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Detection of Imbalance Faults in Industrial Machines by Means of Frequency-Based Feature Extraction Using Machine Learning and Deep Learning Approaches

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ABSTRACT

This study investigated the effectiveness of machine learning and deep learning models in diagnosing imbalance faults in industrial machines, using Fast Fourier Transform (FFT) for frequency-based feature extraction. As imbalance shortens equipment life and increases maintenance costs, vibration data was analysed and frequency components were extracted using FFT for classification. Support Vector Machine, Random Forest and Multi-Layer Perceptron models were then compared using the metrics of accuracy, precision, recall and F1 score. The Multi-Layer Perceptron model performed best with 99% accuracy, capturing the patterns extracted by FFT most effectively. Random Forests made successful predictions, but had a high error rate in some classes. Support Vector Machines, on the other hand, offered lower accuracy. Combining FFT with machine learning contributes to the diagnosis of faults in rotating machines. Model performance could be improved in future using larger data sets, hyperparameter optimisation and methods such as wavelet transformation.

Makine Öğrenimi ve Derin Öğrenme Yaklaşımlarını Kullanarak Frekans Tabanlı Öznitelik Çıkarımı ile Endüstriyel Makinelerde Dengesizlik Hatalarının Tespiti

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ÖZ

Bu çalışmada, endüstriyel makinelerde dengesizlik hatalarının teşhisinde makine öğrenimi ve derin öğrenme modellerinin etkinliği incelenmiş, frekans tabanlı özellik çıkarımı için Hızlı Fourier Dönüşümü (FFT) kullanılmıştır. Dengesizlik, ekipman ömrünü kısaltıp bakım maliyetlerini artırdığından, titreşim verileri analiz edilerek FFT ile frekans bileşenleri çıkarılmış ve sınıflandırma yapılmıştır. Destek Vektör Makinaları, Rastgele Ormanlar ve Çok Katmanlı Algılayıcı modelleri; doğruluk, hassasiyet, geri çağırma ve F1-skoru metrikleriyle karşılaştırılmıştır. Çok Katmanlı Algılayıcı, %99 doğrulukla en iyi performansı göstermiş, FFT ile çıkarılan örüntüleri en iyi yakalamıştır. Rastgele Ormanlar başarılı tahminler yapmış ancak bazı sınıflarda hata oranı yüksek bulunmuştur. Destek Vektör Makinaları ise daha düşük doğruluk sunmuştur. FFT ve makine öğrenimi kombinasyonu, döner makine arıza teşhisine katkı sağlamaktadır. Gelecekte, daha büyük veri setleri, hiperparametre optimizasyonu ve dalgacık dönüşümü gibi yöntemlerle model performansı artırılabilir.

1. INTRODUCTION

Imbalance faults, which are common in machine systems, reduce equipment performance, increase vibration levels and cause serious productivity losses in industrial processes due to increased maintenance costs. If such imbalance faults in machine elements are not detected and eliminated at an early stage, unexpected equipment failures may occur, resulting in long-term downtime in production processes. Therefore, the development of effective methods for diagnosing and preventing imbalance-related problems is of great importance for the reliability and sustainability of industrial applications. Improving the accuracy of fault diagnosis, particularly through the use of methods such as vibration analysis, signal processing techniques and artificial intelligence-based approaches, can make a significant contribution to extending the life of machinery and reducing operating costs.

In recent years, machine learning and artificial intelligence-based approaches have gained an important place in fault diagnosis and predictive maintenance processes [1]. Traditional methods are usually based on expert knowledge and cannot provide sufficient efficiency in automated decision-making processes with large data sets. In particular, the use of vibration analysis, signal processing techniques and deep learning-based models allows for more accurate detection of imbalance faults [2].

Accordingly, several studies have been conducted to evaluate the impact of different machine learning algorithms on fault diagnosis. Recent studies have shown that classification algorithms such as Support Vector Machines (SVM), Random Forest and Multilayer Perceptron (MLP) provide high accuracy in imbalance fault diagnosis [3]. However, a detailed comparison of model performance and their integration into industrial processes is of great importance for the development of an effective fault diagnosis approach [4].

In this study, a machine learning based model for imbalance fault diagnosis is developed, Fast Fourier Transform (FFT) is used for frequency-based feature extraction and the most appropriate method is determined by comparing different algorithms. The data set used consists of a wide range of vibration measurements including imbalance scenarios under different operating conditions. The time domain signals are decomposed into frequency components using FFT. Through this transformation, important frequency components in the vibration data are extracted as features and given as input to the classification algorithms. Three different classification algorithms such as SVM, Random Forest and MLP were used to evaluate the success of the model and the results obtained were compared using metrics such as accuracy, precision, recall and F1 score. By combining FFT with frequency-based feature extraction and machine learning techniques, the model proposed in the study aims to support early diagnosis in industrial maintenance processes, contribute to the prevention of machine failures and reduce maintenance costs.

2. LITERATURE REVIEW

In this section various studies have addressed data generation and balancing techniques to solve the imbalanced data problem, and especially the effectiveness of deep learning-based methods in this area has been examined.

Zhang et al. addressed the issue of imbalanced data in machine fault diagnosis using generative adversarial networks (GANs). By generating realistic synthetic data, the model's generalization ability was enhanced, enriching the training dataset. Tests on rotating machinery datasets validated the effectiveness of this approach [5].

Jiang et al. developed a temporal-spatial multi-order weighted graph convolution network (TSMOW-GCN) to improve fault diagnosis under imbalanced data conditions. The model enhances feature associations within graph structures and aggregates high-order neighborhood information, avoiding traditional data generation approaches [6].

Zhao et al. introduced an improved weighted extreme learning machine (IWELM) with an adaptive cost-sensitive strategy for fault diagnosis with imbalanced data. The model optimizes a cost-sensitive matrix and employs a multi-objective optimizer, improving classification performance, especially for minority classes [7].

Jia et al. proposed a deep normalized convolutional neural network (DNCNN) to address imbalanced fault classification in machinery diagnosis. The framework integrates a weighted softmax loss function to counter class imbalance and uses neuron activation maximization (NAM) for improved interpretability. Experiments show that DNCNN outperforms conventional CNN-based models [8].

He et al. applied contrastive feature-based deep reinforcement learning (D3QN) for imbalanced fault quantitative diagnosis under variable working conditions. By integrating SimCLR-based contrastive learning with prioritized experience replay, the model optimally learns discriminative features while addressing dataset imbalance [9].

Shi et al. proposed a graph embedding-based deep broad learning system (GEDBLS) for fault diagnosis with imbalanced data in rotating machinery. The model improves the classification loss function by considering class weights and intra-class compactness. Experiments confirm the model's superior feature extraction and data imbalance processing capabilities [10].

Pan et al. introduced a robust smooth constrained matrix machine (RSCMM) for fault diagnosis of roller bearings under imbalanced data conditions. The model employs a dynamically adjusted loss term to improve classification performance, mitigate noise impact, and accelerate convergence. Experimental results show that RSCMM achieves high accuracy under different imbalance ratios [11].

Wang et al. proposed a trackable multi-domain collaborative generative adversarial network (TMCGAN) for rotating machinery fault diagnosis under imbalanced conditions. The model improves data augmentation by integrating multi-domain feature learning and parallel frequency loss, enhancing classification credibility and interpretability [12].

Wu et al. introduced a holistic semi-supervised method for imbalanced fault diagnosis with out-of-distribution samples. Their framework uses pseudo-labelling and consistency regularization combined with an adaptive threshold to enhance class confidence balancing and robustness in real-world industrial applications [13].

Lin et al. developed a generalization classification regularization generative adversarial network (GCRGAN) to tackle data imbalance in machinery fault diagnosis. The model incorporates a generalization module and a novel regularization loss to improve sample diversity and stability under limited training data scenarios [14].

Yang et al. proposed an improved generative adversarial network (IGAN) combined with an enhanced deep extreme learning machine (EDELM) for chiller fault diagnosis under imbalanced data conditions. The method integrates multi-head attention (MHA) in GAN and adaptive boosting (AdaBoost) for sample weighting, achieving high classification accuracy [15].

Chang et al. designed an extended attention signal transformer with adaptive class imbalance loss (EAST-ACIL) to address long-tailed data distribution in rotating machinery fault diagnosis. The framework enhances feature extraction using CNN-transformer architecture while dynamically reweighting training data to prioritize rare fault classes [16].

Li et al. introduced an auxiliary classifier Wasserstein generative adversarial network with gradient penalty (ACWGAN-GP) for rotating machinery fault diagnosis under data imbalance. The method generates high-quality synthetic fault samples to balance datasets, improving model accuracy [17].

3. MATERIAL AND METHOD

3.1. Dataset

The MAFAULDA (Machinery Fault Database) consists of 1951 multivariate time-series data collected using the SpectraQuest Alignment-Balance-Vibration (ABVT) Machinery Fault Simulator (MFS). The dataset includes six different machine states: normal operation, imbalance, horizontal and vertical misalignment, and inner and outer bearing faults. These conditions were systematically simulated to provide a comprehensive dataset for fault diagnosis in rotating machinery [18].

Imbalance faults were introduced by attaching additional weights ranging from 6 g to 35 g to the rotor. The data collection process maintained the same 49 different rotational speed levels used for normal operation. However, for weights 30 g and above, excessive vibration limited the system's maximum operational speed to 3300 rpm due to stability concerns. The measurements for each imbalance weight condition are detailed in the Table 1 below:

Table 1. Weight distribution and number of measurements

Weight (g)	Number of measurements
6	49
10	48
15	48
20	49
25	47
30	47
35	45
Total	**333**

Each dataset instance consists of 5 seconds of recorded data at a 50 kHz sampling rate, totaling 250000 samples per measurement. The imbalance fault conditions were tested using a 1/4 HP DC motor operating within a 700-3600 rpm speed range. The test system, weighing 22 kg, included a 16 mm diameter shaft with a 520 mm shaft length, while the rotor diameter measured 15.24 cm, and the bearing span was 390 mm.

The data acquisition system incorporated various sensors to capture machine dynamics:

- Accelerometers: Three IMI Sensors Model 601A01 were used to measure radial, axial, and tangential vibrations, while a triaxial IMI Sensors Model 604B31 captured three-dimensional acceleration data.
- Tachometer: A Monarch Instrument MT-190 analog tachometer was employed for speed measurement.
- Microphone: A Shure SM81 microphone recorded audio data within a 20 Hz - 20 kHz frequency range.
- Data Acquisition Modules: Two National Instruments NI 9234 modules were utilized, operating at a 51.2 kHz sampling rate to collect vibration, speed, and audio signals.

3.2. FFT

The Fourier transform is a powerful mathematical tool that decomposes a signal in the time domain into its frequency components. This transform, in both continuous and discrete versions, is used in many areas of engineering and science [19]. The Discrete Fourier Transform (DFT) is used for frequency analysis of finite-length signals, and the FFT is an algorithm that optimises the computational process of the DFT [20]. The DFT is defined as

$$X[k] = \sum_{n=0}^{N-1} x[k]\, e^{-j(2\pi/N)kn} \quad (1)$$

Through DFT, the signal can be decomposed into amplitude and phase information of different frequency components, where *X[k]* is the signal in the frequency domain after Fourier transform, *x[n]* is the *n th* data point in the signal in the time domain, *N* is the total number of data points, and j is the imaginary unit.

3.3. SVM Model

SVM is a supervised learning technique that is effectively used in data classification and regression problems [21]. SVM performs classification by determining the best hyperplane that separates data points [22]. This hyperplane is chosen to maximise the margin between two classes. For a linearly separable data set, the hyperplane is expressed as follows:

$$\omega^T x + b = 0 \tag{2}$$

$$min_{\omega,b} \frac{1}{2} \|\omega\|^2 \quad | \quad y_i(\omega^T x_i + b) \geq 1, \qquad \forall i \tag{3}$$

In the equation, ω is the direction that determines the normal vector of the hyperplane that distinguishes which class the data points belong to. The x is the input feature vector that represents each data point. The bias term b optimises the classification process by adjusting the position of the hyperplane.

3.4. RF Model

Random forest is an ensemble learning method based on decision trees and is used in both classification and regression problems [23]. The model created by combining several decision trees provides higher accuracy and generalisation ability than a single tree [24]. For classification, the prediction of the model is expressed as follows:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{4}$$

Where T is the total number of trees, $h_t(x)$ is the prediction class and $\hat{y}$ is the class label. Random forest uses random subsampling (bootstrapping) and random feature selection during training for each tree to increase the diversity of decision trees and avoid overlearning. This method is particularly successful on large and complex datasets.

3.5. MLP Model

MLP is a feedforward Artificial Neural Network model with a fully connected structure and is a powerful deep learning architecture widely used for tasks such as learning and classifying complex non-linear relationships [25]. In this study, an artificial ANN model with MLP architecture is used. The model is designed to solve a multi-class classification problem and has a deep network structure consisting of six hidden layers. Rectified Linear Unit (ReLU) activation function is used in each hidden layer of the model and Softmax activation is preferred in the output layer for multi-class prediction. The weights of the model were initially assigned using the random uniform distribution method and trained using the Adam optimisation algorithm. The loss function used was sparse_categorical_crossentropy, which is widely used in multiclass classification problems. In addition, an early stopping mechanism was added to minimise the risk of overfitting and to prevent unnecessary prolongation of the training process if no improvement is observed within the specified tolerance level. The labels in the input to the model are processed with LabelEncoder and converted into numerical form to convert them into a format suitable for machine learning models. The proposed model is a fully connected neural network structure and is applicable to classification tasks on a large dataset.

3.6. Performance Metrics

To evaluate the success of machine learning models, key performance metrics such as precision, recall, accuracy, and F1 score are used [26,27]. These metrics are critical for measuring the predictive ability of the model and analysing classification errors. TP (True Positive), TN (True Negative), FP (False Positive) and FN (False Negative) values are required for the calculations.

Accuracy is the ratio of the number of samples correctly predicted by the model to the total number of samples and is calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Precision, The proportion of samples predicted to be positive by the model that are actually positive:

$$F1_{score} = \frac{Precision\ x\ Recall}{Precision +\ Recall} \tag{6}$$

4. EXPERIMENTAL RESULTS

In the experimental studies, SVM, RF and MLP models were used to evaluate the classification performance of imbalance errors. Performance metrics such as accuracy, precision, recall and F1-score were calculated and compared to measure the success of the models. The learning processes of each model were examined by analyzing the accuracy and loss values during the training process. In addition, the confusion matrix was used to determine the incorrect predictions between classes and the classification ability of the model was evaluated in detail.

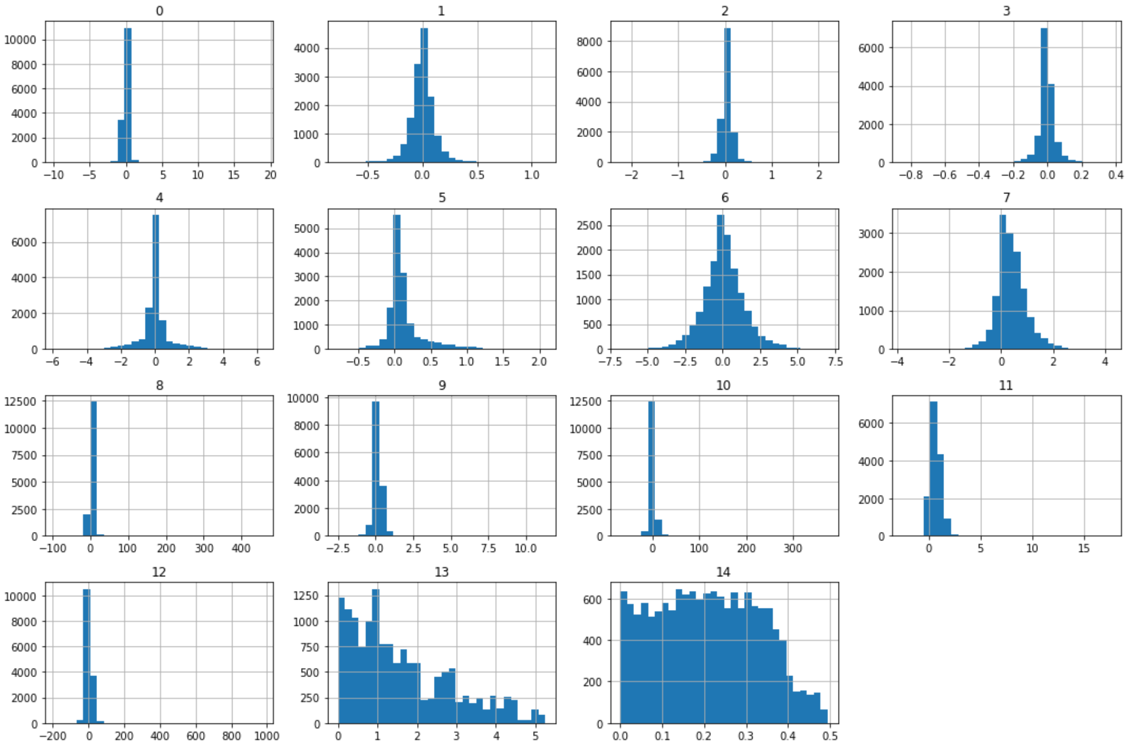


Figure 1. Distribution of attributes in the frequency spectrum

Figure 1 shows histograms showing the distribution of different features in the dataset. These histograms provide information about the overall structure of the dataset by visualising the frequency of values for each variable. The figure shows that some features are close to a normal distribution, while others are skewed to the right or left. In particular, the histograms in the top rows are bell-shaped and close to a normal distribution, while some variables in the bottom rows show significant skewness and irregularity.

These distributional analyses provide important information that should be taken into account as the model learns. While normally distributed characteristics allow the model to learn more consistently, skewed distributions can negatively affect the learning process. In addition, the presence of a high number of outliers in some variables may reduce the generalisation ability of the model and may require the application of special techniques in the data pre-processing phase.

In this context, scaling and transformation of features is an important step to improve model performance. In particular, methods such as Min-Max normalization or StandardScaler can make the data distribution more balanced. For variables with skewed distributions, techniques such as log or square root transformation can be applied to enable the model to learn these variables more efficiently. In conclusion, the histogram analysis presented in Figure 1 plays a critical role in understanding the structure of the dataset and determining appropriate data preprocessing strategies.

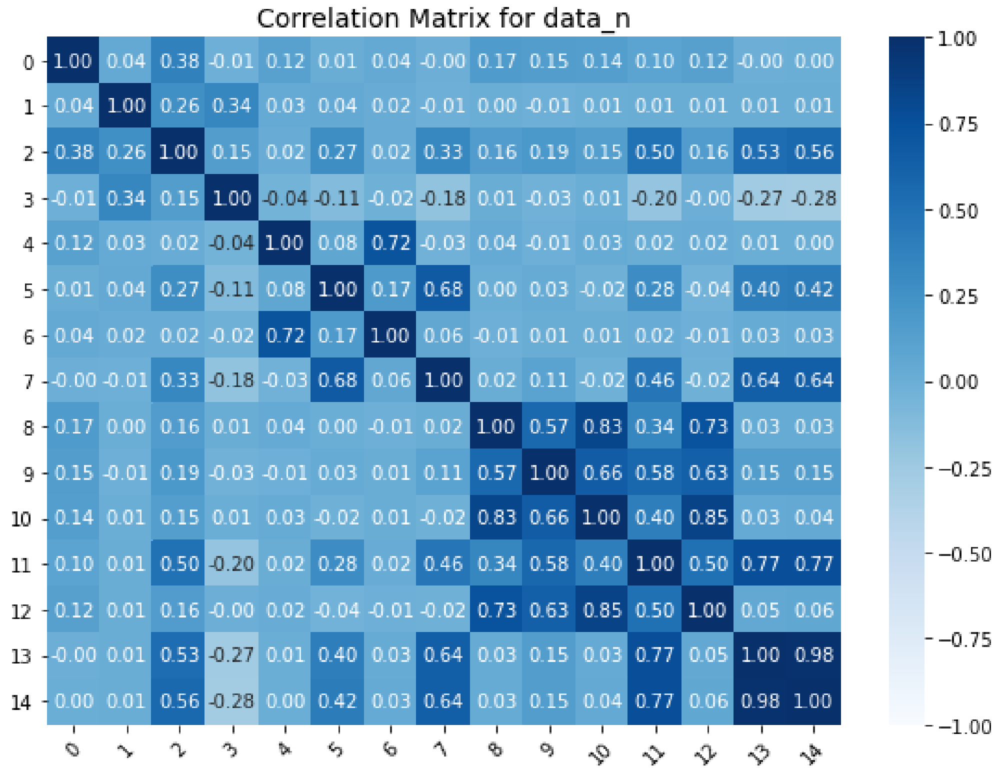
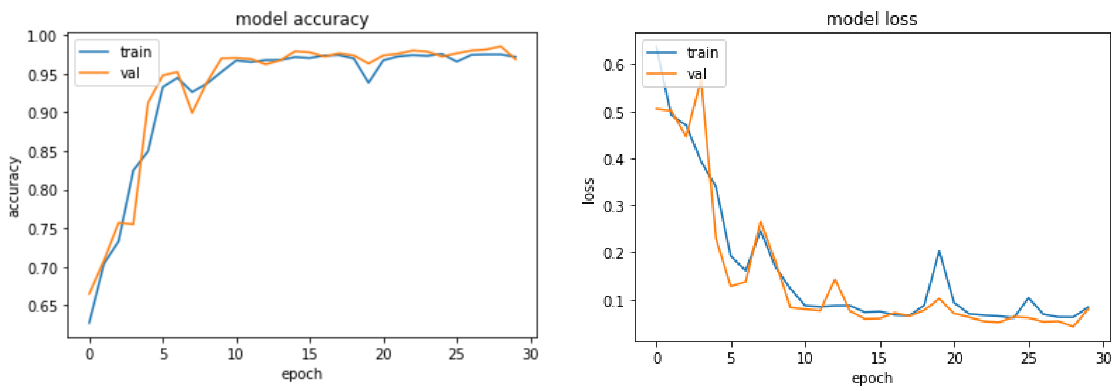


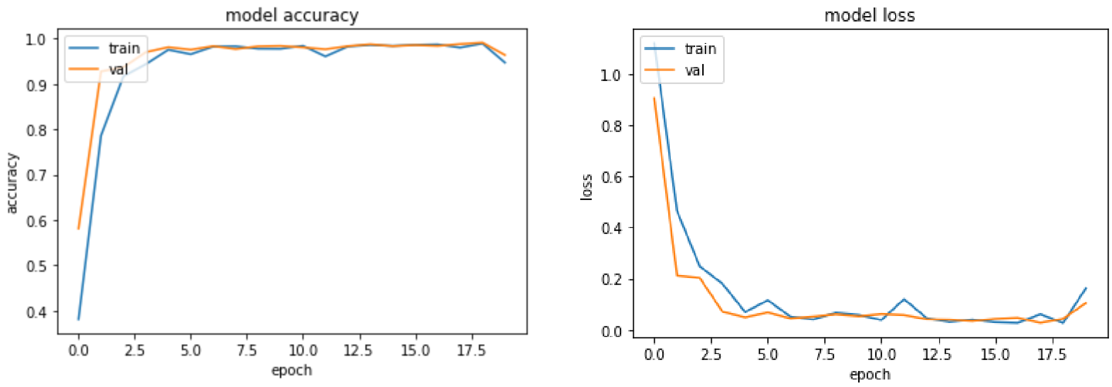
Figure 2. Correlation matrix between attributes

Figure 2 shows the correlation matrix, which visualises the relationship between the attributes in the dataset. The values in the cells represent the Pearson correlation coefficient between pairs of variables. Values range from -1 to 1, with values close to 1 indicating a strong positive correlation and values close to -1 indicating a strong negative correlation. Light blue shades represent low correlation and dark blue shades represent high correlation.

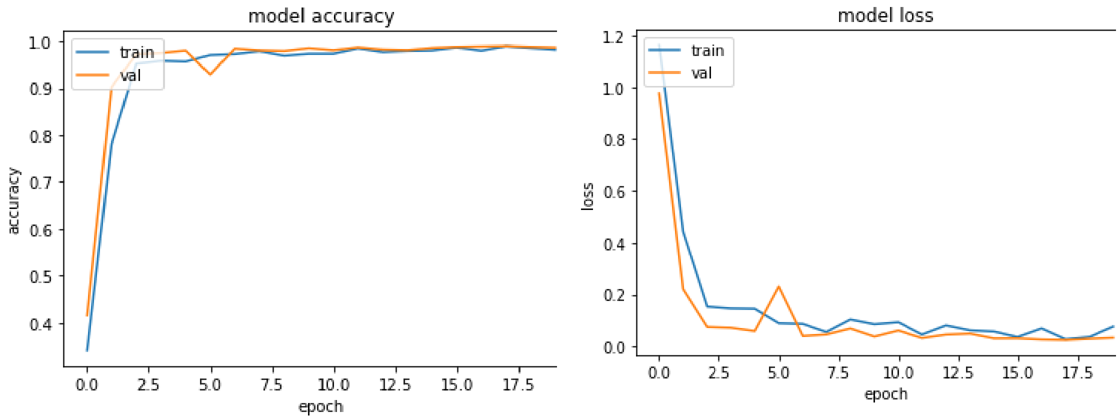
In the figure, high correlations (e.g. 0.85, 0.77) are observed between some variables, which may indicate that these attributes carry similar information. On the other hand, the correlation values between some variables are quite low (e.g. 0.01-0.03), suggesting that these variables are independent. This analysis can help to remove unnecessary or highly correlated variables in the feature selection process and increase the generalisation ability of the model.



a)



b)



c)

Figure 3. Model accuracy and loss during training and validation. a) SVM, b) RF, c) MLP

Figure 3 shows the accuracy and loss values of the SVM, Random Forest and MLP models in the training and validation phases. While all three models have generally high accuracy rates, the MLP model (Figure 3-c) shows the most stable learning process. Especially from the early epochs, the accuracy values increase rapidly and the training and validation accuracies are very close to each other. The loss graph shows that MLP achieved the lowest loss value compared to the other models and completed the learning process in the most balanced way.

The Random Forest model (Figure 3-b) showed a rapid increase in accuracy during the training process and the validation accuracy also reached a high level. However, the fluctuations seen in the loss plot suggest that the model has more variance in some epochs and does not perform fully balanced learning. The SVM model (Figure 3-a), on the other hand, is successful in terms of accuracy, but the difference between the training and validation accuracies is relatively larger in the early epochs, suggesting that the model initially follows a more erratic learning process. Overall, the MLP model had the most stable learning process and achieved high accuracy with lower loss compared to the other models. Due to its deep learning based structure, it has a strong ability to learn more complex patterns in the data.

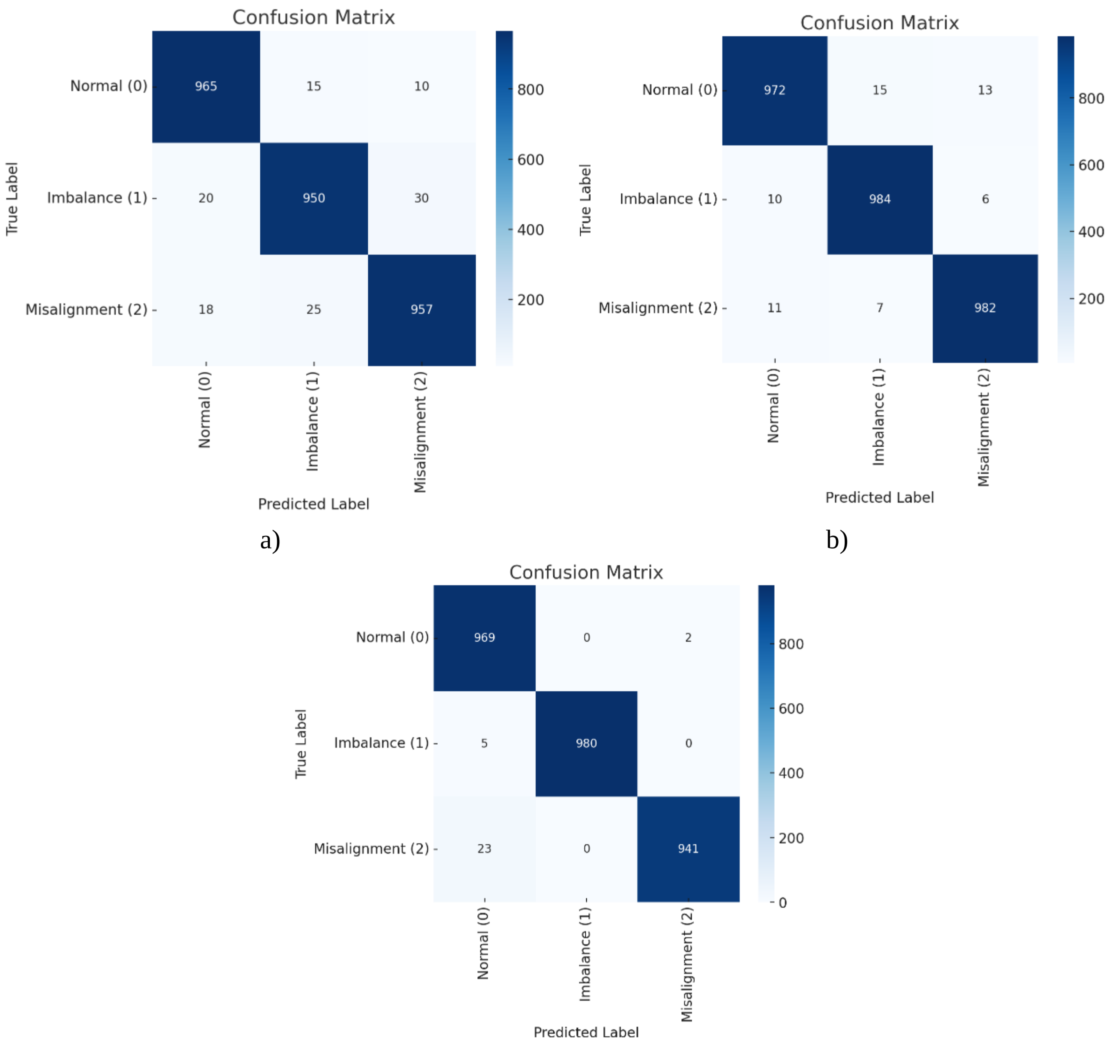
Table 2. Metrics for the classification performance of the models

Algoritma	Accuracy	Precision	Recall	F_1score
SVM	0.96	0.96	0.96	0.96
RF	0.98	0.98	0.98	0.97
MLP	0.99	0.99	0.99	0.99

Table 2 shows the accuracy, precision, recall and F1 scores calculated to evaluate the classification performance of the SVM, Random Forest and MLP models. Although all three models have high accuracy rates, the MLP model performed best by achieving the highest value in all metrics.

The Random Forest model showed a consistent classification performance with an accuracy of 98% and outperformed the SVM model in all metrics. The SVM model, on the other hand, performed a successful classification with an accuracy rate of 96%, but it was observed that it had lower metric values compared to the other models.

Overall, the MLP model achieved the highest success with 99% accuracy, precision, recall and F1 score. These results show that MLP has a high learning capacity in complex data structures and is more successful than other models in classification tasks.



c)

Figure 4. Confusion matrix showing the classification performance of the models. a) SVM, b) RF, c) MLP

Figure 4 shows the confusion matrices generated to compare the classification performance of the SVM, Random Forest and MLP models. Although all three models have generally high accuracy rates, the MLP model (Figure 4-c) has the best classification performance. In particular, it had the lowest error rate in the Normal (0) and Imbalance (1) classes, minimising misclassifications.

The Random Forest model (Figure 4-b), although providing high accuracy in general, made more incorrect predictions, especially in the Misalignment (2) class. Due to its decision tree-based structure, it has difficulty discriminating between some classes. The SVM model (Figure 4-a), on the other hand, made more incorrect predictions than the other models, especially in the Misalignment (2) class, indicating that the model has difficulty discriminating between some classes.

The MLP model achieved the highest accuracy rate and performed more evenly across classes. Thanks to its deep learning-based structure, it has a high capacity to learn more complex data patterns.

Table 3. Bootstrap 95% confidence intervals for classification performance metrics

Model	95% CI (accuracy)	95% CI (precision)	95% CI (Recall)	95% CI (F_1score)
SVM	0.949–0.971	0.948–0.971	0.949–0.971	0.949–0.971
RF	0.973–0.987	0.973–0.987	0.973–0.987	0.969–0.985
MLP	0.985–0.995	0.985–0.995	0.985–0.995	0.985–0.995

Table 3 presents the 95% confidence intervals (CI) for the classification performance metrics—Accuracy, Precision, Recall, and F1-score—of the SVM, RF, and MLP models. The CIs were computed using bootstrap resampling with n = 300 iterations, providing a robust estimation of the variability in model performance. The results demonstrate that the MLP model achieved the narrowest confidence intervals across all metrics, indicating a high degree of stability and consistency in its predictions. The RF model also exhibited strong and reliable performance with relatively tight intervals, whereas the SVM model, despite slightly wider intervals, maintained competitive classification accuracy and balanced metric values.

Table 4. Hyperparameter search ranges, final selections, and rationale for each model

Component	Search range / limit	Final selection (example)	Rationale
SVM (RBF)	C ∈ $[10^{-3}, 10^{3}]$, γ ∈ $[10^{-4}, 10^{1}]$, kernel=RBF	• C=10, γ=0.01 • 5-fold CV Macro-F1, Accuracy; CI narrowing	Prevents overfitting while maintaining a stable decision boundary
Random forest	n_estimators ∈ {200, 400, 800}; max_depth ∈ {None, 10, 20, 40}; min_samples_split ∈ {2,5,10}; max_features ∈ {sqrt, log2}; bootstrap=True	• n_estimators=400, max_depth=20, max_features=sqrt • 5-fold CV Macro-F1; training time	Variance-bias balance and stable performance across classes
MLP	Layers: 3–6; Neurons: {256,128,64,32}; Dropout: 0.2–0.5; Norm: Batch/Layer (opt.); L2: {0, 10^{-5}, 10^{-4}}; Epoch ≤ 200, min_delta=10^{-4}; LR: 10^{-3}→10^{-4} (plateau)	• 256-128-64, Dropout=0.3, BN included, L2=10^{-5}, • 5-fold CV Macro-F1 & Accuracy; CI narrowing; training time	Highest accuracy + narrow CI; prevents overfitting

Table 4 summarizes the hyperparameter search spaces, the final selected configurations, and the rationale for each model. The selection process prioritized high classification performance, narrow bootstrap confidence intervals, and prevention of overfitting, while ensuring balanced performance across all classes.

5. CONCLUSION

This study compares the performance of machine learning and deep learning-based models for imbalance fault diagnosis using FFT for frequency-based feature extraction. In the experimental process, SVM, Random Forest and MLP models were applied and their classification performance was evaluated using metrics such as accuracy, precision, recall and F1 score. Confusion matrices and model learning processes were investigated and the strengths and weaknesses of each model were analysed. In the study, time domain vibration data was decomposed into frequency components using FFT and these components were used as input to the classification models. In this way, imbalance faults can be more accurately distinguished on the basis of distinct frequency features. According to the results obtained, the MLP model has the highest accuracy rate and the lowest error rate, and has the best performance in identifying imbalance faults by learning the features extracted by FFT in the best way. Thanks to its deep learning-based structure, it was found to have a greater ability to learn complex patterns by better modelling the relationships between frequency components. The Random Forest model generally made successful predictions, but the false prediction rate remained relatively high in some classes. Although the SVM model had a stable learning process, it achieved lower accuracy values compared to the other models. This study demonstrates how machine learning and deep learning-based models can be used in rotating machinery fault diagnosis by extracting frequency components with FFT and comparatively evaluates the effectiveness of different algorithms. In the future, the generalisation capability of the models can be increased by using larger and more diverse data sets, and the performance of the models can be further improved by hyper-parameter optimisation. In addition, the accuracy rates for imbalance fault detection can be further improved by using different time-frequency transforms (e.g. wavelet transform) or advanced deep learning architectures.

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