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Enhanced Gearbox Fault Diagnosis with Fusion LSTM-CNN Network

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Abstract

We introduce a novel approach to enhance gearbox fault diagnosis by integrating Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) for vibrational data analysis. Our method aims to improve fault detection accuracy, particularly in identifying subtle anomalies like broken teeth. Our methodology starts with Continuous Wavelet Transform (CWT) applied to the vibrational data to reveal crucial frequency-domain features. Concurrently, a CNN, using the Inception architecture, extracts spatial features. Simultaneously, LSTM networks capture temporal patterns. The unique feature representations from both the CNN and LSTM branches are fused, creating a holistic feature set incorporating spatial, material, and frequency-domain information. This integrated feature set is then classified using a fully connected neural network. Our method's effectiveness is rigorously validated through comprehensive experiments on a diverse dataset. The results demonstrate exceptional accuracy in identifying gearbox faults, even in the early stages. This research advances predictive maintenance, offering a precise and comprehensive approach to gearbox fault diagnosis. The model's ability to detect faults promptly empowers industrial operators to reduce downtime and operational costs. In conclusion, the fusion of LSTM and CNN architectures for vibrational data analysis holds promise for gearbox fault diagnosis, benefiting industries reliant on machinery reliability and operational efficiency.

Keywords: Gearbox Fault Diagnosis; Long Short-Term Memory (LSTM); Convolutional Neural Networks (CNN); Continuous Wavelet Transform (CWT).

1. Introduction

Gearboxes play a critical role in machinery, and their reliability is essential for uninterrupted industrial operations. Timely fault diagnosis is pivotal for preventing costly downtime and ensuring machinery longevity. Therefore, to guarantee safety, growing attention has been paid to fault diagnosis of gearboxes [1]. In previous methods, the aim was to develop a mathematical model to express specific faults, and some methods required prior knowledge for reasoning and diagnosis [2]. In modern problems, due to the complexity of engineering systems, developing a proper model is difficult[3]. Traditional machine learning algorithms have been widely used in the fault diagnosis field. Baraldi et al. [4] aimed to develop a diagnostic system for electric traction motor bearings in variable automotive conditions. Employing a hierarchical structure of K-Nearest Neighbors classifiers, this method selects relevant features from vibrational signals using a Multi-Objective optimization approach, showcasing its effectiveness across diverse operational conditions in experimental testing. These methods require manual feature extraction, relying heavily on human expertise.

In recent years, deep learning has grown rapidly, setting new performance standards. Chen et al. [5] used deep neural networks to effectively identify faults in rolling bearings, demonstrating their reliability in fault diagnosis, which is crucial for maintaining machinery performance and preventing mechanical failures. Jiang et al. [6] present an end-to-end learning-based system that directly learns fault features from raw vibration signals. The method employs a multiscale convolutional neural network (MSCNN) that simultaneously extracts multiscale features, enhancing feature learning and diagnosis performance. Chen et al. [7] proposed an effective method utilizing convolutional neural networks (CNN) and discrete wavelet transformation (DWT) to diagnose fault conditions in planetary gearboxes used in wind turbines. Gao et al. [8] introduced an optimized adaptive deep belief network for rolling bearing fault diagnosis. The paper concludes with empirical validation through simulations based on experimental data, confirming the efficacy of the proposed method in bearing fault identification. Liang et al. [9] introduced WT-IResNet, a novel fault diagnosis method for rolling bearings based on wavelet transform and improved ResNet architecture. It effectively addresses noisy labels and real-world industrial conditions through wavelet transform, an improved residual neural network, and a customized loss function. Xiao Et al. [10] proposed a novel fault diagnosis method for three-phase asynchronous motors using LSTM neural networks, which learn from raw data without feature engineering. Experimental tests demonstrate superior accuracy compared to traditional methods like LR, SVM, MLP, and RNN.

This study presents an innovative approach to gearbox fault diagnosis, combining LSTM and CNN. Vibrational data collected under both healthy and faulty conditions is analyzed, focusing on identifying broken teeth as a common fault scenario. This method begins with Continuous Wavelet Transform (CWT) applied to the data, which is then processed by CNNs to extract spatial features. Simultaneously, LSTM networks capture temporal dependencies within the data. The resulting features from both networks are stacked and used for classification. This integration of LSTM and CNN, along with feature fusion, holds promise for accurate gearbox fault diagnosis. This research contributes to predictive maintenance, enhancing machinery reliability. In the following sections, we present the theoretical background, our methodology, experimental findings, and discussions, evaluating the approach's effectiveness in gearbox fault diagnosis.

2. Theoretical Foundation

2.1 Continuous Wavelet Transform:

The Continuous Wavelet Transform (CWT) [11] is a mathematical technique employed to analyze signals in both the time and frequency domains simultaneously. It provides a way to examine how the frequency content of a signal evolves. This is particularly useful when dealing with non-stationary signals, where the signal's characteristics change over different time intervals. CWT can

effectively decompose the initial signal into various oscillatory components, which originate from the translation and scaling of mother wavelets [12].

The CWT of a signal *f(t)* is calculated as shown in Eq. (1):

$$CWT(a.\tau) = \int_{-\infty}^{\infty} f(t) \cdot \psi^* \left(\frac{t-\tau}{a}\right) dt \quad (1)$$

Where $f(t)$ is the input signal, $\psi(t)$ is the mother wavelet, ψ^* is the complex conjugate of the mother wavelet, τ is the translation parameter, which shifts the wavelet function along the time axis to analyze different time points in the signal, and a is the scale parameter, which controls the width of the wavelet function and determines the level of detail in the analysis.

2.2 Convolutional Neural Network

Convolutional Neural Network (CNN) [13] is a class of deep learning neural networks primarily designed for processing structured grid data, such as images and video. It is inspired by the human visual system and is highly effective in tasks like image classification, object detection, and image segmentation. CNNs begin with one or more convolutional layers. These layers apply filters (also known as kernels) to the input image. Each filter is a small matrix that scans through the input using a mathematical operation called convolution. The convolution operation extracts features like edges, textures, or patterns from the input. Fig. 1 shows the schematic of a CNN containing convolution, pooling, and fully connected layers.

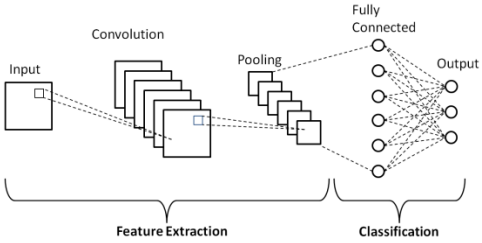

Figure 1. Schematic of a CNN [14].

2.2.1 Inception Module

The Inception architecture, a seminal advancement in deep convolutional neural networks (CNNs), represents a pivotal approach in neural network design, notable for its unparalleled capacity to capture intricate spatial features from multidimensional data. Introduced by Szegedy et al.[15], Inception tackles the challenge of effective feature extraction and dimensionality reduction. At its core, Inception employs multiple filter sizes and operations within a single layer. Unlike conventional layers with fixed-sized filters, Inception simultaneously uses various filter sizes to capture information at different spatial scales. This multi-scale approach helps in capturing both fine and coarse spatial details. In addition, Inception incorporates dimensionality reduction techniques like 1x1 convolutions and pooling to reduce computational complexity while preserving essential features. Integrating the Inception architecture into the CNN branch enhances the model's ability to discern critical information efficiently and accurately. The schematic of the Inception model is shown in Fig. 2.

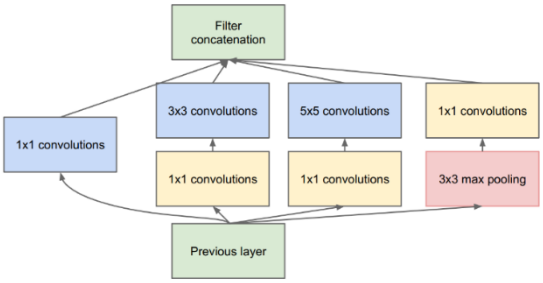

Figure 2. Inception Module.

2.3 Long Short-Term Memory

A Long Short-Term Memory (LSTM) [16] is a type of Recurrent Neural Network (RNN) architecture designed to handle sequential data and address the vanishing gradient problem that traditional RNNs often face. LSTMs are specifically designed for tasks involving data sequences, such as time series, natural language text, or speech. LSTMs maintain a cell state, which serves as a memory buffer. This cell state can carry information across time steps and selectively forget or update information, making it well-suited for capturing long-range dependencies in sequences. In addition to the cell state, LSTMs also maintain a hidden state. This hidden state serves as the memory that carries information to the next time step.

3. Proposed Method

3.1 Framework of the proposed method

Due to their exposure to various operational stresses and environmental conditions, gearboxes are susceptible to faults. Effective fault diagnosis allows for the early detection and mitigation of these issues, preventing costly downtime and reducing maintenance expenses. This process is fundamental to ensuring machinery reliability and the uninterrupted flow of industrial operations.

To prevent the above problems, in this study, we propose a new model for fault diagnosis of the gearbox, named the fusion CNN-LSTM model. This model consists of three main parts: the CNN model, the LSTM model, and classification layers. Fig. 3 reveals the schematic of the model. The detailed steps are as follows:

1. Raw vibrational data are fed to an LSTM, analyzing the temporal dynamics within the vibrational data. LSTM is capable of capturing sequential dependencies and nuanced variations over time.
2. In parallel with the LSTM, through CWT, original data are converted into images and fed to a CNN, extracting spatial features from the data and identifying distinctive patterns and spatial relationships that can aid in fault diagnosis.
3. The outputs from the CNN and LSTM branches are combined. This feature stacking creates a comprehensive representation of the vibrational data, incorporating both spatial and temporal information.
4. The integrated feature set is passed to a fully connected neural network for the classification task. The neural network determines whether the gearbox is operating normally or experiencing a fault based on the combined feature representation.
5. The model's performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques are employed to assess the model's robustness and generalizability.

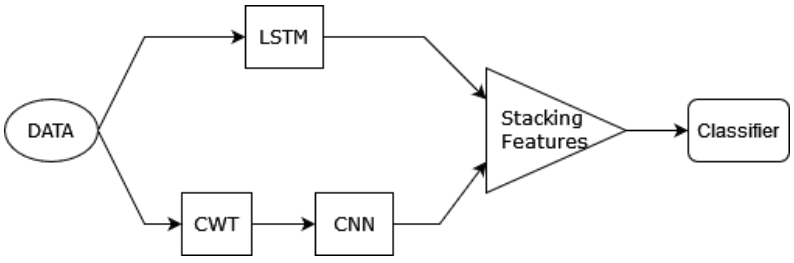

Figure 3. The overall framework.

3.2 LSTM Branch

The LSTM branch begins with the input of vibrational data, a time-series sequence collected from the gearbox. This data is crucial for capturing the temporal dynamics of the system. Before feeding the data into the LSTM network, pre-processing steps such as normalization and sequence

length adjustment are applied to ensure data consistency and compatibility with the network. The core of the LSTM branch consists of one LSTM layer. As the data flows through the LSTM layer, the network analyses the sequential patterns and dependencies within the vibrational data. LSTM units have the unique ability to capture both short-term and long-term temporal dependencies, making them well-suited for time-series data like vibration signals.

The LSTM branch produces either a sequence of hidden states or a summarization of the sequential analysis. Subsequently, an MLP layer is employed to project these hidden states into the desired dimensional space. The LSTM layer configuration remains consistent throughout the study, comprising a single hidden layer with 50 hidden states and yielding 60 output features. These specific parameter values were determined through an extensive grid hyperparameter search process.

3.3 CNN Branch

First, continuous wavelet transform is applied to the original vibrational data to reveal frequency-domain features. CWT enables the extraction of intricate temporal patterns, enhancing the model's ability to identify gearbox faults accurately by capturing subtle variations in the data. Wavelet functions in CWT serve as analysis tools, each representing a specific frequency and time domain. The choice of wavelet function impacts the scale at which features are detected.

The Inception architecture is celebrated for its ability to extract spatial features from complex data efficiently. Therefore, it is used to extract meaningful features from vibrational data. The proposed method is shown in Fig. 4. Table 1 demonstrates the network details. After concatenating filters, Global Average Pooling (GAP) is applied to reduce dimensions. GAP acts as a form of spatial information summarization, producing a compact representation that retains essential features while significantly reducing computational complexity. This operation is particularly beneficial for model efficiency, regularization, and interpretability, making it a fundamental component in various computer vision tasks.

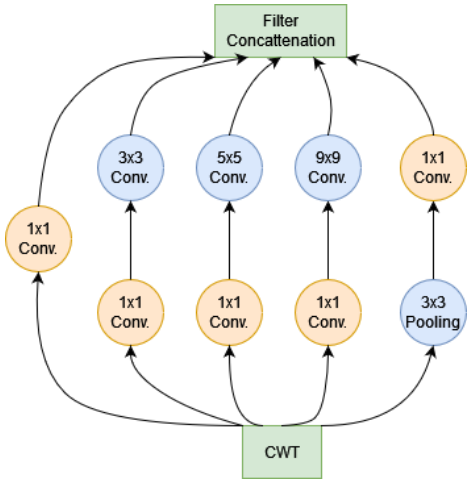

Figure 4. Proposed inception module.

Table 1. Parameters in the CNN

	Seq. Block	input	output	kernel size	padding	stride
Branch1x1	Conv. 1×1	1	10	1	0	1
	ReLU	-	-	-	-	-
Branch3x3	Conv. 1×1	1	10	1	0	1
	ReLU	-	-	-	-	-
	Conv. 3×3	10	10	7	‘same’	1
	ReLU	-	-	-	-	-
Branch5x5	Conv. 1×1	1	10	1	0	1
	ReLU	-	-	-	-	-
	Conv. 5x5	10	10	5	‘same’	1
	ReLU	-	-	-	-	-
Branch9x9	Conv. 1×1	1	10	1	0	1
	ReLU	-	-	-	-	-
	Conv. 9×9	10	10	9	‘same’	1
	ReLU	-	-	-	-	-
Pooling Branch	MaxPool2d	1	1	1	1	1
	-	-	-	-	-	-
	Conv. 1×1	1	10	1	0	1
	ReLU	-	-	-	-	-

3.4 Training and Optimization

After stacking features extracted by CNN and LSTM branches, GPA is applied to reduce dimensions. The integrated feature representation is fed into a Fully Connected Neural Network (FCNN). This neural network is responsible for the final classification task, distinguishing between healthy and faulty gearbox conditions. The FCNN's architecture typically consists of multiple layers of neurons, allowing it to learn complex relationships within the combined feature set. The proposed model is trained on Gearbox Fault Diagnosis Data[17] collected in the National Renewable Energy Laboratory (NREL). This dataset includes examples of both healthy and broken tooth gearbox conditions, recorded under variation of load from '0' to '90' percent load, providing useful samples for training. The health condition of the gear has a remarkable impact on the vibrational characteristic of the gearbox. Fig. 5 shows a gear with broken teeth. During training, the network adjusts its internal parameters (weights and biases) through backpropagation and gradient descent to minimize the classification error. This phase is crucial for the model to learn to classify the data accurately.

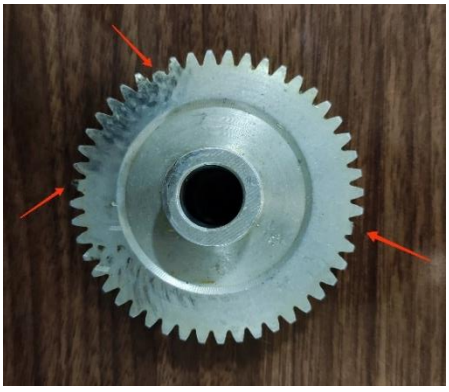

Figure 5. Gear with broken teeth.

3.5 Performance Metrics

The classification results are measured using performance metrics such as accuracy and F1-score. Accuracy measures the proportion of correctly classified instances in a dataset, expressed as a percentage. It indicates how often the model's predictions are correct overall. The expression of accuracy is shown in Eq. (2).

$$acc = \frac{TP + TN}{TP + TN + FN + FP} \tag{2}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives.

The F1-score is a single value that balances precision (accuracy of positive predictions) and recall (ability to find all relevant positive instances). It provides a comprehensive performance measure. The formula of F1-score is shown in Eq. (3).

$$\mathrm{F1-score} = \frac{2 \cdot (\mathrm{Precision} \cdot \mathrm{Recall})}{\mathrm{Precision} + \mathrm{Recall}} \tag{3}$$

where Precision is the ratio of true positive predictions to the total number of positive predictions made by the model, and Recall is the ratio of true positive predictions to the total number of actual positive instances in the dataset.

4. Results

In this paper, different window sizes for Continuous Wavelet Transform (CWT) have been tested, namely 17, 50, and 100. The results are presented below in Table 2 and Table 3. Based on the findings, the window size of 50 yielded the most favorable outcomes in the CNN-LSTM model. It is

noticeable that the separate CNN model has the best performance with a window size of 17. But when combined with LSTM, our proposed method, the window size of 50, yields the best performance.

Table 2. CNN Model Results

window size	f1-score	support
17	0.98	880
50	0.94	880
100	0.35	880

Table 3. CNN-LSTM Model Results

window size	f1-score	support
17	0.98	880
50	1	880
100	0.41	880

The remaining model parameters were fine-tuned using a small grid hyperparameter search method[18, 19]. Further details regarding the specific hyperparameters and their ranges can be found in the referenced sources. The final diagnosis results of the model are presented in Table 4. It can be seen that this method has a remarkable performance.

Table 4. Final results for window size=50

	precision	recall	f1-score	support
Faulty	1	1	1	880
Healthy	1	1	1	880
accuracy	-	-	1	1760
macro avg.	1	1	1	1760
weighted avg.	1	1	1	1760

To demonstrate the enhancement of this method, it is compared with each of its branches separately as a model. It can be seen that the f1-score of the CNN model and LSTM model is 0.94 and 0.98. But when their features are stacked together, as this paper proposes, it would rise to 1. This comparison is shown in Table 5.

Table 5. Comparison of the proposed model

Model	f1-score	support
CNN	0.94	880
LSTM	0.98	880
CNN-LSTM	1	880

5. Conclusions

In this study, we have presented an innovative approach for enhancing gearbox fault diagnosis by integrating LSTM networks and CNNs. Our research aimed to leverage the strengths of these architectures to provide a comprehensive and accurate analysis of vibrational data, ultimately advancing the state-of-the-art in machinery condition monitoring. Through the integration of LSTM and CNN, we achieved exceptional accuracy in identifying gearbox faults, even in the early stages of their development. The fusion of spatial and temporal insights provided by these two architectures created a holistic feature representation that enhanced our model's fault detection capabilities. Our methodology, which included Continuous Wavelet Transform (CWT) for frequency-domain feature extraction and the Inception architecture for spatial feature extraction, showcased its robustness and generalizability through rigorous evaluation and cross-validation. We demonstrated the model's effectiveness in real-world scenarios, where early fault detection proved instrumental in reducing downtime and operational costs.

As we look to the future, further exploration of hybrid deep learning approaches, like the one presented here, holds promise in addressing complex industrial challenges. We anticipate that our research will inspire continued innovation in predictive maintenance strategies and foster collaboration between the fields of machine learning and industrial engineering. Ultimately, this work contributes to the goal of achieving greater efficiency, reliability, and sustainability in industrial operations.

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