Enhancement of Fault Diagnosis in Mechanical Systems using Deep Learning Techniques

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Abstract

This study examines how deep learning improves mechanical fault diagnostics. As equipment becomes more complex, diagnostic methods must improve. Intelligent Industrial Fault Diagnosis utilizing Sailfish Improved Inception with Residual Network (IIFD-SOIR) Model is introduced in this paper. The model performs signal portrayal, highlight extraction, and arrangement. Continuous Wavelet Transform (CWT) pre-processes the vibration signal in the proposed model. High-level features are generated using Inception with ResNet v2 feature extraction. A sailfish optimizer tunes Inception's ResNet v2 model parameters. A multilayer perceptron (MLP) classification method is used to accurately diagnose problems. Extensive experimentation ensures the model's gearbox and motor bearing dataset results. On the gearbox and bearing datasets, the IIFD-SOIR model had a higher average accuracy of 99.8% and 99.68%. Compared to other methodologies, the simulation showed that the proposed model performed well. Advanced deep learning approaches can improve mechanical system failure diagnostics, improving dependability and maintenance efficiency in industrial applications.

Keywords: *Fault diagnosis, Mechanical system, Deep learning, feature extraction, Sailfish Optimized Inception, Residual Network.*

1. INTRODUCTION

As technology advances, mechanical equipment becomes more complicated, automated, and fast, making condition monitoring and defect identification more challenging [1]. Numerous sensors can get more fault information and further develop fault diagnosis; such countless sorts are utilized to gather information in the monitoring of huge scope mechanical gear, which produces different sorts and amounts of monitoring information [2]. Step by step instructions to utilize multisensor information to better hardware glitch diagnostics is an ongoing point [3]. Fault diagnosis requires information combination because of various information sources and types [4]. Choice level and element level combination fault diagnosis utilize numerous sensors [5]. DS proof hypothesis and fluffy choice hypothesis dominate choice level combination diagnosis [6]. These methods use a single sensor to identify equipment state, generate evidence, and make a final conclusion based on rules [7].

1.1. Fault diagnosis

Fault diagnosis involves obtaining and analysing equipment characteristic data to determine its status and abnormality [8]. Fault diagnosis technology has three main tasks: fault detection, which detects equipment failures; fault isolation, which locates and classifies problems; and fault estimate, which determines fault nature and intensity [9].

1.2. Fault diagnosis based on deep learning

Deep learning is new machine learning research. It advances machine learning towards AI. Deep learning replicates complex functions, converts low-level input data features into high-level features, and discovers sample data laws with significant learning ability [10]. Features are the core focus of deep learning fault diagnosis technologies. With the invention and use of CNN, DBN, GAN, Transfer Learning, and other algorithms, deep learning-based defect diagnosis is becoming increasingly common [11].

2. LITERATURE REVIEW

Zhao, Wang, and Hao (2019) [12] provide a revolutionary high voltage circuit breaker energy storage fault diagnosis method. The Journal of Vibroengineering describes how they use CNNs to create a characteristic matrix from sound and vibration signals. This method shows how deep learning can reliably diagnose high voltage circuit breaker failures. CNN can extract significant information from complex sound and vibration inputs, promising advanced fault identification in crucial electrical systems.

Zhang, Miao, Zhang, and Wang (2018) [13] Using the grasshopper optimisation technique, introduce a parameter-adaptive Variational Mode Decomposition (VMD) method. Their Mechanical Systems and Signal Processing research analyses rotating machinery vibration signals. A novel vibration signal analysis method changes settings using the grasshopper optimisation algorithm. This method shows how adjusting VMD parameters to signal characteristics can improve fault diagnosis for rotating machinery, emphasising the relevance of signal processing optimisation for diagnostic accuracy and efficiency.

Wang, Fu, Zhang, Gao, and Zhao (2019) [14] Multilevel information fusion for induction motor fault identification advances fault diagnosis. The IEEE/ASME Transactions on Mechatronics study examines integrating various levels of information to increase diagnostic accuracy. The authors use innovative methods to improve induction motor problem diagnosis by combining data from multiple sources. These findings emphasise the importance of information fusion in tackling induction motor defect detection's complexity.

Saravanakumar, Krishnaraj, Venkatraman, Sivakumar, Prasanna, et al. (2021) [15] Hierarchical symbolic analysis and particle swarm optimisation are used to diagnose rotating machinery faults. Deep neural networks are integrated into a hierarchical symbolic analysis framework in Measurement. The defect diagnostic model is more efficient with particle swarm optimisation. This paper emphasises the need of combining symbolic analysis, optimisation, and deep learning for rotating machine failure diagnostics. The hierarchical approach shows a thorough understanding of fault detection and advances in integrating varied techniques for better diagnostic results.

3. RESEARCH METHODOLOGY

3.1. Proposed model

FIG. 1 portrays the IIFD-SOIR model method. Information is gained, as displayed in the figure. The Continuous Wavelet Transform Scalogram (CWTS) model preprocesses and crops vibration signals. The SFO calculation changed Inception with ResNetv2 model is then carried out as a component extractor. Finally, MLP arranges absconds.

 Journal Volume 11,S. Iss 07, 2022

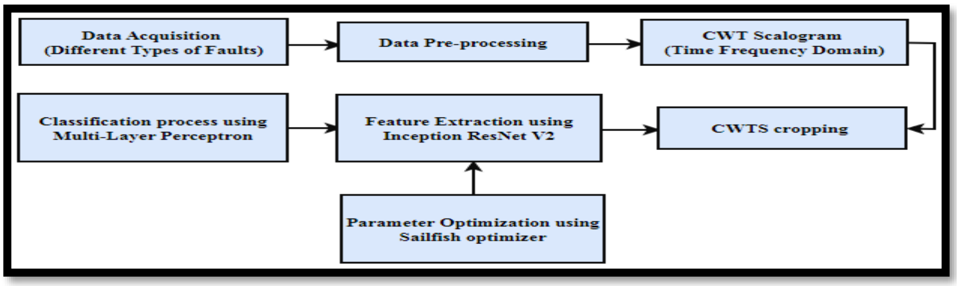

Figure 1: Block diagram of IIFD-SOIR model

3.2. Data Collection

Rotating machinery's performance depends on speed and load. Recording vibration signals at all speeds and loads is necessary for fault diagnosis. When signal frequencies don't match rotating frequencies, Continuous Wavelet Transform Spectrograms vary greatly. Vibration signals and rotating speed data are collected to address this. The DC component is removed and signals are collected extensively to train the system in training samples assuming constant rotating speed during stable operation. Speed-related CWTS fluctuations are noticeable without preprocessing. Resampling with a virtual frequency (VSF) eliminates rotating speed's effect on CWTS, assuring sample uniformity.

3.3. Data Preprocessing

The DC module is removed by removing the mean value from the vibration signal to improve error analysis. Virtual resampling frequency (VSF) is used because operational changes affect rotating speed. The VSF, a multiple (q) of the spinning speed, is constant for each training sample. This tackles the speed-related diversity in CWTS outcomes. Resampling creates a standardised dataset, x(k)(k = 1, 2,...,m), for each rotor revolution. A virtual resampling frequency (fd = qfm) provides a consistent representation for fault diagnosis and investigation. In summary, data preparation eliminates the DC component and uses virtual resampling to maintain uniformity across rotating speeds.

3.4. Sailfish Optimizer Based Parameter Optimization

The Inception with ResNet v2 model's part size, channel count, stowed away hub count, and punishment coefficient vigorously influence results. Selecting the right settings is time-consuming and difficult. The ResNet v2 model uses the SFO algorithm to select Inception's optimal settings. SFO is a population-based meta-heuristic technique based on a group of hunting sailfishes' attack-alternation concept. SFO algorithm workflow is shown in Fig. 2.

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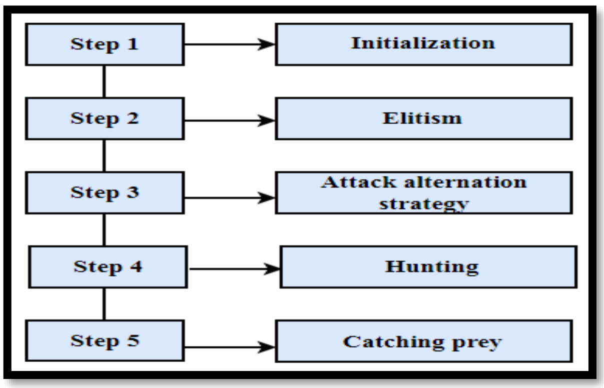

Figure 2: Flowchart of SFO algorithm

3.5. MLP Based Classification

An NN approach with numerous hidden layers, MLP links neurons between layers. This method's structure is shown in Fig. 3. Experience and experimentation determine the parameter selection of newly introduced MLP.

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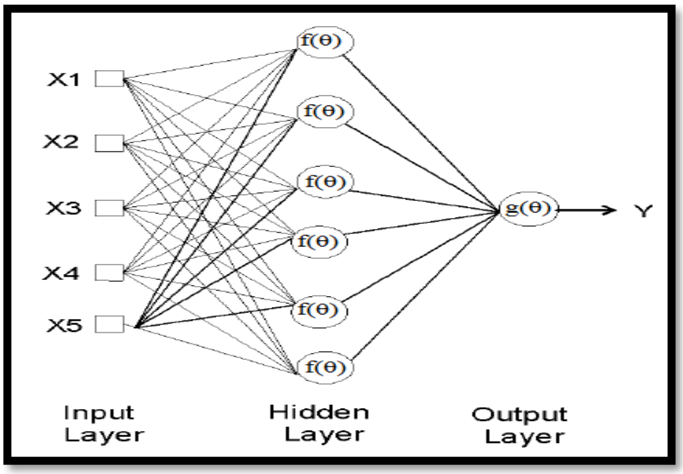

Figure 3: General structure of MLP

3.6. Data Implementation

Proposed model performance is simulated using Python. Automotive gearbox and bearing failure datasets were used to test the model's fault class label detection. The first dataset contains 7 health statuses, including outer race bearing, small chipped gear, missed tooth gear, and compound faults. 1300000 samples are grouped into 200 0.5-s instances per class label. In addition, 400 sample examples are obtained for each health status at different speeds. Final dataset has 3100 sample cases. Normal and fault data are in the second dataset. The bearing flaws are inner race (IF), outer race (OF), and ball. Thus, 10 bearing health statuses under different loads exist. WT transforms 3000 data points per sample into a time-frequency representation. Under load, each health status has 60 instances. To test the algorithm, 3400 samples were collected.

4. RESULTS AND DISCUSSION

Table 1 shows the IIFD-SOIR model's fault class accuracy analysis on the Gearbox dataset.

Table 1: Gearbox dataset accuracy examination of IFD-SOIR technique

Number of Classes	FFT-KNN	FFT-SVM	FFT-DBN	FFT-SAE	CNN	CNN2	IIFD-SOIR
1	85.46%	100%	98.92%	99.99%	100%	100%	100%
2	93.48%	100%	98.89%	100%	100%	100%	100%
3	99.73%	99.91%	99.52%	99.66%	98.60%	98.02%	99.36%
4	100%	100%	99.51%	100%	100%	99.77%	99.87%
5	88.09%	99.92%	99.43%	100%	100%	100%	100%
6	69.40%	97.24%	96.52%	98.26%	99.78%	97.76%	99.28%
7	68.43%	88.70%	95.25%	96.83%	89.81%	92.53%	98.77%

ISSN PRINT 2319 1775 Online 2320 7876
 Journal Volume 11,S. Iss 07, 2022

Table 2 shows IIFD-SOIR fault class accuracy analysis on the Bearing dataset.

Table 2: Bearing dataset IFD-SOIR accuracy analysis

Number of Classes	FFT-KNN	FFT-SVM	FFT-DBN	FFT-SAE	CNN	CNN2	IIFD-SOIR
1	99.02%	100%	100%	100%	99.79%	99.43%	99.84%
2	97.74%	96.58%	98.66%	98.26%	95.89%	93.26%	99.12%
3	99.02%	100%	99.96%	100%	100%	100%	100%
4	95.41%	99.59%	98.81%	98.40%	99.28%	99.01%	99.47%
5	97.58%	99.32%	98.66%	98.25%	99.74%	97.80%	99.83%
6	98.55%	92.54%	97.80%	97.34%	99.11%	99.12%	99.58%
7	98.99%	100%	99.53%	99.45%	100%	100%	98.77%
8	95.51%	95.33%	95.24%	95.17%	98.22%	94.20%	98.82%
9	99.02%	100%	99.78%	100%	99.96%	99.96%	99.98%
10	97.63%	87.82%	96.21%	97.51%	99.96%	99.96%	99.99%

Table 3 and Figs. 4 and 5 show the IIFD-SOIR model's average training and testing accuracy on the gearbox and Bearing dataset.

Table 3: An average of training and method testing results

Methods	Gearbox dataset		Bearing dataset	
	(Training)	(Testing)	(Training)	(Testing)
FFT-KNN	90.86%	86.37%	98.30%	97.85%
FFT-SVM	98.60%	97.97%	98.77%	97.13%
FFT-DBN	100%	98.29%	99.48%	98.47%
FFT-SAE	100%	99.25%	99.13%	98.24%
CNN	99.35%	98.32%	99.63%	99.20%
CNN2	98.89%	98.31%	99.14%	98.10%
IIFD-SOIR	100%	99.62%	99.85%	99.67%

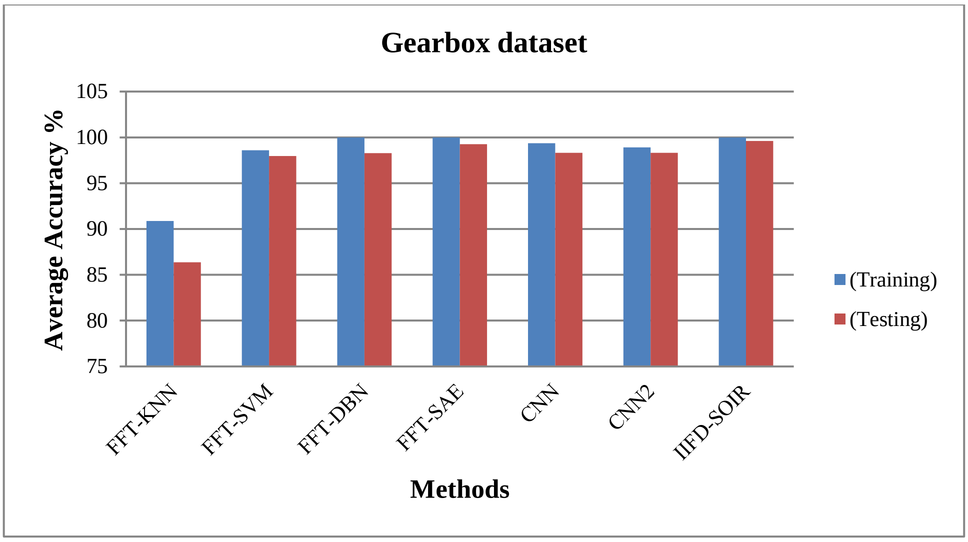

Figure 4: Average IIFD-SOIR model accuracy on gearbox dataset

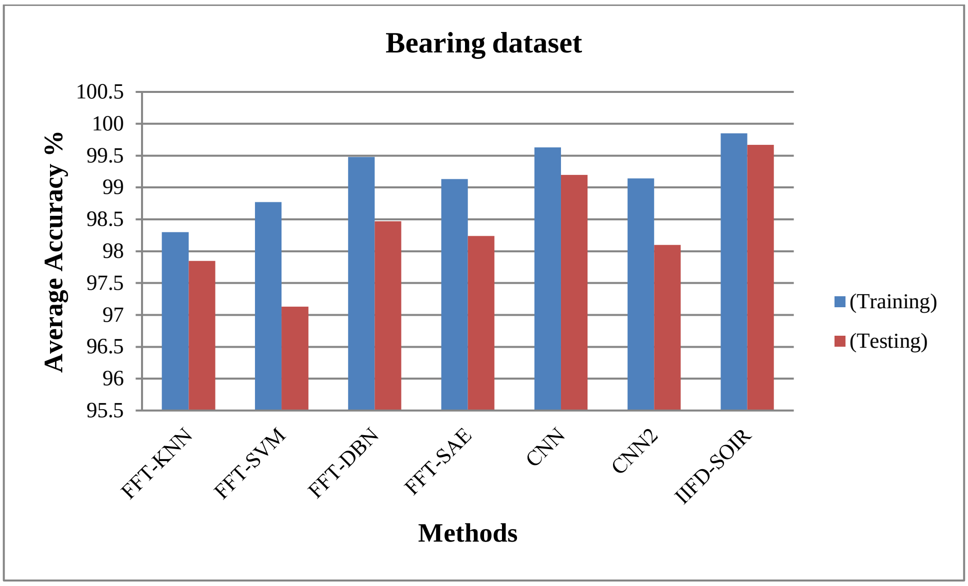

Figure 5: Average IFD-SOIR model accuracy on bearing dataset

5. CONCLUSION

Deep learning in mechanical system deformity diagnostics is a significant turn of events. This paper made an IIFD-SOIR model to distinguish rotating machinery issues. The information collecting process begins first. Then, at that point, the CWTS model preprocesses and crops vibration signals. SFO calculation changed Inception with ResNet v2 model is then used to extricate highlights. The SFO calculation tunes Inception's ResNet v2 model boundaries. Finally, MLP arranges surrenders. Broad trial and error guarantees the IIFD-SOIR model's gearbox and engine bearing outcomes. The IIFD-SOIR model has a higher typical exactness of 99.6% and 99.64% on the gearbox and bearing datasets, separately. Rotating machinery defects can be diagnosed using the IIFD-SOIR model. Future real-time industries can use the IIFD-SOIR paradigm to diagnose issues. This study shows that sophisticated deep learning methods can improve mechanical system problem diagnostics. The findings increase mechanical system maintenance dependability and efficiency and advance scientific understanding of these methods.

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