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Design and Validation of an IoT-Enabled Safety Monitoring System for Agricultural UAV Operations

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Abstract

The challenges faced by Unmanned Aerial Vehicles (UAVs) used in precision agriculture are growing. Operational risks arise from harsh conditions, such as abnormal flight behaviors, extended missions, and environmental circumstances. Current flight controllers primarily focus on navigation and stabilization, with only limited ability to monitor real-time safety. This study presents a low-cost, real-time safety monitoring platform for agricultural UAVs using an ESP32 microcontroller integrated with an MPU6050 inertial measurement unit (IMU) and a DHT11 temperature sensor. The system continuously measures roll, pitch, and on-board temperature, sending telemetry data to a cloud-based IoT platform for visualization and alerts. An empirically derived, threshold-based anomaly detection plan, based on over 100 normal flight data points, more than 20 Pixhawk crash log analyses, and observations of climatic conditions from 28 Indian states, allows for timely detection of abnormal operating conditions. The monitoring module has a sampling rate of 30-40 Hz and uses persistence-based detection logic to ensure that sustained anomalies are present over a 125-165 ms timespan. It was experimentally verified that roll and pitch estimates based on an atan2-based approach have a mean absolute error of 7.62° and 13.52°, respectively, compared to reference flight controller measurements. Temperature validation shows that the DHT11 sensor's temperature readings do not exceed the ±4.6°C deviation limit relative to the reference readings. These findings reveal that the suggested framework offers a scalable, cost-effective, and easily implemented solution for safety monitoring and early detection of abnormal flight conditions in agricultural UAV delivery.

Keywords: DHT11 and MPU6050 Sensors, IoT-Based Monitoring, Safety Monitoring System, Threshold-Based Anomaly Detection, Agricultural UAVs.

1. Introduction

Agriculture operations increasingly employ Unmanned Aerial Vehicles (UAVs) for crop monitoring, precision spraying, and field surveillance. Their autonomy in working on a large scale has enhanced productivity and performance in collecting data. Nevertheless, the nature of agricultural UAVs often involves operating in undesirable environments, such as excessive ambient temperatures, dust exposure, mechanical pressure, and excessive mission durations. These factors may exacerbate the reliability of systems and increase the risk of in-

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flight failures; thus, continuous monitoring of safety is a significant need. Current UAV systems are mainly based on on-board flight controllers to provide stabilization and navigation. These controllers are typically limited in independent safety control and early warning of abnormal thermal and mechanical events, indicating potentially unsafe UAV operating conditions. However, they are practical in real-time control. In practice, numerous fault indicators, abnormal attitude excursions, or internal overheating are not detected until there is a crash or failure. This drawback is especially important in agricultural activities, where UAVs commonly operate beyond visual line-of-sight and cover wide, geographically dispersed areas. Recent work has examined the utilization of vibration analysis, model-based, and data-based approaches for UAV fault detection and safety monitoring. Although they have proven effective at detecting abnormal flight behavior, several of these methods remain computationally expensive, require costly sensor suites, or require large training experiments. Where energy efficiency, robustness, and simplicity are crucial, these specifications restrict their applicability on resource-constrained UAV platforms that are often active in agricultural operations. Further, the majority of existing solutions are either post-flight analysis-based or controller-based and do not provide comprehensive real-time autonomous monitoring of active missions.

These limitations are further compounded by operational difficulties when deploying on a large scale in agriculture. Configuration issues, underperformance, or minor accidents are usually reported manually by pilots to UAV fleet operators. This form of operating is subjective and likely to underreport, and thus partially damaged or ineptly configured UAVs keep on operating without proper examination. Without hardware-based condition monitoring, fleet operators can only see a limited view of the real-time operational conditions and state of deployed UAVs. Also, the majority of agricultural systems do not have specific internal thermal sensors to track the thermal circumstances of flight-crucial electronics, including the flight controller and its power circuit. When operated in long and high ambient temperatures, or in closed structural designs, excessive internal heating can result in component degradation, electrical faults, or, in worst cases, a fire hazard. An internal temperature can thus be continuously monitored to issue early notice of overheating or developing malfunctions, thereby preventing catastrophic failure.

This paper introduces a simple, non-artificial UAV safety surveillance system suitable for agricultural tasks. The suggested system is a self-monitoring system that includes both inertial and temperature readings, without requiring any modifications to the main flight controller. It constantly scans thermal, roll, and pitch values. It identifies deviant operating conditions through empirically determined thresholds derived from long-term regional environmental data, flight experiments, and Pixhawk crash logs. The framework facilitates the generation of alerts and the real-time visualization of missions in geographically distant or visually unreachable areas by adding a cloud-based layer of IoT communication. In contrast to methods based on learning or post-flight diagnostics, the proposed scheme focuses on lightweight, crash-aware, real-time safety monitoring that applies to UAV deployments in large-scale agriculture. The modular architecture also makes fleet management easier, provides early notifications of possible failures, and makes it easier to analyze what has happened after an incident, which subsequently feeds into operational decision-making improvements.

The work has largely been summarized as follows: First, research proposes real-time UAV safety monitoring that uses embedded sensors and cloud connectivity and is independent of the vehicle's core control systems. Second, it develops and evaluates threshold-based anomaly detection, directly based on real agricultural flight data and crash reports. Lastly, it shows a scaled-easy architecture, introduced for use with fleets of UAVs in agriculture.

2. Related Work

In recent years, significant research has comprised UAV safety monitoring and fault detection. Initial research emphasized awareness of faults and monitoring operations across various flight conditions, with a primary focus on assessing safety using sensors and ensuring measurement reliability for UAV systems [1], [2]. Additionally, the implementation of wireless communication and IoT-based platforms to facilitate remote UAV monitoring and system connectivity has also been investigated in related studies [3]. Numerous research works have investigated the application of integrated systems and inertial sensors for determining the safety oversight and state of UAVs. Due to their small size and high performance, MEMS accelerometers and gyroscopes have been widely used as IMUs for orientation estimation and analysis of UAV motion [4], [8]. Additionally, various signal processing techniques exist, including vibration analysis, which can help in detecting mechanical failures, such as electric motor failures, physical imbalance, and structural deterioration [5], [6]. Over the past few years, the application of data and smarter methodologies in monitoring faults in UAVs has become more common. Machine learning and deep learning algorithms have been employed to automatically infer when an aircraft is experiencing problems from sensor, flight log, or vibration data [12], [13]. At the same time, high accuracy is achieved through these techniques for fault identification; the need for large amounts of training data and the expensive power consumption required to run these algorithms typically preclude their use in lightweight UAV systems.

Researchers have studied the use of advanced navigation and sensor-fusion techniques to enhance the reliability of UAVs operating in hostile environments. Multi-sensor fusion techniques for UAV positioning and attitude estimation, particularly when deprived of GPS or magnetometer, have also been proposed using Kalman filter-based approaches [7], [9], [11], [17]. The increased use of UAVs in agriculture, autonomous observation, and environmental sensing has been more recently explored. Internet of Things (IoT)-enabled monitoring systems and smart agricultural platforms have been proposed to provide real-time data visualization and control of remote systems [14], [15]. Also, autonomous, safety-centered UAV monitoring systems have been proposed to maximize operational dependability and situational awareness [16]. Further studies have been conducted on aerodynamics, platform design, and UAV propulsion to enhance flight performance and stability [10], [19], [20], [23]. To enhance the reliability of onboard measurements, another effort has examined vibration isolation, sensor accuracy, and environmental compensation [18], [21], [22]. Even with these improvements, current UAV safety surveillance strategies usually entail trade-offs among detection accuracy, computational complexity, real-time applicability, and hardware cost. Furthermore, little focus has been placed on deploying thermal monitoring in conjunction with attitude-based anomaly detection on a low-weight, standalone framework that could be used in large-scale agricultural UAV applications. The current work addresses this by presenting a low-cost, crash-informed, IoT-based safety monitoring system, designed for the deployment structure of agricultural UAVs. Table 1 provides a comparison of the suggested framework with current methods of UAV safety monitoring. The proposed system combines thermal and attitude observations, real-time warnings, IoT connectivity, and crash-log-informed thresholds, unlike previous studies, which increase its overall scope of functionality.

Table 1. Evalution of the proposed system in relation to current uav safety obseravtion methods

Study	Thermal Monitoring	Attitude (Roll/Pitch)	Real-Time Alerts	IoT Enabled	Crash-Log Informed Threshold
Balestrieri et al.(2021)	×	✓	×	×	×
Ghazali & Rahiman (2022)	×	✓	×	×	×
Shi et al. (2024)	✓	✓	✓	×	×
Sadhu et al. (2023)	×	✓	×	×	×
This Work	✓	✓	✓	✓	✓

3. System Architecture and Methodology

3.1 System Design Overview

The suggested UAV safety monitoring network identifies the presence of abnormal operating conditions of the UAV during agricultural missions in real time and is not dependent on the primary flight controller. This division ensures that safety surveillance does not intrude on navigation or stabilization procedures and does not impose any additional computational load on crucial control practices. Figure 1 illustrates that the system comprises sensing, local processing, and wireless communication, all of which are onboard and modularly structured. During flight, an embedded sensing unit continually obtains the inertial and thermal information. These measurements are processed locally by the embedded controller to assess flight stability and abnormal conditions. After processing, they are sent to a cloud-based IoT platform that provides alerts and visualizations. The modular architecture enables use on various UAV platforms and scales for multi-drone farm tasks under centralized oversight.

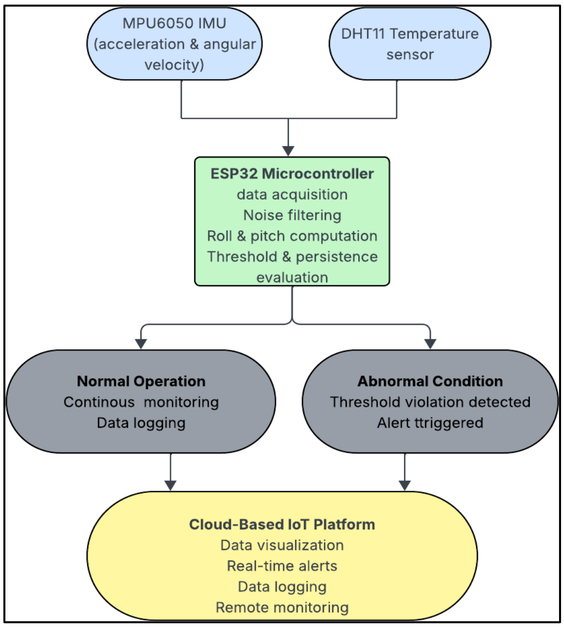


Figure 1. The proposed UAV safety monitoring frameworks the architectural design and data flow

3.2 Design Rationale and Hardware Selection

The focus of the system design is to select economical, dependable, and suitable hardware for agricultural applications. The ESP32 microcontroller is also power-efficient, has built-in Wi-Fi capabilities, and has enough processing power to handle real-time sensor data processing, making it ideal for embedded UAV applications. The device's small size and availability also make it suitable for use in the proposed safety monitoring system. The main features of the proposed monitoring module hardware, communication, and firmware are summarized in Table 2.

Table 2. System specifications of the proposed monitoring module

Parameters	Specification
Embedded Controller	ESP32 Dual-Core Xtensa LX6
Processor Frequency	80–240 MHz
Flash Memory	4MB
SRAM	520 KB
IMU Sensor	MPU6050 (±4*g* accelerometer, ±1000*dps* gyroscope)
Temperature Sensor	DHT11 Digital Sensor
Communication	Wi-Fi 2.4 GHz via 4G LTE Hotspot
Sensor Interface	I^2C / Single-Wire Digital
Operating Voltage	3.3 V
Power Source	16,000 mAh Li-Po via UBEC (5.3V/3A)
Alert-Logic	Threshold + Persistence-based
Cloud Platform	Blynk IoT Platform
Firmware Environment	Arduino IDE (C/C++)
Memory Utilization	~57% Flash /~14% RAM
Deployment Platform	Agricultural Hexacopter UAV Platform

The MPU6050 inertial measurement unit (IMU) measures tri-axial acceleration and angular velocity data to estimate roll and pitch angles for flight stability. The sensor is light, energy-efficient, and widely used in aerial platforms. The DHT11 temperature sensor has been chosen because it is inexpensive, energy-efficient, lightweight, and can easily be integrated with the ESP32 platform. Although the DHT11 has sensor accuracy of ±5°C, this level of precision is sufficient for the proposed threshold-based monitoring framework, where the objective is to detect overheating trends rather than to perform high-precision environmental temperature measurements. Together, these components form a compact and deployable monitoring module for agricultural UAVs. The monitoring module is powered by a UBEC voltage regulator connected to the ESP32's input, and the sensor is powered from the ESP32's regulated 3.3V rail; the UBEC is connected to the UAV's battery. The total power consumption of the ESP32 microcontroller and the sensor attached to it is below 1W under normal operating conditions, according to the typical reporting specifications in the devices' datasheets. With the 16,000mAh 6S LiPo battery and 22.2V (355.2Wh) of the UAVs, this extra load is negligible in relation to the energy available. The monitoring module thus has an insignificant effect on the overall UAV endurance, relative to the propulsion power demands required of an agricultural UAV.

The embedded monitoring firmware provided sensor acquisition, attitude estimation, and threshold analysis in a cyclic loop with an effective sampling frequency of about 30-40 Hz (≈ 25-33 ms/iteration). While experimentally deployed, firmware memory use was within the nominal device limits, at around 57-59 percent of flash memory and 14 percent of RAM, and ensured headroom to handle communication processing and alert logic execution. The program was executed on Arduino IDE using C/C++ to develop and deploy the firmware. This sensing module was mounted on the UAV canopy, near the flight controller, to reduce wiring complexity and provide stable power distribution. The impact of mechanical vibration was reduced by triggering the IMU's digital low-pass filtering mechanism and internal mounting effects, leading to the stabilization of inertial measurements at nominal flight conditions.

Additionally, internal placement also offered a level of passive defense against dust and direct exposure to environmental elements.

3.3 System-Level Data Processing and Alert Generation

The data from the sensors were sampled at about 30-40 Hz, which allowed for timely detection of abnormal flight conditions without excessive computational load. In UAV flight, the onboard sensors continuously collect inertial and thermal data, which is transmitted to the ESP32 microcontroller. The ESP32 works locally in real-time. In order to reduce noise and stabilize signals both crucial for accurate estimation during dynamic flight the system first pre-processes the raw sensor measurements. To enhance the stability of measurements and reduce high-frequency disturbances from motor vibration and environmental noise of UAVs, the system turns on the MPU6050 sensor's internal Digital Low Pass Filter (DLPF). The system writes the CONFIG register (0x1A) with the value 0x03, which gives the accelerator and gyroscope cutoff frequencies of 42 Hz and 44 Hz, respectively. This setup offers a suitable compromise between noise. The atan2()-based method was used to estimate roll and pitch angles, and noise suppression and signal latency (~ 4.9 ms) were achieved to ensure reliable measurements of roll and pitch angles.

The filtered accelerometer measurements are used in the system to estimate the UAV's orientation using light-weight trigonometric relationships. The roll and pitch angles are calculated by the system as follows:

$$\text{Roll}(\phi) = \text{atan2}\left(A_y, \sqrt{A_x^2 + A_z^2}\right) \tag{1}$$

$$\text{Pitch}(\theta) = \text{atan2}\left(-A_x, \sqrt{A_y^2 + A_z^2}\right) \tag{2}$$

where A_x, A_y, and A_z represent the accelerometer components along the X, Y, and Z axes, respectively. The MPU6050 gyroscope data is continuously captured, and the yaw angle is estimated for visualization and post-event analysis in the monitoring framework. Yaw is not used for real-time generation; however, roll and pitch give more reliable indications of abnormal flight behavior. Onboard temperature data are continually analyzed, and calculated roll and turnover angles are monitored against predefined safety thresholds using empirical flight data, crash logs, and long-term environmental studies. Localized sensing of threshold-exceedance events within the embedded controller can be used to have that system react quickly, even in case there is no continuous network connection.

The proposed framework uses persistence-based decision-making logic to minimize false alarms due to short-term exceptions (e.g., gusts of wind or forceful but insignificant actions). An alert will be generated only if the threshold is violated for a specified number of consecutive samples. Isolated persistence counters measure temperature and attitude parameters so that continuous abnormal conditions are sensed and not transient conditions. N=5 successive samples were used as a persistence window to apply the persistence-based anomaly-detection logic. Considering the system sampling frequency of 30-40Hz, the matching sampling interval is 25-33ms. Thus, the detection latency of sustained anomalies can be estimated as:

$$\text{Latency} \approx N \times \frac{1}{f} \tag{3}$$

Where N represents the persistence window, f denotes the sampling frequency. This produces an effective detection latency of about 125-165 ms, allowing sustained abnormal flight conditions to be detected early and short-duration disturbances to be rejected. This latency is the time it takes the monitoring system to verify that a threshold has been violated once abnormal conditions have been reached, in preference to predicting failures. The framework thus offers an early insight into prospective flight instability.

Algorithm 1: Threshold-based UAV safety monitoring

```
Input:
Temperature reading - T
Roll and Pitch angles - R,P
Temperature threshold - T_thresh
Roll and Pitch thresholds - R_thresh,P_thresh
Persistence window - N
Output:
Alert notification
Variables:
Temperature persistence counter - c_T
Attitude persistence counter - c_A
Initialize sensor interfaces and IoT communication
Initialize counters - c_T ← 0, c_A ← 0
while UAV is in operation, do
    Acquire temperature T
    Acquire acceleration data
    Compute roll R and pitch P
    if T > T_thresh, then
        c_T ← c_T + 1
    else
        c_T ← 0
    end if
    if |R| > R_thresh or |P| > P_thresh, then
        c_A ← c_A + 1
    else
        c_A ← 0
    end if
    if c_T ≥ N or c_A ≥ N, then
        Trigger alert notification
    end if
    Transmit sensor data and alert status to the cloud dashboard
end while
```

The persistence window was tested in initial breadboard validation with N = 1,2,5,7, and 8. Smaller values were easier to detect but more susceptible to temporary disturbances and sensor noise, whereas larger values offered greater suppression of short-period events but slower confirmation of anomalies. In this initial analysis, N = 5 was chosen as a reasonable compromise between responsiveness and robustness in detection. This configuration, at the operating sampling frequency of 30-40 Hz, would yield an estimated anomaly confirmation latency of about 125-165 ms, which would give a convenient trade-off between rapid anomaly detection and rejection of short-lived disturbances during normal UAV operation. The embedded controller generates an alert flag locally when the framework identifies sustained threshold violations, and then transmits the related sensor data and alert states to a cloud-based IoT platform through a wireless connection. Real-time visualization, logging, and notification to authorized users are made possible by this procedure. The end-to-end monitoring logic deployed on the embedded platform is described together in Figure 5 and Algorithm 1.

The operational thresholds were established at ±50° for roll, ±65° for pitch, and at 45°C for onboard temperature, with the derivations of these limits explained in section 4.2. In this context, the anomaly detection algorithm conducts real-time threshold analysis of locally processed sensor data. This layered processing approach allows rapid, locally made decisions at minimal computational cost. The proposed framework provides an opportunity to achieve a high degree of reliability and scalability, as well as applicability for the deployment of agricultural UAVs at the fleet level, given the need for continuous safety control and remote situational awareness, by distinctly separating sensing, processing, and communication tasks.

3.4 Threshold Determination Using Long-Term Weather Data

To determine temperature safety limits for agricultural UAV activities that account for environmental factors, this research examined regional temperature surveys from the NASA POWER database. The dataset, inclusive of December 30, 2023, to December 31, 2024, comprises state-level temperature measurements from 28 states in India. Agricultural UAVs are usually flown across different geographic locations for a long duration under high ambient temperatures. Therefore, it is required to use thermal thresholds that reflect operational conditions, not nominal specifications.

We computed the daily average temperatures from the recorded observations as follows:

$$T_{\text{avg,day}} = \frac{1}{m}\sum_{i=1}^{m} T_i \tag{4}$$

Where Ti denotes the individual temperature measured for a day, and m represents the number of observations. The monthly and annual temperature values were then calculated from the daily data, using standard climatological aggregation procedures.

To define the worst-case ambient thermal conditions for UAV electronics, the study established the maximum temperature as:

$$T_{\text{max, year}} = \max\left(T_{\text{max, jan}}, T_{\text{max, feb}}, \dots, T_{\text{max, Dec}}\right) \tag{5}$$

where $T_{max,month}$ is the maximum recorded temperature for each month of the year. Figure 2 shows the variation of temperature in the states analyzed over a year. According to this study, ambient temperatures in various locations can exceed 40°C during the summer months, with high spatial and temporal variability. It emphasizes the need to take into account the environmental context while defining the thermal threshold to ensure proper functioning.

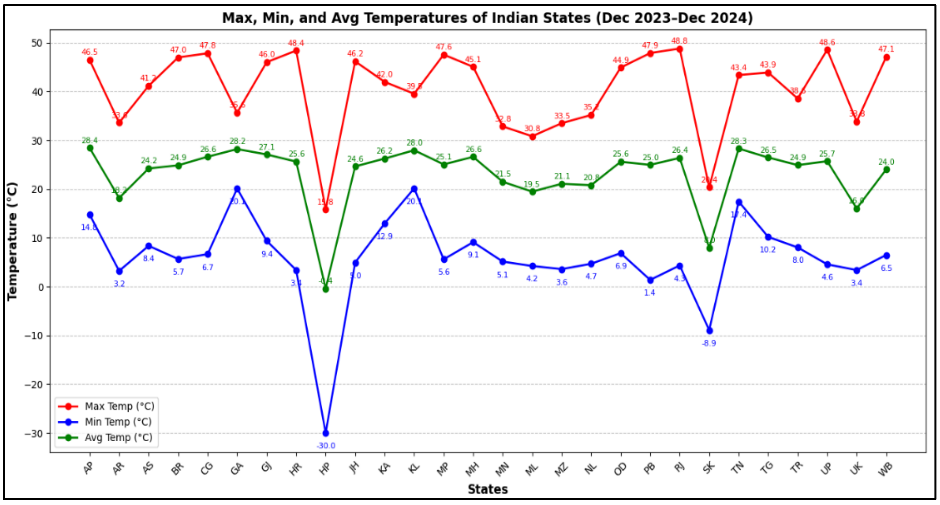


Figure 2. Regional temperature variation based on long-term climatic data used for threshold determination

The framework for anomaly detection compares measured roll, pitch, and temperature values to established safety thresholds. These thresholds were derived from crash-log analysis, nominal flight envelopes, and environmental data. The process followed to set these thresholds is discussed in section 4.2. In this work, adaptive thresholding mechanisms were not implemented, as the main goal was to test a lightweight, real-time monitoring system for resource-constrained UAV platforms.

4. Flight Parameter Analysis and Stability Assessment

4.1 Trends in Flight Parameters

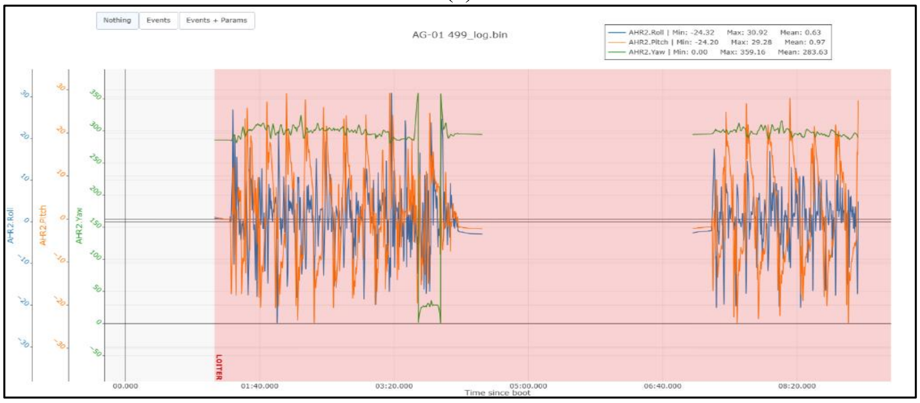
The variation in flight parameters during the recorded UAV crash events are discussed in this section to assess the efficacy of inertial data to recognize abnormal flight behavior. In this study, Pixhawk flight logs were examined for several failure scenarios, and the variations in roll, pitch, and yaw before and during the events were analyzed. Table 3 shows the extracted flight parameters of representative crash scenarios: tree collision, electric wire impact, battery failsafe, and compass malfunction. Significantly abnormal flight dynamics and deviations in attitude parameters were observed before system failure in all events. The collision with a tree had a sudden pitch excursion of more than 50°, and the compass malfunction scenario showed significant yaw instability due to magnetic interference. Battery-related failures, however, led to a loss of control authority due to power instability, resulting in irregular angular behavior.

Table 3. An overview of the parameters from the Pixhawk crash log and the observed anomalies in flight

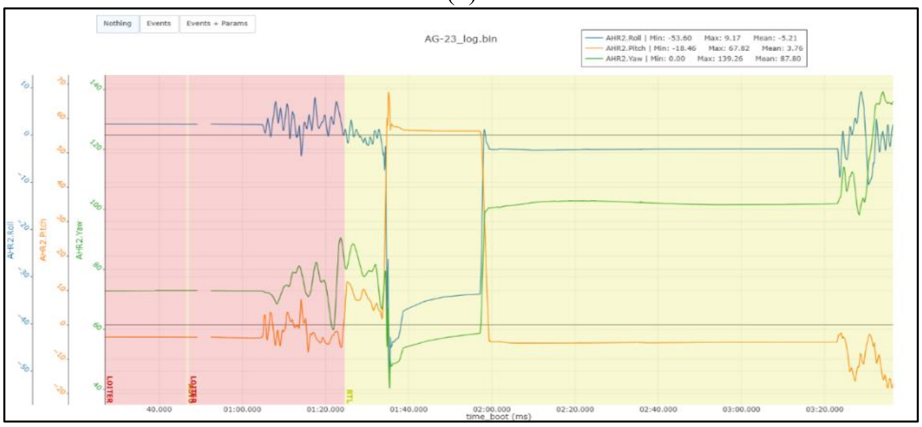
crash type	Pitch (°)	Roll (°)	Yaw (°)	Ang.Error (°)	Remarks
Tree hit	53.24	–	–	>30	EKF failsafe due to compass inaccuracy, drone deactivated even in LAND mode.
Electric Wire Hit	–	–	359.16	–	Direct impact, no error logs prior to the crash
Battery Failsafe	–	–	–	45	Low voltage led to failed AUTO mode entry; the system disarmed.
Compass error	–58.70	–37.33	358.74	30	A magnetic anomaly caused compass failure and yaw realignment

Ang. Error- Angular Error.

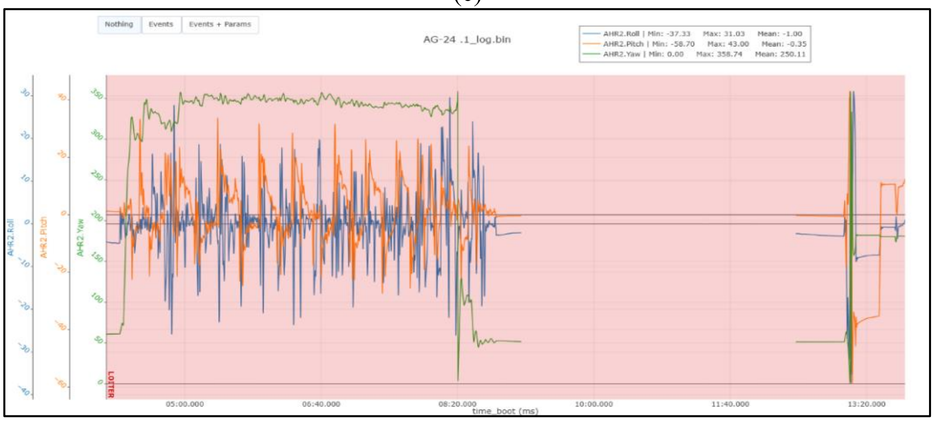
(a)



(b)



(c)



(d)

Figure 3. Roll, Pitch, and Yaw. Anomalies logged during four distinct crash situations: (a) collision with a tree, (b) impact with an electric line, (c) battery failure safety mechanism, and (d) malfunctioning compass

Figure 3 shows the roll, pitch, and yaw during these crash scenarios. The results show sharp turns and incipient instability that occur right before failure. We observe from the above that inertial parameters are useful indicators of abnormal behavior and support the need to consider attitude-based parameters within the proposed safety monitoring framework to capture indicators of abnormal operational conditions online during UAV operation.

4.2 Stability Analysis of the UAV Platform

Flight data obtained from the K++V2 system showed that the operating parameters remained stable under normal conditions, without failures. At normal operation, roll angle and pitch angles were not greater than ±21° and ±25°, respectively, while the yaw was stabilized at ±180°. The GPS signal strength was between 26 and 32, while the vehicle speed was 4.3-5.0 m/s on average, with a maximum of 7.3 m/s.

IMU readings displayed stable acceleration patterns, with values ranging from 0 to 1 on the X and Y axes and from -9 to -11 m/s² on the Z-axis, which aligns with normal gravitational effects. These results confirm that the dynamics of the platform were stable under regular operation. The average roll and pitch variations experienced under nominal flight conditions are shown in Figure 4. The lack of sudden angular changes and the controlled attitude behavior further provide stable functioning, which will provide a baseline reference in comparison with flight dynamics in crash scenarios.

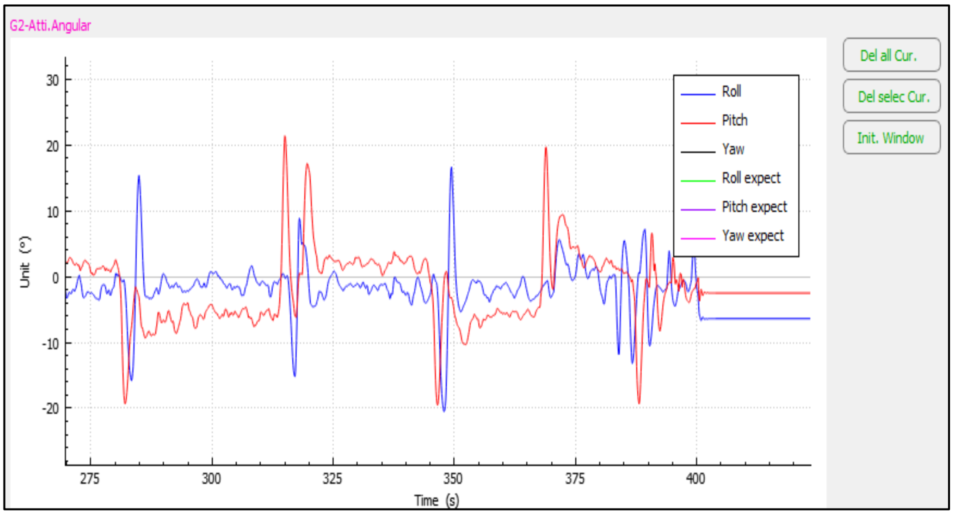


Figure 4. Graphical representation of K++V2's roll and pitch variation during normal UAV's agricultural operation

In this paper, empirical safety levels to distinguish between healthy operation modes and those related to instability, loss of control, or system degradation were constructed by synthesizing the analyses of nominal K++V2 flight data and Pixhawk crash data, validated by onboard estimates of attitude and local environmental data. We came up with the values of the threshold based on a margin approach. We took on more safety margins, depending on the crash logs and estimation error, and took the highest values observed during the stable flight as the reference point. It is a method that allows the system to not only take into consideration sensor noise and temporary disturbances, but also to pre-warn of aberrant behavior. This, therefore, resulted in marginal-based determination of the operational threshold of each parameter being monitored, X:

$$X_{\text{thresh}} = X_{\text{nominal, max}} + M_X \tag{6}$$

X_{thresh} represents the safety threshold used for detection of an anomaly; $X_{nominal,max}$, denotes the maximum safe UAV flight value; and M_x, is a safety margin, obtained from observation of crash logs and estimation errors. This formulation assures that the threshold remains above the envelope of nominal flight dynamics and yet below the extreme values of a crash scenario. In thermal monitoring, the threshold was determined by relating the environmental thermal conditions to anticipated operating temperatures onboard. The temperature threshold was set as:

$$T_{\text{thresh}} = T_{\text{ambient,max}} + M_T \tag{7}$$

Where $T_{ambient,max}$ denotes the maximum ambient temperature obtained from long-term climate analysis, and M_T represents a safety margin accounting for internal electronic heating and sensor measurements uncertainty.

Environmental datasets, like the NASA POWER database, represent ambient atmospheric temperatures. However, the internal temperature of UAV electronics is usually higher due to heat generated by onboard components, including the flight controller, ESCs, power electronics, and communication modules, and the restricted airflow within the UAV canopy. The NASA POWER Climate Dataset analysis suggests that ambient temperatures often exceed 40°C during peak seasonal conditions in agricultural regions. In experimental testing, the DHT11 sensor mounted in the canopy of the UAV was able to record onboard temperatures of up to 38°C in high ambient conditions (Figure 7). Considering the ±5°C measurement uncertainty of the sensor and potential internal heat accumulation during prolonged UAV operation, a conservative safety margin was applied when defining the thermal safety threshold. The empirical analysis resulted in establishing the operational thresholds for the anomaly detection framework as ±50° for roll, ±65° for pitch, and 45°C for onboard temperature. These thresholds provide a clear distinction between nominal and abnormal flight regimes, enabling the identification of unsafe operating conditions in a timely manner, as summarized in Table 4.

Table 4. Safety thresholds for UAV anomaly detection that have been empirically determined

Parameter	Threshold value	Source of Derivation	Justification
Roll angle	±50°	Pixhawk crash-log analysis + nominal K++V2 flight data + attitude estimation validation (Table 6) + threshold formulation Eq.6	Normal agriculture flight stayed within ±21°, but roll excursions exceeded 50° in crash events. The threshold provides separation between normal and abnormal flight regimes while accounting for estimation error, with an MAE of 7.62°.
Pitch angle	±65°	Pixhawk crash-log analysis + nominal K++V2 flight data + attitude estimation validation (Table 6) + threshold formulation Eq.6	While nominal flight stayed within ±25° pitch deviations over 60° were consistently associated with collision events or loss of control. To prevent false alarms the threshold takes estimation uncertainty into account of MAE 13.52°.
Temperature	45°C	NASA POWER long-term climatic analysis (fig.2) + onboard temperature experiments + sensor validation (table 5) + thermal threshold model Eq.7	In agricultural regions peak ambient temperature often surpass 40°C, whereas onboard measurements during testing were 38°. As a result, chosen thresholds offers, additional margin for sensor measurement uncertainty and internal heating during extended UAV operation.

The threshold values were obtained by analyzing over 20 Pixhawk crash logs and over 100 nominal K++V2 flight logs. Space limitations cause only representative crashes and nominal cases to be provided in the manuscript.

5. IoT-Based Architecture and Alert Implementation

The ESP32 microcontroller was integrated with the Blynk IoT platform via a 4G LTE connection to provide real-time monitoring and remote alerting of crucial flight parameters. The sensor data (acceleration, roll, pitch, yaw, temperature, and humidity) was sent to the Blynk dashboard via virtual communication channels, allowing constant visualization and monitoring of the system state through web and mobile applications.

The ESP32 communicates with the Blynk cloud platform via its built-in Wi-Fi interface, using a secure TCP/IP connection. The system ensures communication security by employing Transport Layer Security (TLSv1.2) encryption via the WiFiClientSecure library. The device connects to the network from a JioFi 4G LTE hotspot via a WPA2-secured Wi-Fi connection. While in operation, the monitoring module sends 2 Hz inertial telemetry data from the MPU6050 sensors to the cloud dashboard. The DHT11 sensor sends temperature data every 0.5 Hz (every 2 seconds) to minimize growth in cloud storage and bandwidth usage. According to network traffic observations, the mean network data rate is 275 bytes/sec (≈2.2 Kbps), comprising payload data and TCP/IP and TLS protocol overhead.

The frequency of data transmission to the cloud dashboard was limited mainly by network delay rather than by local processing speed.

The suggested framework established alert levels through empirical research of K++V2 flight data, Pixhawk crash data, and environmental conditions in the region. It established the final alert limits for roll, pitch, and temperature, with safety thresholds determined empirically. For system validation purposes, more conservative (±3° to ±10° for roll and pitch; 30°C to 40°C for temperature) threshold values were temporarily applied to determine if the system can correctly respond and alert the user. When a threshold violation occurred, an alert was sent to the cloud via the ESP32, immediately notifying operators in real-time via Blynk.

Figure 5 gives the overall workflow of the system, from the acquisition of data using sensors, processing data locally, checking with a predefined threshold, generating an alert, and final notification in the cloud. When the network is temporarily lost, the embedded controller keeps local alert assessment and transmits notifications on reconnection. This situational awareness framework is a real-time alerting system that allows continuous situational awareness and timely notification in abnormal flight conditions.

6. Results and Discussion

In this section, we demonstrated testing of the proposed UAV monitoring system and discussed the framework's performance in detecting abnormal flight behavior using integrated inertial and temperature sensors. The data, in the form of controlled flight tests and real-time monitoring via the Blynk IoT platform, is analyzed and evaluated. The integrated controller could stabilize a steady loop frequency of about 30-36 Hz, confirming it to be a valid platform for real-time safety monitoring with minimal processing time requirements. This sampling rate results in a persistence window size of N=5 samples, corresponding to a computed anomaly confirmation latency of approximately 125-165 ms, similar to the theoretically computed detection latency in section 3.3.

6.1 Sensor Validation and Accuracy Assessment

We compared the DHT11 temperature sensor before integrating it into the UAV platform. It was validated to determine whether it was suitable for threshold-based safety monitoring. The purpose of this validation was to confirm that the sensor could provide stable and consistent temperature readings, rather than vastly precise thermal measurements. We compared the DHT11 temperature sensor readings with reference measurements from an HTC-1 digital thermometer and publicly available weather data collected under the same environmental conditions. As summarized in Table 5, the DHT11 sensor closely follows ambient temperature trends, with deviations usually within the manufacturer's specified precision of ±5°C.

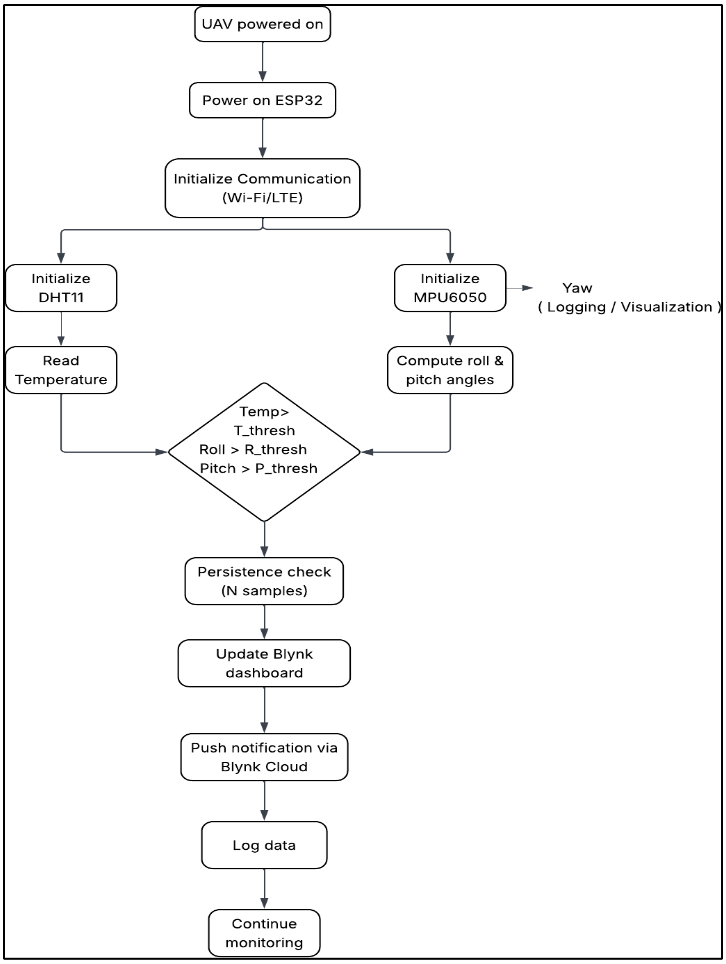


Figure 5. Flow chart of the drone monitoring system's sensor checks, notifications, and cloud integration

The largest deviation observed from the validation data was approximately ±4.6°C, which is within the established tolerance. These deviations are acceptable for safety monitoring applications, as the monitoring framework is based on thresholds for anomaly detection, and the operating temperature threshold used in this study (45°C) is significantly higher than the measured error.

Table 5. Experimental checks of the DHT11 sensor readings, comparing them with the HTC-1 device and a weather data service

Date	Time	DHT11 Temp	HTC-1 Device Temp	Diff dht11–htc1	Weather Data Service Temp(wdst)	Diff (dht11–wdst)
16-07-2024	08:00	23.7	28.3	-4.6	24.4	-0.7
16-07-2024	12:00	26.7	29	-2.3	28.7	-2
16-07-2024	16:00	28.8	30.1	-1.3	28.6	0.2
17-07-2024	08:00	25.2	28.4	-3.2	25.1	0.1
17-07-2024	12:00	28.7	29.9	-1.2	27.4	1.3
17-07-2024	16:00	30.2	30.4	-0.2	29.3	0.9
20-07-2024	08:00	28.6	29.6	-1	24.9	3.7
20-07-2024	12:00	28.4	29.6	-1.2	26.5	1.9
20-07-2024	16:00	27.8	29.5	-1.7	25.6	2.2
21-07-2024	08:00	27.6	28	-0.4	24.4	3.2
21-07-2024	12:00	27.6	29	-1.4	26.6	1
21-07-2024	16:00	27.2	29.1	-1.9	26.3	0.9

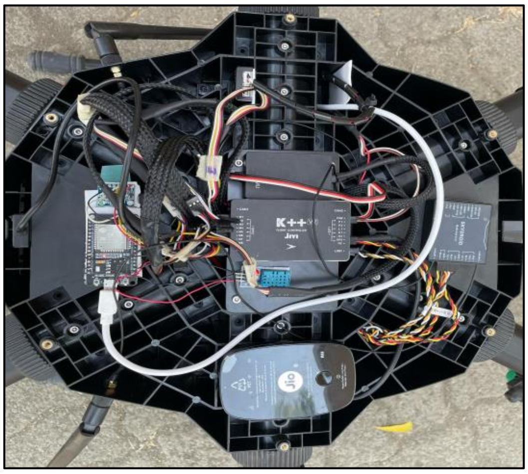
Figure 6 shows the actual hardware setup for the proposed monitoring system–basically, the combined sensing module and the agriculture UAV platform used to run and validate the experiments.

To quantitatively assess the accuracy of the atan2-based attitude estimation, the mean absolute error (MAE) between the estimated angles and the reference flight controller measurements was computed as:

$$\mathrm{MAE}_{\mathrm{roll}} = \frac{1}{n}\sum_{i=1}^{n} \left| R_i^{\mathrm{K{+}{+}V2}} - R_i^{\mathrm{atan2}} \right|$$

$$\mathrm{MAE}_{\mathrm{pitch}} = \frac{1}{n}\sum_{i=1}^{n} \left| P_i^{\mathrm{K{+}{+}V2}} - P_i^{\mathrm{atan2}} \right|$$

Where *n* represents the number of samples, the absolute value prevents sign cancellation and yields a reliable measure of average estimation error. Table 6 summarizes the quantitative comparison between the atan2-based attitude estimates and the reference K++V2 flight controller measurements.



(a)

(b)

Figure 6. The hardware setup of the proposed UAV monitoring system is depicted, showcasing: (a) the integrated sensing module and (b) the agricultural UAV employed for testing

Table 6. Comparison of atan2()-based estimation and roll, pitch angles obtained from K++V2 flight logs

K++V2 Acc.X	K++V2 Acc.Y	K++V2 Acc.Z	K++V2 Roll	K++V2 Pitch	Atan2() Roll	Atan2() Pitch	Roll Diff.	Pitch Diff.
4.43	-0.19	-10.09	-5.02	-19.73	-4.72	23.168	0.3	3.43
0.12	-0.32	-10.83	2.84	13.25	-1.79	-0.671	1.05	12.58
4.29	-0.9	-8.85	7.46	2.41	-5.228	-25.74	2.24	23.33
-0.68	1.74	-10.86	0.56	20.02	9.08	3.537	8.52	16.49
5.4	-2.26	-8.96	-0.07	-18.54	-12.19	-30.3	12.12	11.76
2.02	0.03	-10.34	21	0.54	0.17	11.05	20.83	10.51
0.23	1.07	-10.06	20.25	0.02	6.07	1.3	14.18	1.28
6.05	-2.76	-8.69	-12.91	4.81	-14.61	-33.56	1.69	28.75

The MAE for roll and pitch were 7.62° and 13.52°, respectively, using representative sampling of the flight data. These MAE values were employed to estimate the conservative roll and pitch safety thresholds to be used in the study to ensure that any anomalies were reliable even when uncertain about the estimates. These error levels are still tolerable when it comes to threshold-based safety monitoring, which is not intended to achieve high-precision flight control, but rather to realize significant variations in attitude. The identified differences can primarily be attributed to differences in the onboard filtering and sensor-fusion approaches employed by the flight controller. Consequently, MAE is adopted in the study as the key performance measure in order to determine attitude estimation performance instead of a statistical confidence interval.

6.2 Threshold-Based Alert Evaluation

The study used a series of controlled validation experiments to evaluate the effectiveness of the proposed alert mechanism using predefined thermal and attitude thresholds. The assessment aimed to test the system's ability to identify unusual operational situations and to provide immediate alerts during UAV operations.

For threshold validation experiments, the study used conservative thresholds to evaluate the response of the system. The average alert delivery latency measured in stable network conditions was around 1-3 seconds. The integrated controller identifies prolonged anomalies within 125-165 ms, based on the sampling rate and detection logic configured in section 3.3, thereby providing early warning before potential flight unsteadiness. The system activated a notification if the temperature exceeded 30°C, and it gave warning messages for roll and pitch variations of more than ±30° and ±40°, respectively, as shown in Figure 7. These values were used only for validation to ensure proper alert-triggering behavior and are not representative of operational thresholds used in the field. Along with the alerts, the system documented sensor readings and alert statuses linked to threshold breaches.

The alerts were sent in real-time through the cloud-based IoT platform, which showed reliable communication and alert delivery in operational conditions. The system also documented sensor readings and alert states for threshold violations, allowing for post-event analysis of temperature and attitude behavior during abnormal operation, in addition to real-time alerting.

The experimental outcomes demonstrate that the proposed framework consistently identifies threshold exceedance and provides timely user notifications. Integrating threshold-based alerting with cloud-connected monitoring improves situational awareness and facilitates informed decision-making in agricultural UAV operations. While conservative thresholds were used for validation, operational limits were subsequently derived from long-term environmental analysis, crash-log data, and nominal flight behavior, as discussed in previous sections.

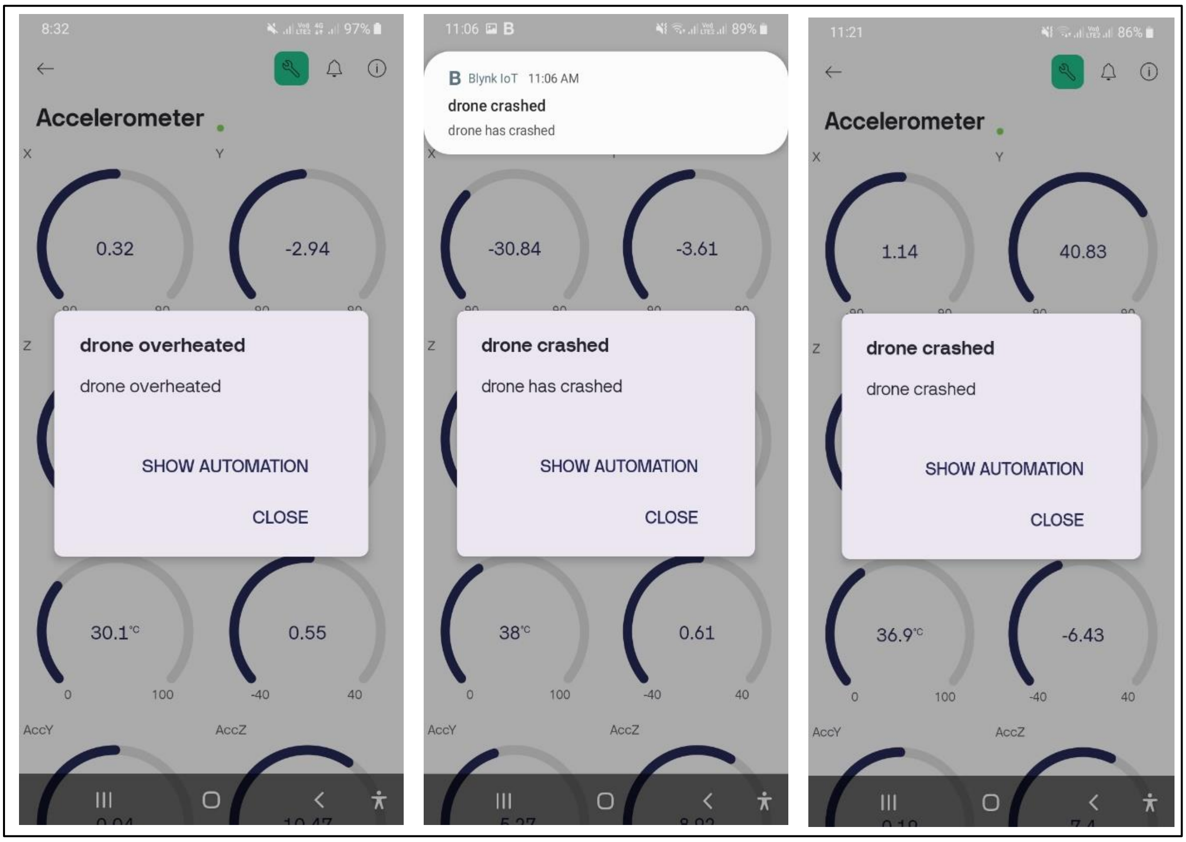


Figure 7. Representative alert notifications were sent during threshold validation experiments, such as thermal and attitude warnings are sent through the blynk platform

7. Limitations and Feature Scope

The suggested safety monitoring system based on UAVs was not only tested in validated controlled experiments and the interpretation of real-world flight data in agriculture, but it also identified a number of limitations. The analysis was conducted on one UAV platform for agricultural applications under specific environmental conditions. Though the system architecture is inherently hardware-agnostic and scaled with ease, the temperature and attitude limits used in this study were set based on local climatic conditions. Thus, implementations in areas with subsequently varying climatic, attitude, or functioning profiles might necessitate slight adjustment of these thresholds. Moreover, a DHT11 temperature sensor is currently used in the implementation, which suffices to validate the proof of concept and to send alerts based on thresholds. It, however, has a limited operating range, which can limit its operation in harsh ambient temperatures. High-range sensor like the DHT22 can be utilized in future versions to achieve high performance and long durability in high-temperature weather conditions. The monitoring system, detection logic, and cloud based alerting mechanism, however, are general across various platforms and deployments. Future work includes extending this framework to incorporate adaptive thresholds that consider environmental factors, historical flight data, and the mission characteristics. The current threshold is an empirically derived limits and fixed value. Additionally, the incorporation of extra onboard sensors, like barometers, magnetometers, and pro-longed field deployment across various geographic areas and UAV platforms, will further improve the system's robustness and applicability.

8. Conclusion

This work designed and experimentally tested a low-weight safety monitoring system for agricultural UAVs. This system, based on an ESP32 microcontroller with inertial and thermal sensors, serves as an autonomous monitoring layer that constantly analyzes roll, pitch, and onboard temperature to identify abnormal flight conditions during UAV missions. Experimental analysis showed that the monitoring module had a constant processing frequency of about 30-40 Hz and identified sustained anomalies within 125-165 ms, based on persistence threshold evaluation. Relative to reference flight controller data, the proposed attitude estimation methodology yielded a mean absolute error of 7.62° in roll and 13.52° in pitch, validating that the estimation error falls within the threshold range for detecting anomalies. Experiments on temperature validation revealed that the DHT11 sensor showed deviations up to ±4.6°C from reference measurements, which is acceptable for detecting overheating conditions given the defined operational threshold of 45°C. The monitoring system transmitted telemetry data at about 275 Bps (≈ 2.2 Kbps). It consumed less than 1W of power, resulting in no significant effect on the UAV's endurance or the ability to continue monitoring. Use of IoT systems with cloud technology offered reliable alert services, with typical delivery speeds of 1-3 seconds, boosting awareness of operators in abnormal operating conditions. The experimental results support the statement that the proposed framework will provide a practical, cost-effective, and scalable safety monitoring system for agricultural UAV applications. This structure is especially relevant to large-scale agricultural UAV service providers because it not only enables centralized, hardware-based monitoring but also enhances safety management and reduces reliance on subjective reporting. To further enhance the robustness and applicability of the framework, future developments include testing it on various UAV platforms and in a broader range of operating conditions.

Conflict of Interest

No Conflict of Interest

Funding Statement

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