Rotating Machinery Fault Diagnosis based on Artificial Intelligence and Vibration Analysis

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Abstract

As science and technology advance, rotary machines in modern industries become more advanced and complex, making maintenance more difficult. Multiple failures can occur in machine components, requiring monitoring and periodic maintenance. Multiple types of failure may occur, causing severe damage. As a result, modern technologies for early fault detection have developed. Vibration analysis of rotating machinery is one of the most often used condition monitoring techniques. Artificial intelligence (AI) approaches are widely used for selecting the features affected by faults. This paper discusses three different types of artificial intelligence methods, which are Artificial Neural Networks, K-nearest neighbor, and Support Vector Machine, and presents a comprehensive review of recent studies on fault diagnosis for various rotary machine elements, comprising the type of failure, feature extraction method, and classification technique performance.

Keywords

Artificial intelligence, Fault diagnosis, Artificial neural network, Support vector machine, K-nearest neighbour, Rotating machinery

1. Introduction

The use of rotating machinery in modern industries is growing more sophisticated and complicated as science and technology development, and maintenance becomes more difficult as the sophistication of these machines increases. Due to the extensive working hours with severe loads of this type of equipment, its components are subjected to multiple faults, requiring monitoring and periodic maintenance. Multiple types of failure may occur in various parts, such as bearings, gears, pulleys, shafts, etc. These faults affect the machine's performance and might result in major issues and financial losses. As a result, modern technologies for early detection of faults, including condition monitoring and fault diagnostics are being investigated and developed to ensure that the machines operate effectively. The main goals of fault diagnostic investigation are to determine the machine's normal operating condition, identify the type of fault, and predict the fault's progression. One of the most common types of condition monitoring is the vibration analysis of rotating machines. However, vibration signals are typically non-stationary, non-linear, and intermixed with noise. consequently, recent research has forecasted the dominance of AI over technological innovations [1, 2, 3, 4, 5]. As a result, the features from these signals are extracted, and artificial intelligence (AI) techniques are employed to identify the exact sensitivity of features for each type of fault. Elaborating that the authenticity and uniqueness of the extracted features are of major concern [6, 7, 8, 9].

This paper discusses the applications of three types of artificial intelligence methods in machinery faults diagnosis, which are the Artificial Neural Networks (ANN), K-nearest neighbor (KNN), and Support Vector Machine (SVM), and presents a comprehensive review of previous studies on fault diagnosis techniques for several components of rotary machines, including the type of failure, feature extraction method, and the performance of classification technique. The remaining of this paper is organized as follows. Section 2 introduces a theoretical basis of AI techniques. Section 3 reviews the applications of AI techniques in fault diagnosis of rotating machinery. Finally, the conclusions are drawn in Section 5.

2. Theoretical basis of Artificial Intelligence techniques

2.1. Artificial neural networks (ANN)

The ability of biological neurons in the human brain has inspired researchers to invent a computational structure, namely the Artificial Neural Network. Frank Rosenblatt, a psychologist, came up with the first artificial neural network in 1958. ANN is made up of a group of linked neurons that are arranged in layers to form a network. Usually, ANN consists of an input layer, an output layer, and at least one hidden layer. The number of neurons in the input and output layers is defined by the number of input and output variables required to define the problem, as well as the nature of the problem, while the process of trial and error dictates the number of hidden layers

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and neurons within each layer. Each neuron in a layer (excluding the input layer) sums the input value with the related weight to determine a single value threshold. Then, the single value threshold is added with a bias to form a net value. Finally, a non-linear activation function is applied to the net value, creating an output value, as shown in Figure 1. For a supervised learning method, input values are compared with the output values, and then a back propagation algorithm is utilized for training the ANN model by adjusting the weights between each neuron in the multiple layers [10]. Many applications have employed ANN due to its great performance [11, 12], such as pattern recognition, fault prediction and classification, speech recognition, handwritten and printed text recognition, image processing, and cancer diagnosis [13, 14, 15, 16].

2.2. K-nearest neighbour

K-NN method is one of the most basic and straightforward classification approaches. It is an instance-based learning technique based on grouping components with similar features; it determines the class category of a test case based on its k closest neighbors. Evelyn Fix and Joseph Hodges developed it in the early 1950s, and Thomas Cover extended it subsequently[17]. Every training sample in KNN classification algorithms is represented as a two-dimensional space based on the value of each of its characteristics. The testing sample is therefore displayed in the same space as its K closest neighbors. The classes of each closest neighbor of K are counted, and the class with the most votes is selected as the testing sample's classification. Typically, the distance between the testing sample and each training sample is used to estimate the K-nearest neighbors. The distance between the testing sample and each training sample is typically used to estimate the K-nearest neighbors. As shown in Figure 2, three factors influence KNN performance: K value, Euclidean distance, and parameters' normalization. KNN is particularly effective for huge training data sets, although it takes more time to compute than other methods. Along with its simplicity, it is generally used in the fault diagnosis of rotating machinery[18, 19]. Likewise, it is used in medical prediction, data mining, face recognition, and financial modeling [20].

2.3. Support Vector Machine

Support vector machines are a model of artificial intelligence technology commonly used for data classification and regression. SVMs, which Vapnik introduced in the middle of the 90s, are supervised learning techniques based on statistical learning theory. Because of their greater capacity to construct an accurate representation of the connection between the input and output from a limited amount of training material, SVMs have lately garnered much attention. An SVM, for instance, will classify a two-class dataset by locating a splitting plane that separates the area containing the data. Each side of the hyper-plane will have its own class of points. A linear boundary in the input feature space can be the best separation plane, while in other instances, a non-linear boundary might be utilized to separate the target classes when a linear boundary would not be able to successfully separate them [21, 22], as shown in Figure 3. SVMs are being used in various research fields, including biological sequence analysis, facial identification, and mechanical problem diagnostics [23]. Even though its performance varies depending on the application, SVM is a robust, effective, and simple tool for various applications such as speech recognition, texture categorization, face detection, heart disease,and fault diagnosis [24, 25, 26].

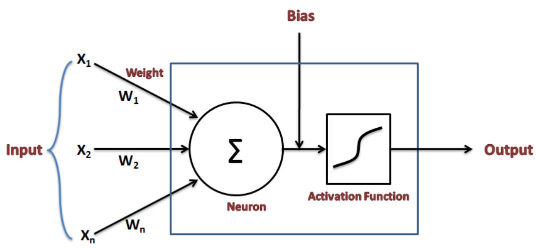


Figure 1: ANN

3. Applications of AI techniques in rotating machinery

3.1. ANN applications

Mohammed et al. [27] developed a method for crack detection using Power Spectrum Density (PSD) in a motor-shaft-generator system. The vibration signals were collected from three piezoelectric accelerometers placed in different places; one attached to the motor bearing housing, the other attached to the generator bearing housing, and the last placed in the center of the shaft covering guard. The vibration signals were fed to the charge amplifiers, which are connected to an analog to digital converter involving a dSPACE-DS1102 DSP controller. Data acquisition instruments were included in the DSP program for acquiring data from the model and are supported by Matlab software. The peak position component method (PPCM) was used to identify the highest peaks and their positions from the PSD analysis and form a matrix for the input data of ANN. The Figure 4 shows the vibration spectrum of the first accelerometer. A multilayer

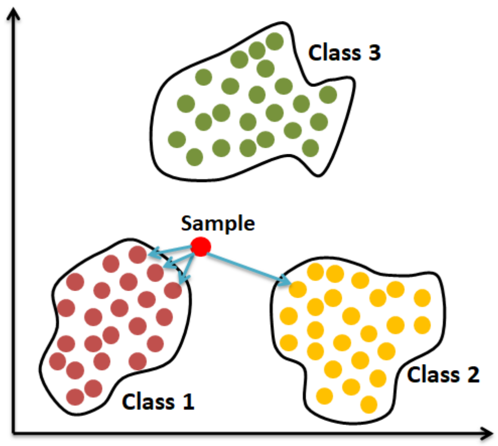


Figure 2: K-NN

Table 1
ANN designing parameters[29]

Number of input layer neurons	24
Number of hidden layer neurons	17
Number of output layer neurons	11
Number of hidden layers	1
Hidden layer activation function	Sigmoid
Output layer activation function	Linear
Training algorithm	To be identified
Learning rate	0.05
MSE stopping criteria	10e−4
Minimum performance gradient	10e−5
Maximum number of epochs	50,000

perceptron ANN for each accelerometer was employed to classify four health cases: normal shaft and a shaft with 40%, 50%, and 60% pre-crack. The Levenerg-Marquart learning algorithm was used as a training method. ANN for the data of the first and the third accelerometer distinguished four conditions with 100% accuracy, and for the second accelerometer data, it achieved 99.7% accuracy in fault classification.

Ali et al. [28] proposed a feature extraction method based on Empirical Mode Decomposition (EMD) energy entropy and ANN to classify seven bearing conditions: a healthy condition, degraded roller, degraded outer race, degraded inner race, failure roller, degraded outer race, and failure inner race. The EMD approach is based on the simple assumption that each signal is made up of various simple intrinsic modes of oscillations, named intrinsic mode functions (IMFs). This adaptive decomposition approach is especially useful for non-linear and non-stationary signal analysis. The data was collected from high-sensitivity accelerometers attached to four bearings. Ten time-domain features were extracted in addition to the EMD energy entropy to create a feature vector for ANN input layer. The three zones of run-to-failure vibration signals are shown in Figure 5 for the outer race failure. A statistical criterion was applied to decide the most effective IMFs for bearing diagnosis. A back-propagation algorithm was employed for training the ANN. The proposed method was able to classify bearing states with an average accuracy of 93%.

Jaber and Bicker [29]developed an intelligent bearing fault diagnosis system using the discrete wavelet transform (DWT). Inner and outer races bearing faults were simulated on the elbow joint of the PUMA 560 robot, which is shown in Figure 6. An Electrical Discharge Machine (EDM) was used to create the faults in the bearing's elements. A 14-bit USB-6009 National Instrument data acquisition is used to collect signals from three calibrated single-axis ADXL001 accelerometers. Labview, Matlab, and C language software were used for data acquisition to extract and analyze vibration data. After the DWT, the statistical features were extracted and used for designing ANN. Only the standard deviation (STD) was chosen as an input to ANN as it was the most sensitive feature for bearing faults. A multilayer perceptron neural network was utilized for fault detection. Table 1 shows the parameters used for designing the neural network. ANN was trained to differentiate between various types of robot-bearing faults and achieved a remarkable level of fault diagnosis with an accuracy of 100%.

Luwei et al. [30]used frequency domain data fusion to classify rotating machine faults with the help of ANN. From four sensors placed on each bearing, higher-order spectra components were extracted at different speeds and various fault conditions. ANN was performed in two stages. In the first stage, five types of one-against-all (OAA) ANN were trained using the Resilient Back-propagation learning algorithm to specify the presence of five faults: bent shaft, loose bearings, shaft misalignment, cracked shaft, and rubbing in the shaft. For the first and second ANN, the accuracy was 100% and very good classification accuracy for the remaining ANN. In the second stage, all-against-all (AAA) ANN was performed to determine the particular fault type using the same learning techniques as in the first stage. The receiver operating characteristics (ROC) curve was utilized for estimating the accuracy of AAA network classification (see Figure 7). The classifier's performance is measured using the area under the curve (AUC).The larger AUC value means its performance is better (perfect classification). The approximate AUC values for the five fault conditions mentioned were 1, 0.992, 0.999, 0.986, and 0.992, respectively, indicating excellent classification performance.

Jaber and Ali [31]developed a fault detection system for a pulley-belt rotating test rig. Two ADXL335 vibra-

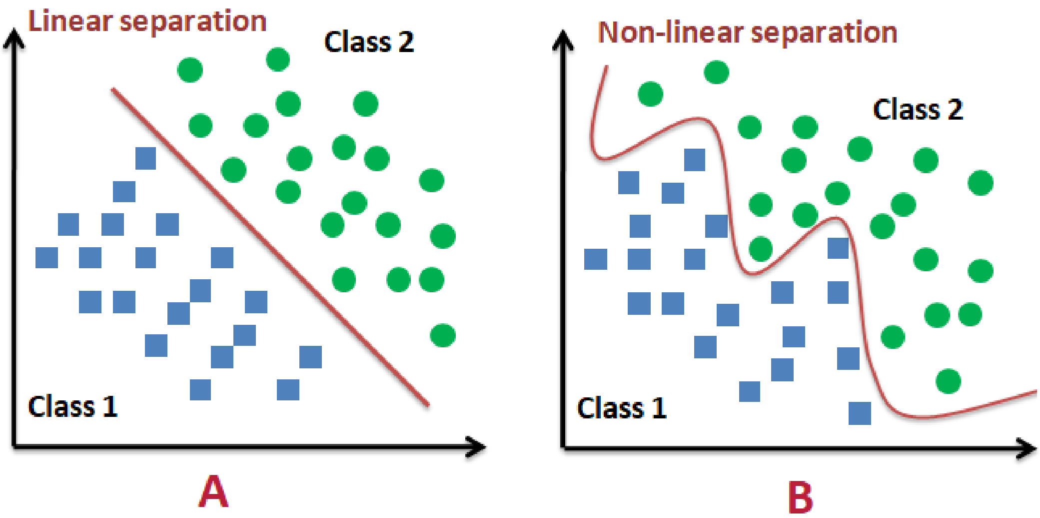


Figure 3: SVM A.Linear B.Non-linear

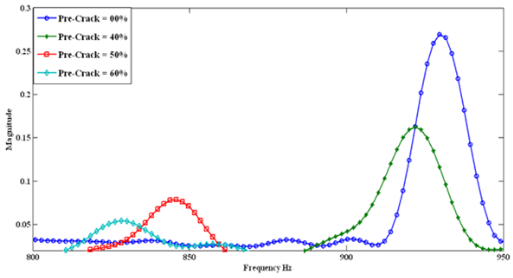


Figure 4: Vibration spectra for different cut depths at frequency range of 800 to 950 Hz[27]

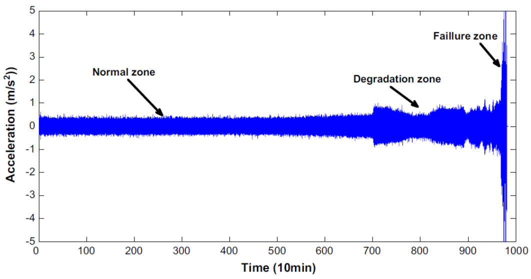


Figure 5: Bearing run-to-failure vibration signals[28]

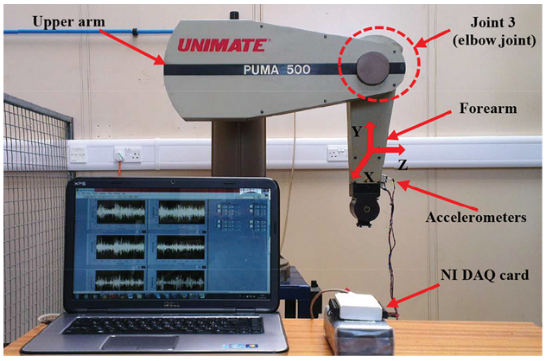


Figure 6: PUMA 560 robot[29]

tion sensors placed on each bearing were employed to extract vibration signal features. These sensors are wired to an Arduino MEGA 2650 based on the ATmega 2560 microcontroller. The Arduino microcontroller was used as a low-cost data acquisition device. For ANN training data, five time-domain features from each sensor were extracted as input data: the mean value, RMS, skewness, kurtosis, and standard deviation. Also, five different faults were studied: unbalance, driving pulley fault, a side cut-out in the belt, belt slippage, and misalignment in pulleys. Labview software was employed for collecting vibration signals and extracting their data features. The extracted features are then uploaded to Matlab to design a multilayer ANN. As a result, the designed ANN was able to identify each fault perfectly. The performance plot is shown in Figure 8.

Sharma et al. extracted [32]frequency-domain features from the vibration signals of a three-phase induction mo-

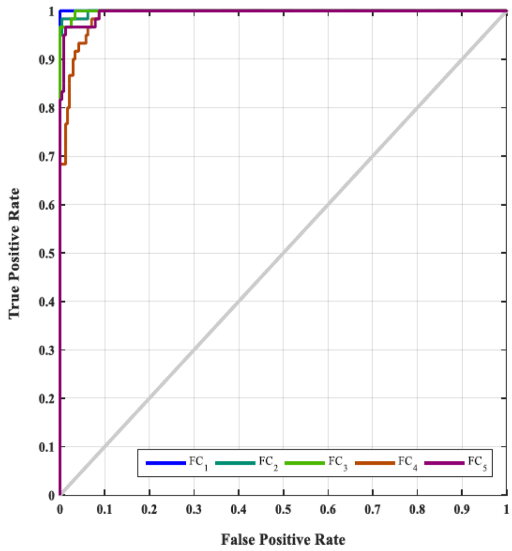


Figure 7: ROC plot[30]

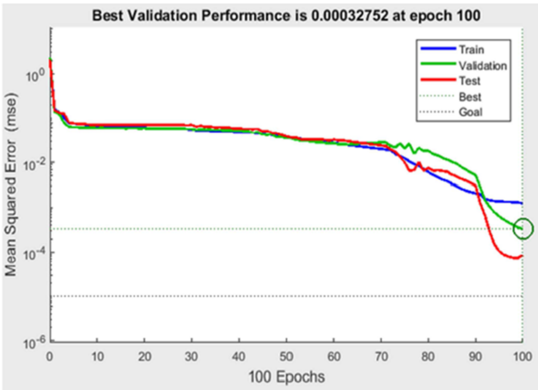


Figure 8: ANN perfomance plot[31]

tor. The vibration signal was collected from a single-axis accelerometer. The extracted features are used to classify three bearing conditions: healthy, inner race defect, and outer race defect. The electric discharge machine (EDM) was used to create 2 mm holes in the inner and outer races. For each condition, five features are extracted from the frequency domain: mean frequency, median frequency, lower band power, upper band power, and band power ratio. The acquired features were normalized to increase classification accuracy and distinguish any bias. As a result, ten sets of five normalized characteristics were collected for each bearing condition. Six sets were used for training ANN, while the remaining four were used for testing. A single-layer ANN was utilized for fault classification. To train ANN, two different techniques, scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM), are used, and their performance is compared. For greater network sizes, the SCG algorithm outperforms the LM algorithm, and the proposed ANN could identify each fault condition with great accuracy.

Rao and Reddy [33]used wavelet transforms to identify a method for detecting irregularities such as open cracks or grooves on a rotating stepped shaft with several discs. The vibration signals were extracted from the displacement sensor and transformed into discrete and continuous wavelet transforms (DWT and CWT) at a specific rotor speed. The detailed process and techniques of analysis are shown in the Figure 9. The difference in wavelet coefficients of rotors with and without grooves is analyzed to identify the damage or groove locations. A reduction in the shaft's diameter was used to model the cracks and grooves classified as radial cracks. A numerical analysis of various cases was used to find each case's first five natural frequencies. In this research, a three-layer feed-forward ANN was utilized. The DWT coefficient of various crack locations and depths was used to train ANN. The Levenberg-Marquardt algorithm is employed to train ANN. Consequently, the overall prediction accuracy of the developed ANN is 99.53%. It was able to detect cracks as small as 1% of their diameter.

Espinoza and Sinha [34]developed a smart vibration-based machine learning model that uses ANN. The model is then tested blindly to detect the rig's healthy and faulty conditions when running at different speeds. The test rig has four accelerometers placed on four bearings. Four scalar features were extracted from vibration data samples and arranged in three scenarios. In the first scenario, each sample is obtained randomly from an accelerometer from only one bearing. The second scenario considers the measurement from only one bearing with a fixed location. The third scenario considers a simultaneous vibration signal collection from all four bearings. The scalar features are: root mean square (RMS),kurtosis, variance, and skewness. Spectral analysis is also used to examine the dynamic behavior of the rig under various conditions. ANN of multilayer perceptron (MLA) based on the back propagation was utilized to classify acquired data. Depending on the results obtained in the particular scenario, either Bayesian regularization functions or scaled conjugate gradient are used to train the network. The results found that the first scenario observed has an almost 25% chance that the health conditions will be misdiagnosed as faulty. The second scenario performs relatively better than the first because consistent data from a specific bearing point exposes some features of machine behavior. The third scenario indicates the best performance, with 100% accuracy. The model was trained at a rotational speed of 1800 rpm and was tested blindly using test rig data at 2400 rpm without training. The results showed

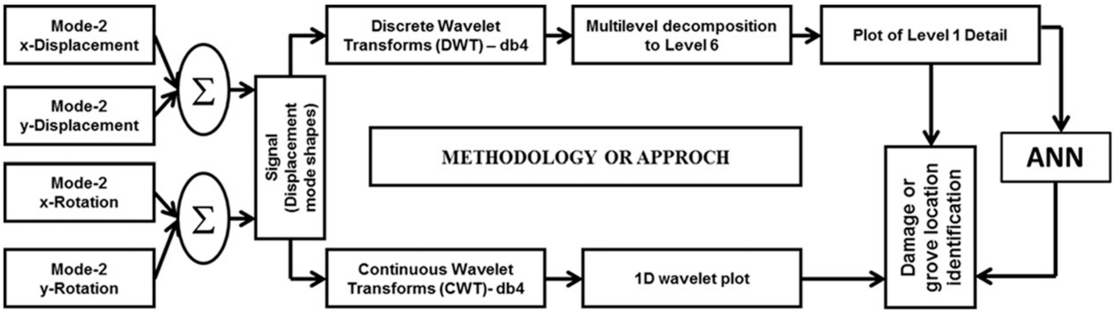
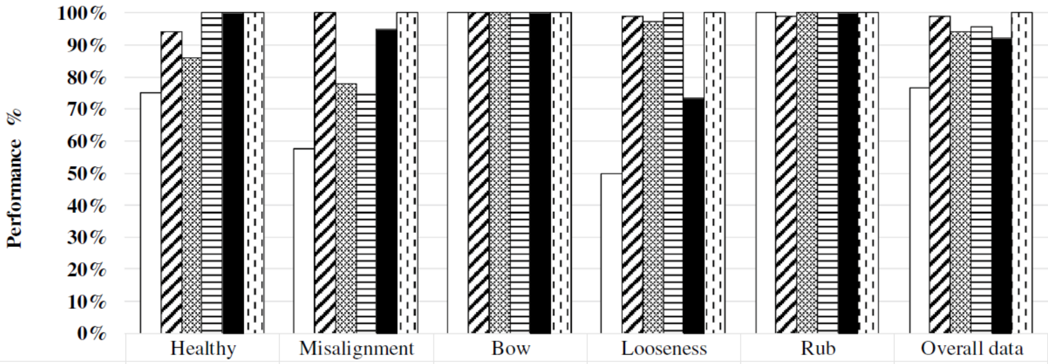


Figure 9: Analysis block diagram[33]



	Healthy	Misalignment	Bow	Looseness	Rub	Overall data
S1_30_30	75.00%	57.60%	100.00%	50.00%	100.00%	76.50%
S2_30_30 (B1)	94.20%	100.00%	100.00%	99.00%	99.10%	98.90%
S2_30_30 (B2)	86.00%	77.70%	100.00%	97.40%	100.00%	93.90%
S2_30_30 (B3)	100.00%	74.40%	100.00%	100.00%	100.00%	95.70%
S2_30_30 (B4)	100.00%	95.00%	100.00%	73.40%	100.00%	92.10%
S3_30_30	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Figure 10: Overall performances, training and testing at 1800 RPM[34]

100% accuracy in machine condition diagnosis, as shown in Figure 10.

3.2. K-NN applications

He et al. [35] proposed a two-step plastic-bearing fault diagnostics method. This approach investigated cage fault, rolling element fault, and surface contact faults in the inner and outer race. Two accelerometers attached to the surface of the bearing house were used to collect vibration data with NI PCI-4472B data acquisition. Frequency domain features were extracted from vibration signals by the envelope analysis technique and fed to the statistical classification method. The first step only used the statistical classification method to classify the outer race fault, as shown in Figure 11. As a second step, entropy and distance (time-domain features) were extracted by EMD and used for training the KNN to detect the remaining faults. The results showed an accuracy of 100% for the first step, and the overall accuracy exceeded 90% for the second step.

Pandya et al.[36] presented a fault classification method based on acoustic emission for bearing health monitoring. Five conditions were examined: healthy bearing, outer race, inner race, ball, and combined defect. The data was collected using an acoustic emission sensor installed on the housing of the test bearing and an OROS 3 SERIES acoustic analyzer, and it was processed using NVGATE software. The Hilbert–Huang Transform (HHT) was employed in this method. Band-pass filtering with empirical mode decomposition was performed on the collected signals, and IMFs were optimized. IMFs were used to extract nine time-frequency domain features: peak, mean, RMS, kurtosis, crest factor, impulse

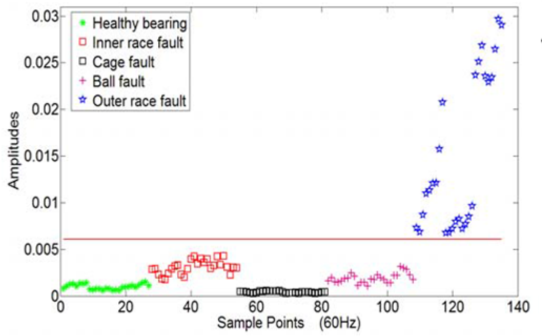


Figure 11: Frequency domain features[35]

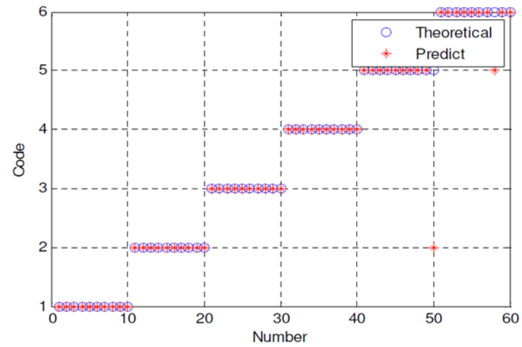


Figure 12: Theoretical and predict classification[37]

factor, shape factor, ring down count, and energy. Multiple supervised machine learning techniques were used for the fault classification using WEKA software, and the weighted KNN was the most efficient technique. Then, a modified KNN method based on an asymmetric proximity function (APF) was developed to improve classification accuracy even further. The results demonstrate that the proposed APF-KNN algorithm with optimized features surpasses the KNN method by 96.6667%.

Wang et al.[37] developed a bearing fault diagnosis method based on combining the Kernel Principal Component Analysis (KPCA) with the KNN algorithm. KPCA is a method for applying the kernel method to generalize linear Principal Component Analysis (PCA) to non-linear cases. An electro-discharge machine was used to artificially seed a single point fault in the bearing inner race, outer race, and rolling element. The accelerometers were used to sample vibration signals positioned at the drive end. The extracted features are the clearance factor, the greatest peak, impulse factor, kurtosis, mean absolute difference, peak factor, peak-to-peak value, rad amplitude, RMS value, skewness, variance, waveform index, and kurtosis value. KPCA was applied to the extracted signal and used to define KNN. As a result, this method could classify bearing faults with an accuracy of 96.67%, as shown in Figure 12.

Safizadeh and Latifi[38] developed a unique bearing fault diagnostic approach based on KNN and a combination of an accelerometer and a load cell. This method was used to classify three bearing conditions: a healthy, outer race defect, and ball defect. Spark erosion techniques were employed to create the defects in bearing elements. A Piezoelectric IMI 608A111 accelerometer was used to collect vibration data, and a SEWHACNM SM601 load cell was used with a DACELL DNAM100 amplifier to measure the load. The output of each sensor was connected to the NI-USB-9233 DAQ. Two frequency domain features were extracted (amplitude in ball pass frequency of the outer race and ball spin frequency) with ten time-domain features (RMS, standard deviation, skewness, crest factor, kurtosis, peak level, K factor, mean value, variance, and median). PCA was used to reduce features. The waterfall fusion model was used as the fusion approach to merge sensor data effectively. The results of the experiments indicate that the proposed method improves fault identification and diagnostic accuracy, as shown in the Table 2.

Tain et al.[39] proposed a method for detecting and monitoring bearing faults in an electric motor. Four faults were investigated: the outer race, inner race, rolling element, and cage fault. Vibration signals were extracted from two accelerometers installed on the bearing housing and decomposed in the frequency domain to obtain a set of sub-signals. Different fault features were extracted based on cross-correlation and spectral kurtosis (SK). The principal component analysis (PCA) technique was utilized to reduce the redundancy of fault features. KNN is used to combine the features with a health index, which is further analyzed for defect detection. Following various experiments, a gearbox was mounted to create signals that mask bearing signals and cause false-negative detection. As a result, this method was effective in fault classification and isolating bearing signals from gear signals to detect previously unknown faults.

Gohari and Eydi [40] used KNN to identify shaft unbalance in multi-disc rotors and compared the results with the Decision Tree (DT) Algorithm. Various masses were mounted in three radiuses to create an unbalanced condition. Two ADXL335 accelerometers attached to the shaft were employed to collect vibration data from the test setup. A data acquisition device (ADVANTECH 4711A) was used for data collection. A program was developed in Labview Software for signal processing and recording, and filtering of unwanted noises. Eight statistical features were extracted from time and frequency domain signals: the peak value, skewness, average, RMS error, absolute average, the peak of average ratio, crest

Table 2
Effectiveness of each technique[38]

Bearing condition	Accelerometer detection	Load cell detection	Data fusion technique
Healthy	Outer race fault	Healthy	Healthy
Outer race fault	Outer race fault	Outer race fault	Outer race fault
Outer race fault	Outer race fault	Outer race fault	Outer race fault
Outer race fault	Outer race fault	Outer race fault	Outer race fault
Ball fault	Ball fault	Outer race fault	Ball fault
Ball faul	Ball fault	Outer race fault	Ball fault

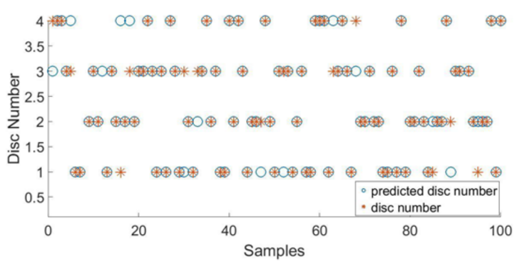


Figure 13: KNN perfomance in unbalance locating [40]

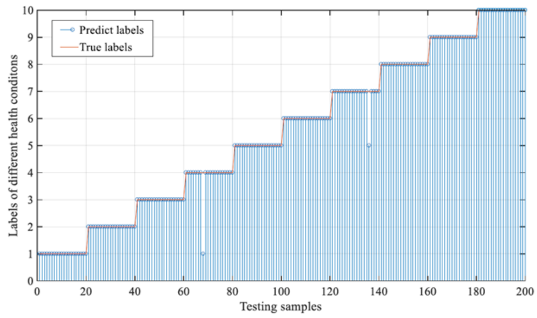


Figure 14: Classification accuracy of EKNN[41]

factor, standard deviation, kurtosis factor, and peak in the frequency domain. The extracted features were fed to the KNN and the DT algorithms. The study revealed that the KNN surpasses the Decision Tree in estimating unbalance parameters and can classify the faults with an average accuracy of 86.6%. The Figure 13 shows the KNN performance of unbalanced locating.

Lu et al. [41] proposed a fault diagnosis method for rotating machinery called Enhanced K-Nearest Neighbor (EKNN), based on KNN and spare coding. This method investigated four bearing conditions: normal conditions, inner race faults, outer race faults, and roller faults. An accelerometer attached to the bearing was utilized to collect vibration signals. Fast Fourier Transform (FFT) was applied to gather frequency domain features for creating the training dataset. Then, discriminative features were extracted by applying Spare Filtering (SP) to the training dataset. Finally, the discriminative features were optimized by the L-BFGS algorithm and transferred into the feature vector. The feature vector was fed to the EKNN and the traditional KNN. As shown in Figure 14, the proposed method could classify faults with 99% accuracy, surpassing the traditional KNN.

Li et al. [42] presented a bearing fault detection method based on the Orthogonal Wavelet Transform K-Nearest Neighbor Algorithm (OWT-KNN). The OWT can decompose the signals into the equivalent local detail signals at each scale in terms of time and frequency. The Figure 15 shows the flowchart of (OWT-KNN). EDM was used to implant faults in the inner race and the ball. The vibration signals were collected from three accelerometers placed in different positions and subjected to a multilayer orthogonal wavelet transform. Peak-to-peak values were found on each scale to create the feature vectors. Lately, the created feature vectors are utilized to generate the classification model and train the KNN classifier. The classification results show that this approach can achieve a 100% fault classification.

3.3. SVM Applications

Jiang et al. [43] used SVM and multi-sensor information fusion to develop a fault diagnosis approach for rotating machines. This approach investigated different cases for machine elements: three conditions for the gears (normal, missing, and chipped tooth), four conditions for the bearing (normal, defect, inner race defect, and outer race defect), and three conditions for the shaft (normal, 3mm crack depth, and 5mm crack depth). IMI 608A11 accelerometers collected vibration signals with the Dewetron data acquisition system. Twelve time-domain features were extracted for each condition, including mean, peak, amplitude square, RMS, root amplitude, standard deviation, skewness, kurtosis, waveform factor, pulse factor, and margin factor. The multi-sensor information fusion model was utilized to establish a mul-

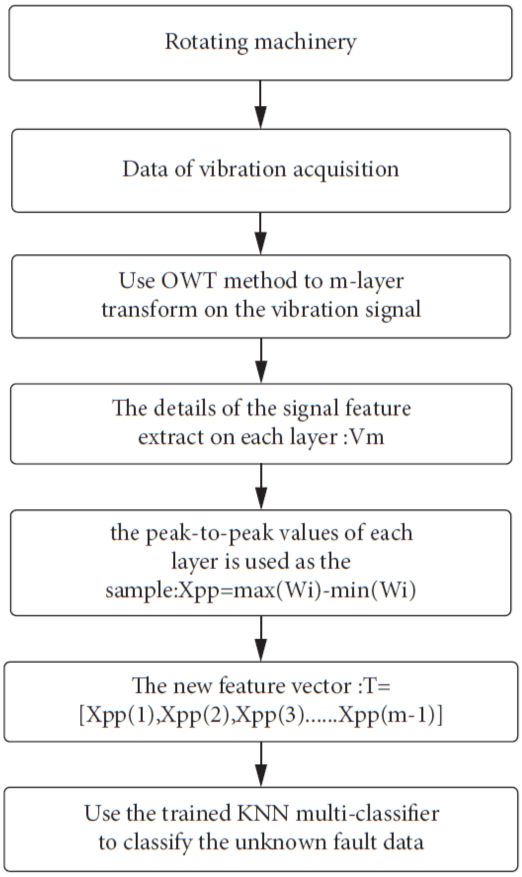


Figure 15: OWTKNN Flowchart[42]

tidimensional vector by extracting the same character from different sensors. The SVM was applied to each case for fault classification. According to the results, the highest accuracies achieved by the SVM classifier were 93.33%, 100%, and 99.67% of gears, rolling bearing, and cracked shaft cases, respectively.

Tabrizi et al. [44] proposed a combined automatic method for detecting tiny defects on roller bearings that uses Wavelet Packet Decomposition (WPD) with Ensemble Empirical Mode Decomposition (EEMD). Tri-axial accelerometers were used to collect vibration data at three different shaft speeds and external loads. Afterward, the original signals were extracted from the noisy signals using WPD, and EEMD was applied to decompose the vibration signals into IMFs. Then, a feature vector was created from the normalized IMFs energy and fed to the SVM. With Daubechies DB10 Denoising, the proposed method was able to detect the defects with 100% accuracy.

Senanayaka et al. [45] presented a method based on the SVM algorithm for the early detection and classifica-

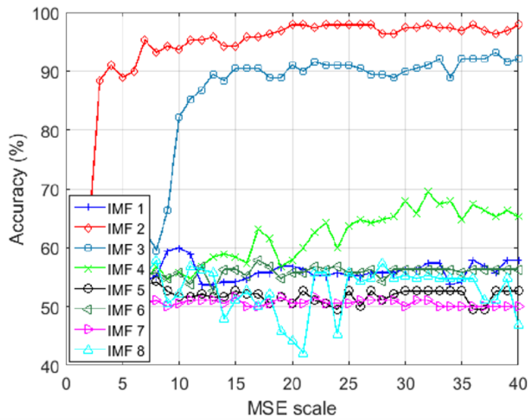


Figure 16: Accuracy results[46]

tion of bearing faults. This method studied the following cases: healthy, inner and outer race degradation, and inner and outer race failure. A run-to-failure test provided the data for this investigation. Vibration data was collected by four accelerometers attached to four bearings. The RMS was calculated from the collected time-domain signals; the Hilbert transformation was used to detect the envelope of a time-domain signal. Then, the envelope signal is converted into the frequency domain using the fast Fourier transformation. Fault-specific frequencies are found in the frequency spectrum, and energy associated with each frequency band is collected. Four frequency domain features were extracted in addition to RMS, and all these features were used to train the SVM classifier. The obtained classification accuracy for healthy, inner and outer race degradation and inner and outer race failure is 99.3%, 86.2%, 97.7%, 87.8%, and 84.2%, respectively.

Huo et al. [46] proposed a fault diagnosis method for rotating shafts based on Multi-Scale Entropy (MSE). This method investigated two shaft conditions: healthy and 4 mm cracked shaft. The vibration data for each condition were collected from the PT 500 machinery diagnostic system. WPD and EMD were employed to decompose the signals to obtain reconstruction vectors and IMFs data sets. Afterward, Shannon entropy criteria were utilized to select the largest entropy in the decomposed vectors. The MSE method was then used to define fault symptoms and create feature vectors. Finally, the feature vectors were fed to the SVM for fault classifying. Experimental results showed that WPD combination with MSE achieved a classification accuracy of 97.3%, whereas EMD combination with MSE had a better classification rate of 98.5%. The Figure 16 shows the accuracy results using EMD, MSE, and SVM.

Gu et al. [47] developed a fault diagnosis for rolling bearings based on SVM and PCA. Four deep groove ball

Table 3
Classifier Results[49]

Method	Best Model	Accuracy	Training time
10% Data Validation	Cubic SVM	95.6%	15.947
15-Fold Cross Validation	Quadratic SVM	94.7%	60.62
10-Fold Cross Validation	Quadratic SVM	94.7%	19.401
5-Fold Cross Validation	Quadratic SVM	93.8%	10.283

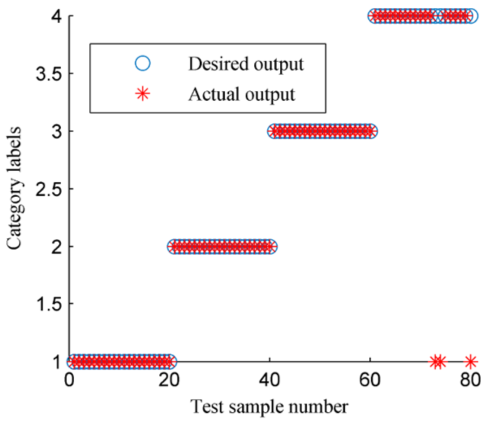


Figure 17: Classification results[48]

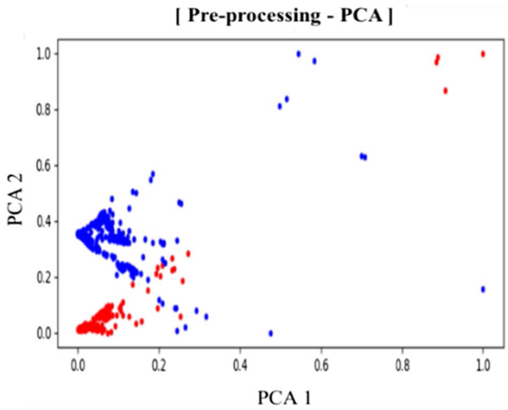


Figure 18: PCA using the pre-processing data[50]

bearings conditions were examined: normal condition, roller flaking, inner ring flaking, and outer ring flaking. An IMI 601A1 accelerometer was used with a UUA300 data acquisition card for vibration signal monitoring. A wavelet packet was used to decompose the collected signals and create the feature vectors. Then, the feature vectors were integrated by PCA and fed to the SVM classifier. Different kernel functions and SVM classification algorithms were used to compare and verify the influence of kernel functions and classification algorithms on the accuracy of the SVM classifier. Finally, the developed method achieved a performance of more than 97%. Pang et al. [48] proposed a novel rotor fault diagnosis method based on Characteristic Frequency Band Energy Entropy (CFBEE) and SVM to investigate three rotor faults: imbalance, rubbing, and oil film instability failures. The shaft vibration signals were collected using two eddy-current sensors attached to the mounting blocks. The time-frequency features were decomposed by improved singular spectrum decomposition (ISSD) into a series of singular spectrum components (SSCs). The Hilbert Transform (HT) demodulates the obtained SSCs to determine their instantaneous amplitude (IA) and instantaneous frequency (IF). IF and IA reflect the time-frequency information of SSC, and the Time-Frequency Spectrum (TFS) can be derived by integrating the time-frequency information of all SSCs. Time-frequency entropy (TFE) was calculated from TFS to build CFBEE. Then a feature vector was obtained from calculated CFBEEs and fed to the SVM, and the SVM was able to classify rotor faults, as shown in Figure 17.

Parmar and Pandaya [49] developed a fault diagnosis method for cylindrical bearings based on SVM. Four conditions were investigated: healthy bearing, defects in the inner race, outer race, and the rolling element (defect sizes are around 0.5 mm). A three-axis sensor was used to collect vibration signals, and CoCo-80 Dynamic Signal Analyzer processed the collected signals. The collected signals were analyzed by wavelet packet decomposition (with mother wavelet 'sym20), then mathematical parameters were extracted, such as mean value, mean square value, skewness, kurtosis, standard deviation, crest factor, and energy. Then these parameters were normalized and fed to two classification methods: ANN and SVM. The results showed that ANN classification accuracy did not exceed 90%, while the SVM (cubic model) was able to classify faults with 95.6% accuracy. Table 3 shows the SVM classification results.

Lee et al. [50] developed a method to detect misalignment in a rotating machine shaft based on the SVM algorithm. A gyro vibration sensor was attached to the shaft's end between the rotor and the shaft to collect normal and abnormal vibration data. The SVM was applied to the collected data without preprocessing, and its classification accuracy was 49.71%. Then, the FFT technique was used to extract the power spectrum from the time domain data, and the PCA algorithm was used to reduce the dimensions (see Figure 18). The SVM algorithm was applied to the processed data and could predict the normal and abnormal conditions with an average accuracy of 98.8%.

4. Conclusion

Rotating machinery fault diagnosis plays an important role in saving maintenance costs, downtime, and safety risks. In this study, a variety of AI approaches for rotating machinery diagnostics are discussed. The theoretical approach and fault diagnostic application of ANN, K-NN, and SVM have been reviewed. This study advises performing feature selection on the feature vector before employing AI classification techniques to identify the most sensitive feature for each fault case. Further, this study suggest using other AI classification techniques such as, Random Forest, Decision Tree, Naive Bayes, and Deep learning. As AI techniques grow more sophisticated, it is expected that AI approaches will remain interesting and effective for detecting faults in rotating machinery.

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