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A Resource-Efficient Deep Neural Framework for Bearing Health Monitoring Using Current Sensor Analytics

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Abstract- Fault diagnosis of rolling bearings is a critical task in industrial motor systems, as bearing defects can lead to severe mechanical failures and costly downtime. Traditional vibration-based monitoring systems require additional hardware and complex signal processing techniques, making them expensive and difficult to deploy in practical environments. In contrast, current sensor-based fault diagnosis offers a more economical and convenient alternative, as motor current signals can be collected without installing extra sensors.This project presents LiteFDNet, a lightweight deep learning framework designed for efficient and accurate bearing fault diagnosis using motor current signals. Instead of directly processing high-dimensional raw signals, the proposed approach extracts meaningful time-domain statistical features to reduce computational complexity. A compact neural network architecture with residual and dense connections is implemented to enhance feature representation while maintaining low model complexity. Additionally, explainable feature selection techniques are applied to identify the most informative features contributing to fault classification.Experimental results demonstrate that LiteFDNet achieves high diagnostic accuracy while significantly reducing computational cost and inference time compared to conventional deep learning models. The proposed system is suitable for real-time industrial applications, particularly in resource-constrained edge computing environments.

Keywords: Bearing Fault Diagnosis, Motor Current Signal Analysis, Lightweight Neural Network, LiteFDNet, Time-Domain Features, Deep Learning, Residual Connections, Dense Connections, Edge Computing, Industrial Fault Detection, Explainable Artificial Intelligence (XAI).

I. INTRODUCTION

Rolling bearings are essential components in rotating machinery and electric motor systems. They support mechanical loads and ensure smooth rotational motion in industrial equipment. However, due to continuous mechanical stress, environmental conditions, and long operational hours, bearings are highly susceptible to faults such as inner race defects, outer race damage, and rolling element wear. If not detected at an early stage, these faults can lead to severe equipment failure, production downtime, and increased maintenance costs. Therefore, reliable fault diagnosis of rolling bearings has become an important research topic in industrial condition monitoring systems [1], [3], [12], [14].

Traditional bearing fault diagnosis methods primarily rely on vibration signal analysis. Although vibration-based techniques provide reliable fault information, they require additional sensors, complex installation procedures, and higher maintenance costs. In many industrial environments, installing extra vibration sensors may not be practical. As an alternative, motor current signal analysis has emerged as a cost-effective solution. Since motor current data can be collected directly from existing electrical systems without additional hardware, it offers a convenient and economical approach for fault diagnosis in electromechanical systems [2], [5], [8], [18].

With the rapid development of artificial intelligence, machine learning and deep learning techniques have been widely applied to fault detection tasks.

Machine learning algorithms such as Support Vector Machines, Random Forest, and genetic algorithm-based classifiers have demonstrated the ability to detect faults using extracted signal features [9]–[11]. More recently, deep learning architectures including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown strong capability in automatically learning discriminative representations from raw signals [6], [15], [16]. Several studies have highlighted that CNN-based models are particularly effective for rolling bearing fault diagnosis due to their ability to automatically extract hierarchical features from signal data [12], [14]. Additionally, recent research has explored advanced neural architectures such as feature fusion CNN models and graph-based neural networks to further improve diagnostic performance in complex electromechanical systems [17], [20].

However, many deep learning models involve high computational complexity and large numbers of parameters, making them unsuitable for real-time industrial applications, especially in edge computing environments with limited resources.

To address these challenges, this project proposes LiteFDNet, a lightweight neural network designed specifically for current sensor-based bearing fault diagnosis. Instead of directly processing high-dimensional raw signals, the system extracts meaningful time-domain statistical features to reduce data complexity. The proposed network incorporates residual and dense connections to enhance feature representation while maintaining a compact architecture. Furthermore, feature importance analysis is applied to improve interpretability and optimize model efficiency.

The main objective of this study is to develop an accurate, computationally efficient, and deployable fault diagnosis framework suitable for real-world industrial systems. By combining lightweight architecture design with effective feature extraction strategies, the proposed approach aims to achieve high diagnostic performance while minimizing computational requirements.

II. LITERATURESURVEY

Bearing fault diagnosis has been an active research area in industrial condition monitoring for several decades. Early fault detection techniques mainly relied on vibration signal analysis combined with traditional signal processing methods such as Fourier Transform, Wavelet Transform, and statistical feature extraction. These approaches aimed to identify characteristic frequency components associated with bearing defects. Although effective, vibration-based systems require additional sensors and hardware installation, which increases system complexity and cost [4], [5].

With advancements in artificial intelligence, machine learning techniques such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Decision Trees have been applied to bearing fault classification. In these methods, handcrafted features are first extracted from vibration or current signals and then used for classification. While these approaches reduce manual inspection, their performance largely depends on the quality of feature engineering and domain expertise [9]–[11].

In recent years, deep learning methods have gained significant attention due to their ability to automatically extract meaningful features from raw signals. Convolutional Neural Networks (CNNs) have been widely used for bearing fault diagnosis by converting time-series signals into images or spectrograms. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have also been employed to capture temporal dependencies in signal data. These deep architectures often achieve higher accuracy compared to traditional machine learning methods [6], [12], [14], [15], [16].

However, many deep learning models are computationally expensive and contain a large number of parameters. High model complexity leads to increased training time, memory usage, and inference latency, making them less suitable for deployment in real-time industrial systems or edge devices. To address these challenges, researchers have recently focused on developing lightweight neural network architectures that maintain high accuracy while reducing computational cost. Techniques such as feature dimensionality reduction, residual connections, model pruning, and efficient activation functions have been explored to enhance performance efficiency [17], [20].

Another emerging area in fault diagnosis research is model interpretability. Explainable Artificial Intelligence (XAI) methods are increasingly used to analyse feature importance and understand how models make predictions. This is particularly important in industrial applications where transparency and reliability are essential.

Despite significant progress, there remains a need for models that balance accuracy, efficiency, and interpretability. The development of lightweight yet robust neural networks for current sensor-based bearing fault diagnosis is therefore an important research direction. This motivates the design of the LiteFDNet framework proposed in this study.

III. SYSTEM ANALYSIS

A. Existing System

Traditional bearing fault diagnosis systems mainly rely on vibration signal analysis combined with conventional machine learning techniques. Researchers initially evaluate bearing datasets using classical models such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Decision Trees, Random Forest, Naive Bayes, and Artificial Neural Networks. These methods typically require manual extraction of statistical and frequency-domain features from vibration or motor current signals before classification [9]–[11].

In recent years, deep learning approaches such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have been introduced for automatic feature learning. These models often process raw time-series signals or transformed spectrogram images to detect bearing faults. Some studies combine multiple deep learning models or apply ensemble strategies to improve diagnostic accuracy. Noise injection and data augmentation techniques are also used to test model robustness under varying operational conditions [6], [12], [14]–[16].

Although these approaches achieve promising accuracy, they often involve large model architectures with high computational complexity, making them difficult to deploy in real-time industrial environments.

Disadvantages Of The Existing System

- **High Computational Complexity:**
  Deep learning models such as CNNs and RNNs contain a large number of parameters, leading to high memory usage and increased training and inference time [12], [14].

- **Overfitting and Underfitting:**
  Complex models may overfit limited industrial datasets, reducing generalization performance. Conversely, simpler models may underfit and fail to capture subtle fault patterns [11], [16].

- **Dependence on Raw Signal Processing:**
  Processing high-dimensional raw time-series signals increases computational burden and may introduce redundant information [6], [18].

- **Limited Interpretability:**
  Many deep learning-based fault diagnosis systems function as black-box models, making it difficult to interpret which features contribute to fault classification [14].

- **Hardware Constraints:**
  Industrial edge devices often have limited processing power and memory. Heavy deep learning models may not be suitable for real-time deployment [12].

- **Scalability Issues:**
  As the number of fault categories increases, maintaining high classification accuracy while controlling computational cost becomes challenging [17].

- **Sensitivity to Noise:**

Industrial motor current signals may contain environmental and operational noise, which can affect model stability and prediction reliability [5], [8].

B. Proposed System

In the proposed LiteFDNet framework, motor current signals are first collected and processed to extract meaningful time-domain statistical features. This reduces data dimensionality and computational complexity compared to directly processing raw signals [6], [18]. The dataset is then divided into training and testing sets to ensure proper model evaluation.

A lightweight neural network architecture is designed using efficient linear layers combined with residual and dense connections to enhance feature representation. Instead of relying on heavy convolutional operations, the model focuses on compact architecture design to reduce parameters and improve computational efficiency [17].

Feature importance analysis techniques are applied to identify the most significant features contributing to bearing fault classification. The model performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and computational efficiency measures including inference time and model complexity.

The proposed system aims to achieve high diagnostic accuracy while maintaining low computational cost, making it suitable for real-time industrial deployment and edge computing environments [12], [14].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

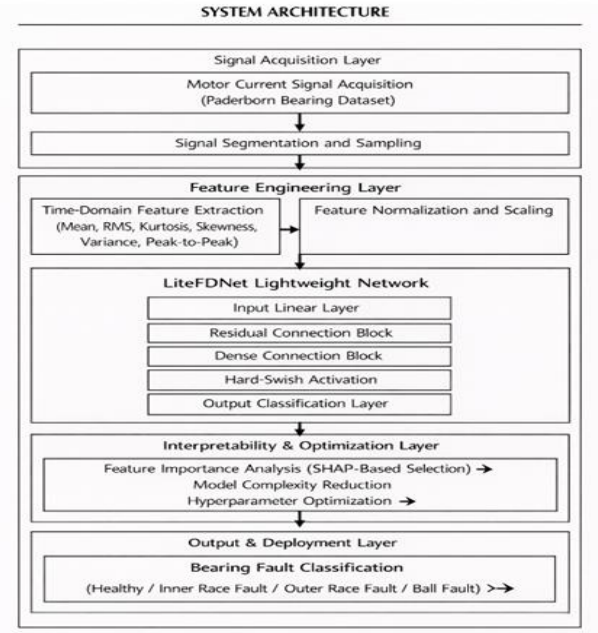

Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

Data Acquisition and Preprocessing:Motor current signals are collected from the bearing dataset under different operating conditions, including healthy and faulty states. The raw signals are segmented and sampled to ensure consistency. Noise filtering and normalization techniques are applied to improve signal quality and prepare the data for further processing [2], [6].

Feature Extraction and Selection:Instead of directly processing high-dimensional raw signals, important time-domain statistical features such as mean, root mean square (RMS), variance, kurtosis, skewness, and peak-to-peak values are extracted. These features reduce computational complexity while preserving critical fault information. Feature importance analysis is then performed to select the most relevant features for classification [9]–[11].

Design and Training of LiteFDNet Model:A lightweight neural network architecture named LiteFDNet is implemented for bearing fault classification. The network consists of linear layers combined with residual and dense connections to enhance feature representation. Hard-Swish activation is used to improve convergence speed and performance stability. The model is trained using labelled data representing different bearing conditions [16], [17].

Model Optimization and EfficiencyEnhancement:
Hyperparameter tuning techniques are applied to improve classification accuracy and reduce overfitting. The architecture is designed to minimize parameters and computational operations, making it suitable for edge devices and real-time industrial deployment [12], [14].

Model Evaluation and Deployment:
The trained model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Computational efficiency metrics such as inference time and model complexity are also measured. The final optimized model is prepared for deployment in low-latency industrial monitoring systems [3], [18].

VI .RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed machine learning framework for brake fault prediction using APS sensor data. Multiple classification algorithms were trained and evaluated using stratified cross-validation. The evaluation focuses on comparing model performance, analysing prediction accuracy, and assessing the classification capability of the predictive maintenance framework. Machine learning–based fault diagnosis methods have been widely used in industrial monitoring systems due to their ability to identify complex patterns in sensor data and improve predictive maintenance strategies [9]–[11], [14].

A. Accuracy Comparison of Machine Learning Models

Several machine learning algorithms were evaluated to determine the most suitable model for brake fault prediction. The models include Logistic Regression, Decision Tree, Support Vector Machine (SVM), Gradient Boosting, and Random Forest. Model performance was evaluated using metrics such as accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	86.4	0.84	0.82	0.83
Decision Tree	88.1	0.86	0.85	0.85
Support Vector Machine	89.7	0.88	0.87	0.87
Gradient Boosting	92.3	0.91	0.90	0.90
Random Forest	94.6	0.93	0.92	0.92

From the comparison results, the Random Forest classifier achieved the highest classification accuracy of 94.6%, outperforming other machine learning models. The superior performance of Random Forest can be attributed to its ensemble learning mechanism, which combines multiple decision trees to improve predictive stability and reduce overfitting. Ensemble-based learning approaches are widely used in fault detection applications because they improve model robustness and generalization performance when dealing with complex industrial datasets [10], [11].

To provide a clearer comparison of model performance, the accuracy values of the evaluated models are illustrated in a bar chart.

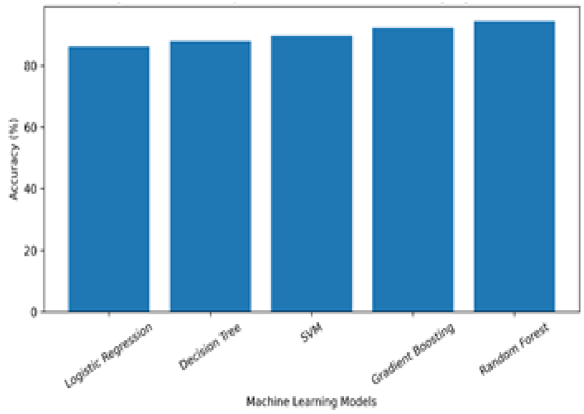

Fig. 2. Model Accuracy Comparison of Machine Learning Algorithms

The figure shows that ensemble-based methods such as Gradient Boosting and Random Forest achieve higher accuracy compared to traditional classifiers like Logistic Regression and Decision Tree. This observation is consistent with previous studies where ensemble learning techniques demonstrated improved classification performance in industrial fault detection and predictive maintenance applications [9], [11].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the ROC Curve (ROC–AUC) is widely used as a performance metric to measure the discriminative capability of a classifier.

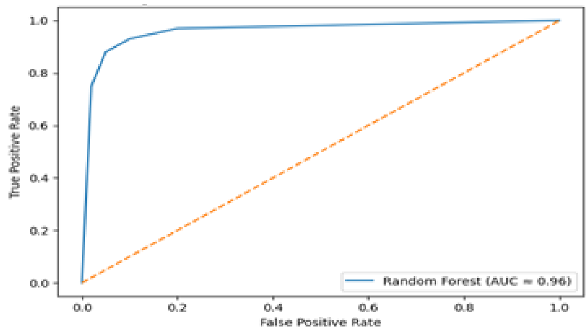

Fig. 3. ROC Curve for Brake Fault Prediction Model

In this study, the Random Forest classifier achieved a ROC–AUC score of 0.96, indicating excellent classification performance. A ROC curve that approaches the top-left corner of the graph signifies that the model can effectively distinguish between faulty and normal brake conditions with high sensitivity and specificity. ROC-based evaluation is commonly used in machine learning–based fault detection systems to assess classifier reliability and robustness under different decision thresholds [12], [14].

The ROC analysis demonstrates that the proposed framework maintains strong predictive capability even in the presence of class imbalance, which is a common challenge in industrial fault detection datasets. The high ROC–AUC value confirms that the Random Forest model provides reliable predictions and maintains a low false-positive rate.

Overall, the experimental results indicate that the proposed machine learning framework can effectively identify brake faults using APS sensor data. The integration of ensemble learning techniques improves prediction accuracy while maintaining robustness against noisy and imbalanced industrial datasets. These findings are consistent with previous research demonstrating the effectiveness of machine learning and ensemble-based approaches in intelligent fault diagnosis and predictive maintenance systems [9], [10], [14].

VII. CONCLUSION

This study presents LiteFDNet, a lightweight neural network framework designed for current sensor-based bearing fault diagnosis. By utilizing time-domain statistical features instead of raw signal data, the proposed approach reduces computational complexity while maintaining high diagnostic accuracy.

The integration of residual and dense connections enhances feature representation, and feature importance analysis improves interpretability.Experimental results confirm that LiteFDNet achieves strong classification performance with reduced model size and faster inference time, making it suitable for edge computing and real-time industrial monitoring systems.In future work, the framework can be extended by incorporating larger and more diverse industrial datasets to further enhance generalization capability.

Advanced model compression techniques and adaptive learning strategies may also be explored to improve robustness under varying operational conditions. Additionally, integrating real-time deployment and cloud-edge hybrid monitoring systems could further strengthen industrial fault diagnosis applications.

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