SERBIAN JOURNAL OF ELECTRICAL ENGINEERING
Vol. 23, No. 1, February 2026, 1-19

UDC: 621.313.333: 004.42 MATLAB **DOI: https://doi.org/10.2298/SJEE2601001S**

Original scientific paper

Enhance Motor Fault Diagnosis Using Vibration Analysis and Machine Learning: A Comparative Study of mRMR, PCA, and Hybrid Method

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Abstract: This study presents a comparative evaluation of feature selection and dimensionality-reduction techniques for vibration-based fault diagnosis of induction motors using machine learning. Three approaches are systematically analyzed: Minimum Redundancy Maximum Relevance, Principal Component Analysis, and their combined application. A broad benchmark of thirty-three classification models was conducted using the MATLAB Classifier Learner App to assess classification accuracy, model complexity, and prediction speed. The use MATLAB environment ensured reproducibility and facilitated systematic comparison across different algorithms. The results show that PCA in combination with a Quadratic Support Vector Machine achieves the highest diagnostic accuracy (99.8 %). Meanwhile, mRMR paired with a Narrow Neural Network offers an optimal balance between accuracy (99.5 %) and computational efficiency, delivering a prediction speed nearly 7.5 times faster than the leading PCA model. The combined mRMR–PCA approach demonstrates reduced effectiveness, indicating limited benefit from sequential feature selection and extraction for this dataset. The proposed methodology highlights the practical value of integrating vibration data with machine learning techniques.

Keywords: Induction motor, Fault detection, mRMR, PCA, Hybrid method.

1 Introduction

Induction motors (IMs) are often susceptible to various mechanical and electrical failures. The most common failures in industrial applications are bearing failures, rotor imbalance, and shaft misalignment [1]. Early detection of

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*An earlier version of this paper was presented at the 12th International Conference on Electrical, Electronic and Computing Engineering (IcETRAN), Čačak, Serbia, June 2025.

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such failures is essential to prevent efficiency losses, increased operating costs, and unplanned downtime. Given that IMs are the most widely used machines due to their low cost, ease of maintenance, and reliability in different operating conditions, timely fault detection and identification remain critical for ensuring sustainable performance and operational continuity [2 – 4].

Traditional maintenance methods based on fixed time intervals are often insufficient to detect the motor's actual condition in time. This is why the concept of predictive maintenance, based on the analysis of real operating data, is increasingly applied. Vibration analysis [5, 6] has proven to be one of the most effective traditional methods for identifying and classifying failures. Combining vibration data with machine learning (ML) enables the development of models capable of automatically recognizing patterns characteristic of different types of failures [7 – 10], reflecting a broader industrial shift toward Artificial Intelligence (AI) for operational reliability. The primary challenge in IM fault diagnosis lies in the high dimensionality of vibration signals. Processing numerous signals with varying characteristics directly impacts the computational speed and classification accuracy of ML models. To address this challenge, effective feature engineering, specifically feature selection and feature extraction, is essential for transforming raw data into a compact, highly discriminative representation. Among the most effective are Minimum Redundancy Maximum Relevance (mRMR) and Principal Component Analysis (PCA).

The mRMR method, introduced in [11], optimizes classification by selecting features that maximize relevance to the target class while minimizing mutual redundancy. Conversely, PCA utilizes matrix transformations to reduce data dimensionality while preserving maximum variance [12]. Integrating these methods can significantly enhance the accuracy and efficiency of AI techniques.

Despite the growing body of literature underscoring the importance of this field, many representative studies remain limited by their focus on single fault types or controlled laboratory environments, with techniques such as mRMR and PCA often examined in isolation or applied to restricted fault scenarios.

A review of the existing literature indicates that traditional approaches predominantly rely on Principal Component Analysis (PCA) for dimensionality reduction [13 – 15]. However, since PCA is an unsupervised method that does not account for class labels, it may lead to the loss of discriminative information essential for precise fault differentiation. While some studies have utilized mRMR to select dimensionless indicators for Support Vector Machine (SVM) algorithms [16], or applied PCA to monitor motor health via statistical indices [14], there is a clear need for more flexible approaches capable of detailed fault classification in complex scenarios.

This paper addresses these gaps by providing a comprehensive benchmarking study of three distinct workflows: mRMR-based selection, PCA-based extraction, and a sequential hybrid (mRMR+PCA) approach. Utilizing a dataset encompassing six distinct motor conditions, we evaluate thirty-three ML models to determine the optimal balance between diagnostic precision and computational throughput. This work significantly extends our preliminary findings presented in [1] by introducing a more rigorous validation framework and a deeper investigation into the information loss (e.g., PCA discarding low-variance components that might actually be fault-sensitive) phenomena associated with hybrid feature processing.

The primary contributions of this work are summarized as follows:

1. Multi-Scenario Feature Analysis – A comprehensive evaluation of feature relevance and dimensionality reduction was performed across three distinct strategies: (i) feature selection via mRMR, (ii) feature extraction via PCA, and (iii) a hybrid mRMR+PCA approach.
2. Rigorous Algorithmic Benchmarking – A systematic comparison of thirty-three ML algorithms was conducted under all three feature-processing scenarios. By implementing these models within a unified framework, this study establishes a robust performance benchmark, identifying the most effective classifier-feature combinations for fault diagnosis under varying operating conditions.

The rest of this paper is organized as follows: Section 2 provides a theoretical background of mRMR and PCA. Section 3 details the data preprocessing and feature engineering procedures. Section 4 reports the comparative results of the three analysis scenarios, while Section 5 concludes the paper with a summary of the findings and their industrial implications.

2 Theoretical Backgrounds of mRMR and PCA

As mentioned in the introduction, for effective fault detection and identification, it is important to transform raw data into a simple set of features that still gives important information. This study compares three fundamental approaches: feature selection via mRMR, feature extraction via PCA, and a hybrid integration of both.

2.1 Minimum Redundancy Maximum Relevance (mRMR)

The mRMR algorithm is a feature selection technique that optimizes the data set by simultaneously maximizing the statistical dependency between features and the target variable, while minimizing redundancy among the features themselves [11, 17]. This algorithm is based on mutual information (MI) to quantify the mentioned relationships. MI for two random features x and y can be calculated as follows [11, 17]:

$$I(x;y)=\sum_{x,y} p(x,y)\log\frac{p(x,y)}{p(x),p(y)}, \tag{1}$$

where $p(x,y)$ is the joint probability mass function of variables x and y, $p(x)$ and $p(y)$ are the marginal probability mass functions of x and y, respectively.

The first criterion is maximum relevance (D), which ensures that the selected features are highly correlated with the target value. It is defined by maximizing the mean of mutual information between individual features and the target value, and can be defined as [10, 18]:

$$\max D(S,c);\, D=\frac{1}{|S|}\sum_{x_i\in S} I(x_i;c), \tag{2}$$

where $I(x_i;c)$ is the mutual information between feature x_i and the target value c in the set S, $|S|$ is the number of features in the set S.

The second criterion is minimum redundancy, since selecting features only by maximum relevance may lead to significant redundancies, the minimum redundancy criterion is introduced to ensure that the chosen features are not highly dependent on each other [18]. Minimum redundancy of the features is defined as [11]:

$$\min R(S);\, R=\frac{1}{|S|^2}\sum_{x_i,x_j\in S} I(x_i;x_j), \tag{3}$$

where $I(x_i,x_j)$ is the mutual information between features x_i and x_j.

The combination of maximum relevance and minimum redundancy forms is the optimization criterion of the mRMR algorithm, expressed as [11]:

$$\max \phi(D,R);\, \phi=D-R. \tag{4}$$

The core concept of mRMR is to choose features that provide the most useful information for fault classification, while minimizing redundancy between them, which enhances the performance of ML algorithms.

2.2 Principal Component Analysis (PCA)

PCA is a robust unsupervised method for feature extraction and dimensionality reduction. The primary objective of PCA is to transform the high-dimensional vibration feature set into a new orthogonal space, minimizing information loss while preserving as much variance as possible. This process effectively reduces redundancy and noise, retaining the most discriminative components for fault diagnosis in IMs [19, 20].

The process begins with the computation of the covariance matrix (S) of the dataset, which quantifies the relationships between the extracted vibration features [19]:

$$S = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^T (x_i - \mu)\,, \tag{5}$$

where x_i is the i-th observation, μ is the mean vector, and N is the total number of observations in the dataset.

Next, the principal components are obtained by solving the eigenvalue problem for the covariance matrix S [19]:

$$ST_i = \lambda_i T_i\,, \tag{6}$$

where λ_i is the eigenvalue indicating the amount of variance captured by the component, and T_i is the corresponding eigenvector defining the direction of the principal component in the new space.

Then, feature transformation should be performed. For a given observation vector x, the transformation into the reduced PCA space is expressed as [19,15]:

$$\boldsymbol{y} = [y_1, y_2, ..., y_m] = [T_1^T \boldsymbol{x}, T_2^T \boldsymbol{x}, ..., T_m^T \boldsymbol{x}] = \boldsymbol{T}^T \boldsymbol{x}\,, \tag{7}$$

where $T = [T_1^T, T_2^T, ..., T_m^T]$ is the projection matrix consisting of the m selected eigenvectors associated with the largest eigenvalues, and y is the transformed vector in the principal component space.

Finally, in multi-fault (multi-target) problems, a global covariance matrix can be defined to account for the distribution across different motor conditions, and can be defined as [19]:

$$S_{global} = \frac{1}{N}\sum_{j=1}^{K}\left(\sum_{i=1}^{N_j}(x_{ji} - \mu_{global})^T (x_{ji} - \mu_{global})\right), \tag{8}$$

where K is the number of fault classes (targets) N_j is the number of samples in the target j,

$$N = \sum\nolimits_{j=1}^{K} N_j$$

and μ_{global} is the global mean vector across all classes.

3 Dataset and Classifier Learner App Setup in MATLAB

3.1 Dataset

The dataset comprises vibration signals in the time domain, Fig 1.

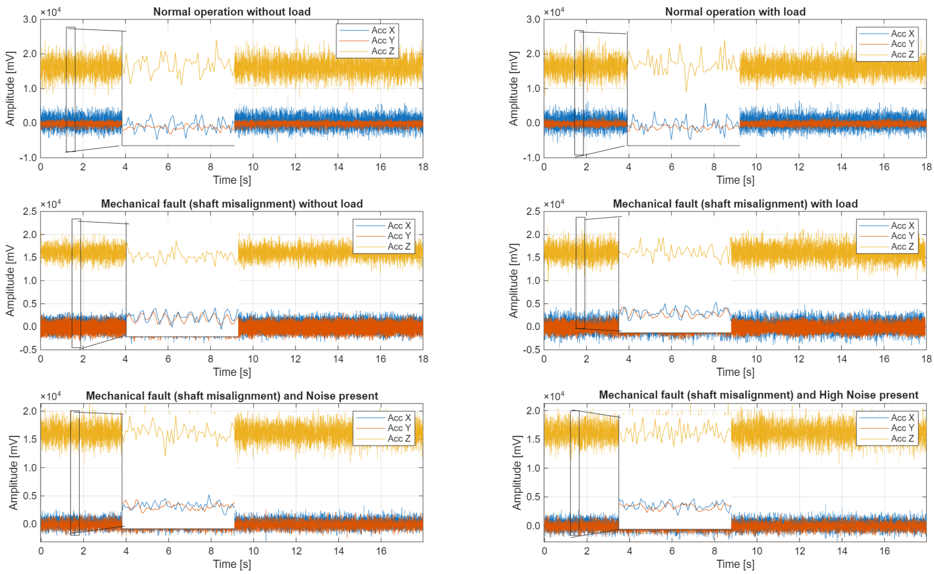
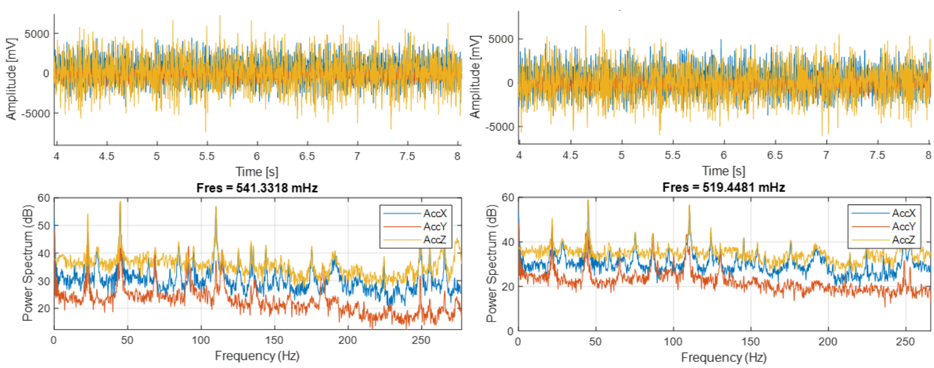


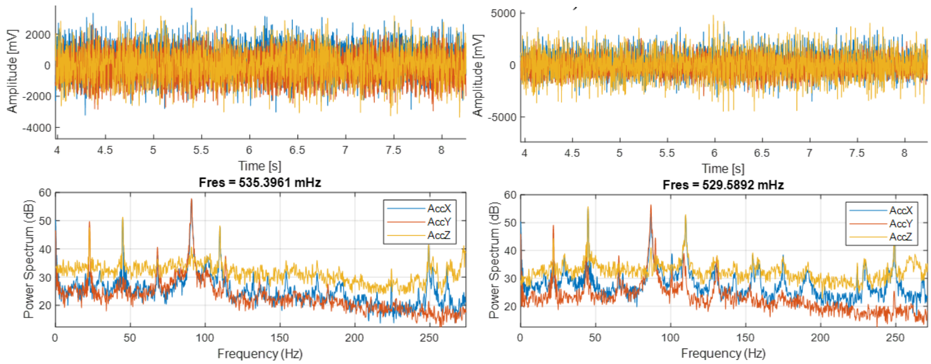
Fig. 1 – *IM raw vibration signals in the time domain for six different conditions* [1].

Figs. 1 – 4 are reproduced from our previous work [1], where the vibration signals in both time and frequency domains were analyzed in detail. In this study, they are referenced only to illustrate the preprocessing steps.



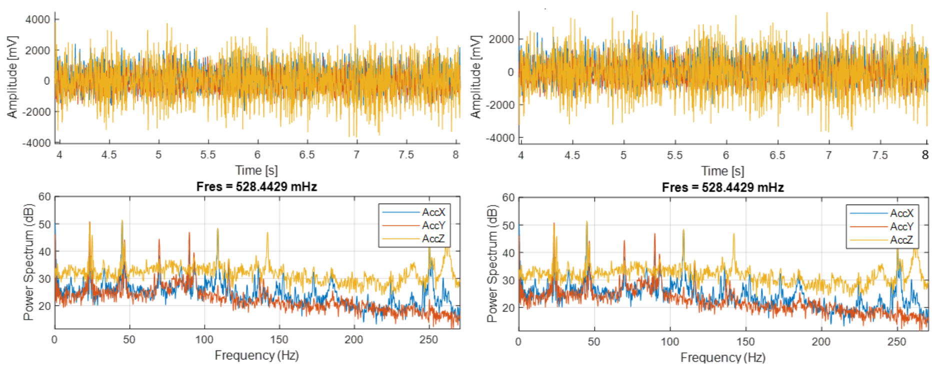
(a) (b)

Fig. 2 – *Vibration signals in the frequency domain for normal operation:* (a) *without and* (b) *with load* [1].



(a) (b)

Fig. 3 – *Vibration signals in the frequency domain for a mechanical fault (shaft misalignment),* (a) *without load and* (b) *with load* [1].



(a) (b)

Fig. 4 – *Vibration signals in the frequency domain for a mechanical fault (shaft misalignment) and* (a) *noise present,* (b) *high noise present* [1].

However, the dataset comprises vibration signals in the time domain under six conditions: normal operation (with/without load), shaft misalignment (with/without load), and shaft misalignment with noise and high noise present. The dataset was standardized by resampling the signals at equal time steps. A function sets the sampling rate and applies resampling to the X, Y, and Z axes. In addition, the DC offset in the Z-axis signal was removed to improve the accuracy of the later analysis. In the next preprocessing step, vibration signals were converted from the time domain to the frequency domain using FFT, which made it possible to detect induction motor fault frequencies. The FFT resolution used was 0.55 Hz. After applying Fast Fourier Transform (FFT), 260 features were extracted [1].

For preprocessing, the raw vibration data were processed using MATLAB functions. The MATLAB version used was 2025, running on a PC with 64 GB of RAM and a Ryzen 7 processor from the 7000 series.

3.2 MATLAB classifier learner app – set-up

The workflows were implemented using the MATLAB Classifier Learner App. This environment allowed for the systematic application of feature selection and extraction techniques to optimize ML models' performance. Three distinct workflows were established to evaluate the impact of dimensionality reduction (Fig. 5).

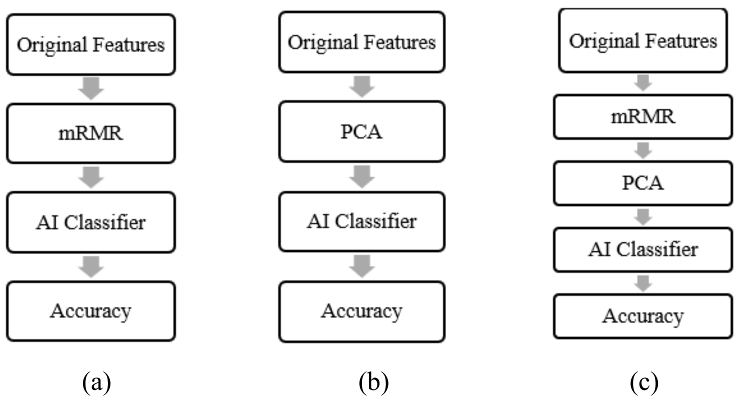


Fig. 5 – *Workflow* (a) *1 using mRMR* (b) *2 using PCA, and* (c) *3 using Hybrid method.*

Workflow 1 – mRMR: As previously mentioned, after applying FFT, 260 features were extracted from the vibration signals. To avoid overfitting and reduce model complexity, a feature selection method, mRMR was used. This algorithm helped to choose the most important features, **Table 1**. As a result, four key frequencies were identified, including 82 Hz, 94 Hz, 110 Hz, and 136 Hz, which carried the most relevant information for fault detection. These selected features were then used as inputs for training several ML models. Unlike unsupervised methods, mRMR directly utilizes class labels to ensure that the chosen features contribute effectively to fault discrimination while minimizing information overlap.

Workflow 2 – PCA: PCA was configured to retain enough principal components (PCs) to explain at least 95 % of the total cumulative variance. In this workflow, 4 PCs were required to meet the variance threshold.

A key limitation addressed here is that PCA focuses solely on variance, which may not always perfectly align with the predictive relevance of the features. The details about all three workflows are shown in **Table 2**.

Workflow 3 – Hybrid mRMR + PCA: This hybrid approach leverages a two-stage pipeline. First, mRMR filters the 260 features down to the 4 most relevant frequency components. Second, PCA is applied to these 4 features to further decorrelate them and produce a highly compact orthogonal feature set. As shown in **Table 2**, in this workflow, a single principal component was sufficient to explain 99.9% of the variance within the pre-filtered subset.

Table 1
Feature importance scores sorted using the mRMR algorithm.

Feature name	Corresponding frequency	mRMR score
Column_111	110	1.3599
Column_137	136	1.3406
Column_95	94	0.9887
Column_83	82	0.9195

Table 2
Configuration and Variance Statistics for the Three Workflows.

<table>
<tr><td rowspan="2">Feature Parameter</td><td colspan="2">Workflow 1</td><td colspan="2">Workflow 2</td><td>Workflow 3</td></tr>
<tr><td colspan="2">Supervised</td><td colspan="2">Unsupervised</td><td>Hybrid</td></tr>
<tr><td>Initial Feature</td><td>4/260</td><td>260/260</td><td>4/260</td><td>Initial Feature</td><td>4/260</td></tr>
<tr><td>Explained Variance</td><td>/</td><td>PC1: 64.9%, PC2: 24.5%, PC3: 4.9%, PC4: 2.1%</td><td>PC1: 99.9%</td><td>Explained Variance</td><td>PC1: 99.9%</td></tr>
</table>

3.3 Models training and evaluation

After selecting the most important feature, several ML algorithms (**Tables 3** and **4**) were trained and evaluated. The training data were mixed to prevent overfitting. Models were trained using 80 % of the data, while 10 % of the data was utilized for cross-validation to assess internal stability. The remaining 10 %

was reserved for final testing to evaluate classification accuracy on unseen samples.

Table 3

ML models used for training and valuations for Workflows.

Category	Model No.	Model Name	Applicable Workflows
Tree	1-2.3	Tree, Fine Tree, Medium Tree, Coarse Tree	1-3
Discriminant	2.4, 2.5	Linear Discriminant, Quadratic Discriminant	1-3
Linear Models	2.6, 2.7	Efficient Logistic Regression, Efficient Linear SVM	1-3
Baye	2.8, 2.9	Gaussian Naive Bayes, Kernel Naive Bayes	1-3
SVM (Support Vector Machine)	2.10-2.15	Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM	1-3
KNN (k-Nearest Neighbors)	2.16-2.21	Fine KNN, Coarse KNN, Cosine KNN, Cubic KNN, Weighted KNN	1-3
Advanced Trees	2.22-2.24	Boosted Trees, Bagged Trees, RUSBoosted Trees	1-3
Neural Network	2.25-2.29	Narrow Neural Network, Medium Neural Network, Wide Neural Network, Bilayered Neural Network, Trilayered Neural Network	1-3
Advanced Hybrid Models	*2.24-*2.33	Subspace Discriminant, Subspace KNN, RUSBoosted trees, Narrow Neural Network, Medium Neural Network, Wide Neural Network, Bilayered Neural Network, Trilayered Neural Network, SVM Kernel, Logistic Regression Kernel	3**

**For Workflow 3 (Hybrid mRMR + PCA), a total of 33 models were benchmarked. This includes the primary 23 models used in Workflows 1 and 2, plus an additional set of 10 specialized models (numbered *2.24 through *2.33) specifically selected to test the performance of the hybrid feature set. These models include advanced Ensemble methods like Subspace Discriminant and various Neural Network architectures.

The preprocessed dataset was then used to train ML models for detecting and classifying motor conditions, helping to identify potential faults in the IM under various working conditions. Fig. 6 shows the original dataset across two primary features (82 Hz and 110 Hz), referred to as the training set, providing a visual representation of the data used to train the classifiers for detecting faults.

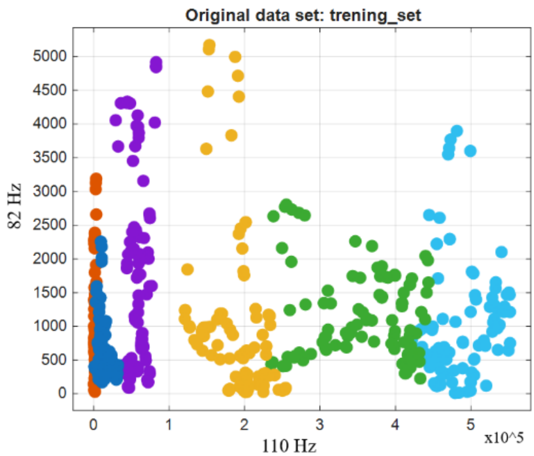


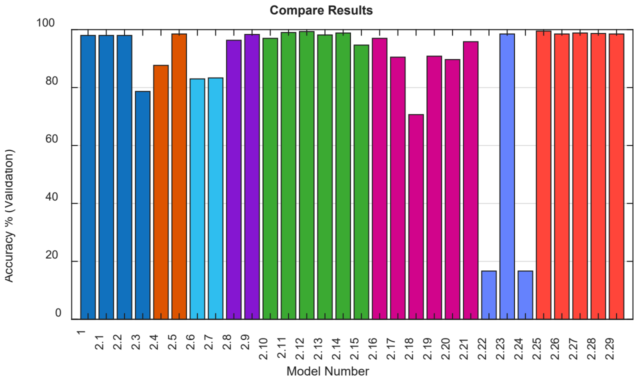
Fig. 6 – *Original training data set* [1].

4 Results

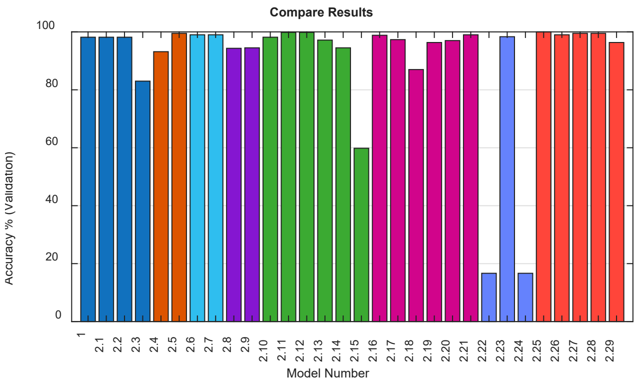
In this section, the obtained results are presented and analysed. The results demonstrate that the choice of dimensionality reduction significantly influences both the accuracy and the computational overhead. A method for feature selection, mRMR, and a method for feature extraction, PCA, as well as their combination, are illustrated, using MATLAB's model Classification Learner App. A critical observation is the trade-off between the high-precision extraction of PCA and the interpretability of mRMR.

Firstly, the accuracy of ML models is presented and analysed, Fig. 7. Fig. 7b illustrates the accuracy of ML models using PCA, where the best-performing model is model 2.11, corresponding to the Quadratic SVM (99.8 %).

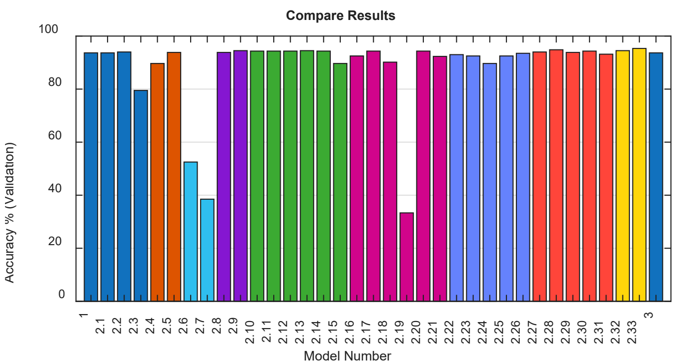
In this case, model 2.25 achieved 100 % accuracy, but it is excluded from the final comparison because it clearly suffers from overfitting. Finally, Fig. 7c presents the accuracy obtained with the combination of mRMR and PCA, with model 2.33, corresponding to the Logistic Regression Kernel, achieving the best result (95.3 %). Furthermore, Fig. 8 presents the predicted values using a) mRMR, b) PCA, and c) mRMR + PCA for the models with the highest accuracy, with the corresponding legend shown in Fig. 9.



(a)



(b)



(c)

Fig. 7 – *Comparison of ML model accuracy using:*
(a) *mRMR,* (b) *PCA, and* (c) *mRMR + PCA.*

In this case, model 2.25 achieved 100 % accuracy, but it is excluded from the final comparison because it clearly suffers from overfitting. Finally, Fig. 7c presents the accuracy obtained with the combination of mRMR and PCA, with model 2.33, corresponding to the Logistic Regression Kernel, achieving the best result (95.3 %). Furthermore, Fig. 8 presents the predicted values using a) mRMR, b) PCA, and c) mRMR + PCA for the models with the highest accuracy, with the corresponding legend shown in Fig. 9.

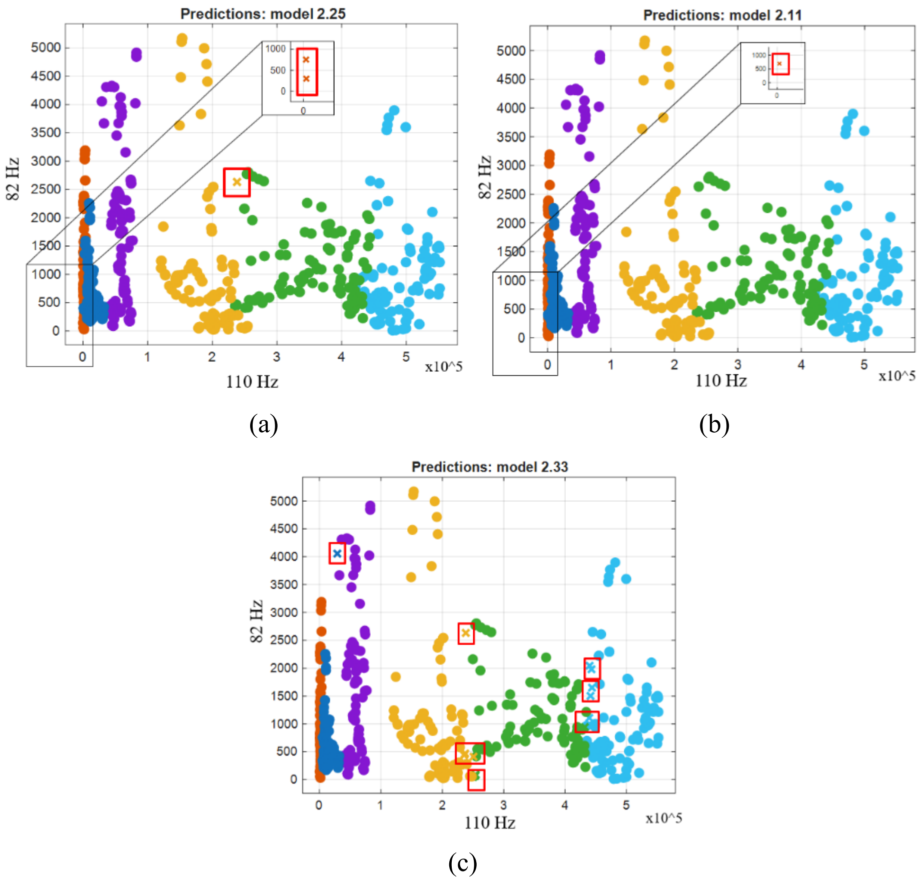


Fig. 8 – *Testing data comparison:* (a) *mRMR,* (b) *PCA, and* (c) *mRMR + PCA* [1].

The results indicate that the proposed method's prediction accuracy is quite promising, and monitoring at different frequencies can enable users to detect early-stage faults.

In summary, the best model for this purpose is model 2.11, which achieved the highest results using the PCA method. Model 2.11 made only one mistake in its predictions: it incorrectly classified a mechanical fault (shaft misalignment) and noise present, whereas the actual condition was shaft misalignment and high noise present, Fig. 8a. Model 2.25 (using mRMR) made two errors, while Model 2.33 (using mRMR+PCA) produced over ten errors. The most common misclassifications occurred between normal operation with load and normal operation without load, Fig. 8b and 8c, respectively.

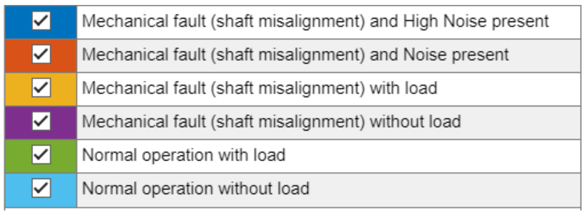


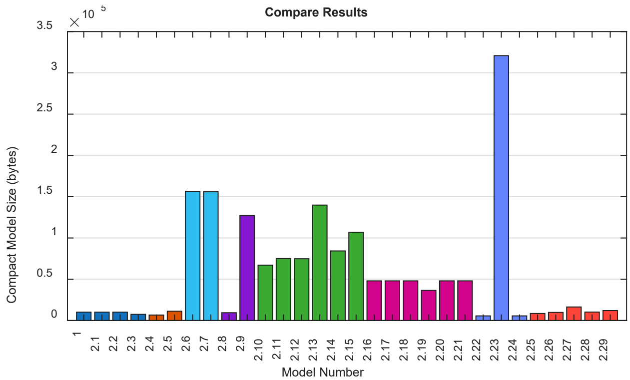
Fig. 9 – *Legend of the Fig. 9* [1].

Additionally, Fig. 10 shows the comparison of model size. In all cases (mRMR, PCA, and mRMR+PCA), the largest models are 2.23 (Bagged Trees) and 2.25 (Narrow Neural Network). Fig. 11 illustrates the prediction speed, where the fastest models are 2.29 (Wide Neural Network) and 2.1 (Fine Tree), depending on the choice of feature selection method (mRMR, PCA, or mRMR+PCA).

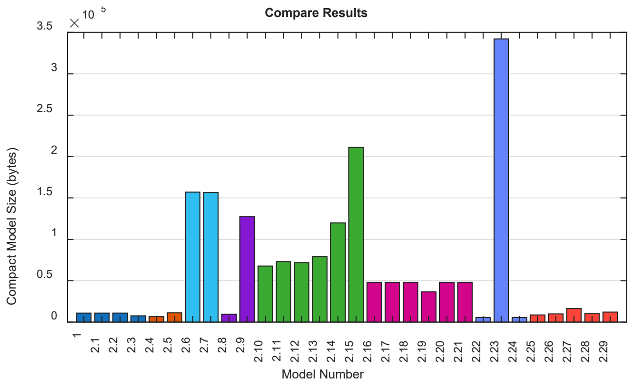
Among the best-performing models, model 2.11 (Quadratic SVM - QSVM) using PCA showed superior results, achieving an accuracy of 99.83 %, compared to Model 2.25 (Narrow Neural Network - NNN) using mRMR, which reached 99.5 % accuracy, and model 2.33 (Logistic Regression Kernel – LRK) with 95.3 % accuracy, using mRMR + PCA (**Table 4**).

Although PCA (Quadratic SVM) provides the highest diagnostic precision, mRMR (Narrow Neural Network) offers a superior balance for time-sensitive applications. The drastic difference in prediction speed (12.806 vs. 1.700 obs/sec) suggests that feature selection via mRMR is more efficient for processing continuous, high-frequency vibration data.

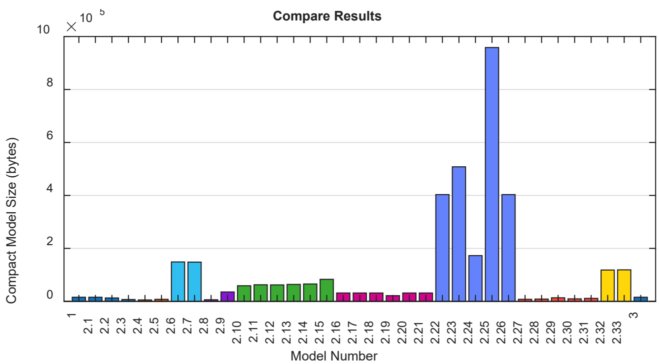
Although Model 2.11 achieved the highest classification accuracy, Model 2.25 represents the most practical solution for real-time, high-frequency online fault diagnostics, as it provides an optimal balance between diagnostic accuracy, significantly higher prediction speed, and reduced computational complexity suitable for embedded industrial controllers.



(a)

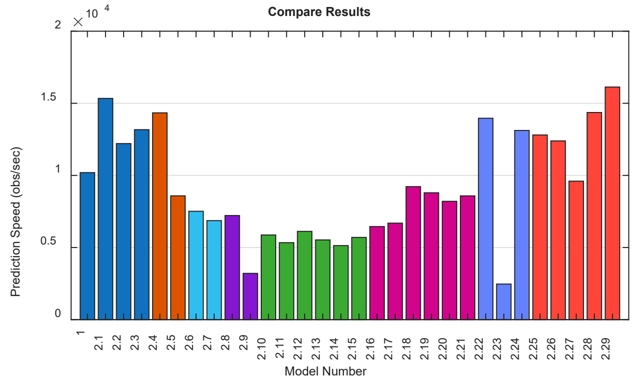


(b)

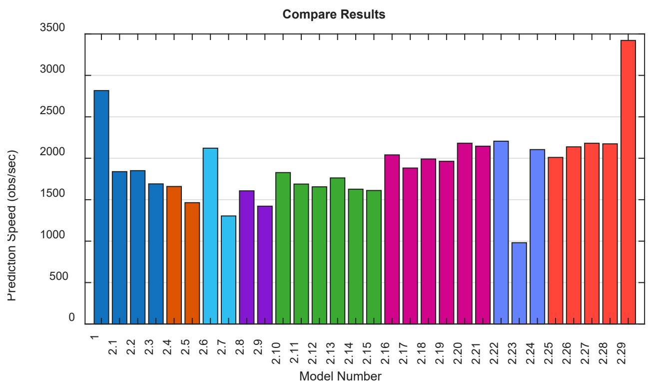


(c)

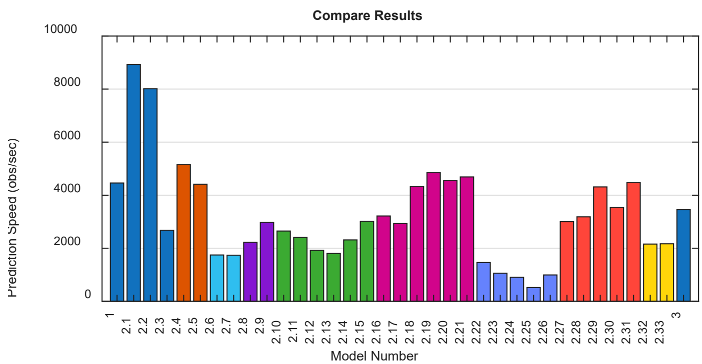
Fig. 10 – *Comparison of model size:*
(a) *mRMR,* (b) *PCA, and* (c) *mRMR + PCA.*



(a)



(b)



(c)

Fig. 11 – *Comparison of prediction speed:*
(a) *mRMR,* (b) *PCA, and* (c) *mRMR + PCA.*

Table 4
Summary of the results.

Technique	mRMR	**PCA**	mRMR+PCA
ML model	NNN	**QSVM**	LRK
Accuracy [%]	99.5	**99.8**	95.33
Error Rate [%]	0.5	**0.2**	4.7
Model Size [kB]	8.49	**73.06**	116
Prediction Speed [obs/s]	12806	**1700**	2200
Training Time [s]	2.2508	**28.069**	13.889

6 Conclusion

This study investigated the effectiveness of various feature-processing techniques for the automated diagnosis of IM faults using vibration analysis and ML. By evaluating three distinct workflows: mRMR, PCA, and a hybrid (mRMR + PCA), across a library of thirty-three classification models using MATLAB Classification Learner App, several key insights were established.

The obtained results confirm that PCA-based dimensionality reduction, specifically when paired with a Quadratic SVM, provides the highest diagnostic precision, reaching an accuracy of 99.8 %. However, mRMR-based feature selection proved to be the most appropriate solution for real-time industrial applications. The Narrow Neural Network trained on mRMR-selected features achieved a nearly identical accuracy of 99.5 % while delivering significantly higher prediction speeds (7 times faster than Quadratic SVM) and a more compact model architecture.

A significant finding of this research is the suboptimal performance of the hybrid mRMR + PCA approach. Logistic Regression Kernel-based model resulted in 95.33 % accuracy, with the largest model size and slowest prediction speed, indicating limited benefit from integration. While mRMR effectively identifies features with high relevance to the target class, it may inadvertently discard features that, although individually redundant, contain critical variance components necessary for PCA to construct optimal orthogonal projections. By pruning the feature set before applying dimensionality reduction, the hybrid process likely suffered from significant information loss, stripping away the nuanced data relationships that global methods like PCA rely on to achieve high-precision classification. Therefore, for high-fidelity vibration datasets, standalone dimensionality reduction strategies are superior to sequential hybrid pipelines.

In conclusion, this work demonstrates that a carefully selected feature set, even if reduced to only four dominant spectral components, can provide robust fault detection across varying load and noise conditions. Future work will focus on extending vibration analysis with other diagnostic signals (such as current, temperature, and acoustic emissions) to enhance robustness, as well as exploring deep learning and wavelet-based techniques for richer representation of vibration data.

7 Acknowledgments

This work has been supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia [Grant Numbers: 451-03-34/2026-03/200102, 451-03-33/2026-03/200102].

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