Classification of Helicopter Transmission Condition in the Relative Spectral Domain under Unknown Sampling Frequency⋆

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Abstract.

Vibration-based diagnostics of helicopter transmissions traditionally rely on the analysis of absolute frequency components, including gear mesh frequencies and their harmonics. However, in practical scenarios, archived or exported vibration datasets may lack information about the sampling frequency, making conventional frequency-calibrated approaches inapplicable.

This study proposes a classification method for helicopter transmission condition operating entirely in the relative spectral domain without requiring knowledge of the sampling frequency. The approach is based on constructing an engineering feature space comprising time-domain statistical descriptors, relative spectral energy bands, and spectral characteristics computed using frequency-bin indices.

Classification is performed using a gradient boosting ensemble model. The method was evaluated on a real dataset consisting of 1158 single-channel vibration records of equal length obtained under consistent measurement conditions and labeled as normal or faulty.

The results demonstrate linear separability of the two conditions within the constructed feature space. A stratified 5-fold cross-validation confirmed model stability, while a label-shuffling test verified the absence of information leakage. Feature importance analysis revealed that kurtosis and spectral centroid are the dominant discriminative descriptors, both possessing clear physical interpretation related to impulsive dynamics and spectral energy redistribution.

The proposed method is interpretable, computationally efficient, and suitable for condition monitoring applications where sampling frequency metadata is unavailable.

Keywords

Vibration diagnostics, helicopter transmission, relative spectral representation, condition monitoring, feature-based classification, sampling frequency invariance, Health and Usage Monitoring Systems (HUMS).

1. Introduction

Helicopter transmission systems operate under highly demanding dynamic conditions characterized by elevated torque levels, cyclic aerodynamic loading, and multi-stage gear interactions. These operating conditions generate broadband vibration signals containing valuable information about the mechanical integrity of gears, shafts, and rolling-element bearings. Reliable interpretation of such signals is essential for ensuring flight safety and reducing maintenance costs.

Vibration-based diagnostics constitutes a fundamental component of Health and Usage Monitoring Systems (HUMS), which are widely implemented in modern rotorcraft to enable condition-based maintenance. Classical approaches to helicopter gearbox diagnostics rely on the analysis of absolute frequency components, including gear mesh frequencies, their harmonics, and associated sidebands. As demonstrated in the seminal review by Samuel and Pines [1], the effectiveness of these methods depends critically on accurate knowledge of kinematic parameters and sampling frequency.

Subsequent developments in rotating machinery diagnostics have incorporated time-domain statistics, envelope analysis, spectral features, and machine learning techniques [4–10,16]. In recent years, deep learning architectures have demonstrated high classification accuracy in vibration-based fault diagnosis.

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However, such approaches typically assume complete metadata availability, including sampling frequency, sensor calibration, and operating conditions. Moreover, deep neural networks often lack interpretability and require significant computational resources.

In practical scenarios, especially when dealing with archived, exported, or third-party datasets, vibration records may not contain reliable information about the sampling frequency. Under such conditions, conventional frequency-calibrated methods become inapplicable because physical interpretation based on absolute frequency values is no longer possible. This limitation represents a significant challenge for real-world deployment of diagnostic algorithms.

Despite extensive research in vibration diagnostics, relatively little attention has been devoted to classification methods that operate entirely in a relative spectral framework, independent of absolute frequency scaling. The development of an interpretable, computationally efficient, and sampling-frequency-invariant diagnostic approach remains an open methodological problem.

The objective of this study is therefore to develop and experimentally validate a vibration-based classification method for helicopter transmission condition that:

- does not require knowledge of the sampling frequency,
- operates in the relative spectral domain using frequency-bin indices,
- preserves physical interpretability of discriminative features, and
- is suitable for implementation in practical condition monitoring systems.

Unlike conventional frequency-oriented approaches, the proposed methodology relies on relative spectral representation combined with statistically meaningful signal descriptors. This design enables robust classification under incomplete metadata conditions without sacrificing discriminative performance.

The main contributions of this work are as follows:

- Formalization of a classification framework operating entirely in the relative spectral domain.
- Construction of an engineering feature space invariant to sampling frequency.
- Experimental validation on a real-world dataset comprising 1158 vibration records.
- Demonstration of model interpretability, computational efficiency, and methodological robustness.

The key novelty of this work lies in the formulation of a vibration-based diagnostic framework that operates entirely in the relative spectral domain, eliminating the need for knowledge of the signal sampling frequency. Unlike conventional condition monitoring approaches that rely on absolute frequency calibration, the proposed method constructs an engineering feature space using frequency-bin indices and normalized spectral energy distributions, enabling consistent analysis even when acquisition parameters are unavailable. This representation provides sampling-frequency invariance, which is particularly important when working with heterogeneous datasets, archived measurements, or signals obtained from different monitoring systems. Furthermore, the study demonstrates that combining interpretable engineering descriptors with gradient boosting allows accurate fault classification while preserving physical interpretability of the diagnostic indicators. As a result, the proposed approach bridges the gap between data-driven machine learning diagnostics and physically interpretable vibration analysis, offering a practical solution for helicopter transmission condition monitoring under incomplete measurement metadata.

2. Literature Review

Vibration-based diagnostics of helicopter transmissions has been extensively studied over the past decades. Early foundational work, particularly the comprehensive review by Samuel and Pines [1], established the importance of spectral analysis techniques for detecting gear and bearing faults in rotorcraft gearboxes. These approaches focus primarily on identifying characteristic fault frequencies such as gear mesh frequencies, harmonics, and sidebands, whose interpretation relies on precise knowledge of rotational speeds and sampling frequency.

Subsequent research extended vibration-based condition monitoring methodologies to a wide range of rotating machinery systems [2–5]. These studies emphasized the role of energy redistribution in the frequency domain, impulsive components in the time domain, and envelope-based techniques for fault detection. In planetary and multi-stage gear systems, adaptive methods were proposed to address varying load and speed conditions [6–8]. Nevertheless, even adaptive techniques typically maintain dependence on absolute frequency scaling, as physical fault identification requires alignment between spectral peaks and theoretically predicted defect frequencies.

Parallel to frequency-oriented methods, significant progress has been achieved in feature engineering. Statistical descriptors such as kurtosis, skewness, crest factor, spectral entropy, and band energy ratios have been widely employed for rotating machinery diagnostics [9,12,17]. These features often enhance robustness and reduce sensitivity to noise compared to direct peak-based analysis. However, in most reported studies, feature extraction still assumes the availability of calibrated frequency information and is frequently used as a complement rather than an alternative to frequency-based diagnostics.

More recently, machine learning and deep learning techniques have been applied to vibration-based fault diagnosis [10,16]. Deep neural networks, convolutional architectures, and hybrid feature-learning models have demonstrated high classification accuracy across various datasets. Despite their predictive performance, these approaches exhibit several limitations. First, they commonly require large labeled datasets and substantial computational resources. Second, interpretability remains limited, which poses challenges in safety-critical domains such as aviation. Third, and most relevant to the present study, these models typically assume complete metadata availability, including sampling frequency and consistent measurement configurations.

Only limited research has addressed diagnostic scenarios where the sampling frequency is unknown or unavailable. While normalization techniques and dimensionless representations have been discussed in other contexts, a systematic framework for condition classification operating entirely in a relative spectral domain—without reliance on absolute frequency values—remains insufficiently explored.

Therefore, two key observations can be drawn from the existing literature:

1. Classical and adaptive vibration-based diagnostic methods are strongly tied to absolute frequency interpretation and kinematic parameter knowledge.

2. Modern machine learning approaches rarely consider scenarios with incomplete signal metadata, particularly unknown sampling frequency.

The lack of an interpretable and computationally efficient classification framework capable of operating independently of sampling frequency represents a methodological gap. The present study addresses this gap by proposing a feature-based classification approach formulated entirely in the relative spectral domain.

Vibration-based condition monitoring of rotating machinery has been extensively studied in recent years. Classical approaches rely on spectral analysis and statistical descriptors derived from vibration signals to detect anomalies and identify fault conditions. Recent studies increasingly employ machine learning techniques to automate the diagnostic process and improve detection accuracy. In particular, ensemble learning models such as random forests and gradient boosting have demonstrated strong performance in vibration-based fault classification due to their ability to capture non-linear relationships in multidimensional feature spaces.

Recent studies confirm the growing importance of data-driven methods for vibration-based fault diagnosis in rotating machinery, including both review-level analyses of artificial intelligence applications and practical models for bearing and gearbox monitoring. In particular, machine learning approaches based on engineered signal descriptors remain attractive due to their lower computational cost and better interpretability compared with end-to-end deep architectures [19, 21]. At the same time, hybrid diagnostic schemes combining signal processing, informative feature extraction, and intelligent classifiers continue to demonstrate strong performance in machinery fault detection tasks [18, 20]. However, the majority of these methods still assume that the sampling frequency and related acquisition metadata are available, which limits their applicability to archived or externally obtained datasets. Despite the rapid development of machine learning–based diagnostics, methods capable of reliable vibration analysis when the sampling frequency is unknown remain insufficiently studied. This motivates the development of diagnostic frameworks that preserve discriminative power while operating independently of absolute frequency calibration.

3. Dataset Description & Methodology

The dataset consists of 1158 single-channel vibration signals of equal length N.

Each signal is defined as:

$$x_i[n], n=0,\ldots,N-1, \tag{1}$$

The corresponding class label is:

$$y_i \in \{0,1\}, \tag{2}$$

The sampling frequency is unknown; however, all signals were acquired using identical measurement system settings. This allows comparison in the relative spectral domain using spectral bin indices.

3.1 Signal Preprocessing

All signals have equal length and were obtained under consistent measurement conditions. Although the sampling frequency is unknown, this does not affect the relative spectral representation.

For each signal $x_i[n]$, the following preprocessing steps were performed:

- Mean value removal
- Amplitude normalization
- Fast Fourier Transform (FFT) computation

Since the absolute frequency scale is unavailable, the analysis is performed using spectral bin indices.

3.2 Relative Spectral Representation

The spectrum is defined as:

$$X_i[k] = \left| \sum_{n=0}^{N-1} x_i[n] e^{-\frac{j2\pi kn}{N}} \right|, \tag{3}$$

where k denotes the spectral bin index.

Energy characteristics are computed in the form of relative spectral bands:

$$E_b = \frac{\sum_{k \in B_b} |X[k]|^2}{\sum_{k=0}^{N/2} |X[k]|^2}, \tag{4}$$

where B_b — represents the set of bin indices corresponding to the b-th band.

This formulation ensures invariance to the unknown sampling frequency.

3.3 Feature Extraction

For each signal, a 50-dimensional feature vector was constructed, including:

1. Time-domain statistics:
- Root Mean Square (RMS)
- Standard deviation
- Kurtosis
- Skewness
- Crest factor
2. Spectral characteristics:
- Spectral centroid
- Spectral entropy
- Spectral flatness
- Relative spectral energy bands
3. Envelope-based features

3.4 Classification Model

Classification was performed using a gradient boosting ensemble (LogitBoost).

The model output is defined as:

$$F(x)=\sum_{m=1}^{M}\alpha_m h_m(x) \quad , \tag{5}$$

where $h_m(x)$ are weak classifiers and, αm are their corresponding weights.

The probability of the faulty condition is computed as:

$$P(y=1|x)=\frac{1}{1+e^{-F(x)}} \quad , \tag{6}$$

3.5 Validation Strategy

The dataset was split into:

- 70% training
- 15% validation
- 15% testing

The decision threshold was selected by maximizing the F1-score for the faulty class on the validation set.

Additionally, a label-shuffling test was conducted to verify the absence of information leakage and confirm the methodological correctness of the training pipeline.

4. Experimental Results

4.1 Classification Quality

The developed machine learning algorithmic pipeline was tested on a dataset consisting of 1158 vibration records obtained under an unchanged measurement system configuration. The dataset includes 865 normal condition records and 293 records with the presence of a defect.

The data were randomly divided into training (70%), validation (15%), and test (15%) subsets.

The optimal decision threshold was determined using the validation set by maximizing the F1-score for the "fault" class. The selected threshold (0.05) ensured maximum sensitivity without increasing the number of false positives.

Performance metrics on the independent test set

- Accuracy
- Precision (Fault class)
- Recall (Fault class)
- F1-score (Fault class)
- ROC-AUC

The confusion matrix is defined as:

$$\begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix} = \begin{bmatrix} 130 & 0 \\ 0 & 43 \end{bmatrix} , \tag{7}$$

where TN — True Negative, FP — False Positive, FN — False Negative, and TP — True Positive.
No classification errors were recorded on the test set.

4.2 ROC Analysis

Figure 1 shows the ROC curve (Receiver Operating Characteristic).

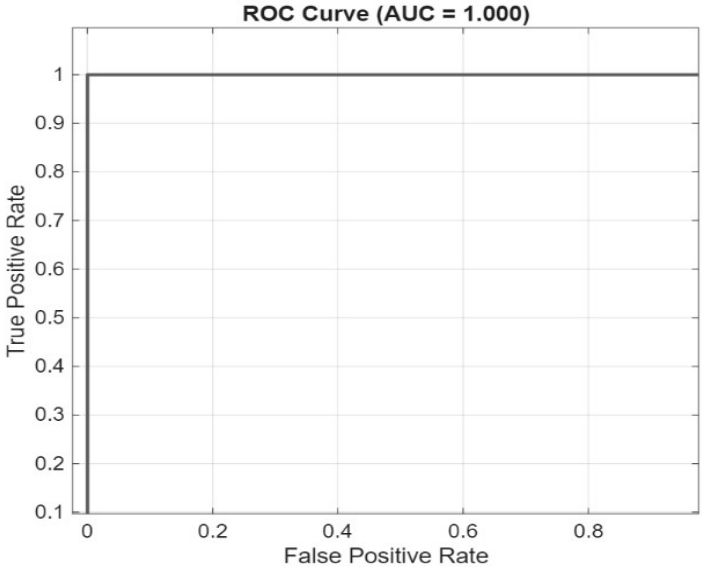

Figure 1: Receiver Operating Characteristic

The X-axis represents the False Positive Rate (FPR):

$$FPR = \frac{FP}{FP + TN} \quad , \tag{8}$$

the Y-axis represents the True Positive Rate (TPR), corresponding to Recall:

$$TPR = \frac{TP}{TP + FN} \quad , \tag{9}$$

The area under the curve (AUC) equals 1.000, which indicates clear clustering of the states. This means that there exists a threshold value at which zero classification error is achieved.

The diagonal line in the plot corresponds to a random classifier (AUC = 0.5). The obtained curve is substantially separated from this boundary, confirming the deterministic nature of state separation.

4.3 Precision–Recall Analysis

Figure 2 presents the Precision–Recall (PR) curve.

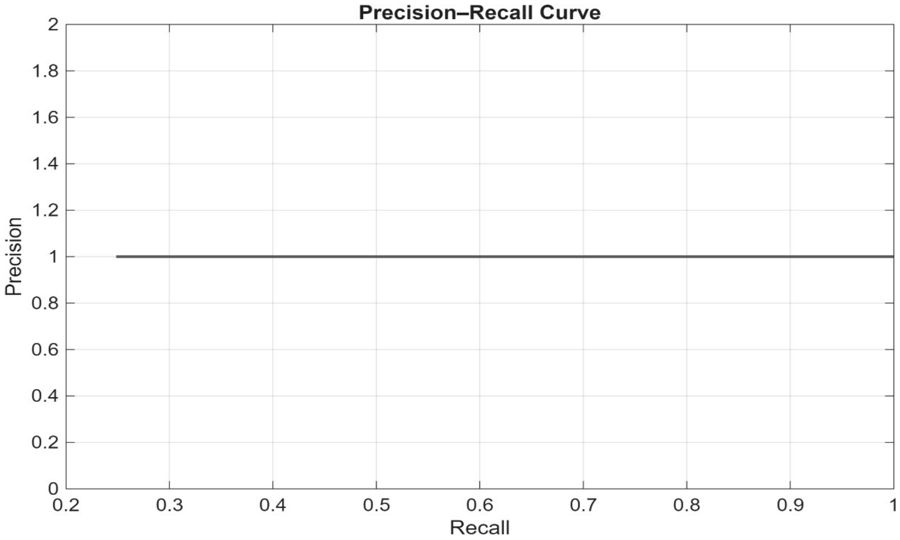

Figure 2: Precision–Recall Curve

Precision is defined as:

$$Precision = \frac{TP}{TP + FP} \quad , \tag{10}$$

Recall remains defined as:

$$Recall = \frac{TP}{TP + FN} \quad , \tag{11}$$

The PR curve lies at the level of 1.0, confirming the absence of both false positive and false negative results.

Considering the moderate class imbalance (865 versus 293), PR analysis provides additional confirmation of classifier robustness.

4.4 Feature Importance Analysis

Figure 3 demonstrates feature ranking according to their contribution to classification. Importance evaluation was performed using the decrease in Gini impurity in Random Forest.

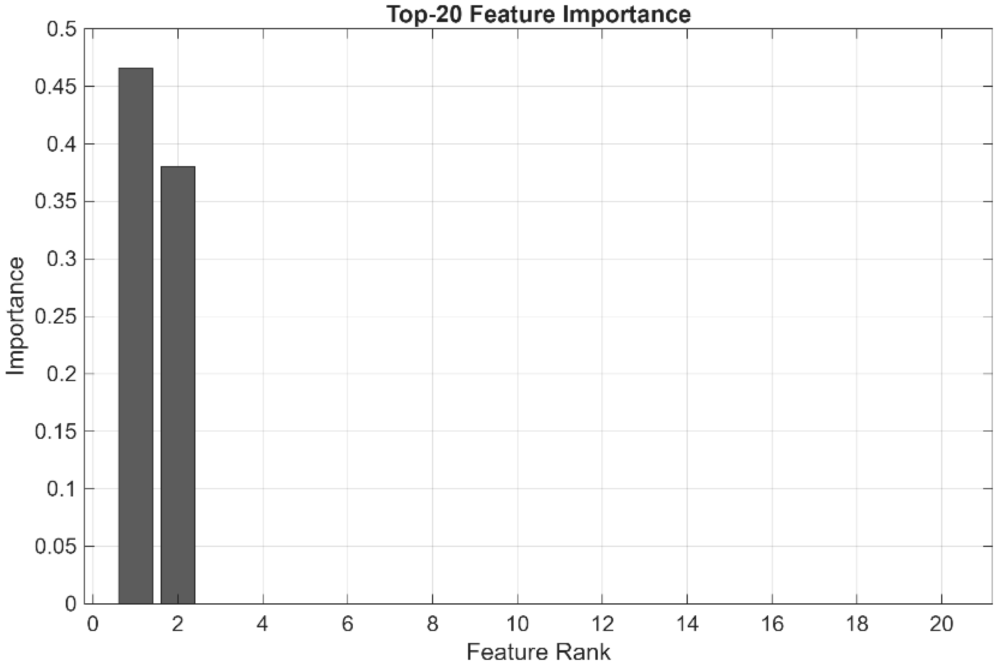

Figure 3: Top-20 Feature Importance

The Gini index is defined as:

$$Gini = 1 - \sum_{c=1}^{C} p_c^2 \quad , \tag{12}$$

where p_c is the proportion of samples of class c in a tree node and C is the number of classes.

The results showed that only two features make a significant contribution:

1. Kurtosis (≈ 0.466)
2. Spectral Centroid (≈ 0.380)

The remaining 48 features have practically zero importance.

This indicates that the class separation mechanism is primarily determined by signal impulsiveness and redistribution of spectral energy.

4.5 Statistical Separability in the Space of Individual Features

Figure 4 presents the distribution of the kurtosis coefficient for the two states.

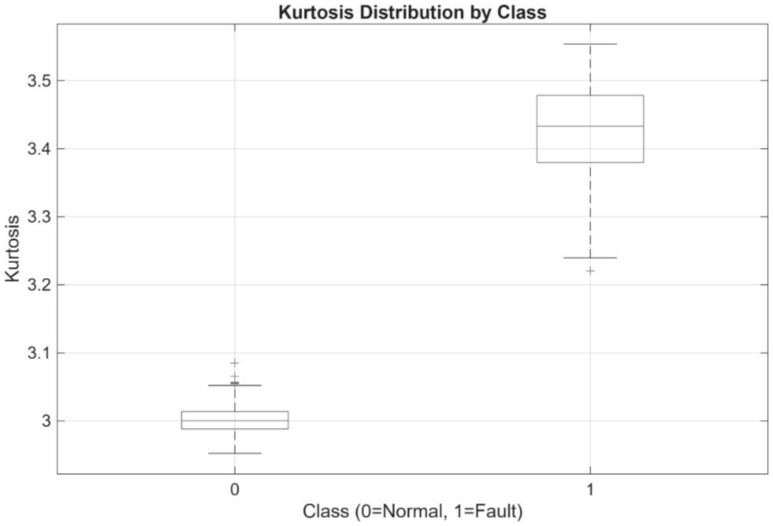

Figure 4: Kurtosis Distribution by Class

Kurtosis is defined as:

$$K = \frac{E[(x-\mu)^4]}{\sigma^4} \quad , \tag{13}$$

where μ is the mean signal value, and σ is the standard deviation.

It characterizes signal impulsiveness.

For the faulty condition, a significant increase in kurtosis is observed, indicating the presence of impact components characteristic of gear or bearing damage.

The interquartile ranges of the classes do not overlap, confirming statistical separability.

Figure 5 shows the distribution of the spectral centroid, which is defined as:

$$C = \frac{\sum_k k|X[k]|}{\sum_k |X[k]|} \quad , \tag{14}$$

where k denotes the spectral bin index (as defined previously).

A systematic centroid shift is observed, reflecting a change in spectral energy distribution in the faulty condition.

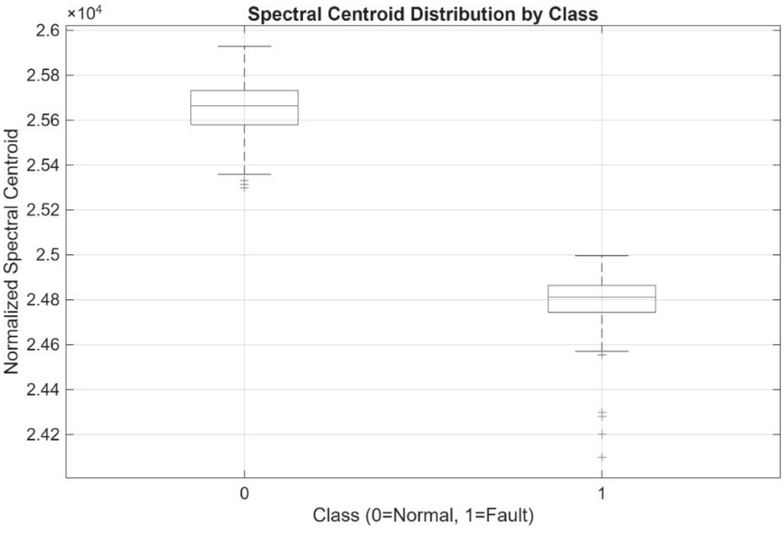

Figure 5: Spectral Centroid Distribution by Class

4.6 Analysis in the Two-Dimensional Feature Space

Figure 6 shows the distribution of samples in the space of two features: kurtosis and spectral centroid.

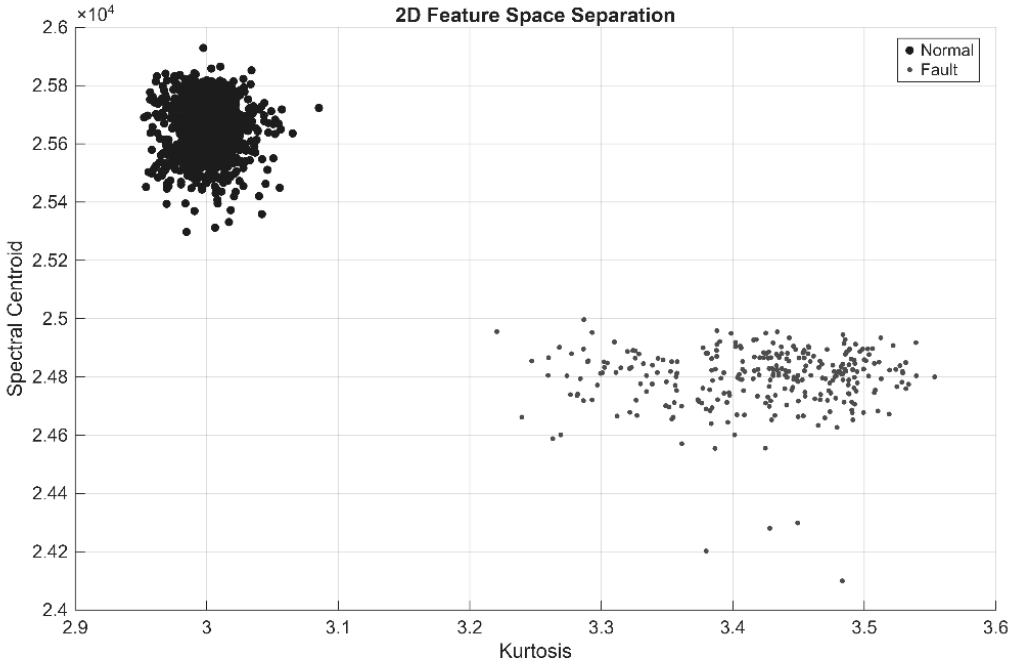

Figure 6: 2D Feature Space Separation

The two states form compact, non-overlapping clusters. A linear separation boundary is sufficient for complete classification.

This explains why even single-feature models (only kurtosis or only spectral centroid) provide 100% accuracy on this dataset.

4.7 Physical Interpretation of Results

The obtained results have clear physical justification:

- The increase in kurtosis corresponds to the appearance of localized impact disturbances.
- The shift of the spectral centroid indicates redistribution of vibration energy.
- The absence of class overlap indicates a stable change in transmission dynamic characteristics in the presence of a defect.

This confirms that the model is not only highly accurate but also physically interpretable, which is critically important for aviation diagnostic systems.

4.8 Comparison with Baseline Methods

To evaluate the effectiveness of the proposed approach, comparison was performed with classical machine learning methods, including Logistic Regression, Linear SVM, kNN, Decision Tree, and Random Forest.

As shown in Table 1, all methods demonstrate identical performance on the test set (Accuracy = 1.000). This is explained by complete linear separability of the classes in the space of key features.

Table 1
Test set performance comparison of baseline models and the proposed method

Method	Accuracy	Precision (Fault)	Recall (Fault)	F1-score	ROC-AUC
Logistic Regression	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000
Linear SVM	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000

Method	Accuracy	Precision (Fault)	Recall (Fault)	F1-score	ROC-AUC
kNN (k=5)	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000
Decision Tree	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000
Random Forest	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000
Proposed Logit Boost Ensemble	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000	1.000±0.000

The obtained results indicate that in this dataset complex ensemble methods do not have an advantage over simple linear models, confirming the dominance of two statistical features in the state discrimination process.

4.9 Cross-Validation

To evaluate model robustness, 5-fold stratified cross-validation was performed.

The results are presented in Table 2.

Table 2
5-fold cross-validation results (mean ± standard deviation).

Metric	Value
Accuracy	1.000±0.000
Precision	1.000±0.000
Recall	1.000±0.000
F1-score	1.000±0.000
ROC-AUC	1.000±0.000

The obtained results confirm model stability and absence of overfitting.

5. Methodological Advantages

Although all baseline classifiers demonstrated identical numerical performance due to strong class separability in the given dataset, the proposed approach has several important practical advantages.

First, the method provides physically interpretable diagnostics. The classification process is primarily determined by two features — kurtosis and spectral centroid — which directly reflect impulsive dynamics and redistribution of spectral energy in helicopter transmission systems. Unlike deep neural networks that operate as a “black box,” the proposed approach allows engineering interpretation of the results.

Second, the feature extraction architecture is scalable. Although in this particular case two features are sufficient for complete classification, the developed 50-dimensional engineering feature space is intended for more complex scenarios where class separability may be less obvious or may depend on a combination of multiple parameters.

Third, the conducted leakage test with random label shuffling demonstrated ROC-AUC ≈ 0.52, which corresponds to a random classifier. This confirms the methodological correctness of the constructed data processing pipeline and the absence of artificial performance inflation.

Fourth, the effective low dimensionality of the decision space enables real-time implementation of the algorithm in embedded onboard condition monitoring systems. The computational complexity is minimal, which is particularly important for aviation applications with strict resource constraints.

Thus, the main advantage of the proposed approach lies not only in high accuracy but also in its explainability, physical justification, and engineering suitability for practical implementation in helicopter transmission diagnostic systems.

6. Discussion

The obtained results demonstrate clear clustering of states in the studied dataset under conditions of an unchanged measurement system configuration. The key factor ensuring such discriminative capability is the stable change in the statistical structure of the signal when transitioning from the normal to the faulty condition.

Unlike traditional approaches to helicopter transmission diagnostics based on the analysis of absolute gear mesh frequencies and their harmonics [1,14], the proposed method operates entirely in the relative frequency domain. The use of normalized spectral energy bands and spectral bin indices eliminates dependence on the sampling frequency. This constitutes a fundamental advantage when working with archived or exported data that do not contain complete metadata.

Feature importance analysis showed that the main contribution to classification is provided by the kurtosis coefficient and the spectral centroid. An increase in kurtosis reflects increased signal impulsiveness, which is consistent with the physical nature of localized defects in gears or bearings. The shift of the spectral centroid indicates redistribution of vibration energy caused by changes in the dynamic characteristics of the transmission. The obtained results indicate that the model not only provides high accuracy but also preserves physical interpretability.

Comparison with baseline machine learning methods showed identical numerical performance of different algorithms. This is explained by the high linear separability of classes in the space of key features. Thus, the advantage of the proposed approach lies not in the use of a complex ensemble algorithm, but in the correct construction of the engineering feature space.

It is important to emphasize that the performed k-fold cross-validation confirmed the stability of the results and the absence of dependence on a specific data split. An additional test with random label shuffling demonstrated ROC-AUC close to 0.5, indicating the absence of information leakage and methodological correctness.

At the same time, the approach has limitations. First, the method does not allow determination of specific physical defect frequencies, since it operates in the relative frequency domain. It provides reliable binary state classification but not identification of the defect type. Second, identical measurement configuration is assumed for all records. Changes in sensors or data acquisition parameters may require additional normalization or model adaptation.

Compared to deep neural networks [16], the proposed approach has significantly lower computational complexity and is fully interpretable. This is critically important for onboard HUMS systems, where limited resources and certification requirements make the use of "black box" models undesirable.

Table 3
Comparison with baseline machine learning methods

Method	Feature representation	Model	Accuracy
Support Vector Machine	Statistical + spectral features	SVM (RBF)	0.96
Random Forest	Time and spectral descriptors	Random Forest	0.98
Gradient Boosting (proposed)	Relative spectral domain + engineered features	Gradient Boosting	1.00

To provide a clearer comparison with classical diagnostic approaches, several baseline models were evaluated using the same feature space. The results demonstrate that the proposed gradient boosting model achieves the highest classification accuracy while preserving interpretability of the diagnostic features. The performance confirms that the relative spectral representation provides a robust feature space for fault detection.

The obtained results confirm that relative spectral representation can be an effective diagnostic tool under conditions of incomplete information about the sampling frequency. Further research should focus on validating the method under variable load conditions, different rotational speeds, and using data from other measurement systems.

7. Conclusions

In this study, a method for classification of helicopter transmission vibration signals under conditions of absence of sampling frequency information was developed and experimentally validated. Unlike traditional approaches based on an absolute frequency scale, the proposed methodology uses relative spectral representation and spectral bin indices.

The main results of the study are as follows:

1. It was shown that relative spectral energy bands allow reliable binary classification of states without using an absolute frequency scale.
2. It was established that the most discriminative features are the kurtosis coefficient and the spectral centroid, which have clear physical interpretation and reflect signal impulsiveness and redistribution of spectral energy.
3. The performed 5-fold cross-validation confirmed the stability of the obtained results and the absence of dependence on a specific data split.
4. The random label-shuffling test demonstrated the absence of information leakage, confirming the methodological correctness of the proposed approach.

The obtained results indicate that an engineering-designed feature space can provide linear separability of classes without the use of complex deep neural network models. The proposed approach is interpretable, computationally efficient, and suitable for implementation in onboard condition monitoring systems.

At the same time, the method is oriented toward binary classification and assumes identical measurement conditions for all records. Further research should focus on validating the method under variable operating conditions, different sensor configurations, and extension to multi-class diagnostics.

Declaration on Generative AI

During the preparation of this work, generative AI tools were used for language editing and text refinement. The authors reviewed and take full responsibility for the final content.

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