

TRIBHUVAN UNIVERSITY
INSTITUTE OF ENGINEERING
PULCHOWK CAMPUS

DEVELOPMENT OF REAL-TIME FOREST FIRE DETECTION AND ALERTING SYSTEM USING UAV-BASED COMPUTER VISION WITH RGB CAMERA

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DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERING
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LETTER OF APPROVAL

The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a project report entitled **"DEVELOPMENT OF REAL TIME FOREST FIRE DETECTION AND ALERTING SYSTEM USING UAV BASED COMPUTER VISION WITH RGB CAMERA" submitted by Abinash Ghimire B.K, Abinash Kumar Yadav, Chandan Kumar Rajak and Dipak Raut Amat** in partial fulfillment of the requirement for the Bachelor's Degree in Aerospace Engineering.

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ABSTRACT

Forest fires pose a serious threat to ecosystems, human life, and economic stability, particularly in countries like Nepal, where rugged terrain and limited infrastructure hinder rapid response. Early detection and timely confirmation of fire incidents are crucial to minimizing damage and improving disaster management efficiency.

This project presents the development of a UAV-based real-time forest fire detection and alerting system using computer vision with an RGB camera. The proposed system utilizes an unmanned aerial vehicle equipped with an RGB camera and an onboard processing unit (Raspberry Pi) to continuously monitor areas at high risk of fire. A deep learning-based object detection model, YOLO (You Only Look Once), is employed to detect fire and smoke in real-time from aerial imagery. The YOLOv8n model was trained on a combined dataset of 22,000 images, integrating the public D-Fire dataset with custom data collected from local community forests to ensure regional adaptability. The system achieves a mean Average Precision (mAP@0.5) of 0.671, an overall precision of 0.724, and a recall of 0.604.

Upon detection, the system records the drone's GPS location and heading at the moment the fire is captured. It then transmits alerts, along with visual evidence, to a ground control station through a dashboard, enabling rapid decision-making.

The system is designed to operate effectively in remote and infrastructure-limited regions, offering improved detection before spreading, faster response times, and adaptability to diverse environmental conditions. This approach supports community-based forest monitoring and contributes to sustainable forest management and disaster mitigation efforts in Nepal.

Keywords: Computer Vision, Forest fire detection, GPS, Real-time alerting, RGB, UAV, YOLO

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LIST OF ABBREVIATIONS

AGL	Above Ground Level
AI	Artificial Intelligence
AP	Average Precision
AUW	All Up Weight
AWS	Amazon Web Services
BLDC	Brushless Direct Current
BLOS	Beyond Line of Sight
CATIA	Computer Aided Three-Dimensional Interactive Application
CNN	Convolutional Neural Network
CoG	Center of Gravity
CPU	Central Processing Unit
CSI	Camera Serial Interface
CSP	Cross Stage Partial
CUDA	Compute Unified Device Architecture
DFL	Distribution Focal Loss
ECEF	Earth Centered Earth Fixed
EKF	Extended Kalman Filter
ESC	Electronic Speed Controller
FCU	Flight Computer Unit
FN	False Negative
FP	False Positive
FPS	Frames Per Second
GCS	Ground Control Station
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GPU	Graphics Processing Unit
HDOP	Horizontal Dilution of Precision
ICIMOD	International Centre for the Integrated Mountain Development
IMU	Inertial Measurement Unit
IoT	Internet of Things
IoU	Intersection over Union
KV	RPM per Volt (motor constant)
LAN	Local Area Network
Li-Po	Lithium Polymer
LoRa	Long Range
LPWAN	Low Power Wide Area Network

mAP	Mean Average Precision
MAVLink	Micro Air Vehicle Link
NB-IoT	Narrowband Internet of Things
NED	North East Down
NMS	Non-Maximum Suppression
ONNX	Open Neural Network Exchange
OpenCV	Open Source Computer Vision
PAN	Path Aggregation Network
PID	Proportional Integral Derivative
PR	Precision-Recall
PWM	Pulse Width Modulation
PX4	Pixhawk 4 Autopilot Firmware
QGC	QGroundControl
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RGB	Red Green Blue
RPi	Raspberry Pi
RPM	Revolutions Per Minute
RTL	Return to Launch
SATCOM	Satellite Communication
SMS	Short Message Service
SMTP	Simple Mail Transfer Protocol
SSH	Secure Shell
TP	True Positive
UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle
UART	Universal Asynchronous Receiver Transmitter
VTOL	Vertical Takeoff and Landing
WiFi	Wireless Fidelity
YOLO	You Only Look Once

CHAPTER ONE:
INTRODUCTION

1.1 Background of the Study

Forests are a critical component of the Earth's ecosystem, acting as the planet's lungs, regulating climate, harboring biodiversity, and providing essential resources for human communities. However, these vital ecosystems face a constant threat from forest fires. Each year, wildfires devastate millions of hectares of forest land worldwide, leading to staggering ecological and economic losses. Beyond the immediate destruction of flora and fauna, forest fires contribute significantly to air pollution, soil erosion, and the acceleration of climate change through the release of massive quantities of carbon dioxide.

In the context of Nepal, about 46.08% of the land area is made up of forests [1], which are essential ecosystems that maintain biodiversity, control the climate, and provide for the livelihoods of over 80% of the population [2]. However, a significant hazard has emerged from the growing frequency and severity of forest fires, which are exacerbated by climate change-related factors like rising temperatures, protracted droughts, and unpredictable rainfall patterns. These fires contribute significantly to greenhouse gas emissions, which fuel the cycle of climate change, in addition to destroying biodiversity and important forest resources. Between 2001 and 2019, Nepal saw more than 38,000 forest fire incidents, with over 6,000 fire events in 2021 alone [2]. These fires have had a significant impact on local residents and protected areas.

In Nepal, most forest fires are caused by humans, either intentionally or unintentionally [2]. Most of these incidents (approximately 58–64%) are intentional forest fires, started by people like hunters, poachers, grazers, and collectors of non-timber forest products in order to facilitate hunting, encourage the growth of new grass, or clear areas for resource collection [2]. Intentional burning is also influenced by resource disputes and traditional slash-and-burn farming methods. Non-intentional fires, on the other hand, are caused by uncommon natural factors like lightning as well as carelessness, such as recklessly dropped cigarettes, unattended campfires, or unintentional spread from agricultural burning. Fire hazards have been further heightened by socio-political reasons, such as the decrease in community forest user group participation brought on by regulatory constraints. These factors have also resulted in less forest stewardship and a greater buildup of flammable items.

There are still recurring gaps in on-ground fire management, rapid response, and fuel load reduction, despite the fact that technological advancements like the Forest Fire Detection and Monitoring System, created by the International Centre for the Integrated Mountain Development (ICIMOD) and the Department of Forests and Soil Conservation, have enhanced early warning and risk mapping capabilities. Growing built-up areas and unmanaged biomass continue to increase the risk of fire.

The ongoing threat of forest fires might jeopardize attempts to preserve carbon stocks and sustainable forest management goals, notwithstanding Nepal's commitment to global

climate goals through Reducing Emissions from Deforestation and Forest Degradation (REDD+) and similar programs. In order to supplement remote sensing technology with community engagement and field-level initiatives, it is imperative that site-specific, quickly deployable early warning and mitigation systems be strengthened.

The conventional approach to forest fire detection relies heavily on human observation through watchtowers and public reports. These methods are fraught with limitations. Manned aerial surveillance is expensive, logistically complex, and poses significant risks to pilot safety. Lookout towers offer a limited field of view and are susceptible to human error, particularly during periods of fatigue. Furthermore, the time lag between the ignition of a fire and its official confirmation often allows small, manageable blazes to escalate into large-scale, uncontrollable wildfires. The critical need, therefore, is for a detection system that is rapid, accurate, cost-effective, and capable of operating in remote and hazardous environments without risking human life.

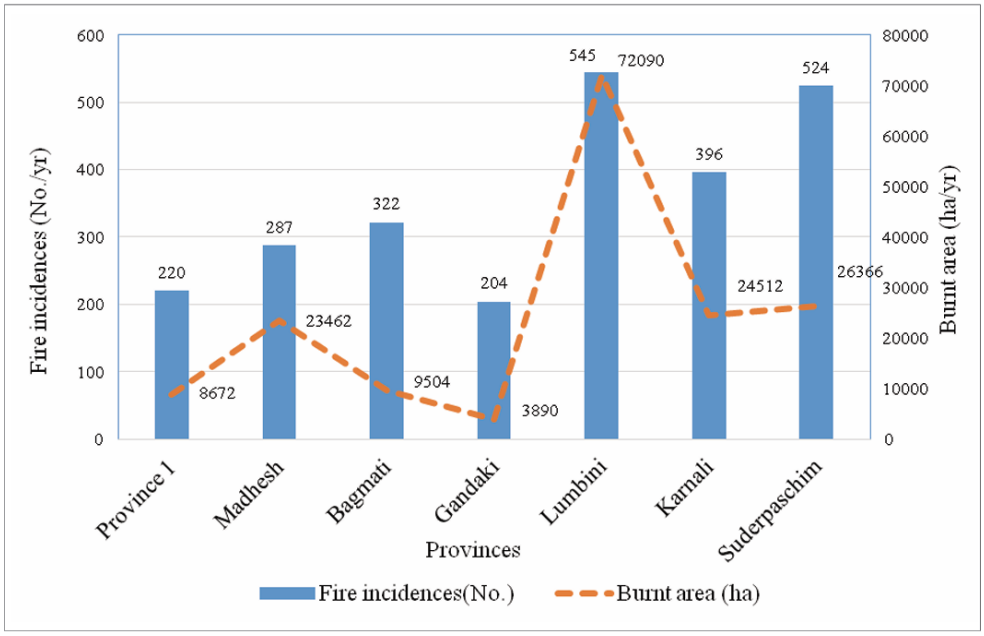


Figure 1.1: Annual Forest Fire Incidences and Burnt Area by Province [2]

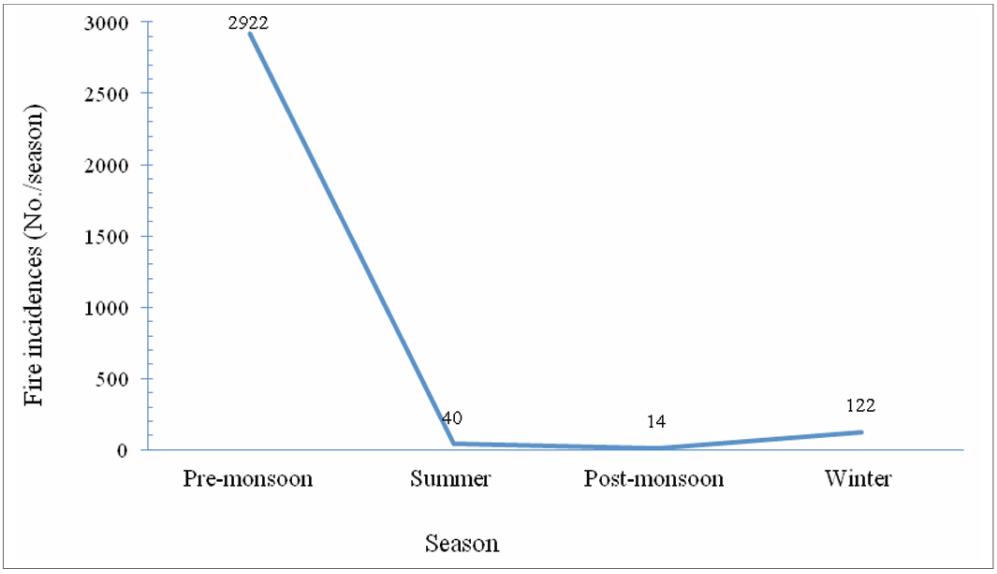


Figure 1.2: Average Forest Fire Incidences Across Seasons in Nepal [2]

1.2 Problem Statement

Forest fires continue to cause devastating ecological and economic damage, largely due to delays in detection and response [14]. Traditional monitoring methods such as watchtowers and satellites suffer from limited coverage, latency, and high operational costs. While Unmanned Aerial Vehicles (UAVs) offer a flexible and cost-effective platform for aerial surveillance, existing systems often rely on expensive thermal sensors or suffer from poor accuracy when using standard RGB cameras, especially in complex forest environments with varying lighting, smoke, and occlusions.

To address these challenges, this research focuses on developing a real-time forest fire detection system using UAVs and RGB-based computer vision. The key problem lies in achieving high detection accuracy and low false alarm rates while operating within the computational constraints of onboard UAV hardware. Therefore, a lightweight yet reliable detection algorithm is required to enable timely alerts and effective early response without dependence on specialized sensors.

1.3 Objectives

1.3.1 Main Objective

To develop a real-time forest fire detection and alerting system using UAV-based aerial surveillance integrated with computer vision for real-time monitoring and rapid response.

1.3.2 Specific Objectives

1. To assemble a UAS and integrate computer vision for aerial forest surveillance and fire detection.
2. To obtain the UAV GPS location and heading upon fire/smoke detection and transmit real-time alerts with visual evidence to a ground control station.
3. To evaluate the system performance in terms of detection accuracy and response times in different flight conditions.

1.4 Feasibility Analysis

1.4.1 Economic Feasibility

The proposed system is economically feasible due to the use of low-cost hardware components and open-source software. Compared to traditional fire detection methods such as satellite monitoring or manned patrols, the system significantly reduces operational and deployment costs while maintaining reliable performance.

1.4.2 Technical Feasibility

The system is technically feasible as it utilizes readily available UAV platforms, cameras, sensors, and onboard processing units. Computer vision libraries and flight control software required for implementation are well-established and supported by open-source communities. The integration of these components can be achieved using existing communication protocols and development tools.

1.4.3 Operational Feasibility

The system is operationally feasible as it requires minimal human intervention during operation. Once deployed, the UAV can perform autonomous monitoring missions and transmit alerts in real-time. The system can be operated by trained personnel with basic UAV and computer knowledge, making it suitable for practical field deployment.

1.5 System Requirements

1.5.1 Hardware Requirements

1. Airframe

The quadcopter frame serves as the aerial platform that carries all system components during flight. It is selected for its ability to hover stably, maneuver precisely, and operate in low-speed conditions, which are essential for continuous monitoring and accurate image capture. The frame is designed to fulfill specific requirements such as payload capacity, flight time, and maneuverability.



Figure 1.3: Quadcopter Frame [3]

2. Flight Controller

The flight controller serves as the brain of the UAV, acting as the central processing unit responsible for flight stability, navigation, and autonomous operation. It continuously reads and processes data from onboard sensors, including the accelerometer, gyroscope, and magnetometer, fusing this information using algorithms such as the Extended Kalman Filter (EKF) to maintain an accurate estimate of the UAV's position, orientation, and velocity at all times. Based on this state estimation, the flight controller generates precise motor speed commands to the Electronic Speed Controllers (ESCs), independently varying each motor's speed to control thrust, roll, pitch, and yaw with high precision. It also manages higher-level autonomous functions such as GPS-based position hold, waypoint navigation, Return to Launch (RTL), and low battery failsafe, communicating with the ground control station via the MAVLink protocol through QGroundControl. In this project, the Pixhawk flight controller running PX4 firmware is used due to its reliability, open-source flexibility, and full compatibility with the autonomous mission requirements of the system.

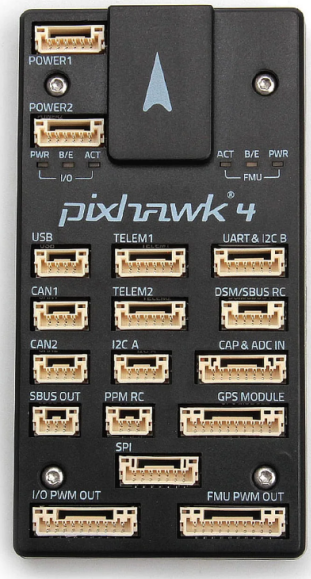


Figure 1.4: Pixhawk 4 Flight Controller [4]

3. Companion Computer

The Raspberry Pi 5 serves as the onboard companion computer of the UAV, responsible for handling all real-time fire and smoke detection processing during flight. It continuously receives the live camera feed from the onboard Raspberry Pi Camera Module 3 Wide, passing each captured frame through the YOLOv8n deep learning model to detect the presence of fire or smoke with high accuracy. The YOLOv8n model was selected for its lightweight architecture, which is optimized for inference on resource-constrained hardware, making it well-suited for onboard deployment on the Raspberry Pi 5 without requiring a dedicated GPU. The Raspberry Pi 5 was chosen for its enhanced processing power compared to previous iterations, allowing faster real-time inference. Since all detection processing is performed entirely onboard the UAV in real-time, the system operates independently of any ground-based computer during flight, significantly reducing detection latency and ensuring reliable operation even in remote forest areas where communication links may be limited. Upon detecting fire or smoke, the Raspberry Pi 5 immediately triggers an alert and transmits the detection result along with the current GPS coordinates to the ground control station via the onboard WiFi router for rapid emergency response.

4. Camera (RPi Camera Module-3 Wide)

The Raspberry Pi Camera Module 3 Wide is used as the primary imaging sensor in this project, responsible for capturing high-resolution aerial footage of the forest terrain during UAV flight. It features a 12-megapixel sensor combined with a 120-degree wide-angle lens, allowing it to cover a significantly wider ground area in a single frame compared to standard camera modules. This is particularly advantageous for forest fire monitoring, where maximizing spatial coverage is critical. The camera connects directly to the Raspberry Pi 5 via a CSI (Camera Serial Interface) ribbon cable, enabling high-speed and low-latency image data transfer between the camera and the onboard computer. Each captured frame is passed in real-time to the YOLOv8n detection model

running on the Raspberry Pi 5, ensuring continuous and uninterrupted monitoring of the forest area throughout the entire UAV mission.



(a) Component of Rasp Pi 5 [6]

(b) Camera at 45°

Figure 1.5: Camera Configuration

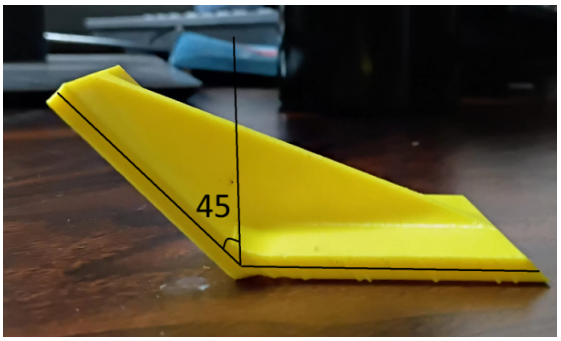


Figure 1.6: Camera Mount

The camera was mounted at an angle of 45° relative to both the vertical and horizontal planes to achieve an optimal balance between ground coverage and forward field of view. This orientation allows the system to capture both distant and near-ground regions simultaneously, improving the chances of early fire detection. Additionally, the 45° tilt helps reduce blind spots directly beneath the drone while maintaining sufficient perspective for accurate object detection using the onboard vision system.

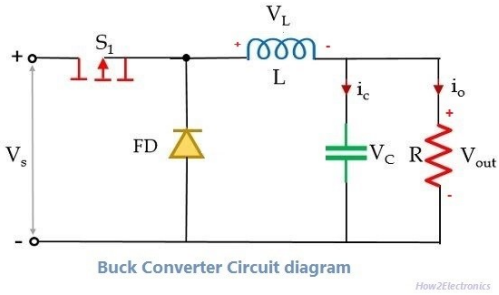
5. Buck Converter

The buck converter is a DC-DC step-down converter that plays a critical role in the power management of the UAV system, ensuring that all onboard electronics receive a stable and regulated voltage supply throughout the flight mission. In this project, the 5000mAh LiPo battery delivers a nominal voltage of 12V, which exceeds the safe operating voltage of sensitive components such as the Raspberry Pi 5 and other onboard electronics. The buck converter efficiently steps this down to a stable 5.2V output using high-frequency switching technology, which, unlike linear regulators, converts excess voltage into usable power rather than dissipating it as heat, resulting in significantly improved power efficiency. This efficient voltage conversion is particularly important in UAV applications where every milliampere of battery capacity directly impacts flight duration and overall mission performance. By maintaining a consistent and regulated output

voltage regardless of fluctuations in the battery charge level, the buck converter effectively protects all onboard components from voltage spikes and ensures uninterrupted and reliable operation of the entire detection system from takeoff to landing.



(a) Buck converter [7]



(b) Circuit of Buck Converter

Figure 1.7: Quadcopter Configuration

6. GPS Module

The GPS module serves as the primary positioning system of the UAV, continuously providing accurate real-time geographic coordinates, including latitude, longitude, and altitude, throughout the entire flight mission. It communicates with a network of satellites orbiting the Earth to calculate the UAV's precise position at any given moment, enabling reliable autonomous navigation, waypoint following, and position hold functionality under the control of the Pixhawk flight controller. In this project, the GPS module plays a dual role: it not only supports autonomous flight operations but also provides critical location data for fire detection events. When the YOLOv8n model running on the Raspberry Pi 5 detects the presence of fire or smoke in the camera feed, the corresponding GPS coordinates are immediately recorded and transmitted to the ground control station via the onboard WiFi router, pinpointing the exact geographic location of the detected incident. This precise and timely location information is essential for guiding emergency response teams directly to the affected forest area, significantly reducing response times and enabling faster containment of the fire before it spreads further.



Figure 1.8: GPS Module [9]

7. Communication Module

The communication module in this project utilizes a WiFi router placed at the ground control station, which establishes a dedicated local wireless network between the UAV and the ground personnel. The Raspberry Pi 5 onboard the UAV connects to this ground-based WiFi router wirelessly during flight, enabling real-time transmission of fire detection alerts and GPS coordinates from the UAV to the ground station without the need for any additional communication hardware onboard. Once the YOLOv8n model detects fire or smoke in the aerial camera feed, the detection results, along with the corresponding GPS coordinates, are instantly transmitted over the WiFi network to the ground control station. If fire or smoke is confirmed, an immediate alert is triggered and displayed on the ground station monitoring dashboard, notifying the ground personnel in real-time with the detection status, severity, and the exact GPS location of the incident. This dashboard-based alerting system ensures that emergency response teams are informed without delay and can take immediate action to dispatch resources to the affected forest area. The ground-based WiFi router setup also keeps the onboard payload of the UAV minimal by avoiding the need to carry additional communication hardware during flight, contributing to better power efficiency and longer flight durations, while the high-speed and stable nature of the WiFi connection ensures that all critical detection data is delivered to ground personnel with minimal latency throughout the entire monitoring mission.

8. ESC and Power Supply (Lithium-Polymer Battery)

Four 30A Electronic Speed Controllers form the critical link between our Pixhawk flight controller and 1000KV brushless motors. They take standard PWM throttle signals (1000-2000µs pulse width at 50Hz) and convert them into smooth three-phase AC power, giving each motor precise speed control. Running on our 3S LiPo battery, these ESCs handle 30A continuous with 40A burst capacity—safely covering the 22-25A draw from our 10x4.5 propellers at full throttle.

The single 3S1P 5000mAh LiPo battery powers the entire system, from the power-hungry brushless motors to the Raspberry Pi 5 and camera. Fully charged to 12.6V (11.1V nominal), it stores 55.5Wh of energy with a 150A maximum discharge capability:

$$I_{max} = 30C \times 5Ah = 150A \tag{1.1}$$

$$E = 11.1V \times 5Ah = 55.5Wh \tag{1.2}$$

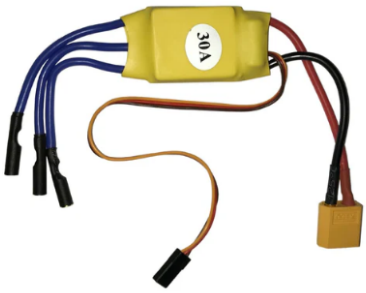
With a typical hover current of 25-30 A across all four motors, we achieve 15-20 minutes of flight time:

$$T_{flight} = \frac{5000mAh \times 60}{27.5A} \approx 18\,\text{minutes} \tag{1.3}$$

Each ESC's built-in Battery Elimination Circuit (BEC) delivers clean 5 V/2 A to power the Pixhawk, while a separate buck converter provides a stable 5.2 V for the Raspberry Pi and camera electronics.

Table 1.1: ESC and Battery System Specifications

ESC (x4)	**Specification**
Continuous Current	30 A (40 A burst)
Voltage Range	3S LiPo (9-12.6 V)
BEC Output	5 V/2 A
Weight	35 g each (140 g total)
3S LiPo Battery	
Capacity	5000 mAh
Voltage	12 V nominal (12.6 V full)
Max Discharge	150 A (30 C)
Energy	60 Wh
Weight	≈320 g
System Performance	
Hover Current	25-30 A
Max Draw (burst)	100 A
Flight Time	15-20 minutes



(a) ESC [10]



(b) Li-Po Battery [11]

9. Brushless Motor and Propeller
Four A2212 1000 KV brushless motors serve as primary propulsion actuators, converting 3S LiPo electrical energy into high-torque rotational force for efficient propeller operation. The 1000 KV rating delivers an 11,100 RPM theoretical no-load speed on 11.1V, ideal for 10-inch propellers that balance thrust, efficiency, and 30A ESC current limits. Each motor connects to a dedicated 30 A ESC receiving PWM signals from the Pixhawk for precise thrust vectoring.

Motor-propeller thrust follows the quadratic relationship:

$$F_i = k\omega_i^2 \tag{1.4}$$

where F_i is individual motor thrust, k is the propeller thrust coefficient, and ω_i is angular velocity (rad/s). Total quadcopter thrust is:

$$F_{total} = k \sum_{i=1}^{4} \omega_i^2 \tag{1.5}$$

Power consumption scales cubically due to aerodynamic drag:

$$P_{motor} = b\omega_i^3 \tag{1.6}$$

where b is the aerodynamic drag constant.

No-load RPM calculation for system validation:

$$\text{RPM}_{no-load} = KV \times V = 1000 \times 11.1 = 11,100\,\text{RPM} \tag{1.7}$$

The 1000KV motors with 10x4.5 propellers deliver ≈750-900 g static thrust per motor at 75% throttle (10 A draw), providing a 2:1 thrust-to-weight ratio for the ≈1.8 kg AUW. Vibration isolation prevents camera motion blur, which is essential for YOLOv8n fire detection accuracy during autonomous forest monitoring missions.



(a) Brushless Motor[12]



(b) Propeller[13]

1.5.2 Software Requirements

1. Operating System (Raspberry Pi OS)
The operating system provides a stable software environment for running image processing algorithms, communication services, and system management applications. It manages hardware resources and ensures the smooth execution of all onboard software processes.

2. Computer Vision Library (OpenCV)
OpenCV is used to process real-time image data captured by the camera. It enables tasks such as image filtering, color detection, motion analysis, and pattern recognition, which are essential for identifying fire and smoke characteristics accurately.

3. Deep Learning Frameworks
Machine learning frameworks such as PyTorch and Ultralytics can be used to implement trained models that classify fire and non-fire images. These models improve system accuracy by adapting to different lighting conditions, backgrounds, and environmental variations.

4. Flight Control Software (QGroundControl)
Flight control software is used to configure the flight controller, define autonomous flight paths, monitor telemetry data, and control UAV operations. It also provides real-time visualization of the UAV status during missions.

5. Communication Software (MAVLink)
Communication protocols and custom scripts manage data exchange between the UAV and the ground station. They ensure the reliable transmission of alerts, sensor data, and system health information in real-time.

6. Ground Control Station Software
The ground station software provides a user interface for operators to monitor visual confirmation, receive fire alerts, and view fire locations on a map. It supports decision-making by presenting all relevant information in an organized and accessible manner.

7. Programming Languages (Python)
Python is used to develop computer vision algorithms, communication routines, and system integration logic. It provides flexibility, efficiency, and compatibility with embedded and real-time applications.

8. CATIA
Computer-Aided Three-Dimensional Interactive Application (CATIA) is software for product development from conceptualization, design, and engineering to manufacturing. It is used for designing and 3D modeling various parts as per requirements. For the purpose of this project, CATIA was used to design 3D parts like the camera mount and Raspberry Pi Case, which provide protection in the occurrence of a crash.

9. Visual Studio Code
Visual Studio Code is a source-code editor developed by Microsoft. It can be run on a variety of operating systems and provides support for multiple languages like Python. It offers efficient and comprehensive tools for code editing and writing. VS Code was chosen for its intelligent code completion and simple yet effective extension library.

1.6 Significance of the Project

The proposed Fire Detection and Reporting System has a wide range of practical applications, particularly in disaster prevention and environmental monitoring. The system can be effectively used for the detection of forest fires, allowing authorities to take timely action and minimize damage to natural resources. It is also suitable for monitoring fire-prone and remote areas where ground-based surveillance is difficult or impossible. Additionally, the system can support wildlife conservation efforts by reducing fire-related habitat destruction. The integration of real-time monitoring and location-based reporting makes the system valuable for emergency response and disaster management operations.

1.6.1 Applications

- Helps prevent the spread of forest fires by providing the UAV location at the time of detection, enabling faster response to the affected area.
- Monitors factories and high-risk zones to identify fire hazards.
- Protects agricultural fields by detecting accidental fires and helping save crops.

- Supports monitoring of parks and green areas in cities to improve safety.
- Assists disaster management teams by providing quick information about fire locations using drones.
- Helps in studying fire behavior and understanding its impact on the environment.

CHAPTER TWO:
LITERATURE REVIEW

Forest fires are among the most destructive natural hazards affecting ecosystems, biodiversity, and human settlements worldwide. In recent decades, the combined effects of climate change, prolonged droughts, and increased human activity have significantly increased both the frequency and severity of wildfire incidents. Large-scale events such as the 2019 Australian bushfires and major fires in California and the Amazon demonstrate the devastating consequences of delayed detection and response [14]. In Nepal, the challenge is particularly severe due to rugged terrain and the limited accessibility of forest regions. Seasonal dryness in the Terai and mid-hill regions, combined with agricultural burning practices, further increases fire susceptibility [2]. Conventional monitoring approaches such as watchtowers, satellite imaging, and manual patrols suffer from limitations including delayed detection, high operational costs, and safety risks. A review by Ahmed et al. (2022) provides a comprehensive overview of autonomous UAVs, highlighting advances in navigation, control, and AI-based perception that enable fully autonomous flight in complex environments. The study emphasizes the role of sensor fusion, path-planning algorithms, and machine-learning techniques in improving the reliability and mission capability of UAVs. It also discusses emerging applications such as inspection, surveillance, and environmental monitoring, where autonomy reduces dependence on human operators. Finally, the review identifies key challenges including limited endurance, robustness in adverse conditions, and regulatory barriers for the large-scale deployment of autonomous UAVs [14].

In recent years, Unmanned Aerial Vehicles (UAVs) have emerged as a practical platform for wildfire monitoring because they can capture high-resolution imagery from low altitudes, operate over remote terrain, and provide fast situational awareness during fire events. One of the earlier contributions demonstrated that UAV-based fire detection could be performed using handcrafted visual features. Hossain et al. proposed a method for detecting forest fire flames and smoke from UAV-captured images using multi-color-space local binary pattern features and an artificial neural network. Their study showed that flames and smoke could be identified effectively from aerial imagery, but performance remained limited in cases involving small flames, smooth smoke textures, and cluttered backgrounds. This work is important because it established the feasibility of aerial fire detection while also revealing the challenges that later deep learning models would seek to address [16]. Unlike purely vision-based classification methods, a related contribution by Sousa et al. integrated fire detection with geolocation and monitoring capabilities, enabling the system to estimate fire locations in latitude, longitude, and altitude. The work was tested in controlled burn conditions and demonstrated that UAVs can support not only fire detection but also rapid situational assessment. This study helped expand the literature from simple image recognition toward operational wildfire monitoring systems [17].

With the rapid progress of deep learning, researchers began using convolutional neural networks and object detectors to improve detection accuracy and real-time performance. VGG16 is a foundational convolutional neural network that demonstrated the effec-

tiveness of using deep architectures with small 3×3 filters for image recognition. It became widely used in computer vision because of its strong feature extraction capability and transfer learning performance. It provides strong feature extraction capabilities; however, it requires high computational resources, and the model is computationally heavy and contains a very large number of parameters, making training and deployment resource-intensive. Its high memory and processing requirements limit its suitability for real-time and edge-based applications. Despite these limitations, VGG16 remains an important benchmark and reference model in deep learning research [18]. Another study also suggests that VGG16 provides strong feature extraction capability but requires high computational resources, and has shown that VGG16 achieves high accuracy in fire classification tasks; however, it struggles to detect smoke-only scenarios, limiting its effectiveness for early fire detection.

Mukhiddinov et al. proposed an improved (You Only Look Once) YOLOv5-based system for detecting wildfire smoke from UAV images. Their method was designed for early smoke recognition, which is especially valuable because smoke often appears before visible flames. The study reported strong detection performance and showed that lightweight deep learning architectures can be effective for onboard or near-real-time UAV fire monitoring [19]. CNN-based systems have demonstrated higher accuracy, faster response, and reduced false alarm rates compared to traditional methods. Recent advancements in UAVs, deep learning-based computer vision, and long-range communication technologies have introduced effective alternatives. UAVs enable rapid aerial surveillance, while deep learning allows automated detection of fire and smoke patterns in real-time [20]. Recent studies indicate that YOLOv8 is a more effective framework for fire and smoke detection than earlier YOLO variants because it achieves a better balance of detection accuracy, speed, and model efficiency, making it suitable for real-time early warning systems in forest and surveillance environments [21].

The development of fire and wildfire detection methods has progressed from early smoke-focused monitoring to highly optimized YOLOv8-based systems. Initial studies concentrated on detecting smoke in challenging outdoor scenes, establishing the importance of early recognition in wildfire prevention. Subsequent research introduced YOLOv8 with attention mechanisms such as CBAM to improve feature extraction and reduce background interference. Later work further refined YOLOv8n by modifying the backbone and loss function to improve both accuracy and efficiency for real-time applications. More recent studies have emphasized lightweight model design and multi-scale feature fusion to support deployment on resource-constrained devices. Earlier research in wildfire detection focused on identifying smoke as an early sign of fire, especially in forest and surveillance settings. These works established the core challenge: smoke is often faint, partially hidden, and difficult to distinguish from clouds or haze, which motivated later deep-learning-based approaches [22].

Another important direction is the application of deep learning to RGB imagery for fire and smoke detection. The GitHub project by A. Tleuliyev reflects this trend by using YOLOv8 trained on the D-Fire dataset, which contains 21,000 labeled images and includes both fire and smoke classes. The repository also notes that model size, speed, and deployment practicality were considered, which aligns with the broader literature's emphasis on balancing detection accuracy with real-time performance [23]. However, challenges remain, including dataset limitations, high computational requirements, and

difficulty distinguishing smoke from visually similar environmental elements. Despite these improvements, challenges such as false positives due to cloud similarity and high computational requirements remain. M. Fu et al. describe how YOLOv8 is trained and optimized for forest fire detection in satellite/remote sensing images, using the FIRESENSE dataset and several training-phase improvements such as data augmentation, small-target optimization, and efficient non-maximum suppression. The paper shows that YOLOv8 outperforms YOLOv5 and YOLOv7 in key metrics such as mAP@0.5, mAP@0.5:0.95, precision, and recall, while remaining suitable for real-time and edge-computing deployment. It is therefore a strong reference for this thesis regarding a formal training algorithm and setup for YOLOv8 in forest fire detection [24].

We also need to have onboard sensors on the UAV. Guilherme Lereno Santos Vale presents a small UAV system that uses a Raspberry Pi as an onboard computing module to gather image data and transmit it to a ground-based base station. The mobile station on the UAV integrates a low-cost GPS module and a standard webcam, acquiring GPS coordinates and images, then encoding and compressing the data for wireless transmission via Wi-Fi to the base station. At the base station, the software receives and processes the telemetry and images, using the GPS coordinates to visualize the UAV's trajectory and sensor data in real-time on a map-based user interface built with Node.js. The work focuses on designing and implementing the software components that interface the Raspberry Pi with the sensors, manage the communication link, and display the data on the ground, showing that a low-cost embedded platform can effectively support distributed data acquisition and visualization in UAV systems [25].

2.1 Summary

Forest fires are increasingly severe due to climate change, drought, and human activities, causing major ecological and societal damage worldwide. In Nepal, the problem is intensified by difficult terrain, seasonal dryness, and agricultural burning. Traditional fire monitoring methods—such as watchtowers, satellites, and patrols—are limited by delays, cost, and safety concerns. Unmanned Aerial Vehicles (UAVs) have emerged as an effective solution for wildfire monitoring because they provide high-resolution imagery, fast coverage, and access to remote areas. Early research used handcrafted image features and neural networks for fire detection, proving feasibility but struggling with small flames, smoke, and complex backgrounds. Later work integrated geolocation with detection, enabling better situational awareness.

With advances in deep learning, models like CNNs and object detectors significantly improved detection accuracy and speed. While models such as VGG16 offer strong feature extraction, they are computationally heavy and less suitable for real-time use. More efficient approaches like YOLOv5 and especially YOLOv8 provide a better balance of accuracy, speed, and lightweight design, making them suitable for real-time UAV-based fire detection. Recent improvements focus on attention mechanisms, small-object detection, and efficient architectures.

Despite progress, challenges remain, including false positives (e.g., confusion with clouds), dataset limitations, and computational demands. Modern systems also integrate onboard UAV sensors such as cameras, GPS, and embedded processors (e.g., Raspberry Pi) to collect and transmit real-time data to ground stations for monitoring and

visualization. Overall, wildfire detection has evolved from basic smoke detection to advanced, real-time UAV-based deep learning systems, with YOLOv8 representing a leading approach for efficient and accurate fire monitoring.

CHAPTER THREE:
THEORETICAL BACKGROUND

3.1 Quadcopter Dynamics

Quadcopter dynamics is a broad topic involving a multitude of parameters. To model the dynamics of a quadcopter, some assumptions are needed to simplify the process. The assumptions are made for the forces, torques, motors, propellers, and structural components of the quadcopter. Those assumptions are:

1. The resistance of the motors is negligible.
2. The quadcopter structure is rigid and symmetric.
3. Blade flapping, or the deformation of propeller blades brought on by high velocities and flexible materials, is neglected.
4. The surrounding fluid velocities, such as wind and freestream velocity, are negligible.
5. The quadrotor's center of gravity (CoG) aligns with the origin of the body-fixed frame.

With these assumptions set, the next consideration is the frame of reference. A frame of reference is a set of coordinates, such as positions and velocities of a quadcopter, in the frame being observed. There are mainly two different frames of reference called the inertial and non-inertial frames of reference. The inertial frame of reference is also commonly denoted as the inertial frame or the Earth frame (NED: North-East-Down or ECEF: Earth-Centered, Earth-Fixed). The non-inertial frame of reference is the body-fixed frame, with the origin at the CoG of the quadcopter. Wind frame and Stability frame are some other frames of reference. Each reference frame serves a specific purpose in the dynamics and modeling of a quadcopter.

The quadcopter moves by changing its thrust, where thrust is generated by the rotation speed of the motor. In the current configuration, pitch, which is the lateral motion, is achieved by changing the rotation speed of motors 2 and 4 (shown in the figure below), which causes variation in thrust forces 2 and 4. The longitudinal motion, roll, is achieved by changing the rotation speed of motors 1 and 4, which causes variation in thrust forces 1 and 4. Yaw motion is generated by the difference in counter-torque between the pairs of propellers (T_1, T_2) and (T_3, T_4). This occurs when the clockwise-rotating rotors speed up while the counter-clockwise ones slow down, or the reverse. The overall thrust required for hovering or ascending is achieved by summing the individual forces produced by all the rotating propellers.

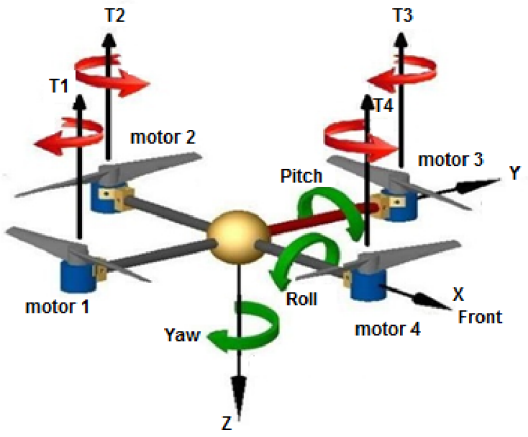


Figure 3.1: Quadcopter Dynamics

3.1.1 Rotor Dynamics

The modeling of the thrust forces and torques generated by the rotors can be represented by a simplified model. Each rotor with angular speed ω generates a force F in a direction perpendicular to the plane of rotation of the rotor given by:

$$F_i = \left(\frac{K_v * K_\tau}{\sqrt{2\rho A K_t}} \omega \right) \approx k\omega^2 \tag{3.1}$$

where K_v and K_t are constants related to the motor properties, ρ is the density of the air, A is the area the rotor sweeps out, K_τ is a constant determined by the blade configuration and parameters, and k is the thrust factor [26].

The quadcopter's total thrust (in the body frame) is determined by adding up all of the forces, which is given by:

$$T_B = \sum_{i=1}^{4} T_i = k \begin{pmatrix} 0 \\ 0 \\ \sum \omega_i^2 \end{pmatrix} \tag{3.2}$$

The torque contributed by the rotor about the body frame z-axis, which is required to keep the propeller spinning and providing thrust, generated due to drag is given by [27]:

$$\tau_i = \frac{1}{2} R\rho C_D A(\omega_i R) \approx b\omega_i^2 \tag{3.3}$$

where R represents the propeller radius, C_D is a drag coefficient, and b is the drag constant.

The total torque around the z-axis is calculated by summing the individual torques produced by each propeller:

$$\tau_\psi = b(\omega_1 - \omega_3 + \omega_2 - \omega_4) \tag{3.4}$$

The roll and pitch torques are obtained from standard mechanics. The motors on the roll axis are arbitrarily chosen to be $i = 1$ and $i = 3$, thus:

$$\tau_\phi = \sum r \times T = L(k\omega_1^2 - k\omega_3^2) = Lk(\omega_1^2 - \omega_3^2) \tag{3.5}$$

The pitch torque is given by the expression below:

$$\tau_\theta = Lk(\omega_2^2 - \omega_4^2) \tag{3.6}$$

where L is the center distance of the propellers. Summing all, the torques in the body frame are found to be:

$$\tau_B = \begin{pmatrix} Lk(\omega_1^2 - \omega_3^2) \\ Lk(\omega_2^2 - \omega_4^2) \\ b(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2) \end{pmatrix} \tag{3.7}$$

3.1.2 Kinematics

The quadcopter in this model is considered a rigid body with a body-fixed frame attached to it. The inertial frame is stationary with respect to the ground, with gravity acting along the negative z-axis. In contrast, the body frame is attached to the quadcopter and moves with it; in this frame, the rotor axes point in the positive z-direction, while the quadcopter's arms extend along the x and y axes. Let (x_B, y_B, z_B) be the body-fixed frame of reference, where x_B and y_B are parallel to the arms of the quadcopter and orthogonal to each other, whereas z_B is oriented orthogonally to the plane Ox_By_B. The inertial frame coordinate system (x_I, y_I, z_I) is fixed with respect to the ground.

The position of the quadcopter in the inertial frame is $\mathbf{x} = (x, y, z)^T$ and velocity is $\dot{\mathbf{x}} = (\dot{x}, \dot{y}, \dot{z})^T$. In the body frame, roll, pitch, and yaw are defined as $\theta = (\phi, \theta, \psi)^T$ and angular velocity as $\dot{\theta} = (\dot{\phi}, \dot{\theta}, \dot{\psi})^T$.

The data and calculations make more sense when they are in the inertial frame. But the flight computer unit (FCU) calculates all data in the body-fixed frame. So, to transform these data, a rotation matrix is required. The rotation matrix is obtained by applying three successive rotations around the axes of the body-fixed frame. Quadcopter orientation relative to the ground is described using XYZ fixed Euler angles. These angles are defined as follows: the roll angle ϕ is bounded by $-\frac{\pi}{2} < \phi < \frac{\pi}{2}$, the pitch angle θ is within $-\frac{\pi}{2} < \theta < \frac{\pi}{2}$, and the yaw angle ψ ranges from $-\pi < \psi < \pi$ [28].

To convert from the body-fixed to the inertial frame, the rotation matrix is given in Equation 3.8:

$$R_I = \begin{pmatrix} C_\psi C_\theta & C_\psi S_\theta S_\phi - S_\psi C_\phi & C_\psi S_\theta C_\phi + S_\psi S_\phi \\ S_\psi C_\theta & S_\psi S_\theta S_\phi + C_\psi C_\phi & S_\psi S_\theta C_\phi - C_\psi S_\phi \\ -S_\theta & C_\theta S_\phi & C_\theta C_\phi \end{pmatrix} \tag{3.8}$$

Here $C_\cdot = \cos(\cdot)$ and $S_\cdot = \sin(\cdot)$.

3.1.3 Equations of Motion

There are two types of equations to define quadcopter dynamics. The first set of equations is due to the Principle of Action, called the Euler-Lagrange or Lagrangian formulation. The second equation, which describes the rotational and translational motion of rigid bodies, is called the Newton-Euler equations. The Newton-Euler approach allows us to model both rotational and translational movement dynamics simultaneously [29].

The forces acting on the quadcopter in the inertial frame result from thrust, gravity, and friction. The thrust forces in the inertial frame are calculated by applying the rotation matrix to the thrust in the body frame. Thus, the translational motion is described as:

$$m\ddot{\mathbf{x}} = \begin{pmatrix} 0 \\ 0 \\ -mg \end{pmatrix} + F_D + RT_B \tag{3.9}$$

Here $\mathbf{x}$ is the quadcopter's position, g is the acceleration due to gravity, F_D is the drag force, and T_B is the body frame thrust vector.

Since the quadcopter rotates as well, another equation is needed to describe its angular motion, just like how Newton's second law describes linear motion. This is given by Euler's rotational equation:

$$I\dot{\omega} + \omega \times (I\omega) = \tau \tag{3.10}$$

where ω is the angular velocity (how fast it is rotating), I is the inertia matrix (describes how mass is distributed), and τ is the external torque. The term $\omega \times (I\omega)$ accounts for the rotational effects due to angular velocity. This can be rewritten as:

$$\dot{\omega} = I^{-1}(\tau - \omega \times (I\omega)) \tag{3.11}$$

The inertia matrix I is symmetrical, based on the above-mentioned assumptions, and is given by:

$$I = \begin{pmatrix} I_{xx} & 0 & 0 \\ 0 & I_{yy} & 0 \\ 0 & 0 & I_{zz} \end{pmatrix} \tag{3.12}$$

The final expression for the rotational equations of motion is:

$$\dot{\omega} = \begin{pmatrix} \tau_\phi I_{xx}^{-1} \\ \tau_\theta I_{yy}^{-1} \\ \tau_\psi I_{zz}^{-1} \end{pmatrix} - \begin{pmatrix} \frac{I_{yy}-I_{zz}}{I_{xx}}\omega_y\omega_z \\ \frac{I_{zz}-I_{xx}}{I_{yy}}\omega_x\omega_z \\ \frac{I_{xx}-I_{yy}}{I_{zz}}\omega_x\omega_y \end{pmatrix} \tag{3.13}$$

This completes the set of equations of motion describing the dynamics of the quadcopter.

CHAPTER FOUR:

METHODOLOGY

In this chapter, we explain the approach taken to develop a UAV-based system capable of detecting fire and smoke while simultaneously tagging the location using GPS and sending alerts to a ground station for effective fire management. The system is built around a UAV equipped with high-resolution RGB cameras, which continuously capture aerial footage of fire-prone areas. Advanced computer vision algorithms, specifically YOLO, are then applied to automatically detect fire and smoke in the captured video frames, even under varying lighting and environmental conditions. The GPS data collected by the UAV allows the system to accurately determine the geographical location from where fire is detected. Upon detection, the system immediately transmits alerts, including annotated images and precise coordinates, to the ground control station, enabling a timely response and efficient monitoring. This integrated approach ensures that fire incidents are quickly identified and addressed, improving situational awareness and supporting proactive disaster management.

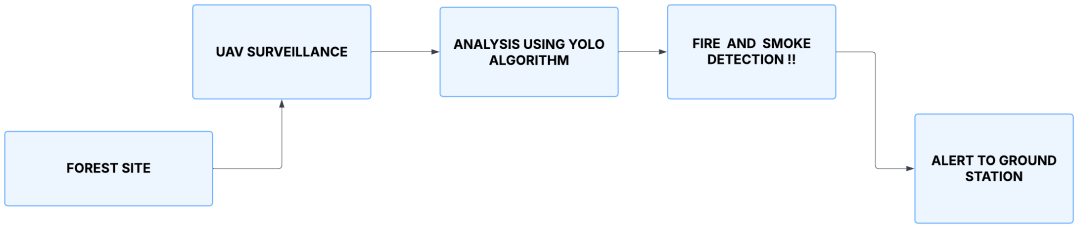


Figure 4.1: Framework for forest fire monitoring

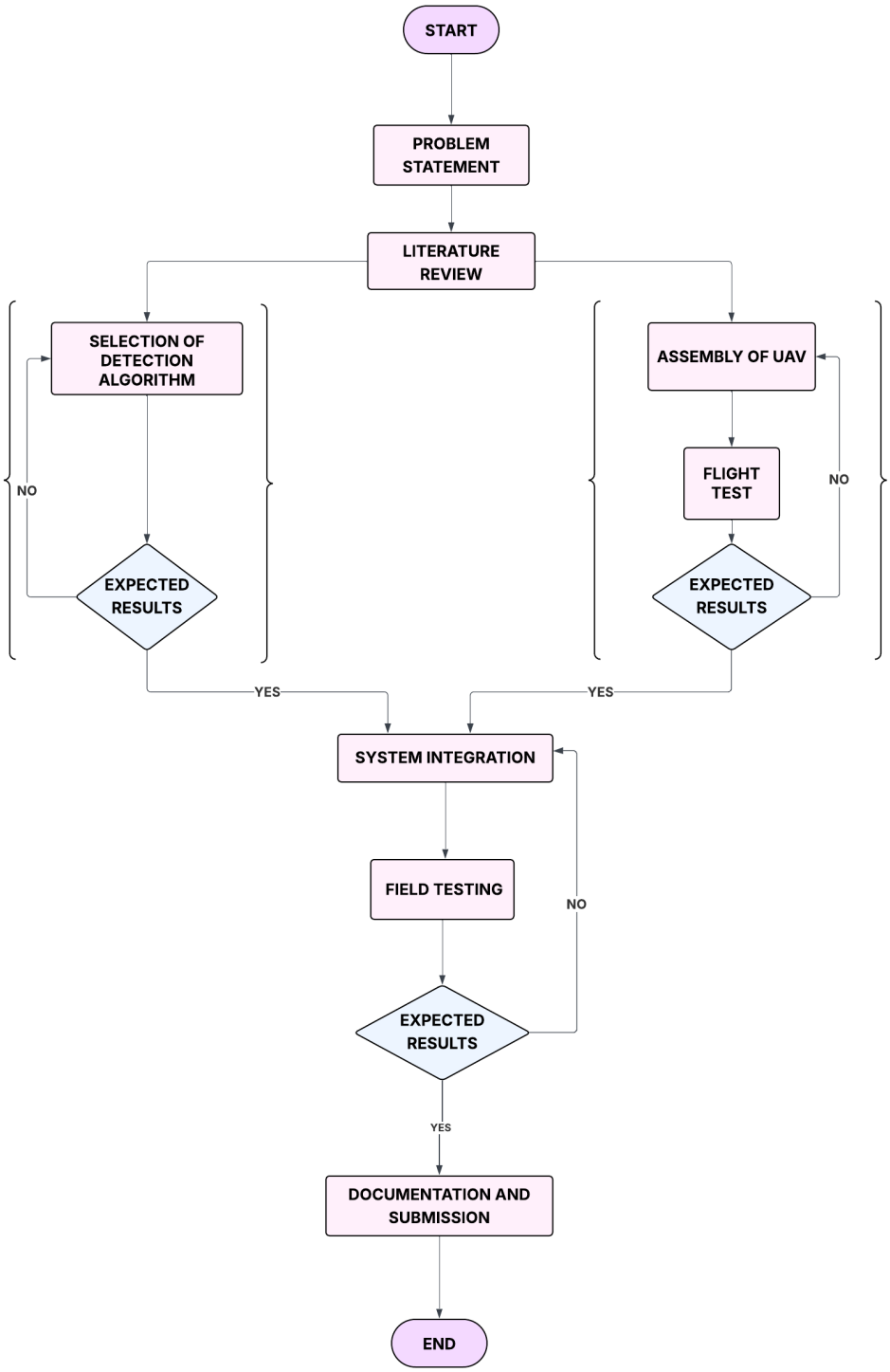


Figure 4.2: Overall Workflow of the project

This is the overall workflow of this project. It is divided into two parts: one is the selection of the detection algorithm, and the other is the assembly of the quadcopter. At the end of both parts, they will be integrated to achieve the goal of our project.

4.1 Hardware Interface Diagram

Figure 4.3 shows how all the hardware components in our UAV system are connected to each other. The 5000mAh 12V LiPo battery is connected to the buck converter, which steps down the voltage to 5V to safely power the Raspberry Pi 5. The Raspberry Pi Camera Module is attached to the Raspberry Pi 5 using a 15-pin FFC cable through the CSI port for capturing aerial images during flight. The Raspberry Pi 5 is connected to the Pixhawk 4 flight controller via UART serial communication using TXD, RXD, and GND pins, and the GPS module is plugged directly into the Pixhawk through its dedicated GPS MODULE port.

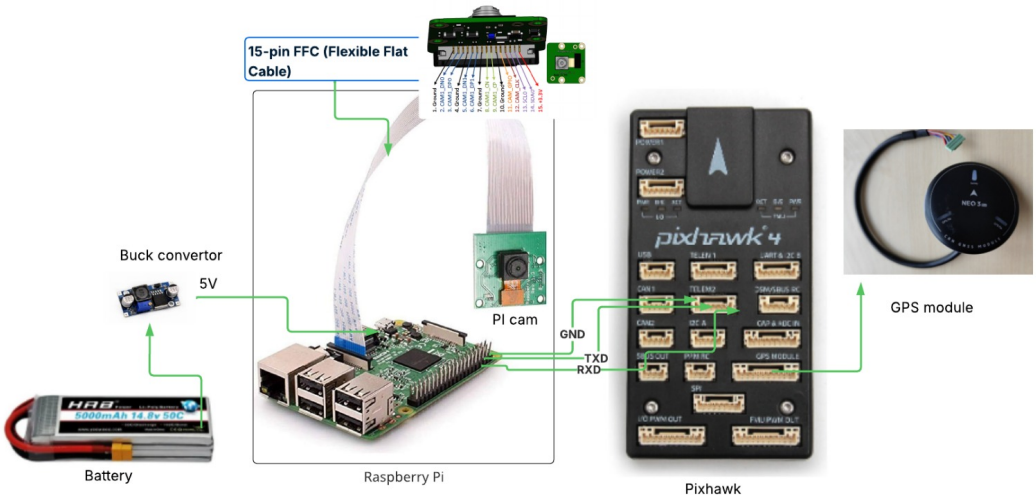


Figure 4.3: Hardware Interface Diagram of the UAV System

4.2 Overall System Architecture

The overall system architecture consists of an integrated UAV platform, onboard processing unit, communication system, and ground control station. The quadcopter, equipped with a Pixhawk 4 flight controller, GPS module, and RGB camera, performs autonomous flight and data acquisition. The Raspberry Pi 5 acts as a companion computer, processing captured images using fire detection algorithms. Communication between the UAV and the ground control station is established through a LAN using SSH and MAVLink protocols for secure data transmission and control. The Ground Control Station monitors telemetry data, displays alerts, and visualizes detected images with GPS coordinates, enabling efficient real-time forest surveillance and decision-making.

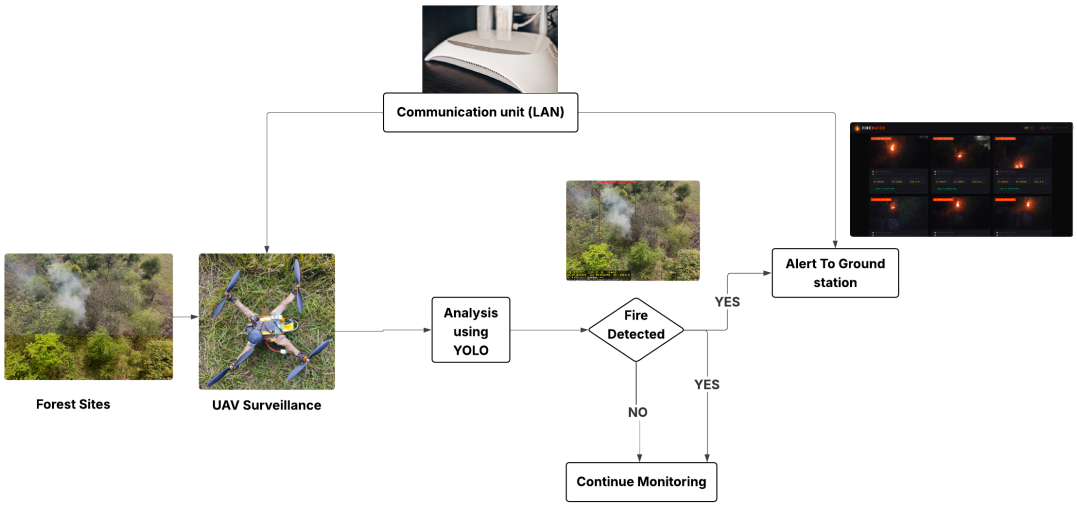


Figure 4.4: Overall System Architecture

4.3 Quadcopter Assembly

The quadcopter serves as a highly flexible and efficient platform for forest surveillance by enabling aerial monitoring over vast, remote, and difficult-to-access terrains. Its four-rotor configuration provides excellent stability, maneuverability, and control, making it suitable for low-altitude inspection and real-time observation tasks. The system is powered by four Brushless DC motors with a 1000 KV rating, which ensure efficient thrust generation and stable flight performance under varying environmental conditions. To support surveillance operations, the quadcopter is equipped with an RGB camera (PiCam) capable of capturing high-resolution images and videos in real-time. This facilitates early detection of forest fires by identifying smoke or flame patterns. The integration of a GPS module allows accurate positioning and navigation, enabling the drone to follow predefined waypoints and cover large forest areas systematically. The flight controller (Pixhawk 4) acts as the central unit, managing flight stability, sensor integration, and autonomous navigation. It communicates with the companion computer (Raspberry Pi 5), which processes image data and runs advanced algorithms such as YOLO for fire detection. Electronic Speed Controllers (ESCs) regulate the speed of each motor based on commands from the flight controller, ensuring precise control of the quadcopter's movement. Power is supplied by a 5000 mAh Lithium-Polymer (Li-Po) battery, providing sufficient flight time for surveillance missions. An AUX power module and a buck converter are used to regulate and distribute voltage safely to different components, ensuring stable and reliable operation of both high-power and low-power devices. All components, including motors, propellers, ESCs, flight controller, GPS module, camera, companion computer, and power systems, are carefully assembled and mounted on the UAV frame. Proper placement ensures optimal weight distribution, vibration minimization, and aerodynamic efficiency. This integrated system enables the quadcopter to perform continuous, reliable, and accurate forest surveillance, making it an effective tool for early forest fire detection and environmental monitoring.

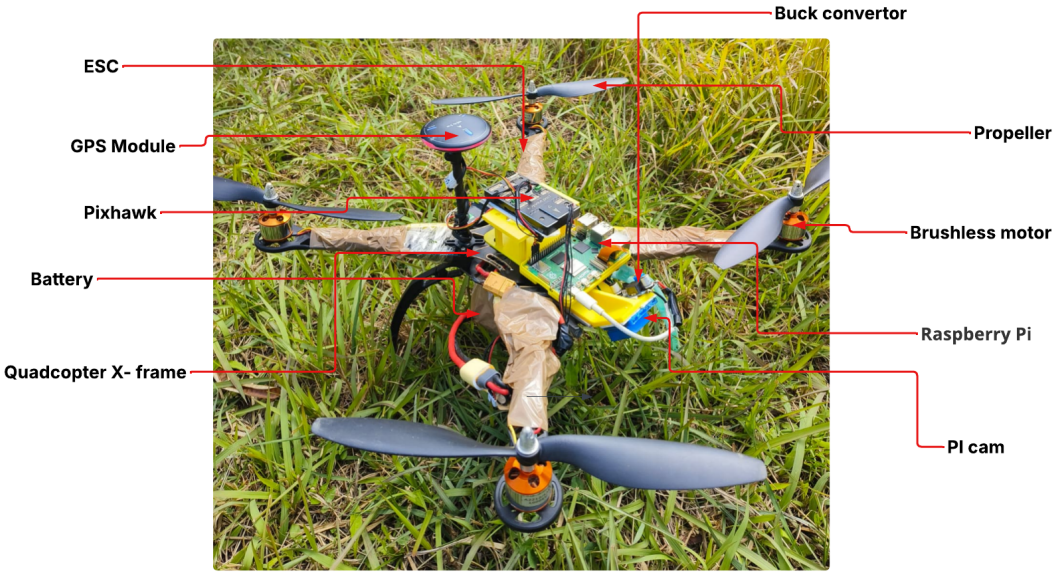


Figure 4.5: Quadcopter Assembly

4.3.1 Communication and Data Transfer

The communication system is established using a Local Area Network (LAN) to enable real-time data exchange between the quadcopter and the ground station. The Raspberry Pi 5 connects to the LAN and functions as a communication bridge between onboard systems and the ground station. Secure communication is achieved using SSH (Secure Shell), which enables remote access, monitoring, and control of the Raspberry Pi. Through this network, telemetry data, GPS information, and alert notifications are transmitted, while control commands and mission updates are sent from the ground station to the UAV. This setup ensures reliable, secure, and continuous communication during forest surveillance operations.

To optimize bandwidth usage and reduce system complexity, the UAV is designed to transmit captured images instead of continuous video streaming. When fire or smoke is detected, a still image is captured by the onboard camera and tagged with essential metadata, including GPS coordinates and a timestamp. This data is then transmitted to the ground control station for further analysis and confirmation. The received image enables operators to verify the detection and accurately determine the location and time of the event, thereby improving the reliability and effectiveness of the surveillance system.



Figure 4.6: Router

4.3.2 Ground Control Station Integration

The Ground Control Station (GCS) serves as the central interface for monitoring and controlling the UAV throughout its mission. It receives real-time telemetry data from the UAV, including position, altitude, battery status, and overall system health, via the MAVLink protocol. The GCS also receives alerts and GPS coordinates when a fire is detected, allowing the operator to respond promptly. Detected images captured by the UAV are uploaded and displayed on the GCS dashboard, providing visual confirmation of fire events and enhancing situational awareness.

In this project, QGroundControl is used as the GCS software due to its compatibility with the PX4 flight stack, user-friendly interface, and comprehensive support for mission planning. The GCS dashboard simultaneously displays the detected fire images along with their GPS locations on the map, enabling operators to quickly verify and assess the situation. This integration of visual and positional data improves the efficiency and accuracy of forest surveillance operations.

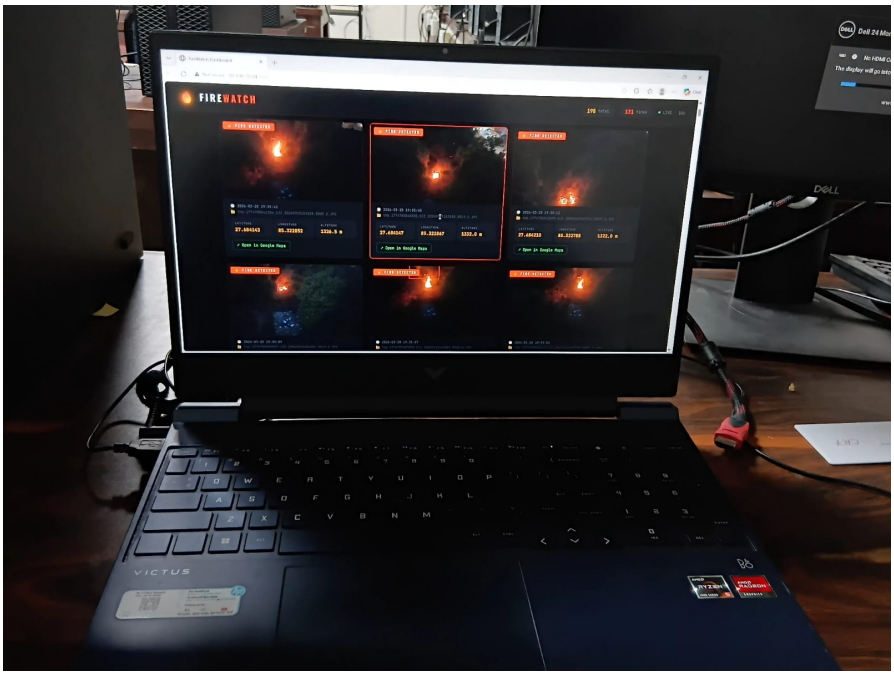


Figure 4.7: Ground Control Station

4.4 YOLO model

YOLO (You Only Look Once) is a real-time object detection model that processes an entire image with a single convolutional neural network (CNN). The image is divided into a grid, and each grid cell predicts bounding boxes and class probabilities for potential objects. YOLO combines these predictions to determine what objects are present and where they are located. Its unified architecture allows fast and accurate detection in a single pass, making it efficient for deployment on systems with limited computational resources.

4.4.1 Yolo general architecture

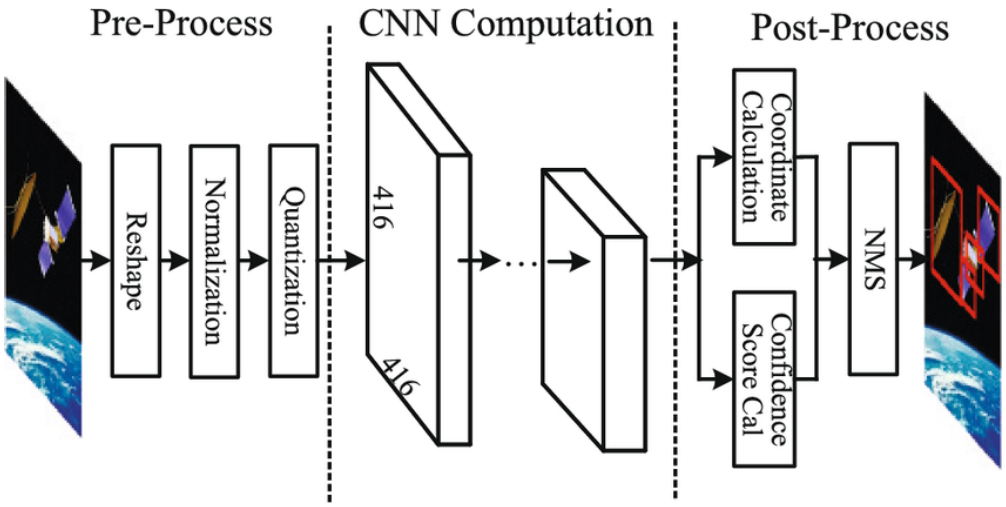


Figure 4.8: YOLO Architecture

YOLOv8n is an end-to-end deep learning object detection model that builds upon the YOLO family but is more modular, flexible, and optimized for speed and accuracy. Its architecture consists of three main components: Backbone, Neck, and Head.

4.4.1.1 Input

Input images are resized to a fixed size (e.g., 640×640 pixels). Images are normalized and augmented if needed during training (e.g., flips, rotations).

4.4.1.2 Backbone

YOLOv8n uses a CSP (Cross Stage Partial) Darknet-like backbone to extract feature representations from the input image. The backbone processes the image through multiple convolutional layers, capturing low-level features such as edges and textures in the earlier layers, and high-level features such as shapes and objects in the deeper layers. It is designed to be lightweight and fast, making it suitable for real-time detection applications.

4.4.1.3 Neck

The neck combines features from different scales using a PAN (Path Aggregation Network). This multi-scale feature fusion allows YOLOv8n to detect small, medium, and large objects within the same image simultaneously. In the context of this project, this is particularly useful as fire or smoke may appear at different sizes depending on the UAV's operating altitude and distance from the source.

4.4.1.4 Head

The detection head takes the fused features from the neck and produces the final predictions. For each detected object, the head outputs the following:

- **Bounding box coordinates:** The position and size of the detected object defined by (x, y, w, h).
- **Confidence score:** The probability that an object exists within the predicted bounding box.
- **Class probabilities:** The likelihood of the detected object belonging to each class (in this case, fire or smoke).

YOLOv8n uses an anchor-free detection approach, which simplifies the training process and improves inference speed. All predictions are made in a single forward pass through the network, enabling real-time detection performance.

4.4.1.5 Post-Processing

After the head produces its predictions, Non-Maximum Suppression (NMS) is applied to remove overlapping bounding boxes and retain only the most confident detection for each object. The final output of the model is a set of bounding boxes, each labeled with a class name and an associated confidence score.

4.5 Field Testing

The field testing of the UAV-based forest fire detection system was conducted within the Cricket Ground area of our campus due to restrictions on flying in uncontrolled forest regions. Despite the controlled environment, the testing simulated realistic operational conditions by including multiple altitudes, varying angles, and different artificial fire scenarios. These tests allowed evaluation of the UAV's flight stability, image capture, real-time processing, and alert transmission. Conducting the trials on campus provided a safe and manageable environment while still validating the overall functionality and reliability of the system before potential deployment in larger forest areas and fire-prone areas, as shown in the figure.



Figure 4.9: Our Test Site - Inside Pulchowk Campus

CHAPTER FIVE:

IMPLEMENTATION AND ANALYSIS

5.1 YOLO Model Implementation and Edge Deployment

5.1.1 Strategic Model Selection

The chance of successfully detecting fire and smoke relied heavily on choosing the right neural network. We selected YOLOv8-Nano (YOLOv8n) because it's extremely lightweight, with only about 3.2 million parameters, allowing it to run smoothly on the Raspberry Pi 5 without requiring heavy power or memory demands. Despite its small size, YOLOv8n's smart anchor-free detection keeps its accuracy on par with much larger models, making it perfect for real-time UAV-based fire detection.

5.1.2 Custom Dataset Development and Rigorous Domain Adaptation

The efficacy of a neural network is inherently dependent upon the quality of its training data and the integrity of the target database. Consequently, this project prioritized a rigorous manual compilation and curation process over the use of generic, pre-existing datasets. A domain adaptation strategy was intentionally integrated to ensure the model accurately captures the unique geographical and environmental characteristics of Nepal. This approach culminated in the development of a robust, hybrid dataset comprising approximately 22,000 distinct, high-fidelity images.

We leveraged a solid foundational understanding of flame physics and smoke plume structure from nearly twenty thousand high-quality images in the D-Fire dataset. Nearly 20,000 high-quality images were systematically downloaded and integrated from the available D-Fire academic dataset. However, we found that this dataset primarily features images of North American and European forests. If we only trained on this, the drone would likely fail when deployed over the distinct, terraced terrain of Nepal.

In order to bridge this domain gap, an additional 2,000 images (representing a crucial, highly concentrated 10% of the total dataset) were exclusively curated by us. This custom subset was painstakingly compiled using proprietary video footage captured directly from our own quadcopter test flights over local areas, combined with highly targeted regional photographs of community areas covered with trees and vegetation that closely mimicked our community forests.

We used Roboflow as an annotation tool for labeling the images with bounding boxes. This allowed us to meticulously and manually hand-draw bounding polygons around localized flora. By feeding this custom, locally-adapted 10% subset into the twenty-thousand-image D-Fire baseline, the neural network effectively fine-tuned its weights to adapt to Nepal's terrain. This process drastically decreased regional false positives while maintaining the model's broad, generalized fire detection capabilities and efficiency.



Figure 5.1: Sample of datasets used to train the model

5.1.3 Local Model Training Pipeline (CUDA/PyTorch)

Training a neural network on 22,000 high-definition images is a computationally intensive task that exceeds the capabilities of standard CPUs. To ensure efficiency, the training was conducted on a high-performance GPU-equipped workstation using Python and the PyTorch framework. By utilizing NVIDIA's CUDA API to parallelize tensor multiplications, the computational load was offloaded to the GPU cores. This acceleration enabled rapid hyperparameter tuning, reducing the optimization timeline from weeks to hours. The process concluded successfully over 144 epochs, achieving smooth mathematical convergence without overfitting.

5.1.4 Training Results and In-Depth Evaluation

The hyperparameters carefully selected prior to training proved to be highly effective. The model training process autonomously halted after exactly 144 epochs. To thoroughly and academically assess the model's true reliability and its readiness for dangerous real-world UAV deployment, several highly complex evaluation metrics were extracted and analyzed. These include the mathematical loss curves, the normalized confusion matrix, the Precision-Recall (PR) curves, and the highly telling F1-score dynamics.

5.1.4.1 Overall Training and Validation Losses

Figure 5.2 presents the raw, unfiltered training and validation metrics exported by the Ultralytics framework across the entire 144-epoch training run.

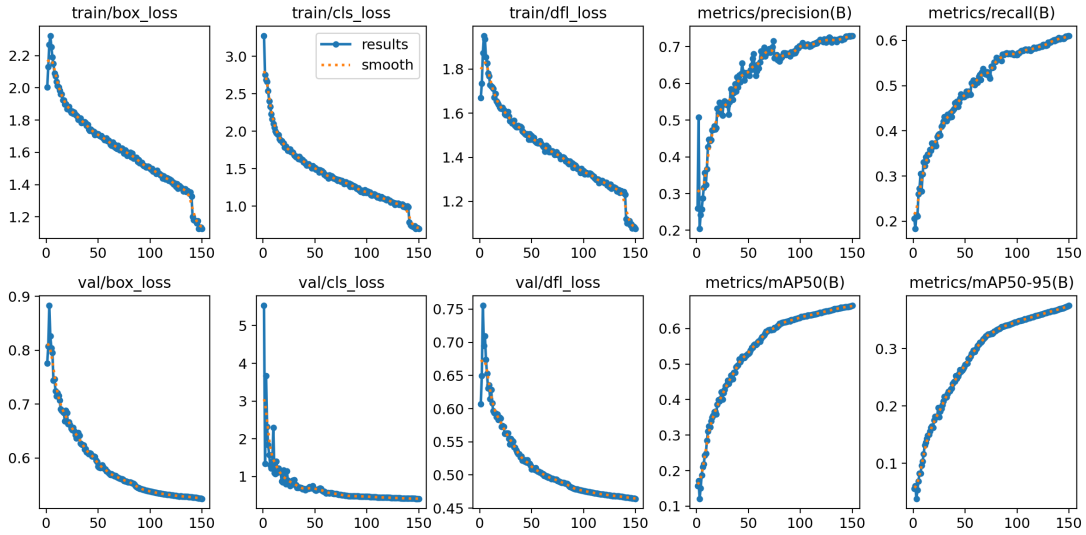


Figure 5.2: Training and validation metrics across 144 epochs, displaying box loss, class loss, DFL loss, and precision/recall curves.

In complex object detection architectures like YOLOv8, the total mathematical Loss (the penalty assigned to the network for guessing incorrectly) is not a single number. It is a highly complex combination of three completely distinct penalty components:

- **Box Loss (box_loss):** This metric measures exactly how well the network component predicted bounding boxes enclose the actual, physical boundaries of the objects. A sharply decreasing box loss curve mathematically proves the model is becoming highly accurate at localizing the exact geometric coordinates of fire and smoke boundaries.
- **Class Loss (cls_loss):** This metric measures the categorical accuracy of the model in correctly identifying the pixel data within the bounding box as either ”fire” or ”smoke”. It penalizes the model heavily if it successfully finds a box but calls a fire ”smoke”.
- **Distribution Focal Loss (dfl_loss):** This is an advanced metric that specifically evaluates the fine-grained, fractional details of the bounding box edges. It heavily assists the network in mathematically handling highly ambiguous, blurry boundaries (like the incredibly diffuse, fading edges of a dispersing smoke plume).

As clearly evidenced in the generated graphs, there is a continuous, highly stable downward trajectory in both the training losses and, crucially, the validation losses. The stabilization of the validation loss curves alongside the training curves is the ultimate proof that the model is genuinely generalizing well to new, unseen data, and is not simply memorizing the training images (a catastrophic failure known as overfitting). By the absolute final epoch, the model achieved a highly respectable Mean Average Precision at a 50% Intersection over Union (mAP@0.5) of 0.659, and a strict mAP@0.5:0.95 of 0.369.

This is a highly robust, operationally viable result for a heavily pruned, lightweight Nano model attempting to run on an edge CPU.

5.1.4.2 Confusion Matrix Mathematical Analysis

To understand exactly where the mathematical model succeeds and where its logic breaks down into errors, a normalized confusion matrix was programmatically generated against the validation dataset (Figure 5.3).

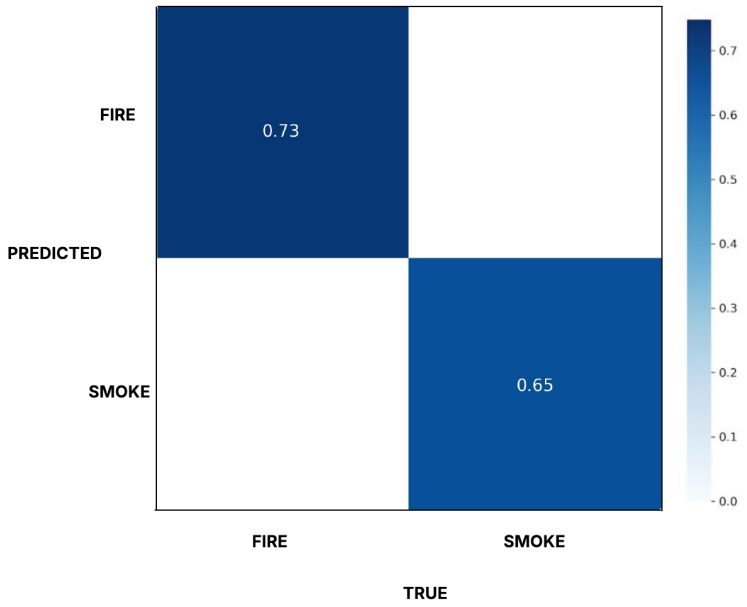


Figure 5.3: Normalized Confusion Matrix quantifying Fire and Smoke detection accuracy

A formal confusion matrix is a statistical tool that directly compares the actual, human-labeled ground truth (True classes) against the model's final mathematical predictions (Predicted classes).

- **True Positives (The Diagonal):** The starkly colored values running along the main diagonal represent completely correct predictions. The high percentages located here conclusively indicate that when a fire or smoke plume is physically present in the pixels, the model correctly identifies it with a very high degree of statistical reliability.
- **False Positives/Negatives (The Off-Diagonal):** The values located outside the main diagonal mathematically represent the network's errors. For example, if the neural network predicts the class "smoke" but the actual image was human-labeled as just background (such as a highly deceptive, low-lying cloud bank or morning fog), it statistically registers as a False Positive (a false alarm).

Deeply analyzing this matrix allows us to quantify the system's operational viability. In the incredibly high-stakes domain of forest fire detection, maintaining a near-zero false negative rate (the catastrophic error of missing a massive, real fire) is absolutely critical for public safety. Conversely, maintaining a strictly low false positive rate is logistically necessary to prevent the system from routinely sending firefighting ground

crews and helicopters on incredibly expensive, dangerous, and exhausting wild goose chases triggered by false alarms.

5.1.4.3 Precision-Recall Mathematical Trade-off

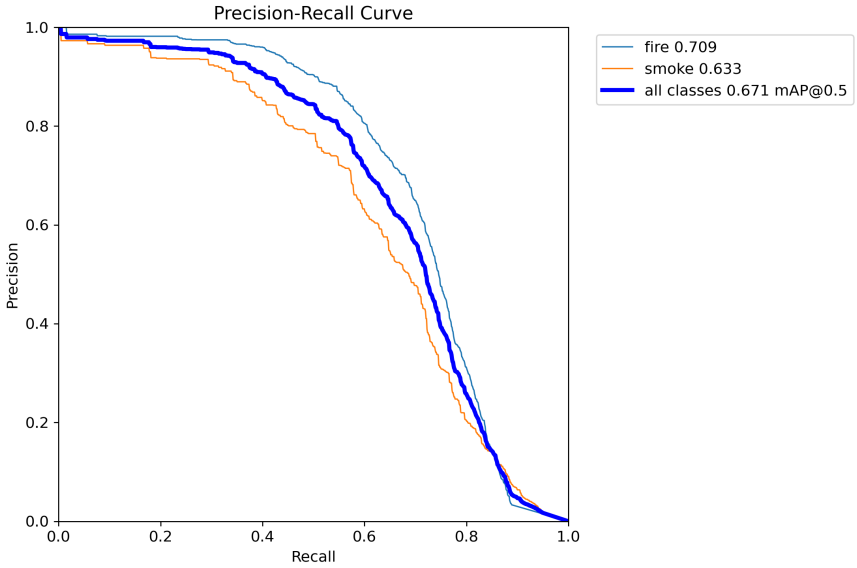


Figure 5.4: Precision-Recall curve for YOLOv8n validation phase

The Precision-Recall (PR) curve is a powerful graphical representation that visually plots the brutal, mathematical trade-off between two entirely opposed, crucial evaluation metrics:

- **Precision:** Out of all the detections the model made during testing, precision tells us how many of them were actually correct. If the model has high precision, it means we can trust its detections and it does not raise too many false alarms. It is defined as:
$$\text{Precision} = \frac{TP}{TP+FP} \tag{5.1}$$
where TP is True Positives and FP is False Positives.
- **Recall:** Out of all the actual fire and smoke present in the test images, recall tells us how many of them the model was able to find. If the model has high recall, it means it is not missing many real fire or smoke events during the flight. It is defined as:
$$\text{Recall} = \frac{TP}{TP+FN} \tag{5.2}$$
where TP is True Positives and FN is False Negatives.

As perfectly illustrated in Figure 5.4, any detection model must violently balance these two opposing forces. If the threshold is lowered to make the model extremely sensitive and paranoid, it will undoubtedly find every single fire (achieving extremely High Recall), but it will also constantly flag bright solar reflections on leaves as fires (resulting in devastatingly Low Precision). The plotted curve in our results manages to stay remarkably high along both the X and Y axes, ultimately achieving a steady precision of

approximately 0.724 and a strong recall of 0.604. This graphically indicates that we have achieved a highly capable, operationally balanced detection threshold that effectively identifies true threats without overwhelmingly flooding the ground dashboard with false targets.

5.1.4.4 F1-Score and Algorithmic Confidence Threshold Optimization

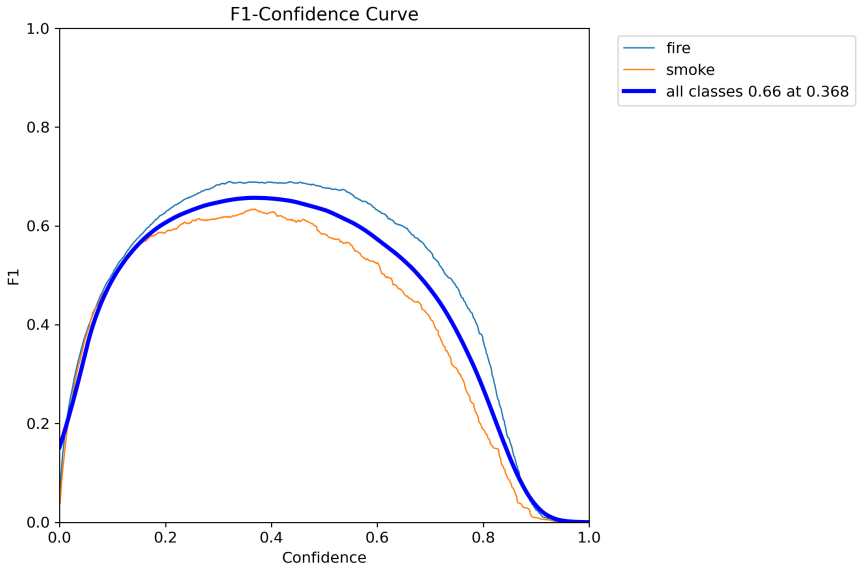


Figure 5.5: F1-Score Curve mathematically mapped across varying confidence thresholds

The F1-score is an elegant statistical measurement defined as the harmonic mean of both Precision and Recall. It provides a single, unified metric to perfectly evaluate the model's overall balance.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5.3}$$

Figure 5.5 plots this critical F1-score directly against the model's variable confidence threshold. When the UAV is actively flying, the YOLOv8 model calculates and assigns a raw confidence score (a floating-point number from 0.0 to 1.0) to every single detection it makes. If we program the Raspberry Pi to alert us anytime the model is merely 10% sure it sees a fire (a 0.1 threshold), we will undoubtedly receive a barrage of false alarms. Conversely, if we strictly set it to only alert us at 90% certainty (0.9), we will dangerously miss a very real, but incredibly small or distant, fire.

The prominent, towering peak of the F1-curve shown in the graph dictates the exact mathematical sweet spot: the highly optimal confidence threshold where the devastating combination of false positives and false negatives is minimized to its absolute lowest possible value. By programming the Python alerting logic of our Raspberry Pi 5 to perfectly mirror the threshold indicated near this peak, we ensure maximum, mathematically verified operational efficiency for the Ground Control Station team.

5.1.5 YOLOv8 Performance Analysis by Parameter Size

As derived directly from our stringent benchmark testing, the YOLOv8n (Nano) model delivered an absolutely exceptional inference speed, clocking in at an incredibly fast 0.422 ms per frame during raw tensor processing. This renders it nearly twice as fast as the next largest model size variant. Astonishingly, despite its incredibly stripped-down, lightweight architectural footprint, it maintains a remarkably high precision of 0.790, which surprisingly outperforms several of the exponentially heavier, larger variants in specific fire-detection edge cases. This perfect balance of raw processing speed and robust precision firmly cements YOLOv8n as the unequivocally optimal, necessary choice for deployment on the thermally constrained Raspberry Pi architecture.

5.1.6 Performance Analysis of the Custom Domain-Adapted Model

In order to validate the efficacy of our aggressive domain adaptation strategy by feeding 2,000 highly specific community terrain images into the 20,000-image D-Fire dataset, we analyzed the performance metrics of our custom-trained YOLOv8n model. The results demonstrate the critical balance between theoretical metrics and practical, real-world deployment reliability.

Table 5.1: Validation Performance: Custom Hybrid Dataset (YOLOv8n)

Evaluation Metric	**Custom Adapted Model**
Overall mAP@0.5	0.671
Overall Precision	0.724
Overall Recall	0.604
Class mAP@0.5 (Fire)	0.709
Class mAP@0.5 (Smoke)	0.633
Validation Loss Trend	Smooth Convergence (No Overfitting)

Analysis of the Empirical Performance: The custom hybrid model achieved an overall theoretical mAP@0.5 of 0.671. Rather than reflecting a limitation, this metric perfectly validates our methodology. The standard D-Fire dataset primarily features pristine North American and European forests. By injecting 2,000 images of complex local area backgrounds featuring harsh topography glare, complex terraced hills, and incredibly chaotic local flora, we intentionally made the dataset mathematically harder for the neural network to solve. The resultant custom model prioritizes real-world reliability, having learned to mathematically reject localized geographical false positives that occur in the field.

Class-Specific Confidence: A notable dynamic occurs in the model's class detection capabilities. The custom model performs better at detecting *fire* (0.709) than *smoke* (0.633). This directly highlights the specific environmental challenges of Nepal, where morning fog, low-hanging clouds across valleys, and intense dust storms act as aggressive visual confounders. The custom dataset correctly forced the neural network to become far more conservative and strict when predicting smoke against local forest backgrounds, prioritizing the elimination of devastating real-world false alarms.

Generalization and Stability: Finally, an analysis of the training phase confirms the structural integrity of our custom model. The validation loss curves (`val_loss`) for our custom domain-adapted dataset drop smoothly and continuously stabilize throughout the entire 144-epoch run. The added complexity of the hybrid dataset successfully allowed the model to generalize effectively without blindly memorizing the data, resulting in a highly stable, robust edge-computing platform.

5.2 Test Images for YOLOv8 Fire Detection

Several pictures were tested with the selected model (YOLOv8n) to verify its performance, and the results are shown below:



(a) Input image



(b) Output image

Figure 5.6: Non-fire/smoke image



(a) Input image



(b) Output image

Figure 5.7: Smoke image only



(a) Input image (b) Output image

Figure 5.8: Fire image only

The implemented YOLOv8 model was validated using a set of test images representing various forest fire scenarios. The validation process assessed the model's ability to accurately detect fire regions while minimizing false positives. Results showed that YOLOv8 consistently identified fire instances with high precision and reliability, confirming its suitability for real-time detection in the UAV-based monitoring system. This validation demonstrates the robustness of the model and its effectiveness in ensuring timely and accurate forest fire alerts.

5.3 Autonomous Flight Test Validation

The autonomous flight tests were carried out to check how well the UAV could fly on its own and collect data reliably. GPS readings were used to make sure it followed waypoints accurately, while pitch, yaw, and roll measurements confirmed that it maintained stable orientation during maneuvers. Vibration data from the onboard sensors showed that the UAV operated smoothly without shaking that could affect image capture or processing. Overall, these tests proved that the system can fly steadily and reliably while supporting real-time forest fire detection and alerting.

5.3.1 GPS Validation

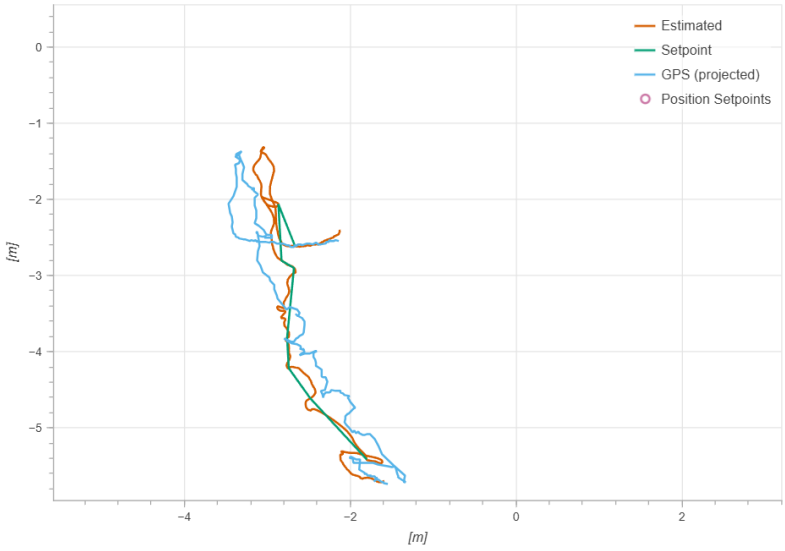


Figure 5.9: Setpoint vs. projected GPS

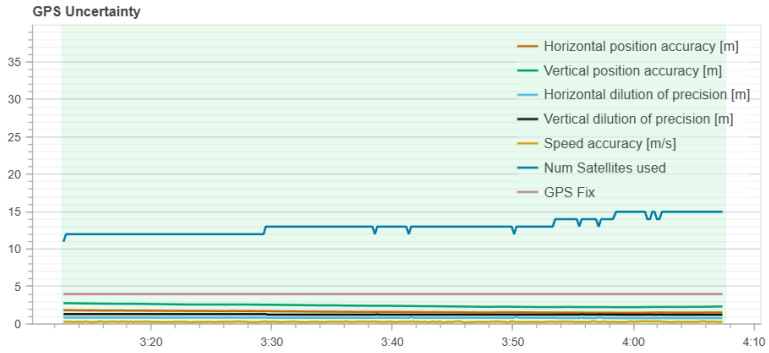


Figure 5.10: GPS Uncertainty

The GPS-based navigation system was validated by analyzing position tracking and GPS uncertainty during the autonomous flight. The UAV's estimated trajectory closely follows the predefined setpoints, indicating accurate waypoint tracking. Although minor deviations are observed in the GPS data due to noise and environmental factors, the overall position accuracy remains within acceptable limits. The GPS uncertainty plot shows stable horizontal and vertical accuracy with a consistent number of satellites, ensuring reliable positioning throughout the flight. These results confirm that the GPS system provides sufficient accuracy and stability for effective UAV navigation.

5.3.2 Vibration

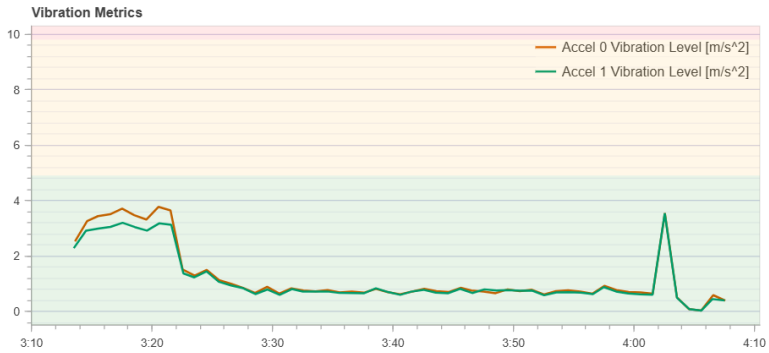


Figure 5.11: Vibration metrics

The Vibration Metrics indicate excellent mechanical health, with both accelerometers staying well within the safe green zone. The initial elevated levels are attributed to takeoff procedures and motor spool-up, while the sharp spike at the end and the subsequent drop correspond directly to the landing phase. Outside of these transitions, the operational vibration remains remarkably stable near 1 m/s^2, confirming that the system's dampening and structural integrity are performing as intended.

5.3.3 Pitch Angle

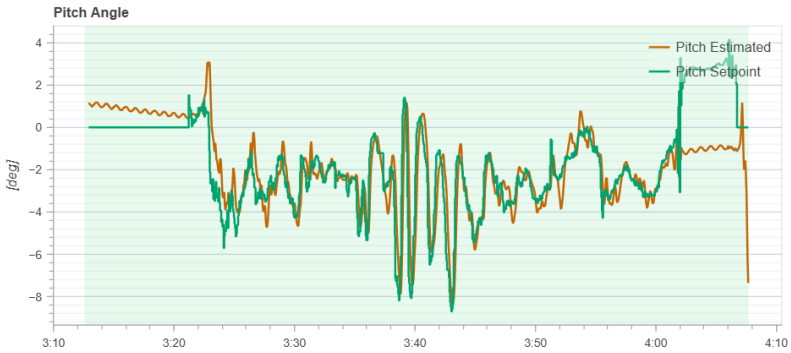


Figure 5.12: Pitch Angle vs Time

The pitch response reflects the UAV's forward and backward motion. The estimated pitch generally follows the setpoint but exhibits moderate oscillations and slight lag, particularly during dynamic phases of the flight. Larger deviations (down to about 8°) suggest aggressive maneuvers or external disturbances. While overall tracking is acceptable, the oscillatory behavior indicates that controller tuning (e.g., PID gains) could be improved for smoother response.

5.3.4 Roll Angle

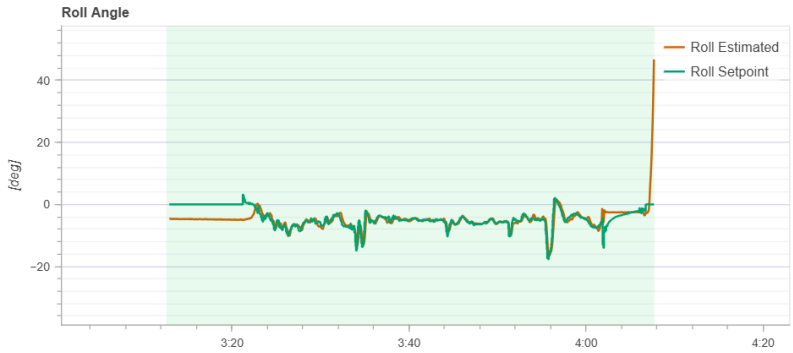


Figure 5.13: Roll Angle vs Time

The roll setpoint remains close to 0°, indicating a command for level flight. The estimated roll tracks this well with small deviations, demonstrating good lateral stability. Occasional disturbances (up to ±10–15°) are observed, likely due to environmental effects or corrective actions. A significant spike near the end suggests a non-nominal condition, such as a landing impact or controller disengagement.

5.3.5 Yaw Angle

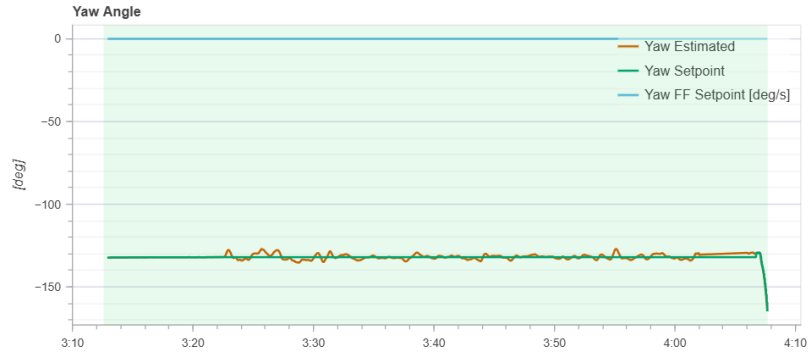


Figure 5.14: Yaw Angle vs Time

The yaw setpoint remains nearly constant at approximately 135°, and the estimated yaw closely follows it with very small deviations (within ±2–3°). This indicates strong heading stability and accurate yaw control. The near-zero feedforward input also shows that no significant rotational command was required. A brief deviation at the end is likely due to landing or a sudden maneuver, not sustained instability.

The flight test confirms that the UAV operates with stable dynamics and reliable performance. Yaw and roll show good stability with minimal deviation, while pitch follows the setpoint with slight oscillations, indicating scope for controller tuning. The GPS validation demonstrates accurate waypoint tracking with minor noise-related deviations. Vibration levels remain within safe limits, confirming good structural integrity. Overall, the system performs effectively and is suitable for integration with the fire detection module.

CHAPTER SIX:

RESULTS AND DISCUSSION

This chapter presents the results obtained from the implementation and field testing of the UAV-based forest fire detection and alerting system developed in this project. The field testing was carried out in forest areas of Lalitpur district under real environmental conditions to evaluate how well the complete system performs in practice. The evaluation covers three main areas: the detection performance of the trained YOLOv8n model on fire and smoke targets during controlled field tests, the effect of different operating altitudes on detection accuracy and ground coverage, and the reliability of the WiFi-based alert transmission to the ground station desktop after a confirmed detection. Each result is presented along with a discussion of what it means for the practical use of the system in real forest monitoring operations.

6.1 Implementation Results

6.1.1 Non-Fire/Smoke Detection (True Negative)

Before testing whether the system could detect fire and smoke, it was first important to check that the model does not give false alerts when there is nothing to detect. If the system keeps raising false alarms in normal conditions, the ground operators will stop trusting it, which defeats the whole purpose of the system. To check this, the UAV was flown over forest areas in Lalitpur district where no fire or smoke was present, and the camera frames were run through the detection model in real-time to see if any unwanted detections were produced.



(a) Aerial view of forest – no fire or smoke present



(b) Model output – no detections, no bounding boxes drawn

Figure 6.1: True Negative Test 1: YOLOv8n model correctly produces no detection over normal forest terrain



(a) Aerial view of forest – no fire or smoke present



(b) Model output – no detections, no bounding boxes drawn

Figure 6.2: True Negative Test 2: YOLOv8n model correctly produces no detection

As seen in Figures 6.1 and 6.2, the model did not produce any bounding boxes across all test frames captured over the forest. The dry vegetation and uneven ground texture did not trigger any false detections. This confirms that the false positive rate of the system under normal forest conditions is low enough for practical field deployment.

6.1.2 Smoke Detection Result

Smoke is usually the first thing that appears when a forest fire starts. In the early stages, before the flames get big enough to be seen from the air, smoke rises up through the trees and above the canopy where the UAV camera can pick it up. Because of this, the system was built to treat smoke as the main early warning sign rather than waiting for visible flames to appear. To test this, controlled smoke sources were lit at known locations on the ground, and the UAV was flown at different distances and angles above them to see how well the model could detect smoke of different sizes and thicknesses.



(a) Aerial view showing smoke rising above forest canopy



(b) Model output – smoke detected with bounding box at 49% & 77% confidence

Figure 6.3: Smoke Detection Test 1: YOLOv8n model successfully detects smoke plume rising above the forest canopy



(a) Aerial view showing smoke plume at different angle and density



(b) Model output: smoke detected with accurate bounding box at 73% confidence

Figure 6.4: Smoke Detection Test 2: YOLOv8n model correctly detects smoke under varying plume density and viewing angle

As shown in Figures 6.3 and 6.4, the model successfully detected the smoke plume and correctly drew a bounding box around the visible smoke region. Across all smoke tests, the model achieved an Average Precision (AP) of 0.724. Smoke scored higher than fire because a rising plume covers a larger portion of the image frame than a fire at the same altitude, giving the model more visual information to work with.

6.1.3 Fire Detection Result

Detecting fire from a moving UAV is harder than detecting smoke. At our operating altitude, a small fire covers only a tiny part of the camera frame, and the orange and red color of the flames can easily be confused with the dry brown ground and dead leaves common in Nepal's forests during the pre-monsoon season. Because of this, testing how well the model could spot active fire from the air was one of the most important parts of the evaluation. To test this, small controlled fires were lit at known locations on the ground and the UAV was flown over them at different angles to collect a range of fire appearances in the captured frames. The goal was to check whether the model could consistently place a correct bounding box around the fire region even when the surrounding terrain looked visually similar to the flames.



(a) Aerial view showing active fire on forest ground



(b) Model output: fire detected with bounding box

Figure 6.5: Fire Detection Test 1: YOLOv8n model successfully detects active fire on the forest floor



(a) Aerial view showing fire spreading across dry vegetation



(b) Model output: fire region correctly localised with bounding box

Figure 6.6: Fire Detection Test 2: YOLOv8n model correctly localises fire region across dry pre-monsoon forest terrain

As shown in Figures 6.5 and 6.6, the model successfully detected the fire and placed a bounding box around the fire region with good accuracy. The fire class achieved an Average Precision (AP) of 0.723 across all field tests, which is lower than the smoke class mainly because fire covers fewer pixels in the frame and its color looks similar to the dry vegetation on Nepal's forest floor during the pre-monsoon season. Even so, an AP of 0.723 is good enough for this system since the ground operator always makes the final decision on whether to send an emergency response team.

6.2 System Performance

6.2.1 Multi-Altitude Detection Results

Choosing the right flying height is important for getting the best detection results from the UAV. Flying at a lower height gives a clearer and larger view of the fire or smoke in the frame, but it covers less ground in each pass and increases the risk of the UAV hitting tree branches. Flying at a higher height covers more ground in a single pass but makes

the fire and smoke appear smaller in the frame, which can make it harder for the model to detect them correctly. To figure out which height works best for our system, we tested the UAV at three different heights during field testing. At each height, we checked three situations – no fire or smoke, smoke only, and active fire. The detection confidence and false detections were noted down at each height and compared to find the most suitable flying height for forest fire monitoring in our target area.



(a) Aerial frame at low height – fire visible and large in frame



(b) Model output at low height – fire detected with high confidence

Figure 6.7: Detection result at low flying height – large target size produces high confidence but covers less ground area



(a) Aerial frame at medium height – balanced view of fire and surroundings



(b) Model output at medium height – accurate detection with good coverage

Figure 6.8: Detection result at medium flying height – best balance between detection accuracy and ground coverage area



(a) Aerial frame at high height – wide area view, fire appears smaller



(b) Model output at high height – detection successful

Figure 6.9: Detection result at high flying height – wider ground coverage but reduced detection confidence compared to lower heights

6.2.2 System Performance Under Different Light Conditions

This section shows how the system performed under different lighting conditions during field testing. The UAV was tested under two conditions – sunny and night – to see how well the camera and the YOLOv8n model could detect fire and smoke in different real-world lighting situations.

6.2.2.1 Sunny (High Brightness)

The system was tested during the daytime under bright sunny conditions. The strong natural light helped the camera capture clear and sharp frames with good color contrast between the fire, smoke, and the surrounding forest area. The model was able to detect fire and smoke correctly in most frames and placed accurate bounding boxes around the detected regions. Very few false detections were observed during the sunny condition tests, and the detection alerts, along with GPS coordinates, were sent to the ground station desktop successfully in real-time.



(a) Aerial frame under sunny conditions – fire visible in frame



(b) Model output – fire correctly detected under bright sunlight



(c) Aerial frame under sunny conditions – smoke rising above canopy



(d) Model output – smoke correctly detected with bounding box

Figure 6.10: YOLOv8n detection results under sunny (high brightness) conditions

6.2.2.2 Night (Low Visibility)

The system was tested at night to see how it handles low-light conditions. Fire was actually easier to detect at night because the flames and glowing regions stood out clearly against the dark background, which gave the model a strong visual signal to work with. Smoke was a bit harder to detect at night since it does not contrast as well against the dark sky compared to daytime. Overall, the system still performed well at night, and the detection alerts and GPS coordinates were sent to the ground station desktop without any issues.



(a) Aerial frame at night – fire glowing against dark background



(b) Model output – fire detected under low light conditions



(c) Aerial frame at night – low visibility with partial smoke visible



(d) Model output – detection result under nighttime conditions

Figure 6.11: YOLOv8n detection results under night (low visibility) conditions

6.2.3 Alert System Validation

The alert system was tested across 30 controlled detection events to check how reliably the detection alert reached the ground station after a fire or smoke was detected. In this project, only one alerting method was used: once the YOLOv8n model confirmed a detection, the Raspberry Pi 5 immediately sent the detection result along with the GPS coordinates to the ground station computer over the WiFi network. The alert appeared directly on the ground station desktop as a notification showing the detected image with the bounding box drawn around the fire or smoke region and the GPS coordinates of the UAV.

The WiFi-based alert successfully delivered the detection notification to the ground station desktop on all 30 test activations, giving a 100% success rate. The alert appeared on the desktop within 1 to 3 seconds of the detection being confirmed, which is fast enough for the ground operator to take immediate action. Each alert showed the detected image with the bounding box drawn around the fire or smoke region along with the GPS coordinates, giving the operator a clear picture of what was detected and exactly where it was. This confirms that the WiFi-based alerting pipeline works reliably.

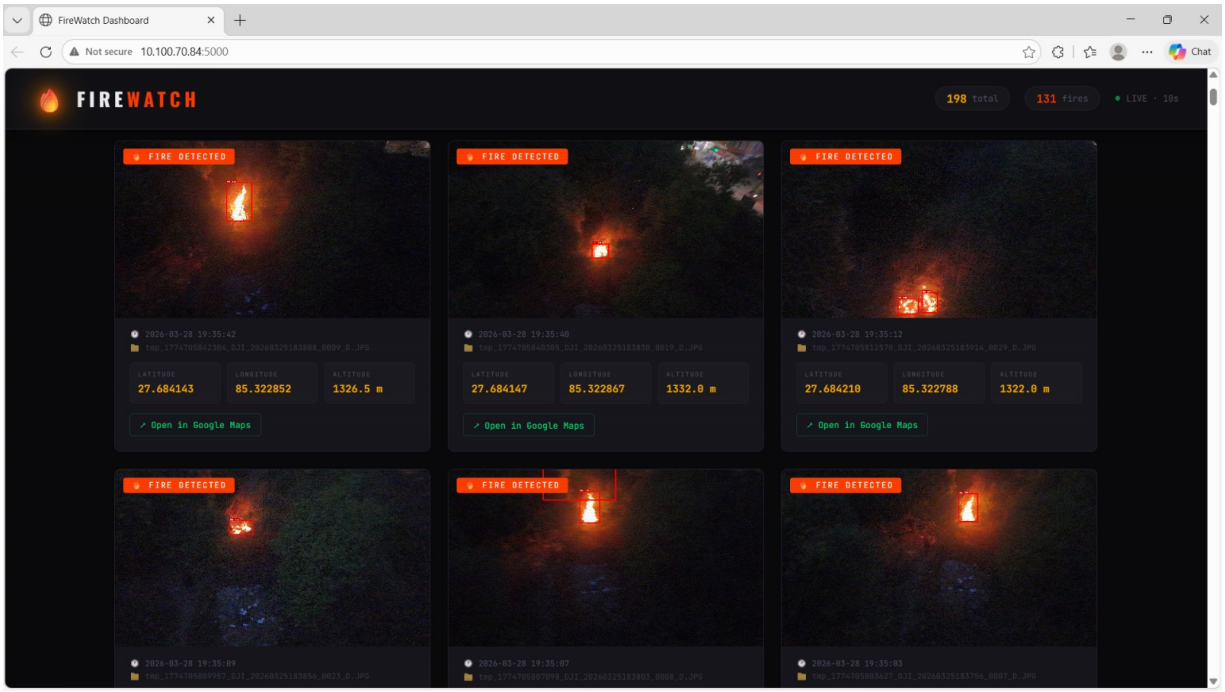


Figure 6.12: Alert on laptop Web dashboard

6.3 Discussion

6.3.1 Analysis of Detection Performance

The YOLOv8n model, trained on our own dataset combined with the D-Fire dataset and deployed on the Raspberry Pi 5, gave acceptable results for a UAV-based forest fire detection system in Nepal's forest environment. The overall precision of 0.724, recall of 0.604, and mAP@0.5 of 0.671 are reasonable numbers for a lightweight model running on embedded hardware without any GPU. The fire class scored an mAP@0.5 of 0.709, and the smoke class scored 0.633. Fire was generally easier to detect because the bright flames stand out clearly against the dark ground and vegetation, especially during low-light conditions where the contrast was even stronger. Smoke, on the other hand, sometimes blended in with clouds, haze, or the sky background, making it harder for the model to detect it confidently in every frame. In a few cases, the model missed some detections, mostly when the fire or smoke covered a very small area in the frame at higher flying heights or when the smoke color was too similar to the surrounding sky. However, these missed detections were very few and occurred only in specific challenging conditions, and they did not significantly affect the overall usefulness of the system during field testing. The precision of 0.724 also shows that when the model did raise a detection, it was correct most of the time, which means the ground operator can generally trust the alerts that appear on the ground station desktop.

During all the field tests, the system did not produce any major false alarms under normal forest conditions. The dry vegetation and uneven ground texture did not cause any significant unwanted detections, which is an important result for a system that is meant to be used in real forest monitoring operations. A system that raises too many false alarms would quickly become unreliable, and the ground operators would stop trusting it, so keeping false positives low was one of the key goals of this project. Adding our own

locally collected images from Nepal's forest areas to the D-Fire dataset during training played an important role in achieving this, as it helped the model learn the specific visual characteristics of Nepal's terrain, dry vegetation, and local fire and smoke appearances that the general D-Fire dataset alone would not have captured well enough. Since the UAV continuously captures frames during flight, any detection missed in one frame is likely to be caught in the following frames, which reduces the practical impact of the occasional misses and keeps the overall alerting pipeline reliable for round-the-clock forest fire monitoring operations in Nepal's forest areas.

6.3.2 Effect of Altitude on Detection Performance

The field tests carried out at three different flying heights showed that altitude has a direct effect on how well the camera can see fire and smoke and how confidently the model can detect them. At a lower flying height, the fire and smoke targets appeared larger in the camera frame, which made it easier for the model to identify them and produce higher confidence detections. However, flying too low brought its own problems – the UAV was closer to the tree canopy, which increased the risk of obstruction, motor vibrations had a bigger effect on image sharpness, and the ground coverage per pass was much smaller, meaning more flight time would be needed to cover the same forest area. At a higher flying height, the camera could cover a much wider area of the forest in a single pass, but fire and smoke appeared smaller in the frame and were sometimes harder to detect, especially when the smoke blended with the sky or haze at that altitude. The medium flying height gave the best overall balance between image clarity, detection confidence, and ground coverage, and was selected as the recommended operating height for this system.

It is also important to note that detection confidence does not depend only on flying height. Several other factors also played a role in how well the model detected fire and smoke during testing. Lighting conditions had a significant effect – under bright sunny conditions, the camera captured clearer frames with better color contrast, while at night, the low ambient light reduced the overall image quality even though the fire was more visible due to its glow. Wind also affected detection, as strong wind caused the smoke plume to spread and thin out quickly, making it harder to detect compared to calm conditions where the smoke rose in a more concentrated column. The size of the fire or smoke source on the ground also mattered – a larger fire produced more pixels in the frame and was detected more reliably than a small spot fire, regardless of the flying height. Background terrain was another factor, as dry brown vegetation and dusty ground during the pre-monsoon season created a visually similar appearance to fire, which occasionally reduced the model's confidence or caused it to miss a detection. All these factors together show that altitude is just one part of the overall detection picture, and that real-world deployment needs to take all these conditions into account when planning a forest fire monitoring mission.

6.4 Limitations

- **Environmental Conditions:** Detection accuracy may decrease in fog, heavy smoke, low light, rain, or extreme weather.
- **Canopy and Obstructions:** Fire or smoke hidden under dense forest canopy or

buildings may remain undetected.

- **Dataset Coverage:** The D-Fire dataset may not include all fire and smoke variations, limiting model generalization.
- **Hardware Constraints:** UAV processors may reduce inference speed for real-time applications.
- **Sensor Limitations:** The model relies on RGB images only, so detection may fail in cases requiring thermal or multispectral data.
- **Dynamic Scenarios:** Rapidly moving UAVs or fast-changing fire patterns may affect detection accuracy.

6.5 Problems Faced

- Environment conditions and canopy delayed the detection of the system, which decreased the accuracy.
- Since the model was trained under a selected dataset, it should be trained with additional local data to increase reliability.
- Onboard processing can increase the inference time.
- Low endurance UAV results in less area coverage.

6.6 Budget Analysis

Table 6.1: Budget Analysis for Forest Fire Detection System

Component	**Qty**	**Total (NPR)**
Battery	1	7,500
UAV Frame	1	10,000
Pixhawk Flight Controller	1	45,000
GPS Module	1	10,000
Raspberry Pi 5	1	36,000
Raspberry Pi Camera Module 3 (Wide)	1	14,500
Communication Module	1	10,000
ESC	4	5,500
Buck Converter	1	500
Brushless Motor	4	10,000
Transmitter and Receiver	1	10,000
Misc. (Wires, Mounts, Enclosure)	–	10,000
Total		**1,69,000**

6.7 Work Timeline

The Gantt chart below represents the workflow of the project.

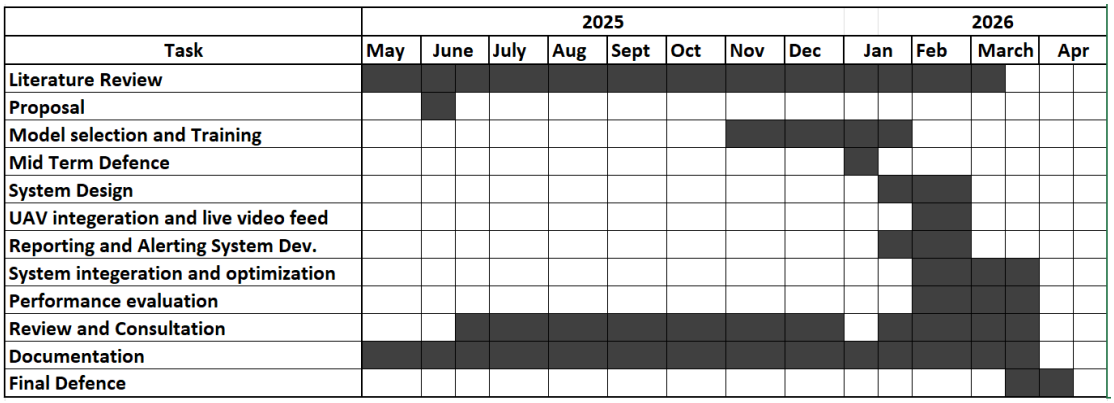


Figure 6.13: Gantt Chart

CHAPTER SEVEN:
CONCLUSION AND FUTURE ENHANCEMENT

7.1 Conclusion

The developed UAV-based forest surveillance system successfully integrates autonomous flight, real-time image processing, and reliable communication to support the early detection of forest fires. The quadcopter demonstrated stable and controlled flight throughout the mission, maintaining consistent yaw, pitch, and roll behavior, along with accurate waypoint navigation and dependable GPS performance. These characteristics highlight the system's ability to carry out reliable area coverage and continuous monitoring, even under varying environmental conditions.

In addition to its flight stability, the system showed consistent performance across different lighting conditions, operating effectively in both bright daylight and relatively low-light environments. The platform also maintained stable functionality at different flight altitudes, indicating its adaptability to diverse mission requirements without a significant loss in performance.

The onboard processing unit, based on the Raspberry Pi 5, efficiently executes fire detection algorithms in real-time, allowing for rapid identification of potential fire incidents. Complementing this, the communication system ensures the timely transmission of critical data, including images, telemetry, and alerts, to the ground control station. The alert mechanism was observed to function reliably, displaying real-time warnings and relevant information on the ground station dashboard. This enables quick situational awareness and supports immediate response from the concerned fire management authorities.

Overall, the system demonstrates a balanced combination of reliability, efficiency, and practical applicability for real-time forest monitoring. While the current performance is promising, future improvements can focus on enhancing detection accuracy, improving robustness under extreme low-light conditions, and incorporating advanced sensing technologies such as thermal or multispectral cameras to further strengthen early fire detection capabilities.

7.2 Scope for Future Enhancement

The following sectors can be enhanced in the future to make this system more robust and applicable for real-world implementations:

- **Improved Detection Model:** The detection accuracy can be improved by training the model with a larger dataset that includes more fire and smoke variations from Nepal's forest environment to make the model more reliable in real field conditions.
- **Thermal Camera Integration:** Adding a thermal camera alongside the RGB camera would help the system detect fire better at night and in heavy smoke conditions where the normal camera cannot capture clear images.

- **Extended Flight Time:** Flight duration and area coverage can be increased by improving power management and using alternative UAV platforms such as fixed-wing or flying-wing designs that consume less power and can cover larger forest areas in a single flight.
- **Autonomous Decision-Making:** Adding dynamic path planning and obstacle avoidance to the UAV would allow it to automatically adjust its flight path based on detection results and fly closer to a suspected fire location to confirm the detection before sending an alert.
- **AI Accelerator:** Using a dedicated AI accelerator such as the Coral Edge TPU or NVIDIA Jetson Nano instead of the Raspberry Pi 5 alone would increase the detection speed and allow the UAV to cover more ground at higher speeds without missing any fire or smoke events.
- **Cloud-Based Monitoring:** Connecting the system to a cloud platform would allow all detection events, GPS locations, and flight data to be stored and viewed remotely, making it easier for forest authorities to track fire incidents and respond quickly.
- **Multi-UAV System:** Using multiple UAVs working together would allow much larger forest areas to be monitored at the same time, reducing the total mission time and making the overall system more reliable.

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CHAPTER EIGHT:

APPENDICES

8.1 APPENDIX A: Python Code for Fire Detection and Alerting

```
import os
os.environ["QT_QPA_PLATFORM"] = "xcb"
os.environ["DISPLAY"] = ":0"
os.environ["OPENCV_LOG_LEVEL"] = "SILENT"

from ultralytics import YOLO
import cv2
import threading
import numpy as np
from collections import deque
from queue import Queue
import time
import subprocess
from pymavlink import mavutil
from datetime import datetime
import piexif
import re
from flask import Flask, jsonify, send_from_directory,
    render_template_string

# ======= MODEL =======
model = YOLO("/home/chandanrajak07/fire_detection/fire_n.pt")
classnames = model.names

# ======= CAMERA / RESOLUTIONS =======
CAM_W, CAM_H     = 640, 480
INFER_W, INFER_H = 224, 224
DETECT_EVERY_N   = 10

# ======= SNAPSHOT SETTINGS =======
SNAPSHOT_DIR        = "/home/chandanrajak07/fire_detection/
    snapshots"
os.makedirs(SNAPSHOT_DIR, exist_ok=True)
SNAPSHOT_COOLDOWN   = 5.0
_last_snapshot_time = 0.0

# ======= GPS READER =======
class GPSReader:
    def __init__(self, port="/dev/ttyAMA0", baud=57600):
        self._lat  = None
        self._lon  = None
        self._alt  = None
        self._fix  = 0
        self._sats = 0
        self._lock    = threading.Lock()
        self._running = True
        self._master  = None
        threading.Thread(target=self._connect_and_read,
```

```
                            args=(port, baud), daemon=True).start()

    def _connect_and_read(self, port, baud):
        try:
            self._master = mavutil.mavlink_connection(port, baud=baud)
            self._master.wait_heartbeat()
            self._master.mav.request_data_stream_send(
                self._master.target_system,
                self._master.target_component,
                mavutil.mavlink.MAV_DATA_STREAM_POSITION,
                10, 1
            )
            while self._running:
                msg = self._master.recv_match(
                    type="GPS_RAW_INT", blocking=True, timeout=5)
                if msg:
                    with self._lock:
                        self._lat  = msg.lat / 1e7
                        self._lon  = msg.lon / 1e7
                        self._alt  = msg.alt / 1000.0
                        self._fix  = msg.fix_type
                        self._sats = msg.satellites_visible
        except Exception as e:
            print(f"[GPS] Error: {e}")

    def get(self):
        with self._lock:
            if self._lat is None:
                return None
            return (self._lat, self._lon, self._alt,
                    self._fix, self._sats)

    def stop(self):
        self._running = False

# ======= CAMERA CLASS =======
class RPiCamera:
    def __init__(self):
        cmd = [
            "rpicam-vid",
            "--width",     str(CAM_W),
            "--height",    str(CAM_H),
            "--framerate", "30",
            "--codec",     "mjpeg",
            "--timeout",   "0",
            "--output",    "-",
            "--nopreview"
        ]
        self.process       = subprocess.Popen(
            cmd, stdout=subprocess.PIPE, stderr=subprocess.DEVNULL)
        self._lock         = threading.Lock()
        self._latest_frame = None
        self._running      = True
        self._jpeg_queue   = deque(maxlen=2)
```

```
        self._q_lock       = threading.Lock()
        threading.Thread(target=self._reader,  daemon=True).
            start()
        threading.Thread(target=self._decoder, daemon=True).
            start()

    def _reader(self):
        buf = b""
        while self._running:
            chunk = self.process.stdout.read(16384)
            if not chunk:
                break
            buf += chunk
            while True:
                s = buf.find(b'\xff\xd8')
                e = buf.find(b'\xff\xd9')
                if s == -1 or e == -1 or e < s:
                    break
                with self._q_lock:
                    self._jpeg_queue.append(buf[s:e+2])
                buf = buf[e+2:]

    def _decoder(self):
        while self._running:
            jpg = None
            with self._q_lock:
                if self._jpeg_queue:
                    jpg = self._jpeg_queue[-1]
                    self._jpeg_queue.clear()
            if jpg is None:
                time.sleep(0.001)
                continue
            frame = cv2.imdecode(
                np.frombuffer(jpg, np.uint8), cv2.IMREAD_COLOR
                    )
            if frame is not None:
                with self._lock:
                    self._latest_frame = frame

    def read(self):
        with self._lock:
            if self._latest_frame is None:
                return False, None
            return True, self._latest_frame.copy()

    def release(self):
        self._running = False
        self.process.terminate()
        self.process.wait()

# ======= FIRE DETECTOR CLASS =======
class FireDetector:
    def __init__(self):
        self.queue         = Queue(maxsize=1)
        self.latest_boxes  = []
        self._lock         = threading.Lock()
        self._running      = True
```

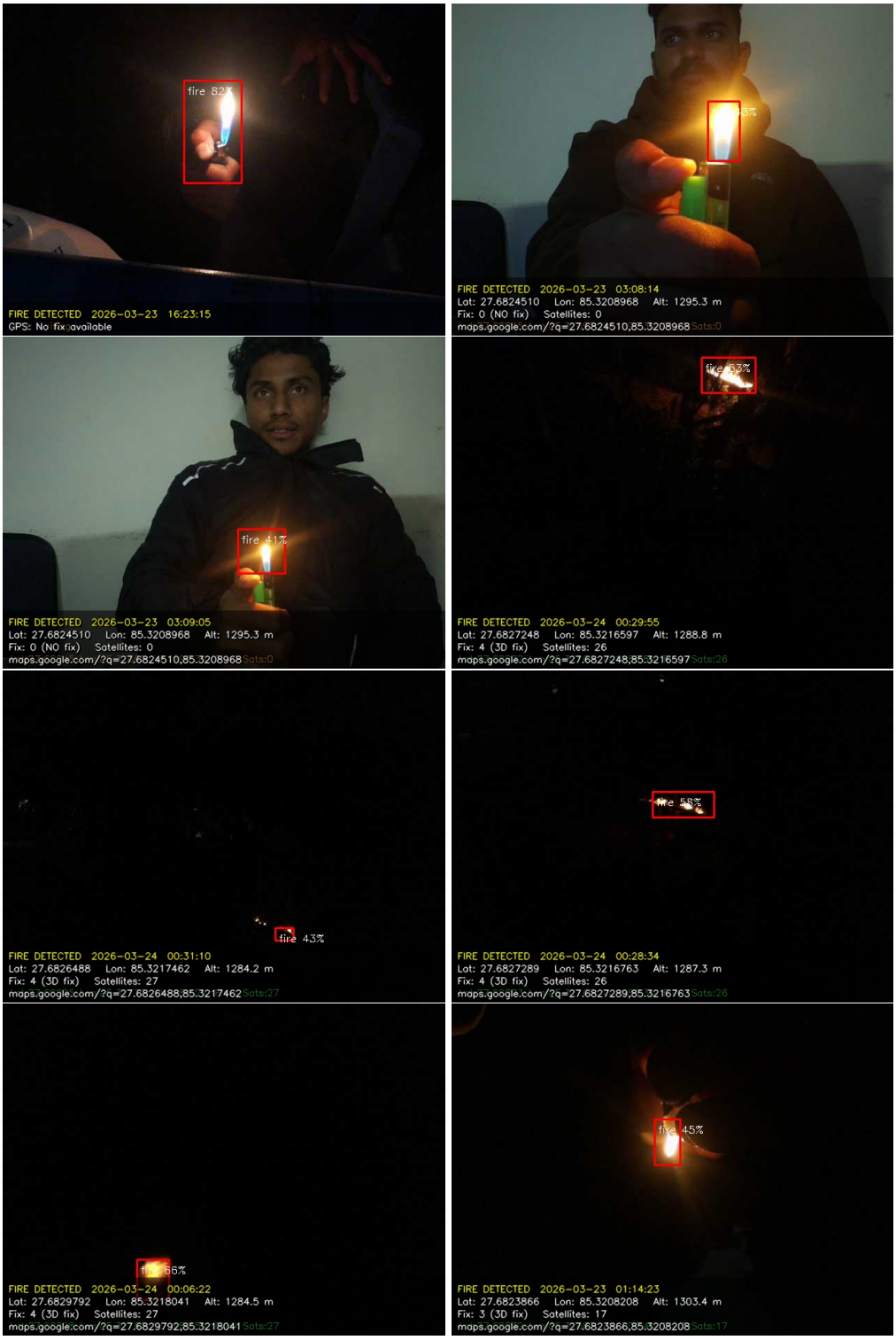
```
        threading.Thread(target=self._worker, daemon=True).start()

    def submit(self, frame):
        if self.queue.full():
            try:
                self.queue.get_nowait()
            except Exception:
                pass
        self.queue.put(frame)

    def get_boxes(self):
        with self._lock:
            return list(self.latest_boxes)

    def _worker(self):
        while self._running:
            frame = self.queue.get()
            small = cv2.resize(frame, (INFER_W, INFER_H))
            boxes = []
            for info in model(small, stream=True, verbose=False):
                for box in info.boxes:
                    conf = int(box.conf[0] * 100)
                    cls  = int(box.cls[0])
                    if conf > 40:
                        x1, y1, x2, y2 = map(int, box.xyxy[0])
                        boxes.append(
                            (x1, y1, x2, y2, classnames[cls], conf))
            with self._lock:
                self.latest_boxes = boxes

    def stop(self):
        self._running = False

# ======= SNAPSHOT HELPER =======
def save_snapshot(frame, gps_data):
    global _last_snapshot_time
    now = time.time()
    if now - _last_snapshot_time < SNAPSHOT_COOLDOWN:
        return
    _last_snapshot_time = now
    ts       = datetime.now()
    stamp    = ts.strftime("%Y%m%d_%H%M%S")
    img_path = os.path.join(SNAPSHOT_DIR, f"fire_{stamp}.jpg")
    txt_path = os.path.join(SNAPSHOT_DIR, f"fire_{stamp}.txt")
    cv2.imwrite(img_path, frame, [cv2.IMWRITE_JPEG_QUALITY, 95])
    if gps_data:
        lat, lon, alt, fix, sats = gps_data
        location_str = (
            f"Timestamp  : {ts.strftime('%Y-%m-%d %H:%M:%S')}\n"
            f"Latitude   : {lat:.7f}\n"
            f"Longitude  : {lon:.7f}\n"
            f"Altitude   : {alt:.2f} m\n"
            f"Fix Type   : {fix}\n"
```

```
            f"Satellites : {sats}\n"
            f"Google Maps: https://maps.google.com/"
            f"?q={lat:.7f},{lon:.7f}\n"
        )
    else:
        location_str = (
            f"Timestamp  : {ts.strftime('%Y-%m-%d %H:%M:%S')}\
               n"
            "GPS data   : Not available\n"
        )
    with open(txt_path, "w") as f:
        f.write(location_str)

# ======= FLASK DASHBOARD =======
flask_app = Flask(__name__)

@flask_app.route("/")
def index():
    return "Fire Detection Dashboard"

@flask_app.route("/api/events")
def api_events():
    events = []
    if not os.path.isdir(SNAPSHOT_DIR):
        return jsonify(events)
    txt_files = sorted(
        [f for f in os.listdir(SNAPSHOT_DIR) if f.endswith(".
           txt")])
    for txt in txt_files:
        stem     = txt[:-4]
        img_name = stem + ".jpg"
        if not os.path.exists(
                os.path.join(SNAPSHOT_DIR, img_name)):
            continue
        lat = lon = alt = None
        try:
            with open(os.path.join(SNAPSHOT_DIR, txt)) as f:
                for line in f:
                    if line.startswith("Latitude"):
                        lat = float(line.split(":")[1].strip()
                            )
                    elif line.startswith("Longitude"):
                        lon = float(line.split(":")[1].strip()
                            )
                    elif line.startswith("Altitude"):
                        alt = float(
                            line.split(":")[1].strip().split()
                                [0])
        except Exception:
            pass
        events.append(
            {"image": img_name, "lat": lat,
             "lon": lon, "alt": alt})
    return jsonify(events)

@flask_app.route("/snapshot/<filename>")
def serve_snapshot(filename):
    if not re.match(r'^fire_\d{8}_\d{6}\.jpg$', filename):
```

```
        return "Not found", 404
    return send_from_directory(SNAPSHOT_DIR, filename)

def start_dashboard():
    flask_app.run(host="0.0.0.0", port=5000,
                  debug=False, use_reloader=False)

# ======= MAIN =======
gps      = GPSReader(port="/dev/ttyAMA0", baud=57600)
cap      = RPiCamera()
detector = FireDetector()

for _ in range(50):
    ret, _ = cap.read()
    if ret:
        break
    time.sleep(0.05)

threading.Thread(target=start_dashboard, daemon=True).start()

frame_count = 0
sx = CAM_W / INFER_W
sy = CAM_H / INFER_H

while True:
    ret, frame = cap.read()
    if not ret:
        continue
    frame_count += 1
    if frame_count % DETECT_EVERY_N == 0:
        detector.submit(frame.copy())
    boxes          = detector.get_boxes()
    fire_detected = len(boxes) > 0
    for x1, y1, x2, y2, class_name, conf in boxes:
        dx1, dy1 = int(x1 * sx), int(y1 * sy)
        dx2, dy2 = int(x2 * sx), int(y2 * sy)
        cv2.rectangle(frame, (dx1, dy1), (dx2, dy2),
                      (0, 0, 255), 2)
        cv2.putText(frame, f"{class_name} {conf}%",
                    (dx1 + 5, dy1 + 20),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.5,
                    (255, 255, 255), 1)
    gps_data = gps.get()
    if fire_detected:
        save_snapshot(frame.copy(), gps_data)
    cv2.imshow("Fire Detection", frame)
    if cv2.waitKey(1) & 0xFF == 27:
        break

detector.stop()
cap.release()
gps.stop()
cv2.destroyAllWindows()
```

Listing 8.1: Python code for fire detection and alerting system

8.2 APPENDIX B: Preliminary Testing of detection module



8.3 APPENDIX C: Additional Project Glimpses

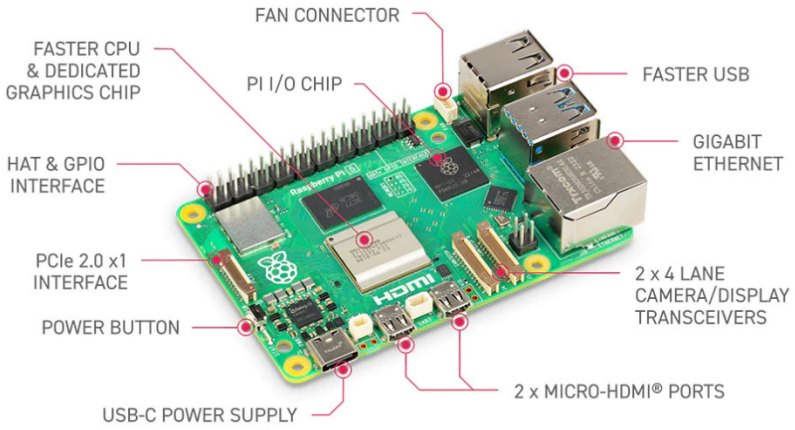
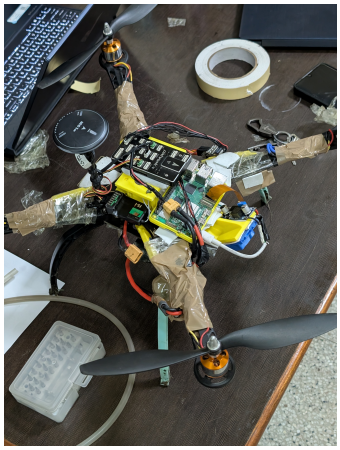
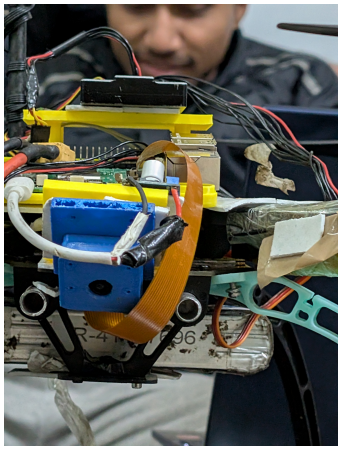


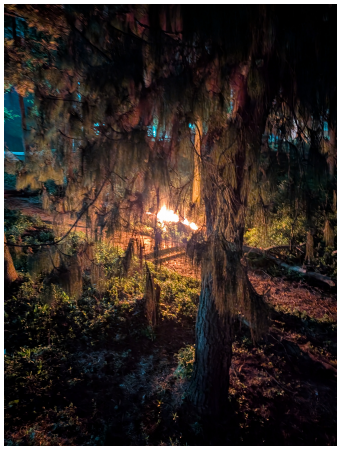
Figure 8.2: Raspberry Pi 5 [5]



(a) Glimpse 1



(b) Glimpse 2



(c) Glimpse 3



(d) Glimpse 4



(e) Glimpse 5



(f) Glimpse 6



(g) Glimpse 7



(h) Glimpse 8



(i) Glimpse 9



(j) Glimpse 10