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# Faulty Classification System for VTOL UAV Acoustic Signal using Machine Learning

(Sistem Pengelasan Kerosakan untuk Isyarat Akustik VTOL UAV menggunakan Pembelajaran Mesin)

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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*

*ABSTRAK*

*Pemantauan prestasi Kenderaan Udara Tanpa Pemandu (UAV) adalah penting untuk keselamatan dan operasi penerbangan yang efisien. Pendorong, sebagai elemen utama dalam prestasi penerbangan, merupakan fokus kajian kami. Sebagai komponen penting dalam mekanisme penerbangan UAV Lepas Landas dan Mendarat Secara Menegak (VTOL), kegagalan pendorong boleh menyebabkan kejadian berbahaya dan peningkatan kos penyelenggaraan. Kertas ini memperkenalkan pembangunan antara muka pengguna grafik (GUI) yang mesra pengguna untuk sistem klasifikasi kerosakan pendorong UAV VTOL menggunakan Aplikasi Reka Bentuk MATLAB. GUI, yang direka dengan keselesaan dalam fikiran, membolehkan pengenalan pelbagai keadaan pendorong berdasarkan ciri-ciri akustik dalam domain masa dan domain frekuensi. Pengguna boleh dengan mudah memilih ciri pilihan mereka untuk ramalan kerosakan menggunakan algoritma pembelajaran mesin yang diselia. Kajian kami menunjukkan bahawa GUI untuk klasifikasi kerosakan pendorong boleh memberikan wawasan prestasi penerbangan masa nyata yang pantas dan ketepatan tinggi, dengan ketara meningkatkan kecekapan kerja pemantauan dalam teknologi UAV dan keselamatan penerbangan.*

*Kata Kunci: Akustik, UAV VTOL, Pembelajaran Mesin, Antara Muka Grafik Pengguna (GUI)*

## INTRODUCTION

Generally, UAV was divided into two types: fixed-wing UAVs and rotary-wing UAVs. Rotary-wing UAVs, which include multirotor and helicopters, are known for their vertical takeoff and landing (VTOL) capabilities. The size, shape, and weight of the drone, along with the various characteristics of its propellers, all affect the drone's flight behavior (Subramaniam et al. 2024). These UAVs are prized for their agility, ability to hover, and maneuverability in confined spaces, making them suitable for tasks like aerial photography, surveillance, and delivery services.

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. It is important to consider variation in propeller performance as it directly affects the flight performance and energy consumption of the UAV (Liu et al. 2023).

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 application. 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.

## METHODOLOGY

The flowchart below represents both framework of fault classification model development and GUI development.

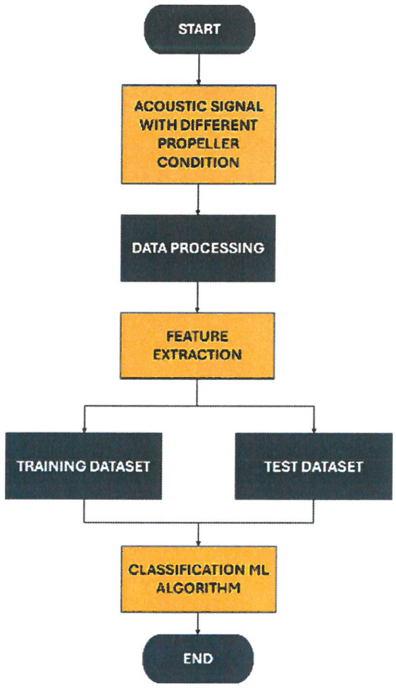


FIGURE 1. Framework of Faulty Classification Model

### Development

The initial stage in developing the model was to gather the audio data in various conditions then followed by data processing, model training and development of the model as step below:

Step 1: Data collection
Step 2: Data processing
Step 3: Feature Extraction
Step 4: Training Model
Step 5: Model Development

The audio data was collected from previous experiment conducted in (Zulaikha et al., 2024). The data was then processed for the time domain and frequency domain, respectively. In the data processing phase, the characteristics of the features were extracted from audio signal in both domains. The extracted features were then divided into training phase and testing phase to enhance its performance. These features served as an input to the ML classification to predict and provide an accurate result.

### 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.

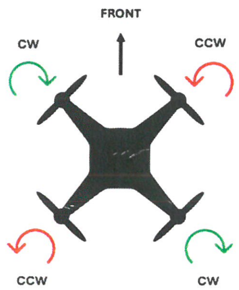


FIGURE 2. The top view of the UAV.

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, Short Time Energy (STE) and Zero Crossing Rate (ZCR). The audio waveform is typically divided into short frames using techniques such as windowing. 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(Zulaikha et al., 2024).

### 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

Figure 3 illustrates the framework for UAV faulty classification system. Once imported, the raw audio data was divided into two signal types: time domain and frequency domain. Time domain analysis involves examining the signal's amplitude changes over time, while frequency domain analysis focuses on the signal's frequency components. This dual analysis helps in capturing comprehensive characteristics of the propeller sounds.

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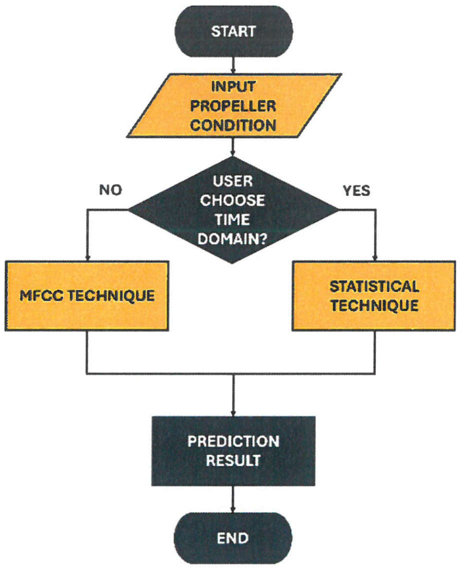


FIGURE 3. Framework of Faulty Prediction System

Users could choose in either the time domain or the frequency domain for data processing. In the time domain, the informative time domain features consist of pitch, ZCR and STE. In the frequency domain, the audio waveform is transformed to extract MFCC. These extracted features are then used to train machine learning models, ensuring precise and reliable predictions.

The primary goal of this system is to predict propeller faulty class using the best selected ML algorithms. The system includes a GUI that allows users to view prediction results. After the data processing and classification, the health class of the propellers was displayed based on the classification model's analysis. Users were able to monitor the health of UAV propellers by using audio sensor through propeller class.

## 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, displays 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 typically contain audio recordings generated from the rotation of UAV propellers under various conditions. These datasets serve as inputs for the GUI's prediction system.

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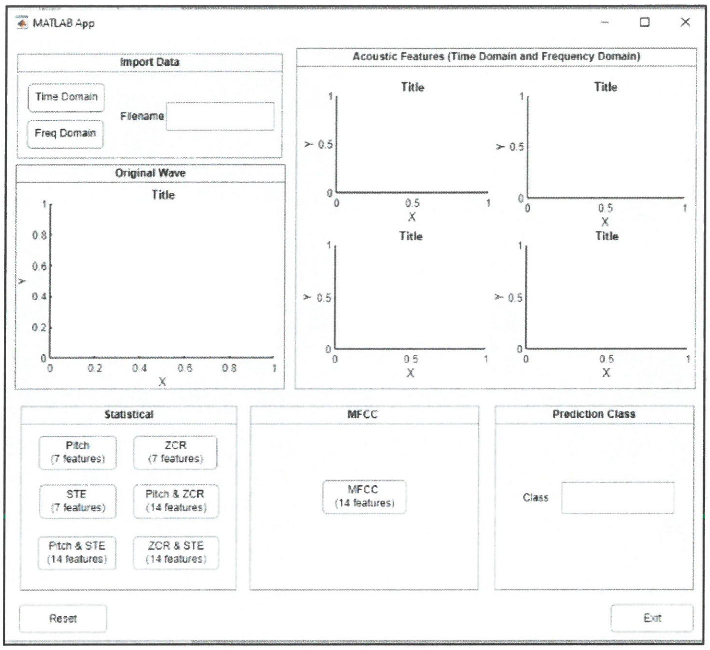


FIGURE 4. GUI Screen

Figure 5 shows the system generated for the time domain. The system generated the audio wave and processed data for acoustic features after imported the audio data in original wave and acoustic features panel. The informative audio features for time domain consists of pitch, STE and ZCR. The processed data will then be calculated using seven parameters for each audio features in statistical panel. The statistical panel allows users to select individual features such as pitch, ZCR, and STE, or combination features. These combinations include pitch with ZCR, pitch with STE, or ZCR with STE. Therefore, the combination features had 14 statistical parameters.

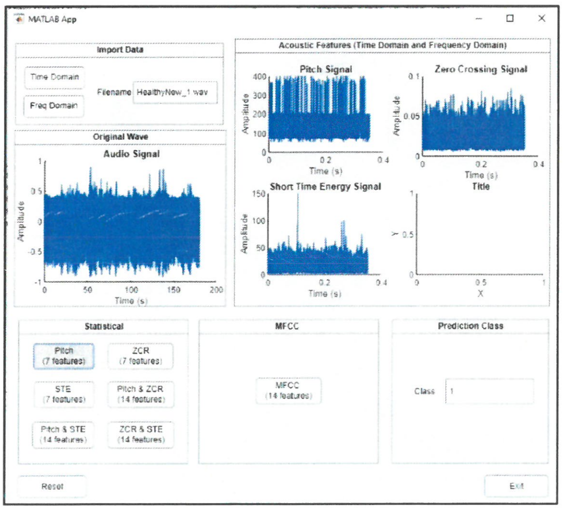


FIGURE 5. Time domain.

In Figure 6, displays interface mainly focuses on frequency domain. In frequency domain, the MFCC extracted features represent the acoustic characteristics of the signal. MFCC is commonly used in speech and audio processing to capture the essential features of a signal in the frequency domain. In this research, MFCC features in frequency domain have 14 variables extracted from the audio signal (Zulaikha et al., 2024).

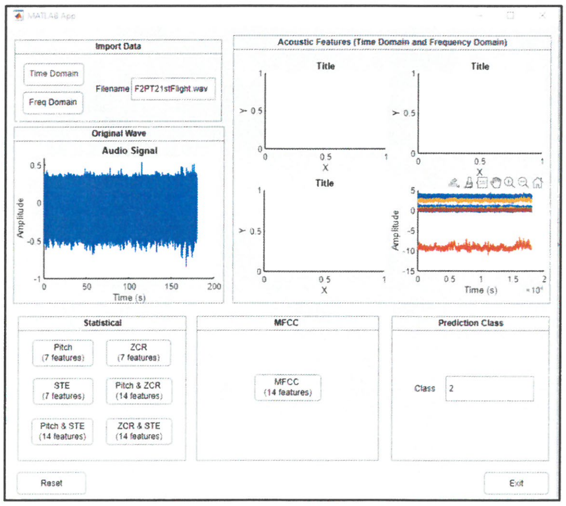


FIGURE 6. Frequency domain.

After processing the audio signal and extracting features from both the time and frequency domains, a ML classification model is applied to predict the class of the input data. Using the most optimal ML classification model, the system analyzes the processed audio dataset to determine the propeller's fault classification. The results of the propeller's fault classification for the time and frequency domains are displayed in Figures 5 and 6, respectively. The developed GUI for fault classification, integrated with an embedded ML classification model, enables efficient monitoring of the VTOL UAV's health, ensuring safe flight performance.

## CONCLUSION

This paper presented a development of audio based faulty classification system for various propeller's health conditions. The audio signal was analyzed using both time domain and frequency domain technique. In the time domain, statistical features were extracted to acquire the characteristics of the audio signals. In the frequency domain, Mel-Frequency Cepstral Coefficients (MFCC) were used for feature extraction, providing a detailed representation of the spectral properties of the audio signals. The selected algorithm will utilize the extracted features to make predictions. The results demonstrate that the GUI can effectively display the propeller's label based on the selected algorithm.

The performance of the audio-based faulty classification system can be affected by several factors such as environmental noise, recording equipment quality and operational conditions of the UAV. Moreover, the algorithm's efficiency is highly dependent on the quality of the training dataset, as well as the effectiveness of data processing methods. For future research, it is crucial to explore alternative sensors and advanced feature extraction techniques. This approach can help provide more comprehensive data and improve the accuracy and reliability of the fault classification.

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