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Research Paper

On the Usefulness of Pre-processing Methods in Rotating Machines Faults Classification using Artificial Neural Network

Ahmad Alzghoul[1], Anwar Jarndal[2,3], Imad Alsyouf[3,4], Ahmed Ameen Bingamil[3,4], Muhammad Awais Ali[3], Saleh AlBaiti[3,4]

[1] Data Science Department, Princess Sumaya University for Technology, Amman, Jordan

[2] Electrical Engineering Department, University of Sharjah, Sharjah, United Arab Emirates

[3] Sustainable Engineering Asset Management (SEAM) Research Group, University of Sharjah, Sharjah, United Arab Emirates

[4] Industrial Engineering and Engineering Management Department, University of Sharjah, Sharjah, United Arab Emirates

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Corresponding author: A. Alzghoul (A.Alzghoul@psut.edu.jo)

Abstract. This work presents a multi-fault classification system using artificial neural network (ANN) to distinguish between different faults in rotating machines automatically. Rotation frequency and statistical features, including mean, entropy, and kurtosis were considered in the proposed model. The effectiveness of this model lies in using Synthetic Minority Over-sampling Technique (SMOTE) to overcome the problem of imbalance data classes. Furthermore, the Relief feature selection method was used to find the most influencing features and thus improve the performance of the model. Machinery Fault Database (MAFAULDA) was deployed to evaluate the performance of the prediction models, achieving an accuracy of 97.1% which surpasses other literature that used the same database. Results indicate that handling imbalance classes hold a key role in increasing the overall accuracy and generalizability of multi-layer perceptron (MLP) classifier. Furthermore, results showed that considering only statistical features and rotational speed are good enough to get a model with high classification accuracy.

Keywords: Rotating machines, Multi-fault diagnostic, Data Pre-processing, Handling Imbalance Dataset, Machine Learning.

1. Introduction

Rotating machinery has become an essential component of the modern world with a wide range of applications such as construction, manufacturing, transportation, etc. Reliability in these machines is highly important to prevent premature failure, which can result in significant financial losses and safety problems. Thus, efficient monitoring plan and correct fault identification are critical to ensure the long-term healthy operation of the rotating machines [1]. Therefore, fault detection in rotating machines has been a subject of extensive research to develop a real-time automatic recognition system with high accuracy.

The literature produced a lot of fault detection and diagnosis models on different fault types of rotating machines including unbalance [2]–[4], shaft misalignment [3], [5] and bearing faults [6], [7].

Artificial neural network (ANN) is considered as one of the most effective and competitive models in machine learning in terms of accuracy, processing speed, fault tolerance and performance. In addition, the ANNs are capable of handling complex problems with high efficiency. With a variety of applications such as classification and image recognition, the ANNs are widely used in different fields, including medical science, education, security, manufacturing, etc. [8]. The ANNs are continuously improved and new technologies are being developed to make neural networks training fast and energy-efficient. For instance, using the analogue non-volatile memory can significantly accelerate the neural network training algorithm. This could be achieved by implementing a parallelized multiply–accumulate operations in the analogue domain at the location of the weight data [9]. Another study developed a conventional neural network (CNN) based system with simulated memristor crossbar to improve parallel-computing efficiency and reduce energy consumption [10].

Condition monitoring (CM) technologies are applied to mechanical and electrical components to collect data about the state of these components. With diagnosis and knowledge, operators can detect or predict fault occurrences. Hence, preventing it from happening and planning the maintenance logistics wisely. In mechanical diagnosis, it is common to use CM techniques such as vibration, oil analysis, acoustics emission, and thermal imaging to monitor the condition of the machine [1].

Vibration condition monitoring is the observation of axial and/or radial displacement of a rotating part. It utilizes time domain and frequency domain analysis for diagnosis. Fast Fourier Transform (FFT) is the method utilized to transform the collected time-series magnitude data into frequency data, providing a better view of the mechanical condition [11].

Due to the complexity of the vibration analysis, there is no rule of thumb for the diagnosis. Thus, fault detection in rotational machines using vibration is done through feature extraction. Feature extraction uses a combination of statistical and/or spectral

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parameters, and feature selection in which irrelevant features are discarded to devise a fast and correct conclusion about the current state of the rotating components [12]. Research work applied machine learning methods in fault detection and diagnosis applications. Some of the applicable techniques are ANN, support vector machine (SVM), and fuzzy logic [6]. ANN is an interconnected architecture of nodes that utilizes raw data as an input that goes through columns of nodes, called layers, where the weight of the nodes guides the data to be classified into predefined classes [1].

This work will investigate the effect of different pre-processing methods and adopt the neural network classifier, which will take the extracted features from the vibration data, and classify the data into the predefined classes of faults.

2. Literature Review

In recent years, machine learning tools (such as ANN, SVM, fuzzy logic systems (FLS), etc.) have been widely used as failure diagnosis and fault classification tool, particularly for rotating machines.

Marins et al. [13] applied similarity-based model, which is a non-machine learning technique applied to classify faults using the same database presented in this study. Other authors considered machine learning techniques, for example, Liu et al. [4] applied wavelet support vector machine (WSVM). Using WSVM, a bearing vibration data are processed first using empirical model decomposition (EMD) and then distance evaluation technique to remove irrelevant features and process the effective features only to classify the data into the different classes of faults. Bordoloi and Tiwari [14] analysed the multi-fault classification of a gearbox based on time-frequency domain vibration data through a SVM model, while using different optimizing tools (GSM), genetic algorithm (GA), and artificial bee colony (ABC) across four-fault situations. Tang et al. [15] trained SVM model using chaos particle swarm optimization (PSO) to classify inputs into the multiple faults of rotating machines. Just like [4], [14], [15], other authors in the literature applied SVM in fault classification models [7], [16]–[18].

ANN was applied in the literature as well to classify faults of rotational machines. Konar and Chattopadhay [19] built an ANN to categorize bearing condition into normal or abnormal (faulty); while handling three statistical features: root mean square value (RMS), crest, and kurtosis. Chandel and Patel [20] took a similar approach as [19]. However, they extracted eight features then normalized them to the same standard level to classify bearing faults. Unal et al. [21] proposed a method for diagnosis of rolling-element bearing fault based on envelope, Fast Fourier Transform (FFT), Hilpert Transform (HT), and ANN.

Hajnayeb et al. [22] used utility additive (UTA) method and GA on twelve features to select the salient features that will go into the ANN and the model achieved high accuracy percentages in detecting different classes of gearbox faults. Chen et al. [23] used four time-series statistical features and RMS of the frequency-domain in a CNN to classify gearbox faults. Wang et al. [24] used autoregressive method to extract signal features and applied them on the back-propagation neural network (BPNN) for fault classification.

Jia et al. [25] proposed a deep neural network (DNN) based method for both, fault characteristic mining and intelligent fault diagnosis of rotating machines. Viana et al. [26] used kurtosis and entropy measures in their classification model across different fault situations and tested their influence on fault diagnosis. Zhang et al. [27] developed a DNN-based technique that controls imbalance classes using Synthetic Minority Over-sampling Technique (SMOTE) and Generative Adversarial Networks (GAN). The GAN generates additional fake samples to balance and further expand the training dataset, and accordingly improve overall classifying accuracy.

This work extends the work of [26] by applying SMOTE and using a smaller number of features to classify the rotating machine state. Relief [28] was selected as a feature selection method as it showed a good performance in [29]. The authors addressed the class imbalance problem using (SMOTE) and scaled extracted features for equal contribution to the artificial neural network. Also, the model development was based only on statistical features and the rotational speed and did not include the spectral features.

3. Machinery Fault Database

The Machinery Fault Database (MAFAULDA) [30] was selected to evaluate the performance of the proposed prediction models. This database imitates problematic failure scenarios that result from misalignment, unbalance, and bearing's failures in rotating machines. Signals, Multimedia, and Telecommunication Laboratory constructed it by using machine fault simulator (MFS), known as Spectra Quest Alignment/Balance Vibration Trainer (ABVT) [31]. In essence, this database will be used to search for the best possible performance with our proposed approach given different fault scenarios and operating conditions.

The entire database compromise of 1951 data files which corresponds to different fault situations for six operating conditions: Normal, Imbalance, Horizontal and Vertical misalignment, underhang and overhang bearings. Figure 1 shows the actual machine fault simulator that was used to generate the data set in this work. A Schematic representation of the mounted accelerometers on the inner and outer bearings is shown in Fig. 2.

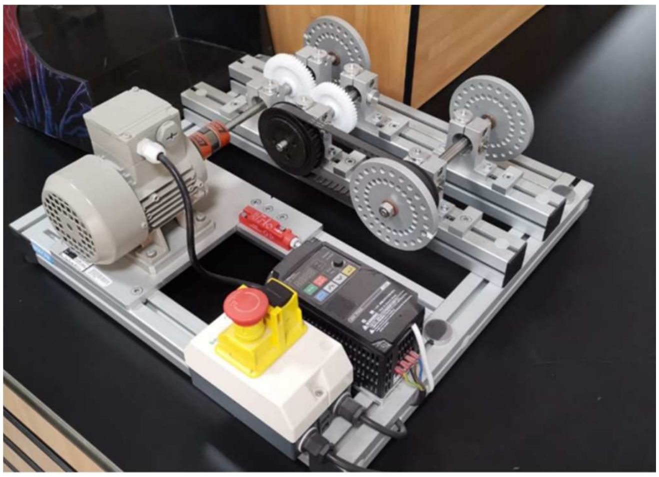

Fig. 1. Machine Fault Simulator

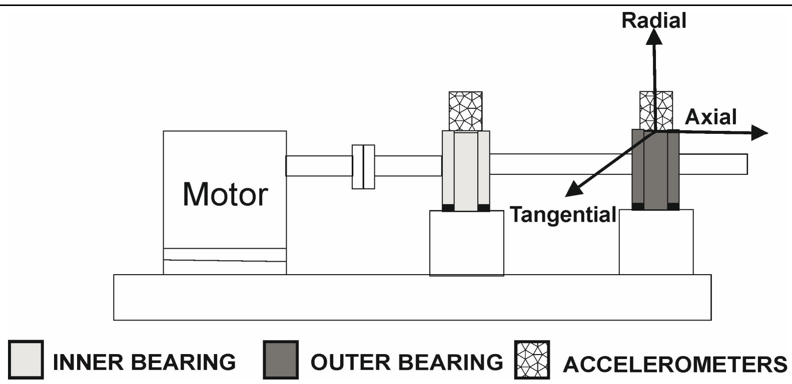

Fig. 2. Schematic configuration of a machine fault simulator

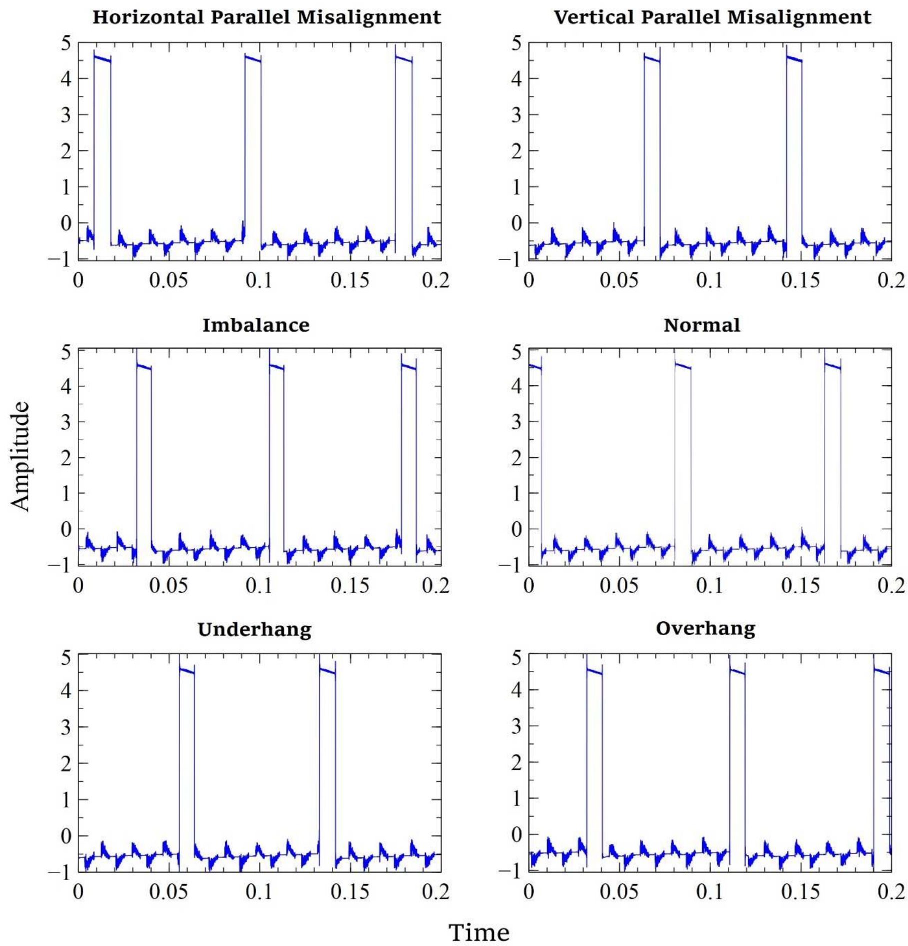

Fig. 3. Time-domain signal plot

The multivariate time-series data was collected at a rate of 50 KHz for 5 seconds and each file consists of eight data columns of a tachometer, accelerometers data from an internal and external bearing for the three dimensions and noise data collected from a microphone. For a better understanding of the database, Fig. 3 shows the time domain signal taken from the tachometer signal. They represent the tachometer signal amplitudes at different conditions. For our work, all possible fault scenarios were considered to validate the model further. The database covered the following operating states:

- Normal condition: the ideal condition where there is no faults or defects in the bearings and motor shaft. It includes a total of 49 data samples with a rotating speed ranging from 12.288 Hz to 61.44 Hz.
- Imbalance: scenarios of the imbalance state was created using different load values. The loads are 6 g, 10 g, 15 g, 20 g, 25 g, 30 g and 35 g. Every load has between 44 to 49 data sets, with a total of 333 data samples for the whole class.
- Horizontal misalignment: misalignment was made by shifting the motor shaft horizontally by a fixed degree of displacement; 0.5 mm, 1.0 mm, 1.5 mm and 2.0 for multiple rotational speeds, making a total of 197 data samples.
- Vertical misalignment: misalignment was done by shifting the motor shaft vertically by a fixed degree of displacement; 0.51 mm, 0.63 mm, 1.27 mm, 1.40 mm, 1.78 mm, 1.90 for various rotational speeds, making a total of 301 data samples.
- Bearing faults: both lower and upper bearings are subjected to three types of faults (retainer, outer race, and ball). Two Bearings are placed in two distinct locations underhang and overhang. Underhang is referred to the position between the rotor and motor, and overhang is located at the outer most position after the rotor. Three unbalancing load values of 6 g, 20 g and 35 g were simulated for all faults, leading to 558 underhang and 513 overhang data samples.

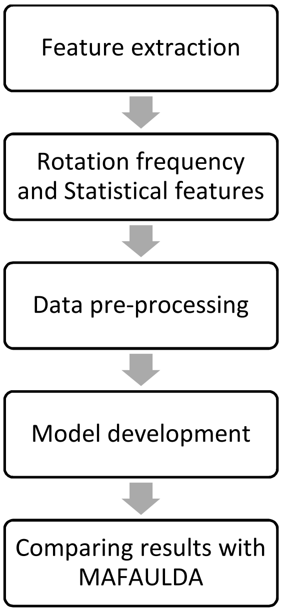

Fig. 4. Process of the classification system

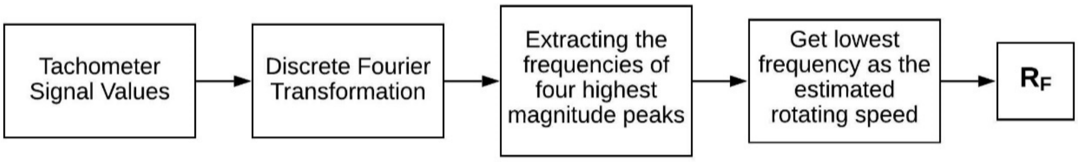

Fig. 5. Calculating Rotation Frequency using DFT

4. Paper Methodology

This section briefly describes our proposed technique and the experimental methodology that was used to achieve it. Our approach combines between three main elements: (1) *feature extraction* to extract necessary information from the time-series signals, (2) *data preprocessing* through handling imbalance class problem to provide an equal distribution for the whole set, feature selection to choose the most relevant ones, and feature scaling to standardize the extracted features and reduce the impact of large valued features extracted on different scales, and finally (3) *model development and test* to classify faults in rotating machines using multilayer perceptron classifier with different setups. Figure 4 shows the process of the proposed technique. Each step in the process is explained in further detail in subsections.

4.1 Feature Extraction

Feature extraction is a necessary step in machine learning mainly because it reduces the complexity of the learning problem and improves data quality by transforming original features into more significant ones. Moreover, this procedure is very helpful to remove the unnecessary features which do not carry any information for the classification problem at hand. In our model, two types of measures were extracted from the vibration signals and used as inputs for the proposed system which are the rotation frequency and the statistical features.

- Rotation Frequency, (F_r): the exact procedure which was taken to calculate the rotating frequency of the motor is explained in [29]. The authors have applied the Discrete Fourier Transform (DFT) on the tachometer signal to estimate the final Rotation frequency R_f. The flow chart of this approach is shown in Fig. 5. The rotating speed is estimated from the lowest frequency.
- Mean: mean is commonly used as an appropriate measure for the central tendency. In this paper, the mean was calculated for each signal in the database, as mentioned in [32].
- Entropy: entropy is specified as a measure for the degree of changeability or unpredictability of a random variable. To measure entropy, we used Parsen-Rosenblatt window method on eight input signals taken from the database (e.g. tachometer, accelerometers, and microphone), generating eight new features. The whole process is explained in further detail in [26].
- Kurtosis: kurtosis is considered as a measure of the sharpness of the signal curve. Same as entropy, kurtosis was applied on input signals from data set to generate newly optimized features. Hence, seven new characteristics were generated from the original signal, respectively. The process of determining kurtosis was mentioned in [26].

Figure 6 shows the statistical feature extraction procedure by applying statistical measures on the vibration signals.

As compared to the feature extraction technique presented in [26], [32], rather than extracting twice the number of features as the previous approaches, our technique utilizes three statistical features and a DFT to produce more significant features and a rotation frequency based on vibration signals. Hence, in addition to the dimensionality reduction of the feature vector, it was possible to reduce the computational cost of the system. Therefore, the feature vector is made of 25 features, including *Fr, mean*, entropy and *kurtosis*, serving as an input for our fault classification model. In contrast, in [32], the authors have used a feature vector having 31 dimensionality vectors by applying two statistical measures and spectral analysis for classifying mechanical faults.

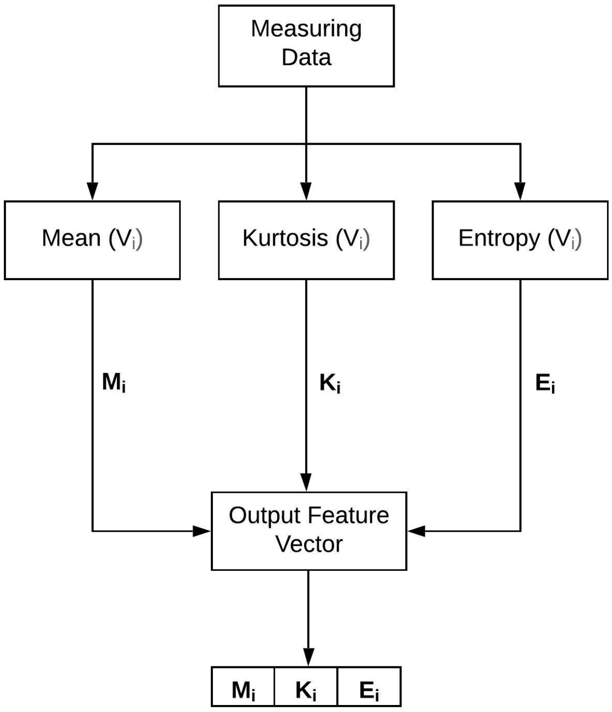

Fig. 6. Generating Statistical Features using Mean, Kurtosis and Entropy

In sum, our generated vector V_f is comprised of rotation frequency from the tachometer signal. In addition to *mean*, entropy and kurtosis features produced from triaxial accelerometers and microphone. The final vector V_f can be written as the following:

$$V_f = \{F_r, M_{xi}, M_{yi}, M_{zi}, K_{xi}, K_{yi}, K_{zi}, E_{xi}, E_{yi}, E_{zi}, M_i, K_i, E_i\} \quad (1)$$

where *x, y, z* correspond to the three dimensions of the accelerometer and *i* is the signal index.

4.2 Data pre-processing

In this work, we investigated the effect of different data pre-proceesing methods on the performance of ANN when used for rotating machines faults classification. The Relief algorithm, which is a feature weight-based algorithm, was selected to determine the subset of features that is sufficient to describe the target. Imbalanced data classes can create unpredictable fluctuations in the learning algorithm, which influences the overall predictive accuracy of the system. Therefore, it is necessary to distribute the data equally by resampling the whole data set. There are two well-known processes for resampling data which are: oversampling the minority class by, for example, generating new artificial data points that we expect to belong to the minor class. The other option is to under-sampling the majority class.

In this work, we adopted the Synthetic Minority Over-sampling Technique (SMOTE) to balance data samples. In this case, instead of oversampling by replacement, the oversampling is done by creating synthetic examples [33]. This technique works in line with the k-nearest neighbour (k-NN) method to identify the nearest neighbour for the minority class. Synthetic data will be generated across the line based on the rate of over-sampling. Therefore, SMOTE works on the values of features and by considering the relationships between features instead of considering the data points as a whole [34]. In this work, the SMOTE algorithm was applied on the training data set; while the test set left without any modifications.

Applying feature scaling is of great significance in machine learning. By scaling features, we allow feature with different values to contribute equally in the proposed model. Feature scaling also helps to speed up the calculations of machine learning algorithms which ultimately optimizes the performance of the system by utilizing the available computational resources effectively.

4.3 Model development

In order to construct and test the classification system, the data was divided into training (70%) and testing (30%) sets using *stratified* splitting. We ran different experiments based on the use of SMOTE and/or Relief techniques to investigate their effects. In the experiments, which involved the use of SMOTE, we only balanced the training data set using SMOTE before being used to train the multilayer perceptron. Thereafter, the test data set was used to measure the performance of the classifier on unseen examples.

A multilayer perceptron (MLP) ANN was used to categorize the mechanical faults in our model. The input layer of the MLP classifier consists of a similar number of neurons as the number of features selected as an input. The number of neurons in the hidden layer was selected based on the average performance of 10-fold cross-validation. The output layer was selected to have six neurons which are equal to the number of classes (i.e. type of fault) to be predicted by the model (i.e. 6).

5. Experimental Results and Discussion

5.1 Experimental Description

This subsection highlights the experiments that were performed during the development and validation procedures of the multilayer perceptron model considering the following variation:

Experiment 1: evaluates the performance of the MLP classifier on MAFAULDA database without applying Relief nor SMOTE.

Experiment 2: impact of oversampling (using SMOTE) on the performance of MLP classifier.
Experiment 3: impact of feature selection using Relief on the performance of MLP classifier.
Experiment 4: impact of applying both Relief and SMOTE on the performance of MLP classifier.

5.1.1 Experiment 1

In this experiment, all features were used, and the data was only scaled. The average classification accuracy of 10-fold cross-validation on the training data set was 95.53%. While the classification accuracy of the test data set was 95.39%. The confusion matrix in Table 1 shows the performance of the MLP in classifying the different categories of the test set. The high classification accuracy of the model shows that rotational speed and statistical features are not only enough to get a good accuracy but also are able to outperform the model presented in [26]. Thus, rotational speed and statistical features are good enough to distinguish between different fault classes in the rotating machine. In the next experiment, we applied the SMOTE oversampling technique on the training data set and tested the model.

5.1.2 Experiment 2

In Experiment 2, we oversampled the training data using SMOTE and data was also scaled. The average classification accuracy of 10-fold cross-validation (when applied to the training data set) increased to 97.69%. This is expected as we oversampled the training data set. In addition to that, the classification accuracy of the test set slightly increased to 96.25%. This indicates that SMOTE did raise the overall performance of the model. The confusion matrix of the test set is shown in Table 2.

5.1.3 Experiment 3

In this experiment, we investigated the effect of reducing the number of features on the performance of the MLP model. The features were reduced using the Relief algorithm. Based on the performance of testing a different number of features, the minimum number with the best performance was 17. The classification accuracy of this experiment was around 96.04% for the 10-fold cross-validation and 96.93% on the test data set. The confusion matrix of the test set is shown in Table 3. The results indicate that reducing the number of features improved, when compared to using ANN alone in experiment 1, the performance on both the training and the test data sets. We can notice that Relief algorithm and SMOTE influence the classification accuracy; thus, in the next experiment, we tested a model which involves both feature selection and oversampling techniques.

Table 1. Confusion matrix for Experiment 1

		Predicted Class					
		Horizontal misalignment	Imbalance	Normal	Overhang	Underhan g	Vertical misalignment
Actual Class	Horizontal misalignment	56	0	0	3	0	0
	Imbalance	2	97	0	1	0	0
	Normal	2	0	13	0	0	0
	Overhang	1	1	0	148	3	1
	Underhang	0	3	0	4	160	1
	Vertical misalignment	1	0	0	4	0	85

Table 2. Confusion matrix for Experiment 2

		Predicted Class					
		Horizontal misalignment	Imbalance	Normal	Overhang	Underhan g	Vertical misalignment
Actual Class	Horizontal misalignment	57	0	0	0	1	1
	Imbalance	0	96	0	0	1	1
	Normal	1	0	14	0	0	0
	Overhang	0	0	0	151	1	2
	Underhang	2	3	0	4	158	1
	Vertical misalignment	1	0	0	3	0	86

Table 3. Confusion matrix for Experiment 3

		Predicted Class					
		Horizontal misalignment	Imbalance	Normal	Overhang	Underhang	Vertical misalignment
Actual Class	Horizontal misalignment	57	0	0	2	0	0
	Imbalance	2	97	0	0	1	0
	Normal	1	0	14	0	0	0
	Overhang	0	0	0	152	1	1
	Underhang	0	5	0	0	162	1
	Vertical misalignment	2	0	0	2	0	86

Table 4. Confusion matrix for Experiment 4

Actual Class \ Predicted Class	Horizontal misalignment	Imbalance	Normal	Overhang	Underhang	Vertical misalignment
Horizontal misalignment	57	0	0	0	1	1
Imbalance	1	99	0	0	0	0
Normal	2	0	13	0	0	0
Overhang	0	1	0	150	1	2
Underhang	0	2	0	0	165	1
Vertical misalignment	3	0	0	2	0	85

5.1.4 Experiment 4

In this experiment, the MLP Classifier was tested using the combination of SMOTE and Relief. The confusion matrix of Experiment 4 is shown in Table 4. The model was able to achieve an average classification accuracy of 98.80% on the training data set, and 97.10% when applied on the test set. The improvement on the accuracy shows that combining Relief and SMOTE algorithms results in a better performance than when applying them separately.

5.2 Comparison with the previous work

Previous literature applied different techniques along with various filters and algorithms in developing their classification model. In terms of performance, [26] employed MAFAULDA Database to build a multilayer perceptron and reached an average classification accuracy of 95.8% using 31 features. The proposed model in this paper used a smaller number of features and achieved a better accuracy of around 97.1%. It was also shown that combining Relief and SMOTE algorithms results in a better performance than when applying them separately.

As for [32], the authors built 3-layer ANN-based classifier for distinguishing between three fault situations: standard condition, unbalanced load, and misaligned axes. After introducing spectral characteristics and balancing the dataset, the classification accuracy of their final model reached 93.5%. Hence, our system has surpassed their proposed system in terms of diversity by discriminating between six fault classes and overall accuracy.

6. Conclusion

Correct Fault diagnosis and condition monitoring of rotating machines is essential due to maintenance expenses and safety risks. Therefore, highly accurate techniques are needed to predict systematic faults before developing to complete machine failures. Several tests have been conducted on our model to select the best approach for classifying faults in rotating machines. The final approach showed its effectiveness in handling different classification problems such as imbalance loads with higher classification accuracy while using both SMOTE and Relief algorithm. The proposed model has achieved 97.4% of overall accuracy on the MAFAULDA database while using only statistical features and the rotational speed data. When compared to previous approaches done using the same database, our proposed model showed its overwhelming capability and performance in classifying mechanical faults. Furthermore, our study indicates that combining different pre-processing techniques such as Relief algorithm (an example of feature selection method) and SMOTE algorithm (an example of handling imbalance dataset method) may further enhance classification systems and give more accurate results. Taking into account the age of the machine and its expected rate of occurrence of failure, the normal behavior of the machine may changes and consequently the prediction accuracy might be affected as time passes. Thus, future work may involve investigating the possibility to simulate the changes of behavior of rotating machines with time, and then explore what are the best times to retrain the model or how to update the model continuously.

Author Contributions

A. Alzghoul conducted the experiments, wrote the code and analysed the simulation results. A. Jarndal and I. Alsyouf have identified major issues with the correctness of the paper and supervised the whole project. The manuscript was written through the contribution of all authors. All authors discussed the results, reviewed and approved the final version of the manuscript.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Bingamil, A., Alsyouf, I., Cheaitou, A., Condition monitoring technologies, parameters and data processing techniques for fault detection of

internal combustion engines: A literature review, *ICETA International Conference on Electrical and Computing Technologies and Applications,* Ras Al Khaimah, UAE, 2017.
[2] Reda, K., Yan, Y., Online continuous detection of an unbalanced metallic shaft using electrostatic sensors, *I2MTC IEEE International Instrumentation and Measurement Technology Conference: Discovering New Horizons in Instrumentation and Measurement,* Houston, TX, 2018.
[3] Kumar, C., Krishnan, G., Sarangi, S., Experimental investigation on misalignment fault detection in induction motors using current and vibration signature analysis, *ABLAZE 1st International Conference on Futuristic Trends in Computational Analysis and Knowledge Management,* Noida, India, 2015.
[4] Liu, Z., Cao, H., Chen, X., He, Z., Shen, Z., Multi-fault classification based on wavelet SVM with PSO algorithm to analyze vibration signals from rolling element bearings, *Neurocomputing*, 99, 2013, 399–410.
[5] Giraldo, E., Verucchi, C., Acosta, G., Ferrari, M., Detection of misalignment in elastic couplings through fuzzy logic, *RPIC 17th Workshop on Information Processing and Control,* Mar del Plata , Argintine, 2017.
[6] Tyagi, S., Panigrahi, S. K., A DWT and SVM based method for rolling element bearing fault diagnosis and its comparison with Artificial Neural Networks, *Journal of Applied and Computational Mechanics,* 3(1), 2017, 80–91.
[7] Attaran, B., Ghanbarzadeh, A., Bearing Fault Detection Based on Maximum Likelihood Estimation and Optimized ANN Using the Bees Algorithm, *Journal of Applied and Computational Mechanics*, 1(1), 2014, 35–43.
[8] Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., Arshad, H., State-of-the-art in artificial neural network applications : A survey, *Heliyon*, 4, 2018, e00938.
[9] Ambrogio, S. *et al.*, Equivalent-accuracy accelerated neural-network training using analogue memory, *Nature*, 558, 2018, 60–67.
[10] Yao, P. *et al.*, Fully hardware-implemented memristor convolutional neural network, *Nature*, 577, 2020, 641–646.
[11] Randall, R. B., *Vibration-based Condition Monitoring: INDUSTRIAL, AEROSPACE AND AUTOMOTIVE APPLICATIONS*. John Wiley and Sons, Australia, 2011.
[12] Sugumaran, V., Ramachandran, K. I., Automatic rule learning using decision tree for fuzzy classifier in fault diagnosis of roller bearing, *Mechanical Systems and Signal Processing*, 21(5), 2007, 2237–2247.
[13] Marins, M., Ribeiro, F., Netto, S., da Silva, E. , Improved similarity-based modeling for the classification of rotating-machine failures, *Journal of the Franklin Institute*, 355(4), 2018, 1913–1930.
[14] Bordoloi, D. J., Tiwari, R., Support vector machine based optimization of multi-fault classification of gears with evolutionary algorithms from time-frequency vibration data, *Measurement: Journal of the International Measurement Confederation*, 55, 2014, 1–14.
[15] Tang, X., Zhuang, L., Cai, J., Li, C., Multi-fault classification based on support vector machine trained by chaos particle swarm optimization, *Knowledge-Based Systems*, 23(5), 2010, 486–490.
[16] Fatima, S., Guduri, B., Mohanty, A. R., Naikan, V. N. A., Transducer invariant multi-class fault classification in a rotor-bearing system using support vector machines, *Measurement: Journal of the International Measurement Confederation*, 58, 2014, 363–374.
[17] Wu, S. De, Wu, P. H., Wu, C. W., Ding, J. J., Wang, C. C., Bearing fault diagnosis based on multiscale permutation entropy and support vector machine, *Entropy*, 14(8), 2012, 1343–1356.
[18] Shen, C., Wang, D., Kong, F., Tse, P. W., Fault diagnosis of rotating machinery based on the statistical parameters of wavelet packet paving and a generic support vector regressive classifier, *Measurement: Journal of the International Measurement Confederation*, 46(4), 2013, 1551–1564.
[19] Konar, P., Chattopadhyay, P., Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs), *Applied Soft Computing*, 11(6), 2011, 4203–4211.
[20] Chandel, A. K., Patel, R. K., Bearing fault classification based on wavelet transform and artificial neural network, *IETE Journal of Research*, 59(3), 2013, 219–225.
[21] Unal, M., Onat, M., Demetgul, M., Kucuk, H., Fault diagnosis of rolling bearings using a genetic algorithm optimized neural network, *Measurement: Journal of the International Measurement Confederation*, 58, 2014, 187–196.
[22] Hajnayeb, A., Ghasemloonia, A., Khadem, S. E., Moradi, M. H., Application and comparison of an ANN-based feature selection method and the genetic algorithm in gearbox fault diagnosis, *Expert Systems with Applications*, 38(8), 2011, 10205–10209.
[23] Chen, Z., Li, C., Sanchez, R.-V., Gearbox fault identification and classification with convolutional neural network, *Shock and Vibration*, 2015, 1–10.
[24] Wang, C. C., Kang, Y., Shen, P. C., Chang, Y. P., Chung, Y. L., Applications of fault diagnosis in rotating machinery by using time series analysis with neural network, *Expert Systems with Applications*, 37(2), 2010, 1696–1702.
[25] Jia, F., Lei, Y., Lin, J., Zhou, X., Lu, N., Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data, *Mechanical Systems and Signal Processing*, 72–73, 2016, 303–315.
[26] Pestana-Viana, D., Zambrano-López, R., De Lima, A. A., De Prego, M. T., Netto, S. L., Da Silva, E. A. B., The influence of feature vector on the classification of mechanical faults using neural networks, *LASCAS 7th IEEE Latin American Symposium on Circuits and Systems,* Florianopolis, Brazil, 2016.
[27] Zhang, W., Li, X., Jia, X. D., Ma, H., Luo, Z., Li, X., Machinery fault diagnosis with imbalanced data using deep generative adversarial networks, *Measurement: Journal of the International Measurement Confederation*, 152, 2020, 107377.
[28] Kira, K., Rendell, L. A., The Feature selection Problem: Traditional Methods and A New Algorithm, *AAAI-92 Proceedings*, 1992.
[29] Spolaôr, N., Cherman, E. A., Monard, M. C., Lee, H. D., A comparison of multi-label feature selection methods using the problem transformation approach, *Electronic Notes in Theoretical Computer Science*, 292, 2013, 135–151.
[30] MAFAULDA - Machinery Fault Database. [Online]. Available: http://www02.smt.ufrj.br/~offshore/mfs/page_01.html.
[31] SpectraQuest, Inc. [Online]. Available: http://www.http//spectraquest.com/.
[32] De Lima, A. A. *et al.*, On fault classification in rotating machines using fourier domain features and neural networks, *LASCAS IEEE 4th Latin American Symposium on Circuits and Systems*, Cusco, Peru, 2013.
[33] Chawla, N. V., Bowyer, K. W., Hall, L. O., Kegelmeyer, W. P., SMOTE: Synthetic Minority Over-sampling Technique, *Journal of Artificial Intelligence Research*, 16, 2002, 321–357.
[34] Skryjomski, P., Krawczyk, B., Influence of minority class instance types on SMOTE imbalanced data oversampling, *Proceedings of the First International Workshop on Learning with Imbalanced Domains: Theory and Applications*, Skopje, Macedonia, 2017.

ORCID iD

Ahmad Alzghoul https://orcid.org/0000-0002-5716-6832
Anwar Jarndal https://orcid.org/0000-0002-1873-2088
Imad Alsyouf https://orcid.org/0000-0002-6200-8919
Ahmed Ameen Bingamil https://orcid.org/0000-0002-9017-0075
Muhammad Awais Ali https://orcid.org/0000-0001-9742-2653
Saleh AlBaiti https://orcid.org/0000-0002-2335-5096

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