IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 58, No. 1, January, 2025, pp. 89-96
Journal homepage: http://iieta.org/journals/jesa

Classification of Bearing Fault Signals in Rotating Machinery Using Neural Networks

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https://doi.org/10.18280/jesa.580110

Received: 17 December 2024
Revised: 14 January 2025
Accepted: 22 January 2025
Available online: 31 January 2025

Keywords:
condition monitoring, bearing fault signals, signal sampling, signal classification, convolution neural network

ABSTRACT

Rotating Machinery is a vital component in the manufacturing process. Its health conditions directly affect production, and any failure of the Machinery may reduce production and cause accidents. Condition-based monitoring detects faults in the early stages, which, in turn, reduces machine failures. Machine learning condition monitoring has made remarkable achievements in fault detection, but it requires various feature calculations and is a time-consuming process. Recently, deep learning-based models outperformed traditional machine learning techniques as they automatically identify features through the learning process. This paper proposes a deep-learning model to classify bearing faults, specifically a convolution Neural Network Model (CNN) and Convolution Invariant Neural Network (CINN). The bearing dataset from Case Western Reserve University (CWRU) is used for training and testing the proposed CNN and CINN Models. The performance of model is evaluated on different working conditions of the bearing faults with varying loads, demonstrating 99% and above accuracy.

1. INTRODUCTION

In modern life, Machinery serves as a utility integrated into domestic and industrial appliances, designed to operate reliably for extended periods. Rotating machines are the crucial component required for smooth and efficient machine operation. As the machines operate uninterrupted for extended periods, they are vulnerable to failures, and prediction of machinery failure is of paramount important. The risk of sudden breakdowns or failures of the Machinery can be minimized if regular maintenance is accomplished and failures are detected early [1]. Early fault detection of machinery optimizes operational efficiency, thereby averting costly downtime, production losses and potential safety hazards [2]. The predominant component contributing to these machine breakdowns is the rolling bearings component, and 90% of failures are related to bearing faults [3]. The root causes of bearing failures and their fault modes include defamation, fracture and wear [4], which are identified during predictive maintenance based on continuous machine monitoring. Early identification of faults is possible based on the analysis and inspection of available data collected from various sensors such as voltage, vibration, temperature, and pressure [5]. A specific predictive maintenance strategy utilizes vibration signal analysis, where data is collected with a microprocessor and distinct vibration frequency components, amplitude changes generated during machine operating conditions are analyzed. However, microprocessor-based data collected cannot capture accurate data and generate low-frequency vibrations [6]. Thus, signal analysis performed on low-frequency vibration components is not precise. These findings on signal have inspired researchers to propose various techniques to capture high-frequency data and diagnose the faults of bearings in rotating Machinery through vibration monitoring [7].

Most of the research hitherto has concentrated on identifying faulty Machinery by monitoring the signal amplitude and its frequency transitions, which include manual extraction of signal features: statistical time-domain, frequency-domain, spatial domain, and time-frequency features [8]. Statistical time features of the time domain include max, mean, root amplitude, standard deviation, variance, standard error, peak-peak, root mean square, skewness, entropy, kurtosis, margin, clearance, crest, shape and impulse factor. Frequency domain or spectral features include applying fast Fourier transform (FFT) and performing envelope analysis Time-frequency features include wavelet transforms, Fourier transforms like short-term Fourier transform (STFT); the derived spectrograms, wavelets, and decomposed wavelets are inspected, and wavelet analysis is performed [9]. According to the task requirements, a selective approach with only a subset of features is adopted to analyze machine faults. Many supervised and unsupervised machine learning models, namely, decision trees, k nearest neighbors, random forest, artificial neural networks, support vector machines, backpropagations and convolution neural networks (CNN), are trained on these selected features [10-13]. While many supervised learning models have been utilized in fault diagnosis, the incorporation of deep learning models remains crucial.

The application of neural networks across various domains has seen a surge, and recent advancements in deep learning have become popular in bearing fault diagnosis. The deep learning models applied on bearing datasets convert raw vibration signals to time-frequency images using various wavelet transforms. Wavelet transforms like continuous wavelet transform (CWT) [14-25], CWT of complex morlet [26], two-level discrete wavelet transform (DWT) [27], Non-uniform Fast Fourier Transform (NFFT) [28] and Short-time Fourier Transform (STFT) [29] were applied to convert one-dimensional vibration signals to 2-dimensional spectrograms. These time-frequency images are given as input to convolution neural networks for fault identification. While neural networks are integrated into the system, but their operations are not directly applied on the raw signal.

The following researchers employed deep learning approaches for fault diagnosis and achieved the following performance metrics. Xia et al. [30] proposed a CNN model incorporating multiple sensors. The model is trained using spatial and temporal information from raw data signals. Manual feature extraction and selection are avoided, and is tested, which results in 99.41% accuracy. Sonmez et al. [31] proposed real-time condition monitoring based on combining one—and two-dimensional deep convolution neural networks combined with wide first-layer kernels (WD-CNN). The model's effectiveness is tested, and 96.45% accuracy is achieved on different operating loads. van den Hoogen et al. [32] introduced an adaptive wide kernel in one-dimensional CNN architecture to classify multivariate signals without data pre-processing. The model's performance is trained and evaluated, and an average accuracy of 89.39% is achieved. Eren et al. [33] proposed an intelligent-based diagnosis using CNN without encapsulating distinct blocks for feature extraction, selection, and classification. One-dimensional CNN is applied directly to the raw time-series sensor data, learning optimal features automatically and achieving 93.22% accuracy. Jin et al. [34] proposed variational mode decomposition (VMD) to decompose the signal and CNN for bearing fault diagnosis. High-correlated components acquired are given as input to the classification model. The fault diagnosis method achieved 96.41% accuracy on CWRU dataset. Kulevome et al. [35] proposed rolling element-bearing classification using a deep neural network. The features from the input vibration signals are classified using a modified VGG16 architecture. The classification model achieved 99.23% accuracy and a healthy indicator framework for varying operating conditions of faults is proposed.

As evidenced by the previous studies, there remains a research potential to propose an efficient fault diagnosis model to diagnose bearing faults in rotating Machinery. While CNNs are primarily designed for two-dimensional image processing, their applicability can be extended to one-dimensional signals through appropriate modifications of parameters. The main objective of the proposed work focuses on,

1. Processing raw input vibration signals directly.
2. Signals are segmented to make them appropriate for neural networks.
3. A neural network and a two-level invariant Neural Network Model is proposed to classify fault signals and to improve the classification accuracy.

The following sections outline the paper's organization, 'Theoretical Background' provides a functional overview of the theoretical underpinnings of the Neural Network Models. The 'Proposed Methodology' provides a systematic approach and description of the fault diagnosis model. 'Experimental Results and Discussions' demonstrates a comprehensive and detailed performance analysis of the proposed models' capabilities. The section 'Conclusion' summarizes the essential findings and contributions of the paper, highlighting the potential of the proposed model in improving the efficiency and accuracy of model.

2. THEORETICAL BACKGROUND

The Neural Network models are computational models in which nodes are connected and adapted with weights during model use. These computational elements are densely interconnected to achieve better performance.

2.1 CNN

The basic CNN consists of three important layers. The first layer is a convolutional layer, involving multiple kernels where input features are learnt as feature maps. These feature maps are connected to neighboring neurons in the previous layer and are obtained by first performing convolution operation on the input tensor with a kernel filter. To the convolved result, element-wise activation functions such as ReLU, tanh and sigmoid, are applied. A pooling layer is applied to reduce the feature map resolutions, and operations include max and average pooling. By stacking multiple convolutional and pooling layers, higher-level abstracted features are detected [36].

The architecture of CNN [37] model is presented in Figure 1.

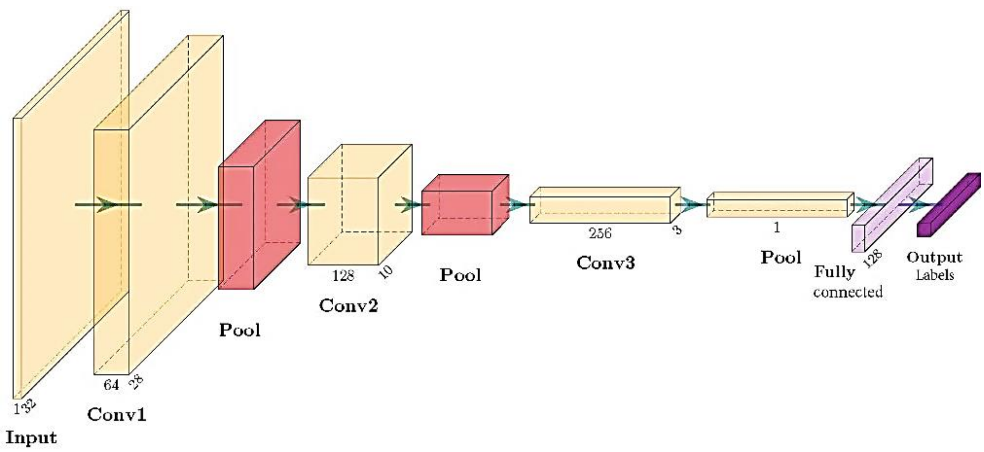


Figure 1. CNN

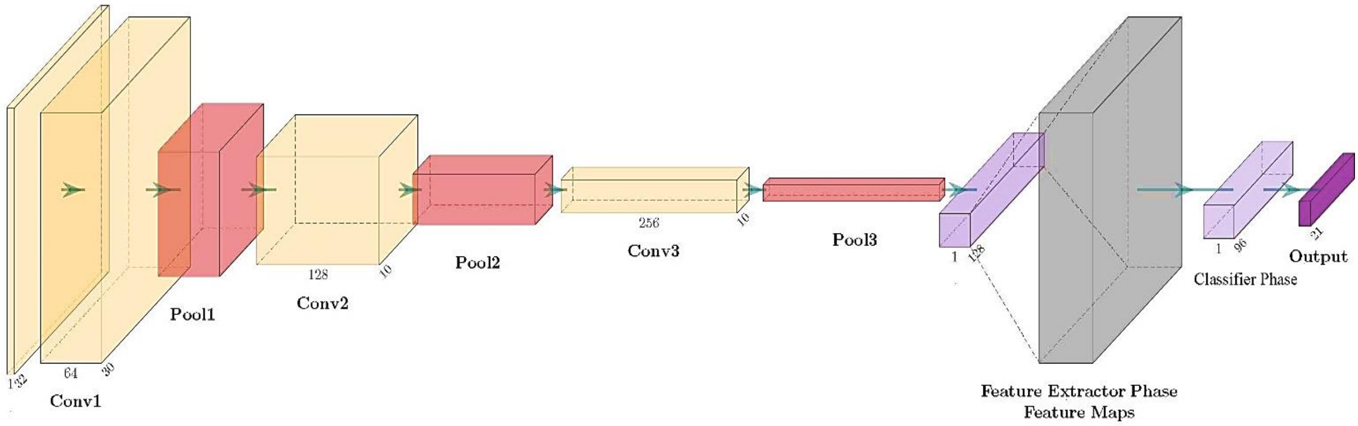


Figure 2. CINN

2.2 CINN

The fundamental CINN design integrates a feature extractor and classifier into a unified sequential model. The feature extractor comprises convolutional, pooling, and fully connected layers. The pertinent characteristics of the input signal are derived in the feature extractor component of the model through convolution and pooling layers. The classifier component forecasts the acquired features utilising the fully linked layers. The integrated model is trained to reduce loss and enhance classification accuracy. Figure 2 above illustrates the architecture of the Convolution Invariant Neural Network (CINN) Model [37].

3. PROPOSED METHODOLOGY

This study uses convolutional neural networks to automatically extract features and classify vibration signals for the diagnosis of bearing faults. The subsequent sections detail the data preparation for the proposed model and the findings obtained.

3.1 Data collection and processing

The dataset utilized in the research is the Case Western Reserve University (CWRU) bearing dataset [38], a publicly accessible benchmark dataset found in reference [39], which has been employed in the majority of prior publications. The bearing dataset is produced using a 2hp Reliance electric motor equipped with a dynamometer, encoder and transducer, as seen in Figure 3, sourced from publication [38].

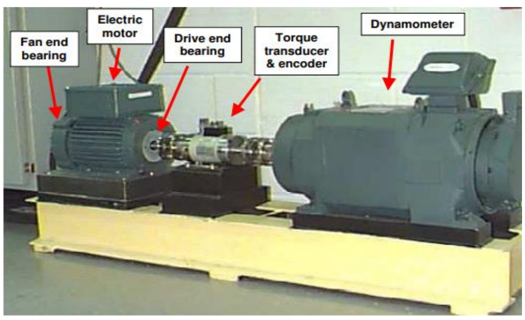


Figure 3. CWRU bearing test rig

Sensors are placed at different locations. Data were collected at two different frequencies, 12 KHz and 48 KHz, from three different ends: bearing end, Drive-end (DE) and fan-end (FE).

A total of 161 data files were utilized, and defects were introduced to bearings with diameters varying from 0.007 to 0.040 inches. Data was collected at several speeds ranging from 1720 to 1797 rpm. Each data file comprises multiple properties, specifically: drive end signal (DE_Time) and fan end signal (FE_Time) – acceleration data measured in vertical direction, base signal (BA). Only DE_time data is utilized for analysis, as it is proximate to the bearing.

This research examines data sampled at a frequency of 48 kHz. Three categories of faults are examined: bearing ball fault, race inner and race outer fault, in conjunction with data from normal conditions. All files are in .mat format. Each file is renamed to indicate the defect kind, its diameter, and the motor run load. The file name I7_2 signifies that the fault type is Inner Fault, occurring while the motor operates at a 2hp load, with a fault diameter of "0.007", the file name B21_1 indicates the fault type is Bearing Fault generated when the motor is run at 1hp load, and the fault diameter is "0.021" and the file name O14_3 indicates the fault type is Outer Fault generated when the motor is run at 3hp load, and the fault diameter is "0.0014". The data is designated with distinct names for each class type and provided as input to the models.

Despite 48 KHz sampling rate for 10 seconds, certain data files exhibit a smaller number of data points indicating potential error during data acquisition, storage or hardware malfunctions. To standardize the varying sample rate of data files recorded across the dataset, 48 KHz samples are resampled to a consistent 420 samples of 1024 data points each to streamline computations and facilitate focused analysis of data processing. To enable accurate diagnostics and predictions, fault diameter under varying loads is considered which provides the impact of fault severity and its influence on the machine. Therefore, the vibration signals are divided into 420 segments, each containing 1024 data points for processing. The sampled signals are categorized into four types of dataset cases: A, B, C, and D. Dataset A comprises 9,728 data samples of 0.007 diameter faults, encompassing three distinct fault types and normal faults. Dataset B has 6,475 instances of three distinct fault types at a diameter of 0.014. Dataset C has 9,759 data samples with a fault diameter of 0.0021. Dataset D encompasses all varieties of faults under three distinct load circumstances and fault sizes. Table 1 presents the configuration of instances from the CWRU dataset under consideration.

Table 1. Dataset cases of CWRU

Dataset	Case A			Case B			Case C			Case D
Bearing Type	Ball (B)	Inner (I)	Outer (O)	Ball (B)	Inner (I)	Outer (O)	Ball (B)	Inner (I)	Outer (O)	All
Normal		Yes			Yes			Yes		Yes
Fault Diameter		0.007			0.0014			0.0021		All
Load		0/1/2/3			0/1/2/3			0/1/2/3		0/1/2/3
Data Samples		9728			6475			9759		22650

3.2 Classification models

A multiclass fault diagnosis system is proposed for various data-organized groups of bearing faults. The data samples of each dataset are partitioned into training and testing sets. The training samples include 80% of the data, whereas the testing samples constitute 20% of the data. The classification models are executed for 35 epochs with a batch size of 128.

3.2.1 CNN

In this study, Layer 1 of the Convolution has a kernel size of (3, 3) with 64 filters, and the input shape is (30, 30, 64), featuring 640 parameters which facilitates balance between diverse feature extraction capability and computational efficiency of the signals. The second layer of the convolutional layer comprises 128 filters with a kernel size of (3, 3), and the input shape is (15, 15, 64). The produced feature maps have a shape of (13, 13, 128) and contain 73,856 parameters. The employed activation function is a ReLU function, characterized by continuity and an unbounded signal. Layer 3 of the Convolution layer comprises 256 filters with a kernel size of (3, 3), and the input shape is (6, 6, 128) which facilitates the hierarchical extraction of complex features contributing to fault detection. The produced feature maps have a shape of (4, 4, 256) and contain 295,168 parameters. To standardize the activations of preceding layers, batch normalization is utilized. The feature maps from the first, second, and third Conv2D layers are downscaled by a factor of two by the selection of the maximum value. The pooling layer's feature maps are converted into a one-dimensional vector appropriate for the following layers. The initial dense layer comprises 1024 neurons that process flattened feature vectors to generate a 128-dimensional vector. A dropout rate of 0.5 is established to mitigate overfitting. The model's final output layer executes categorization by transforming a 128-dimensional vector into six output classes. The condensed architecture of the network model is presented in Table 2.

Table 2. Overview of CNN layer configurations

Layer	Filter Size	Output	Parameters
Conv 1 (ReLU)	3×3	(30,30,64)	640
BatchNormalization		(30,30,64)	256
Pool 1	2×2	(15,15,64)	0
Conv 2 (ReLU)	3×3	(13,13,128)	73856
BatchNormalization		(13,13,128)	512
Pool 2	2×2	(6,6,128)	0
Conv 3 (ReLU)	3×3	(4,4,256)	295168
Batch Normalization		(4,4,256)	1024
Pool 3	2×2	(2,2,256)	0
Flatten		(1024)	0
Dense 1 (ReLU)		(128)	131200
Output (Softmax)		(None,6)	774
Total Parameters			503430

3.2.2 CINN

Feature extractor: The convolutional layers of the model manage the feature extraction process. The three convolutional layers acquire intricate aspects of the signal and utilize 64 filters of kernel size (3, 3) with a ReLU activation function. The pooling layer down-samples by selecting the maximum value with a stride, so mitigating overfitting and reducing computational expenses. This pertains to learning and feature extraction. The pooling layer's feature maps are converted into a one-dimensional vector appropriate for the following layers.

The initial dense layer of the classifier has 1024 neurons utilizing ReLU activation, processing a flattened feature vector that captures the intricate patterns and characteristics identified in the preceding feature-extraction phase. The second layer, utilizing softmax activation, generates the predicted probabilities for each class within the dataset.

The combined model integrates the feature extractor and classifier into a singular sequential framework for comprehensive training and prediction.

Table 3 presents a summarized architecture of the Convolution Invariant Neural Network Model.

Table 3. Overview of CINN layer configurations

Layer	Filter Size	Output	Parameters
	Feature Extractor		
Conv 1 (ReLU)	3×3	(30,30,64)	640
BatchNormalization		(30,30,64)	256
Pool 1	2×2	(15,15,64)	0
Conv 2 (ReLU)	3×3	(13,13,128)	73856
BatchNormalization		(13,13,128)	512
Pool 2	2×2	(6,6,128)	0
Conv 3 (ReLU)	3×3	(4,4,256)	295168
Batch Normalization		(4,4,256)	1024
Pool 3	2×2	(2,2,256)	0
Flatten		(1024)	0
	Classifier		
Dense_1 (ReLU)		(128)	131200
Dense_2 (ReLU)		(256)	33024
Output (Softmax)		(None,6)	1542
Total Parameters			165766

4. RESULTS AND DISCUSSION

The experimental research was carried out on a core i7 processor computer system equipped with 16GB RAM, utilizing the TensorFlow library within a Jupyter Notebook interface.

4.1 Performance metrics

The performance metrics used to evaluate the classifiers are accuracy, precision, recall and F1-score. The two class samples can be categorized [39] as denoted in the confusion matrix as shown in Table 4.

Table 4. Confusion matrix

		Predicted Class		
		Bearing Fault	**Normal**	
Actual Class	**Bearing Fault**	True Positive (TP)	False Negative (FN)	TP+TN
	Normal	False Positive (FP)	True Negative (TN)	FP+TN
		TP+FP	TN+FN	All

The classification models' performance metrics are:

Accuracy: Quantifies the models' performance in terms of correct classifications, calculated using Eq. (1) of the study [40].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision: For a given specific class, Precision quantifies the ratio of positive predictions that were actually correct [40]. Precision assesses positive predictive power of the model, given as in Eq. (2) of the study [40],

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall: quantifies the correctly identified instances [41]. It assesses the model's ability to find all relevant instances, given by as in Eq. (3) of the study [42].

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F1-Score: F1-Score is a balanced measure of model that combines precision and recall, given by as in Eq. (4) of the study [40].

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

4.2 Experimental results

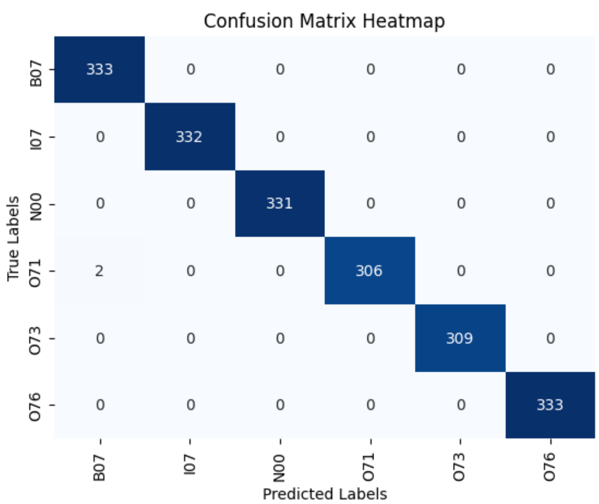
The classification models' performance is evaluated on all testing sets of CWRU-bearing datasets. The performance of the two classification models, CNN and CINN, are tabulated in Table 5.

Table 5. CNN and CINN performance results

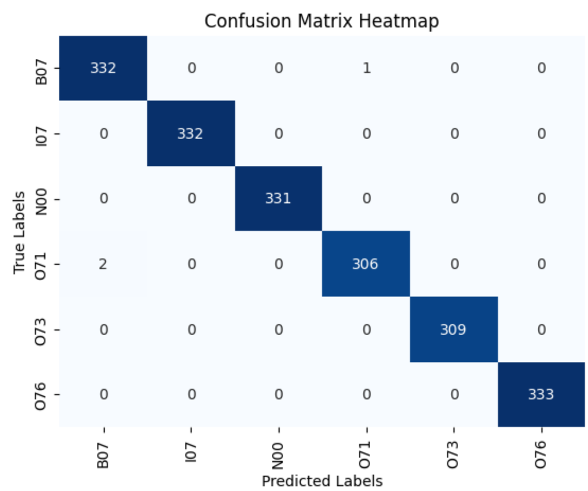
Model	**CNN**				**CINN**			
Dataset	Case A	Case B	Case C	Case D	Case A	Case B	Case C	Case D
Precision	0.998	0.998	0.998	0.98	1	1	0.998	0.968
Recall	0.998	0.998	0.998	0.982	1	0.998	0.998	0.978
F1 – Score	1	0.995	0.998	0.982	1	1	0.998	0.978
Accuracy (%)	99.90	99.69	99.80	98.28	100	99.77	99.74	97.60

4.2.1 Dataset Case A

Dataset A contains three fault types and a normal condition signal with a fault diameter of 0.007 mm, run on varying load conditions. The total testing samples are 1946; both CNN and CINN models achieved a classification accuracy of 99.8% and 100%, respectively. Out of 1946, only two samples of Outer fault were misclassified as bearing fault. The confusion matrix of both models is depicted as in Figure 4. Class-specific performance, although challenging, models correctly predict the majority of instances with an excellent overall performance. Precision measure, recall measure and F1-score of CNN are 99.8% and 100% for CINN.



(a)



(b)

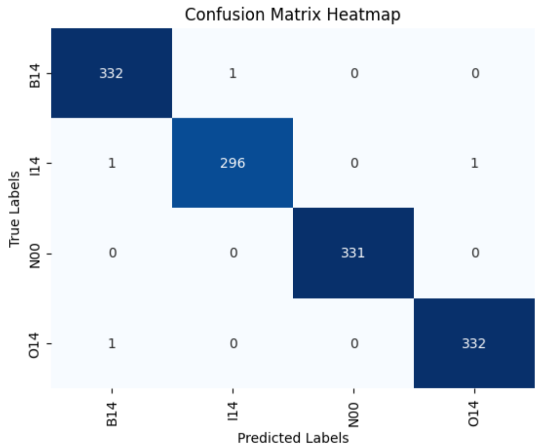
Figure 4. Confusion matrix for Dataset A using (a) CNN and (b) CINN

4.2.2 Dataset Case B

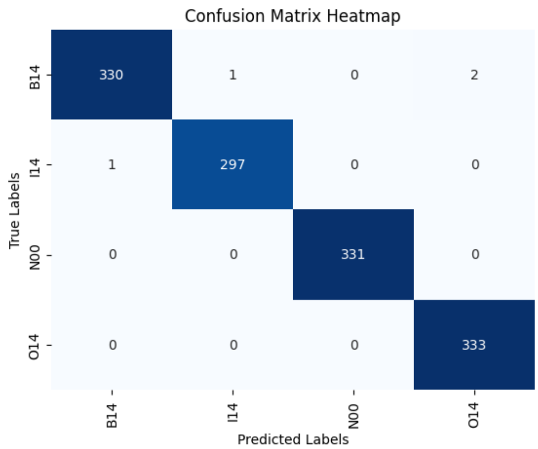
Dataset B contains signals with fault diameters of 0.0014mm of varying load conditions. Models CNN and CINN are tested on 1295 samples; four samples of inner fault are misclassified as bearing fault.

In CINN, one bearing fault is misclassified as an inner fault, and one is an outer race fault. Recall for both models is 99.8%, precision and f1 score for CNN is 99.8% and 100% for the CINN model. Both models performed well on normal and other classes. The respective models achieve an accuracy of 99.69% and 99.77%; the confusion matrix is presented in

Figure 5.



(a)

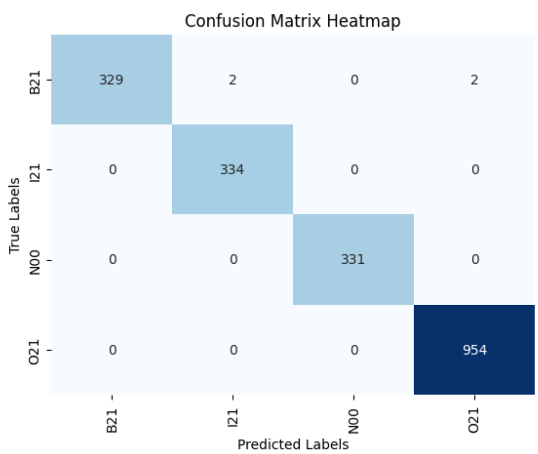


(b)

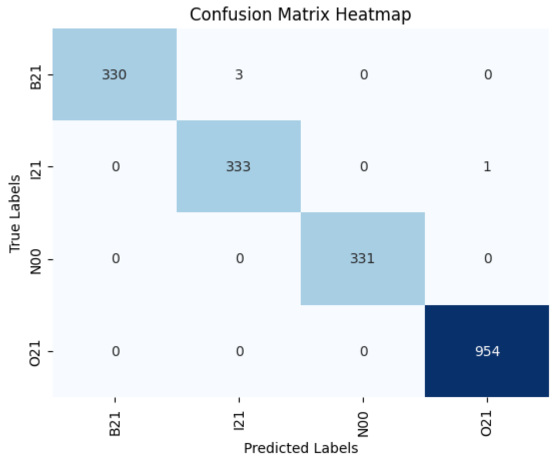
Figure 5. Confusion matrix for Dataset B using (a) CNN and (b) CINN

4.2.3 Dataset Case C

Dataset C contains signals with a fault diameter of 0.0021mm and varying load conditions. Models CNN and CINN were tested on 1952 samples, and two samples of bearing faults were misclassified as inner and outer faults. The respective models achieve an accuracy of 99.80% and 99.74%. Precision measure, recall measure and F1-score of both models are 99.8%, and their confusion matrix is shown in Figure 6.



(a)

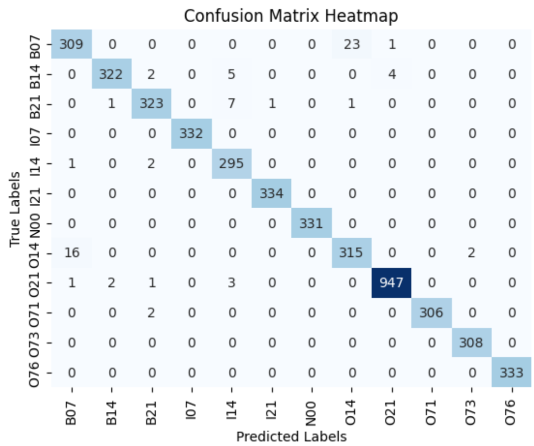


(b)

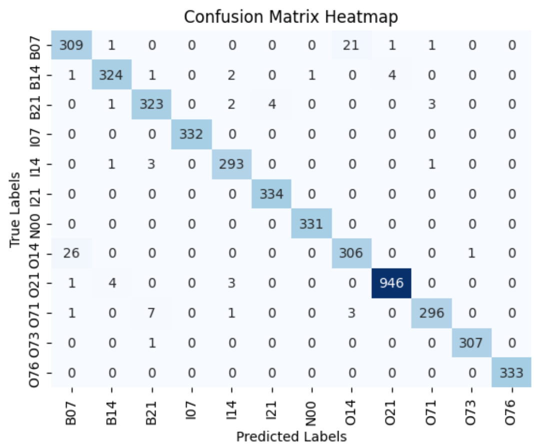
Figure 6. Confusion matrix for Dataset C using (a) CNN and (b) CINN

4.2.4 Dataset Case D

Dataset D contains signals of all fault diameters run on varying load conditions. Few samples of bearing faults were classified as outer faults and vice versa. Both CNN and CINN models achieved an accuracy of 98.28% and 97.60%, respectively. The confusion matrix of this dataset was evaluated, and Precision measure, recall measure and F1-score of the CNN model is 98.2%, and for CINN is 97.8%, as shown in Figure 7.



(a)



(b)

Figure 7. Confusion matrix for Dataset D using (i) CNN and (ii) CINN

In dataset case A, both models demonstrates strong overall performance with only a 0.0065% misclassification error of outer faults as bearing faults. In Dataset cases B and C, both models exhibit strong performance and an average 0.006% of misclassification error of bearing faults as inner faults. In Dataset D, a 0.06% of bearing faults were misclassified and 0.06% of outer faults as bearing faults. The negligible misclassification error that exists between bearing faults and outer faults suggest potential similarity or overlapping characteristics in the data samples. The main factors contributing to misclassification in vibration signals are noisy data, varying operating conditions and similarities in fault characteristics. Although both models significantly performed well on the data, few misclassification errors can be addressed by resampling, experimenting with ensemble methods, or alternative model architectures to optimize performance.

5. CONCLUSIONS

This research presents an innovative automated deep learning-based convolutional neural network for a bearing problem diagnosis system capable of directly analyzing raw input vibration data. This thus decreases the time necessary for pre-processing, feature extraction, and selection methodologies. Two models, specifically the convolutional neural network (CNN) and the convolution invariant neural network (CINN), were trained on an 80/20 dataset split and showed exceptional performance, achieving average accuracies of 99.42% and 99.28%, respectively. The confusion matrix assesses the efficacy of classifier models, specifically on the misclassification of vibration signals. Furthermore, under diverse operational conditions of the machine with variable loads from the CWRU dataset, both models attain elevated classification accuracy.

REFERENCES

[1] Heng, A., Zhang, S., Tan, A.C., Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. Mechanical Systems and Signal Processing, 23(3): 724-739. https://doi.org/10.1016/j.ymssp.2008.06.009

[2] Ahmed, H., Nandi, A.K. (2020). Condition Monitoring with Vibration Signals: Compressive Sampling and Learning Algorithms for Rotating Machines. John Wiley & Sons.

[3] Sahu, D., Dewangan, R.K., Matharu, S.P.S. (2024). An investigation of fault detection techniques in rolling element bearing. Journal of Vibration Engineering & Technologies, 12(4): 5585-5608. https://doi.org/10.1007/s42417-023-01202-1

[4] Xu, F., Ding, N., Li, N., Liu, L., et al. (2023). A review of bearing failure modes, mechanisms and causes. Engineering Failure Analysis, 152: 107518. https://doi.org/10.1016/j.engfailanal.2023.107518

[5] Jovicic, E., Primorac, D., Cupic, M., Jovic, A. (2023). Publicly available datasets for predictive maintenance in the energy sector: A review. IEEE Access, 11: 73505-73520. https://doi.org/10.1109/ACCESS.2023.3295113

[6] Snyder, S.D. (2001). Active control-A bigger microprocessor is not always enough. Noise Control Engineering Journal, 49(1): 21-29.

[7] Samanta, B., Al-Balushi, K.R., Al-Araimi, S.A. (2006). Artificial neural networks and genetic algorithm for bearing fault detection. Soft Computing, 10: 264-271. https://doi.org/10.1007/s00500-005-0481-0

[8] Goyal, D., Pabla, B.S. (2016). The vibration monitoring methods and signal processing techniques for structural health monitoring: A review. Archives of Computational Methods in Engineering, 23: 585-594. https://doi.org/10.1007/s11831-015-9145-0

[9] Alharbi, F., Luo, S., Zhang, H., Shaukat, K., Yang, G., Wheeler, C.A., Chen, Z. (2023). A brief review of acoustic and vibration signal-based fault detection for belt conveyor idlers using machine-learning models. Sensors, 23(4): 1902. https://doi.org/10.3390/s23041902

[10] Mishra, K., Jigyasu, R., Singh, S., Chikkam, S. (2023). Motor bearing fault prediction using artificial intelligence techniques. In 2023 International Conference on Microwave, Optical, and Communication Engineering (ICMOCE), Bhubaneswar, India, pp. 1-4. https://doi.org/10.1109/ICMOCE57812.2023.10165790

[11] Jamil, M.A., Khan, M.A.A., Khanam, S. (2021). Feature-based performance of SVM and KNN classifiers for diagnosis of rolling element bearing faults. Vibroengineering Procedia, 39: 36-42. https://doi.org/10.21595/vp.2021.22307

[12] Jian, B.L., Chang-Jian, C.W., Guo, Y.S., Yu, K.T., Yau, H.T. (2020). Optimising back propagation neural network parameters to judge fault types of ball bearings. Sensors & Materials, 32(1): 417-430. https://doi.org/10.18494/SAM.2019.2605

[13] de Almeida, L.F., Bizarria, J.W., Bizarria, F.C., Mathias, M.H. (2015). Condition-based monitoring system for rolling element bearing using a generic multi-layer perceptron. Journal of Vibration and Control, 21(16): 3456-3464. https://doi.org/10.1177/1077546314524260

[14] Xu, Y., Li, Z., Wang, S., Li, W., Sarkodie-Gyan, T., Feng, S. (2021). A hybrid deep-learning model for fault diagnosis of rolling bearings. Measurement, 169: 108502. https://doi.org/10.1016/j.measurement.2020.108502

[15] Zhang, J., Zhou, Y., Wang, B., Wu, Z. (2021). Bearing fault diagnosis base on multi-scale 2D-CNN model. In 2021 3rd International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI), Taiyuan, China, pp. 72-75. https://doi.org/10.1109/MLBDBI54094.2021.00021

[16] Djaballah, S., Meftah, K., Khelil, K., Sayadi, M. (2023). Deep transfer learning for bearing fault diagnosis using CWT time–frequency images and convolutional neural networks. Journal of Failure Analysis and Prevention, 23(3): 1046-1058. https://doi.org/10.1007/s11668-023-01645-4

[17] Kaya, Y., Kuncan, F., ERTUNÇ, H.M. (2022). A new automatic bearing fault size diagnosis using time-frequency images of CWT and deep transfer learning methods. Turkish Journal of Electrical Engineering and Computer Sciences, 30(5): 1851-1867. https://doi.org/10.55730/1300-0632.3909

[18] Yuan, L., Lian, D., Kang, X., Chen, Y., Zhai, K. (2020). Rolling bearing fault diagnosis based on convolutional neural network and support vector machine. IEEE Access, 8: 137395-137406. https://doi.org/10.1109/ACCESS.2020.3012053

[19] Wei, H., Zhang, Q., Shang, M., Gu, Y. (2021). Extreme

learning Machine-based classifier for fault diagnosis of rotating Machinery using a residual network and continuous wavelet transform. Measurement, 183: 109864. https://doi.org/10.1016/j.measurement.2021.109864

[20] Wang, Y., Zhu, C., Wang, Q., Fang, J. (2023). Research on fault detection of rolling bearing based on CWTDCCNN-LSTM. Engineering Letters, 31(3): 12.

[21] Liang, P., Deng, C., Wu, J., Yang, Z. (2020). Intelligent fault diagnosis of rotating machinery via wavelet transform, generative adversarial nets and convolutional neural network. Measurement, 159: 107768. https://doi.org/10.1016/j.measurement.2020.107768

[22] Eltotongy, A., Awad, M.I., Maged, S.A., Onsy, A. (2021). Fault detection and classification of machinery bearing under variable operating conditions based on wavelet transform and CNN. In 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), Cairo, Egypt, pp. 117-123. https://doi.org/10.1109/MIUCC52538.2021.9447673

[23] Han, T., Chao, Z. (2021). Fault diagnosis of rolling bearing with uneven data distribution based on continuous wavelet transform and deep convolution generated adversarial network. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 43(9): 425. https://doi.org/10.1007/s40430-021-03152-9

[24] Lai, Y., Chen, J., Wang, G., Wang, Z., Miao, P. (2021). Rolling bearing fault diagnosis based on continuous wavelet transform and transfer convolutional neural network. In 2021 International Conference on Neural Networks, Information and Communication Engineering, Qingdao, China, pp. 23-29. https://doi.org/10.1117/12.2615182

[25] Neupane, D., Kim, Y., Seok, J. (2021). Bearing fault detection using scalogram and switchable normalisation-based CNN (SN-CNN). IEEE Access, 9: 88151-88166. https://doi.org/10.1109/ACCESS.2021.3089698

[26] Gao, D., Zhu, Y., Wang, X., Yan, K., Hong, J. (2018). A fault diagnosis method of rolling bearing based on complex morlet CWT and CNN. In 2018 Prognostics and System Health Management Conference (PHM-Chongqing), Chongqing, China, pp. 1101-1105. https://doi.org/10.1109/PHM-Chongqing.2018.00194

[27] Xie, Y., Zhang, T. (2017). Feature extraction based on DWT and CNN for rotating machinery fault diagnosis. In 2017 29th Chinese Control and Decision Conference (CCDC), Chongqing, China, pp. 3861-3866. https://doi.org/10.1109/CCDC.2017.7979176

[28] Lu, T., Yu, F., Han, B., Wang, J. (2020). A generic intelligent bearing fault diagnosis system using convolutional neural networks with transfer learning. IEEE Access, 8: 164807-164814. https://doi.org/10.1109/ACCESS.2020.3022840

[29] Zhang, Q., Deng, L. (2023). An intelligent fault diagnosis method of rolling bearings based on short-time Fourier transform and convolutional neural network. Journal of Failure Analysis and Prevention, 23(2): 795-811. https://doi.org/10.1007/s11668-023-01616-9

[30] Xia, M., Li, T., Xu, L., Liu, L., De Silva, C.W. (2017). 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

[31] Sonmez, E., Kacar, S., Uzun, S. (2023). A new deep learning model combining CNN for engine fault diagnosis. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 45(12): 644. https://doi.org/10.1007/s40430-023-04537-8

[32] van den Hoogen, J., Bloemheuvel, S., Atzmueller, M. (2021). Classifying multivariate signals in rolling bearing fault detection using adaptive wide-kernel CNNs. Applied Sciences, 11(23): 11429. https://doi.org/10.3390/app112311429

[33] 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

[34] Jin, Z., Chen, D., He, D., Sun, Y., Yin, X. (2023). Bearing fault diagnosis based on VMD and improved CNN. Journal of Failure Analysis and Prevention, 23(1): 165-175. https://doi.org/10.1007/s11668-022-01567-7

[35] Kulevome, D.K.B., Wang, H., Wang, X. (2022). Deep neural network based classification of rolling element bearings and health degradation through comprehensive vibration signal analysis. Journal of Systems Engineering and Electronics, 33(1): 233-246. https://doi.org/10.23919/JSEE.2022.000023

[36] Gu, J., Wang, Z., Kuen, J., Ma, L., et al. (2018). Recent advances in convolutional neural networks. Pattern Recognition, 77: 354-377. https://doi.org/10.1016/j.patcog.2017.10.013

[37] Iqbal, H. (2018). HarisIqbal88/PlotNeuralNet v1.0.0.Zenodo. https://doi.org/10.5281/zenodo.2526396

[38] Smith, W.A., Randall, R.B. (2015). Rolling element bearing diagnostics using the Case Western Reserve University data: A benchmark study. Mechanical Systems and Signal Processing, 64: 100-131. https://doi.org/10.1016/j.ymssp.2015.04.021

[39] Case School of Engineering. https://engineering.case.edu/bearingdatacenter/welcome.

[40] Tharwat, A. (2021). Classification assessment methods. Applied Computing and Informatics, 17(1): 168-192. https://doi.org/10.1016/j.aci.2018.08.003

[41] Miao, J., Zhu, W. (2022). Precision–recall curve (PRC) classification trees. Evolutionary Intelligence, 15(3): 1545-1569. https://doi.org/10.1007/s12065-021-00565-2

[42] Wan, X., Liu, J., Cheung, W.K., Tong, T. (2014). Learning to improve medical decision making from imbalanced data without a priori cost. BMC Medical Informatics and Decision Making, 14: 111. https://doi.org/10.1186/s12911-014-0111-9