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Comparative Study of Informative Acoustic Features for VTOL UAV Faulty Prediction using Machine Learning

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ABSTRACT

The propeller is one of the critical components in unmanned aerial vehicle (UAV) systems. The risk of the mechanism's failure could result in significant harm, hazardous events and primary maintenance services. Thus, early flying condition monitoring is necessary to ensure a stable and safe UAV operation. The sound emitted by Vertical Take Off and Landing (VTOL) UAVs offers valuable insights into their flight performance, serving as a crucial element for the efficient monitoring of flying conditions and early detection of potential faults. This paper will focus on developing fault detection and identification using audio data of different propeller conditions. The propeller faulty conditions are predicted based on informative features extracted from statistical time domain parameters of three audio wave features. Pitch, zero-crossing and short-time energy are selected as the significant audio features for the machine learning classification algorithm. UAV sounds collected in the experiment will be analysed and divided into a 60:40 ratio for training and testing datasets. Medium tree, Gaussian Naive Bayes and Ensemble Subspace k Nearest Neighbour algorithms are used for classification performance comparison. Among the three features, pitch produced the highest accuracy with 78.75% of training and 77.50% of testing using the Medium Tree algorithm.

1. Introduction

Drones, also referred as unmanned aerial vehicles (UAVs), have drawn a lot of attention in civilian and applicable in a variety of fields, including delivery, commercial and surveillance. UAVs exist in a variety of shapes and sizes, from small quadcopters to bigger fixed-wing aircraft. Over the past ten years, technology has advanced quickly, which has resulted in considerable advancements in tiny UAVs' cargo capacity, flight time and cost. In comparison to other forms of aircraft, quadrotors have

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an advantage since they can easily hover above stationary or moving targets and take off and land in small locations. There are two types of UAV, fixed wing and multirotor. An aircraft that can take off and land vertically without using a runway is known as a Vertical Take-Off and Landing (VTOL) aircraft. Drone propellers are one of the most basic parts of a drone. As they are in charge of producing the thrust that moves a UAV forward, propellers are frequently regarded as its most important component.

In recent years, there has been an increasing amount of literature on damaged blades for UAV fault detection system. Liu *et al.*, [1] set up a technique for identifying propeller damage from the noise the UAV's flight produces in the form of audio. In this research, two different types of broken propellers with lengths of 9.6 inches and 8.6 inches were used with a healthy 10-inch propeller. A study by Yang *et al.*, [2] developed an intelligent fault diagnosis method for improving the robustness and generalization ability of fault diagnosis model. The author used different degrees and types of damage of individual blades were set to simulate the damage of the VTOL UAV blades in the actual flight. Cahabug *et al.*, [3] presented an UAV failure detection system that can identify propeller failures to lower the risk of collisions. Several cases of propeller problems with 7 mm cut propellers are used in this paper. In an investigation into deep learning, Zhang *et al.*, [4] found that due to simulation-to-reality gap often leads to poor performance of the classifier when applied in real flight. Puchalski *et al.*, [5] proposed fault detection and isolation method for UAVs capable of early detection of failures. The flight experiments were conducted in seven different scenarios: two with damaged propellers on opposing sides, two with damaged propellers adjacent to each other and four with a single damaged propeller.

In facing difficulties in UAV stability, many researchers explore the method for engaging the vibration effect on UAV systems. Pourpanah *et al.*, [6] developed a monitoring system that uses vibration signals analysis to identify potential faults with the blades and motors of UAVs early on. Hu *et al.,* [7] evaluated the motor's performance using the measuring vibration signal of a UAV motor. Ghazali *et al.,* [8] introduced real-time vibration-based fault detection using AI techniques and IoT to analyze the multirotor’s arm.

There is a large volume of published research describing the audio specification. Al-Emadi *et al.,* [9] aims is to demonstrate an autonomous system that can identify drones based on their acoustic signals. The experiment was carried out using a smartphone's built-in microphone for audio clip recording. The audio recordings are saved in MPEG-4 audio format (m4a) and have a maximum bit-rate of 64 Kbps, with a sample rate of 44.1 KHz. A real-time technique for identifying propeller, eccentric and bearing failure [10]. Iannace *et al.,* [11] trained a machine learning model with sound recordings in order to develop a propeller imbalance detection system. Four different areas were measured at 90-degree angles from a UAV that was positioned in the center of a circle with a radius of 1.2. Yaman *et al.*, [12] presented a fault detection that can be made for UAVs with single or multi motors. The mobile application's audio recording parameters are shown below while the sound dataset is being collected.

A group of researchers recently conducted a study focusing on feature extraction of audio signal. Pitch period, FFT and Mel Cepstral Coefficient (MFCC) are the three feature extraction algorithms that Jin *et al.,* [13] investigated. It explains that essential parameter that effectively describes the vibration of the excitation source is the pitch period. Koduru *et al.,* [14] proposed pitch as one of the features algorithms to improve speech emotion recognition. Based on the research, pitch can be calculated as in Eq. (1).

$$S(n) = \sum_{t=a1}^{a2-n} y(l)y(l+n) \quad ` \tag{1}$$

Sharma *et al.,* [15] discussed the temporal domain, frequency domain, cepstral domain, wavelet domain and time-frequency domain. Zaw *et al.,* [16] proposed an algorithm that uses spectral entropy and short time features such as zero crossing rate, short time energy, linear prediction error are used for voice activity detection (VAD). The author composed the formula of ZCR as in Eq. (2).

$$Z_n = \sum_{m=-\infty}^{\infty} |sign[s(m)] - sign(s[m-1])| \tag{2}$$

In response to reports of drones flying over sensitive places, Bernardini *et al.,* [17] aims to propose efficient and affordable countermeasures. In order to develop a machine learning-based UAV, this research presented various short-term parametrizations in the temporal and frequency domain of environmental audio data. It is computed according to the Eq. (3).

$$STE = \frac{1}{L} \sum_{i=0}^{L-1} |s(i)|^2 \tag{3}$$

Many studies have utilized machine learning, an advanced technique that is essential in analyzing UAV data for fault detection and identification. In their comparison of an improved fault diagnostic algorithm, Yang *et al.,* [18] produced a favourable outcome for the field of UAV health detection. Baskaya *et al*., [19] and Bronz *et al.*, [20] proposed SVM method due to its improvement in accuracy for detection faulty and nominal flight conditions. With the same purpose, Bondyra *et al.,* [21] employed SVM based on three distinct feature extraction techniques to identify both the type and frequency of rotor faults.

As technology evolved, machine learning has emerged as an important field in fault detection acoustic research. Wang *et al.,* [22] applied machine learning techniques to identify drones that are carrying payloads based on the sound signals produced. Casabianca *et al.,* [23] performed a similar model as Wang *et al.* [22], showing that the CNN model was the best suited for this acoustic UAV detection application. A recent study by Salman *et al.,* [24], performed machine learning technique to determine the best parametric representation for audio drone identification. The study has demonstrated and concluded that combining audio features yields the best categorization results.

This paper aims to evaluate and validate whether the time domain features are capable to classify the faulty mechanism using machine learning classification. The procedure involves an experiment performed in an indoor laboratory. The equipment involves wireless microphone and mobile phone applications for data recording. As the main reason of this study is to classify the faulty mechanism, thus several real damaged propeller will be used as main subject for this research.

2. Methodology

This section discusses the framework employed in the research, outlining the techniques used to gather and analyze acoustic data. The audio signal undergoes data processing, where three key features were extracted and calculated through statistical equations before being applied as an input into machine learning for classification.

Data collection is necessary for the machine learning approach based on analysis of the literature related to machine learning. Moreover, it plays a significant role in shaping machine learning model performance and its outcome. This paper aims in fault detection and identification for machine learning classification using acoustic features.

The fundamental process of diagnosis, classification, clustering, recognition and detection involves feature extraction. Statistical technique is one of the feature extraction methods used for increasing the efficiency of the model's performance.

In this research, seven parameters were selected including mean, interquartile range, skewness, kurtosis, variance, standard deviation and root mean square. Interquartile Range (IQR) is the middle 50% of the total data which indicates the difference between the value that represents 25% of the total data and the value that represents 75% of the total data. In short, it is used to explain the difference between the upper and lower quartiles in the set of data. Since it is based on values from the middle half of the distribution and is therefore unlikely to be affected by outliers, it is the best measure of variability for skewed distributions or data sets containing outliers. Kurtosis and skewness are the measurement of distribution shapes. Kurtosis measures the tails of distribution which indicate positive or negative kurtosis compared to normal distribution. Kurtosis aids in the analysis of a dataset's characteristics and outliers. Skewness measures the asymmetrical of the probability distribution which indicates positive and negative skewness. Skewness benefits in understanding the shape and outliers in a dataset. Standard deviation gives important information about the consistency of results and aids in understanding variability. Both variance and standard deviation reflect variability, however, variance provides more informative about variability than the standard deviation. Root mean square (RMS) value of a signal is calculated as the square root of average of squared value of the signal. The computation of a waveform's mean square value is one of the common applications. This is significant because it indicates the amount of energy that the waveform contains.

Machine learning has been widely used for exploring development of algorithms based on the dataset to make predictions. The model iteratively updates parameters as it learns by comparing its predictions with known target labels. This process keeps going until the model meets the required accuracy or performance standards. After training, the model is capable of predicting target labels for new cases by analyzing their input features. The representativeness and quality of the data are essential to the generalization and accuracy of the model. The framework of the proposed method is shown in Figure 1.

Fig. 1. Framework of the research

2.1 Experimental Setup

The primary recording equipment for this investigation is a DJI Mavic Pro equipped with pre-assigned various faulty mechanisms. The DJI Mavic Pro is an adaptable and user-friendly drone featuring a variety of applications. It was prepared under various conditions and utilized as the primary diagnostic technique. The drone has four rotors equipped with battery of 3830 mAh and weight of 743g include gimbal cover. The maximum speed of the quadrotor is 40 mph and flight distance are 13km with no wind disturbance.

The experimental setup takes place in an indoor laboratory environment. The room is outfitted with soundproof materials designed to absorb and dampen sound waves effectively. In order to ensure stable UAV operation and equipment performance, environmental parameters including temperature and humidity were maintained within ideal ranges. On top of the quadrotor, we attached a wireless microphone, Ulanzi J12 Wireless Microphone as shown in Figure 2. When conducted the experiment, the microphone was linked to the mobile application device to record the sound signals. This project used the high specifications microphone to extract the best sound data and provide the best result for the sound classification. The microphone is an omnidirectional microphone that can transmit a good quality sound at up to 20 meter and has a battery capacity of 80 mAh. The sound data was created in m4a format with a 48kHz sampling frequency. The DJI Mavic Pro drone was controlled by a mobile application that connected to the controller, allowing for easy and precise movement control.

Fig. 2. UAV attached with wireless microphone

2.2 Data Collection with Different Propeller Cases

This paper begins with the data collection in the form of acoustic. Measurements of sound were made to describe the sound emissions from the UAV propeller. The flight was conducted in four different propeller conditions labeled as: Healthy, Faulty 1, Faulty 2 and Faulty 3. A propeller is a fundamental component that controls the device's performance and the volume of noise produced by the UAV. The flying was performed with damaged propeller as shown in Figure 3.

Fig. 3. Damaged propeller

Flight experiments conducted in four conditions: all propellers operational (Healthy), two propellers on opposite sides damaged (Faulty 1) and two scenarios with damage to two adjacent propellers each (Faulty 2 and Faulty 3). The transmitter was put at the same height as the receiver during hovering which was fixed at 2 meters from the ground to achieve high efficiency. During the data recorded, the UAV was hovering in indoor laboratory environment and the flight was recorded for three minutes for each condition without any external disturbance. The following Table 1 displays the label and position of propeller:

Table 1
Propeller's label and position

Label	Position
Healthy	All
Faulty 1	3 and 4
Faulty 2	1 and 4
Faulty 3	1 and 3

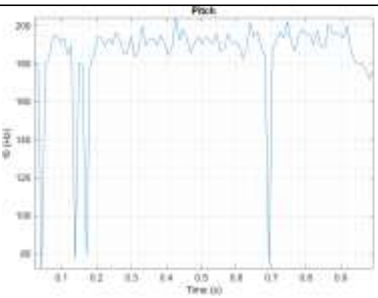
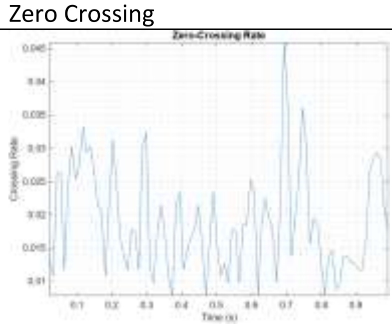
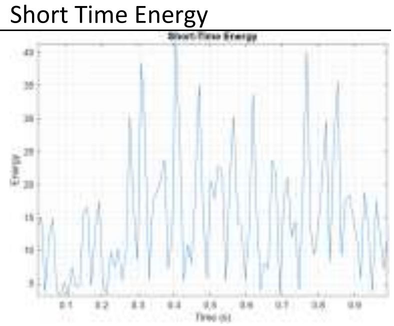
2.3 Data Processing of Audio Features

Data processing is one of the early stages before classification machine learning. The extraction technique must be used to ensure an accurate classification. In statistical signal processing, preprocessing stages aid in improving the quality of the data, removing relevant features and lowering noise interference. Time series for audio refers to the representation of audio data over time. Time series analysis may involve extracting relevant features from the audio signal such as temporal features (zero-crossing rate, energy) and spectral features. The significant audio features are chosen as an input for machine learning and proposed using Audio Toolbox in MATLAB 2023b. Three significant audio features are selected for the time series parameter: Pitch, STE and ZCR.

To extract these features from an audio signal, the audio waveform is typically divided into short frames using techniques such as windowing. Each frame is then analyzed to compute the desired features. Some of the common types of windows used in audio features extraction were rectangular window, Hamming window, Hann window and Blackman window.

This paper applied Hamming window with 1024 samples, 48kHz for sampling rate and an overlap of 50% for each audio feature. In signal processing, the Hamming window is an type of window function that reduces spectral leakage and improves the analysis's frequency resolution. A sampling rate of 48 kHz indicates that the audio signal is sampled 48,000 times per second while an overlap of 50% implies that each window overlaps with the adjacent window by 50% of its length. It help to reduce spectral leakage and improve the temporal resolution of the analysis by ensuring that each sample contributes to multiple analysis windows. Table 2 shows graphs illustrating audio features of pitch, STE and ZCR for a 1-second audio sample. It displayed a different pattern of audio features between four different propeller conditions.

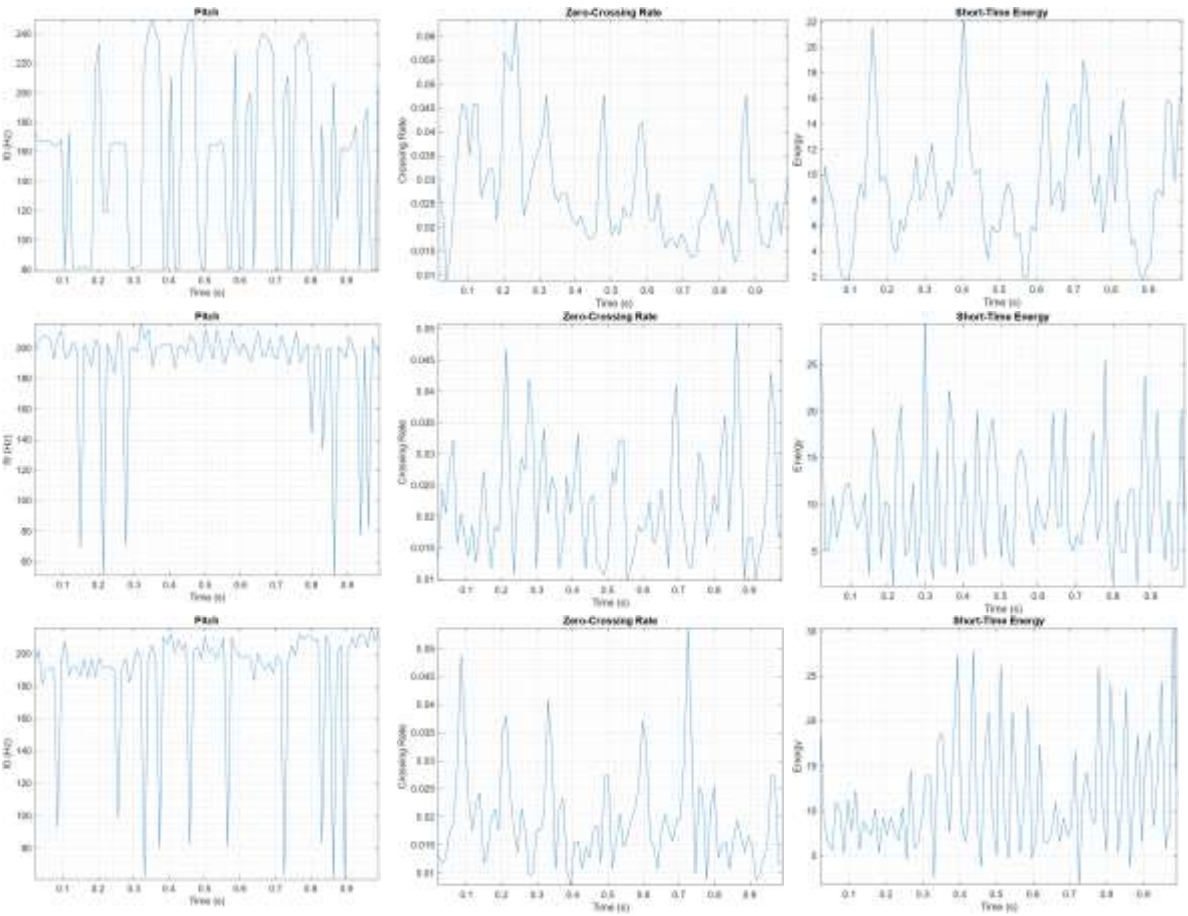
Table 2
Audio features of 1 sec audio sample

Label	Pitch	Zero Crossing	Short Time Energy
Healthy			

Faulty 1

Faulty 2

Faulty 3



After the informative audio features are selected, the data will be calculated using seven statistical parameters. Mean, IQR, standard deviation, skewness, kurtosis, variance and RMS were selected as time domain parameters for each condition. Machine learning is essential for classifying complex audio patterns like pitch, STE and ZCR in VTOL UAV due to its ability to detect variations patterns thus able to differentiate between healthy and faulty propellers.

2.4 Data Splitting

Commonly, data is divided into two sections. Training is employed in one of these sections and the prediction performance is evaluated on the other. According to past research, data splitting can have different ratios, such as 10:90, 20:80, 30:70, 40:60, 50:50, 60:40, 70:30, 80:20 and 90:10. The training dataset is used for developing the model and the testing dataset is used to evaluate the model's predictive ability [25]. Among the main reasons for data splitting are to prevent overfitting and bias in model selection, improve hyper-parameters on the development test, evaluate the predictive capability of the model and measure the generalization performance. In machine learning, overfitting occurs when a model becomes so effective at capturing noise and fluctuations in training data that it becomes inaccurate on test. In this research, the parameters were divided into the training set 60% for training and 40% for testing before employed into machine learning.

2.5 Machine Learning Classification

The feature extracted in the previous section was used as an input in machine learning classification using MATLAB 2023b software. Classification Learner allows to train and validate classifiers' algorithms using binary or multiclass problems. It also allows to plot class predictions to visualize results, compare models based on accuracy values and assess performance using ROC curves and confusion matrix. In order to accurately predict new data, a model based on labeled input with known output label is trained in this study using machine learning.

One of the strong statistical tools for data manipulation, interpretation, prediction and categorization is the decision tree approach which is Medium Tree (MT). The algorithm produces significant subgroups from the original input variables, which simplifies complex interactions between input variables and target variables. However, it is potential to become overfitting and underfitting, especially when using a small data set. Maximum number of splits refers to maximum number of decision nodes from the root node to the leaf nodes. Gini index, Entropy and Information Gain were the common split criteria in Decision Tree. In this study, Gini index was used as split criteria in MT algorithm.

Gaussian Naïve Bayes (GNB) is one of the simple algorithms often used when dealing with continuous data that has class values associated with a normal distribution. The algorithm needs to estimate the mean and the standard deviation from training data. So, the probability is given by Eq. (4).

$$P\,(x_i \mid y = y') = \frac{1}{\sqrt{2\pi\sigma_x^2}} exp(-\frac{(x_i - \mu_x)^w}{2\sigma_x^2}) \tag{4}$$

Where, x is the feature vector, μ is the mean of the feature values, σ is the standard deviation of the feature values and exp is the base of the natural logarithm.

On the other hand, Ensemble Subspace KNN (ESKNN) which combines several classifiers, can enhance learning algorithm prediction. A common ensemble technique called random subspace creates distinct classifiers from randomly selected data subspaces [26]. This ensemble generalizes efficiently when there are unnecessary features in the dataset. These algorithngms are preferred because their performance performs better than other algorithms. Table 3 shows the specification of each classification algorithm.

Table 3
Specification of classification algorithm

Classification algorithm	
Medium Tree	Preset: Medium Tree Maximum number of splits: 20 Split criterion Gini's diversity index Surrogate decision splits: Off
Gaussian Naive Bayes	Preset: Gaussian Naïve Bayes Distribution name for numeric predictors: Gaussian
Ensemble Subspace KNN	Preset: Subspace KNN Ensemble method: Subspace Learner type: Nearest Neighbors Number of learners: 30 Subspace dimension: 4

3. Results

This section discusses the results obtained from classification learner. The accuracy of each audio wave features confusion matrix and comparison of classifier algorithms are discussed in the next sub section.

3.1 Pitch

In the case of UAV audio propeller, pitch represents the highness or lowness of the sound generated by the propeller's rotation. Analyzing pitch over time can help detect anomalies, such as sudden changes in propeller speed or unexpected vibrations.

3.1.1 Accuracy

Pitch features in Table 4 produced the best training value accuracy, which the MT algorithm calculated to be 78.75%. Accuracy values for the GNB and ESKNN algorithms were calculated as 74.17% and 71.67%, respectively. For the testing dataset, the MT algorithm produced a highest accuracy of 77.50%, while the GNB and ESKNN algorithms obtained results of 66.88% and 62.50%, respectively.

Surprisingly, MT algorithm produced the highest accuracy rate in both training and testing. The GNB algorithm obtained lower accuracy rate than MT algorithm. However, ESKNN yielded the lowest accuracy rate compared to MT and GNB algorithm. These results demonstrate how proficiently pitch characteristics perform in accurately classifying the dataset, especially when integrated with the MT algorithm.

Table 4
Classifier model training and testing for pitch features

Algorithm	Accuracy	
	Training (%)	Testing (%)
Medium Tree	78.75	77.50
Gaussian Naive Bayes	74.17	66.88
Ensemble Subspace KNN	71.67	62.50

3.1.2 Scatter plot

Scatter plot which indicates the distribution of data points belonging to various classes, can be used to identify class imbalances within the dataset. Figure 4 displayed the distinct data points from several UAV conditions for pitch features.

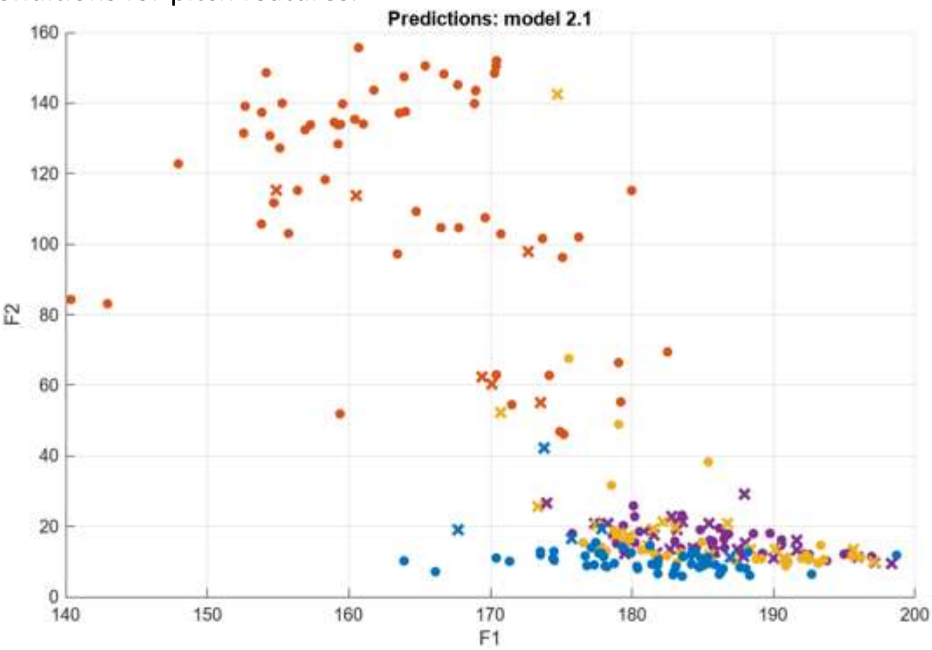


Fig. 4. Scatter plot of pitch features for each condition

3.1.3 Confusion matrix

Confusion matrix is the summarize of machine learning model of a dataset. It presents a summary of the predicted class labels against the actual class labels for a set of data. Figure 5 displays the confusion matrix of the proposed method for three chosen algorithms. For the pitch features, the highest value for the Healthy class (Class 1) and Faulty 2 (Class 3) was obtained with MT algorithm. The highest value for the Faulty 1 class (Class 2) and Faulty 3 (Class 4) was calculated with GNB algorithm.

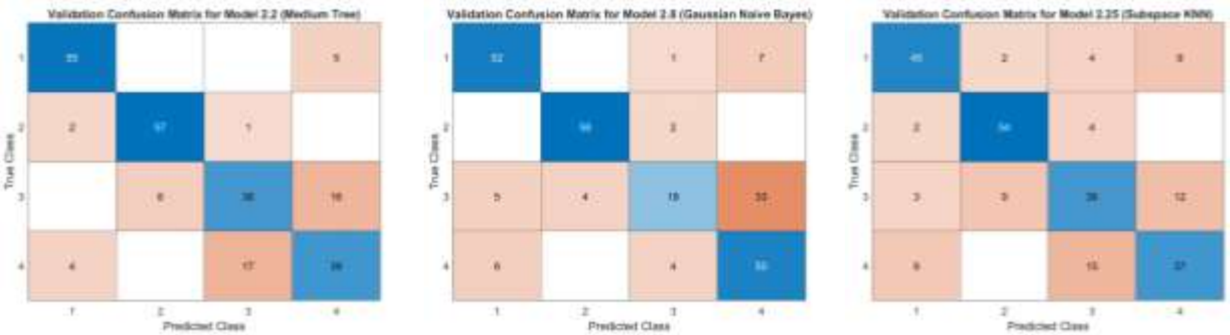


Fig. 5. Confusion Matrix of MT, GNB and ESKNN algorithms of pitch features

3.2 Short Time Energy (STE)

STE provides a measure of the energy variations of the environmental sound over time. The audio stream is divided into overlapping and non-overlapping frames, usually via frame shifting and windowing, to compute STE. In response to its ability to capture dynamic temporal variations, STE is frequently utilized in audio feature extraction and analysis activities.

3.2.1 Accuracy

The MT algorithm achieved an accuracy of 67.92% on the training dataset, while performing slightly lower with an accuracy of 63.75% on the testing dataset. Conversely, the GNB algorithm demonstrated the highest accuracy among the three algorithms for short time energy features, with 70.83% accuracy on the training dataset and 64.38% on the testing dataset. In contrast, the ESKNN algorithm yielded lower accuracy rates compared to MT and GNB, achieving 65.83% on the training dataset and 63.75% on the testing dataset.

For short time energy, GNB algorithm performed a bit higher accuracy than MT algorithm. This finding may be due to the classification model performed different algorithms depending on the characteristics of the data. On the other hand, ESKNN produced the lowest accuracy rate compared to other algorithms.

Table 5
Classifier model training and testing for STE features

Algorithm	Accuracy	
	Training (%)	Testing (%)
Medium Tree	67.92	63.75
Gaussian Naive Bayes	70.83	64.38
Ensemble Subspace KNN	65.83	63.75

3.2.2 Scatter plot

Based on Figure 6, shows that the data points within each condition are well separated from one another, leads to a potential for precise classification tasks.

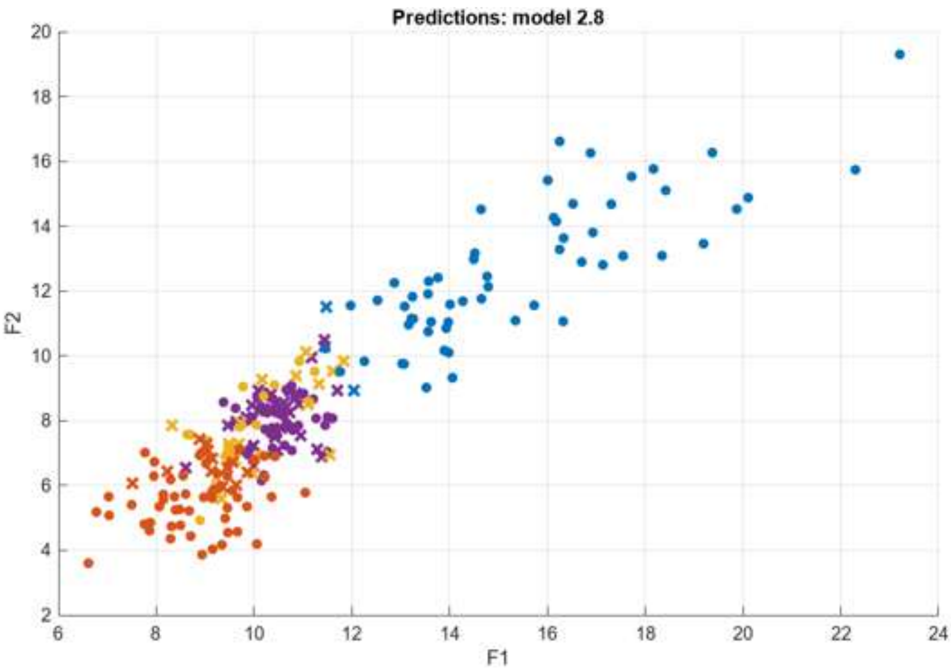


Fig. 6. Scatter plot of STE features for each condition

3.2.3 Confusion matrix

Figure 7 shows the observation of the performance of selected model for short time energy feature. Based on the figure, all algorithms produced the highest result for the Healthy class (Class 1). The highest value for the Faulty 1 class (Class 2) and the Faulty 3 class (Class 4) was acquired using the GNB approaches. The highest value for Class 3 or Faulty 2, calculated by the MT algorithm.

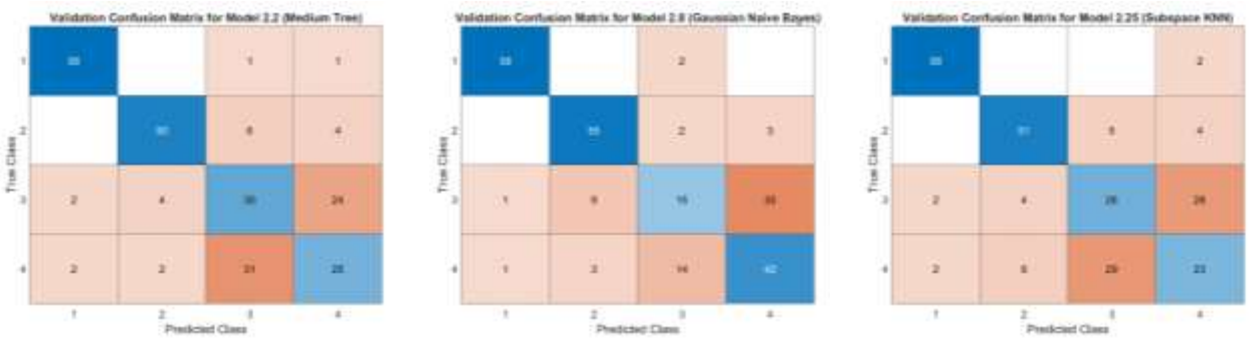


Fig. 7. Confusion matrix of MT, GNB and ESKNN algorithms of short time energy features

3.3 Zero Crossing Rate (ZCR)

The concept of ZCR is essential to audio signal processing since it offers important insights into the frequency content and temporal characteristics of audio signals. ZCR can be used as a feature in machine learning algorithms for various audio processing tasks, including classification, segmentation and pattern recognition.

3.3.1 Accuracy

The MT algorithm achieved a training accuracy of 38.75% and a testing accuracy of 35.63% on the ZCR features dataset. Similarly, the GNB algorithm yielded relatively competitive results with a training accuracy of 37.92% and a testing accuracy of 37.50%. In contrast, the ESKNN algorithm exhibited lower accuracy rates compared to MT and GNB, achieving a training accuracy of 29.58% and a testing accuracy of 25.63%.

Table 6
Classifier model training and testing for ZCR features

Algorithm	Accuracy	
	Training (%)	Testing (%)
Medium Tree	38.75	35.63
Gaussian Naive Bayes	37.92	37.50
Ensemble Subspace KNN	29.58	25.63

3.3.2 Scatter plot

Based on Figure 8, shows a significant overlap between the data points of the two classes. The findings suggested that the plotted features have limited discriminative capability and therefore may be challenging for classification tasks.

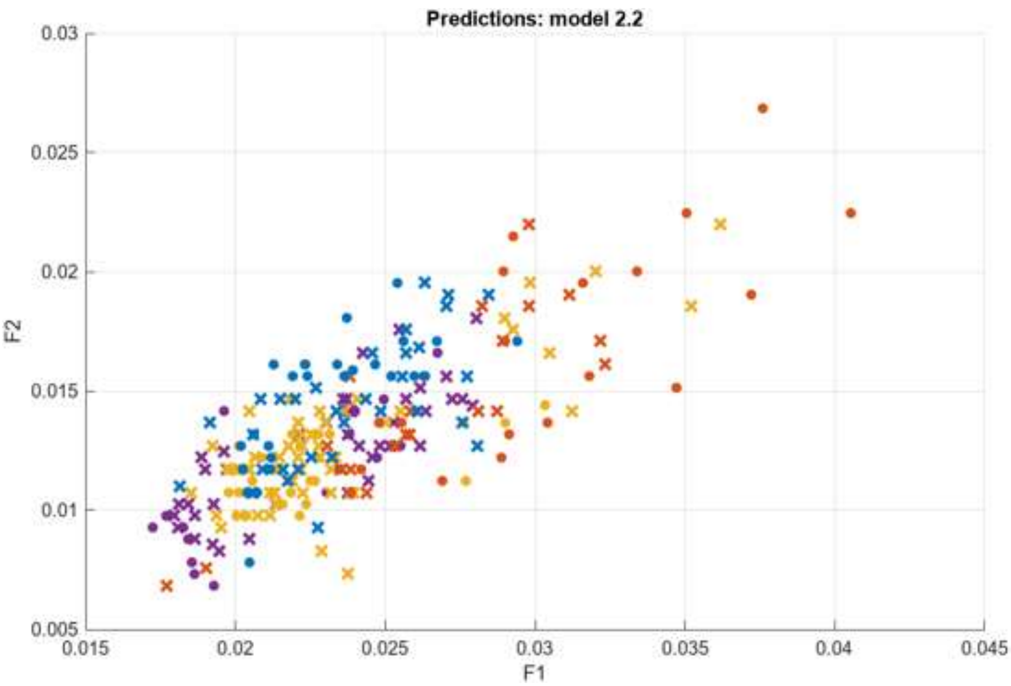


Fig. 8. Scatter plot of ZCR features for each condition

3.3.3 Confusion matrix

For zero crossing rate feature, the highest value of Healthy class (Class 1), Faulty 2 class (Class 3) and Faulty 3 class (Class 4) obtained by MT algorithm while the highest value of Faulty 1 class (Class 2) calculated with GNB algorithm as shown in Figure 9.

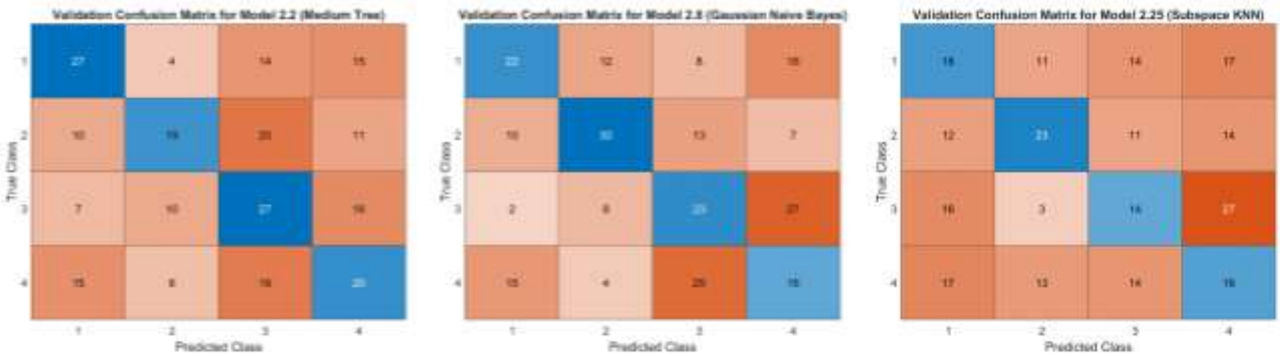


Fig. 9. Confusion matrix of MT, GNB and ESKNN algorithms of zero crossing rate features

3.4 Comparison Results of the Three Audio Features

In order to evaluate the overall of all examined features in UAV faults, Figure 10 displays the percentage accuracy obtained from training and testing based on three algorithms on the set of three extracted audio features. By running a 5-Fold Cross Validation, the best algorithm of training accuracy is MT with pitch feature achieved an accuracy of 78.75% for training and 77.50% for testing. In contrast, the lowest calculated accuracy is ESKNN algorithm with ZCR feature achieved an accuracy of 29.68% and 25.63% for training and testing, respectively. GNB algorithm achieved higher accuracy than MT algorithm with difference of 2.91% of training accuracy and 0.63% of test accuracy for STE feature. It is possible that these results were influenced by several factors such as selection algorithm and feature extraction.

Based on the result, GNB algorithm outperformed the MT algorithm in terms of training accuracy of 2.91% and a test accuracy advantage of 0.63% when using STE features. The findings suggest that the algorithm selection should be given consideration as these results may imply that different features calculated differently with algorithms.

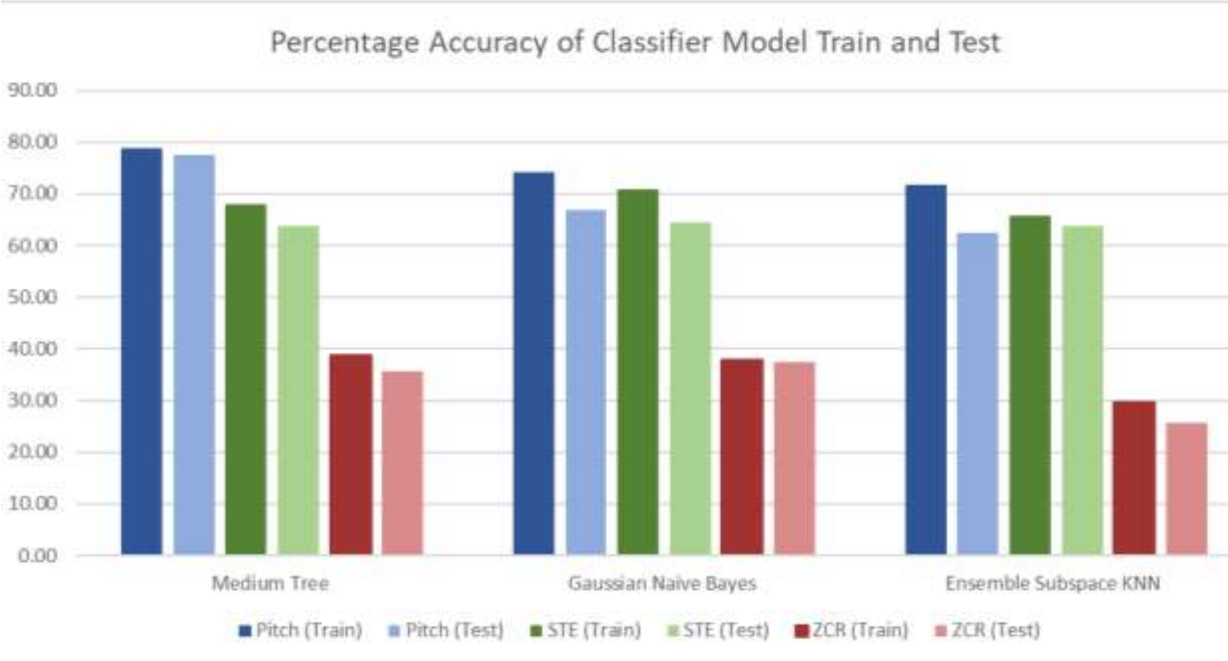


Fig. 10. Classifiers' accuracy of validation and test for each audio features

Statistical signal processing techniques enable the extraction of frequency-domain, time-domain and time-frequency domain features that capture characteristics of the underlying data and enable learning tasks such as classification, regression and clustering. This study is set out to develop a classification model that can classify faulty mechanism.

In this study, the initial step of the process is by gathering and analysing the audio samples. Then, the audio signals were applied with the processing technique by extracting the time domain audio features: pitch, ZCR and STE using MATLAB application. Then, the features were computed using 7 statistical parameters and deployed into machine learning classification. Our finding revealed that, pitch features provide the best result compared to ZCR and STE features. Additionally, the most striking observation to emerge from the data comparison was MT algorithm due to the highest accuracy and best performance metrics. In contrast, ZCR gain the lowest accuracy rate in all the algorithms and performance metrics. The challenges associated with ZCR features may include their sensitivity to noise and variability in signal characteristics, which can impact classification accuracy.

Pitch estimations are commonly created with stability and robustness to withstand a variety of audio signal sources and acoustic environment while ZCR and STE can be affected by noise, amplitude variations and transient sounds. Noise often affects signals in real-world signal processing applications. By using temporal statistical signal processing, allows to analyse the behaviour of noise over time, examine its statistical characteristics and develop algorithms that minimize its impact on signal quality. Algorithm selection that not only satisfies performance standards but also produces reliable and accurate results.

Real-time systems depend on the development of suitable algorithms that can process data streams in real-time. To ensure an efficient operational system, this procedure might be considered to be applied in real-time implementation for fault detection and identification systems.

4. Conclusions

In this research, a framework for faulty classification of UAV propellers has been developed. This research's objective was to choose a machine learning model suitable for the selected audio features that can classify propeller’s condition. To simulate the faults in UAV, four cases were carried out: healthy for all propeller, one opposite damaged propeller and two adjacent damaged propellers. The audio data recorded in a laboratory is ideal and without any external disturbance.

The audio signal caused by the rotation of the propeller blades was recorded using a wireless microphone attached with the UAV. Then, a statistical technique has been used to extract features from these audio samples. MT, GNB and ESKNN algorithm had been chosen for evaluating the performance of the selected models. Based on the accuracy result shows the best classifier for audio faulty prediction based statistical features is pitch. The high classification performance demonstrates the effectiveness of these features in audio classification, which is already well-established and validated. This study has gone some way towards enhancing our understanding of statistical signal processing together with machine learning for classification of faulty mechanism.

However, our study has certain limitations. It focused solely on hovering movement without considering external disturbances. It is recommended that further research be extended in the following area: vibration data and 6 degree of freedom (DOF) including wind disturbance. By exploring these additional factors, researchers can enhance the robustness and applicability of fault detection systems in real-world UAV operations.

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