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Misalignment Severity Classification in Rotor-Bearings using the mRMR Feature Selection Method

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Abstract

The accurate detection and diagnosis of mechanical faults are critical for predictive maintenance and operational safety. While signal processing techniques, particularly entropy measures, are widely used for this purpose, the comparative performance of newer entropy methods and their synergy with traditional features remains an active area of research. This study presents a comprehensive evaluation of nine entropy measures and nine time-domain statistical features for fault classification using an optimized Support Vector Machines (SVM). The optimization of the SVM is done using the Genetic Algorithm (GA). The analysis is conducted on an acoustic dataset comprising normal conditions and four distinct fault severities. Results indicate that while individual entropy measures like Bubble Entropy achieve strong fault detection (95.75% test accuracy), their performance for multi-class fault diagnosis is limited (47.70%). Conversely, a combined set of time-domain features provides a robust baseline, achieving 95.03% and 85.55% accuracy for detection and diagnosis, respectively. To overcome the limitations of individual features, a hybrid framework integrating Minimum Redundancy Maximum Relevance (mRMR) for feature selection is proposed. This mRMR-GA-SVM model demonstrated superior performance, achieving near-perfect fault detection (99.55%) and excellent fault diagnosis (95.21%) accuracy. The findings conclusively show that a strategically selected hybrid feature set in mRMR method, significantly outperforms any single feature type, establishing a powerful and reliable methodology for complex fault diagnosis tasks.

Keywords: Fault Diagnosis, Entropy Measures, Feature Selection, mRMR Feature Selection.

1. Introduction

Rotating machines are ubiquitous in modern industry, found everywhere from large power plants to small workshops. While inherent to their operation, these machines are inevitably susceptible to developing faults after manufacturing and during service. Consequently, accurately estimating the severity of these faults is critically important for the industry, as it enables effective maintenance planning, helps prevent secondary failures, and ultimately reduces operational costs. However, diagnosing these faults from acoustic signals presents a more complex challenge compared to traditional vibration analysis, as audio data is inherently contaminated with ambient noise and environmental interference, making the detection of subtle fault signatures significantly more difficult.

The diagnosis of incipient faults in complex machinery relies heavily on extracting meaningful features from non-linear and non-stationary signals, with entropy serving as a widely used tool for assessing signal complexity. Since its introduction by Shannon [1], entropy has evolved into numerous variants like Rényi [2], slope [3], and fuzzy dispersion entropy [4], with recent parameter-free versions such attention entropy [5] offering more robust and efficient complexity measurement. Complementing these features, time-domain features provide a foundational and computationally efficient approach by calculating intuitive statistical descriptors—such as root mean square (RMS), kurtosis, skewness, and peak-to-peak values—directly from the raw signal waveform to reveal characteristics of amplitude distribution and impulsive content indicative of faults [6]. One of the ways to enhance the accuracy and robustness of the fault diagnosis methods is to use a vector of features instead of a single feature. However, the selection of the best set of features is almost always challenging task.

The Minimum Redundancy Maximum Relevance (mRMR) feature selection method has emerged as a powerful tool in the realm of intelligent fault diagnosis, particularly in the context of complex mechanical systems and infrastructure health monitoring. By leveraging mutual information to quantify both the relevance of features to the target class and the redundancy among the features themselves, mRMR effectively identifies an optimal subset of predictors that enhance model interpretability, reduce computational overhead, and improve generalization performance. In the field of machinery fault diagnosis, for instance, mRMR has been successfully applied to select the most discriminative redefined dimensionless indicators (RDIs) from high-dimensional feature sets derived from vibration signals, leading to significant improvements in classification accuracy for rolling bearings and gearboxes [7]. Similarly, in bridge condition prediction, mRMR—coupled with Pareto analysis—has been employed to identify the most contributory predictors for different structural components (deck, superstructure, substructure), thereby enabling more accurate and efficient condition assessment models [8]. The method's ability to balance feature relevance with minimal redundancy makes it particularly suitable for applications where data dimensionality is high and interpretability is critical, as demonstrated in the work by Yan and Jia (2019), where mRMR was integrated with improved multiscale dispersion entropy (IMDE) and extreme learning machine (ELM) to achieve high diagnostic accuracy for rotating machinery under varying operational conditions. Furthermore, mRMR has been effectively utilized in planetary gearbox fault diagnosis, where it was combined with modified multi-scale symbolic dynamic entropy (MMSDE) and least squares support vector machine (LSSVM), achieving up to 99.75% classification accuracy [9]. It has also been implemented in induction motor stator winding fault detection using hybrid feature selection techniques such as Fisher Score and Relief, alongside machine learning classifiers like k-NN and SVM, resulting in 99.10% accuracy [6]. In reducer fault diagnosis, mRMR was integrated with SVM-RFE to eliminate redundant features from vibration signals processed via improved local mean decomposition (LMD), further validating its utility in enhancing model performance and robustness [10]. As a result, mRMR not only optimizes predictive models but also supports sustainable asset management by reducing data collection costs and enhancing decision-making processes across multiple engineering domains.

This study presents a systematic approach for estimating the severity of horizontal misalignment faults in rotating machinery, utilizing exclusively acoustic data from the MAFAULDA database. The work proposes an intelligent fault diagnosis framework that analyzes acoustic signals captured by a microphone from a Machinery Fault Simulator, addressing the unique challenges of audio-based condition monitoring. The investigated fault is horizontal misalignment, with specific severities induced at 0.5 mm, 1.0 mm, 1.5 mm, and 2.0 mm motor shaft shifts. The methodology begins with segmenting these acoustic signals into standardized non-overlapping sub-signals for robust analysis. A comprehensive feature extraction phase then generates a broad set of candidates from nine entropy measures and nine traditional time-domain statistics. To refine this feature set and isolate the most informative acoustic indicators from background noise, the mRMR algorithm was employed for feature selection, identifying the ten most discriminative and non-redundant features. Finally, a Genetic Algorithm (GA) was integrated to optimize the hyperparameters of a Support Vector Machine (SVM) classifier, forming a complete mRMR-GA-SVM model for automated and precise fault severity estimation from challenging acoustic signals.

2. The Presented Fault Diagnosis Method

In this study, an effective fault diagnosis method for acoustic signals is presented. First, nine time-domain and nine entropy features are extracted from the acoustic signals. Then, using mRMR feature selection method, ten most effective features are selected from the list and entered into an optimized SVM.

2.1 Feature Extraction Method

The feature extraction phase is foundational to the fault diagnosis framework, designed to transform raw signals into a set of discriminative descriptors that capture the underlying mechanical condition. This process was conducted in two domains: the time domain, which describes the signal's statistical properties, and the entropy domain, which quantifies its dynamic complexity and regularity.

In the time domain, a suite of nine statistical features was computed for each signal segment. These features include the mean, standard deviation (STD), RMS, skewness, kurtosis, peak-to-peak amplitude, crest factor, shape factor, and impulse factor. These metrics provide foundational insights into the signal's amplitude distribution, shape, and impulsiveness.

Concurrently, in the entropy domain, the nonlinear dynamic characteristics of the signals were quantified using nine distinct entropy measures. The computed entropy types were Permutation Entropy (PermEn), Bubble Entropy (BubbEn), Attention Entropy (AttnEn), Dispersion Entropy (DispEn), Increment Entropy (IncrEn), Slope Entropy (SlopEn), Entropy of Entropy (EnofEn), Diversity Entropy (DivEn), and Phase Entropy (PhasEn). Each entropy measure captures a different aspect of the signal's complexity, regularity, and predictability, offering a rich, multi-faceted description of the system's underlying dynamics.

Table 1, shows the summary of features used in this study with a brief definition.

Table 1: The eighteen features extracted from the acoustic signals.

Feature Domain	Feature Name	Brief Definition
Time Domain	Mean	The average value of the signal amplitude.
	STD	The measure of the signal's variability or dispersion.
	RMS	The quadratic mean, representing the power content of the signal.
	Skewness	The measure of the asymmetry of the signal's probability distribution.
	Kurtosis	The measure of the "tailedness" and sharpness of the signal's distribution.
	Peak-to-Peak	The difference between the maximum and minimum amplitude of the signal.
	Crest Factor	The ratio of the peak value to the RMS value, indicating impulsiveness.
	Shape Factor	The ratio of the RMS value to the average absolute value.
	Impulse Factor	The ratio of the peak value to the average absolute value.
Entropy Domain	PermEn	Measures complexity based on the order patterns of neighboring values.
	BubbEn	Measures complexity based on the effort to sort signal segments.
	AttnEn	A robust method designed to handle non-stationary signals.
	DispEn	Assesses complexity by mapping the signal to symbolic sequences.

IncrEn	Calculates entropy based on the distribution of sample-to-sample differences.
SlopEn	Quantifies complexity by analyzing the slopes between consecutive points.
EnofEn	A higher-order measure calculating the entropy of a series of entropy values.
DivEn	Assesses complexity by measuring the diversity of vector distances.
PhasEn	Quantifies the regularity of the signal's instantaneous phase.

The hyper-parameters of the entropies are mentioned in Table 2.

2.2 The mRMR Feature Selection Method

The Minimum Redundancy Maximum Relevance (mRMR) feature selection algorithm is a filter method designed to select a feature subset that is maximally informative about the target class (relevance) while minimizing redundancy among the features themselves. This dual objective helps in avoiding multicollinearity and ensures that the selected feature set is compact and non-redundant. The core idea is governed by two principal concepts, which are discussed in this sub-section.

2.2.1 Maximum Relevance

This criterion seeks to select features that have the highest relevance to the target class c. For a feature set S with m features, the maximum relevance is achieved by maximizing the mean value of all mutual information values between individual features x_i and the class label c:

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

where $I(x_i; c)$ is the mutual information between i-th feature, x_i, and the class c.
Mutual Information measures the amount of information obtained about one random variable through another random variable. For two discrete variables X and Y, it is defined as Eq. (2).

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y)\, log\, (\frac{p(x,y)}{p(x)p(y)}) \tag{2}$$

Instead of mutual information, in this study the F-scores from analysis of variance (ANOVA) is used to calculate relevance. The F-score assesses the extent to which a feature's values can be used to separate the different classes. A higher F-score indicates greater discriminatory power. The scores are then normalized to a [0, 1] range.

$$D(x_i) = \frac{F - Score(x_i)}{max\,(all\, F - Scores)} \tag{3}$$

2.2.2 Minimum Redundancy

This criterion aims to remove redundant features by selecting those that are mutually minimally similar. The redundancy of a feature set S is defined as the mean mutual information between all pairs of features:

$$\min R\,(S) = min \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I\big(x_i; x_j\big) \tag{4}$$

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

Redundancy is calculated practically as the average absolute correlation between a candidate feature f_j and all features already selected in the subset S:

$$\mathrm{R}(x_j, S) = \frac{1}{|S|} \sum_{x_i \in S} |corr(x_j, x_i)| \tag{5}$$

where corr is the Pearson correlation coefficient.

2.2.3 The mRMR Criterion

The mRMR method combines these two criteria into a single objective function. In the mutual information difference (MID) scheme, the goal is to maximize the difference between relevance and redundancy:

$$\max\,[I(x_i; c) - \frac{1}{|S|} \sum_{x_i \in S} I(x_i; x_j)] \tag{6}$$

However, the mRMR values are practically calculated using Eq. (7).

$$\max\,[\frac{F - Score(x_i)}{max\,(all\ F - Scores)} - \frac{1}{|S|} \sum_{x_i \in S} |corr(x_j, x_i)|] \tag{7}$$

2.3 Decision Making using GA-Optimized SVM

The fault diagnosis was formulated as both a binary classification problem (normal versus faulty) and a multi-class classification problem (specific fault type identification). An SVM with a Radial Basis Function (RBF) kernel was chosen as the classifier due to its proven effectiveness in nonlinear pattern recognition tasks. To overcome the critical challenge of SVM hyperparameter tuning, a Genetic Algorithm (GA) was integrated for the autonomous optimization of the penalty parameter, C, and the kernel parameter, γ.

The genetic algorithm initialized a population of potential parameter sets and evolved them over generations using tournament selection, arithmetic crossover, and Gaussian mutation. The fitness of each individual parameter set was evaluated based on the average classification accuracy obtained from a 5-fold cross-validation on the training data. This GA-SVM hybrid model ensures that the classifier is tuned for maximum generalization performance. The entire dataset was split into training (70%) and testing (30%) sets, with stratification to preserve the distribution of fault classes in both splits. Model performance was rigorously assessed using cross-validation accuracy, test accuracy, confusion matrices, and detailed classification reports.

3. Comparative Evaluation Framework

A comprehensive comparative analysis was conducted to evaluate the diagnostic performance of individual features, combined feature vectors, and the mRMR-selected feature subset. The performance of each entropy measure and time-domain statistic was evaluated individually as a single-feature input to the SVM. Subsequently, the combined vector of all extracted features was assessed. Finally, the performance of the mRMR-selected feature subset, coupled with the GA-optimized SVM, was benchmarked against all other methods. This evaluation provided critical insights into the trade-offs between computational complexity, represented by feature extraction time, and diagnostic accuracy for both fault detection and diagnosis tasks.

3.1 The MAFAULDA Dataset for Experimental Investigation

The MAFAULDA acoustic database is composed of 1951 multivariate time-series acquired by sensors on a SpectraQuest's Machinery Fault Simulator (MFS) Alignment-Balance-Vibration (ABVT). The 1951 comprises six different simulated states: normal function, imbalance fault, horizontal and vertical misalignment faults and, inner and outer bearing faults.

The acoustic signals acquired using is Shure SM81 microphone through a 4-channel analog data acquisition, National Instrument NI 9234 with sample rate of 51.2 kHz. Each sequence was generated at a 50 kHz sampling rate during 5 s, totaling 250,000 samples per measurement. There are 49 sequences without any fault, each with a fixed rotation speed within the range from 737 rpm to 3686 rpm with steps of approximately 60 rpm. In this study, only the horizontal misalignment fault is considered to show the effectiveness of the fault severity estimation using the presented method. This type of fault was induced into the MFS by shifting the motor shaft horizontally of 0.5 mm, 1.0 mm, 1.5 mm, and 2.0 mm. Using the same range for the rotation frequency as in the normal operation for each horizontal shift, the table below presents the number of sequences per degree of misalignment.

To standardize the input for subsequent analysis, all signals were padded to a uniform length. Furthermore, to enhance the dataset size and better capture transient characteristics, each original signal was segmented into non-overlapping segments of 16,384 samples. This segmentation process increases the number of available samples for training and testing, thereby improving the robustness of the diagnostic model.

Label	Condition	Measurements
0	Normal	49
1	Horizontal Misalignment – 0.5 mm	50
2	Horizontal Misalignment – 1.0 mm	49
3	Horizontal Misalignment – 1.5 mm	49
4	Horizontal Misalignment – 2.0 mm	49
Total Samples		246

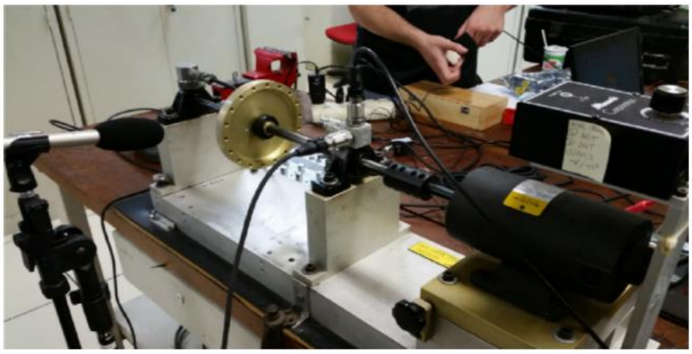

Fig. 1: The rotor-bearing test rig used to collect the MAFAULDA dataset.

3.2 The Results and Discussion

This section presents and discusses the experimental results of applying various entropy measures and time-domain statistical features for fault detection and diagnosis, using an SVM classifier. The dataset consisted of 3,690 segmented signal samples, each of 16,384 data points, representing one normal condition and four fault states (0.5mm, 1.0mm, 1.5mm, and 2.0mm).

3.2.1 Performance of Individual Entropy Measures

The performance of nine distinct entropy measures—Permutation Entropy (PermEn), Bubble Entropy (BubbEn), Attention Entropy (AttnEn), Dispersion Entropy (DispEn), Increment Entropy (IncrEn), Slope Entropy (SlopEn), Entropy of Entropy (EnofEn), Diversity Entropy (DivEn), and

Phase Entropy (PhasEn)—was evaluated individually for both binary fault detection (normal vs. faulty) and multi-class fault diagnosis.

For binary fault detection, BubbEn demonstrated superior performance among the single entropy measures, achieving a cross-validation accuracy of 96.26% (±0.02) and a test accuracy of 95.75%. This indicates a high capability to distinguish between healthy and faulty system states. AttnEn and DivEn also showed commendable performance, with test accuracies of 85.73% and 85.55%, respectively. In contrast, PermEn, SlopEn, and EnofEn all reached a baseline test accuracy of approximately 80.04%, suggesting limited discriminative power for the binary task in this specific application.

For the more challenging multi-class fault diagnosis, the performance of individual entropy measures was significantly lower. BubbEn again yielded the best result with a test accuracy of 47.70%, followed by DispEn (44.81%) and AttnEn (43.18%). The low accuracies across all measures highlight the difficulty in precisely identifying the fault severity level using a single entropy feature. The high standard deviation in the cross-validation results for measures like DispEn and DivEn further indicates a lack of model stability.

3.2.2 Performance of Time-Domain Features

A set of nine standard time-domain statistical features was evaluated for comparison. When combined into a feature vector, these time-domain features achieved an excellent test accuracy of 95.03% for fault detection and a robust 85.55% for fault diagnosis. This demonstrates the strong baseline performance of conventional statistical methods.

Analyzing individual time-domain features revealed that the mean value was the most effective single feature for diagnosis, achieving a test accuracy of 40.38%. Other features like skewness and kurtosis also showed moderate diagnostic capability. However, for binary detection, most individual time features plateaued around 80% accuracy, with standard deviation and RMS achieving the highest individual test accuracy of 80.67%.

3.2.3 Enhanced Performance with mRMR Feature Selection and GA-SVM

To leverage the strengths of both entropy and time-domain features, a hybrid approach was employed. The mRMR algorithm was used to select an optimal subset of features from the combined pool of 9 entropy and 9 time-domain features (18 total). The mRMR method selected 10 features, with diversity entropy and the signal mean ranking as the top two most relevant and non-redundant features.

The selected feature subset was then used to train an SVM model whose hyperparameters (C and gamma) were optimized using a Genetic Algorithm (GA). This combined mRMR-GA SVM framework yielded the best overall performance.

For fault detection, the model achieved a near-perfect test accuracy of 99.55%, with a high cross-validation accuracy of 98.05% (±0.01). For fault diagnosis, the model achieved a remarkably high accuracy of 95.21%, significantly outperforming any single entropy measure and matching the performance of the combined time-domain features.

The GA-optimized SVM parameters were consistent for both tasks (C=141.52, gamma=0.01), indicating a robust parameter set that generalizes well across different classification objectives.

3.2.4 Comparative Analysis and Final Rankings

A final comparison of all methods was conducted, ranking them by test accuracy for both tasks. The results are summarized in Table 2 and Table 3, for fault detection and fault diagnosis, respectively.

The mRMR algorithm selected DivEn, Mean value, IncrEn, DispEn, Peak-to-Peak value, PhasEn, PermEn, BubbEn, Skewness, and Shape Factor as the ten selected features. In addition, the GA optimized the SVM parameters to $C = 141.52$ and $\gamma = 0.0107$.

The results clearly demonstrate that the mRMR-GA-SVM framework is the most effective model for both fault detection and diagnosis in this study. While BubbEn is the most powerful single entropy measure for detection, and the combined time-domain features are strong for diagnosis, the hybrid model's ability to intelligently select and combine features from both domains leads to superior and more reliable performance.

Furthermore, an analysis of accuracy-time efficiency for binary detection highlighted several individual time-domain features (Peak-to-Peak, RMS, Mean) as being highly efficient, providing reasonable accuracy with minimal computational cost. However, for applications demanding maximum reliability, the higher computational cost of the mRMR-GA-SVM approach is justified by its exceptional accuracy.

Table 2: Top 6 Feature Extraction Methods for Fault Detection (Binary Classification).

Rank	Method	Test Accuracy (%)	Computation Time (s)
1	The mRMR selected features	99.55	412.62
2	BubbEn	95.75	193.59
3	Time-domain nine features	95.03	2.224
4	AttnEn	85.73	59.24
5	DivEn	85.55	3.74
6	DispEn	85.64	96.95

Table 3: Top 6 Feature Extraction Methods for Fault Diagnosis (Multi-class Classification).

Rank	Method	Test Accuracy (%)	Computation Time (s)
1	The mRMR selected features	95.21	412.62
2	Time-domain nine features	85.55	2.224
3	BubbEn	47.70	193.59
4	DivEn	44.35	3.74
5	DispEn	44.81	96.95
6	AttnEn	43.18	59.24

4. Conclusions

This study undertook a systematic investigation into the efficacy of various entropy measures and time-domain features for diagnosing the severity of horizontal misalignment faults in rotating machinery, utilizing exclusively acoustic data from the MAFAULDA dataset. The core objective was to develop and validate an intelligent fault diagnosis framework capable of accurately distinguishing between normal operation and multiple fault severities (0.5 mm, 1.0 mm, 1.5 mm, and 2.0 mm motor shaft shifts) using challenging acoustic signal analysis, a task more difficult than traditional vibration-based approaches due to inherent ambient noise.

The experimental results lead to several key conclusions, briefly outlined as follows:

1. Among the nine entropy measures evaluated individually, bubble entropy (BubbEn) proved to be the most discriminative for both binary fault detection and multi-class diagnosis, though the diagnostic accuracy of single entropy measures was generally modest. This underscores that while powerful, individual entropy measures may not capture the full complexity required for precise fault severity identification.
2. Traditional time-domain statistical features, when combined, established a very strong baseline, rivaling even the best single entropy measures for detection and showing remarkable competence for diagnosis. This confirms the enduring value of these well-established features.
3. Individual features, whether entropy or time-domain, proved insufficient for accurate fault diagnosis. The best single-feature result belonged to BubbEn, which diagnosed faults with only 47.70% accuracy.
4. The proposed hybrid feature selection framework, which employs mRMR for selecting a potent and non-redundant subset from a combined pool of entropy and time-domain features followed by GA for optimizing the SVM classifier, achieved superior accuracy. By leveraging the complementary strengths of different feature types, the mRMR-GA-SVM model

achieved near-perfect fault detection (99.55%) and exceptional fault diagnosis (95.21%) accuracy, substantially outperforming all standalone methods and the combination of the nine time-domain features.

REFERENCES

[1] C. E. Shannon, “A mathematical theory of communication,” *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423, 1948.

[2] A. Rényi, “On measures of entropy and information,” 1961. [Online]. Available: http://www.maths.gla.ac.uk/~tl/Renyi.pdf%5Cnhttp://projecteuclid.org/euclid.bsmsp/1200512181

[3] G. B. Moody, R. G. Mark, and A. L. Goldberger, “PhysioNet: a web-based resource for the study of physiologic signals,” *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 3, pp. 70–75, 2001.

[4] M. Rostaghi and H. Azami, “Dispersion entropy: A measure for time-series analysis,” *IEEE Signal Process. Lett.*, vol. 23, no. 5, pp. 610–614, 2016.

[5] J. Yang, G. I. Choudhary, S. Rahardja, and P. Franti, “Classification of Interbeat Interval Time-Series Using Attention Entropy,” *IEEE Trans. Affect. Comput.*, vol. 14, no. 1, pp. 321–330, 2023, doi: 10.1109/TAFFC.2020.3031004.

[6] R. Kumar and R. S. Anand, “Machine Learning Approach with Multiple Feature Selection Techniques to Diagnose the Inter-Turn Winding Faults in Induction Motor,” *Arab. J. Sci. Eng.*, vol. 50, no. 8, pp. 5945–5961, 2025, doi: 10.1007/s13369-024-09681-4.

[7] Q. Hu, X. S. Si, A. S. Qin, Y. R. Lv, and Q. H. Zhang, “Machinery Fault Diagnosis Scheme Using Redefined Dimensionless Indicators and mRMR Feature Selection,” *IEEE Access*, vol. 8, no. Vmd, pp. 40313–40326, 2020, doi: 10.1109/ACCESS.2020.2976832.

[8] V. Dayan, N. Chileshe, R. Hassanli, and A. Parvaneh, “Sustainable bridge management using refined feature selection for machine learning-aided bridge condition prediction: Incorporation of Pareto distribution in MRMR method,” *Appl. Soft Comput.*, vol. 184, no. September, 2025, doi: 10.1016/j.asoc.2025.113878.

[9] Y. Li, Y. Yang, G. Li, M. Xu, and W. Huang, “A fault diagnosis scheme for planetary gearboxes using modified multi-scale symbolic dynamic entropy and mRMR feature selection,” *Mech. Syst. Signal Process.*, vol. 91, pp. 295–312, 2017, doi: 10.1016/j.ymssp.2016.12.040.

[10] X. Zhang, Z. Song, D. Li, W. Zhang, Z. Zhao, and Y. Chen, “Fault diagnosis for reducer via improved LMD and SVM-RFE-MRMR,” *Shock Vib.*, vol. 2018, 2018, doi: 10.1155/2018/4526970.