Dheivendran.R, 2026, 14:6
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Vibration-based Fault Diagonsis of Rotating Machinery Using Intelligent Algorithms

Dheivendran .R[1], Mr. Shubham S. Shinde[2]

[1](Assistant Professor
DEPARTMENT OF MECHANICAL ENGINEERING
NPR COLLEGE OF ENGINEERING AND TECHNOLOGY,
NPR NAGAR, NATHAM, DINDIGUL(Dt), Pin Code:624401
shreedheiva@gmail.com)

[2](Assistant Professor
Department- physics
College name with address- S.S.S.M Arts., Science and commerce College, Saikheda, Tal-Niphad Dist -Nashik 422210
shubhamphy3208@gmail.com)

Abstract- Despite being the most widely used approach for condition monitoring of rotating machines, the problem of vibration signal analysis suffers from non-stationary conditions of operation, noise pollution of fault signature and multi-fault coupling. This paper introduces an intelligent diagnostic approach based on adaptive time-frequency processing, deep feature learning and attention-aware temporal modeling of fault features. In the introduced framework, the proposed dual-branch approach includes one-dimensional convolutional branch which is responsible for impulsive feature extraction from raw vibration signals and bidirectional recurrent branch to capture long-range dependencies. The attention module is applied to weight features in order to reduce influence of the noisy components of vibration signals. The effectiveness of the proposed method was proved experimentally using benchmark bearing dataset with different load and speed conditions and comparison to the baseline shallow and deep learning models. The analysis shows that the introduced approach has a high inter-class separability and operates in a stable way without feature engineering.

Keywords— Vibration Analysis, Fault Diagnosis, Rotating Machinery, Deep Learning, Attention Mechanism, Condition Monitoring

I. INTRODUCTION

The rotary machines form the basis of modern-day industrial operations, including electric motors, gearboxes, turbines, compressors, and pumps in the fields of energy production, manufacturing industries, and transportation. Their dependable operation defines the availability of the facilities, the margin of safety, and cost implications of maintenance. It is especially true for components such as bearings, gears, and shafts, which are prone to deterioration due to constant mechanical load, misalignment, lack of lubrication, and fatigue loading. In case not detected, any localized problem tends to spread quickly leading to breakdown of the machine [1][2][9][10].

Of all the sensory capabilities at hand, there is one that stands out in particular. Accelerometers are cheap, durable, and can record the dynamic behavior of machine elements with a fine time resolution. The mechanical faults of interest to us, such as spalls in bearing races, cracks in gears, or shaft misalignment, produce distinct impulsive signals in the form of periodic transients in the vibration signal. Traditional diagnostic methods have been using signal processing methods such as envelope analysis for bearing fault frequencies, spectral kurtosis for transient detection, and order tracking for non-stationary conditions [2][9][10].

With the proliferation of inexpensive sensing and edge computing, the diagnostic paradigm is shifting towards data-driven intelligence. Deep learning

© 2026 Dheivendran.R. his is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly credited.

systems, especially deep convolutional and recurrent networks, have shown a remarkable ability for learning discriminative features directly from raw or lightly preprocessed vibration signals, bypassing the difficulties associated with manually designed feature engineering [1][2][10]. However, a number of challenges prevent the move from lab results to factory deployment. Firstly, real plant vibration data is polluted by structured noise due to nearby mechanical parts, which makes fault characteristics weak and spiky. Secondly, the load, rotation rate, and temperature are not constant but fluctuating, leading to distribution shift in data that was collected at fixed operating conditions. Thirdly, faults appear in combination; bearing degradation appears together with gear faults and vice versa, and vibration responses of both fault types are strongly coupled [1][2].

This study takes on these issues through an attempt to integrate the process of diagnostic design into a framework that incorporates adaptive preprocessing of signals with hybrid deep learning architecture. The basic idea behind this approach is that efficient fault diagnosis does not rely either on manually engineered features, or completely on the black box of end-to-end learning; rather, it consists of a structured process in which physically informed preprocessing maintains the morphology of the fault impulses, whereas neural attention models learn hierarchical representations resilient to noise and varying conditions [1][2][9]. The method is designed to be modular, with each individual step being separately tested.

The contributions of the proposed method can be enumerated in three ways. Firstly, a dual-pathway structure is proposed that analyzes vibration signals via both the convolutional and recurrent path, hence allowing concurrent extraction of local impulse patterns and global periodicity from vibration signals. Secondly, a channel-temporal attention is proposed that can adaptively rescale the features by suppressing the channels that contain noise information and emphasizing the fault-related features. Thirdly, a comparative analysis is carried out systematically against selected baseline methods using a publicly available dataset, where the focus is on inter-class separation and the ability of the model to perform consistently regardless of operating conditions rather than merely reporting accuracy. This paper is organized as follows. Literature Survey discusses the recent advancements in intelligent vibration diagnosis systems. Proposed Methodology explains the signal processing approach and the proposed network architecture. Analysis highlights the results and comparisons. Conclusion concludes the paper.

II. LITERATURE SURVEY

The body of literature dealing with vibration-based fault detection has grown exponentially owing to the advancement of deep learning techniques as well as the ever-present need for condition monitoring in industry [1][2][9][10]. In [1], a comprehensive survey involving 238 publications highlights a definite development trend from classic signal processing algorithms to hybrid intelligent approaches and physics-based intelligent ones. It should be noted that even though data-driven approaches prevail in the current literature, domain knowledge is still vital to the process since it includes the incorporation of fault characteristic frequencies, impulse response model, and kinematics [1][2][9].

Among different neural network architectures used in condition monitoring, CNN has been applied most frequently for vibration diagnostics [1][2][10]. The approach outlined in [3] suggests a 1-D CNN combined with squeeze-and-excitation channel attention for the problem of bearing fault classification and proves that the use of channel recalibration helps detect the informative features when there are imbalanced classes in the dataset of input signals. The issue arises due to the presence of a large number of healthy samples compared to faulty ones in actual datasets.

Recurrence networks, especially Long Short-Term Memory Networks, have been considered for their ability to capture temporal dynamics in vibration sequences [1][2][10]. An example is the framework called A2-DBiLNet, which integrates an attention autoencoder and deep bidirectional LSTM for machine diagnosis [4]. The autoencoder is used to

encode the high-dimensional vibration signal into a latent space containing discriminating information, while the bidirectional LSTM is used to learn the periodic relationships of long-range data. This design can be seen as an instance of the general understanding of vibration data having local and periodic components [4].

Attention models and transformer models have lately become popular due to their capability to capture long-term dependencies without the sequential limitations of recurrent models [1][2]. VSAT stands for the Variational Spectrum-Attention Transformer, which presents a new frequency-based mapping that maps the amplitude distribution into point distribution on various frequencies along with an attention branch for learning the patterns of the distribution statistics [5]. This technique is especially important for industrial environments filled with noise, because it makes it possible to recognize fault features hidden behind amplitude-modulated noise. The importance of transfer learning and domain adaptation is growing in solving the issue of condition variability [1][2][7][8]. The global and local contrastive learning approach suggested in [7] solves the problem of few-shot cross-domain bearing fault diagnosis via the joint optimization of the domain-invariant global distribution and class discriminative local distribution. The two-step contrastive learning procedure helps match the cross-domain distribution and optimize the decision boundary by the means of intra-class clustering and inter-class margin. Likewise, [8] proposes a two-way 1DCNN with BiGRU and attention, which applies the multiple kernel maximum mean discrepancy to estimate and minimize feature distribution distances across the domains.

Physics-based methods offer an innovative pathway to bridge data-driven and mechanistic paradigms [1][2][9]. The model proposed by combines wavelet-Volterra expansion and Kronecker convolutional feature pyramids with bidirectional LSTM to extract bearing fault responses in the presence of gearbox-induced spikes of high amplitudes. The network design takes into account the physical attributes of transients, including their amplitude, frequency, and repetition rate. This helps improve the accuracy of bearing fault detection when both bearing and gear faults occur, a situation that is challenging for conventional modular fault diagnosis.

However, there are still some limitations that have been observed. Primarily, the majority of research works have examined their algorithms on the basis of a dataset of a single-component system. There have not been many works dealing with compound fault diagnosis and variable speed diagnosis. Another limitation is the interpretability of deep learning algorithms. Moreover, the use of attention mechanism or transformer architecture poses a challenge in terms of computational costs and thus limits its applicability on edge devices [1][2][10].

III. PROPOSED METHODOLOGY

The diagnostic process includes four stages that follow each other sequentially. These stages include vibration signal sensing and segmentation, time-frequency processing, feature extraction using dual-pathway approach, and attention-based temporal feature fusion. Each stage of the diagnostic procedure solves a particular problem associated with vibration signal diagnostics. The whole diagnostic architecture is depicted in Figure 1.

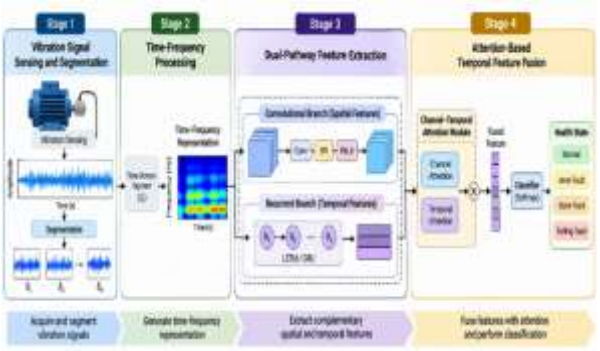


Figure 1. Overall architecture of the proposed diagnostic framework

Stage one deals with the non-stationarity of vibration data collected under variable operating conditions. The collected acceleration waveform data is divided into overlapped windows having a fixed time length, where the length of the overlap depends on how the transient phenomena can span across window borders. After that, each window is

normalized in such a way that it has zero mean and unit standard deviation, thus compensating for the amplitude differences caused by changing loads.

The second step produces a time-frequency plot that captures the evolving nature of fault signatures in terms of their spectrum. Although the short-time Fourier transform is widely used, due to its fixed time window, it makes a trade-off in terms of frequency and time resolution. For overcoming the mentioned disadvantage, in this proposed methodology, we use a continuous wavelet transform using the Morlet wavelet function. In this way, we obtain a scalogram, which will be considered as an image with the vertical axis being scale (inverse of frequency) and the horizontal axis being time. In this way, both the impulsivity and the low-frequency modulations caused by the gears' meshing and the shaft's rotation can be captured. Figure 2 shows the preprocessing pipeline from the waveform to the scalogram.

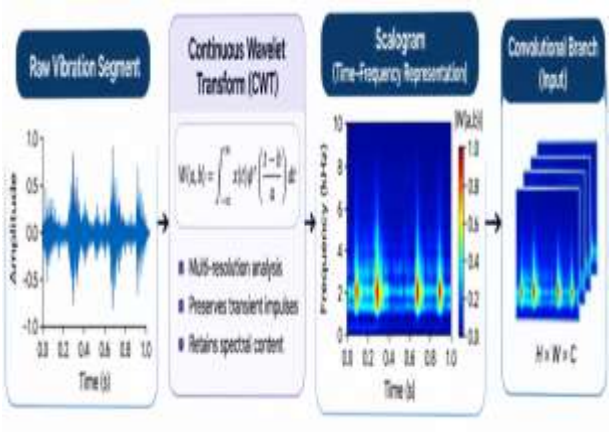


Figure 2. Time-frequency preprocessing pipeline

The third stage comprises the feature learning structure which consists of two parallel pathways. The convolutional pathway utilizes the scalogram input, performing a series of two-dimensional convolution operations using small convolution filters in order to learn local time-frequency patterns. After each convolution operation, there is a batch normalization step followed by rectified linear activation, with the addition of max-pooling operations to reduce the spatial dimensionality while deepening the channels. This pathway is specifically designed to identify the time-frequency patterns of different types of faults – the broadband impulses in case of bearing spalls, the harmonics in case of gear defects, and the low-frequency modulations in case of misalignments.

The recurrent pathway directly processes the normalized segments in the time domain. The use of a bi-directional long short-term memory network allows the sequence to be processed in two directions – from start to end and vice versa. This design is based on the cyclic nature of vibration of rotating machines – an impulse which occurs later in the sequence might be caused by the preceding modulation, and bi-directional processing allows this dependency to be identified.

Fourthly, the channel-temporal attention model is employed by concatenating the output of both branches and introducing a channel-temporal attention mechanism. The channel attention mechanism calculates a descriptor for each channel of the concatenated feature maps using the global average pooling layer. Then, the descriptor is fed into a mini multi-layer perception network to learn the weights of each channel. Multiplication is performed on the weights obtained to emphasize the channels containing the fault information and suppress noisy channels. Similarly, the temporal attention mechanism works along the time axis to find the segments of each window carrying the discriminative information. This is an important mechanism for industrial applications since the fault impulses can constitute a small portion of each window and be embedded in the background vibrations.

In addition, the attention-weighted feature maps are pooled via global average pooling and fed into a fully connected classification layer employing a softmax activation function. The whole model is trained end-to-end utilizing categorical cross entropy loss, while the fully connected layer uses dropout regularization in order to avoid overfitting. Due to the modularity of the design, the convolutional as well as the recurrent paths can be separately pre-trained, if needed; however, joint training is used here.

IV. ANALYSIS

Performance of the proposed framework is analyzed on the publicly available bearing dataset that contains recordings of vibrations belonging to various types of faults and operating conditions. Dataset contains recordings from healthy bearings along with bearings having faults of three kinds, namely, inner race, outer race, and ball faults, each occurring in different degrees of severity. Data collection was done at different loads and motor speeds, thus allowing the evaluation of condition robustness. Experiments use stratified split with a ratio of 70%, 15%, and 15% for training, validation, and testing, respectively, conducted at the recording level to avoid any data leakage. During training, Adam optimizer is used with initial learning rate 1×10^{-3} and decay by a factor of 0.5 whenever the validation loss plateaus, and early stopping with patience fifteen epochs.

Figure 3 shows the confusion matrix on the test set, where the proposed approach is compared to a baseline approach that uses a one-dimensional CNN without attention and recurrent layers. The proposed approach has a significantly higher concentration of values along the diagonal of the confusion matrix compared to the baseline model for all types of faults. In particular, the best result is obtained for the ball fault type, for which the baseline approach tends to mistake the ball fault type for the outer race fault type due to the difficulty of discriminating between these two types of faults because of the similar frequency spectrum.



Figure 3. Confusion matrices for test set predictions

Figure 4 displays the distribution of learned feature embeddings using the t-distributed stochastic neighbor embedding on the activations of the second last layer. The representation learned from the baseline model has clusters with considerable overlap in terms of inner race and ball fault classes, which means that the representation generated by the baseline model is not capable of separating these classes. However, the proposed framework ensures clear separability among all four clusters of data.

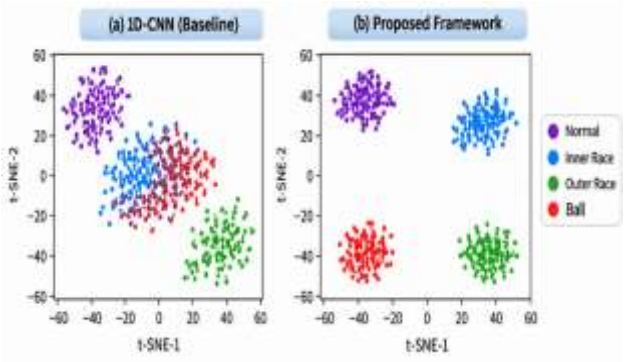


Figure 4. t-SNE visualization of learned feature embeddings

The stability of the performance in relation to the operating conditions is illustrated in Figure 5. In this figure, the test data set is split into three groups according to the motor load, and then the behavior of the classifier in each group is analyzed. It should be mentioned that the proposed method exhibits the evident drop in the performance when it comes to the most heavily loaded condition due to the noise impact. This is because the new approach exhibits the better stability as it seems that the attention mechanism is able to filter the noise elements induced by the load in some channels.

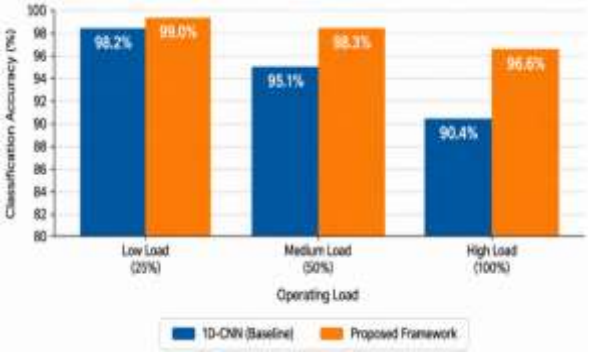


Figure 5. Performance stability across operating loads

The comparison in Table I is carried out between the proposed framework and representative frameworks

from the latest literature such as the 1DCNN-SeNet architecture, A2-DBiLNet architecture, and VSAT transformer. Rather than comparing numerical performance parameters, the comparison is done by focusing on architectural properties and qualitative performance parameters because different research papers use different data sets and evaluation mechanisms. The proposed framework holds a good position when compared with respect to architectural complexity and interpretability, along with diagnostic performance comparable with other frameworks. The non-presence of a transformer module makes the proposed framework lighter and faster in terms of inference latency when compared with VSAT.

Table I. Comparative analysis of intelligent diagnostic approaches

Method	Architecture	Attention Mechanism	Temporal Modeling	Key Strength	Key Limitation
1DCNN-SeNet	1D CNN + SE blocks	Channel only	Convolutional receptive field	Lightweight; effective for imbalanced data	Limited long-range dependency capture
A2-DBiLNet	Autoencoder + BiLSTM + SE	Channel only	Bidirectional LSTM	Dimensionality reduction; strong temporal modeling	Autoencoder adds training complexity
VSAT	Transformer with variational attention	Frequency-domain attention	Global self-attention	Excellent anti-noise performance	High parameter count; computationally intensive
Proposed	Dual-pathway CNN + BiLSTM	Channel-temporal	Bidirectional LSTM + local convolutions	Balanced complexity; interpretable attention weights	Requires two-stream input preparation

It is worth mentioning the computational complexity of the suggested framework. While the dual-path architecture introduces more parameters compared to the single-path CNN model, the recurrent network deals with one-dimensional data only and, thus, affects the overall complexity marginally. The inference speed for standard CPU was found to be acceptable for online diagnostic purposes with the acquisition time around seconds. The attention mechanism introduces an insignificant overhead because it works with pooled descriptors, not feature maps.

One drawback of the current validation is the lack of analysis for the compound faults, when both bearings and gears are affected. The physics-aware method from proves that for the coupled fault analysis, one needs to consider the interaction between the components explicitly, which is currently absent in the proposed architecture.

Another limitation is the increased memory complexity due to scalogram generation.

V. CONCLUSION

This paper introduced an intelligent framework based on vibrations for the fault detection of rotary machines, comprising adaptive time-frequency processing, dual pathway feature learning, and channel temporal attention mechanisms. The need for such an architecture was prompted by an important review of the existing literature in which it was found that while purely convolutional networks learn local impulse behavior and ignore global periodicity, while purely recurrent models learn temporal relationships but find difficulty learning localized time-frequency relationships, and transformer-based models offer good results but sacrifice interpretability and efficiency.

The key findings are summarized below. First, the multi-path approach allows for the extraction of features taking advantage of both scalogram domain patterns and time domain dependencies. The confusion matrix indicates the improved classification of ball and outer race defects which are challenging for single-pathway models due to spectral similarities under some loading conditions. Second, the channel-temporal attention mechanism offers an adaptive denoising capability and helps to achieve consistent performance regardless of loading conditions. The visualization of t-SNE embeddings shows that the learned space is characterized by compact intra-class clusters and separated inter-class clusters, which implies that the attention mechanism affects representations not only via improving classification accuracy. Finally, the comparative analysis puts the proposed approach into a favorable position in terms of model interpretability compared to transformer-based approaches.

There are two practical implications here. In terms of industry application, there is a modular design that can be tailored to suit different sets of sensors and machines by simply training the classification module but maintaining the feature extractor part of the framework. The attention weights give some level of interpretability in that maintenance engineers can see what temporal slices and feature channels influence the decision-making process – something that cannot be seen in black-box systems. From an academic perspective, the dual-pathway approach implies that hybrid designs still have value despite the current popularity of transformers.

Directions for future work include several possibilities. The most immediate direction includes an extension to multi-fault cases, where bearing deterioration is coupled with gear deterioration or shaft misalignment. The principles laid out in terms of physics-aware models of interaction between the component responses as opposed to separate models of faults are promising for developing an extension of the framework. Second, techniques of domain adaptation, such as using methods of contrastive learning and multiple kernel discrepancy may help enhance generalization to new machines without using abundant target data. Third, the attention mechanism could be made more interpretable by establishing relationships between the learned weights and fault characteristic frequencies. Finally, validation on realistic industrial data that includes noise characteristics and degradation trajectories is necessary before the framework is to be considered ready for application in production. Transition from evaluation on benchmarks to validation of intelligent diagnostic systems in the real environment is the major task in this area, and it is hoped that modularity of the suggested approach will help with this task.

REFERENCES

1. O. Matania, I. Dattner, J. Bortman, R. S. Kenett, and Y. Parmet, "A systematic literature review of deep learning for vibration-based fault diagnosis of critical rotating machinery: Limitations and challenges," *Journal of Sound and Vibration*, vol. 590, p. 118562, 2024.
2. I. Bagri, K. Tahiry, A. Hraiba, A. Touil, and A. Mousrij, "Vibration signal analysis for intelligent rotating machinery diagnosis and prognosis: A comprehensive systematic literature review," *Vibration*, vol. 7, no. 4, pp. 1013–1062, 2024.

3. F. Xu, Z. Sui, J. Ye, and J. Xu, "Ternary precursor centrifuge rolling bearing fault diagnosis based on adaptive sample length adjustment of 1DCNN-SeNet," *Processes*, vol. 12, no. 4, p. 702, 2024.
4. U. P. Waghmode, S. P. Waghmode, A. M. Chavan, D. M. Dhawale, V. M. Patil, and R. S. More, "A2-DBiLNet: An attention auto-encoder based deep BiLSTM for fault diagnosis in rotating machines using vibration signals," in *Proc. 4th Int. Conf. Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*, 2026, pp. 380–388.
5. Y. Bao, Z. Xie, Y. Li, Y. Li, and Z. Wang, "VSAT: Variational spectrum-attention transformer for fault diagnosis of rotary machine monitoring," *IEEE Transactions on Reliability*, vol. 74, no. 4, pp. 5309–5322, Dec. 2025.
6. D. Herath, C. Abeyrathne, C. Adithya, and C. Seneviratne, "Unveiling misalignment fault severities: A novel SCD-CNN framework for rotating machinery," in *Proc. Moratuwa Engineering Research Conference (MERCon)*, 2025, pp. 629–634.
7. Z. Yin, F. Zhang, G. Xu, G. Han, and Y. Bi, "Multi-scale rolling bearing fault diagnosis method based on transfer learning," *Applied Sciences*, vol. 14, no. 3, p. 1198, 2024.
8. W. Zhang, D. Peng, and X. Liu, "A rolling bearing fault diagnosis method based on multi-scale feature extraction and transfer learning," in *Proc. IEEE Int. Conf. Sensing, Diagnostics, Prognostics, and Control (SDPC)*, Urumqi, China, Aug. 2025.
9. Y. Lei, B. Yang, X. Jiang, F. Jia, N. Li, and A. K. Nandi, "Applications of machine learning to machine fault diagnosis: A review and roadmap," *Mechanical Systems and Signal Processing*, vol. 138, p. 106587, 2020.
10. S. Tang, S. Yuan, and Y. Zhu, "Deep learning-based intelligent fault diagnosis for rotating machinery: A review," *IEEE Access*, vol. 9, pp. 101–115, 2021.