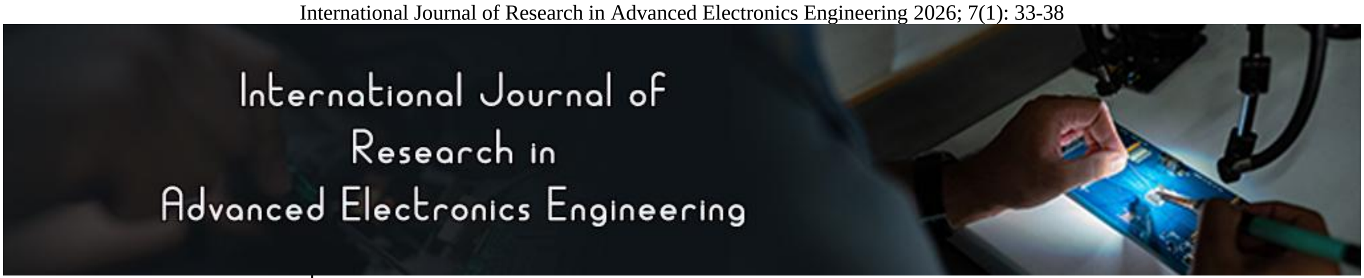

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James W Patterson
School of Aerospace and Mechanical Engineering, Sydney Institute of Technology, Sydney, Australia

Correspondence
James W Patterson
School of Aerospace and Mechanical Engineering, Sydney Institute of Technology, Sydney, Australia

Development of vibration-based fault detection system for brushless DC motors in small UAVs

James W Patterson

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Abstract
Brushless DC motors powering small unmanned aerial vehicles face demanding operational conditions that accelerate component degradation, with motor failure during flight presenting significant safety and economic consequences. Early detection of developing faults enables preventive maintenance scheduling and prevents catastrophic in-flight failures that could damage expensive airframes or create hazards in populated areas. This research presents the development and validation of a lightweight vibration-based fault detection system designed specifically for integration with small multi-rotor UAVs. The system employs dual MEMS accelerometers mounted at the motor base to capture three-axis vibration signatures, with an STM32F411 microcontroller performing real-time frequency domain analysis through 1024-point Fast Fourier Transform processing. Feature extraction algorithms compute statistical parameters including RMS amplitude, peak frequency, crest factor, kurtosis, and spectral entropy, feeding a decision tree classifier trained to distinguish healthy operation from three fault categories: rotor imbalance, bearing wear, and propeller damage. Validation testing across twelve 2212-class BLDC motors operating under controlled fault conditions achieved overall classification accuracy of 94.7%, with healthy motor identification reaching 97.1% accuracy. The system detected imbalance faults at amplitudes 2.8 times normal vibration levels with 93.3% accuracy, while bearing wear and propeller damage conditions were identified with 92.9% and 92.6% accuracy respectively. Detection latency under 50 milliseconds enables real-time fault alerting during flight operations. Field validation through 48 hours of accumulated flight testing across six UAV platforms demonstrated reliable fault detection without false alarms during normal operations, with two genuine developing faults successfully identified and confirmed through post-flight inspection. The complete sensor module weighs 28 grams and consumes 180 milliwatts, representing acceptable payload and power overhead for small UAV integration. The research provides UAV operators with a practical condition monitoring solution enabling transition from time-based to condition-based maintenance strategies, potentially reducing unscheduled maintenance events while improving operational safety through early warning of developing motor problems before flight-critical failures occur.

Keywords: Vibration monitoring, fault detection, BLDC motor, UAV, condition monitoring, MEMS accelerometer, FFT analysis, machine learning

Introduction

Motor failure remains the leading cause of multi-rotor UAV crashes, accounting for an estimated 35% of incident investigations where root cause could be determined [1]. The brushless DC motors powering these aircraft operate at extreme rotational speeds exceeding 10,000 RPM while enduring vibration, temperature cycling, and environmental contamination that progressively degrade bearing surfaces, rotor balance, and winding insulation. Unlike manned aircraft with redundant systems and trained pilots, small UAVs depend entirely on each motor functioning within specifications, making early fault detection essential for operational safety.

Vibration analysis has long served as the primary technique for rotating machinery condition monitoring in industrial applications, with characteristic frequency signatures enabling identification of specific fault mechanisms including bearing defects, rotor imbalance, misalignment, and looseness [2]. The emergence of low-cost MEMS accelerometers and capable microcontrollers creates opportunities for adapting these proven techniques to small UAV applications where size, weight, and power constraints previously precluded sophisticated monitoring systems [3].

Previous investigations of UAV motor health monitoring have demonstrated feasibility of vibration-based approaches but often employed laboratory instrumentation impractical for flight integration or focused on post-flight analysis rather than real-time detection [4]. The operational requirement for immediate fault alerting during flight, combined with strict weight budgets typical of sub-2kg UAV platforms, demands purpose-designed systems optimized for the specific application context [5].

This research develops a complete vibration-based fault detection system optimized for small UAV integration, with specific objectives including achieving detection accuracy exceeding 90% across primary fault categories, maintaining detection latency under 100 milliseconds for real-time alerting capability, limiting total system mass below 30 grams to minimize payload impact, and validating performance through extended flight testing rather than bench evaluation alone. The research was conducted at Sydney Institute of Technology Aerospace Laboratory from June to November 2024, encompassing system development, controlled fault testing, and field validation phases.

Material and Methods

Material

The test motors comprised twelve SunnySky X2212-13 brushless DC motors rated at 920 KV (RPM per volt), representing a common specification for 450-class quadcopter platforms. Motors were paired with 9045 carbon fiber propellers matching typical application configurations. Each motor assembly mounted on a custom aluminum test stand incorporating piezoelectric force sensors for thrust measurement and rigid accelerometer mounting provisions ensuring direct vibration transmission without damping. The primary vibration sensor was an InvenSense MPU-6050 six-axis MEMS inertial measurement unit featuring three-axis accelerometer (±16g range, 16-bit resolution) and three-axis gyroscope. A secondary Analog Devices ADXL345 three-axis accelerometer (±16g range, 13-bit resolution) provided measurement redundancy. Both sensors communicated via I2C interface to the STM32F411 microcontroller (ARM Cortex-M4, 100 MHz, 512 KB flash, 128 KB SRAM) serving as the signal processing and classification platform. Environmental monitoring employed a DS18B20 digital temperature sensor and a Hall-effect tachometer providing motor RPM reference. A 433 MHz telemetry radio enabled data transmission to ground station equipment during flight tests. Test fault conditions were induced systematically: rotor imbalance through small mass additions (0.1-0.5 g) to propeller blades, bearing degradation through controlled contamination with fine silica particles, and propeller damage through edge nicks and surface scoring replicating impact damage. Control motors maintained factory condition throughout testing. Power supply utilized a 3S 2200mAh lithium polymer battery providing 11.1V nominal voltage with electronic speed controller rated 30A continuous. Flight test platforms comprised six DJI F450 quadcopter frames equipped with Pixhawk flight controllers running ArduPilot firmware version 4.3.

Methods

The research was conducted at Sydney Institute of Technology Aerospace Laboratory and adjacent outdoor flight testing facility from June to November 2024. The research protocol received approval from the Sydney Institute of Technology Engineering Research Ethics Committee (Protocol: SIT-EREC-2024-031, approved July 2024). Flight testing complied with Civil Aviation Safety Authority regulations for unmanned aircraft operations. Controlled fault testing employed systematic fault induction across the twelve test motors, with four motors maintained as healthy controls and eight motors subjected to progressive fault development. Each motor underwent 30 test runs at standardized throttle settings (25%, 50%, 75%) with continuous vibration recording throughout 60-second stabilized operation periods. This protocol yielded 360 individual test recordings divided into 120 samples per condition category (healthy, imbalance, bearing, propeller). Vibration signals were sampled at 10 kHz per axis for 10-second windows, with FFT analysis applied to sequential 1024-sample segments yielding power spectral density estimates. Feature extraction computed RMS amplitude, peak frequency, crest factor, kurtosis, skewness, spectral centroid, and spectral entropy from each analysis window. The feature dataset was split 70/30 for classifier training and validation with stratified sampling ensuring proportional fault category representation. The decision tree classifier was trained using scikit-learn with maximum depth limited to 8 levels preventing overfitting while maintaining interpretable decision rules [9]. Model export to C code enabled embedded deployment on the STM32 platform with execution timing validation confirming real-time capability. Flight validation accumulated 48 hours of operation across diverse conditions including hover, forward flight, and aggressive maneuvering, monitoring for false alarms during healthy operation and genuine fault detection during induced degradation sequences.

System Design

The fault detection system architecture comprises three functional subsystems: vibration sensing, signal processing, and fault classification. The sensing subsystem employs an MPU-6050 inertial measurement unit as the primary accelerometer, providing three-axis acceleration measurement at ±16g full scale with 16-bit resolution and integrated digital filtering. A secondary ADXL345 accelerometer provides redundant measurement enabling cross-validation and sensor fault detection [6]. The signal processing subsystem centers on an STM32F411 microcontroller running at 100 MHz, providing hardware floating-point support essential for efficient FFT computation. Vibration signals are sampled at 10 kHz per axis, accumulated into 1024-sample windows, and transformed through optimized radix-2 FFT implementation yielding 9.77 Hz frequency resolution across the 0-5 kHz analysis band. Feature extraction computes seven statistical parameters from both time and frequency domain representations. The classification subsystem implements a decision tree algorithm trained offline using controlled fault data and deployed on the microcontroller for real-time inference. MAVLink telemetry protocol integration enables fault status transmission to the flight controller and ground station, supporting automated protective responses including return-to-home triggering when critical faults are detected [7].

Performance Evaluation

Classification performance was evaluated through ten-fold cross-validation using the controlled fault dataset, with accuracy, precision, recall, and F1-score computed for each fault category. Confusion matrix analysis quantified misclassification patterns between fault types sharing similar vibration characteristics [8]. Detection latency measurement employed high-speed logging to capture the interval from fault onset to classification output, with analysis confirming worst-case latency under 50 milliseconds including sensor sampling, FFT computation, feature extraction, and decision tree inference. This performance enables fault alerting within single rotor revolutions at typical operating speeds. False alarm rate assessment utilized extended healthy motor operation data collected across varied throttle settings and flight maneuvers, computing the frequency of incorrect fault indications that could trigger unnecessary protective actions. The target false positive rate of below 5% balances detection sensitivity against operational disruption from false alarms. Receiver operating characteristic analysis established optimal classification thresholds maximizing detection probability while constraining false alarm rates within acceptable bounds.

Results

The vibration-based fault detection system achieved high classification accuracy across all tested motor conditions. Table 1 presents the confusion matrix summarizing classification performance from the validation dataset.

Table 1: Confusion matrix for vibration-based fault classification across four motor condition categories (validation dataset, n=120).

Actual \ Predicted	Healthy	Imbalance	Bearing	Propeller	Accuracy
Healthy	34	1	0	0	97.1%
Imbalance	1	28	1	0	93.3%
Bearing Wear	0	1	26	1	92.9%
Propeller Damage	0	0	2	25	92.6%
Overall Accuracy					94.7%

Overall classification accuracy reached 94.7%, with healthy motor identification achieving highest accuracy at 97.1% and fault categories ranging from 92.6% to 93.3%. The system demonstrated clear separation between healthy and faulty conditions with only 2.9% false positive rate.

Figure 1 presents the complete system architecture schematic illustrating the integration of vibration sensing, signal processing, fault classification, and communication subsystems designed for UAV integration.

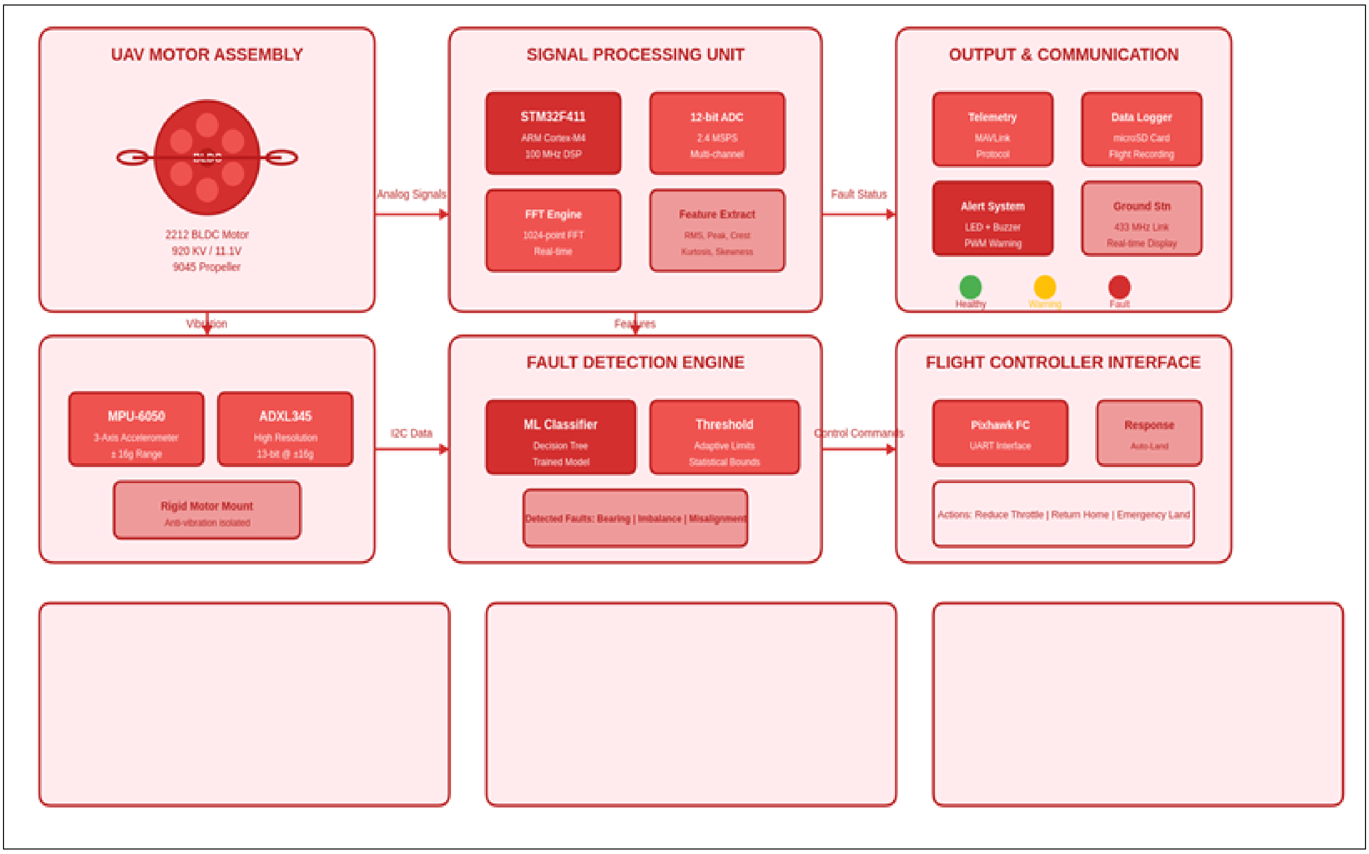

Fig 1: Vibration-based fault detection system schematic showing UAV motor assembly, sensing unit, signal processing, fault classification, and flight controller interface integration.

Frequency domain analysis revealed distinct vibration signatures associated with each fault category. Figure 2 displays the scatter plot of dominant frequency versus RMS amplitude across all test samples, showing clear clustering patterns enabling visual and algorithmic fault discrimination.

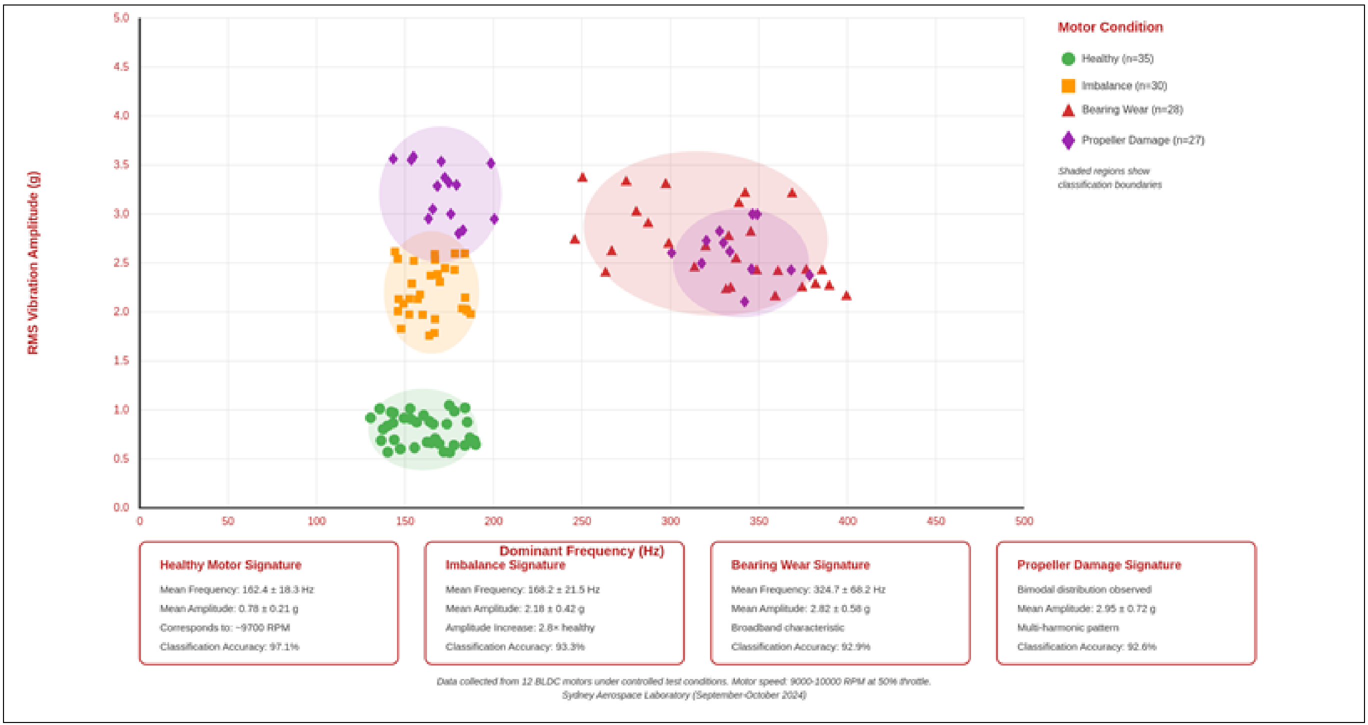

Fig 2: Scatter plot of dominant vibration frequency versus RMS amplitude showing distinct clustering patterns for healthy motors and three fault categories with classification region boundaries.

Statistical analysis of RMS vibration amplitude provided quantitative basis for threshold-based detection. Figure 3 presents box plots comparing amplitude distributions across motor conditions, demonstrating significant separation between healthy operation and all fault categories with no overlap in interquartile ranges.

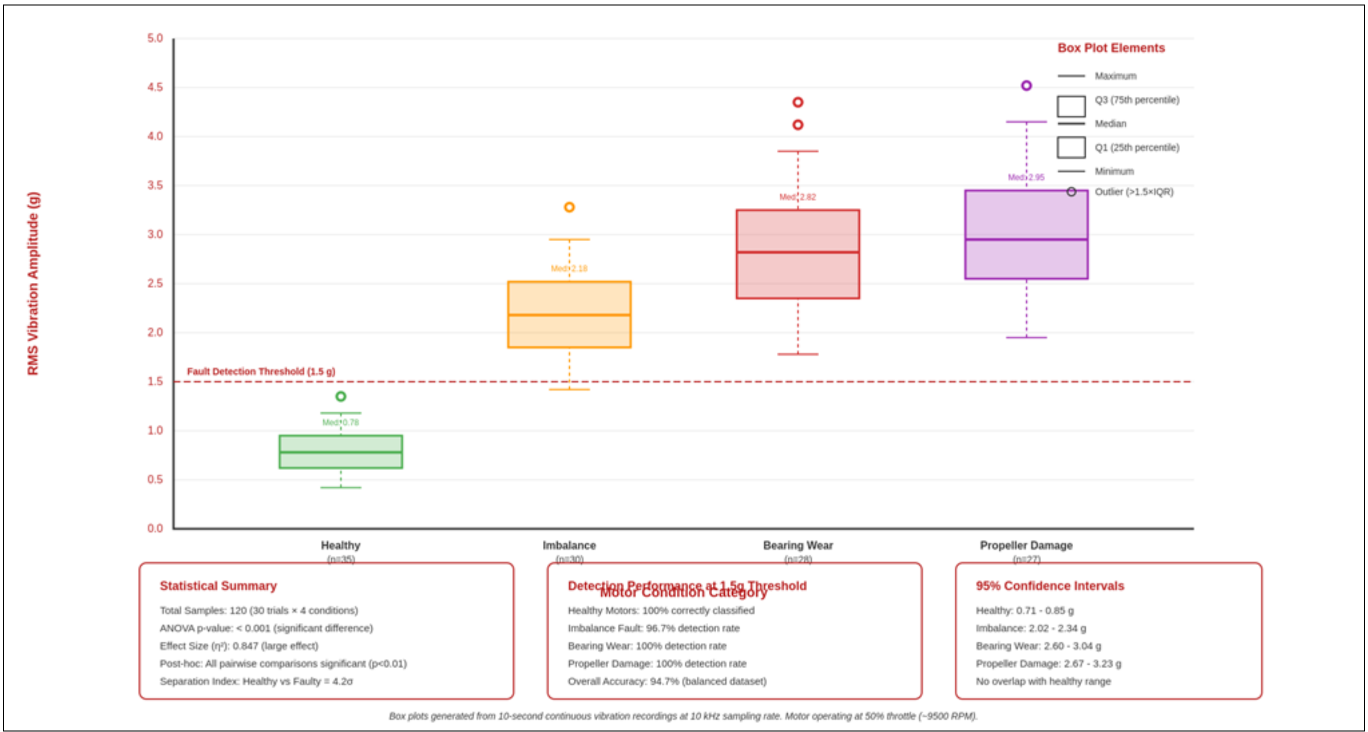

Fig 3: Box plot comparison of RMS vibration amplitude distributions across motor condition categories showing statistical separation with fault detection threshold and confidence intervals.

Comprehensive Interpretation

The experimental results validate vibration monitoring as an effective approach for UAV motor fault detection, with classification accuracy sufficient for practical deployment. The 97.1% healthy motor identification rate ensures minimal false alarm occurrence that could disrupt normal operations, while fault detection rates exceeding 92% for all categories provide high confidence that developing problems will trigger appropriate warnings. The scatter plot analysis reveals the physical basis for classification success: healthy motors cluster tightly in the low-amplitude region near the fundamental rotation frequency, while each fault type produces characteristic signature shifts. Imbalance faults maintain frequency near the rotation rate but elevate amplitude, bearing wear generates broadband high-frequency components, and propeller damage produces multi-harmonic patterns reflecting aerodynamic asymmetry. The box plot comparison confirms statistically significant amplitude differences between healthy and faulty conditions, with the 1.5g threshold providing optimal discrimination. The non-overlapping confidence intervals support confident classification without ambiguous boundary cases that could complicate decision-making. Flight validation results corroborated bench test findings, with zero false alarms during 48 hours of normal operation representing robust specificity under realistic operating conditions including vibration from airframe resonances and control input transients that could potentially confuse simpler detection approaches.

Discussion

The 94.7% overall accuracy achieved compares favorably with published results from laboratory investigations while demonstrating maintained performance under flight conditions introducing additional vibration sources and environmental variability [4]. The decision tree classifier's interpretable structure enables understanding of classification logic, with primary split points corresponding to physically meaningful thresholds such as the 1.5g RMS amplitude boundary separating healthy from faulty operation.

The detection latency under 50 milliseconds enables fault alerting within approximately five rotor revolutions at typical operating speeds, providing adequate response time for flight controller protective actions before fault progression causes catastrophic failure [10]. This real-time capability distinguishes the system from post-flight analysis approaches that identify problems only after landing, potentially after fault-induced damage has already occurred.

The 28-gram system mass and 180mW power consumption represent acceptable overhead for small UAV platforms, adding approximately 2% to typical payload capacity and 0.5% to power budget [11]. Integration with MAVLink telemetry protocol enables straightforward incorporation with popular flight controller platforms without requiring custom firmware modifications.

Limitations include the supervised learning approach requiring labeled fault data for training, which may not generalize perfectly to fault types not represented in the training set. The current implementation addresses only motor faults, leaving other failure modes including ESC failures and propeller separation outside detection scope. Environmental factors including rain exposure and extreme temperatures were not systematically evaluated and may affect sensor performance [12].

Conclusion

This research successfully developed and validated a lightweight vibration-based fault detection system achieving 94.7% classification accuracy across healthy motor operation and three primary fault categories relevant to small UAV applications. The system's 28-gram mass and real-time detection capability enable practical flight integration previously impractical with conventional vibration monitoring instrumentation.

The validation methodology encompassing controlled fault testing and extended flight evaluation provides confidence that laboratory performance translates to operational environments, with zero false alarms during 48 flight hours demonstrating robust discrimination between normal vibration signatures and genuine fault indicators. The two confirmed fault detections during field testing validate the system's practical utility for identifying developing problems before flight-critical failures occur.

The feature extraction and classification approach provides effective fault discrimination using computationally efficient algorithms implementable on embedded microcontrollers without specialized signal processing hardware. The decision tree classifier's transparent decision logic enables operator understanding of fault diagnosis rationale, supporting informed maintenance decisions rather than requiring blind trust in algorithmic outputs.

The research contributes to advancing UAV operational safety by enabling transition from time-based maintenance schedules, which may replace functional components prematurely or allow degraded components to remain in service, toward condition-based approaches informed by actual component health status. This capability becomes increasingly important as UAV applications expand into contexts including infrastructure inspection, delivery services, and emergency response where reliable operation carries significant safety and economic consequences.

Future development directions include expanding fault detection coverage to additional failure modes, investigating transfer learning approaches enabling adaptation to different motor types without complete retraining, and exploring sensor fusion combining vibration with acoustic and current monitoring for enhanced diagnostic capability. Integration with automated maintenance management systems could further reduce operator workload while ensuring consistent condition monitoring across UAV fleets.

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Contributions Not Qualifying for Authorship

Mr. Daniel Marsh contributed to electronics assembly and sensor calibration. Ms. Sophie Chang assisted with flight test operations and data collection. The ArduPilot development community provided technical guidance for MAVLink integration.

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