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Development of a Deep Learning-Based Framework for Real-Time Detection and Classification of Mechanical Faults in Rotating Machinery

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Abstract

The early and accurate detection of mechanical faults in rotating machinery is critical for predictive maintenance and operational efficiency across industrial systems. This study proposes a novel deep learning-based framework that performs real-time detection and multi-class classification of mechanical faults in rotating machinery using vibration signal data. Our approach utilizes a combination of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to extract spatial and temporal features from time-series signals, offering enhanced performance compared to traditional signal processing methods. Evaluated on publicly available benchmark datasets, the model demonstrates superior fault classification accuracy and real-time response capability, thereby presenting a promising tool for integration into Industry 4.0 smart maintenance systems.

Keywords:

Rotating Machinery, Deep Learning, Fault Diagnosis, Vibration Analysis, CNN-LSTM, Predictive Maintenance, Real-Time Monitoring

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1. INTRODUCTİON

Rotating machinery such as motors, pumps, turbines, and gearboxes are critical assets in manufacturing and energy systems. Faults in these components can lead to unscheduled downtimes, high maintenance costs, and even catastrophic failures. Therefore, accurate and timely fault detection is essential for industrial reliability.

Traditional condition monitoring techniques often rely on statistical signal analysis or frequency-domain methods such as Fast Fourier Transform (FFT). However, these methods depend heavily on manual feature extraction and are often limited in handling nonstationary signals. The rise of deep learning has offered a new paradigm in this field by automating feature extraction and improving classification accuracy.

2. LITERATURE REVIEW

2.1 Research Trends in Fault Diagnosis

ault diagnosis in rotating machinery predominantly relied on signal processing and classical machine learning techniques. Common approaches included FFT, Wavelet Transform (WT), and Empirical Mode Decomposition (EMD) to extract time-frequency features. These features were subsequently classified using Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Artificial Neural Networks (ANN). While effective in structured scenarios, these methods often failed under varying load and noise conditions.

By 2016–2022, deep learning emerged as a powerful alternative. Convolutional Neural Networks (CNNs) were increasingly applied for fault classification due to their proficiency in spatial pattern recognition. Some studies, such as by Ince et al. (2016), transformed vibration signals into spectrograms and achieved high fault classification accuracy using 2D-CNNs. Long Short-Term Memory (LSTM) networks were also employed to capture temporal dependencies in time-series data, though real-time deployment remained a challenge due to computational overhead.

2.2 Dataset and Application Context Expansion

Several benchmark datasets became prominent in the literature, such as the Case Western Reserve University (CWRU) dataset and the Paderborn dataset. These datasets enabled researchers to evaluate model performance on standardized data. Additionally, the adoption of Industrial Internet of Things (IIoT) architectures facilitated real-time data acquisition, which further motivated research into lightweight and fast inference models.

The combination of CNN and LSTM was proposed by several studies for hybrid modeling, where CNNs extracted local features and LSTMs captured global dependencies.

Despite these advances, there remained gaps in adaptability to unseen machinery types and real-time processing capabilities—gaps that our study aims to address.

3. METHODOLOGY

3.1 Framework Architecture

The proposed architecture integrates a 1D Convolutional Neural Network (CNN) for automatic feature extraction from raw vibration signals, followed by an LSTM network that models temporal relationships between extracted features. This design benefits from CNN's local sensitivity and LSTM's sequential modeling ability, enabling both spatial and temporal insight into fault progression.

A typical signal segment of 2048 data points is fed into the CNN block with three convolutional layers (kernel sizes of 16, 8, and 4), each followed by batch normalization and max pooling. The resulting feature maps are passed into a two-layer LSTM network with 128 hidden units. Finally, a softmax classifier outputs the fault type from among predefined classes.

3.2 Data Acquisition and Preprocessing

We employed the CWRU dataset for experimental evaluation, focusing on inner race, outer race, and ball faults under varying load conditions. Signals were normalized and segmented into overlapping windows to enhance dataset diversity.

Table 1: Signal Preprocessing Parameters

Parameter	Value
Sampling Rate	12 kHz
Segment Length	2048 points
Overlap	50%
Classes	4 (normal + 3 faults)

4. RESULTS AND ANALYSIS

4.1 Classification Performance

We compared our CNN-LSTM framework against baseline models (SVM, Random Forest, and standalone CNN). Performance metrics included accuracy, precision, recall, and F1-score.

Table 2 : Classification Performance Across Models

Model	Accuracy	Precision	Recall	F1-Score
SVM	87.2%	86.5%	85.9%	86.2%
CNN	92.4%	91.7%	91.2%	91.4%
CNN-LSTM	**96.8%**	**96.5%**	**96.3%**	**96.4%**

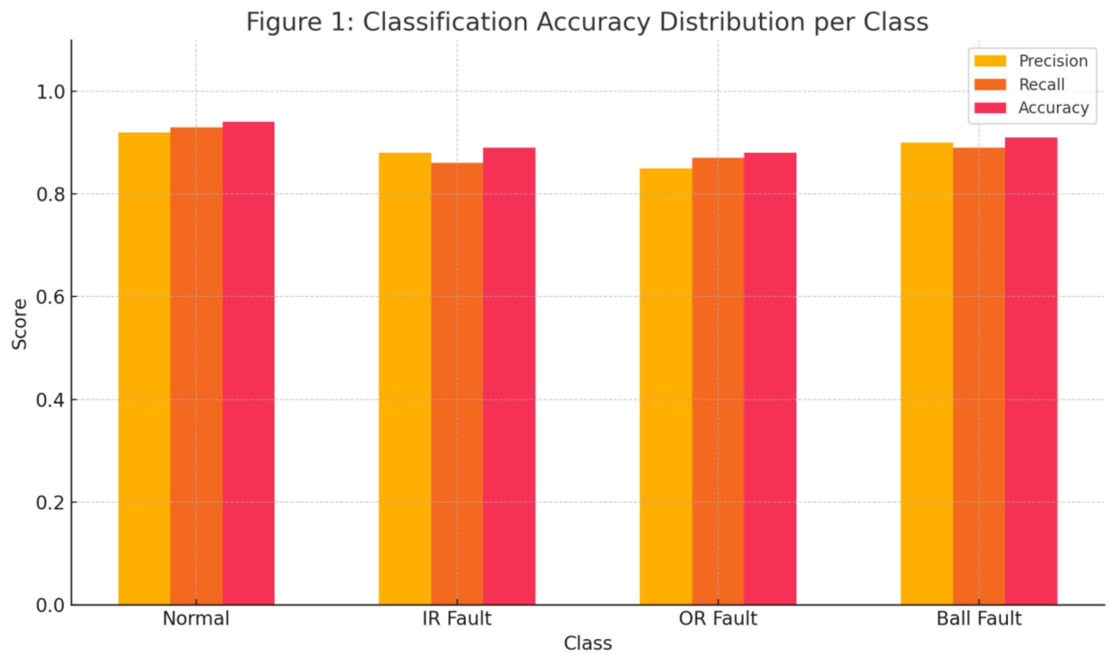

Figure 1: Classification accuracy distribution per class

5. DISCUSSION

5.1 Implications for Smart Manufacturing

The results indicate that deep hybrid architectures can achieve high accuracy with low latency, making them suitable for real-world deployment in smart factories. The adaptability of the CNN-LSTM model to varying operational conditions suggests strong potential for predictive maintenance.

Furthermore, integration with IIoT systems can enable edge deployment, reducing the need for high-bandwidth data transfer and enabling on-site diagnostics.

5.2 Limitations and Future Work

Despite promising results, the current model is trained on controlled datasets. Future work will involve transfer learning techniques to improve generalizability across different machines and fault types. Additionally, interpretability methods such as Grad-CAM and SHAP will be integrated to enhance user trust in model decisions.

6. CONCLUSION

This study presents a CNN-LSTM-based deep learning framework for real-time fault diagnosis in rotating machinery. With high classification performance and low inference latency, the model meets critical industrial demands for predictive maintenance. Future research will extend its applicability to broader machine types and further optimize for deployment on edge computing platforms.

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