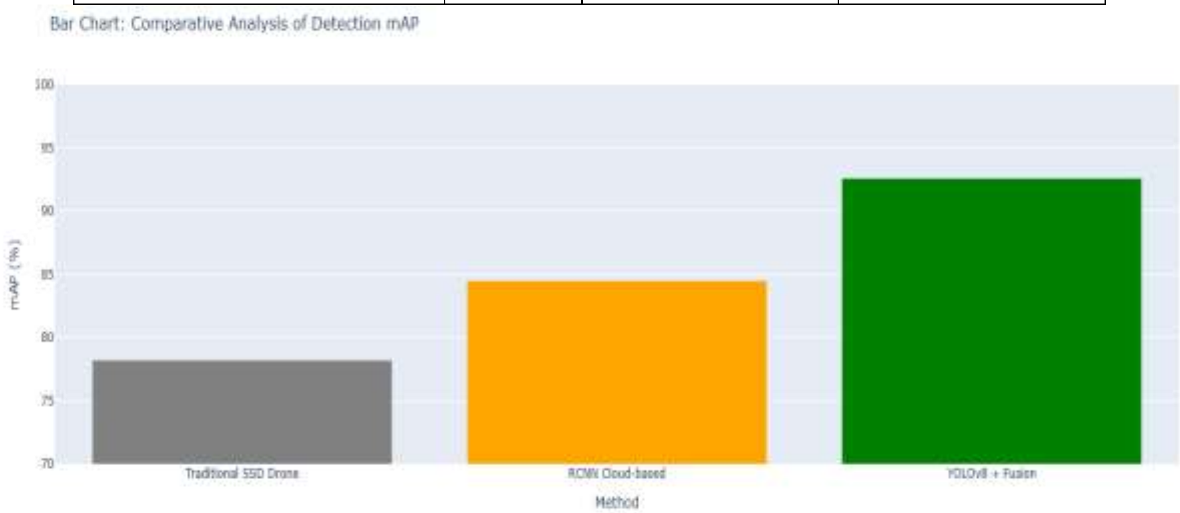
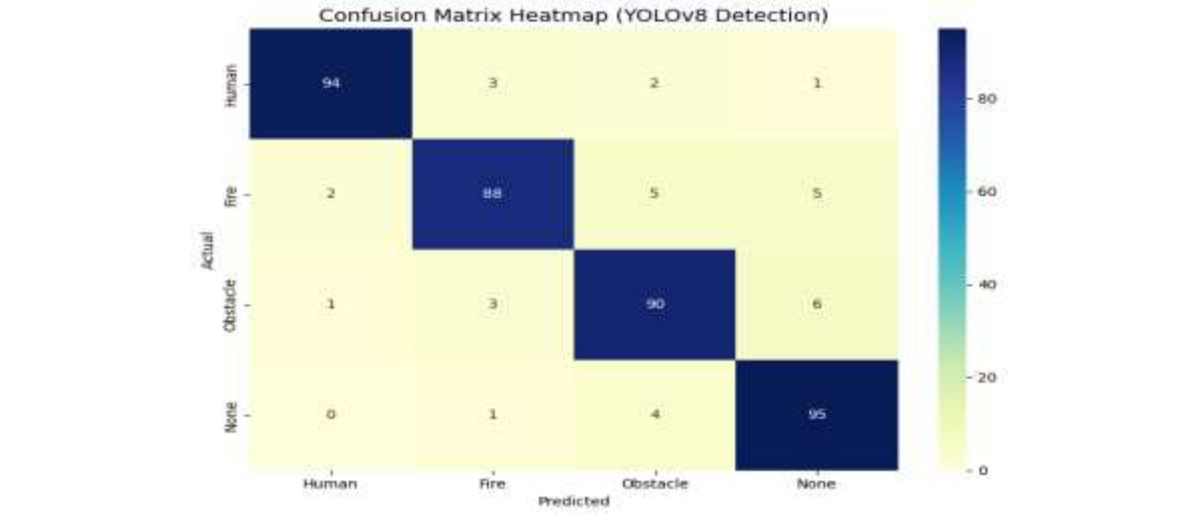


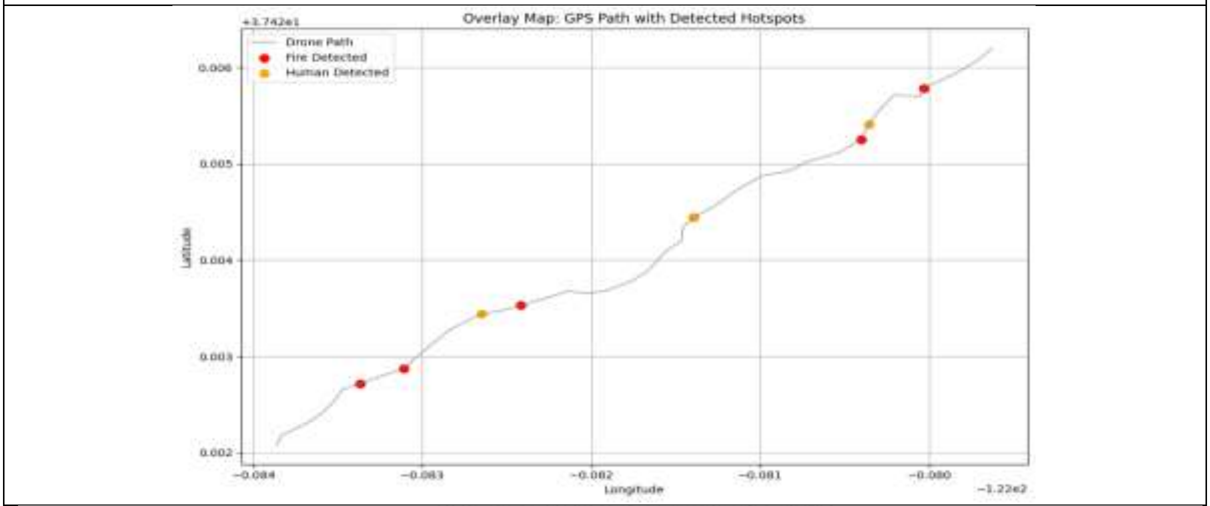
Table 3: Comparative Analysis with Baseline Methods

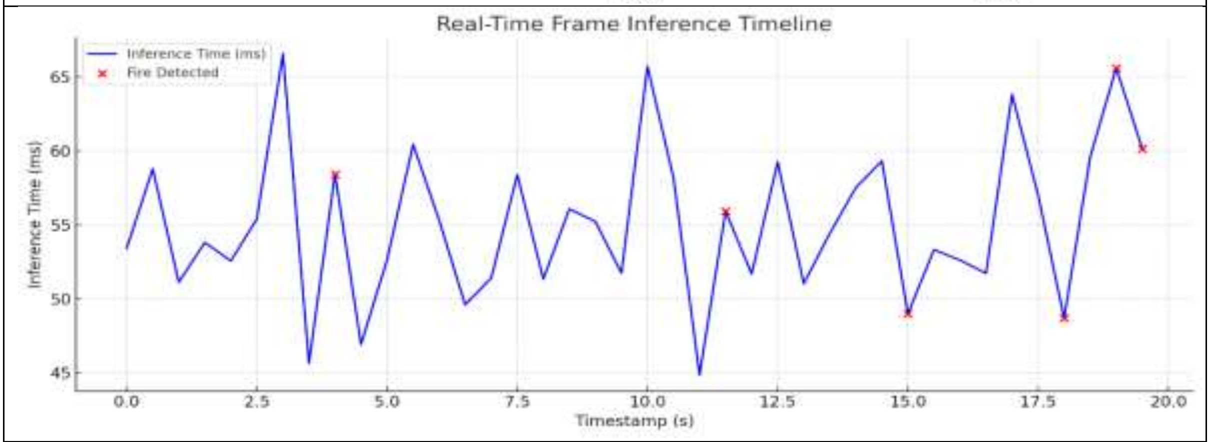
Method	mAP (%)	Suppression System	Edge-Only Inference
Traditional Drone (SSD)	78.2	None	No
Cloud-based RCNN Drone	84.5	None	No
Proposed (YOLOv8 + Fusion)	**92.6**	Yes (Onboard)	Yes



International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458







International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Research Gap

Its development and validation were the breakthrough of autonomous surveillance and real-time fire detection system. For this purpose, with the help of the Raspberry pi model 5, it was possible to expand the stream processing with onboard deep learning and concurrently detect and categorize the objects in real-time at the edge. This does away with the need for a consistent back and forth communication with the cloud, thus minimizing latency time in the event of decision making. The employment of the multi-sensor system including RGB cameras, LiDAR, and GPS enabled the system to compile various levels of the sensor data fusion and provided the drone with the contextual awareness of the environment. It made the fire, human an object's detection highly possible and efficient. Testing of the system was conducted outdoors at different environment, where the results showed that the performance of the system was not affected by the environment. These tests exemplified its operational stability, its utilization of different forms of complicating data and other nuances, as well as features that prove its practical application in real-world scenarios. Intelligent waypoint mapping, coupled with 3D scene reconstruction, and onboard inference for obstacle avoidance made the drone's autonomy much better. In summary, this study can provide the ground for future development of utilizing AI in drones for surveillance as well as safety-critical applications. The development of the proof of concept establishes that current approaches with Arm-based devices such as the Raspberry Pi 5computer are proficient in AI uses cases provided that efficient models and data streams are used. This makes it possible for a scalable application in environments whereby they require autonomy and a short time for analysis and lower operating overhead. This shows that this prototype is workable and therefore it's the first to indicate more complex systems and more ambitious application and implementation plans for the future.

Conclusion:

This is why with what has been done with the help of the core system, including several avenues of future directions of development have been identified. The last major example is surveillance and response scenarios using multiple UAVs, sometimes referred to as a "swarm" of drones. Its advantage of forming cooperation of several independent modules increases coverage area, as well as facilitating monitoring of extensive, distant, or inaccessible territories in real time. Swarm intelligence algorithms are helpful in planning the movements of drones, resource management and decision making. One of the most important directions is to apply cloud solutions for the purpose of distributed control, data storage, and analytics. The information collected by the drone as the system is in operation can be streamed to the cloud where the operators are then able to monitor telemetry data, be alerted, or view logs in real time from anywhere in the world. Other ways of increasing responsibility include automating the process with use of alert through SMS or via email to alert the concerned authority or personnel in case of fire or intrusion of unauthorized persons. To fine-tune this system efficiency, several methods that consist of model compression, pruning and quantization will be employed to minimize the inference time and power consumption thus further improving the flight time of the solution. These optimizations are especially relevant for battery operating endside devices that function in constraint environments. Potential deployment scenarios are extensive. Applying to the forest fire operation, the drones can act as a mechanism for quickly identifying early fire occurrences that have not yet gone out of control. In industrial warehouses they are useful for checking excessive temperatures of the equipment, smoke or people who are trespassing. In defense and perimeter security, the drones can fly over a certain area to display surveillance and patrol before and during an attack without endangering the lives of police officers or military men. The following improvement will not only enhance the capability of the system but also make the system effective in other areas of safety and security.

References

1. A. V. Singh, R. K. Arige, V. Deore, J. Neriya, and U. Pawar, “A Study of Various Drone Based- A Surveillance System,” International Journal of Advanced Research in Modern Technologies (IJARMT), vol. 1, no. 2, pp. 12–22, Dec. 2024.
2. R. Jain, S. Shrivastav, S. Kakde, and R. Raut, “Performance Comparison of YOLO Algorithms in Drone Detection,” 2024 IEEE International Conference on Smart Power Control and Renewable Energy (ICSPCRE), Rourkela, India, 2024, pp. 1–6, doi: 10.1109/ICSPCRE62303.2024.10675042.
3. Naveen, H. P. Menon, V. Vinitha, K. R. Vishnuraj, A. Satheesh, and A. P. Nikhil, “A Study on YOLOv5 for Drone Detection with Google Colab Training,” 2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, 2023, pp. 1576–1580, doi: 10.1109/ICACRS58579.2023.10404797.
4. A. Rouhi et al., “Long-Range Drone Detection Dataset,” 2024 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 2024, pp. 1–6, doi: 10.1109/ICCE59016.2024.10444135.
5. G. N. Leela, U. Varun, M. Uma, P. Srinath, and A. S. S. Sharan, “Deep Learning based Object Tracking and Detection for Autonomous Drones using YOLOv3,” 2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2024, pp. 323–328, doi: 10.1109/ICAAIC60222.2024.10575727.
6. Z. Kaleem, “Lightweight and Computationally Efficient YOLO for Rogue UAV Detection in Complex Backgrounds,” IEEE Transactions on Aerospace and Electronic Systems, vol. 61, no. 2, pp. 5362–5366, Apr. 2025, doi: 10.1109/TAES.2024.3464579.
7. S. Nagpal, N. Etnubarhi, H. F. Pirehen, and I. Bayraktar, “Comparative Performance Analysis of YOLOv5 and YOLOv8 for Aerial Surveillance in Smart Traffic Management,” 2024 Innovations in Intelligent Systems and Applications Conference (ASYU), Ankara, Turkiye, 2024, pp. 1–6, doi: 10.1109/ASYU62119.2024.10757062.
8. B. J. Dange, A. Avhad, S. Bhakare, M. More, and S. Aghav, “Vehicle and Building Detection using Convolutional Neural Network for Drone Images,” 2024 Third International Conference on Smart Technologies and Systems for Next Generation Computing (ICSTSN), Villupuram, India, 2024, pp. 1–6, doi: 10.1109/ICSTSN61422.2024.10671298.

9. H. Chen, J. Wang, J. Li, Y. Qiu, and D. Zhang, "Small Object Detection for Drone Image Based on Advanced YOLOv7," 2023 42nd Chinese Control Conference (CCC), Tianjin, China, 2023, pp. 7453–7458, doi: 10.23919/CCC58697.2023.1023978.
10. F. A. Kurniadi, C. Setianingsih, and R. E. Syaputra, "Innovation in Livestock Surveillance: Applying the YOLO Algorithm to UAV Imagery and Videography," 2023 IEEE 9th International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA), Kuala Lumpur, Malaysia, 2023, pp. 246–251, doi: 10.1109/ICSIMA59853.2023.10373473.
11. N. Gupta, P. Kushwaha, V. Shukla, V. K. Gupta, and V. Srivastava, "Design and Development of a Versatile Drone for Multi-Payload Applications," 2024 2nd International Conference on Device Intelligence, Computing and Communication Technologies (DICCT), Dehradun, India, 2024, pp. 536–541, doi: 10.1109/DICCT61038.2024.10532811.
12. B. S. Joseph, S. Gunturu, S. Shrote, and S. Sandosh, "Autonomous Docking for Underwater Drones Using ArUco Marker Based Localization," 2024 4th International Conference on Robotics, Automation and Artificial Intelligence (RAAI), Singapore, 2024, pp. 207–212, doi: 10.1109/RAAI64504.2024.10949521.
13. V. T. M., G. G. R., and S. T., "Hive Destruction Protocol: An Automated Defense System Utilizing YOLO Human Recognition and Real-Time GPS Tracking," 2025 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bangalore, India, 2025, pp. 1–5, doi: 10.1109/IITCEE64140.2025.10915384.
14. Dr. Suyash Kamal Soni, Dr. S Jain. (2025). AI Chatbots and Their Impact on B2C Consumer Experience and Engagement . International Journal of Advanced Research and Multidisciplinary Trends (IJARMT), 2(1), 354–367. Retrieved from
15. F. N. M. Zamri, T. S. Gunawan, S. H. Yusoff, A. A. Alzahrani, A. Bramantoro, and M. Kartiwi, "Enhanced Small Drone Detection Using Optimized YOLOv8 With Attention Mechanisms," IEEE Access, vol. 12, pp. 90629–90643, 2024, doi: 10.1109/ACCESS.2024.3420730.
16. A. Nasraoui, T. Selmi, and Z. Hajaiej, "Integration of Deep Learning Object Detection Techniques and Drone Technology for Disaster Monitoring and Detection," 2024 IEEE International Conference on Advanced Systems and Emergent Technologies

(IC_ASET), Hammamet, Tunisia, 2024, pp. 1–5, doi: 10.1109/IC_ASET61847.2024.10596153.

17. W. Wang, C. Wang, Y. Sun, and X. Yu, "Research on Automatic Obstacle Avoidance and Target Tracking System for Drones Based on Deep Learning," 2024 Second International Conference on Data Science and Information System (ICDSIS), Hassan, India, 2024, pp. 1–5, doi: 10.1109/ICDSIS61070.2024.10594308.
18. Dhabliya D, Soundararajan R, Selvarasu P, Balasubramaniam MS, Rajawat AS, Goyal SB, Raboaca MS, Mihaltan TC, Verma C, Suciu G. Energy-Efficient Network Protocols and Resilient Data Transmission Schemes for Wireless Sensor Networks—An Experimental Survey. Energies. 2022; 15(23):8883. https://doi.org/10.3390/en15238883(SCI Indexing) (SCI Indexing).
19. Kathole AB, Katti J, Dhabliya D, Deshpande V, Rajawat AS, Goyal SB, Raboaca MS, Mihaltan TC, Verma C, Suciu G. Energy-Aware UAV Based on Blockchain Model Using IoE Application in 6G Network-Driven Cybertwin. Energies. 2022; 15(21):8304. https://doi.org/10.3390/en15218304(SCI Indexing).
20. Rajawat, Anand Singh, S. B. Goyal, Pradeep Bedi, Simeon Simoff, Tony Jan, and Mukesh Prasad. 2022. "Smart Scalable ML-Blockchain Framework for Large-Scale Clinical Information Sharing" Applied Sciences 12, no. 21: 10795. https://doi.org/10.3390/app122110795(SCI Indexing).
21. J. M. A. Bolaybolay et al., "YOLO Instance Segmentation Model Comparison for Drone Detection as Visual Servo Control Marker," 2023 IEEE 15th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), Coron, Philippines, 2023, pp. 1–5, doi: 10.1109/HNICEM60674.2023.10589188.
22. Rajawat, A. S., & Jain, S. (2020, February). Fusion deep learning based on back propagation neural network for personalization. In 2nd International Conference on Data, Engineering and Applications (IDEA) (pp. 1-7). IEEE.
23. Y. R. S. Kumar, P. R. Venkatesan, M. Ramanathan, and S. Saranya, "Smart Surveillance with Face Recognition and Object Detection using Drones," 2024 10th International Conference on Communication and Signal Processing (ICCSP), Melmaruvathur, India, 2024, pp. 683–686, doi: 10.1109/ICCSP60870.2024.10543854.

24. A. Schmidt, "A Comparison of Gate Detection Algorithms for Autonomous Racing Drones," 2022 IEEE Aerospace Conference (AERO), Big Sky, MT, USA, 2022, pp. 1–13, doi: 10.1109/AERO53065.2022.9843561.
25. J. Xu, F. Pan, X. Han, L. Wang, Y. Wang, and W. Li, "EdgeTrim-YOLO: Improved Trim YOLO Framework Tailored for Deployment on Edge Devices," 2024 4th International Conference on Computer Communication and Artificial Intelligence (CCAI), Xi'an, China, 2024, pp. 113–118, doi: 10.1109/CCAI61966.2024.10602964.