Fault diagnosis of Machines using Deep Convolutional Beta-Variational Autoencoder

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1 Intelligent Maintenance System Bearing Dataset

The dataset [51] is provided by the University of Cincinnati Center for Intelligent Maintenance Systems. The experimental setup for data collection is shown in Figure 1. The data was collected from the run to failure experiment, consisting of four bearings on a loaded shaft; for each bearing, two high-precision accelerometers were installed. The load on the shaft was 6000 pound-mass, and it was rotating at the speed of 2000 Revolutions Per Minute (RPM). The dataset consists of individual files for each bearing, which contain vibration signals for 1 second. The vibration signal is sampled at the rate of 20KHz. There are $20,480$ data points in each file for each sensor. It can be computed that there are $600(20$ KHz$/2000$RPM$=$ $20 * 10^3/(2000/60) = 600)$ data points per revolution. The dataset comprises Normal, Inner Race, Outer race, and Roller health states. In this experiment, to prepare samples for each state (normal, inner race fault, outer race fault, and roller element fault), three consecutive files from bearing 3 and bearing 4 has been considered. An auto-encoder-correlation algorithm has been used to determine the different states in the dataset.

2 Data Pre-processing, Sampling, and Shape conversion

The value of compression factor C_f for IMS bearing dataset is 6000 for $l = 10$. The value of h and w of equation (11) of manuscript should be optimal; otherwise, the consecutive convolution layers will have a

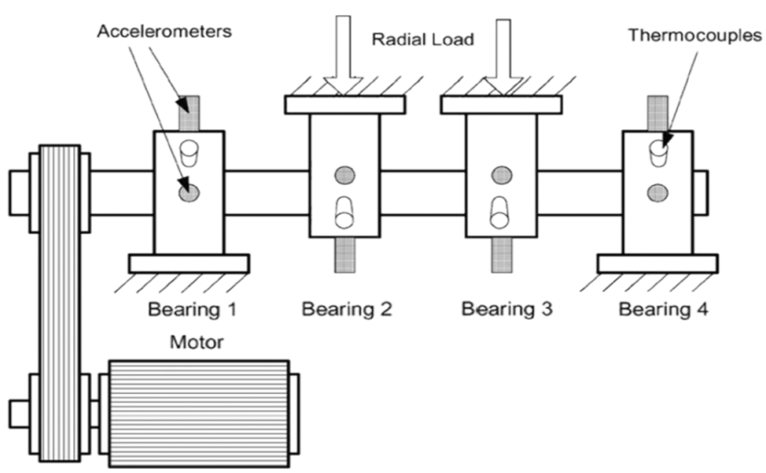

Figure 1: Experimental setup collecting the IMS dataset [51].

Table 1: Description of the generated 2D samples from IMS dataset

Health states	Label	Number of samples
Normal	1	4000
Inner Race	2	4000
Outer Race	3	4000
Roller	4	4000

huge number of parameters and can lead to overfitting and increases training time. And if the value of h and w is low, the model will underfit and struggle in extracting useful features. As shown in Table 1, the number of generated 2D samples for each health states is 4000, when h and w are fixed to 50.

2.1 Results and Discussions

A multi-layer neural network-based classifier has been used with 64 neurons in the latent space side, 32 and 16 in intermediate layers, and 4 neurons with softmax in the last layer. All the training setting on the IMS bearing dataset are same as in the ball-bearing dataset and air compressor dataset except the number of neurons in the last layer. Rmsprop is used as a optimizer with learning and decay rate 0.001 and 10^{-6}, respectively. As shown in Table 2, the authors have experimented with three different architectures to show how accuracy is varying with beta values. The authors have proposed dynamic beta-based VAE as given in equation (14) of the manuscript, and it is plotted in the above Figure 2. As shown in this Figure, the accuracy of 99.56% and 98.21% is achieved using the proposed scheme on IMS bearing dataset with the same value of c, k, and μ as in the ball-bearing dataset and reciprocating type air compressor dataset. In the proposed scheme, dynamic beta-based VAE gives the best performance compared to fixed beta VAE without any exclusive search of beta. The confusion matrix using the proposed scheme on IMS bearing dataset is plotted in Figure 3.

2.1.1 Learned features visualization

The visualization of the learned features in the last layer of the proposed scheme is shown in Figure 4. The learned features are plotted using t-SNE [50] to demonstrate that the proposed scheme can learn useful distinct features. The dimension of the latent-space (d) is fixed to 25. It can be seen from Figure 4 that there is a well-separated boundary among the health states.

Table 2: Accuracy (in %) of the Proposed Scheme on IMS Data with Different Range of beta with three Different Initialisation

Proposed Architectures	$\beta < 1$		$\beta > 1$		$\beta >> 1$	
	$\beta = 0.025$	$\beta = 0.25$	$\beta = 2.5$	$\beta = 5$	$\beta = 25$	$\beta = 250$
Arch1	**99.25**	94.29	92.21	90.02	61.29	55.97
	99.20	94.31	92.15	89.02	61.35	56.01
	99.23	94.34	92.10	89.02	61.66	56.23
Arch2	90.89	93.78	92.10	88.56	55.67	51.29
	90.85	93.88	92.15	88.71	55.68	51.23
	90.81	93.81	92.08	88.65	55.61	51.20
Arch3	88.23	86.35	90.01	87.60	52.78	45.89
	88.21	86.31	90.15	87.67	52.72	45.91
	88.29	86.27	90.09	87.69	52.65	45.75

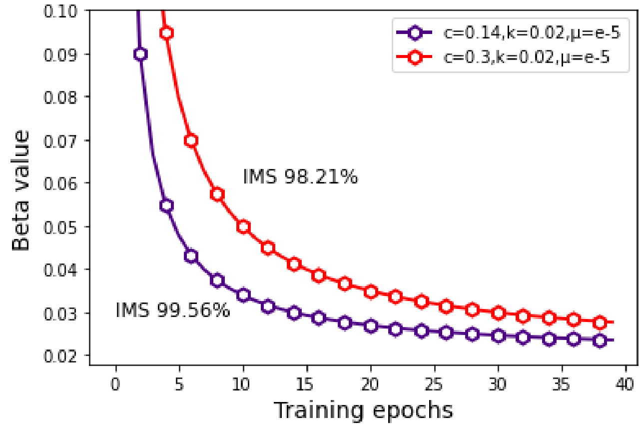

Figure 2: Variation of beta with training epochs on IMS bearing dataset.

Table 3: Comparison of accuracy (in %) of the proposed scheme with state-of-the-art methods

Methods	**IMS Bearing**
Proposed Scheme	**99.56**
Fixed Beta-VAE	**99.25**
CNN+LSTM [1]	97.13
Semi-supervised VAE[2]	92.01
Compact 1D-CNN[3]	93.90
Normalized CNN[4]	99.20
DNN with Temporal Coherence [5]	96.00

**The citations of this table are given at the end of this response sheet in the reference section.*

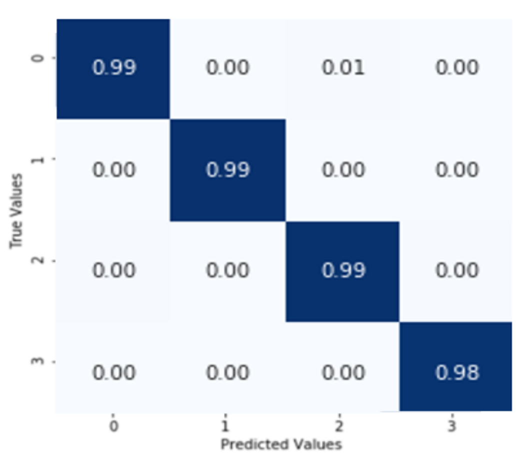

Figure 3: Confusion matrix on IMS bearing dataset using the proposed scheme.

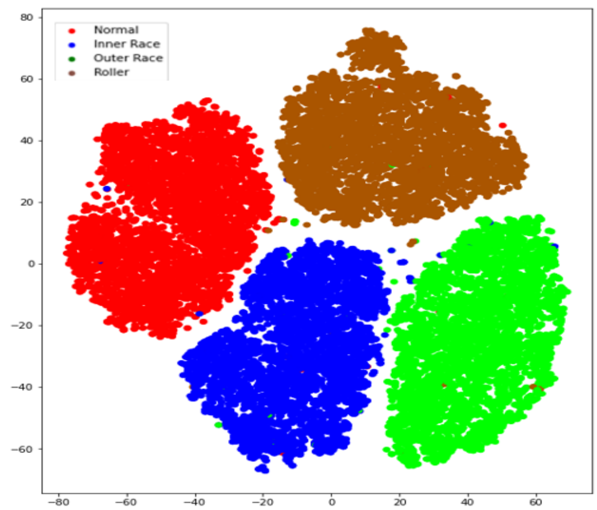

Figure 4: Visualization of learned features on IMS bearing Dataset.

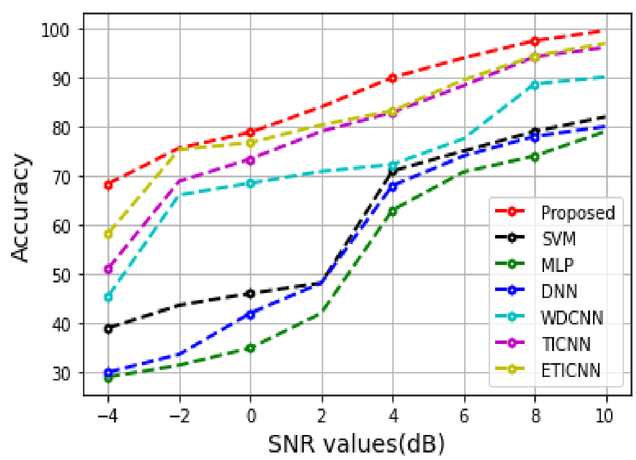

Figure 5: Comparison of accuracy (in %) of proposed scheme with other state-of-the-art methods under different level of noise (in dB) on IMS bearing dataset.

2.1.2 Comparison of Proposed scheme with state-of-the-art methods

A comparative study has been performed on IMS Bearing dataset between proposed and other state-of-the-art methods as shown in Table 3. It can be seen from this Table that the performance of the proposed scheme is superior compared to other state-of-the-art methods. In [1], the authors have presented end to end deep learning model with the combination of CNN and LSTM. The best accuracy of this method is 97.13%, which is inferior by 2.43% as compared to the best accuracy of the proposed scheme. The performance of the semi-supervised approach using VAE [2] is 99.80% on CWRU bearing dataset and 92.01% on IMS Bearing dataset. Similarly, other recent deep learning methods; Compact 1D-CNN [3], Normalized CNN [4], and DNN with Temporal coherence [5] have been compared with proposed scheme.

2.1.3 Comparison of Proposed scheme with state-of-the-art methods under noisy condition

The raw time-series data are corrupted with different levels of noise, and the level of Gaussian noise is measured in terms of Signal to Noise Ratio (SNR) in dB defined as $SNR_{dB} = 10log_{10}\frac{P_{signal}}{P_{noise}}$. For training the model with noise, batch normalization and dropouts are used at every intermediate layer to deal with internal co-variance shift and non-stationary input distribution. The proposed scheme is compared with Support Vector Machine (SVM)[3], Multilayer Neural Network (MLP)[36], DNN[14], Deep Convolutional Neural Networks with Wide First-layer Kernels (WDCNN)[15], and Convolution Neural Networks with Training Interference (TICNN) and Ensemble TICNN[16] under different level of noisy environments. As shown in the following Figure 5, the performance of the proposed scheme is superior compared to other state-of-the-art methods under noisy environments on the IMS Bearing dataset.

References

[1] A. Khorram, M. Khalooei, and M. Rezghi, "End-to-end CNN + LSTM deep learning approach for bearing fault diagnosis," *Applied Intelligence*, vol. 51, no. 2, pp. 736-751, 2021.

[2] S. Zhang, F. Ye, B. Wang, and T.G. Habetler, "Semi-Supervised Bearing Fault Diagnosis and Classification using Variational Autoencoder-Based Deep Generative Models," *IEEE Sensors Journal,* vol. 21, no. 5, pp. 6476-6486, 2021.

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