Jurnal Kejuruteraan 37(3) 2025: 1495-1503
https://doi.org/10.17576/jkukm-2025-37(3)-32

Faulty Classification System for VTOL UAV Acoustic Signal using Machine Learning

Siti Noormiza Makhtar[a,b*], Fareisya Zulaikha Mohd Sani[a], Elya Mohd Nor[a], Nur Diyana Kamarudin[c] & Syaril Azrad Md Ali[d,e]

[a]*Department of Electrical and Electronics, Faculty of Engineering, National Defence University of Malaysia, Kem Sungai Besi, 57000 Kuala Lumpur, Malaysia*

[b]*Department of Industrial Revolution, Centre for Cyber Security & Digital Industrial Revolution, National Defence University of Malaysia, Malaysia*

[c]*Department of System & Communication Security, National Defence University of Malaysia, Malaysia*

[d]*Department of Aerospace Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia*

[e]*Aerospace Malaysia Research Center, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia*

Corresponding author: noormiza@upnm.edu.my

Received 30 October 2024, Received in revised form 10 February 2025
Accepted 14 March 2025 , Available online 30 May 2025

ABSTRACT

Unmanned Aerial Vehicle (UAV) performance monitoring is essential for safety and efficient flight operation. The propeller, a key element in flying performance, is the focus of our research. As a vital part of the Vertical take-off and landing (VTOL) UAV flight mechanism, propeller failure could lead to hazardous incidents and increased maintenance costs. This paper introduces a user-friendly graphical user interface (GUI) development for the VTOL UAV propeller faulty classification system using the MATLAB Design App. The GUI, designed, enables the identification of different propeller conditions based on time-domain and frequency-domain acoustical features. Users can select their preferred features for faulty prediction using a specified supervised machine learning algorithm. Our study demonstrates that the GUI for propeller faulty classification can provide fast and high-accuracy real-time flying performance insights, significantly improving the efficiency of monitoring work in UAV technology and aviation safety.

Keywords: Acoustic; VTOL UAV; machine learning; GUI

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are broadly categorized into fixed-wing UAVs and rotary-wing UAVs, each designed for specific operational needs. Rotary-wing UAVs, which include multirotor drones and helicopters, are particularly valued for their Vertical Takeoff and Landing (VTOL) capabilities, enabling them to hover, maneuver in tight spaces, and operate efficiently in dynamic environments. The size, weight, and aerodynamic properties of a UAV, particularly its propeller characteristics, play a crucial role in determining its flight stability, energy efficiency, and overall performance (Subramaniam & Salim 2024). Due to their high agility and precise control, rotary-wing UAVs are extensively utilized in applications such as aerial photography, surveillance, infrastructure inspection, and autonomous delivery systems. As these UAVs continue to evolve, ensuring optimal propeller performance remains critical to enhance their flight efficiency, reliability, and safety.

A critical component of UAVs that directly influences their performance, stability, and efficiency is the propeller. Propellers are rotating blades that generate the thrust needed for a UAV to lift off, maneuver, and maintain stable flight (Hage et al. 2023). The effectiveness of a UAV's propeller system significantly impacts its flight characteristics, including speed, agility, and payload capacity. Propeller design, material, and aerodynamics play a crucial role in reducing drag, enhancing lift efficiency, and optimizing power consumption, making them essential for mission-specific UAV operations.

Variations in propeller performance can directly affect energy consumption, flight endurance, and maneuverability (X. Liu et al. 2023). Imbalanced or damaged propellers may introduce unwanted vibrations, increase mechanical wear, and compromise flight stability, potentially leading to navigation errors or even system failures. Additionally, optimized propeller configurations are vital for extending battery life, reducing operational costs, and improving overall UAV reliability and safety. As UAV applications continue to expand into military, industrial, and commercial sectors, understanding and refining propeller dynamics remains essential for achieving high-performance, energy-efficient, and safe UAV operations.

A group of researchers actively conducted an experiment in identifying and diagnosing UAV faults by analyzing acoustic signals. Liu et al. (2020) proposed a deep learning method for fault diagnosis framework using audio signal caused by propeller rotational to analyze faulty diagnosis model performance. Soria Gomez et al. (2023) aimed to recognize the difference between damaged and undamaged propellers using sound to evaluate the health condition of UAS propellers. Kołodziejczak et al. (2023) proposed an acoustic-based approach of damaged rotor blade for UAV fault detection and identification scheme. The study aims to reduce computational load and improve the system through modified algorithms. Soria Gomez et al. (2022) presented a method for detecting damage to UAV propellers during flight using acoustics signature.

Several researchers actively explored vibration analysis for detecting faults in UAV. Baldini et al. (2023) collected vibration data along the x, y, and z axes to detect faults in multirotor drones. The study simulated mechanical damage by chipping the blades to create damaged conditions. Wu et al. (2021) uses UAV for collecting images from pine tree canopy for early diagnosis of pine wilt disease (PWD). Al-Haddad et al. (2023) transformed recorded vibration signal to frequency domain using fast Fourier transform (FFT) spectrum analysis. Tong et al. (2023) used revolution per minute (RPM), thrust and torque propeller as an input for UAV fault detection. Ozkat (2024) proposed a monitoring vibration signal using wavelet scattering and long short-term memory (LSTM). The author created a groove around 75% of the thickness of one of the blades to induce vibration.

Various studies have explored different feature types to enhance model accuracy. Hayajneh et al. (2024) used time series forecasting models with both Deep Neural Networks (DNNs) and Long Short-Term Memory (LSTM) networks to estimate soil moisture levels. This paper applied min-max normalization to the dataset and used the Seasonal Trend decomposition using Loess (STL) technique for data decomposition. Gemayel et al. (2024) conducted an analysis of three key features—STFT, wavelet, and time-based—which were used to train the models. In this paper, amplitude, mean, and standard deviation were used for feature extraction in the time domain. Liu et al. (2024) stated that spectrograms provide additional information in the time domain, unlike spectrums, which show the energy distribution of audio data in the frequency domain. Jiao et al. (2023) conducted STFT and MFCC feature extraction, thus creating three features' datasets used for CNN training. Frid et al. (2024) used power spectrum density (PSD), MFCC, GammaTone cepstral coefficients (GTCC) and Wavelets as spectral features, extracted from both RF and audio datasets.

Recent studies have focused on advancing techniques for UAV health inspection and enhancing its performance reliability using machine learning. Harras et al. (2023) proposed passive and active learning techniques for UAV propeller health inspection using a Convolutional Neural Network (CNN) model. Passive learning involves traditional supervised learning, while active learning aims to improve model accuracy by minimizing the labeling effort required. Al-Haddad et al. (2024) conducted different flight experiments of several actuator conditions and classification analysis for improving UAV dependability and security. Al-Haddad et al. (2023) introduced two improved machine learning models, Support Vector Machine (SVM) and k-Nearest Neighbor (kNN) for blade unbalanced classification in UAV to improve prediction accuracy.

Graphical User Interface (GUI) is a visual representation for the user to interact with software applications. Researchers have employed a GUI for predictive analysis in various fields beyond UAVs. Ravi et al. (2023) proposed machine learning and GUI for Alzheimer's Disease (AD) status prediction. The SVM algorithm has been used for prediction as it has produced the best result for AD classification. Similarly, Kumar et al. (2022) deployed a GUI Python for prediction disease based on symptoms. The author's aim was to develop an autonomous health status prediction system by using machine learning algorithms. Pabreja et al. (2022) developed a GUI for stress level prediction for working professionals by using machine learning algorithm. Rosasn-Arias et al. (2019) focused on creating a user-friendly interface that allows users to evaluate the performance of the classifier using different datasets. The GUI was developed in Python for its ease of editing and sharing for various purposes.

Despite significant advancements in UAV fault detection, existing methods often require complex computations, making real-time monitoring and user accessibility challenging. Most current approaches rely on raw sensor data analysis without an intuitive interface, limiting their usability in UAV maintenance and operations for non-expert users. To address this gap, this study aims to develop a user-friendly GUI-based UAV propeller fault classification system using MATLAB. The proposed system integrates acoustic signal processing and machine learning-based classification to enhance fault detection accuracy and efficiency. The key contributions of this research include: (1) designing a GUI for UAV propeller fault classification, and (2) implementing a feature selection mechanism based on time-domain and frequency-domain acoustic features. By bridging the gap between complex UAV fault detection techniques and practical usability, this study provides an accessible and high-accuracy solution for improving UAV operational safety and real-time performance monitoring.

METHODOLOGY

Traditional fault detection methods often require manual data analysis, making them time-consuming and prone to errors, especially for operators with limited technical expertise. A GUI provides a visual, interactive, and intuitive platform for users to easily access and interpret UAV fault data without requiring deep knowledge of signal processing or machine learning. By integrating real-time acoustic analysis with a machine learning-based classification system, the proposed GUI streamlines the fault diagnosis process, reduces computational complexity, and enhances the accessibility of UAV health monitoring. Additionally, implementing the GUI in MATLAB allows for seamless data visualization, feature selection, and classification, making it a valuable tool for researchers, UAV operators, and maintenance teams. This motivation drives the development of an innovative, real-time UAV propeller fault detection system that prioritizes usability, efficiency, and accuracy. The flowchart in Figure 1 represents framework of fault classification model development.

CLASSIFICATION MODEL DEVELOPMENT

The initial stage in developing the classification model involved collecting, processing, and analyzing UAV audio data, followed by feature extraction, model training, and evaluation. The following steps outline the development process:

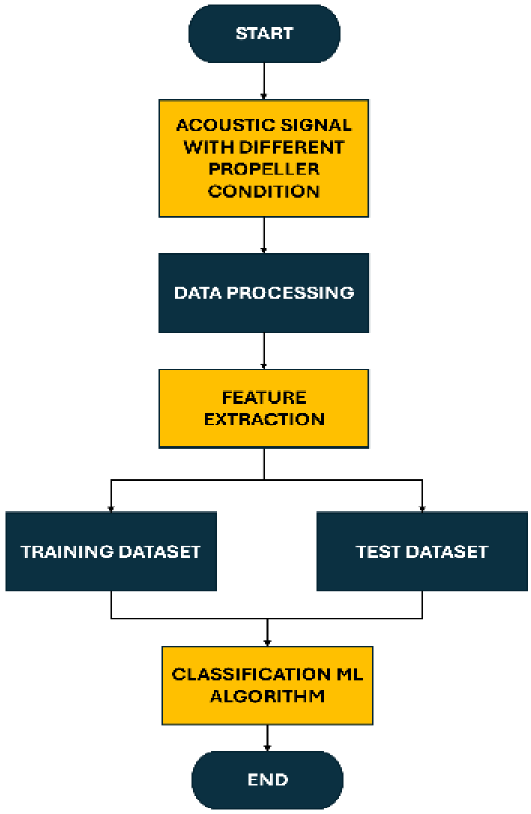

FIGURE 1. Framework of Faulty Classification Model

Step 1: Data Collection

The audio dataset used in this study was obtained from a previous experiment conducted by (Sani et al. 2024)where UAV propeller sounds were recorded under various operating conditions (e.g., normal and damaged propellers). The recordings were conducted in a controlled environment using wireless microphones to minimize external noise interference.

Step 2: Data Processing

The collected audio signals were filtered and segmented to remove unwanted noise and standardize sample durations. Two primary domains were considered:

1. Time-domain analysis involved statistical and amplitude-based features such as Pitch, Short Time Energy (STE) and Zero Crossing Rate (ZCR).
2. Frequency-domain analysis included Fourier Transform (FFT) and spectrogram-based transformations to extract spectral features.

Step 3: Feature Extraction

Key acoustical features were extracted to distinguish between faulty and non-faulty propeller conditions in both time-domain and frequency-domain. The extracted features were divided into training and testing dataset for model training and evaluation.

Step 4: Training Model

A supervised learning approach was employed, testing multiple classifiers to optimize classification accuracy.

Step 5: Model Development & Validation

The best-performing model was integrated into a GUI to provide interactive fault classification system using time-domain and frequency-domain features. The final GUI system allows users to select features, input real-time UAV audio data, and receive instant classification results.

UAV PROPELLER'S CONDITION

Figure 2 shows the propeller's rotation from the top view of UAV. The clockwise (CW) propellers spin in the right-hand direction while counterclockwise (CCW) spin in the left-hand direction. The combination of these two propeller rotations is crucial for maintaining balanced lift and thrust, ensuring stability in flight dynamics.

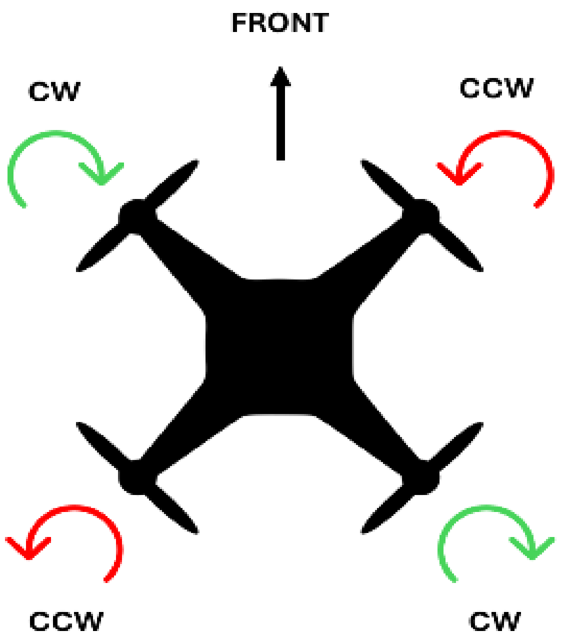

FIGURE 2. The top view of the UAV.

In this research, the dataset contains four different propeller's condition: all healthy propellers, one case for two opposite propellers damaged and two cases for two adjacent propellers damaged. This dataset was labeled according to Table 1.

TABLE 1. Propeller's label and condition

Label	Condition
1	All propellers non-damaged
2	Both CCW damaged
3	CW front and CCW front damaged
4	CW front and CCW back damaged

DATA PROCESSING AND FEATURE EXTRACTION

Data processing is an important step in the machine learning process, as it involves preparing raw data to be used effectively by algorithms. In the context of analyzing UAV audio signals for detecting propeller conditions, both time domain and frequency domain techniques are employed. Proper data processing in both domains not only enables accurate predictions but also enhances the overall performance of the machine learning model by improving its efficiency and robustness.

Three significant audio features are selected for the time domain parameter: Pitch, STE and ZCR. The audio waveform is divided into short frames using windowing techniques. This paper applied Hamming window with 1024 samples, 48kHz for sampling rate, and an overlap of 50% for each audio feature. After the informative audio features are processed, the data will be calculated using seven statistical parameters. Mean, Interquartile Range (IQR), standard deviation, skewness, kurtosis, variance and Root Mean Square (RMS) were selected as time domain parameters for each condition. For frequency domain, Mel Frequency Cepstral Coefficients (MFCC) technique is implemented to extract valuable features from the recorded sound signal.

CLASSIFICATION ML ALGORITHM

The features were then imported as an input into the machine learning classifier for the algorithm to learn the pattern and identify different conditions of the propellers. The model's performance is evaluated using a separate training and testing dataset to learn the relationship between the variables.

In this study, the Medium Tree algorithm was applied for time domain features, as it offers a flexible decision-making approach by constructing a decision tree that effectively captures complex relationships among features. Other than that, the Gaussian Naïve Bayes algorithm was chosen to analyze frequency domain features due to its proficiency in probabilistic classification and its capability to handle continuous feature distributions. Both algorithms were assessed on their ability to accurately classify different UAV propeller conditions, with their performance evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

GUI DEVELOPMENT

The Graphical User Interface (GUI) was developed to provide an intuitive and efficient tool for analyzing UAV propeller health using acoustic signals. Figure 3 illustrates the framework for operating the UAV faulty classification system. Once imported, the raw audio data was categorized into two signal types: time-domain and frequency-domain analysis. Time-domain analysis examines variations in the signal's amplitude over time, while frequency-domain analysis extracts spectral components to identify unique patterns. This dual-analysis approach ensures a comprehensive representation of propeller sound characteristics, improving the accuracy of fault detection.

Users can select their preferred analysis method within the GUI, choosing between time-domain or frequency-domain processing. In the time domain, essential features such as Pitch, ZCR and STE help capture variations in propeller sound patterns. In the frequency domain, MFCC are extracted to analyze spectral changes caused by propeller faults. These features are then used as inputs for machine learning models, ensuring a robust and reliable classification system.

The system employs the best accuracy ML algorithms to classify propeller health conditions accurately. After processing the selected features, the best-performing model predicts whether the propeller is in a healthy or faulty state. This predictive capability allows UAV operators and maintenance teams to detect potential issues early, minimizing the risk of in-flight failures and reducing maintenance costs. The classification results are displayed in real-time, allowing users to monitor UAV propeller conditions effectively.

To enhance usability, the GUI provides an interactive interface where users can upload audio recordings, select preferred analysis methods, and view classification results in a clear and intuitive manner. By integrating machine learning-based fault detection with a user-friendly design, this system enables real-time UAV health monitoring without requiring advanced technical expertise. Ultimately, this automated approach enhances UAV safety, operational reliability, and maintenance efficiency, making it a valuable tool for UAV operators and researchers.

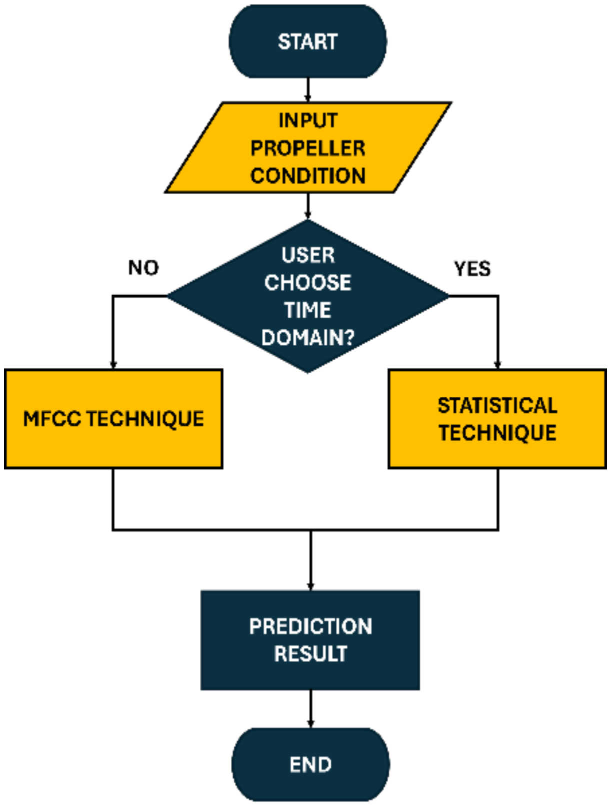

FIGURE 3. Framework of Faulty Prediction System

RESULTS AND DISCUSSION

Faulty prediction system of UAV propellers was developed for effective monitoring and real-time prediction for UAV flight. This system is able to classify propeller faulty conditions using acoustic features recorded during flight operation. The prediction system consists of an ML classification model trained using informative features from both time domain and frequency domain. In Figure 4, GUI displays consist of Import Data panel, Original Wave panel, Acoustic Features panel, Statistical panel, MFCC panel and Prediction Class panel.

The "Time Domain" and "Frequency Domain" buttons in Import Data panel enable users to import audio files and select suitable prediction method for faulty classification according to their preferred signal domain. The imported datasets should contain audio recordings from the rotation of UAV propellers under various conditions. These datasets will be displayed in Original Wave panel and serve as inputs for the GUI's prediction system.

Once the data is processed in time-domain, the system calculates seven statistical parameters for each extracted feature, which are displayed in the statistical panel. Users have the flexibility to analyze individual features—such as Pitch, ZCR, or STE—or select combinations of features for a more comprehensive assessment. Available feature combinations include Pitch & ZCR, Pitch & STE, and ZCR & STE, allowing for a total of 14 statistical parameters to be evaluated.

The Statistical panel enhances the system's analytical capabilities by providing users with a detailed numerical representation of the extracted features. This flexibility enables more precise fault classification, as different feature combinations may yield improved predictive performance. By integrating statistical analysis within the GUI, users can easily interpret feature distributions and assess their relevance to UAV propeller condition monitoring.

This structured approach ensures that time-domain analysis provides meaningful insights for detecting propeller faults. The ability to compare individual and combined feature sets allows for optimized fault detection accuracy, making the system a valuable tool for UAV maintenance and performance monitoring.

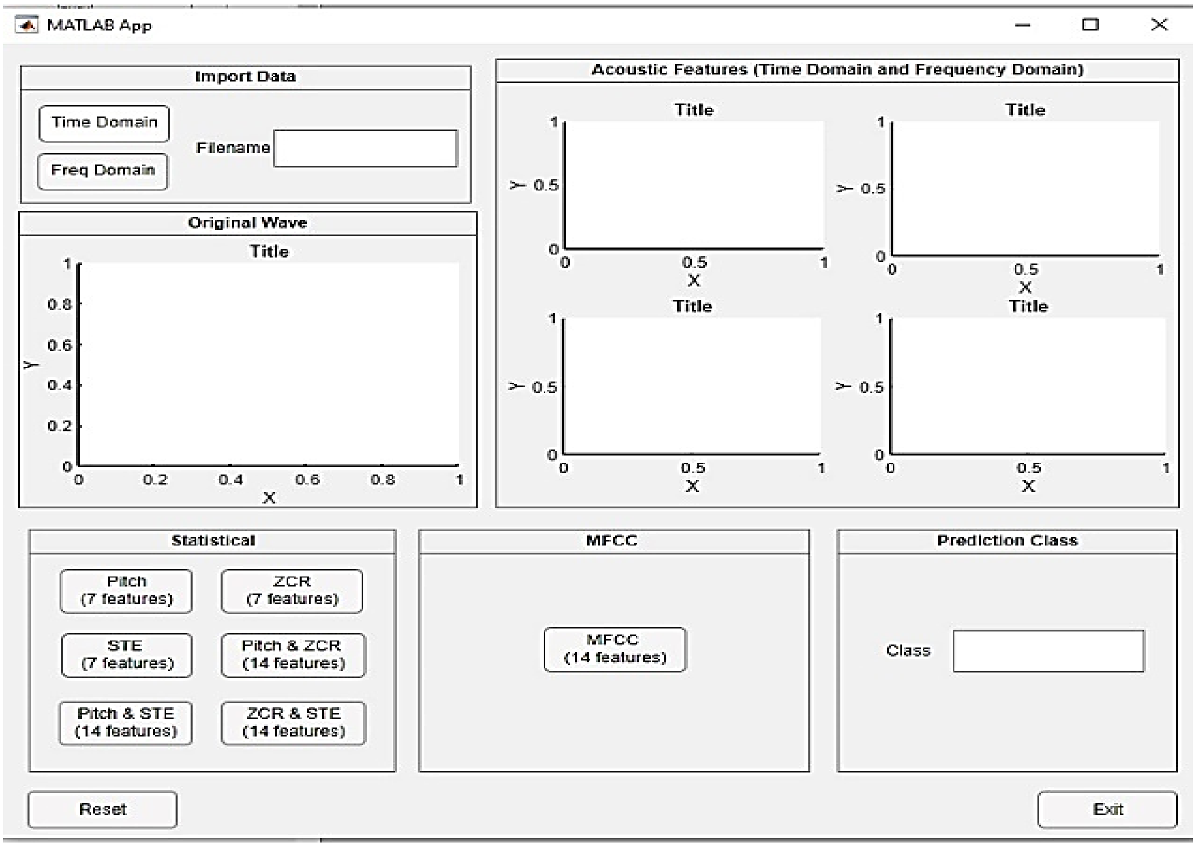

FIGURE 4. GUI Display

Figure 5 illustrates the system's output for time-domain analysis. After importing the audio data, the system processes the original waveform and extracts key acoustic features, which are displayed in the Acoustic Features panel. The primary time-domain features analyzed in this system include Pitch, STE and ZCR. These features provide valuable insights into the sound variations caused by different propeller conditions.

Figure 6 presents the system interface for frequency-domain analysis, where MFCC are extracted to capture the acoustic characteristics of the signal. In this study, 14 MFCC variables were extracted from the audio signal, providing detailed insights into frequency-domain variations associated with propeller conditions.

After processing the audio signal and extracting features from the time or frequency domains, a machine learning (ML) classification model is applied to predict the propeller's condition. The system utilizes the best ML classification model to analyze the processed dataset and classify the propeller's fault status. The developed GUI-integrated ML classification model enhances the efficiency of VTOL UAV monitoring, offering real-time insights into propeller conditions. This system plays a crucial role in ensuring safe flight performance, minimizing maintenance efforts, and preventing potential in-flight failures through early fault detection.

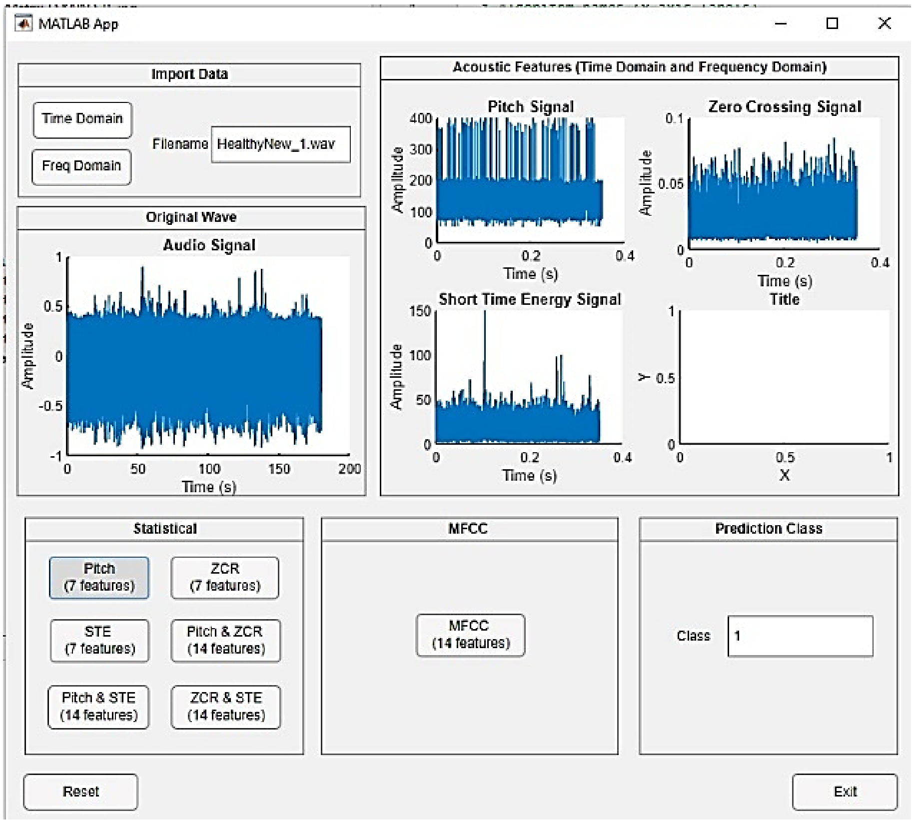

FIGURE 5. GUI display for time domain analysis.

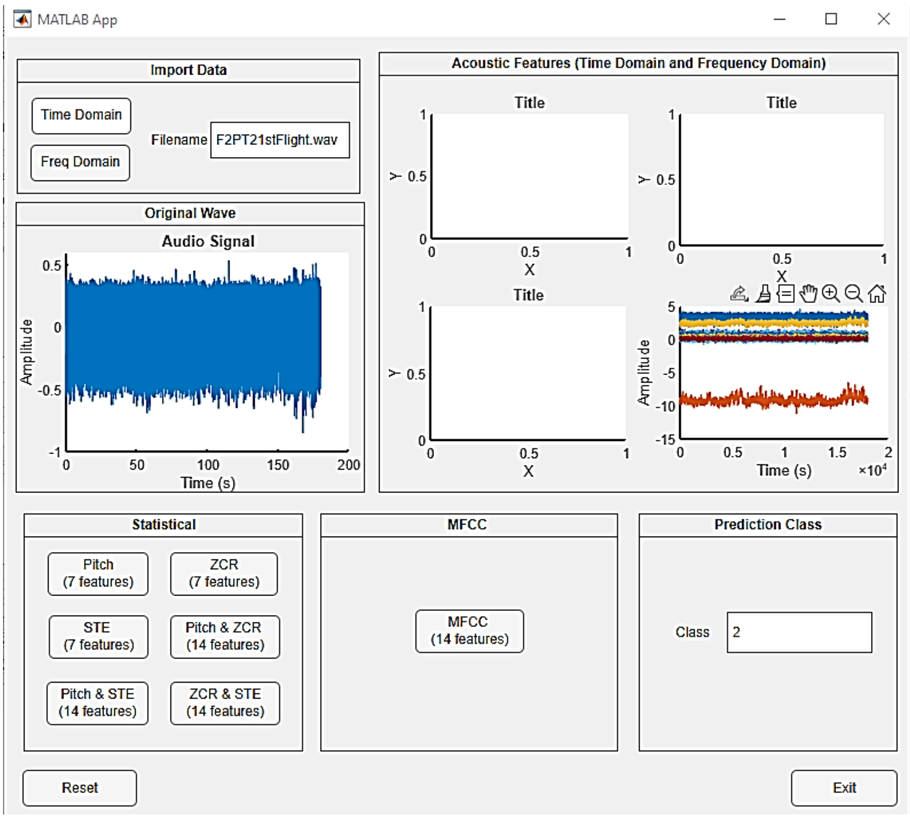

FIGURE 6. GUI display for frequency domain analysis.

CONCLUSION

This paper presented the development of an audio-based fault classification system for assessing various UAV propeller health conditions. The system analyzes audio signals using both time-domain and frequency-domain techniques to extract meaningful features for classification. In the time domain, statistical features were computed to capture variations in the acoustic signal, while in the frequency domain, MFCC were utilized to provide a detailed spectral representation. These extracted features were then processed by a machine learning algorithm, enabling accurate fault classification. The results demonstrate that the GUI effectively visualizes the propeller's health condition based on the selected classification model, offering a user-friendly and efficient tool for UAV monitoring.

The performance of the classification system can be influenced by several factors, including environmental noise, recording equipment quality, and UAV operational conditions. Additionally, the accuracy of the algorithm depends on the quality of the training dataset and the effectiveness of data preprocessing techniques. Ensuring a diverse and well-labeled dataset is crucial for improving classification reliability.

For future research, exploring alternative sensor technologies and advanced feature extraction techniques could enhance system performance. Integrating multi-sensor fusion approaches, such as combining acoustic and vibration sensors, may provide a more comprehensive assessment of UAV propeller health. Additionally, implementing deep learning models and real-time data processing could further improve fault detection accuracy and adaptability. Future work should also focus on optimizing the system for real-time deployment, ensuring low-latency performance and compatibility with various UAV platforms. By enhancing scalability and robustness, this system has the potential to revolutionize UAV maintenance in industries such as aerospace, defense, and autonomous delivery services, improving safety, efficiency, and operational reliability.

ACKNOWLEDGEMENT

This project is supported by grant Fundamental Research Grant Scheme :FRGS/1/2022/TK07/UPNM/02/10 from The Ministry of Higher Education Malaysia.

DECLARATION OF COMPETING INTEREST

None.

REFERENCES

Al-Haddad, L. A., & Jaber, A. A. 2023a. Improved UAV blade unbalance prediction based on machine learning and ReliefF supreme feature ranking method. *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 45(9). https://doi.org/10.1007/s40430-023-04386-5

Al-Haddad, L. A., & Jaber, A. A. 2023b. Influence of operationally consumed propellers on multirotor UAVs airworthiness: Finite element and experimental approach. *IEEE Sensors Journal* 23(11): 11738–11745. https://doi.org/10.1109/JSEN.2023.3267043

Al-Haddad, L. A., Jaber, A. A., Al-Haddad, S. A., & Al-Muslim, Y. M. 2024. Fault diagnosis of actuator damage in UAVs using embedded recorded data and stacked machine learning models. *The Journal of Supercomputing* 80(3): 3005–3024. https://doi.org/10.1007/s11227-023-05584-7

Baldini, A., Felicetti, R., Ferracuti, F., Freddi, A., Iarlori, S., & Monteriù, A. 2023. Real-time propeller fault detection for multirotor drones based on vibration data analysis. *Engineering Applications of Artificial Intelligence* 123: 106343. https://doi.org/10.1016/j.engappai.2023.106343

Frid, A., Ben-Shimol, Y., Manor, E., & Greenberg, S. 2024. Drones' detection using a fusion of RF and acoustic features and deep neural networks. *Sensors* 24(8). https://doi.org/10.3390/s24082427

Gemayel, A., Manias, D. M., & Shami, A. 2024. *Machine Learning for Pre/Post Flight UAV Rotor Defect Detection Using Vibration Analysis*. http://arxiv.org/abs/2404.15880

Hage, C., Sophy, T., & Aglzim, E. H. 2023. Investigating UAV propellers performances near moving obstacles: CFD study, thrust control, and battery energy management. *IEEE Open Journal of Vehicular Technology* 4: 590–609. https://doi.org/10.1109/OJVT.2023.3309103

Harras, M. S., Saleh, S., Battseren, B. & Hardt, W. 2023. Vision-based propeller damage inspection using machine learning. *Embedded Selforganising Systems* 10(7): 43–47. https://doi.org/10.14464/ess.v10i7.604

Hayajneh, A. M., Aldalahmeh, S. A., Alasali, F., Al-Obiedollah, H., Zaidi, S. A. & McLernon, D. 2024. Tiny machine learning on the edge: A framework for transfer learning empowered unmanned aerial vehicle assisted smart farming. *IET Smart Cities* 6(1): 10–26. https://doi.org/10.1049/smc2.12072

Jiao, Q., Wang, X., Wang, L., & Bai, H. 2023. Audio features based ADS-CNN method for flight attitude recognition of quadrotor UAV. *Applied Acoustics 211*. https://doi.org/10.1016/j.apacoust.2023.109540

Kołodziejczak, M., Puchalski, R., Bondyra, A., Sladic, S., & Giernacki, W. 2023. Toward lightweight acoustic fault detection and identification of UAV rotors. *2023 International Conference on Unmanned Aircraft Systems (ICUAS):* 990–997. https://doi.org/10.1109/ICUAS57906.2023.10156624

Kumar, K. S., Sai Sathya, M., Nadeem, A. & Rajesh, S. 2022. Diseases Prediction based on Symptoms using Database and GUI. *2022 6th International Conference on Computing Methodologies and Communication (ICCMC):* 1353–1357. https://doi.org/10.1109/ICCMC53470.2022.9753707

Liu, W., Chen, Z. & Zheng, M. 2020. An audio-based fault diagnosis method for quadrotors using convolutional neural network and transfer learning. *2020 American Control Conference (ACC): 2020-July*, 1367–1372. https://doi.org/10.23919/ACC45564.2020.9148044

Liu, W., Liu, C., Sajedi, S., Su, H., Liang, X. & Zheng, M. 2024. An audio-based risky flight detection framework for quadrotors. *IET Cyber-Systems and Robotics* 6(1). https://doi.org/10.1049/csy2.12105

Liu, X., Zhao, D., & Oo, N. L. 2023. Comparison studies on aerodynamic performances of a rotating propeller for small-size UAVs. *Aerospace Science and Technology* 133: 108148. https://doi.org/10.1016/J.AST.2023.108148

Ozkat, E. C. 2024. Vibration data-driven anomaly detection in UAVs: A deep learning approach. *Engineering Science and Technology, an International Journal 54*: 101702. https://doi.org/10.1016/j.jestch.2024.101702

Pabreja, K., Singh, A., Singh, R., Agnihotri, R., Kaushik, S., & Malhotra, T. 2022. Prediction of stress level on Indian working professionals using machine learning. *International Journal of Human Capital and Information Technology Professionals 13*(1): 1–26. https://doi.org/10.4018/IJHCITP.297077

Ravi, S., K, V. R. P., Satuluri, Y., Ali, S. M., Nekkanti, C., & Ramesh, P. 2023. GUI Based Machine Learning Algorithms to Predict Alzheimer's Disease. *2023 10th International Conference on Signal Processing and Integrated Networks (SPIN):* 296–300. https://doi.org/10.1109/SPIN57001.2023.10116616

Rosasn-Arias, L., Sanchezn-Perez, G., Toscano-Medina, L. K., Perez-Meana, H. M., & Portillo-Portillo, J. 2019. A graphical user interface for fast evaluation and testing of machine learning models performance. *2019 7th International Workshop on Biometrics and Forensics (IWBF):* 1–5. https://doi.org/10.1109/IWBF.2019.8739238

Sani, F. Z. M., Zin, A. A. I. M., Nor, E. M., Kamarudin, N. D., & Makhtar, S. N. 2024. Comparison of VTOL UAV battery level for propeller faulty classification model. *JOIV : International Journal on Informatics Visualization 8*(2): 717–723. https://doi.org/10.62527/JOIV.8.2.2177

Soria Gomez, M., Koschlik, A.-K., Arts, E. & Raddatz, F. 2022. Non-destructive evaluation of the condition of a UAV's propellers by means of acoustics. In *NDE 4.0, Predictive Maintenance, and Communication and Energy Systems in a Globally Networked World*, edited by N. G. Meyendorf, C. Niezrecki, & S. Farhangdoust, 19. SPIE. https://doi.org/10.1117/12.2612770

Soria Gomez, M., Koschlik, A.-K., Arts, E., Raddatz, F. & Wende, G. 2023. Acoustic non-destructive testing of UAS´s propellers during predeparture and post-flight checks. *Research and Review Journal of Nondestructive Testing* 1(1). https://doi.org/10.58286/28093

Subramaniam, K., & Salim, W. S.-I. W. 2024. A review of experimental approaches for investigating the aerodynamic performance of drones and multicopters. *Journal of Advanced Research in Experimental Fluid Mechanics and Heat Transfer* 14(1): 1–24. https://doi.org/10.37934/AREFMHT.14.1.124

Tong, J. J., Zhang, W., Liao, F., Li, C. F. & Zhang, Y. F. 2023. Machine Learning for UAV Propeller Fault Detection based on a Hybrid Data Generation Model. *ArXiv*.

Wu, B., Liang, A., Zhang, H., Zhu, T., Zou, Z., Yang, D., Tang, W., Li, J., & Su, J. 2021. Application of conventional UAV-based high-throughput object detection to the early diagnosis of pine wilt disease by deep learning. *Forest Ecology and Management* 486: 118986. https://doi.org/10.1016/j.foreco.2021.118986