AI-Driven Anomaly Detection in Quadcopters Using ADXL345 Accelerometer Vibration Data and IoT Integration

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Abstract

This study investigates artificial intelligence methods for offline anomaly detection in quadcopters to improve flight safety. Vibration data were collected using ADXL345 accelerometers interfaced with ESP32 modules. Eight time-domain features were extracted from triaxial acceleration signals. Four machine learning classifiers—Random Forest (RF), Support Vector Machine, K-Nearest Neighbors, and Neural Networks—were trained and evaluated on a dataset representing a healthy state and four propeller damage levels (10% to 40% cuts). The RF classifier achieved the highest accuracy of 98% using standard deviation features. The results demonstrate the effectiveness of time-domain features and tree-based models for propeller fault diagnosis. This benchmarking approach enables precise identification and quantification of propeller damage severity, supporting rapid maintenance decisions and proactive flight risk management for UAV platforms.

Keywords: Quadcopter, ADXL345, SVM, Extraction features, Anomaly detection

1. Introduction

The global multirotor sector is experiencing rapid growth, attracting researchers worldwide to investigate this field. As a class of unmanned aerial vehicles (UAVs), multirotor have been widely employed in diverse applications such as agriculture, military reconnaissance, photography, cartography, and long-range communication and navigation, as highlighted by Valavanis and Vachtsevanos [1], Wang et al. [2], Mohsan et al. [3], and Szóstak et al. [4]. With the expanding applications of UAVs, ensuring their operational safety and reliability has become paramount. Prompt defect identification and reaction through effective diagnostics are crucial for enhancing operational safety and enabling fast interventions, as demonstrated by Baldini et al. [5].

Vibration analysis has emerged as a powerful technique for UAV diagnostics, providing exceptional precision and sensitivity in defect detection. The analysis of vibration signatures can reveal incipient faults in critical components like propellers and motors, making it essential for maintaining UAV integrity, as shown by Zhang et al. [6] and Al-Haddad et al. [7]. The advent of low-cost, high-performance Micro-Electro-Mechanical Systems (MEMS) sensors, such as the ADXL345 accelerometer, has further facilitated the adoption of vibration-based monitoring in cost-sensitive UAV applications, as shown by Guntupalli [8]. IoT architectures provide frameworks for UAV health monitoring. This approach leverages IoT system design principles to support scalable monitoring while utilizing edge computing for on-board processing and cloud integration for advanced diagnostics, Yu et al [9]. The distributed architecture facilitates efficient fault detection and predictive maintenance, with industrial applications demonstrating the effectiveness of combining edge computing with machine learning techniques such as auto-encoders for real-time anomaly identification, Omol et al [10].

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Anomaly detection in UAV flight data encompasses various technological approaches, which can be broadly categorized into knowledge-based, model-based, and data-driven methods. A recent survey by Yang et al. [11] comprehensively examines these approaches, emphasizing issues such as acquiring anomalous data, ensuring model accuracy, and managing computational costs, while proposing potential solutions. Diagnosis methodologies can be further divided into model-based and data-driven approaches, with the latter being either supervised or unsupervised.

Model-based approaches, while theoretically sound, present several practical disadvantages for quadcopter fault detection, including complexity, susceptibility to model inaccuracies, high computational demands, and restricted adaptability to different UAV platforms. For instance, Asadi [12] utilized parity space and extended Kalman filters to detect and identify rotor faults in quadrotors, effectively recognizing faults during real-time trials. Lopez Estrada et al. [13] employed a Linear Parameter Varying model for tracking control and resilient sensor fault detection. Jung and Bang [14] developed a fault-tolerant model predictive control methodology to address actuator faults. However, the limitations of model-based approaches have led to increased interest in data-driven diagnostics for supervised fault detection and identification.

Data-driven methods have shown significant promise across various domains that involve complex signal analysis. For example, in the field of neuroscience, Šverko et al. [15] effectively demonstrated the use of data processing and machine learning for EEG data analysis in ADHD diagnosis and neurofeedback. Zhang et al. [6] presented a data-driven approach using vibration signals and LSTM networks, exhibiting enhanced accuracy compared to conventional methods. Cabahig and Eslamiat [16] implemented a failure detection system using K-Means clustering for mid-flight failure identification through vibration data analysis. Bondyra and Gardecki [17] introduced a technique for fault detection and condition monitoring of UAV rotor blades using signal processing and Support Vector Machines (SVM). Recent studies by Ghazali and Rahiman [18-19] have further investigated vibration-based fault detection using artificial intelligence and assessed the reliability of different MEMS sensors for real-time vibration-based anomaly inspection in drones.

Complementary approaches have also been explored. Schmal et al. [20] characterized the acoustic emissions from quadcopter components to detect mechanical problems. Lai et al. [21] examined the application of frequency domain analysis and wavelet scattering for structural health assessment. Tong et al. [22] described a machine learning approach for UAV propeller failure identification employing a hybrid data generation model. A very relevant study by Baldini et al. [5] demonstrated real-time propeller fault detection for multirotor drones based on vibration data analysis implemented on an embedded flight controller, achieving high performance with computationally efficient algorithms.

Despite the extensive research in UAV anomaly detection, several gaps remain in the literature. Many existing approaches focus on single-sensor systems or limited feature extraction techniques, lacking a comprehensive evaluation of multiple machine learning algorithms for vibration-based anomaly detection. There is a notable need for systematic benchmarking of different time-domain features to identify the most effective parameters for fault classification in quadcopter systems. Furthermore, while some studies like Baldini et al. [5] have achieved embedded real-time detection, there remains a need for detailed comparative analysis of classifier performance and feature effectiveness for offline diagnostic applications and severity classification, particularly using accessible IoT-enabled hardware setups.

To address these gaps, this study proposes a comprehensive, AI-driven framework for propeller fault detection and severity classification in quadcopters. The principal objective is to develop and comparatively evaluate an IoT-enabled diagnostic system using vibration data from an ADXL345 accelerometer and an ESP32 microcontroller. This study systematically assesses the performance of four supervised machine learning classifiers, Random Forest, SVM, K-Nearest Neighbors, and Neural Network, across eight time-domain statistical features. The work distinguishes itself by providing a detailed benchmarking analysis on a well-defined, multi-level fault dataset, establishing a robust baseline for propeller fault severity classification using an accessible hardware setup. This research contributes to the field by identifying the most effective feature-classifier combinations and providing a clear path for future development towards real-time, onboard fault detection systems.

The paper is structured as follows: Section 2 details the experimental setup and hardware description. Section 3 outlines the comprehensive methodology, including data collection, feature extraction, and model training. Section 4 presents and discusses the results, evaluating the efficacy of different classifiers and features. Finally, Section 5 concludes the paper by summarizing the principal findings and proposing directions for future research.

2. Hardware Experimental Setup

(1) Quadcopter hardware description

The following subsection describes the anomaly detection system architecture implemented on the quadcopter platform, focusing on hardware components and signal processing procedures designed for effective fault detection. The quadcopter features are defined in Fig.1 and details as follows:

(a) DJI F450-sized frame with an integrated power distribution board,
(b) Four 2200kV motors paired with 10x4.5 propellers
(c) Electronic speed controllers (ESCs)
(d) 3S 2600mAh 30C LiPo battery
(e) STM32F103C8T6 microcontroller
(f) MPU-6050 gyro/accelerometer
(g) Flysky FS-T6 transmitter

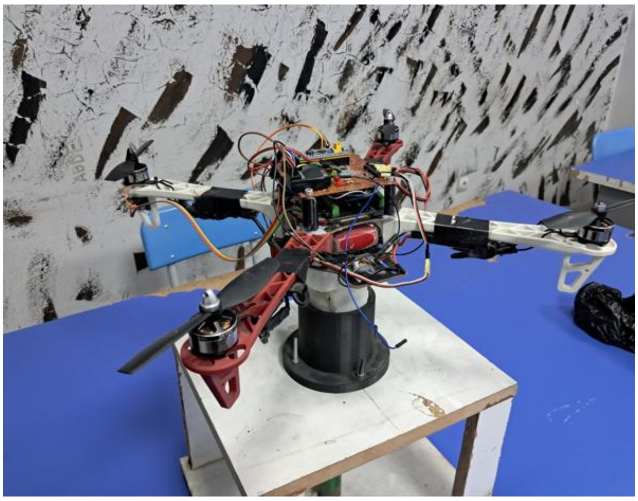


Fig. 1 Quadcopter illustration components

(2) Diagnosis hardware description

The integration of the ESP32 microcontroller and ADXL345 accelerometer forms a compact, efficient hardware system for UAV health monitoring, as shown in Fig. 2. Powered by a 3.3V battery, the system ensures portability and low power consumption, with the ADXL345 operating at 2.0–3.6V and consuming as little as 23 μA in measurement mode. The sensor captures triaxial acceleration data with selectable ranges (±2g to ±16g) and high resolution (13-bit, down to 4 mg/LSB), communicating via I2C with the ESP32, which features dual-core processing, 520 KB SRAM, and integrated Wi-Fi/Bluetooth. Data is acquired at configurable rates up to 3.2 kHz, processed locally, and transmitted wirelessly in real time, enabling remote monitoring. This combination of precise sensing, on-board analytics, and seamless connectivity reflects modern IoT-enabled frameworks, supporting scalable, connected diagnostic architectures for UAVs.

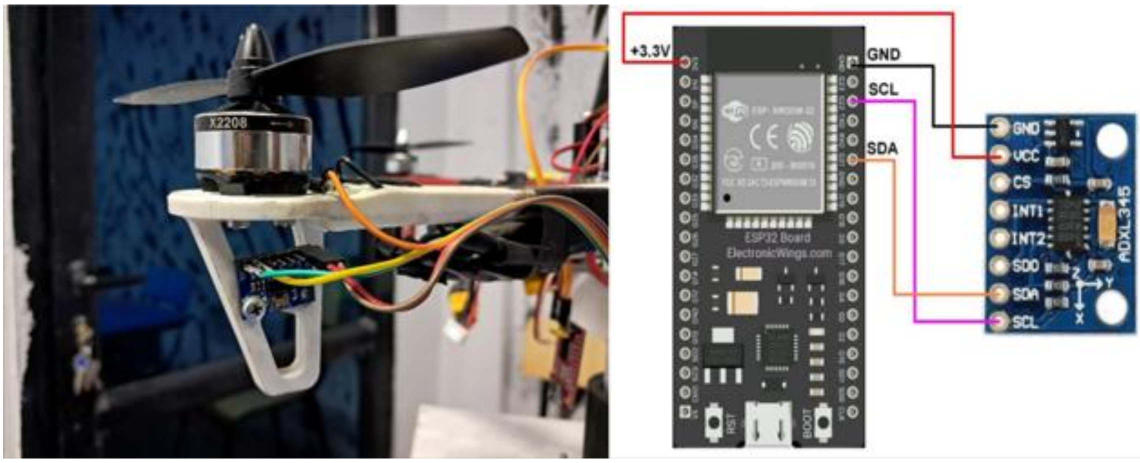


Fig. 2 Designed data acquisition and anomaly detection hardware

(3) Propeller's fault cases

The diagnostic systems of the DJI F450 quadcopter collect vibration data essential to identifying faults, with the objective of averting crashes in both urban and rural environments. The proposed study investigated many propeller fault situations, with damage levels spanning from undamaged (Case A: healthy) to 40% cut (Case E), incorporating intermediate phases of 10% (Case B), 20% (Case C), and 30% (Case D) damage as delineated in Fig. 3. Defective propellers were readily replaced with a simple wrench between flights. The variety of fault circumstances enabled a comprehensive examination of the impact of differing levels of propeller damage on the quadcopter's stability and performance. This research extensively enhances the current knowledge base by clarifying the effects of propeller damage on UAV flight dynamics and improves fault identification accuracy beyond the achievements of prior studies, as compared to Puchalski et al. [23].

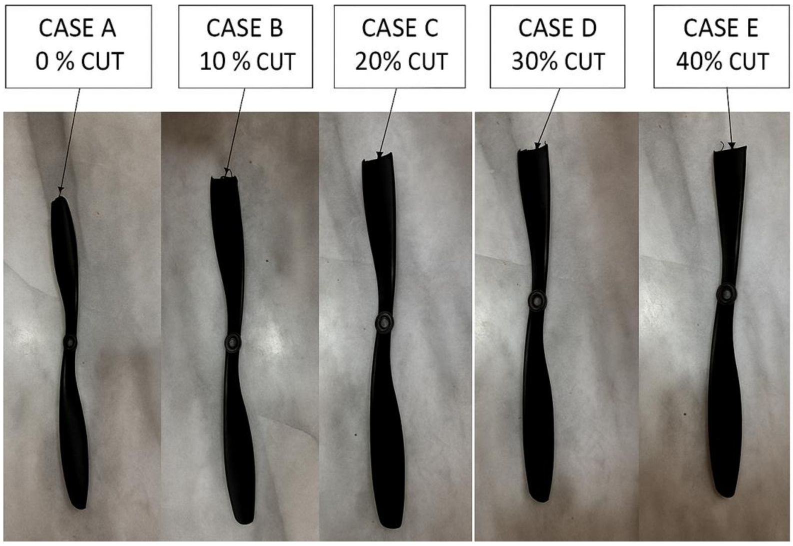


Fig. 3 Cases for Propeller 8045 Faults

By highlighting the significance of monitoring various fault severities, the essential requirement for precise and prompt defect identification is to guarantee flight safety and operational reliability. The proposed research augments and expands upon previous studies, emphasizing the imperative for comprehensive assessments to avert crashes and improve UAV robustness.

3. Methodology

This study focuses on propeller damage, simulated by altering the degree of propeller cuts from a normal condition to increments of damage ranging from 10% to 40% cut. Damage models enable the examination of how different degrees of degradation influence vibration patterns and the overall performance of quadcopters.

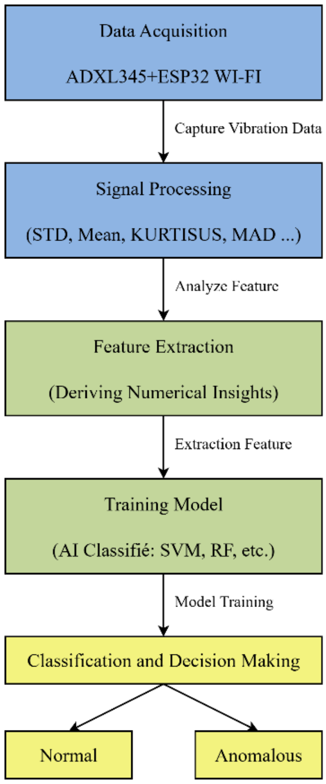


Fig. 4 Flowchart of quadcopter anomaly detection process.

The anomaly detection procedure comprises the phases illustrated in Fig. 4: Data Acquisition: Gathering vibration data utilizing the ADXL345 accelerometer, with transmission facilitated through ESP32 Wi-Fi. Signal Processing: Utilizing time domain techniques, including standard deviation, mean, kurtosis, and Mean Absolute Deviation (MAD) for feature extraction. Feature Extraction: Obtaining quantitative insights from processed signals. Training Models: Employing AI classification techniques (SVM, K-means clustering, etc.) to develop models based on the retrieved characteristics. Classification and Decision Making: Classifying the data to ascertain whether the quadcopter is in a normal or anomalous state, depending on the training model.

3.1. Experimental setup (hardware)

The experimental setup comprises a comprehensive anomaly detection system developed for quadcopter fault diagnosis, featuring a DJI F450-sized frame with an integrated power distribution board, four 2200kV motors paired with 10x4.5 propellers, electronic speed controllers (ESCs), a 3S 2600mAh 30C LiPo battery, an STM32F103C8T6 microcontroller, MPU-6050 gyro/accelerometer, and a Flysky FS-T6 transmitter for flight control operations. The diagnostic hardware integration consists of an ESP32 microcontroller, ADXL345 accelerometer, and 3.3V battery forming a compact and efficient data acquisition system, where the ESP32 acquires three-axis acceleration data from the ADXL345 via the I2C communication protocol for real-time vibration monitoring and wireless data transmission capabilities. The propeller fault investigation encompasses damage levels ranging from healthy conditions (Case A) to 40% cut damage (Case E), incorporating intermediate phases of 10% (Case B), 20% (Case C), and 30% (Case D) damage to enable comprehensive examination of varying fault severity impacts on quadcopter stability and performance characteristics.

3.2. Data collection and preprocessing

A sophisticated data acquisition system was developed using an ESP32 microcontroller and an ADXL345 accelerometer to capture acceleration signals from the quadcopter during flight operations. The ESP32 acquires 200 acceleration samples per second from the ADXL345 sensor, structuring data as JSON strings for real-time remote monitoring and analysis. This configuration gathers accelerometer data for 120 seconds, archiving data in CSV files while the quadcopter operates in hovering mode, with data organized in folders corresponding to each propeller damage state from Case A (normal) to Case E (varying damage levels). Python programming environment, including NumPy, Pandas, Matplotlib, and SciPy. Stats libraries were employed for signal processing, data manipulation, visualization, and statistical computations.

3.3. Feature extraction

Statistical feature extraction methodologies transformed raw acceleration signals into meaningful representations suitable for machine learning classification. Time-domain features were computed from three-axis acceleration data, including mean values, Root Mean Square (RMS), and standard deviation for baseline characterization, energy analysis, and variability assessment. Advanced features captured comprehensive signal characteristics: Median Absolute Deviation (MAD), kurtosis, variance, skewness, and peak-to-peak values for central tendency, distribution behavior, spread quantification, asymmetry, and range assessment. These features were applied to each axis, creating comprehensive vectors representing vibrational signatures of each propeller condition, enabling effective differentiation between normal and anomalous conditions across varying damage severity levels.

3.4. Model training

Model selection involved systematic evaluation of multiple machine learning classifiers to identify the most appropriate algorithms for propeller fault detection as defined on Al-Haddad et al. [24], with each classifier offering distinct advantages suitable for different data characteristics and classification tasks:

(1) Support Vector Machine (SVM) is exceptionally proficient for high-dimensional datasets and exhibits strong performance when a distinct margin of separation exists between classes. SVMs operate by identifying the best hyperplane that maximizes the margin between distinct classes, as demonstrated by Wang and Liu [25].
(2) Random Forest (RF) adeptly manages non-linear data by generating numerous decision trees during the training phase and providing the mode of the classes for classification or the mean forecast for regression from the individual trees. They exhibit resilience against overfitting and can handle complex, large datasets, as shown by Kamat et al. [26].
(3) K-Nearest Neighbors (KNN) is a straightforward and intuitive technique that classifies a data point according to the predominant class of its KNN. Its simplicity in implementation and comprehension renders it an excellent option for novices, as discussed by Wang et al. [27].
(4) Neural Networks (NN) are proficient at identifying intricate patterns via several layers of interconnected neurons. They have significant flexibility and can be employed for various tasks, including classification and regression, as found by Ki Range et al. [28].

3.5. Model evaluation and making a decision

Model evaluation ensured efficient and reliable performance in practical fault detection applications through systematic assessment on test datasets. The evaluation protocol employed standard metrics, including accuracy, precision, recall, and F1-score, which are defined as follows. Feature set testing assessed statistical subsets to determine optimal combinations yielding the highest classification accuracy. The evaluation methodology utilized a single train-test split approach with 70%-30% data division and a fixed random seed (42) for reproducible results in real-world deployment scenarios. The equations can be computed as:

$$Accuracy = \frac{True\_Positive + True\_Negative}{Total\_Number\_of\_instances} \tag{1}$$

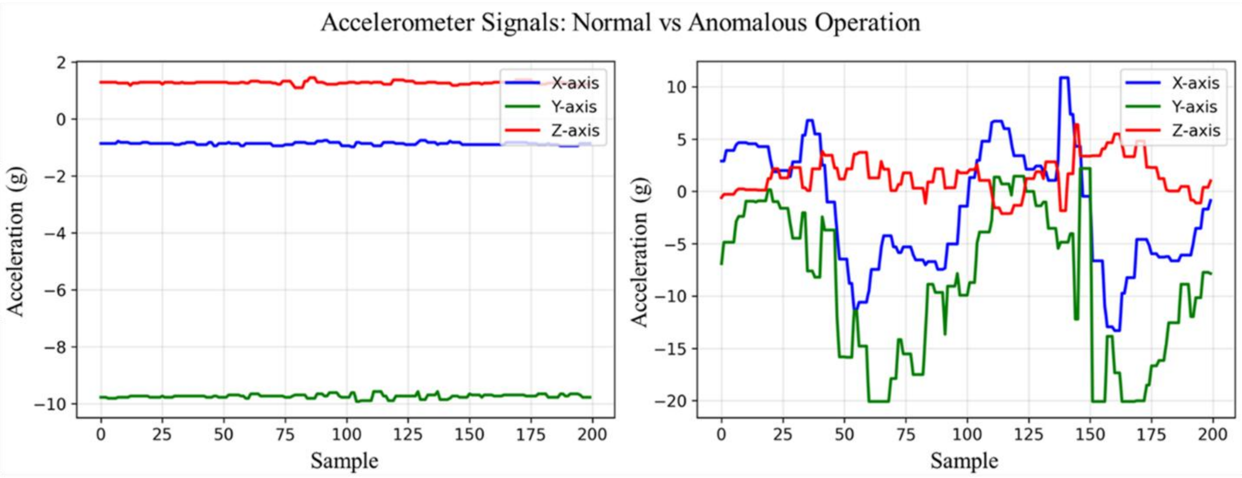
$$Precision = \frac{True\_Positive}{True\_Positive + False\_Positive} \tag{2}$$

$$\text{Re}\,call = \frac{True\_Positive}{True\_Positive + False\_Postive} \quad (3)$$

$$F1_{score} = \frac{\text{Re}\,call \times \text{Pr}\,ecision}{\text{Re}\,call + \text{Pr}\,ecision} \quad (4)$$

4. Results and Discussion

The vibration signals were captured during the critical phases of take-off and hovering. These phases were chosen as they provide crucial data for assessing propeller performance. The collected data specifically reflects two operational states: normal and anomalous. The analysis was conducted using Python, implemented through Visual Studio, and visualized using Matplotlib functions. This approach enabled a comprehensive evaluation of different classifiers and feature extraction methods, ensuring accurate classification of the propeller's operational states. Starting by visualizing sample examples from both the normal and anomalous datasets to identify differences between them, as indicated in Fig. 5. In the anomalous cases, there appeared to be significant disturbances and instability in the data due to the increased vibrations caused by the damaged propeller. These vibrations indicate the instability resulting from the propeller's damage, highlighting clear distinctions between normal in Fig. 5(a) and faulty operations in Fig. 5(b).



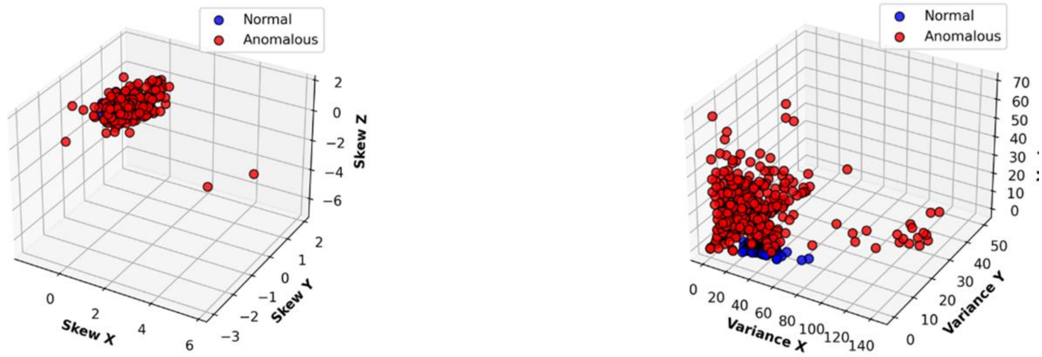
(a) Normal Operation Signal (b) Anomalous Operation Example Signal

Fig. 5 Example signals for normal and anomalous 3-axis dataset

The feature extraction analysis reveals three distinct tiers of effectiveness in anomaly detection. The 3D scatter plot of Mean features Fig.6(a) shows distinct separation between anomalous (red) and normal (green) samples, with a clear boundary around -9.5, indicating strong discriminative capability. Conversely, Kurtosis features Fig.6(b) exhibit poor separation with dispersed distributions, suggesting limited reliability for outlier identification. The 3D scatter plot analysis reveals varying effectiveness across feature types. Skewness features Fig.7(a) show dense anomalous clustering with a separation boundary at -1, though less distinct than other features. Variance features Fig.7(b) demonstrate clear separation with concentrated anomalous clusters at the boundary value 80. RMS features Fig.8(a) exhibit highly effective outlier identification with a separation boundary at 10.5. Standard Deviation (Std) features Fig.8(b) display clear separation with concentrated anomalous clustering at boundary value 6. PtP features Fig.9(a) shows distinct separation with dense anomalous clusters at boundary 30. MAD features Fig.9(b) demonstrate clear separation, though more dispersed than PtP, with a boundary at 11.5.

(a) Mean Features Distribution (b) Kurtosis Features Distribution

Fig. 6 Mean and Kurtosis Features for Quadcopter's Anomaly detection

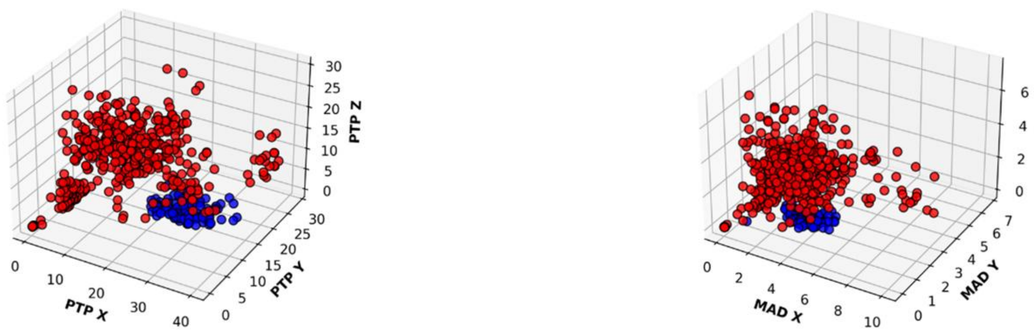


(a) Skew Features Distribution (b) Variance Features Distribution

Fig. 7 Skew and variance Features for Quadcopter's Anomaly detection

(a) RMS Features Distribution (b) Std Features Distribution

Fig. 8 RMS and Std Features for Quadcopter's Anomaly detection



(a) PtP Features Distribution (b) MAD Features Distribution

Fig. 9 PtP and MAD Features for Quadcopter's Anomaly detection

Overall, Std, PtP, and MAD features prove most effective for anomaly detection, showing superior separation and clustering compared to Mean, Kurtosis, and Skewness features. Variance and RMS features show promising but secondary performance.

Table 1 Comparing extraction feature performance using KNN.

KNN Feature	Accuracy	Precision (Normal)	Precision (Anomalous)	Recall (Normal)	Recall (Anomalous)	F1 Score (Normal)	F1 Score (Anomalous)
Mean	0.75	0	0.75	0	1	0	0.86
RMS	0.97	0.86	0.98	0.96	0.95	0.91	0.97
Std	0.96	0.95	0.98	0.93	0.99	0.94	0.98
MAD	0.96	0.93	0.98	0.93	0.98	0.93	0.98
Kurtosis	0.83	0.73	0.85	0.49	0.94	0.59	0.89
PtP	0.96	0.89	0.98	0.93	0.96	0.91	0.97
Skew	0.75	0	0.75	0	1	0	0.86
Variance	0.97	0.95	0.98	0.93	0.99	0.94	0.98

Table 1 demonstrates that the KNN classifier achieves optimal performance using RMS and Variance features, both attaining an accuracy of 0.97, with Variance showing the highest normal precision (0.95) and RMS achieving the best anomalous F1-score (0.97). Std, MAD, PtP, and Variance deliver consistently high results, confirming their effectiveness in capturing discriminative vibration patterns. In contrast, Mean, Skew, and Kurtosis yield significantly lower metrics, highlighting their insensitivity to fault-related changes. These findings underscore the superiority of amplitude-based and dispersion-sensitive features—particularly RMS and Variance—for reliable KNN-based anomaly detection in UAV systems.

Table 2 Comparing extraction feature performance using NN.

NN Feature	Accuracy	Precision (Normal)	Precision (Anomalous)	Recall (Normal)	Recall (Anomalous)	F1 Score (Normal)	F1 Score (Anomalous)
Mean	0.79	0.64	0.82	0.40	0.93	0.49	0.87
RMS	0.97	0.93	0.99	0.96	0.98	0.95	0.98
Std	0.97	0.91	0.98	0.96	0.97	0.93	0.98
MAD	0.96	0.90	0.98	0.96	0.96	0.92	0.97
kurtosis	0.83	0.72	0.85	0.51	0.93	0.60	0.89
PtP	0.96	0.91	0.98	0.93	0.97	0.92	0.97
Skew	0.76	0.57	0.76	0.09	0.98	0.15	0.86
Variance	0.96	0.91	0.98	0.93	0.97	0.92	0.97

Furthermore, Table 2 shows that the NN classifier achieves peak performance with RMS and Std features, both reaching an accuracy of 0.97. RMS delivers the highest precision for the anomalous class (0.99) and the best F1-score (0.98), while maintaining strong recall (0.98). Std follows closely, with balanced metrics across both classes. Variance, PtP, and MAD achieve slightly lower accuracy (0.96) but still demonstrate robust and consistent detection capability. In contrast, Mean, Skew, and Kurtosis yield significantly weaker results, confirming their inadequacy for fault detection. These findings highlight RMS and Std as the most effective features for NN-based anomaly identification, emphasizing the model's reliance on high-discriminative input for optimal performance. The discussion has been condensed to improve clarity and narrative flow while preserving key insights from the results.

Table 3 Comparing extraction feature performance using RF

RF Feature	Accuracy	Precision (Normal)	Precision (Anomalous)	Recall (Normal)	Recall (Anomalous)	F1 Score (Normal)	F1 Score (Anomalous)
Mean	0.75	0	0.75	0	1	0	0.86
RMS	0.95	0.86	0.98	0.96	0.95	0.91	0.97
Std	0.98	0.95	0.98	0.93	0.99	0.94	0.98
MAD	0.96	0.93	0.98	0.93	0.98	0.93	0.98
kurtosis	0.83	0.73	0.85	0.49	0.94	0.59	0.89
PtP	0.96	0.89	0.98	0.93	0.96	0.91	0.97
Skew	0.75	0	0.75	0	1	0	0.86
Variance	0.97	0.95	0.98	0.93	0.99	0.94	0.98

Table 3 demonstrates that the RF classifier achieves optimal performance with Std features, delivering the highest accuracy of 0.98 and superior precision-recall balance for both classes. Variance closely follows with 0.97 accuracy, while MAD and PtP maintain consistent performance at 0.96 accuracy. RMS achieves moderate results (0.95), yet significantly outperforms ineffective features like Mean and Skew, which yield only 0.75 accuracy. These results confirm Std and Variance as the most reliable features for RF-based anomaly detection, highlighting the algorithm's effectiveness with dispersion-based statistical measures for UAV fault identification.

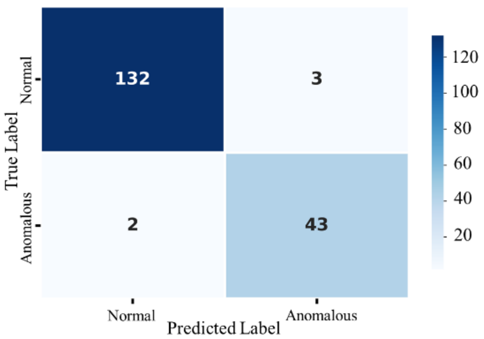
Table 4 Comparing extraction feature performance using SVM

SVM Feature	Accuracy	Precision (Normal)	Precision (Anomalous)	Recall (Normal)	Recall (Anomalous)	F1 Score (Normal)	F1 Score (Anomalous)
Mean	0.75	0	0.75	0	1	0	0.86
RMS	0.94	0.84	0.98	0.96	0.94	0.9	0.96
Std	0.97	0.93	0.99	0.96	0.98	0.95	0.98
MAD	0.97	0.93	0.98	0.93	0.98	0.93	098
kurtosis	0.78	0.88	0.78	0.16	0.99	0.26	0.87
PtP	0.97	0.91	0.98	0.96	0.97	0.93	0.98
Skew	0.75	0	0.75	0	1	0	0.86
Variance	0.97	0.93	0.98	0.93	0.98	0.93	0.98

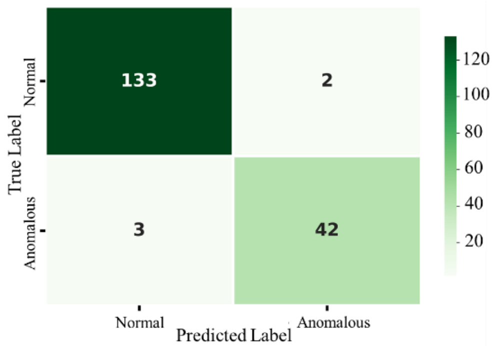
Table 4 shows that the SVM classifier achieves its highest accuracy of 0.97 with Std, MAD, PtP, and Variance features, demonstrating excellent precision (0.99) and recall (0.98) for the anomalous class. Std delivers the best overall balance, with strong performance across all metrics. RMS achieves good results (0.94 accuracy) but is slightly lower, while Mean, Skew, and Kurtosis perform poorly (≤0.78), confirming their inadequacy. These findings highlight Std and variance-based features as the most effective for SVM-based fault detection in UAV systems. Moreover, confusion matrices are emphasized as essential instruments for enhancing detection methodologies. Confusion matrices explain the effectiveness of various machine learning models in distinguishing between normal and abnormal data.

In Fig. 10, both KNN (via RMS features) and NN (via Std features) models demonstrate outstanding performance, correctly classifying the majority of anomalous samples (KNN: 141/144, NN: 143/144) and normal samples (KNN: 34/36, NN: 34/36) with minimal false positives (KNN: 2–3, NN: 2). This illustrates strong overall separation and reliable detection of both classes.

In Fig. 11, SVM (via Std features) also achieves high-classification accuracy, correctly identifying 143 out of 144 anomalous and 34 out of 36 normal samples. RF demonstrates the highest anomalous classification rate (144/144), but a slightly increased number of false positives (4 vs 2 for SVM) in normal samples. Scatter plots and confusion matrices collectively confirm robust classification for all models. RF achieves the highest overall accuracy (0.98), with KNN, NN, and SVM closely following (0.97 each). While all classifiers excel in normal detection, RF provides unmatched anomalous detection, as highlighted by its perfect identification of anomalous data.

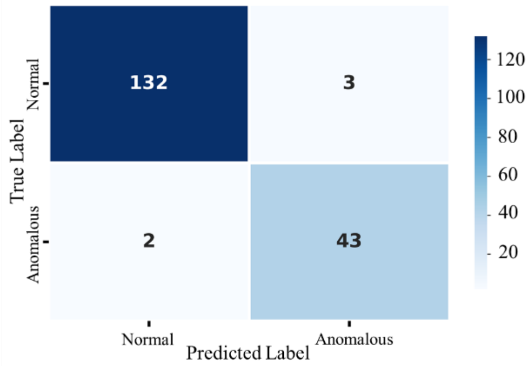


(a) KNN Confusion Matrix (rms)

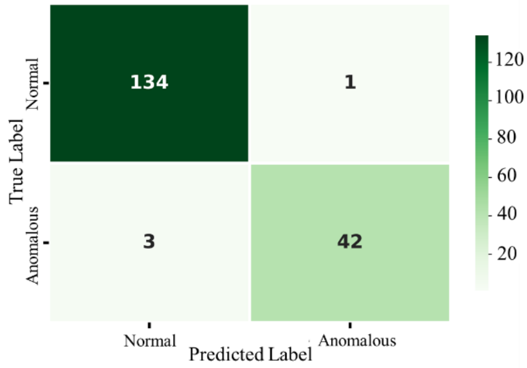


(b) Neural Network Confusion Matrix (Std)

Fig. 10 Confusion Matrix using KNN via RMS and NN via Std



(a) SVM Confusion Matrix (Std)



(b) Random Forest Confusion Matrix (Std)

Fig. 11 Confusion Matrix using SVM and RF via Std

This statement will be substantiated based on Fig. 12. The accuracy comparison curve indicates that the RF classifier, employing Std and variance as feature extraction techniques, attained the maximum accuracy of 98%, establishing it as the superior model. The KNN and SVM classifiers exhibited robust performance, achieving accuracy rates of 97% utilizing RMS and standard deviation features, respectively. The NN classifier attained a noteworthy accuracy of 97% with standard deviation features, albeit significantly lower. This thorough comparison underscores the strength and dependability of the standard deviation and RMS feature extraction techniques, guaranteeing precise problem identification in the propeller system. The continuous performance of RF demonstrates its adaptability and efficacy, establishing it as the most dependable model for real-time diagnostics.

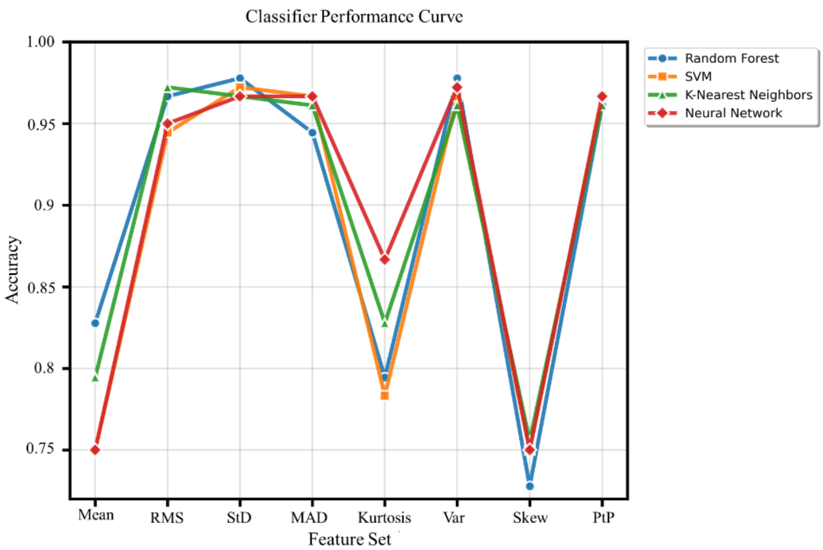


Fig. 12 Accuracy Comparison Curve of Classifiers Using Different Feature Extraction Methods

The current prototype establishes a validated foundation for operational UAV monitoring systems. Laboratory validation must transition toward real-world deployment through three critical enhancements. First, integrate the ESP32-ADXL345 architecture with enterprise IoT platforms (AWS IoT Core, Azure IoT Hub), enabling centralized fleet monitoring and real-time classification during active flight operations rather than post-flight analysis. Second, optimize the RF algorithm (98% accuracy) through quantization and pruning for embedded deployment on flight controllers, supporting immediate anomaly alerts and automated safety responses. Third, expand beyond single-sensor hover-only testing through federated learning across diverse flight regimes, environmental conditions, and real wear patterns, enabling adaptive models that improve operationally while supporting predictive maintenance scheduling and fleet-level health analytics for scalable UAV safety systems.

This study acknowledges several methodological limitations that may influence the generalizability and practical applicability of the findings. The experimental setup relies on a single ADXL345 accelerometer sensor, which may limit vibration signature comprehensiveness compared to multi-sensor fusion approaches that could enhance fault detection across different frequency domains. The controlled hovering flight conditions in indoor environments do not fully represent complex real-world UAV operations, including variable wind conditions and aggressive maneuvers that could affect vibration patterns. The propeller damage simulation using artificial cuts may not accurately replicate natural wear patterns or gradual degradation processes occurring during actual operational use. Additionally, dataset size constraints may limit model robustness and generalization capability when deployed across diverse quadcopter platforms and operational environments.

5. Conclusions

This research proposed a propeller fault detection system for DJI F450 quadcopter platforms using multiple artificial intelligence classification methodologies to enhance UAV operational safety and reliability. To validate the effectiveness of the proposed method, an experimental setup was developed incorporating an ESP32 microcontroller with an ADXL345 accelerometer for vibration data acquisition. The propeller faults were modeled across five scenarios (normal operation and four damage levels from 10% to 40% cut), and comparative analyses were conducted using SVM, RF, KNN, and NN to evaluate classification performance, feature extraction effectiveness, and anomaly detection capability.

The main conclusions are highlighted as follows:

(1) The five-scenario propeller fault modeling approach effectively captures varying degrees of damage severity, enabling comprehensive anomaly detection from 10% to 40% propeller cuts.
(2) The proposed system demonstrates the potential for real-time application through continuous vibration data acquisition and wireless transmission, supporting practical health monitoring for UAV systems under operational conditions.
(3) The RF classifier demonstrates superior fault detection performance, achieving the highest accuracy of 97.78% compared to other tested algorithms.
(4) Std, MAD, variance, and RMS provide the most effective time-domain feature extraction techniques for propeller fault identification.
(5) The IoT-based data acquisition system successfully collected and transmitted vibration data at 200 samples per second, validating the feasibility of wireless fault detection approaches for UAV applications.
(6) Multiple AI classification algorithms (NN, KNN, and SVM at 97%) demonstrate competitive performance, including improved performance at 98% using RF, indicating robust fault detection capabilities across different methodological approaches.
(7) Future work should address multi-sensor integration, diverse flight testing, real-world investigation, and dataset expansion for improved robustness across different quadcopter platforms and operational environments.
(8) The integration of IoT-enabled hardware with AI models, particularly RF using Std and variance features, offers a reliable, scalable solution for UAV fault detection, enhancing operational safety and enabling proactive maintenance in real-world deployment scenarios.

Conflicts of Interest

The authors declare no conflict of interest.

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