Frequency domain tensor-based 1D-convolutional neural network and multilinear principal component analysis for machinery fault detection

Ayantha Senanayaka[1], Qing Liu[2], Nayeon Lee[3], Sungkwang Mun[4], Amin Amirlatifi[5], Joe Jabour[6], Thomas Arnold[7], Maria Seale[8]

[1,2,3,4] *Center for Advanced Vehicular Systems, Mississippi State University, Starkville, MS, 39762, US*

aus20@cavs.msstate.edu
ql90@cavs.msstate.edu
nayeon@cavs.msstate.edu
sungkwang@cavs.msstate.edu

[5] *Swalm School of chemical Engineering, Mississippi State University, Starkville, MS, 39762, US*

amin@che.msstate.edu

[6,7,8] *U.S. Army Engineer Research and Development Center, Vicksburg, MS, 39180, US*

joseph.e.jabour@erdc.dren.mil
maria.a.seale@erdc.dren.mil
thomas.l.arnold@erdc.dren.mil

ABSTRACT

Challenges in detecting machinery faults, particularly in multivariate sensor environments, necessitate advanced feature extraction and classification techniques. This study introduces a novel approach that combines Multilinear Principal Component Analysis (MPCA) with a 1D-Convolutional Neural Network (1D-CNN) for efficient fault detection. By constructing Frequency Domain (FD) tensors from multivariate sensor data and applying MPCA for dimensionality reduction, our methodology enhances the capabilities of a 1D-CNN in feature learning and fault classification. The efficacy of this approach is validated through experiments on a Machinery Fault Simulator (MFS) with acoustic and vibration sensors, demonstrating notable improvements in fault detection accuracy compared to benchmark methods. The study results demonstrate that the proposed approach exhibits high accuracy in identifying machine fault conditions and outperforms the benchmark methods. The findings of this study have significant inferences for machine fault detection and fill the gap of more effective and reliable techniques in this domain.

Keywords: Predictive maintenance, Prognostic health monitoring, Real-time fault diagnosis, Condition monitoring, Rotating machinery faults, Multilinear principal component analysis, 1D-convolutional neural network

1. INTRODUCTION

The process of identification of malfunctions or faults in machinery systems is critical for maintaining proper equipment health. The primary objective of this process is to minimize downtime, lower maintenance costs, and ensure safe and efficient machinery operations (Nallusamy & Majumdar, 2017). Industrial practitioners utilize various methods and tools for monitoring and diagnosing machinery faults. Among these practices, data-driven techniques have proven to be the most efficient and effective compared to visual inspections or regular tests (Gonzalez-Jimenez et al., 2021). In the last two decades, advancements in sensing devices have led to a revolution in their capacity for sensing and computation efficiency, enabling real-time monitoring and diagnosis to improve the system's health and ensure productivity (Javaid et al., 2021; Kalsoom et al., 2020). Researchers have also found that multi-sensor information can achieve more accurate fault diagnosis, providing comprehensive information on the machinery system's operation compared to using single sensor information. This is known as multi-sensor fusion (Liton Hossain et al., 2018). Acoustic, vibration, pressure, temperature, and current trends are frequently used signals for multi-sensor fusion (Mallegni et al., 2022). After collecting data from multi-sensors, extracting the essential features from the data is the next vital step. This process helps ML algorithms to identify relationships by providing appropriate input features. By accurately determining the essential features, the ML algorithms can successfully identify patterns and trends of data and can assist with a productive way of decision-making about the machinery system (Aguileta et al., 2019; Kullu & Cinar, 2022; Zoghlami et al., 2021).

The decisions about machinery systems depend heavily on the features extracted from the collected multi-sensor data (Y. Liu et al., 2019). However, obtaining significant knowledge from this data for use in ML models can be complicated by several factors. These factors incorporate correlation effects, extreme noise associated with various conditions, data inadequacy, the complex nature of machinery-related catastrophic faults, and various fault types or combinations of them (Tripathi et al., 2021). These factors irritate the feature extraction procedure, eventually lowering decision-making accurateness and identifying the source and cause of any faults. Therefore, it is imperative to pay significant attention to the feature extraction of multi-sensor fused data to ensure the decision-making process's precision. Over the years, Principal Component Analysis (PCA) has been widely used as an unsupervised linear feature extraction and reduction technique for fault diagnosis problems in machinery systems (Chen et al., 2018; Jollife & Cadima, 2016). However, using PCA in high-volume tensor objects necessitates vectorization, growing computational cost, and memory requirements. Multilinear Principal Component Analysis (MPCA) is a process for dimensionality reduction that serves on a tensor object rather than its vectorized arrangement, providing a novel approach (Lu et al., 2008). A few research have been conducted using this technique in the fault diagnosis domain and showed that it is dependable and enhances the accuracy with multi-sensor data captured from machinery systems (Guo et al., 2021;Al Mamun et al., 2023; Fu et al., 2020; Hu et al., 2021).

Convolutional Neural Network (CNN) architecture and its variations have been widely used in fault diagnosis (Jiao et al., 2020; Jing et al., 2017). Most of the research in this domain focused on using CNN-based approaches to identifying faults in machinery systems using single-sensor-based analysis (Ince et al., 2016). These studies have converted time-based signals into fault-related images and then used these images to analyze faults (Ma et al., 2019). However, there needs to be more research on analyzing high-volume data obtained from multi-sensors in machinery systems, which is essential for accurate decision-making. A few studies have attempted to identify faults using deep CNN models on raw vibration data obtained from multi-sensors (H. Chen et al., 2019; Lee et al., 2017). Still, highly redundant noise in the raw data and the effects of correlations between the multi-sensor data can make the fault identification process computationally intensive and less accurate. Few researchers have explored tensor data analysis using MPCA and CNN to overcome the issues mentioned above (Y. Guo et al., 2021). However, the increased number of heterogeneous sensors equipped to record the system behaviors or high-volume data may reduce the ability of fault identification using this method. Furthermore, utilizing multivariate sensor types such as vibration, acoustic, temperature, etc., limited this approach's performance.

There is currently a high demand for intelligent and dependable techniques that can be used to identify faults in machinery systems using multi-sensor data. To reach this goal, a novel improvement to the previous methodological approach is proposed (Al Mamun et al., 2023). The contribution of this study is two-fold. Firstly, an improved version of method for machinery fault diagnosis is introduced. The methodology proposes using MPCA to extract low-dimensional features from FD tensors built with multivariate sensor signals and a supervised 1D-CNN architecture for identifying faults. Secondly, a performance comparison study is used to show the advantage of using MPCA over traditional PCA for tensor data analysis on machinery fault identification. Comparison analysis combines state-of-the-art ML methods with features extracted from MPCA and PCA on FD tensors for multi-sensor fused data. Also, compare the relative performance of previous and new methods for benchmarking. A case study about rotating machinery fault classification using MFS sensor data is conducted to compare the performance. It has been demonstrated that the suggested approach outperformed the traditional PCA-based benchmarking ML methods and was trustworthy for detecting machinery faults using multi-sensor tensor-based data.

The paper is structured in the following way: Section 2 presents the literature review of multi-sensor data-based fault diagnosis, MPCA-related studies, and recent studies of machinery fault diagnosis. Section 3 outlines the proposed methodology, which describes the two steps involved. Section 4 analyzes the proposed methodology's experimental performance in rotating machinery experiments and compares it with existing feature reduction techniques using popular ML algorithms. Finally, Section 5 presents a conclusion and suggests possibilities for future research.

2. LITERATURE REVIEW

2.1. Multi-sensor fusion-based fault diagnosis

Sensor fusion techniques are widely applied to combine data collected from multi-sensor to obtain a more understandable and reliable perception of a machinery system. Data-level fusion, feature-level fusion, and decision-level fusion are the three types of fusion techniques commonly used in machinery health monitoring and diagnosis (Al Mamun et al., 2023). Data-level fusion combines multi-sensor data into a comprehensive dataset synchronized in time or frequency domain to capture correlations between different sensors. Researchers combined raw vibration signal from multiple datasets and increased data size prior to the process of feature learning and training (W. Zhang et al., 2018). Also, ML models are utilized to fuse data for pattern recognition instead of manually combining data (Banerjee & Das, 2012; Jiao et al., 2019). A recent investigation shows that feature-level fusion provides more accurate and detailed information for diagnosis problems compared to data-level fusion (Z. Chen & Li, 2017). Instead of combining raw signal data, feature-level fusion aims to extract meaningful features from raw data to generate more informative representation of the machinery system. For example, extracting time-domain statistical features, spectral features, then merge all features to establish a dataset for fault detection (L. Guo et al., 2016; Xia et al., 2018). Decision-level fusion involves analyzing and combining decisions from multiple classifiers, generating an outcome at a higher level. Techniques such as fuzzy rules, Min rule, Compromise rules, one-vs-all lookup tables, etc. (S. Chen et al., 2020; Le Bris et al., 2019). (Niu et al., 2007) designed a decision fusion system for motor fault diagnosis by generating decision vectors and feeding the vectors to multi-agent classifiers. (X. Liu et al., 2009) incorporated feature-level fusion and decision-level fusion using fuzzy measures and fuzzy integrals for accurate rolling bearing fault diagnosis.

Multiple studies have shown that sensor fusion techniques are highly effective in diagnosing faults in machinery systems. These methods involve placing sensors at various locations within the system environment to represent the system comprehensively. This approach provides a more complete and accurate view of the system's performance, improving overall operational efficiency.

2.2. Multilinear principal component analysis

PCA is one of the most widely used algorithms for feature extraction and dimension reduction. It creates a linear projection of the original data onto a new orthogonal coordinate system. Because of the limitation of PCA on high dimensional data, such as high computational and memory demand and ignorance of high order dependencies present in the original data (Z. Chen & Li, 2017), variations of PCA are developed (Choi et al., 2005; Wang et al., 2017). Among the variants, multilinear principal component analysis (MPCA) (Lu et al., 2008) is more efficient when dealing with higher dimensional data. It extends feature reduction in feature extraction and data reduction by directly operating on the original high-order tensors to decompose them into n-mode core components and performing PCA in each mode. In the study of (Paynabar et al., 2013), multi-sensor time series data was processed by uncorrelated MPCA to effectively capture the interrelationships of data from various sources. According to research findings, the application of MPCA allows for successfully capturing the correlation between data from multi-sensor compared to PCA. Further, MPCA can effectively retain the shared patterns across various sensors. These influences emphasize the potential use of MPCA in the context of multi-sensor data-based fault diagnosis.

2.3. Recent development of machinery fault diagnosis

With the advancements in data-driven ML methods and tools, machinery health monitoring has significantly improved. Data-driven ML methods in fault diagnosis involve learning the observed patterns of normal operating conditions and classifying deviations as potential faults according to patterns detected in the real-time operating machines. Among these methods, deep learning-based fault identification practices have gained more attention due to their proven ability to automatically learn deep features. Deep learners, such as Artificial Neural Networks (ANN), Deep Belief Networks (DBN), Autoencoders (AE), Stacked Autoencoders (SAE), Recurrent Neural Networks (RNN), and CNN, are the learning architectures that perform relatively more promisingly than traditional methods in fault pattern identification (Gao et al., 2015; Senanayaka et al., 2022; Yu et al., 2022).

CNN has made significant progress in detecting machinery anomalies and diagnosing faults across various applications. (Hoang & Kang, 2017) converted 1-D time series vibration data into 2-D images for automatic learning and classification for fault identification. However, practitioners prefer 1D-CNN for vibration-based fault classification problems than 2D-CNN-based models because it is not mandatory for comprehensive dimension conversion from 1-D to 2-D (Yu et al., 2022). In a study (S. Chen et al., 2020), the feature vectors generated by a 1-D CNN were exported to another 1-D CNN for bearing fault diagnosis. (Eren et al., 2019) conducted a study where they introduced an adaptive 1D-CNN classifier for fault identification. Their experiments demonstrated the method's effectiveness for bearing fault diagnosis and confirmed that it required no dimension conversion. In a further study, researchers used envelope spectrum and 1D-CNN for rotating machinery fault diagnosis, varying the rotary machine speed. They found that 1D-CNN was easily adaptive for fault identification and classification of defects (Appana et al., 2018). Additionally, the frequency spectrogram provides a deeper insight into frequency behaviors of the frequencies that are not obvious in raw time-based data. A study shows that an imbalance of the rotor occurring at a high amplitude can be captured using the frequency spectrum analysis and used for fault identification (Janssens et al., 2016). (Souza et al., 2021) proposed a CNN-based framework to detect machine faults with vibration data in the frequency domain. The utilization of CNN-based methodologies has demonstrated its proficiency in detecting faults in machinery systems.

2.4. Research gaps in related works

In the context of rotatory machines, issues such as bearing faults tend to show periodically, giving rise to distinct frequency peaks (Janssens et al., 2016). These peaks are often challenging to determine in the time domain. Also, frequency domain analysis provides considerable advantages over time domain analysis. These include enhancing signal quality by eliminating unwanted noise through transforming time into frequency, streamlining specific frequency component identification within a signal, the usefulness of linear systems with periodic signals, and the representation of the signal's energy as a distribution. Consequently, this study integrates frequency domain tensors instead of time domain analysis. Traditional feature reduction methods, such as PCA and its variants, have been widely applied for feature extraction and dimensionality reduction. The MPCA methodology has significant advantages over PCA, particularly its ability to handle multi-dimensional tensor object data (elements of a tensor usually have two or more indices) (Lu et al., 2008). Unlike PCA, MPCA extracts feature directly on each mode (dimension) of the high-order tensor without breaking the tensor structures. Thus, MPCA retains the original multi-dimensional data structure, bringing more insights into the extracted features. In the existing literature, few studies have employed MPCA for high-dimensional feature extraction, yielding significant insights. Notable contributions include the works of Al Mamun et al. (2023), Hu et al. (2021), and Guo et al. (2021). The integration of MPCA features from FD tensors via multi-sensor fusion and 1D-CNN for the purpose of machinery fault diagnosis has received limited attention. As a result, we have developed a novel approach that emphasizes feature-level multi-sensor fusion, low-dimensional frequency domain feature extraction using MPCA, and machinery fault classification employing 1D-CNN.

3. PROPOSED METHODOLOGY

This methodology has been proposed to diagnose faults in machinery systems, which consists of two primary steps. The first step involves creating FD tensors by concatenating multiple frequency domains of acquired data from multi-sensor. For creating FD tensors from the multi-sensor data, time domain data is converted into frequency components. The second step involves decomposing the features into a low-dimensional domain using MPCA to train a 1D-CNN for fault diagnosis. A workflow diagram in Figure 1 extends an overview of the proposed methodology and its essential steps.

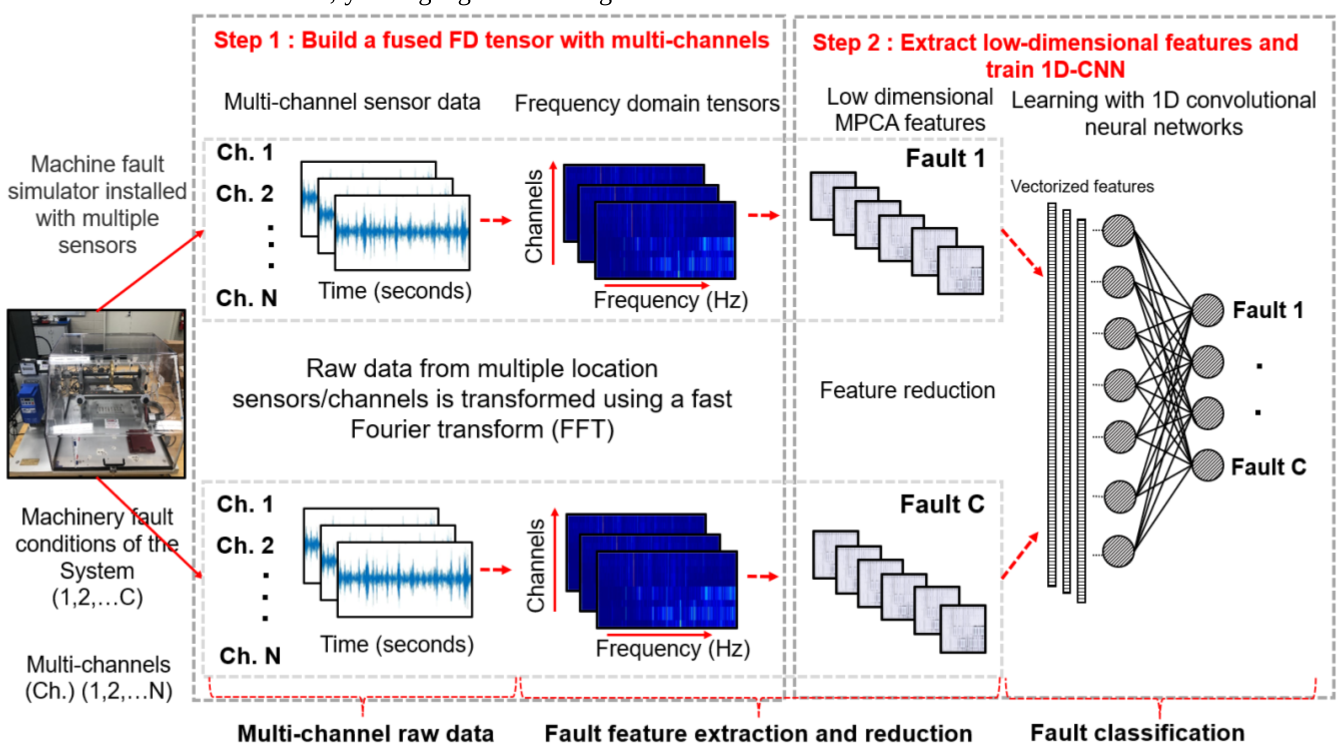

Figure 1: Proposed workflow diagram of the multi-sensor signal fused fault diagnosis.

3.1. Step 1: Build a fused FD tensor with multiple channels

The present study concerns a machinery system equipped with multivariate sensors. The raw data from multiple location sensors is transformed using a fast Fourier transform (FFT) technique. This technique aims to obtain the frequency components of the system's raw signals from different location sensors/channels. The resulting frequency components of sensor arrays are then integrated to form a multi-dimensional tensor.

The space of time domain signals is represented by $\mathcal{X}$, where X_t^p is the observed time signal at time t, where $t =$

$1,2,3\ldots,m$ and from a channel/sensor at location p, where $p = 1,2,3,\ldots,N$. The m and N represent the number of signals recorded and sensors available in various locations, respectively. The label space, $\mathcal{Y}$, consists of Y_t^c labels for recorded time signal at t for c^{th} fault conditions of the operating system, where $c = 1,2,\ldots,C$, number of fault conditions available represents C. The observed time signals at p^{th} location with c^{th} condition of the system can be represented by the following equation (1).

$$\left\{X_{(.)}^p, Y_{(.)}^c\right\} = \{(x_1^p, y_1^c), (x_2^p, y_2^c), \ldots, (x_m^p, y_m^c)\} \quad (1)$$

The spectral decomposition of a time-varying signal can be represented as $f[X_t^{(.)}]$. This involves the determination of the frequency content of a given fault condition at a specific instant in time.

The frequency components of multi-location sensors, each of a unified length d, is integrated to construct an FD tensor of dimension D, $D = d \times N$, where N represents the total number of the available sensors with different locations. This resulting FD tensor $(\boldsymbol{A_t})$ can be represented as in (2).

$$\boldsymbol{A_t} \in \mathbb{R}^{d\times N} \quad (2)$$

For more in-depth insights into the generation of FD tensors, please refer to (Al Mamun et al., 2023).

3.2. Step 2: Extract low-dimensional features and train 1D-CNN

During the feature extraction process, important characteristics or attributes are identified as low dimensions from the FD tensors generated in the previous step. The technique used in this step, MPCA, is a statistical method that can reduce the dimension of tensor data while maintaining its structure. The dimension-reduced FD tensor can be represented as follows,

$$\boldsymbol{A_t^*} = \boldsymbol{A_t} \times_1 \boldsymbol{J}^{(1)^T} \times_2 \boldsymbol{J}^{(2)^T} \quad (3)$$

where $\boldsymbol{A_t^*} \in \mathbb{R}^{r_1 \times r_2}(1 < r_1 < d \; and \; 1 < r_2 < N)$, the $\boldsymbol{J}^{(.)}$ represents the projection matrices, and $\times_{(.)}$ represents the modular product between the given matrix and the tensor (Lu et al., 2008, Guo et al., 2021).

The present study employs a 1D-CNN as an ML algorithm, which is a less sophisticated variant of the traditional 2D-CNN. The 1D-CNN has proven to be effective in fault diagnosis of machinery systems, offering comparable accuracy and facilitating improved decision-making (Eren et al., 2019; Kiranyaz et al., 2019; Yu et al., 2022). In this instance, the input features used for the 1D-CNN model are low-dimensional one-dimensional data extracted from frequency-domain tensors. The convolutional layer primarily aims to transform 1D features into feature maps nonlinearly. The convolutional layer's mathematical model can be stated as follows:

$$h_m^l = f\left(b_m^l + \sum_{j=1}^{C_{l-1}} conv1D\left(w_{jm}^{l-1}, x_j^{l-1}\right)\right) \quad (4)$$

where h_m^l represents the convoluted output after passing through an activation function $f(.)$. In this procedure, the input of the l^{th} layer is determined by the combined bias of the m^{th} neuron, b_m^l. The output of the previous layer's j^{th} neuron, x_j^{l-1}, is linked with the kernel, w_{jm}^{l-1} which is subsequently subjected to a convolution operation (Kiranyaz et al., 2021; Yu et al., 2022). As the process is carried out step by step, the convolution operation is able to identify the distinctive features present in the input data, ultimately leading to the development of feature maps through learned patterns. After the convolution operation, it is typical to apply a pooling operation to the feature maps to decrease dimensionality. In this process, the feature maps have been reduced in size by utilizing max pooling, which involves selecting the maximum value within a local region of the feature map.

As this is a classification problem, categorizing faults for employing a classifier function is crucial. SoftMax classifier is one of the widely used techniques to accomplish this task. This technique is expressed mathematically as a function that determines the probability distribution of the data into various categories. The mathematical expression can be written as follows:

$$Pr_c = \frac{e^{(\omega_c x + b_c)}}{\sum_{i=1}^{C} e^{(\omega_c x + b_c)}}, c = 1,2,\ldots C \quad (5)$$

where Pr_c is the output, the estimation of class probability obtained through the c^{th} class, which is a result of the input feature vector x. The ω_c represent the weight coefficients and b_c is the bias in the fully connected layer. The number of classes is represented by C (Yu et al., 2022).

4. CASE STUDY

This section evaluated the proposed methodology's performance using MFS built by Spectra Quest Inc. The simulator machinery system is installed with multiple types of sensors for real-time fault identification.

4.1. Experimental setup

The MFS system is equipped with three accelerometers and eight microphones to record multi-location directional signals. To capture vibration signatures, single-axis accelerometers were utilized, specifically the Industrial ICP® 608A11 model, with frequencies ranging from 0.2 to 15 kHz. On the other hand, Adafruit® silicon MEMS microphones were used to acquire acoustic signals with a sensitivity frequency range from 100 to 100 kHz. The experimental setup of MFS is illustrated in Figure 2.

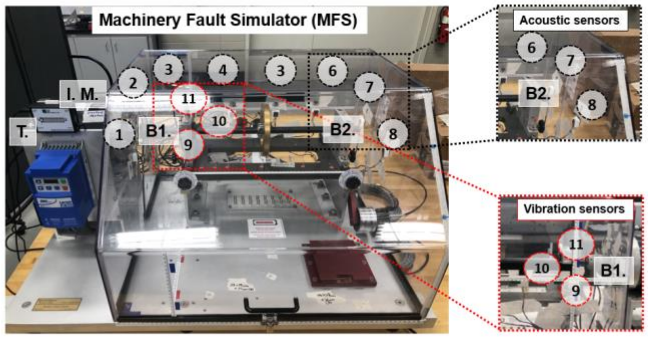

Figure 2: Experimental setup of MFS for multi-sensors data collection

The MFS is setup with an induction motor (notation I.M.) powers the system. A tachometer (notation T) is installed on the motor to accelerate the rotating speed. B1 labels the rolling bearing at the coupling end with fault while B2 Indicates the rolling bearning at the shaft end without fault. The number of 1-8 are where the acoustic sensors (MEMS microphones) placed on system housing. From number 9 to 11 locates accelerometer for vibration data collection.

The experimental design focuses on detecting bearing faults in a single faulty bearing where a fault bearing is installed at the coupling end (B1). The acoustic sensors are installed on the system housing, whereas the vibration sensors are placed in fault-bearing housing. The sampling frequency for vibration and acoustic emission signals is set at 10 kHz. During the experiment, the induction motor runs at a speed of 1800 rpm (30 Hz), and data is collected for five distinct operating conditions, each of which is classified into class labels, as shown in Table 1.

Table 1: Operating condition of MFS

Bearing @ coupling end	Bearing @ shaft end	Condition	Class label	Number of samples
No Fault	No Fault	Standard	Normal	300
Ball Fault	No Fault	Fault	Ball	450
Inner race Fault	No Fault	Fault	Inner	450
Outer race Fault	No Fault	Fault	Outer	450
Combined Fault	No Fault	Fault	Comb	450

The collected data is obtained under steady-state operating conditions of the system, verified by using a Tachometer (T) to ensure that the motor speed is correct. For each run, the data is collected for three replicates of 300 seconds, resulting in a total of 300x10000 data samples for each channel for acoustic and vibration signals. The data samples in each channel is segmented into 2 second time frames, result in 150 samples for each run. After carefully examine the samples, 300 samples of normal condition and 450 samples of each rest fault condition are selected for further analysis.

4.2. Evaluation and performance comparison

Multiple experiments were conducted to assess the effectiveness of the proposed fault diagnosis methodology. The purpose of a comparison study is to demonstrate the superiority of MPCA over traditional PCA for analyzing tensor data. The outcomes were reported as performance measures classified by class/condition, which were computed from the confusion matrix. The measures included accuracy (TP+TN)/(TP+TN+FN+FP)), precision (TP/(TP+FP)), recall (TP/(TP+FN)), and F1-score (average of precision and recall). In this regard, the TP, TN, FP, and FN, respectively, refer to true positive, true negative, false positive, and false negative. Precision is a measure of what proportion of fault identifications was actually correct, while recall is a measure of finding the proportion of actual faults identified correctly.

4.2.1. Detailed configuration of the proposed method

To begin the process, FD tensors were generated. These tensors were built using the methods explained in section 3.1. Two-second time interval of time frames using a 10 kHz sampling rate was captured, which resulted in 450 observations for each condition. The collected vibration and acoustic signals in the time domain were transformed into the frequency domain and concatenated to fuse the signals in FD tensors. Then, FD tensors were subjected to MPCA projection to obtain low dimensional features. The FD tensor feature vectors were of size 32x32 in feature reduction, where each sample is a second-order tensor. The percentage of variation kept in each mode is 97, which allowed the identification of the most critical features that were consequently entered into different classifier models. To identify fault patterns in each category, the resulting features were fed to 1D-CNN learners. Grid search hyperparameter optimization has been performed to select the best combination of parameters. The minimum loss in categorical cross-entropy was optimized using the Adam optimizer. The basic structure and specifications of the 1D-CNN can be found in Table 2, but these were subjected to changes during training to optimize the minimum loss in categorical cross-entropy using the Adam optimizer.

Table 2: The basic structure and specifications of the 1D-CNN

Layers	Specification
Conv 1D	Filters: (64x4), Activation = "relu"
Conv 1D	Filters: (64x4), Activation = "relu"
Dense	Nodes = 16, Activation = "relu"
Max Pooling1D	PoolSize = 2, Stride =2
Flatten	(.)
Dense	Nodes = 5, Activation = "softmax"

4.2.2. Performance comparison

The essential goal of this section is to conduct a comprehensive analysis and comparison of conventional fault identification methods with the proposed techniques under different fault patterns. This study examines the effectiveness of combining PCA or MPCA with advanced ML techniques for machinery fault identification using FD tensors, such as support vector machines (SVM), neural networks, and 1D-CNNs. Also, compare the relative performance of previous and new methods improvements. Besides, these methodologies compared with the proposed preparation flow, identifying specific fault categories without changing the dataset source and targets. For a generalized comparision, all cases were evaluated using the average of 5-fold coss validation test scores. To align with the MPCA methodology, 97% of the variation was retained to facilitate comparison during feature reduction with PCA. During the process of developing classifiers, the SVM classifier was tested with varying combinations of kernels and hyperparameters, and upon careful evaluation, the configuration that yielded the highest accuracy was selected for the final results. The deep learning models were subjected to a fine-tuning process where a basic structure with varying learning rates and filters was employed, as outlined in Table 2. The evaluation results of the performance comparison study have been summarized in Table 3. The results have been averaged over 10 trials, and standard deviation (SD) values have been provided for each. Figure 3 shows the average accuracy of fault classification experiments using traditional and proposed methods.

Table 3: A comparison of the proposed method with currently available methods.

AI methods	Measure	Normal	Ball fault	Inner race fault	Outer race fault	Combined fault
PCA + SVM (Shuang & Meng, 2007)	Precision (SD)	0.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)	0.5868 (0.0006)
	Recall (SD)	0.0000 (0.0000)	0.9733 (0.0018)	0.9978 (0.0000)	0.9911 (0.0000)	1.0000 (0.0000)
	F1-Score (SD)	0.0000 (0.0000)	0.9864 (0.0009)	0.9989 (0.0000)	0.9955 (0.0000)	0.7396 (0.0005)
PCA + NN (You et al., 2022)	Precision (SD)	0.9102 (0.0247)	0.9482 (0.0101)	0.9512 (0.0417)	0.8742 (0.0883)	0.8611 (0.0556)
	Recall (SD)	0.9578 (0.0437)	0.9289 (0.0465)	0.8933 (0.0517)	0.8963 (0.1325)	0.8385 (0.1161)
	F1-Score (SD)	0.9270 (0.0287)	0.9339 (0.0231)	0.9122 (0.0482)	0.8724 (0.1003)	0.8316 (0.0669)
PCA + 1D-CNN (S. Zhang et al., 2023)	Precision (SD	0.9919 (0.0114)	0.9053 (0.0831)	0.9804 (0.0278)	0.9879 (0.0035)	0.8462 (0.0734)
	Recall (SD)	0.9956 (0.0031)	0.8511 (0.1248)	0.9689 (0.0275)	1.0000 (0.0000)	0.8585 (0.1813)
	F1-Score (SD)	0.9935 (0.0044)	0.8417 (0.0642)	0.9709 (0.0134)	0.9938 (0.0018)	0.8120 (0.1537)
MPCA + NN (Al Mamun et al., 2023)	Precision (SD)	0.9989 (0.0016)	0.9943 (0.0035)	0.9654 (0.0474)	0.8521 (0.1121)	0.9586 (0.0509)
	Recall (SD)	0.9956 (0.0042)	0.9978 (0.0031)	0.9349 (0.0922)	0.9252 (0.0949)	0.9037 (0.1037)
	F1-Score (SD)	0.9972 (0.0016)	0.9959 (0.0013)	0.9132 (0.0354)	0.8776 (0.1118)	0.9147 (0.0997)
MPCA + 1D-CNN (Proposed method)	**Precision (SD)**	**1.0000 (0.0000)**	**0.9987 (0.0011)**	**0.9991 (0.0011)**	**1.0000 (0.0000)**	**0.9987 (0.0011)**
	Recall (SD)	**1.0000 (0.0000)**	**0.9987 (0.0004)**	**1.0000 (0.0000)**	**0.9991 (0.0011)**	**0.9987 (0.0011)**
	F1-Score (SD)	**1.0000 (0.0000)**	**0.9987 (0.0005)**	**0.9996 (0.0005)**	**0.9996 (0.0005)**	**0.9987 (0.0005)**

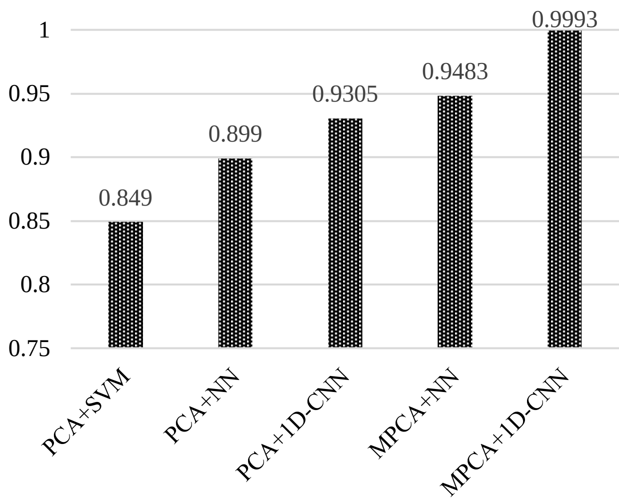

Figure 3: Average accuracy results for fault classification with traditional and proposed methods

The class-wise multi-class fault classification results demonstrate that the proposed method achieved the highest precision, recall, and F-scores. The average accuracy is 99.98%, almost perfect and the best performance. In comparison, the second-best performance was 94.83% in our previous method. The average accuracy of traditional methodologies combined with PCA, SVM classifier, NN, and 1D-CNN classifiers is 84.9%, 89.9%, and 93.05%, respectively.

The proposed method performs superior in all measures, making it a dependable option for real-time fault identification and diagnosis in machinery systems. The MPCA and 1D-CNN combination is particularly strong due to its ability to reduce dimensionality and identify faults based on low-dimensional feature classification. This combination provides a total capacity for both dimension reduction and fault identification.

5. Conclusion

Multivariate sensor-based fault diagnosis in machinery systems often leads to a wide range of high-dimensional information. The nature of destructive faults in machinery is inherently complex, and sensor data variability requires advanced feature extraction, reduction, and pattern recognition, making it a demanding task to analyze them to make real-time decisions. This paper proposes an accurate real-time machinery fault identification method using multivariate sensor data. This approach is two-fold, where the first frequency components of raw time domain multi-sensor data are integrated to build an FD tensor. Then, MPCA with 1D-CNN architecture is used for fault pattern identification. The performance of the proposed approach is validated through multi-class classification using the machinery fault simulator's fault patterns. The experiment results illustrate that the proposed method can accurately detect faults in the machinery system. Moreover, the experimental study is extended to verify the relative performance of the fault identification capability with the currently available state-of-the-art methodologies. Specifically, ML models such as SVM, NN, and 1D-CNN are combined with the PCA technique. The comparison study shows that the proposed FD tensor-based MPCA+1D-CNN outperforms multivariate sensor-based approaches for fault pattern identification. The findings of this study have important implications for practitioners in industrial fault detection and diagnosis, suggesting that the use of FD tensor-based MPCA in combination with 1D-CNN can lead to significant improvements in the dependability and safety of industrial machinery.

A couple of potential directions can be identified for future extensions of this method. The complexity of the multivariate sensor data can be increased by installing a different type of sensors in various locations, and evaluating the performance of the proposed method is one direction that can be addressed in the future. The performance of the proposed method can be evaluated for incorporated faults in the system, where bearing, motor, and shaft faults are simultaneously occurring. This is another direction of study that will be addressed in the future and lead to significant implications in industrial machinery. Also, another concern identified in industrial machinery systems is missing or highly variable data recorded in sensors due to sensor malfunctions or data recording issues. In the future, further advancements will be added to the current methodology to address these issues. Another area of research that can add value is the optimal alignment, sequence, direction, and arrangement of sensor arrays for fault data capture in machinery systems. Hence, exploring the significance of sensor arrangement in detecting faults in machinery systems is another possible area worth investigating.

Acknowledgement

The authors gratefully acknowledge research support from the U.S. Department of Defense (DoD) Program through the US Army Engineering Research and Develop Center (ERDC) Contract W912HZ-23-C0013. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the U.S. Army ERDC or the U.S. DoD. The authors appreciate Ethan Kang's contribution and efforts in collecting the experimental data. The authors also would like to thank the Center for Advanced Vehicular Systems (CAVS) at Mississippi State University for supporting this work. The autho

References

Aguileta, A. A., Brena, R. F., Mayora, O., Molino-Minero-re, E., & Trejo, L. A. (2019). Multi-sensor fusion for activity recognition—a survey. In *Sensors (Switzerland)* (Vol. 19, Issue 17). MDPI AG. https://doi.org/10.3390/s19173808

Al Mamun, A., Bappy, M. M., Mudiyanselage, A. S., Li, J., Jiang, Z., Tian, Z., Fuller, S., Falls, T. C., Bian, L., & Tian, W. (2023). Multi-channel sensor fusion for real-time bearing fault diagnosis by frequency-domain multilinear principal component analysis. *International Journal of Advanced Manufacturing Technology*, *124*(3–4), 1321–1334. https://doi.org/10.1007/s00170-022-10525-4

Appana, D. K., Prosvirin, A., & Kim, J. M. (2018). Reliable fault diagnosis of bearings with varying rotational speeds using envelope spectrum and convolution neural networks. *Soft Computing*, *22*(20), 6719–6729. https://doi.org/10.1007/s00500-018-3256-0

Banerjee, T. P., & Das, S. (2012). Multi-sensor data fusion using support vector machine for motor fault detection. *Information Sciences*, *217*, 96–107. https://doi.org/10.1016/j.ins.2012.06.016

Chen, G., Chen, J., Zi, Y., Pan, J., & Han, W. (2018). An unsupervised feature extraction method for nonlinear deterioration process of complex equipment under multi dimensional no-label signals. *Sensors and Actuators, A: Physical*, *269*, 464–473. https://doi.org/10.1016/j.sna.2017.12.009

Chen, H., Hu, N., Cheng, Z., Zhang, L., & Zhang, Y. (2019). A deep convolutional neural network based fusion method of two-direction vibration signal data for health state identification of planetary gearboxes. *Measurement: Journal of the International Measurement Confederation*, *146*, 268–278. https://doi.org/10.1016/j.measurement.2019.04.093

Chen, S., Meng, Y., Tang, H., Tian, Y., He, N., & Shao, C. (2020). Robust Deep Learning-Based Diagnosis of Mixed Faults in Rotating Machinery. *IEEE/ASME Transactions on Mechatronics*, *25*(5), 2167–2176. https://doi.org/10.1109/TMECH.2020.3007441

Chen, Z., & Li, W. (2017). Multisensor Feature Fusion for Bearing Fault Diagnosis Using Sparse Autoencoder and Deep Belief Network. *IEEE Transactions on Instrumentation and Measurement*, *66*(7), 1693–1702. https://doi.org/10.1109/TIM.2017.2669947

Choi, S. W., Lee, C., Lee, J.-M., Park, J. H., & Lee, I.-B. (2005). Fault detection and identification of nonlinear processes based on kernel PCA. *Chemometrics and Intelligent Laboratory Systems*, *75*(1), 55–67. https://doi.org/10.1016/j.chemolab.2004.05.001

Eren, L., Ince, T., & Kiranyaz, S. (2019). A Generic Intelligent Bearing Fault Diagnosis System Using Compact Adaptive 1D CNN Classifier. *Journal of Signal Processing Systems*, *91*(2), 179–189. https://doi.org/10.1007/s11265-018-1378-3

Fu, Y., Gao, Z., Liu, Y., Zhang, A., & Yin, X. (2020). Actuator and sensor fault classification for wind turbine systems based on fast fourier transform and uncorrelated multi-linear principal component analysis techniques. *Processes*, *8*(9). https://doi.org/10.3390/pr8091066

Gao, Z., Cecati, C., & Ding, S. X. (2015). A survey of fault diagnosis and fault-tolerant techniques-part I: Fault diagnosis with model-based and signal-based approaches. *IEEE Transactions on Industrial Electronics*, *62*(6), 3757–3767. https://doi.org/10.1109/TIE.2015.2417501

Gonzalez-Jimenez, D., Del-Olmo, J., Poza, J., Garramiola, F., & Madina, P. (2021). Data-driven fault diagnosis for electric drives: A review. In *Sensors* (Vol. 21, Issue 12). MDPI AG. https://doi.org/10.3390/s21124024

Guo, L., Gao, H., Huang, H., He, X., & Li, S. (2016). Multifeatures Fusion and Nonlinear Dimension Reduction for Intelligent Bearing Condition Monitoring. *Shock and Vibration*, *2016*, 1–10. https://doi.org/10.1155/2016/4632562

Guo, Y., Zhou, Y., & Zhang, Z. (2021). Fault diagnosis of multi-channel data by the CNN with the multilinear principal component analysis. *Measurement: Journal of the International Measurement Confederation*, *171*. https://doi.org/10.1016/j.measurement.2020.108513

Hoang, D.-T., & Kang, H.-J. (2017). Convolutional Neural Network Based Bearing Fault Diagnosis. In D.-S. Huang, K.-H. Jo, & J. C. Figueroa-García (Eds.), *Intelligent Computing Theories and Application* (pp. 105–111). Springer International Publishing. https://doi.org/10.1007/978-3-319-63312-1_9

Hu, C., He, S., & Wang, Y. (2021). A classification method to detect faults in a rotating machinery based on kernelled support tensor machine and multilinear principal component analysis. *Applied Intelligence*, *51*(4), 2609–2621. https://doi.org/10.1007/s10489-020-02011-9

Ince, T., Kiranyaz, S., Eren, L., Askar, M., & Gabbouj, M. (2016). Real-Time Motor Fault Detection by 1-D Convolutional Neural Networks. *IEEE Transactions on Industrial Electronics*, *63*(11), 7067–7075. https://doi.org/10.1109/TIE.2016.2582729

Janssens, O., Slavkovikj, V., Vervisch, B., Stockman, K., Loccufier, M., Verstockt, S., Van De Walle, R., & Van Hoecke, S. (2016). Convolutional Neural Network Based Fault Detection for Rotating Machinery. *Journal of Sound and Vibration*, *377*, 331–345. https://doi.org/10.1016/j.jsv.2016.05.027

Javaid, M., Haleem, A., Singh, R. P., Rab, S., & Suman, R. (2021). Significance of sensors for industry 4.0: Roles, capabilities, and applications. In *Sensors International* (Vol. 2). KeAi Communications Co. https://doi.org/10.1016/j.sintl.2021.100110

Jiao, J., Zhao, M., Lin, J., & Ding, C. (2019). Deep Coupled Dense Convolutional Network With Complementary Data for Intelligent Fault Diagnosis. *IEEE Transactions on Industrial Electronics*, *66*(12), 9858–9867. https://doi.org/10.1109/TIE.2019.2902817

Jiao, J., Zhao, M., Lin, J., & Liang, K. (2020). A comprehensive review on convolutional neural network in machine fault diagnosis. *Neurocomputing*, *417*, 36–63. https://doi.org/10.1016/j.neucom.2020.07.088

Jing, L., Zhao, M., Li, P., & Xu, X. (2017). A convolutional neural network based feature learning and fault diagnosis method for the condition monitoring of gearbox. *Measurement: Journal of the International Measurement Confederation*, *111*, 1–10. https://doi.org/10.1016/j.measurement.2017.07.017

Jollife, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. In *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* (Vol. 374, Issue 2065). Royal Society of London. https://doi.org/10.1098/rsta.2015.0202

Kalsoom, T., Ramzan, N., Ahmed, S., & Ur-Rehman, M. (2020). Advances in sensor technologies in the era of smart factory and industry 4.0. In *Sensors (Switzerland)* (Vol. 20, Issue 23, pp. 1–22). MDPI AG. https://doi.org/10.3390/s20236783

Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., & Inman, D. J. (2021). 1D convolutional neural networks and applications: A survey. *Mechanical Systems and Signal Processing*, *151*. https://doi.org/10.1016/j.ymssp.2020.107398

Kiranyaz, S., Ince, T., Abdeljaber, O., Avci, O., & Gabbouj, M. (2019). 1-D Convolutional Neural Networks for Signal Processing Applications. *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, *2019-May*, 8360–8364. https://doi.org/10.1109/ICASSP.2019.8682194

Kullu, O., & Cinar, E. (2022). A Deep-Learning-Based Multi-Modal Sensor Fusion Approach for Detection of Equipment Faults. *Machines*, *10*(11). https://doi.org/10.3390/machines10111105

Le Bris, A., Chehata, N., Ouerghemmi, W., Wendl, C., Postadjian, T., Puissant, A., & Mallet, C. (2019). Chapter 11 - Decision Fusion of Remote-Sensing Data for Land Cover Classification. In M. Y. Yang, B. Rosenhahn, & V. Murino (Eds.), *Multimodal Scene Understanding* (pp. 341–382). Academic Press. https://doi.org/10.1016/B978-0-12-817358-9.00017-2

Lee, K. B., Cheon, S., & Kim, C. O. (2017). A convolutional neural network for fault classification and diagnosis in semiconductor manufacturing processes. *IEEE Transactions on Semiconductor Manufacturing*, *30*(2), 135–142. https://doi.org/10.1109/TSM.2017.2676245

Liton Hossain, M., Abu-Siada, A., & Muyeen, S. M. (2018). Methods for advanced wind turbine condition monitoring and early diagnosis: A literature review. *Energies*, *11*(5). https://doi.org/10.3390/en11051309

Liu, X., Ma, L., & Mathew, J. (2009). Machinery fault diagnosis based on fuzzy measure and fuzzy integral data fusion techniques. *Mechanical Systems and Signal Processing*, *23*(3), 690–700. https://doi.org/10.1016/j.ymssp.2008.07.012

Liu, Y., Yan, X., Zhang, C. A., & Liu, W. (2019). An ensemble convolutional neural networks for bearing fault diagnosis using multi-sensor data. *Sensors (Switzerland)*, *19*(23). https://doi.org/10.3390/s19235300

Lu, H., Plataniotis, K. N., & Venetsanopoulos, A. N. (2008). MPCA: Multilinear principal component analysis of tensor objects. *IEEE Transactions on Neural Networks*, *19*(1), 18–39. https://doi.org/10.1109/TNN.2007.901277

Ma, P., Zhang, H., Fan, W., Wang, C., Wen, G., & Zhang, X. (2019). A novel bearing fault diagnosis method based on 2D image representation and transfer learning-convolutional neural network. *Measurement Science and Technology*, *30*(5). https://doi.org/10.1088/1361-6501/ab0793

Mallegni, N., Molinari, G., Ricci, C., Lazzeri, A., La Rosa, D., Crivello, A., & Milazzo, M. (2022). Sensing Devices for Detecting and Processing Acoustic Signals in Healthcare. In *Biosensors* (Vol. 12, Issue 10). MDPI. https://doi.org/10.3390/bios12100835

Nallusamy, S., & Majumdar, G. (2017). Enhancement of Overall Equipment Effectiveness using Total Productive Maintenance in a Manufacturing Industry. In *International Journal of Performability Engineering* (Vol. 13, Issue 2).

Niu, G., Han, T., Yang, B.-S., & Tan, A. C. C. (2007). Multi-agent decision fusion for motor fault diagnosis. *Mechanical Systems and Signal Processing*, *21*(3), 1285–1299. https://doi.org/10.1016/j.ymssp.2006.03.003

Paynabar, K., Jin, J. (Judy), & Pacella, M. (2013). Monitoring and diagnosis of multichannel nonlinear profile variations using uncorrelated multilinear principal component analysis. *IIE Transactions*, *45*(11), 1235–1247. https://doi.org/10.1080/0740817X.2013.770187

Senanayaka, A., Al Mamun, A., Bond, G., Tian, W., Wang, H., Fuller, S., Falls, T. C., Rahimi, S., & Bian, L. (2022). Similarity-based Multi-source Transfer Learning Approach for Time Series Classification. *International Journal of Prognostics and Health Management*, *13*, 1–9. https://doi.org/10.36001/IJPHM.2021.v13i2.3267

Shuang, L., & Meng, L. (2007). Bearing Fault Diagnosis Based on PCA and SVM. *2007 International Conference on Mechatronics and Automation*, 3503–3507. https://doi.org/10.1109/ICMA.2007.4304127

Souza, R. M., Nascimento, E. G. S., Miranda, U. A., Silva, W. J. D., & Lepikson, H. A. (2021). Deep learning for diagnosis and classification of faults in industrial rotating machinery. *Computers & Industrial Engineering*, *153*, 107060. https://doi.org/10.1016/j.cie.2020.107060

Tripathi, S., Muhr, D., Brunner, M., Jodlbauer, H., Dehmer, M., & Emmert-Streib, F. (2021). Ensuring the Robustness and Reliability of Data-Driven Knowledge Discovery Models in Production and Manufacturing. In *Frontiers in Artificial Intelligence* (Vol. 4). Frontiers Media S.A. https://doi.org/10.3389/frai.2021.576892

Wang, J., Xie, J., Zhao, R., Zhang, L., & Duan, L. (2017). Multisensory fusion based virtual tool wear sensing for ubiquitous manufacturing. *Robotics and Computer-Integrated Manufacturing*, *45*, 47–58. https://doi.org/10.1016/j.rcim.2016.05.010

Xia, M., Li, T., Xu, L., Liu, L., & de Silva, C. W. (2018). Fault Diagnosis for Rotating Machinery Using Multiple Sensors and Convolutional Neural Networks. *IEEE/ASME Transactions on Mechatronics*, *23*(1), 101–110. https://doi.org/10.1109/TMECH.2017.2728371

You, K., Qiu, G., & Gu, Y. (2022). Rolling Bearing Fault Diagnosis Using Hybrid Neural Network with Principal Component Analysis. *Sensors*, *22*(22). https://doi.org/10.3390/s22228906

Yu, F., Liao, L., Zhang, K., Xing, H., Zhao, Q., Zhang, L., & Luo, Z. (2022a). A Novel 1D-CNN-Based Diagnosis Method for a Rolling Bearing with Dual-Sensor Vibration Data Fusion. *Mathematical Problems in Engineering*, *2022*. https://doi.org/10.1155/2022/8986900

Yu, F., Liao, L., Zhang, K., Xing, H., Zhao, Q., Zhang, L., & Luo, Z. (2022b). A Novel 1D-CNN-Based Diagnosis Method for a Rolling Bearing with Dual-Sensor Vibration Data Fusion. *Mathematical Problems in Engineering*, *2022*. https://doi.org/10.1155/2022/8986900

Zhang, S., Wei, H.-L., & Ding, J. (2023). An effective zero-shot learning approach for intelligent fault detection using 1D CNN. *Applied Intelligence*, *53*(12), 16041–16058. https://doi.org/10.1007/s10489-022-04342-1

Zhang, W., Li, C., Peng, G., Chen, Y., & Zhang, Z. (2018). A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load. *Mechanical Systems and Signal Processing*, *100*, 439–453. https://doi.org/10.1016/j.ymssp.2017.06.022

Zoghlami, F., Kaden, M., Villmann, T., Schneider, G., & Heinrich, H. (2021). AI-Based Multi Sensor Fusion for Smart Decision Making: A Bi-Functional System for Single Sensor Evaluation in a Classification Task. *Sensors (Basel, Switzerland)*, *21*(13). https://doi.org/10.3390/s21134405