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Article

Rotor system fault detection utilizing semi-supervised and unsupervised machine learning

Nima Rezazadeh*, Donato Perfetto, Alessandro De Luca, Giuseppe Lamanna

Department of Engineering, University of Campania “L. Vanvitelli,”, via Roma 29, Aversa, 81031, Italy

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*Corresponding author
Email address:
nima.rezazadeh@unicampania.it

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ABSTRACT

Detecting multiple simultaneous faults in rotor systems is challenging, especially when labelled data is limited. This paper presents a novel framework combining unsupervised and semi-supervised machine learning to enhance fault diagnosis in rotor systems with various fault types. Using finite element method simulations, 100 vibration signal observations were generated for rotor systems under three fault conditions: imbalance, imbalance with shaft bending, and imbalance with cracking. Features were extracted via a multi-layer autoencoder in an unsupervised manner, followed by sequential feature selection to identify the most informative attributes. Two classification approaches were then applied: k-means clustering for unsupervised fault detection and a semi-supervised model with a Softmax layer for classification. The semi-supervised method achieved over 95% accuracy using only three selected features, effectively distinguishing different fault types. In contrast, the unsupervised approach proved better suited for anomaly detection rather than precise fault identification. These results demonstrate the potential of integrating unsupervised feature extraction with semi-supervised classification for reliable fault diagnosis in rotor systems with scarce labelled data.

1. Introduction

Rotating systems like steam turbines, generators, and wind turbines are now the most widely used devices in the energy trade [1]. When the operation of these systems is abruptly stopped due to faults, financial losses occur; if these defects escalate to catastrophic failures, safety risks are also introduced. In the complex domain of rotating machinery, accurate detection of anomalies, including the identification of their type, magnitude, and severity, is imperative for ensuring optimal operation and longevity. One of the primary reasons vibration analyses are heralded among contemporary diagnostic techniques is its intrinsic capability to provide detailed and precise condition monitoring. This method's fidelity in capturing minute discrepancies allows for timely intervention, thereby potentially averting consequential system failures [2]. Manual or automated methods can be used to analyze real-time vibration signals. That is, in the manual approach, a specialist compares the signals recorded in the field with both the healthy condition and other fault scenarios using damage criteria and standards. However, in the automated approach, the same process can be performed using a pre-trained artificial network, such as machine learning (ML) [3]. A wide range of mechanical and material defects can adversely affect the performance of rotary devices. Although imbalance is the most common abnormality affecting rotor systems, it can also lead to other issues such as shaft cracks, alignment problems, and bearing complications. Conversely, a bowed shaft can exhibit symptoms such as imbalance, making it challenging to differentiate between the two faults [4,5]. Numerous studies on fault detection in rotary machines have utilized ML-based algorithms as a method for automated diagnostic models. For instance, Jablon et al. [6] presented a new method to diagnose unbalancing in a rotating system that is supported on rolling element bearings. Because of the rich information and the simple instrumentation, the authors proposed a combination of ML algorithms and vibration orbital features. To consider the probable impacts of uncertainty, two industrial scenarios, i.e., average and harsh conditions, were studied. Wisal and Oh [7] introduced a deep learning (DL) framework that merged ResNet and a convolutional neural network (CNN) to detect imbalances in rotating shafts. Using accelerometer data and emphasizing the effectiveness of short-time Fourier transform over fast Fourier transform data representation, the algorithm outperformed traditional methods. The research underscored computational challenges for real-time industry applications, but there was a lack of examining different rotor faults, incorporating varied data attributes, and devising an intuitive interface for industrial use.

Rodrigues et al. [8] undertook an analytical investigation of various ML methodologies for fault diagnosis in rotating machinery utilizing images of vibration spectra. The study encompassed a range of faults, including imbalance, misalignment, and rotor-stator rubbing, with data generated from spectral images during machine operation. Classifiers were trained using data simulated via the finite element method and subsequently evaluated using both simulated and experimental data derived from a rotor-disc system. Among the explored methods, CNN exhibited superior diagnostic performance. Notably, the principal component analysis combined with the k-nearest neighbors (KNN) classifier was distinguished by its efficient computational cost. The study did not encompass scenarios with coexisting multiple faults. Rezazadeh et al. [9] investigated unbalanced, cracked, and misaligned rotor-bearing systems using machine learning. Utilizing a 660-system dataset and extracting features from the time, frequency, and time–frequency domains, supervised classifiers achieved high accuracy, whereas k-means clustering demonstrated lower performance. Supervised methods were superior, but clustering was effective for ambiguous damages and outliers.

Ma and Chu [10] developed an ensemble DL method for diagnosing faults in the shaft and bearing parts in rotating machinery. This method combined a convolutional residual network, a deep belief network, and a deep auto-encoder using multi-objective optimization. Tested on an experimental rotor-bearing system, their approach outperformed other models in adaptability and accuracy. They proposed that future research extend this method to complex classification tasks and explore efficiency improvements through parallel computing. Semi-supervised classification algorithms offer an innovative approach to condition monitoring of machinery by leveraging both labelled and unlabeled data. These methods reduce the manual effort required for extensive labelling and enhance the accuracy and robustness of predictive models. As a result, machinery maintenance becomes more initiative-taking, minimizing downtime and prolonging equipment lifespan. To this end, Yu et al. [11] tackled the challenge of bearing fault diagnosis with limited labelled condition monitoring data. They introduced a three-stage semi-supervised learning method that combines data augmentation and metric learning. The process begins with seven data augmentation techniques to enhance the limited labeled samples, and then utilizes k-means to determine cluster centers. The Kullback-Leibler divergence loss then assesses and minimizes variations between feature distributions. The technique was tested on two datasets related to bearing faults, demonstrating its enhanced performance over current methods, particularly when the number of labelled samples is limited. The authors suggested adapting this model to situations where the unlabeled samples might only include healthy samples or samples from specific health conditions. SMGJE (semi-supervised multi-graph joint embedding), a method for reducing dimensionality in rotating machines, was developed by Yuan et al. [12]. Unsupervised and supervised hypergraphs were utilized in a fault diagnosis technique that considered the relationship between high-dimensional fault data. The method also generated straightforward graphs to increase dimensionality reduction and pattern recognition accuracy in a low-dimensional embedding space. Wu et al. [13] employed a semi-supervised learning model for fault diagnosis in rotor systems. The short-time Fourier transform spectrograms were introduced to an autoencoder for feature extraction. Then, a Softmax layer was trained using the extracted features from the images for classification purposes.

Although a limited number of studies have previously utilized semi-supervised convolutional neural networks for rotor system classification, the combined potential of autoencoders and clustering techniques has not been investigated in the context of rotor system fault clustering. Furthermore, a notable gap has been identified in the literature regarding the application of semi-supervised ML to time-series data for rotor systems with multiple faults. To fill these gaps, we propose two ML-driven fault detection strategies for rotor systems, namely, unsupervised and semi-supervised learning. Three distinct health conditions of the rotor system are used to assess the performance of the proposed methodology. An unsupervised autoencoder is employed to extract pertinent features from the system. Once these features are extracted, they are subjected to clustering, and the outcomes are subsequently compared with results from supervised classification methods.

2. Methodology

Figure 1 illustrates the workflow of the proposed method, where the extracted features undergo two distinct learning methodologies: classification and clustering. It is pertinent to note that within the graph and in the empirical applications, the finite element model (FEM) can be replaced with a data acquisition system, a mechanism responsible for transforming analog signals, as captured by accelerometers, into their digital counterparts. While this conversion stage is commonly observed in real-world scenarios, our method generates these digital signals through FEM. The inclusion of this stage in the illustration is primarily to furnish a holistic understanding. This approach focuses on designing a semi-supervised ML model for identifying flawed rotary systems and assessing its performance against that of an unsupervised model. In the preliminary stages, unbalanced, unbalanced-bowed, and unbalanced-cracked rotor-bearing-disc systems were modelled using the FEM. Because simulations were conducted under various operational conditions, one hundred vibration signal observations for each health condition were produced. Given that these vibration signals served as the cornerstone for the subsequent feature extraction process, an autoencoder neural network was employed to extract salient features from them. As these features emerged, the four most pivotal attributes were meticulously isolated using the sequential feature selection (SFS) method, which was chosen to ensure computational efficiency. A hybrid approach was utilized for classification. Initially, the processed data was grouped into distinct clusters using the k-means clustering algorithm. Subsequently, features were isolated through SFS and were then fed into a custom-designed semi-supervised neural network model. Within this model, a Softmax layer was integrated to manage the classification based on various health conditions of the rotary systems.

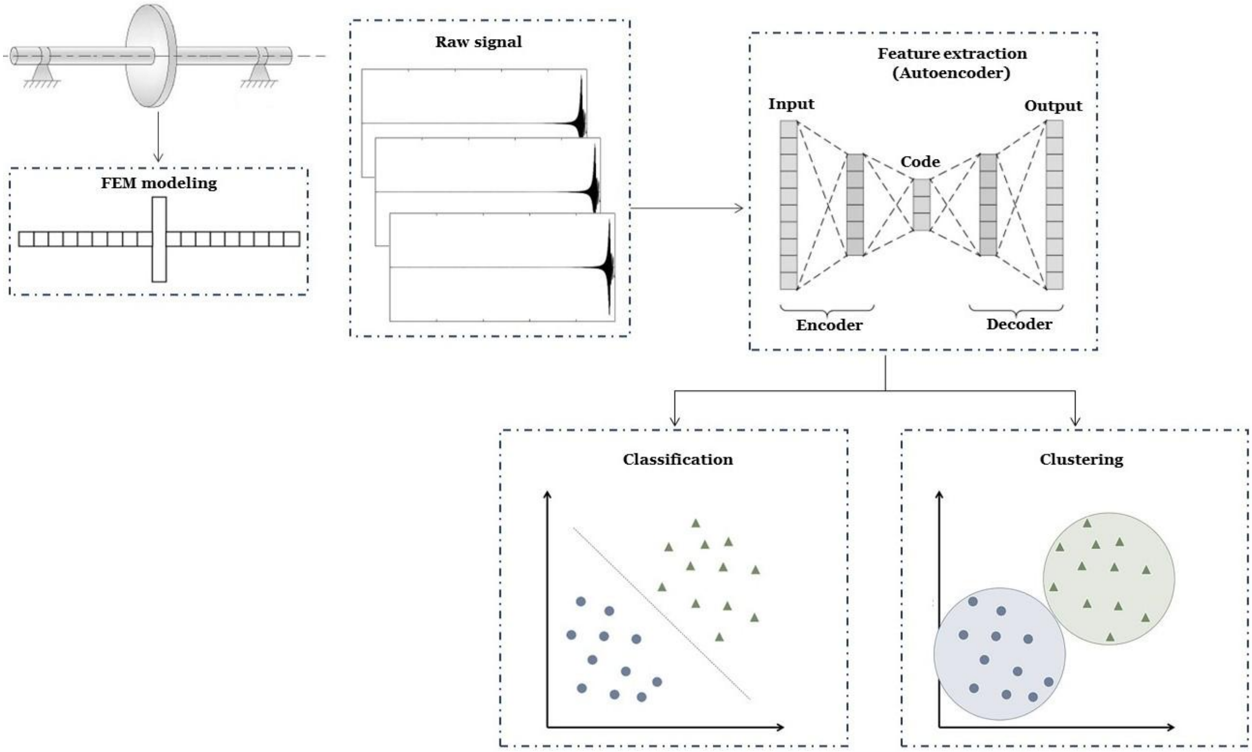

Figure 1. Workflow of the proposed method

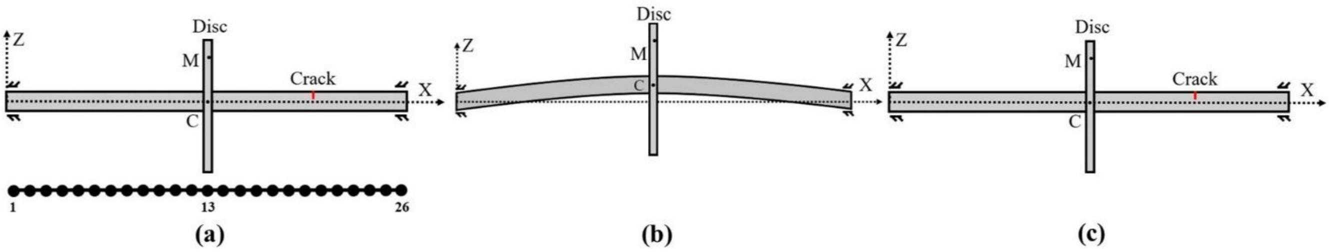

Figure 2. Schematic of a rotor-disc-bearing system (a) unbalanced; (b) unbalanced-bowed; (c) unbalanced-cracked

The results from the k-means clustering and the neural network model were subsequently compared; the comparison was performed based on the acquired accuracies within the two models. A comprehensive review of each step, along with its technical rationale, was provided in the subsequent sections of the paper.

2.1 Simulation of the rotor system

For the rotating systems' FEM model, the shaft was segmented into 25 elements, with assumptions of bearings at both extremities, specifically at nodes 1 and 26; the central disc is positioned at node 13. Figure 2 shows the schematics of the rotor-bearing-disk systems for: the unbalanced condition combined with its FEM node-element depiction, the unbalanced-bowed, and the unbalanced-cracked states, labelled as a-c, respectively. Equation (1) shows the general form of the equation of motion for a dynamic system that includes a rotor-bearing-disc, where: M, C, and K are the mass, damping, and stiffness matrices; F, $\ddot{X}$, $\dot{X}$, and X represent the force, acceleration, velocity, and displacement vectors. These matrices for a healthy rotor system were extracted in [14]. Based on the nature of a fault, mass, damping, stiffness, and/or force, these matrices can change. An external unbalancing force will add an external force term similar to that in equation (2), where: m_d, e, ω, and θ are the values of disc mass, disc eccentricity, rotational velocity, and unbalancing angle (angle between the new mass centre and shaft fundamental axis) [14]. A bowed shaft, on the contrary, introduces the static force terms in equation (3), where: K, δ, and φ are the stiffness matrix, initial bow vector, and initial bow angle to the shaft's main axis [15]. Although a cracked shaft does not add an external force to the system, it will give the element more flexibility. In addition, because of the breathing behaviour of the cracked element, for example, the frequent opening and closing of the crack's edges during a full rotation, a non-linear phenomenon will be added to the dynamics of the system. Equation (4) shows the expression for the stiffness matrix of a shaft with a breathing crack, where K_0, K_1, K_2, K_3, and K_4 are related to the fully opened, half-closed, and fully closed crack conditions [16].

$$[M]\{\ddot{X}\}+[C]\{\dot{X}\}+[K]\{X\}=\{F\} \quad (1)$$

$$F_U= m_d e\omega^2[cos(\omega t+\theta)+ sin(\omega t+\theta)] \quad (2)$$

$$F_B= [K]\{\delta\}[cos(\omega t+\varphi)+ sin(\omega t+\varphi)] \quad (3)$$

$$[K_{Br}]= K_0+(K_1 cos(\omega t))+(K_2 cos(2\omega t))+(K_3 cos(3\omega t))+(K_4 cos(4\omega t)) \quad (4)$$

Once the effects of unbalancing, shaft bow, and shaft crack on the dynamics of a rotor system are calculated, for Class 1 of the current study (which refers to an unbalanced rotor system), only the force F_U needs to be added to the right side of equation (1). For Class 2 and Class 3, both the right and left sides of equation 1 should be modified by inserting the force term F_U+F_B and the stiffness matrix for the breathing crack (e.g., K_{Br}), respectively. For each scenario, the equation of motion was solved employing an implicit manner, i.e., Houbolt's method with a distinguished time increment. Table 1 lists the indicators for each class and their associated damage scenarios.

Table 1. Systems' constant parameters

Class indicator	Fault scenario
Class 1	Unbalanced
Class 2	Unbalanced-bowed
Class 3	Unbalanced-cracked

2.2 Feature extraction

ML algorithms, such as regression and classification, offer advantages over conventional analysis techniques for specific tasks. However, they also carry potential risks due to their data-hungry nature, dependence on labelled data, and diminished accuracy in automatic feature extraction. Consequently, establishing a robust feature extraction framework and learning model, under the assumption of a limited dataset, presents scientific interest [17]. Both manual and automated feature engineering methods can be used to uncover valuable insights within a dataset. Autoencoders are neural networks designed to reconstruct input data, making them especially effective for feature extraction, enabling dimensionality reduction, and capturing essential patterns in complex datasets [18].

An autoencoder consists of an encoder, a bottleneck, and a decoder (as depicted in Figure 1) where the encoder's output can be used as the feature for the next stages [19, 20]. Based on the above, the autoencoder was chosen as a feature extraction tool for this approach. It is essential to maintain a balance between the quality and quantity of extracted features, the time required, and the final accuracy of a learning model. Procedures such as feature selection and ranking are crucial for pinpointing the most significant characteristics within an attribute vector. Sequential feature selection (SFS) stands out in this domain. It is a technique that iteratively adds or removes features to optimize a model's performance, aiming for the most relevant subset of features. By evaluating the contribution of each feature in a systematic sequence, SFS ensures that redundancy is minimized and that the selected features collectively enhance the model's predictive accuracy [21].

2.3 K-means clustering

K-means is an unsupervised ML technique specifically designed for clustering tasks. Its fundamental objective is to partition a dataset into 'k' distinct non-overlapping subsets, or clusters. Each cluster is represented by its centroid, which is essentially the meaning of the data points within that cluster. When deploying k-means, data points are initially assigned to one of the 'k' centroids based on the minimum distance principle, meaning every data point belongs to the cluster whose centroid is nearest to it. As iterations progress, these assignments might change, leading to a shift in the cluster centroids. This process is repeated, with centroids recalculated and data points reassigned, until the centroids no longer change significantly, or a set number of iterations is reached. While k-means has been proven to be effective for a variety of applications, it does come with challenges. One of its major limitations is the necessity to specify the number of clusters, 'k', in advance. Choosing an inappropriate 'k' value can lead to inaccurate clustering. Techniques such as the Calinski-Harabasz criterion, the elbow method, and silhouette analysis have been developed to aid in estimating the optimal number of clusters. Additionally, k-means is sensitive to the initial placement of centroids, which can sometimes result in suboptimal clustering solutions. To mitigate this, the algorithm can be run multiple times with different initializations, and the best result can be chosen [22, 23].

2.4 Semi-supervised classification

Leveraging semi-supervised learning algorithms allows for the integration of the strengths of both unsupervised and supervised models, especially when working with a limited amount of labelled data.

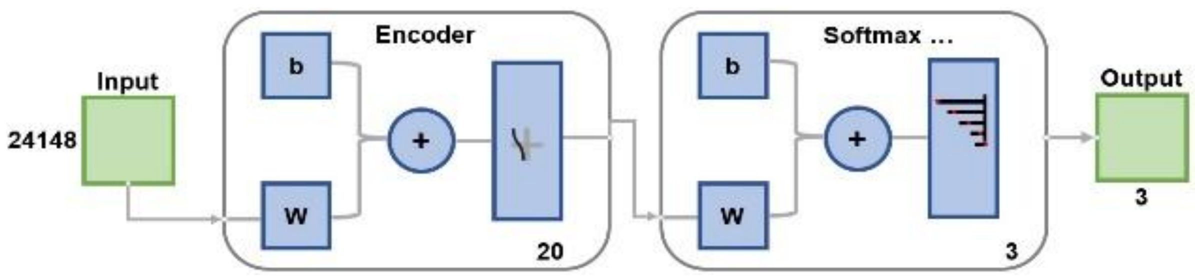

Figure 3. Stacked autoencoder and Softmax layer network

By applying an unsupervised methodology for feature extraction (such as an autoencoder), one can glean informative details without any prior knowledge about the response of the observation. At the subsequent stage, there are two potential pathways. First, a classification layer (such as the Softmax layer) that can be directly attached to the feature extraction layer (in this case, the autoencoder). Alternatively, the extracted features can be stored and later utilized in a separate classification model, such as a support vector machine. The approach that has been adopted in this research opts for the former approach. Figure 3 illustrates the entire network for the semi-supervised case, which includes both the autoencoder and the Softmax layer. The model's performance was subsequently evaluated using the testing dataset.

3. Results and discussion

In this paper, the health scenario for unbalanced, unbalanced-bowed, and unbalanced-cracked rotor systems were modelled employing FEM then the vibration signals were saved as the data. To achieve this, fault parameters were randomly altered 100 times for each health condition. The eccentricity (e) on the assumption of unbalanced systems was chosen to be between 0.005 and 1.5 mm, and its phase angle (θ) was assumed to be between 0 and 2π. Similarly, the magnitudes of the initial bow and its phase angle in the case of Class 2 were also selected at the same limits. For the Class 3 condition, besides the random selection of unbalancing parameters, the crack's depth and the element were assumed to have changes between 0.04r and 0.6r, and 2 to 24, respectively (where r is the shaft radius). Other parameters that remained constant for all 300 sample tests (for the three classes) are listed in Table 2.

The time increment of Houbolt's technique was chosen as 0.001 seconds. Since the initial speed was set to zero, because of the positive initial rotational acceleration, it was assumed that the system was during its start-up, the first 24.148 seconds (immediately after passing the first critical speed). Figure 4 displays random examples of time-domain signals from the three classes. When the rotation begins, the system with an unbalanced bow exhibits a non-zero vibration amplitude. This is highlighted in the magnified section of the diagram, but this effect diminishes over time.

Of the 100 sample tests belonging to each scenario, 85% were designated for training, while the remaining 15% were used for testing in the semi-supervised classification model. It is worth emphasizing that the data for the training and testing phases underwent random selection. For the clustering model, the entire dataset was implemented during the training phase, and the performance of this step was evaluated.

In the feature extraction stage, a 20-layer autoencoder algorithm was implemented. To this end, the number of hidden layers, L2 weight regularisation (ridge regression), sparsity regularisation, and sparsity proportion for the autoencoder were set at 20, 0.001, 4, and 0.05, respectively. It is worth noting that the transfer functions for the decoder and encoder were selected as 'purelin' and 'logsig', respectively. SFS was then used to select the top three informative features (out of the twenty characteristics).

Two approaches were applied in this study to cluster the data. First, the three selected features from the prior stage were put into the k-means model. Second, the same clustering model was examined with three manually extracted features. For the k-means, the method for selecting initial cluster centroid positions, values of replicates, distance metric, and maximum iteration were chosen as 'Plus' 5, 'Cityblock', and 1000, respectively. Using known output labels, clustering accuracy was determined by comparing the clusters assigned to the actual classes. Feature extraction through the autoencoder yielded a 41% accuracy, while k-means clustering, assuming two clusters (with the unbalanced scenario considered typical, and the other two fault types grouped as abnormal conditions), achieved 70% accuracy. This suggests that k-means is more proficient in detecting abnormalities rather than pinpointing specific faults in the rotor system. In another attempt, three features, i.e., signal-to-noise ratio (SNR), spurious free dynamic range (SFDR), and crest factor, were utilized in the same designed k-means model, delivering an 87% accuracy with three clusters.

Figure 5 shows 2D scatter plots representing both the original data points and those obtained after manual feature extraction.

Table 2. Systems' constant parameters

Parameter	Amplitude	Parameter	Amplitude
Initial speed	0	Density	7.8e-6 kg/mm^3
Initial acceleration	250 rad/s^2	Disc mass	20 kg
Shaft length	720 mm	Disc diametral moment of inertia	15.5e3 $kg.mm^2$
Shaft diameter	40 mm	Bearing stiffness	450 N/mm
Young modulus	208 GPa	Bearing damping	0.6 Ns/mm

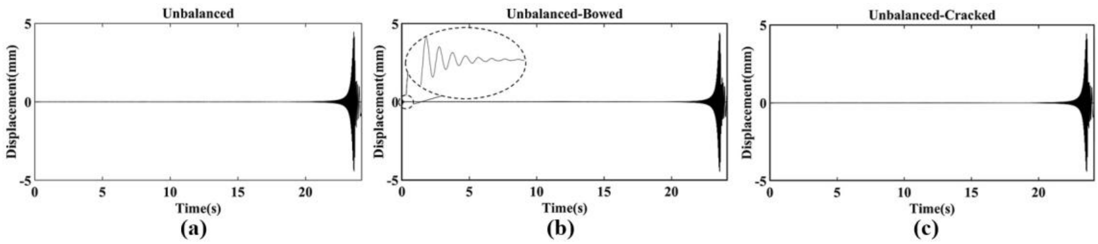

Figure 4. Time-domain signals of a rotor-disc-bearing system (a) unbalanced; (b) unbalanced-bowed; (c) unbalanced-cracked

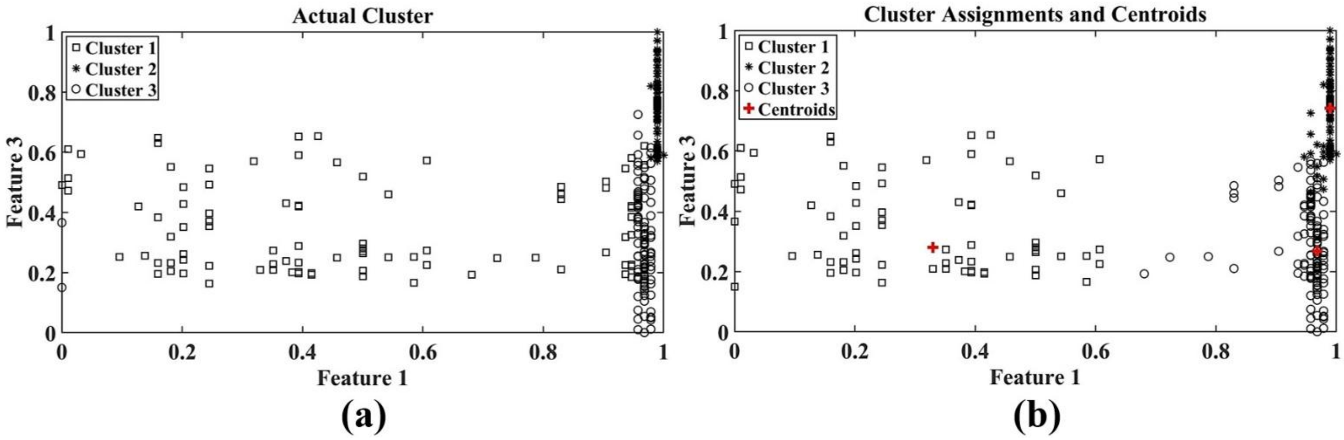

Figure 5. Scatter plot of (a) actual clusters, (b) assigned clusters

The Calinski-Harabasz method was also used to determine the optimum number of clusters. When applied to two different feature extraction methods, i.e., one using the autoencoder and the other using the manual approach, it suggested 6 clusters for the former and 3 clusters for the latter. To evaluate the proficiency of the designed semi-supervised model, the training and testing datasets were fed into it during their respective phases. The confusion matrices presented in Figure 6 provide insight into the classifier's performance during the training phase. During the training phase, the classifier demonstrates exemplary accuracy for Classes 1 and 2, correctly identifying all instances in these categories. However, a challenge arises when distinguishing between Class 2 and Class 3, with 12 instances from Class 3 being misclassified as Class 2. This results in a training accuracy of 243/255, or approximately 95.3%.

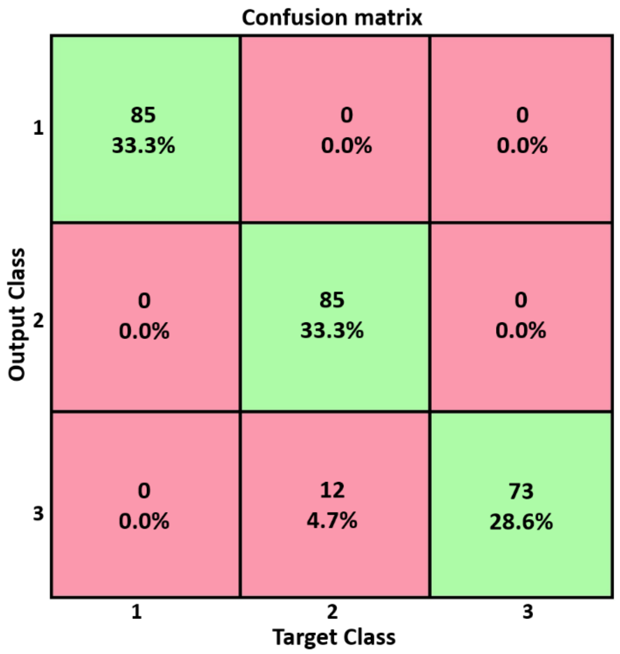

Figure 6. Confusion matrix of the training phase

During the testing phase (Figure 7), the classifier accurately classifies all instances of the first two classes; however, it experiences minor issues with Class 3, misclassifying 2 of its instances as the second class. This yields a testing accuracy of 43/45 (95.6%). Given the consistent difficulty in predicting Class 3 in both phases, the classifier might benefit from further refinement to better differentiate between Class 2 and Class 3.

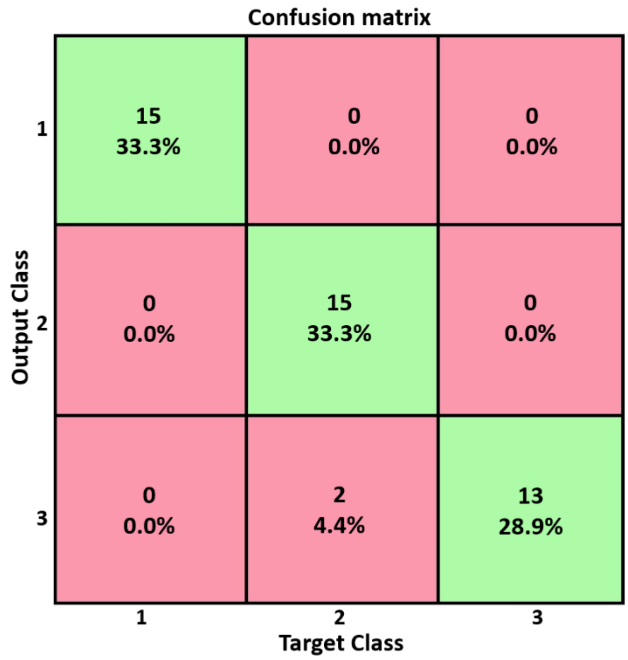

Figure 7. Confusion matrix of the testing phase

4. Conclusion

This paper investigated fault diagnosis in unbalanced rotor systems using machine learning techniques. A dataset comprising 100 observations for each of three fault scenarios, unbalanced, unbalanced-bowed, and unbalanced-cracked, was generated through finite element method simulations in MATLAB®. Features were extracted using a multi-layer autoencoder, followed by the selection of the three most informative features via sequential feature selection. Two approaches were evaluated: unsupervised clustering using k-means and semi-supervised learning with a Softmax classification layer. While k-means clustering initially produced unsatisfactory accuracy, incorporating manually extracted features nearly doubled its performance. The semi-supervised method, utilizing the three selected features, achieved a test accuracy of 95.6%, demonstrating its effectiveness in diagnosing multiple fault types within rotor systems. These findings suggest that combining unsupervised feature extraction with semi-supervised classification offers a promising approach for fault diagnosis when labelled data are scarce. Although fully unsupervised networks may be insufficient for detailed fault identification, they remain valuable for condition monitoring and anomaly detection. Future research should expand this work by considering a broader range of rotor faults to develop a more comprehensive diagnostic framework. Moreover, validating the proposed models on real-world rotor systems is essential to confirm their practical applicability and robustness beyond simulation environments.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically concerning authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere in any language.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] A. Khadersab and S. Shivakumar, "Vibration Analysis Techniques for Rotating Machinery and its effect on Bearing Faults," 2nd International Conference on Materials, Manufacturing and Design Engineering (iCMMD2017), 11-12 December 2017, MIT Aurangabad, Maharashtra, INDIA, vol. 20, pp. 247–252, Jan. 2018, doi: 10.1016/j.promfg.2018.02.036.

[2] A. R. Mohanty, Machinery Condition Monitoring: Principles and Practices, 1st ed. Boca Raton: CRC Press, 2014. [Online]. Available: https://doi.org/10.1201/9781351228626

[3] A. Lorenz, B. Siewertsen, V. Kyhe Clemmensen, J. Blaamann Petersen, J. Friederich, and S. Lazarova-Molnar, "Vibration Data Analysis for Fault Detection in Manufacturing Systems - A Systematic Literature Review," in 2022 IEEE 17th Conference on Industrial Electronics and Applications (ICIEA), Dec. 2022, pp. 851–857. doi: 10.1109/ICIEA54703.2022.10006127.

[4] N. Rezazadeh, A. De Luca, G. Lamanna, and F. Caputo, "Diagnosing and Balancing Approaches of Bowed Rotating Systems: A Review," 2022. doi: 10.3390/app12189157.

[5] N. Rezazadeh, D. Perfetto, M. de Oliveira, A. De Luca, and G. Lamanna, "A fine-tuning deep learning framework to palliate data distribution shift effects in rotary machine fault detection," Struct Health Monit, Nov. 2024, doi: 10.1177/14759217241295951.

[6] L. S. Jablon, S. L. Avila, B. Borba, G. L. Mourão, F. L. Freitas, and C. A. Penz, "Diagnosis of rotating machine unbalance using machine learning algorithms on vibration orbital features," Journal of Vibration and Control, vol. 27, no. 3–4, pp. 468–476, Feb. 2021, doi: 10.1177/1077546320929830.

[7] M. Wisal and K.-Y. Oh, "A New Deep Learning Framework for Imbalance Detection of a Rotating Shaft," Sensors, vol. 23, no. 16, 2023, doi: 10.3390/s23167141.

[8] C. E. Rodrigues, C. L. N. Júnior, and D. A. Rade, "Application of Machine Learning Techniques and Spectrum Images of Vibration Orbits for Fault Classification of Rotating Machines," Journal of Control, Automation and Electrical Systems, vol. 33, no. 1, pp. 333–344, Feb. 2022, doi: 10.1007/s40313-021-00805-x.

[9] N. Rezazadeh, A. Felaco, S. Fallahy, and G. Lamanna, "Application of Supervised and Unsupervised Machine Learning to the Classification of Damaged Rotor-Bearing Systems," Macromol Symp, vol. 411, no. 1, 2023, doi: 10.1002/masy.202200219.

[10] S. Ma and F. Chu, "Ensemble deep learning-based fault diagnosis of rotor bearing systems," Comput Ind, vol. 105, pp. 143–152, Feb. 2019, doi: 10.1016/j.compind.2018.12.012.

[11] K. Yu, T. R. Lin, H. Ma, X. Li, and X. Li, "A multi-stage semi-supervised learning approach for intelligent fault diagnosis of rolling bearing using data augmentation and metric learning," Mech Syst Signal Process, vol. 146, p. 107043, Jan. 2021, doi: 10.1016/j.ymssp.2020.107043.

[12] J. Yuan, R. Zhao, T. He, P. Chen, K. Wei, and Z. Xing, "Fault diagnosis of rotor based on Semi-supervised Multi-Graph Joint Embedding," ISA Trans, vol. 131, pp. 516–532, Dec. 2022, doi: 10.1016/j.isatra.2022.05.006.

[13] X. Wu, Y. Zhang, C. Cheng, and Z. Peng, "A hybrid classification autoencoder for semi-supervised fault diagnosis in rotating machinery," Mech Syst Signal Process, vol. 149, p. 107327, Feb. 2021, doi: 10.1016/j.ymssp.2020.107327.

[14] H. D. Nelson and J. M. McVaugh, "The Dynamics of Rotor-Bearing Systems Using Finite Elements," Journal of Engineering for Industry, vol. 98, no. 2, pp. 593–600, May 1976, doi: 10.1115/1.3438942.

[15] F. D. Sanches and R. Pederiva, "Theoretical and experimental identification of the simultaneous occurrence of unbalance and shaft bow in a Laval rotor," Mech Mach Theory, vol. 101, pp. 209–221, 2016, doi: 10.1016/j.mechmachtheory.2016.03.019.

[16] C. A. Papadopoulos and A. D. Dimarogonas, "Stability of Cracked Rotors in the Coupled Vibration Mode," Journal of Vibration, Acoustics, Stress, and Reliability in Design, vol. 110, no. 3, pp. 356–359, Jul. 1988, doi: 10.1115/1.3269525.
[17] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: an overview and application in radiology," Insights Imaging, vol. 9, no. 4, pp. 611–629, Aug. 2018, doi: 10.1007/s13244-018-0639-9.
[18] E. R. Ardelean, A. Coporîie, A. M. Ichim, M. Dînşoreanu, and R. C. Mureşan, "A study of autoencoders as a feature extraction technique for spike sorting," PLoS One, vol. 18, no. 3 March, 2023, doi: 10.1371/journal.pone.0282810.
[19] S. Lei, X. Lei, M. Chen, and Y. Pan, "Drug Repositioning Based on Deep Sparse Autoencoder and Drug–Disease Similarity," Interdiscip Sci, vol. 16, no. 1, 2024, doi: 10.1007/s12539-023-00593-9.
[20] H. Bai, X. Zhan, H. Yan, L. Wen, Y. Yan, and X. Jia, "Research on Diesel Engine Fault Diagnosis Method Based on Stacked Sparse Autoencoder and Support Vector Machine," Electronics (Switzerland), vol. 11, no. 14, 2022, doi: 10.3390/electronics11142249.
[21] Prastika, E., Sumarno, S., Masruro, Z., Gunawan, I., & Purnamasari, I. (2022). PENERAPAN DATA MINING DALAM MENGANALISA TINGKAT PEROKOK BERDASARKAN USIA MENGGUNAKAN ALGORITMA K-MEANS CLUSTRING. SmartAI: Buletin artificial intelligence, 1(2), 48-54.
[22] J. A. Hartigan and M. A. Wong, "Algorithm AS 136: A K-Means Clustering Algorithm," J R Stat Soc Ser C Appl Stat, vol. 28, no. 1, pp. 100–108, 1979, doi: 10.2307/2346830.
[23] J. Barrera-García, F. Cisternas-Caneo, B. Crawford, M. Gómez Sánchez, and R. Soto, "Feature Selection Problem and Metaheuristics: A Systematic Literature Review about Its Formulation, Evaluation and Applications," 2024. doi: 10.3390/biomimetics9010009.