International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

A Deep-Learning Framework for Robust Feature Extraction from Vibration Data: A Use Case for Rotary Machine Fault Detection

Mrs. Karri. Devika,
Department of Computer Applications
Samata Degree College

ABSTRACT

Wind turbines, generators, motor-derives, and other spinning equipment are particularly vulnerable to catastrophic failures caused by mechanical issues. Vibrations in the structure of the equipment might be caused by various mechanical problems. The early detection and diagnosis of underlying mechanical defects via online vibration monitoring helps minimize catastrophic breakdowns. It is difficult to extract unique vibration characteristics that both enhance fault classification performance and are resistant to different types of noise in vibration signals. Several vibration-features have been suggested in the literature, all based on statistical and signal processing principles. Based on what is already known about the properties of vibration signals from various kinds of faults, several vibration-features were developed. Latest state-of-the-art performance on image and voice recognition tasks was achieved by automatically extracting features using unsupervised learning in deep neural networks. Hence, we propose feature learning on raw vibration signals as an alternative to feature engineering in the hopes of extracting vibration features that might enhance the defect diagnosis performance of the classifiers that follow. We examined Convolutional Neural Networks for unsupervised feature learning on vibration signals and Denoising Auto-Encoders for robust and noise-invariant vibration feature extraction for this purpose. We suggested a hybrid deep model that has a single classification layer on top of a Multi-channel Convolutional Neural Network and a stack of Denoising Auto-Encoders (MCNN-SDAE). We tested the suggested model against others that used vibration characteristics derived from traditional statistical and signal processing methods to see how well it could detect and classify faults. To ensure that all of the models were performing as expected, we used vibration data from an experimental test-rig that was built to analyze the vibration characteristics of bearing-related defects as a benchmark.

Keywords

Vibration-features learning, equipment condition monitoring, bearing fault identification, machine learning, online monitoring.

1. INTRODUCTION

2. Gear boxes, shafts, turbines, generators, motor-drives, and other rotating equipment are prone to mechanical failures as a result of the extreme working conditions and constantly changing loads. To make sure these equipment are running safely, reliably, and economically, online condition monitoring is crucial [1]. By identifying and locating faults early on, it helps lower the cost of maintenance and catastrophic breakdowns. In order to assess the state of equipment using data on vibration, noise, and process parameters, many online monitoring methods have been explored [2]. The most well-known method for tracking the health of rotating machinery, however, is vibration analysis [3]. Many crucial components, such as shafts, couplers, bearings, gearboxes, etc., undergo regular failures. Because they are sensitive to a broad variety of problems associated with rotating equipment and are easy to acquire, vibration signals are often used [4].

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

Research into the identification and detection of faults utilizing analytical, signal processing, and statistically-based vibration signal properties is ongoing. When using passive-mode, defect detection is done manually using characteristics based on expert knowledge [5]. In contrast, a classification/fault diagnosis model based on machine learning receives the extracted information from the active-mode [6]. The data-driven character and real-time performance of machine learning approaches make them particularly appealing. Extracting features and training a classifier model using vibration-features is a common machine learning approach. The inherent noise and high dimensionality of raw vibration data make it unsuitable for direct usage as a defect diagnosis system feature. Consequently, dimensionality reduction by compact feature extraction from raw vibration signals without loss of distinctive information is necessary. Additionally, the quality and representability of the features retrieved from raw data are crucial to the effectiveness of classifiers based on machine learning. Wavelet packet transform (WPT), Fast Fourier Transform (FFT), cepstrum information, Short Time Fourier Transform (STFT), empirical mode decomposition (EMD), and time-domain statistical features (TDSF) are in the list of vibration features that have been suggested in the literature, among others [5]. Each of these feature representations has advantages and disadvantages, and [5] discusses them at length. The aforementioned vibration characteristics have been used to develop several defect diagnosis models that include appropriate classifiers as SVM, ANN, BPNN, PNN, Fuzzy Inference, ANFIS, multinomial, and others.

3. logistical model. Using an example TDSF-ANN/SVM/MLP, WPT-BPNN/SVM/multinomial logistic regression, and many more feature-classifier combinations are available [7–14]. The majority of the research on these feature-classifier combinations has focused on problems with gearboxes, couplings, bearings, and shafts. Therefore, the majority of the characteristics were developed by using prior-knowledge derived from experts on the distinctive vibration signatures associated with these defects. However, in mechanical systems (such as pumps and engines), which share this vibration characteristic, some of the designed characteristics have proven effective in defect diagnostics. [15][16]. Nevertheless, these properties aren't very useful for general vibration monitoring due to their shallowness and fault-specificity. Mechanical systems, such as rotors, turbine engines, aircraft frames, loose components, systems for high-pressure/velocity fluid flows, etc., produce vibration signals with semantic and dynamic properties unique to such systems. Therefore, feature-learning is best for capturing domain-specific failure attributes that lead to good performance, as opposed to feature-extraction. When it's hard to come up with defining characteristics for a task, the feature-learning strategy may help reduce reliance on problem-specific expertise. Recent state-of-the-art performance on image and voice recognition tasks has been achieved using abstract level feature extraction in deep multi-layered neural networks using unsupervised learning [17][18]. Researchers looked at the possibility of deep models extracting more abstract representations on typical vibration characteristics and raw data for the aim of equipment defect diagnosis [19]. Consequently, there are a number of deep-models available for monitoring equipment status based on vibration. Some examples of these are Deep Belief Networks (DBN) [20–23], Auto-Encoder ELM [24], Stacked Denoising Auto-encoders (SDA) [25][26], and CNN-based fault-models [25][26]. According to these studies, deep-architectures outperform shallow ones when it comes to

Index in Cosmos
May 2022 Volume 12 ISSUE 2
UGC Approved Journal

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

defect detection. While deep-models are useful as non-linear classifiers, feature selection is still an initial step in these approaches. In order to locate and identify the severity of bearing problems in rolling bearings, two prominent deep-models use designed characteristics as base-input: WPT-DBN[20][22] and TDSF-DBN [27]. In an ideal world, a deep-model could automatically glean the discriminative characteristics from datasets. To achieve this, we put forth a deep-hybrid model for multi-channel vibration data that combines a Convolutional Neural Network with a stacked denoising-autoencoder for unsupervised feature learning and classification. The conceptualization of the suggested approach is based on the unique problems described in section 5.3. Below is the article's organizational structure. Section 5.4 discusses the difficulties caused by vibration signals and the several deep learning architectures that might be used for mechanical defect modeling based on vibration characteristics. How convolutional neural networks (CNNs) learn features from vibration signals is covered in Section 5.5. In section 5.6, the suggested deep-hybrid model's design is detailed in more detail. A CWRU-benchmark vibration data-set, acquired from an experimental test-rig designed to investigate bearing failure diagnosis techniques in particular, is used to verify the MCNN-SDAE model [28].

4. CHALLENGES IN VIBRATION- BASED FAULT DIAGNOSTICS

Vibration-based fault diagnosis is a challenging task especially for the case of rotating machinery. Some of the difficulties are due to inadequacy of engineered features to capture non-linear fault dynamics hidden in the vibration-data. Vibration signals are often non-stationary with different time- frequency characteristics which further complicate the feature-representation. Here we identified some key contributors to those challenges.

1- Frequency spectrum of the vibration signal is often analyzed to detect presence of bearing related faults. Bearing specific frequencies i.e. BPFO, BPFI and BPF are calculated with the assumption that the rolling elements just roll on the raceways and do not exhibit sliding behavior. However, this assumption seldom holds. In practice, a bearing roll-element undergoes a combination of rolling and sliding. Consequently, the calculated bearing-frequencies may differ from the actual frequencies by a small percentage. This rolling-slipping behavior of bearing manifests itself in the form of frequency shifts. Usually these frequency-shifts are dynamic and exhibit a non-linear behavior against different bearing-faults and their severities.
2- In case of bearing or gear faults the early vibration signals are often non-stationary and are dominated by vibrations from other components in the equipment and transmission path. So, the beneficial information in vibration signals may get distorted, thereby resulting in a reduced recognition rate. Obtaining useful information from a signal polluted by noise is essential for effective fault diagnosis methods.
3- Multiple simultaneous faults can obfuscate important frequencies
4- Interference from additional sources of vibration,
i.e. bearing looseness may also obscure valuable features.

Further, the following deficiencies in classical diagnostic models limit the classification performance especially under above-mentioned challenging scenarios.

1- The features employed in the diagnostic model are manually extracted on the basis of prior knowledge about different fault types and the corresponding suitable signal processing techniques that can extract salient features to characterize the underlying faults. So the extracted features are specific to a particular diagnosis issue and might not be suitable for other fault types.
2- Many diagnostic models, reported in the literature, uses classifiers that have shallow architectures. It limits the model-ability to model complex non- linear relationships for effective fault diagnosis.

5. POTENTIAL DEEP-LEARNING ARCHITECTURES

Extracting features from vibration signals that are robust and global is a challenging task. Instead of extracting and selecting features manually, methods that can adaptively mine the distinctive features hidden in the measured signals are needed to reflect different health conditions of corresponding machinery. Deep learning [17] has the potential to address the

forementioned deficiencies in current intelligent diagnosis methods. The deep learning is outstanding in its ability to model high-level abstractions in the data by using architectures composed of multiple non-linear learning layers. It learns the discriminative features and is helpful in tasks where it is difficult to manually develop the characterizing features.

The deep-learning research has proposed several architectures e.g., Restricted-Boltzmann-Machine (RBM) and Denoising Auto-encoder (DAE) and their variants, to estimate underlying statistical structure in inputs [29][30]. These architectures have been successfully employed for unsupervised feature learning during greedy layer-wise training under deep-learning framework.

However, Convolution Neural Network are specifically interesting due to their unique ability to maintain initial information regardless of shift and distortion in the input.. The CNN-models are optimized using an error-gradient algorithm [31]. CNNs are widely used in image classification [32] speech-processing tasks [33] and various other applications [34-36]. Feature learning through CNNs have several advantages over other deep-architectures. First, hierarichal multiple Convolutional-layers can autonomously learn complex feature representations on raw input data. Second, CNNs can effectively exploit the spatial structure in the data through local receptive fields, shared filter weights and spatial sub-sampling. In case of a frequency spectrum of a vibration signal, the spatial structure is defined as the ordered sequence of frequencies. The convolution operation across frequency provides the CNN-network with immunity to small spectral shifts, such as those introduced by slipping artifiacts of the rolling-bearings. Similarly, convolution across time can be useful in capturing temporal artifacts introduced by non- stationary vibration signals. Hence, making an effective use of convolution both in time and frequency domain might be helpful in extracting robust features on vibration data and could improve the fault detection performance.

Similarly, classical autoencoders (AEs), that are trained to denoise an artificially corrupted version of their input, were found good at learning robust features on input-data.Vincent et.al.[37] further extended the classical denoising autoencoder with greedy layer-wise training procedure of deep learning algorithm that allowed stacking of multiple DA’s to construct a deep-model. Building a deep-model by stacking greedily- trained classical DA’s is a concise and efficient method that can extract features that are robust and invariant to noises. The architecture is interesting for learning robust features from noisy vibration signals. It can improve classification performance for the cases in which fault signature may get distorted by secondary vibration sources from other components in the transmission path.

Considering the advantages of CNN and SDAE architectures, we will investigate a hybrid deep-model for efficient fault diagnosis by extracting robust features on underlying raw vibration signal.

6. FEATURE LEARNING WITH CONVOLUTION NETWORKS

A Convolution-Neural-Network (CNN) is the variant of a standard neural-network. Contrary to the traditional neural architectures where the receptive field for input-layer neurons spans the complete input, the CNNs define a local receptive field on the input. The layers of a CNN are referred as convolution layers. The input field is logically divided into small windows which forms the localized receptive fields for subsequent convolution-layer. Units /operators/kernels in the convolution layers operate on windowed input and computes features of the local region. These convolution-units generate global representations by computing and learning local features. A CNN-layer extracts features from the input signal by convolving the input signal with the filter (or kernel) learnt by the convolution-layer. The activation of a unit in the CNN- layer represents the result of the convolution operation. The convolutional operation detects patterns captured by the kernels, regardless of where the pattern occurs, by computing the activation of a unit on different regions of the same input. In CNNs, the activation levels of kernels corresponding to subsets of classes are optimised as part of the supervised training process. A feature map is an array of units that shares the same kernel-parameterization (weight vector and bias). Their activation yields the result of the convolution of the kernel across the entire input data. The application of the convolution operator to a one-dimensional temporal sequence can be viewed as a filter, capable of removing outliers, filtering the data or acting as a feature detector that respond maximally to specific temporal sequences within the time- span of the kernel.

7. HYBRID DEEP-MODEL ARCHITECTURE

The proposed hybrid-model consists of a multichannel CNN followed by Stacked DAE architecture at the top. A CNN model is trained on individual channel to extract abstract-level Vibration-features which characterize the normal and faulty conditions in individual channels. First unsupervised pre- training is commenced through convolution auto-encoder (CAE). CNN-model parameters are initialized with convolution filters pre-trained by the CAE-model. Finally, supervised training of the CNN-model is done with labeled data. After CNN-model training, in the next step the feature- representations at top-layer of CNN-model of each channel (generated via forward pass in the CNN) are fused by learning a SDAE-model on CNN-based feature representation. The SDAE helps model the collective vibration behavior of rotary system by fusing vibrations-features extracted from multiple channels, monitoring different components or proximity in the system. A greedy layer-wise training strategy is employed to stack multiple DAE’s. Each layer extracts more abstract-level representation to model non-linearity in the underlying vibration system. Finally, a fully-connected neuron-layer is trained for fault classification on the top-encoder-layer of the SDAE-model. Figure 1 depicts the proposed model architecture and corresponding processing pipeline. The proposed method is able to mine vibration-features that are robust to noise, consequently could achieve high classification performance compared to shallow architectures.

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

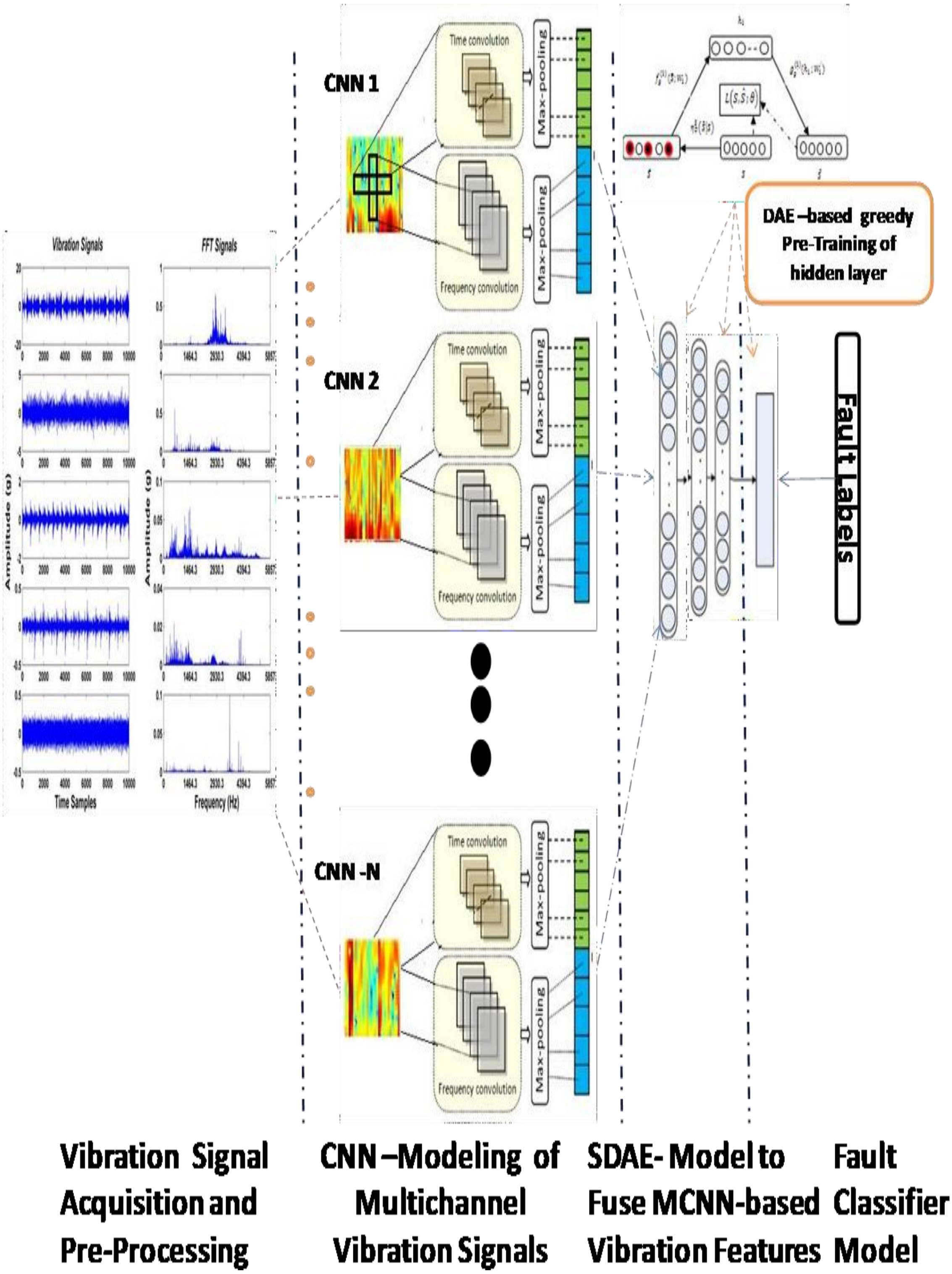


Figure 1: Hybrid MCNN-SDAE model architecture and corresponding processing pipeline.

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

8. MODEL SET-UP AND TRAINING

Input to the CNN-model is organized as input-maps. For the

Equation (1) represents a convolution operation $W_m * f_n$ by a single filter W_m over receptive-blocks f_n of the input-mapF_{r*s}. Similarly, activation maps corresponding to all filters in the filter bank can be generated via convolution in equation 2 followed by non-linear activation operator σ. Now, the pooling operation is independently applied on each of these convolution-based activation-maps. It is usually a simple function such as maximization or averaging and serves as generalizations over the features of the convolution map. The pooling size parameter determines the invariance of the convolution layer filters to small frequency shifts in the spectral representation of vibration signals. Hence, serve as small shift invariance over the local region that is determined by pooling size parameter. The max-pooling function is used as:

9. MODEL VALIDATION

A bearing-fault data-set provided by Case Western Reserve University [28] is used to validate the proposed model. The data-set consists of vibration signals that were collected from an experimental test-rig, as shown in Figure 3. The test-rig apparatus consist of a 2-hp motor, a torque transducer and a dynamometer. The motor shaft was supported by 6205-2RS JEM SKF bearings. The three bearing components under study are (1) the inner race (IR), (2) the outer race (OR) and
(3) the rolling element, the ball (B). Single-point faults ranging in diameter from 0.007 to 0.028 inches were artificially seeded into each of the above-mentioned bearing element at both drive and fan end of the motor drive. For the faults localized to the IR, the B rolling element and the OR, the accelerometers are arranged in the dead-end position at 12 o'clock, 6 o'clock and 3 o'clock, respectively. Vibration signals from three channels were sampled at 12 kHz and in some cases at 48kHz. Figure 4 shows the vibration samples of different bearing health conditions. A dataset comprising vibration signals from healthy and three faulty bearing conditions is used for analysis. For each fault type, the vibration-data is collected against three different fault-sizes. A MCNN-SDAE model is trained on healthy and faulty training samples with parameters listed in Table 1. Different fault- types, fault-sizes and corresponding data-samples for training and testing are detailed in Table 2.

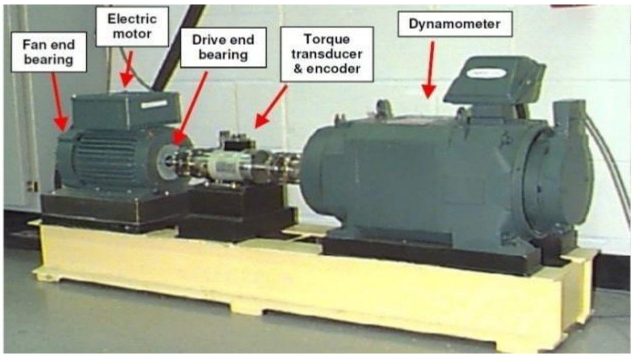
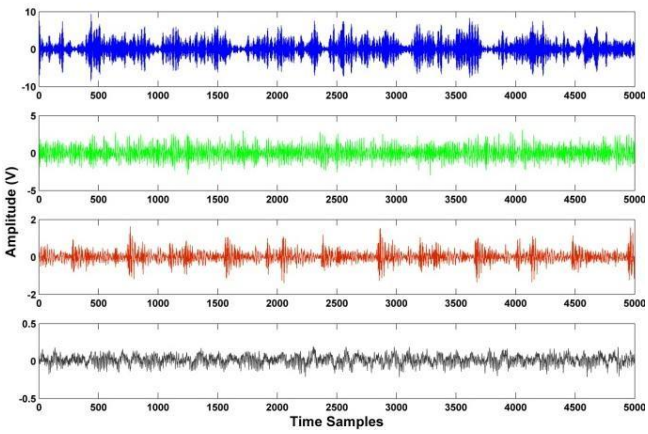


Figure 3 Experimental test-rig to collect benchmark vibration data corresponding to various bearing faults. various bearing faults.



International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

Figure 4 Vibration signals depicting different bearing fault-types.

Table 1 Hybrid-model parameters.

MCNN Parameters	
No. of CNN-layers (convolution and pooling pairs)	2
Input-map size F_{r*s} (No. of vibration-signal frames)	s=10
Block size ($i \times j$) of input receiptive field f	$f_{i \times j}$=[100x5]
Receptive Window overlapping	[50x2]
No. of Feature-Kernels/filters (W)	K=20 for layer 1 K=30 for layer 2
SDAE Parameters	
No. of layers in the Stack	3
Configuration of layers (No. of neurons)	700-500-300
Corruption-type for denoising.	Gaussian Noise (% of nominal value)= [20%]
Noise level (Corrupted Input fraction)	[15-30]%

10. CONCLUSION

11. The trained MCNN-SDAE was compared against deep-models based on WPT-DBN[50] and TDSF-DBN[52], as well as shallow-models based on WPT-ANN[47], WPT-SVM[41], and TDSF-SVM. The test accuracies of all models are evaluated using a five-fold cross-validation process, as shown in table 3. In comparison to the competing approaches, the suggested hybrid achieved an average accuracy of 99.81% for inner race and ball-element faults, 100% for individual errors, and 99.4% for out-race faults, as shown in table 3. Classification accuracies at varied noise-levels and frequency-shifts in both healthy and defective vibration signals were used to further test the resilience of the hybrid model. We tested all of the models with varying levels of artificial noise, ranging from 15 dB to 10 dB, and averaged their test accuracies. The following steps are taken to ensure that frequency shift-invariance is valid.

1- Calculate ball pass frequency for inner and outer race faults (BPFO, BPFI) and ball spin frequency (BSF) for rolling-element assuming no-slip condition.
2- Take FFT of the samples from all three fault-types.
3- Identify the corresponding fault-frequency (i.e. BPFO, BPFI,BSF) in the frequency spectrum of related fault-type (e.g. inner-race, outer-race or rolling element faults).

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

4- Take a frequency band of 100Hz centered at corresponding fault-frequency (i.e. BPFO, BPFI, and BSF) in the frequency spectrum and shift it by offsetting it by gap of 5, 10 or 15Hz.
5- Take the inverse FFT and used the new vibration signal to calculate features corresponding to each model.
6- Calculate average classification-accuracy.

The classification-accuracies of different feature-classifier models against varying noise-levels are reported in table 4. A general trend of decrease in classification-accuracies with increasing noise-level is observed for all models. A minimum classification accuracy of 94.6% is achieved by hybrid-model against 10db SNR which is the highest accuracy among all compared models. Similarly in table 5, a maximum 1% decrease in classification accuracy of hybrid MCNN-SDAE model is observed against a shift in fault-frequency with an offset of 15Hz. However, the classification accuracy of other models decreased by 2-3% against frequency shift with 15Hz offset. The results in table 4 and table 5 show that the hybrid MCNN-SDAE model is robust to noise in vibration signals and small frequency-shifts caused by slipping of roll-bearing.

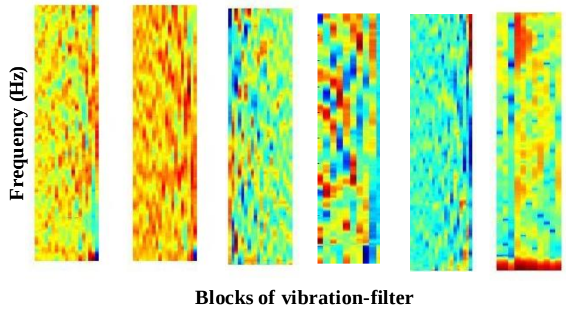


Figure 5 Each block depicts a spectral representation of first-layer CNN-filters learnt by the model. A single block represents spectogram corresponding to 20 base-filters learnt by the CNN. Each filter represents a salient vibration-pattern learnt from training-data. A particular bearing-fault is modeled as a combination of these base vibration-features via higher-order layers in MCNN- SDAE model.

12. REFERENCES

13. A review of condition monitoring approaches including oil analysis, thermography, and vibration analysis was published in 2014 by Verma and Srivastava. International Journal of Enhancement Research in Science and Technology, Volume 3, Issue 4, 2014, Pages 18–25. In 2006, Tandon and Parey published a paper on the topic of rotary machine condition monitoring. Volume 5, Issue 5 (2006), Pages 151–157.

Referenced in [3] El-Thalji and Jantunen (2015). Issue modeling and predictive health monitoring for rolling element bearings summed together. Signal Processing and Mechanical Systems, Volume 60–61, 2015, pages 252-272. (Lei, Y.G., Lin, J., Zuo, M.J., & He, Z.J., 2014).

14. A review on condition monitoring and problem identification of planetary gearboxes. Quantification. 48 (2014), 292–305.

15. In 2016, Boudiaf, Moussaoui, and Dahane published a study. Using Data from Case Western Reserve University, We Compare Different Approaches to Diagnosing Bearing Faults. Journal of Anti-Anal and Preventive Failure 16-2 (2016), 271-284.

16. In 2011, Kankar, Sharma, and Harsha published a study. Ball bearing failure detection using ML techniques. In the 2011 issue of Expert Systems with Applications, volume 38, issue 3, pages 1876–1886, the authors wrote:

17. It was published in 1998 by Weston and Watkins. Support vector machines with many classes. The citation manager
In 2007, Widodo and Yang published a paper. Use support vector machines for monitoring machine health and identifying problems. Journal of Mechanical Systems and Signal Processing, Volume 21, Issue 6, 2007, Pages 2560–2574.
[9] P.K. Kankar, S.C. Sharma, and S.P. Harsha (2011). Neurocomputing, 74(10), 1638-1645 (2011), diagnosing faults in rolling element bearings using wavelet transform.
2010 Konar and 2011 Chattopadhyay. Induction motor bearing failure diagnosis using wavelet and support vector machines Article number: 4203-4211 from the 2011 edition of the Journal of Applied Soft Computing.
This information is sourced from Keskes, Braham, and Lachiri (2013). Using stationary wavelet packet transform and multiclass wavelet support vector machines, we can diagnose broken rotor bars in induction machines. Research in Electric Power Systems, Volume 97, Issue 3, pages 151–157, 2013.
[12]Huang, Liangpei, Chaowei, and colleagues in 2015. The use of wavelet packet decomposition and BP networks for the detection of rolling bearing fault patterns Publication: Sci. J. Inform. Eng., 67(1), 7–13 (2015).
in [13]N. Saravanan and K.I. Ramachandran published in 2010. Early detection of gearbox failures by use of feature extraction and artificial neural network (ANN) classification using discrete wavelet transform (DWT). Applied System Science 37(2010), 4168–4181.
In 2012, Bin, Gao, Li, and colleagues performed research. Use of wavelet packets for early failure detection in rotating equipment by feature extraction using empirical mode decomposition and neural network Proceedings of the 27th Annual Conference on System Theory and Signal Processing, 696-711 (2012)
This information is sourced from Yang et al. (2005). Use of SVMs and artificial neural networks for condition classification of small refrigerator reciprocating compressors Vol. 19, No. 5, pp. 371-390, 2005, Mechanical Systems and Signal Processing
[16]In 2015, Ding, Ma, and Tian published a paper. Classification of hydraulic pump faults and evaluation of pump health using LR and softmax regression Journal of Vibroengineering, 17, 1805–1816 (2015).
[17]As of 2015, Schmidhuber was. An introduction to deep learning using neural networks. Journal of Neural Networks, Volume 61, Issue 1, pages 85–117 (2018).
[18]In 2011, Yu, Deng, Jang, and others published. The field of deep learning and its uses in analyzing signals and data.

18. Journal of Electrical and Signal Processing, Vol. 28, No. 1, 2011, pp. 145–154.
[19] F. Jia, Y. Lei, J. Lin, and colleagues. 2015. One potential use of deep neural networks is the intelligent diagnosis of rotating equipment using large amounts of data and the mining of defect characteristics. Paper published in the journal Mech. Syst. Signal Process in 2015, pages 303–315.
Wang, C., Zhu, C., and Gan, M. (2015). Build a deep learning-based hierarchical diagnostic network and use it to identify rolling element bearing failure patterns. Journal of Mechanical Systems and Signal Processing, 72–73 (2015), 91-304.
In 2015, Chen, Li, and Sánchez published a paper. Deep belief network and multi-layer neural network for defect diagnostics of gearboxes. Published in 2015, volume 17, pages 2379–2392, in the Journal of Vibroengineering.

19. P. Tamilselvan and P. Wang (2013). Failure diagnosis by health status categorization based on deep belief learning. Reliability Engineering System Safety 115(2013), 124–135 (2010). A study conducted by Shao, Jiang, and Zhang in 2015 examined the use of an optimized deep belief network for the identification of rolling bearing faults [23]. Volume 26, Issue 11, Article ID 115002, Measurement Science and Technology, 2015.

20. For example, in 2014, Wong, Yang, and Vong published a study [24]. Use of an extreme learning machine for the real-time diagnosis of gas turbine generator system faults. Neurocomputing, vol. 128 (2014), pp. 249–257.. [25] In 2015, Lei, Jia, and Zhou became the authors. Monitoring the health of machines using large data and a deep learning approach. Articles 49–56 published in the 2015 edition of the Journal of Mechanical Engineering, volume 51, issue 21. [26]The implementation of a hierarchical adaptive deep convolution neural network for the diagnosis of bearing faults was discussed in a 2016 article by Guo, X., Chen, L., and Shen, C. in the journal Measurement, volume 93, issue 11, pages 490–502.

21. [27]Yang, D., Tao, J., and Liu, Y. 2016. Bearing Fault Diagnosis Utilizing Multisensor Data Fusion and Deep Belief Networks. Vibration and Shock. This is article 9306220.

[1] Loparo, K. A. Case Western Reserve University Bearing Data Center. Available online: http://csegroups.case.edu/bearingdatacenter/home.

[2] Larochelle, H., Bengio, Y., Lourador, J. et al. 2009. Exploring Strategies for Training Deep Neural Networks. J. Mach. Learn. Res. 10(2009), 1–40.

[3] Vincent, P., Larochelle, H., Bengio, Y., et al. June 2008 Extracting and composing robust features with denoising autoencoders. In Proceedings of the ACM International Conference, Helsinki, Finland.

[4] Lecun, Y.L., Bottou, L., Bengio, Y., et al. 1998. Gradient-based learning applied to document recognition. Proc. IEEE. 86 (11) (1998), 2278–2324.

[5] Krizhevsky, A., Sutskever, I. and Hinton G.E. 2012. ImageNet classification with deep convolutional neural networks Adv. Neural Inform. Process. Syst. 25 (2) (2012), 1106–1114.

[6] Sainath, T.N., Kingsbury, B., Saon, G., et al. 2015. Deep convolutional neural networks for large-scale speech tasks. Neural Networks. 64 (2015), 39–48.

[7] Leng, B., Guo, S., Zhang, X., et al. 2015. 3D object retrieval with stacked local convolutional autoencoder. Signal Process.112(2015), 119–128.

[8] Lee, H., Pham, P.T., Yan, L., et al. 2009. Unsupervised feature learning for audio classification using convolutional deep belief networks. Adv. Neural Inform.
Process. Syst. (2009), 1096–1104

[9] Chen, X., Xiang, S., Liu, C.L., et al. 2014. Vehicle detection in satellite images by hybrid deep convolutional neural networks. IEEE Geosci. Remote Sens. Lett., 11 (2014).

[10] Vincent, P., Larochelle, H., Lajoie, I., et al. 2010. Stacked Denoising Autoencoders: Learning Useful Representations in a Deep Network with a Local Denoising Criterion. J. Mach. Learn. Res.11(3)(2010), 3371–3408.

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

22. APPENDIX

Table 2 Description of different bearing fault-types included in the benchmark data-set

Items	**Health**	**Fault 1**			**Fault 2**			**Fault 3**		
Fault Location	*None*	*Outer Race*	*Outer Race*	*Outer Race*	*Inner Race*	*Inner Race*	*Inner Race*	*Bearing*	*Bearing*	*Bearing*
Motor Speed (RPM)	*1730,1750 1772, 1797*	*1730,1750, 1772, 1797*			*1730,1750, 1772, 1797*			*1730,1750, 1772, 1797*		
Fault Size	0	0.007”	0.014 ”	0.024”	0.007”	0.014”	0.021”	0.007”	0.014”	0.021”
Testing Samples	50	50	50	50	50	50	50	50	50	100
Training Samples	50	50	50	50	50	50	50	50	1000	1000

Table 3 Bearing-fault classification accuracies of different models.

Health Condition	**(5-fold Cross Validated)**					
	MCNN-SDAE	***TDSF-DBN***	***WPT-DBN***	***WPT-ANN***	***WPT-SVM***	***TDSF-SVM***
Inner-Race fault	**100%**	96.2%	98.1%	95.3%	95.7%	95.6%
Outer-Race fault	**99.4%**	98.7%	97.4%	96.5%	97.6%	92.5%
Ball-fault	**100%**	99%	99.1%	98.9%	98.3%	97.4%
Average Accuracy	**99.81%**	97.96%	98.2%	96.9%	97.2%	95.1%

Table 4 Accuracies of Classifier-models tested against increasing noise-levels in vibration signal.

(5-fold Cross Validated)						
SNR (Signal to Noise Ratio)	***MCNN-SDAE***	***TDSF-DBN***	***WPT-DBN***	***WPT-ANN***	***WPT-SVM***	***TDSF-SVM***
15dB	**99.1%**	96.4%	97.1%	95%	96.2%	93.6%
14dB	**98.6%**	95.7%	96.6%	93.7%	94.9%	91.3%
13dB	**97.7%**	95%	95.8%	92.8%	93.5%	89.5%

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

12dB	**96.2%**	93.8%	94.1%	92%	92.2%	87.6%
11dB	**95.3%**	92.7%	93.4%	90.2%	91.1%	85.2%
10dB	**94.6%**	91.6%	92.2%	88.3%	89.4%	82.6%

Table 5 Accuracies of classifier models tested against small shifts in corresponding bearing-fault related frequencies.

(Five-fold Cross Validated)						
Spectrum Shift Offset *(BPFO,BPFI, BSF)* **+Offset**	***MCNN-SDAE***	***TDSF-DBN***	***WPT-DBN***	***WPT-ANN***	***WPT-SVM***	***TDSF-SVM***
5Hz	**99.53%**	96.83%	97.6%	96%	96.5%	95%
10Hz	**99.23%**	96.33%	96.8%	95.1%	95.3%	94.3%
15Hz	**98.7%**	95.7%	96.35%	94.3%	94.6%	92.7%