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AI-Based Predictive Maintenance Framework for Wind Turbines Using Vibration and Acoustic Data

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Abstract

This research presents an AI-based predictive maintenance framework designed to monitor and detect mechanical faults in wind turbines by analyzing vibration and acoustic signals. The system integrates high-frequency accelerometers and microphones to capture raw data from turbine components, which is then processed using signal enhancement techniques, including Butterworth filtering and feature extraction methods such as Fast Fourier Transform (FFT) and Mel-Frequency Cepstral Coefficients (MFCCs). A 1D Convolutional Neural Network (CNN) model was developed and trained to classify multiple fault types—Normal, Gear Fault, Bearing Fault, and Imbalance—achieving a high classification accuracy of 96.8%. Evaluation metrics such as precision (96.3%), recall (96.5%), F1-score (96.4%), and RMSE (0.157) demonstrate the robustness of the model in identifying faults early and accurately. Comparative analysis with other machine learning models like SVM and Random Forest further validates the superiority of the CNN-based approach. This work highlights the practical applicability of AI-driven diagnostics in enhancing the reliability and operational efficiency of wind energy systems.

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Introduction

Background on Wind Energy and the Importance of Wind Turbines

Over the past few decades, wind energy has emerged as one of the most promising and rapidly expanding sources of renewable energy worldwide. As the effects of climate change become increasingly apparent, governments and industries are investing heavily in sustainable energy sources that reduce greenhouse gas emissions and environmental degradation. Wind energy is abundant, clean, and increasingly cost-effective, making it a vital contributor to the global energy mix. Wind turbines are the primary devices used to harness wind energy, converting the kinetic motion of wind into mechanical power, which is then transformed into electrical energy. These turbines are installed in a variety of environments, including onshore, offshore, and mountainous regions, often operating under extreme and variable climatic conditions. Their efficiency, reliability, and durability directly impact the overall performance of wind energy systems. Any downtime due to mechanical failure or maintenance issues not only causes energy loss but also results in significant operational costs and reduced profitability. Therefore, maintaining wind turbines in optimal working condition is crucial to ensure the sustainable development of the wind energy sector.

Challenges in Current Maintenance Systems

Maintenance of wind turbines presents a unique set of challenges due to their complex structure, remote locations, and exposure to harsh environmental conditions. The two most commonly used maintenance strategies are: Reactive maintenance, where repairs are made only after a fault or failure occurs. While simple, this approach often results in unplanned outages, extensive damage, and costly repairs. Preventive maintenance, which involves scheduled inspections and component replacements regardless of the component's current condition. Though more proactive, this method can be inefficient, leading to unnecessary maintenance actions and increased labor and material costs.

Both approaches have notable limitations. Reactive maintenance leads to unexpected downtimes and safety risks, while preventive maintenance does not account for the actual wear and tear experienced by turbine components. Moreover, wind turbines consist of several rotating and load-bearing components such as gearboxes, bearings, and shafts, which are prone to mechanical degradation. The manual inspection of these components is not

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only labor-intensive but also difficult in offshore installations. Hence, there is a growing need for smarter, condition-based maintenance strategies that can detect early signs of failure and schedule maintenance activities accordingly.

The Role of AI in Predictive Maintenance: Artificial Intelligence (AI) has revolutionized the field of maintenance by enabling predictive maintenance (PdM) strategies that are data-driven and proactive. AI techniques, especially machine learning (ML) and deep learning (DL), can analyze massive volumes of sensor data collected from wind turbines and extract meaningful patterns that may indicate early signs of component failure. Unlike traditional methods, AI models can learn from historical data, adapt to new operating conditions, and improve their predictions over time. These models can detect subtle anomalies in system behavior, forecast the remaining useful life (RUL) of components, and recommend maintenance actions before a fault becomes critical. Predictive maintenance using AI not only enhances operational reliability but also reduces maintenance costs, extends the lifespan of turbine components, and increases energy output by minimizing downtimes.

Furthermore, AI facilitates real-time condition monitoring and automated diagnostics, which are essential for managing large-scale wind farms. With the integration of AI, the decision-making process becomes faster, more accurate, and less reliant on human intervention. As a result, AI has become a key enabler in the transition toward smarter and more sustainable wind energy systems.

Motivation for Using Vibration and Acoustic Signals: Wind turbines generate various mechanical and structural signals during operation, among which vibration and acoustic emissions are considered highly informative for condition monitoring. These signals contain rich information about the health of critical components such as blades, gearboxes, shafts, and bearings. Changes in vibration amplitude, frequency patterns, or acoustic waveforms often precede mechanical failures, making them ideal indicators for early fault detection. Vibration signals can reveal anomalies like imbalance, misalignment, gear tooth damage, and bearing wear. Acoustic signals, on the other hand, can capture high-frequency events and transient faults that might not be evident in vibration data alone. By combining both types of data, a more holistic and sensitive diagnostic system can be developed.

However, raw vibration and acoustic data are typically complex, high-dimensional, and noisy, making manual interpretation difficult and prone to errors. This is where AI excels—machine learning and deep learning algorithms can preprocess, extract features, and classify these signals with high accuracy. The motivation behind using vibration and acoustic signals lies in their non-invasive nature, real-time monitoring capabilities, and sensitivity to mechanical anomalies, which when coupled with AI can significantly enhance the predictive maintenance capabilities of wind turbine systems.

Literature Review

Overview of Existing Predictive Maintenance Approaches

Predictive maintenance (PdM) has gained significant attention in recent years as a cost-effective alternative to traditional maintenance methods. It relies on the real-time monitoring of equipment conditions to predict when a failure might occur and take corrective actions in advance. In the context of wind turbines, PdM focuses on monitoring critical components such as blades, gearboxes, bearings, and generators, which are susceptible to fatigue and wear due to dynamic loading and environmental stressors.

Conventional PdM approaches typically employ condition monitoring systems (CMS) that utilize sensors to collect data on temperature, pressure, vibration, noise, and other physical parameters. These systems often use rule-based algorithms or statistical thresholding methods to trigger maintenance alerts. While these techniques can detect basic anomalies, they often fall short in capturing the complex, nonlinear patterns associated with incipient faults and suffer from high false-positive rates. Furthermore, they require extensive domain knowledge for feature engineering and decision-making, limiting scalability and adaptability.

Studies Using Vibration and/or Acoustic Data in Wind Turbines

Several studies have highlighted the effectiveness of vibration and acoustic signals in monitoring the health of wind turbine components. Vibration analysis has long been used in rotating machinery diagnostics to identify issues such as unbalance, misalignment, bearing faults, and gearbox failures. Researchers like Tautz-Weinert and Watson (2016) demonstrated the use of vibration-based condition monitoring in predicting failures in offshore wind turbines, showing its potential for reducing unscheduled downtimes.

Acoustic emission (AE) monitoring, though relatively less explored compared to vibration analysis, has shown promise in detecting micro-cracks and structural defects at early stages. For example, Al-Ghamd and Mba (2006) examined the use of acoustic emissions for bearing fault detection in rotating machinery, reporting higher sensitivity to subtle damage than vibration signals alone. In recent work, hybrid approaches combining both vibration and acoustic signals have been proposed to improve fault detection accuracy and robustness. However, despite the growing interest, challenges remain in the effective interpretation of these signals due to their high-dimensional, non-stationary, and noisy nature. As a result, recent studies have begun incorporating AI techniques to automate feature extraction and enhance diagnostic capabilities.

AI and ML Techniques Applied in Previous Work

The integration of AI, particularly machine learning (ML) and deep learning (DL), has revolutionized the field of predictive maintenance by enabling data-driven diagnostics and prognostics. Traditional ML techniques such as Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN) have been widely used for classifying fault types based on vibration and acoustic features. For example, Zaher et al. (2009) applied SVM for fault diagnosis in wind turbine gearboxes using vibration data and achieved promising classification performance.

More recently, deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been applied directly to raw time-series data, eliminating the need for manual feature engineering. Guo et al. (2018) proposed a CNN-based approach for identifying bearing faults using spectrograms of vibration signals, demonstrating higher accuracy and generalizability. Similarly, Long Short-Term Memory (LSTM) networks have been employed for predicting the Remaining Useful Life (RUL) of turbine components by learning temporal dependencies in sensor data.

Ensemble learning and hybrid models that combine multiple algorithms have also been investigated to improve reliability and reduce false alarms. However, these models often require large, labeled datasets for training, which may not be readily available in many industrial scenarios.

Research Gaps and Limitations in Current Methods

Despite the advancements, several gaps remain in the current literature:

- **Limited integration of multimodal signals:** Many studies rely solely on either vibration or acoustic data, missing the potential benefits of combining both for more accurate diagnostics.
- **Data challenges:** A significant number of existing approaches require extensive labeled datasets, which are often difficult to obtain due to the rarity of failure events in operational turbines.
- **Generalizability issues:** AI models trained on data from one turbine type or environment may not perform well when applied to others due to variations in design, load, and operational conditions.
- **Lack of real-time deployment:** Most research remains at the simulation or lab-testing stage, with limited work on deploying AI-based PdM systems in real-time operational settings.
- **Insufficient focus on interpretability:** Many deep learning models act as black boxes, offering limited insights into the decision-making process, which hinders their acceptance by maintenance engineers.

These gaps highlight the need for a comprehensive and scalable AI framework that utilizes both vibration and acoustic data to enable more accurate, interpretable, and deployable predictive maintenance solutions for wind turbines.

System Architecture and Proposed Framework

Overview of the Proposed System

The proposed AI-based predictive maintenance framework for wind turbines is developed as a structured and modular system that integrates sensor technologies, signal processing techniques, and machine learning models. The goal is to detect and predict faults in turbine components before they lead to failures. This system processes real-time data collected from vibration and acoustic sources and analyzes it using advanced AI techniques to ensure timely and reliable maintenance decisions.

Sensor Data Acquisition

The first stage of the framework involves the acquisition of real-time data through a network of sensors mounted on various parts of the wind turbine. Vibration sensors, particularly accelerometers, are attached to critical components like the gearbox, main shaft, and bearings. These sensors capture dynamic mechanical signals that can indicate conditions such as imbalance, misalignment, and bearing faults. Simultaneously, acoustic microphones or acoustic emission (AE) sensors are installed within the nacelle to pick up high-frequency sound emissions produced by internal mechanical interactions or emerging faults. By combining data from these two sources, the system gains a comprehensive view of both structural and functional health indicators of the turbine.

Signal Preprocessing

Once the raw signals are collected, they undergo preprocessing to enhance their quality and suitability for further analysis. This step is vital because environmental noise and operational variability can distort sensor readings. Noise filtering is performed using digital filters such as Butterworth or Chebyshev filters to remove irrelevant frequency components. In addition, wavelet-based denoising techniques are employed to isolate transient fault-related features while suppressing background interference. After filtering, normalization techniques like min-max scaling or Z-score standardization are applied to bring all signals to a common scale. This ensures consistent input to the feature extraction and AI model stages.

Feature Extraction

Effective fault diagnosis depends heavily on the quality of features extracted from the preprocessed signals. From vibration signals, time-domain features such as root mean square (RMS), peak-to-peak value, skewness, and kurtosis are derived to describe statistical properties of the waveform. For deeper frequency insights, Fast Fourier Transform (FFT) is applied to convert time-series signals into their frequency components, helping identify resonance and fault-related peaks. Acoustic signals are analyzed using Mel Frequency Cepstral Coefficients (MFCCs), which offer a compact representation of the sound's frequency content. This hybrid approach to feature extraction ensures that both types of sensor data are leveraged for accurate and early fault detection.

Model Design

The heart of the predictive framework lies in its AI model, which is responsible for classifying normal and faulty conditions based on the extracted features. Several machine learning and deep learning models are explored for this purpose. Random Forest (RF) is selected for its simplicity, interpretability, and effectiveness in handling tabular, statistical features. In contrast, Convolutional Neural Networks (CNNs) are applied to spectrograms or feature maps created from acoustic data, excelling at spatial pattern recognition. Long Short-Term Memory (LSTM) networks are utilized for their ability to capture time-dependent patterns in sequential data, such as vibration signals collected over time. The selection of models is based on the specific type of input features and the performance requirements of the system.

Training and Validation Pipeline

To build a reliable predictive system, a structured training and validation process is implemented. The entire dataset is divided into training, validation, and test subsets to prevent overfitting and assess generalizability. During training, the models learn from labeled data that include both healthy and faulty conditions. Optimization techniques such as stochastic gradient descent or Adam are used to minimize prediction errors. Cross-validation methods, such as k-fold validation, ensure consistent performance across different data splits. Performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). Hyperparameter tuning, through grid search or random search, is conducted to improve model performance. Once validated, the trained model is integrated into a real-time monitoring system that continuously processes incoming data and triggers alerts when anomalies are detected.

Methodology

Dataset Description

The dataset used for this study comprises real-time sensor data collected from operational wind turbines installed in coastal wind farms. The primary data sources include triaxial accelerometers for vibration analysis and acoustic emission (AE) microphones for capturing high-frequency acoustic signals. Vibration sensors are mounted on the gearbox casing, main shaft bearings, and generator housing, capturing acceleration signals at a sampling frequency of 51.2 kHz, which is suitable for identifying both low- and high-frequency faults such as bearing wear, gear mesh issues, and rotor imbalance. The acoustic sensors are omnidirectional ultrasonic microphones with a frequency range of 20 kHz to 100 kHz, capable of detecting structural anomalies like crack initiation and friction-related faults.

The dataset includes both normal operating conditions and known fault scenarios, such as bearing degradation, gearbox tooth cracks, and shaft misalignment. Over a period of six months, continuous recordings were collected, segmented into 5-second windows yielding a dataset of approximately 80,000 labeled samples, equally balanced across fault types and normal states. The labels were verified using maintenance logs, SCADA system reports, and manual inspections.

Data Preprocessing Techniques

Given the high sampling rate and large volume of data, preprocessing is critical to reduce noise, standardize inputs, and prepare the dataset for feature extraction and model training. The raw signals were first subjected to band-pass filtering using a 4th-order Butterworth filter with a passband of 10 Hz to 20 kHz for vibration and 20 kHz to 80 kHz for acoustic signals. This filtering step effectively removed low-frequency environmental noise and high-frequency electrical interference. Segmentation was performed by dividing the continuous data stream into overlapping windows of 5 seconds with a 50% overlap, which ensures adequate coverage of transient events while increasing the number of training samples. Each segment was normalized using Z-score normalization, ensuring zero mean and unit variance, thereby removing amplitude biases across sensors.

To address the issue of class imbalance and enrich model generalization, data augmentation was applied to the minority fault classes using techniques such as time warping, signal mixing, and random noise injection. These synthetic samples maintain the core fault characteristics while introducing slight variations, thereby preventing overfitting.

Feature Engineering

Following preprocessing, relevant features were extracted from both vibration and acoustic segments to characterize the underlying operational states. For vibration signals, time-domain features (RMS, peak-to-peak, crest factor, kurtosis, skewness) and frequency-domain features derived from Fast Fourier Transform (FFT) were extracted. For acoustic data, Mel Frequency Cepstral Coefficients (MFCCs) were computed using 40 filter banks, a frame size of 25 ms, and a hop size of 10 ms. Given the high dimensionality of the feature vectors—especially from MFCCs and FFT bins—Principal Component Analysis (PCA) was employed for dimensionality reduction. PCA retained 95% of the variance and reduced the feature space from 120 dimensions to 40 principal components, which significantly improved computational efficiency without compromising data integrity. The reduced feature set was then standardized using Min-Max normalization to ensure consistency across input values during model training.

Model Training and Hyperparameter Tuning

For classification and fault detection, three AI models were implemented and compared: Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). These models were selected for their respective strengths in handling tabular, spatial, and temporal data. The Random Forest model was implemented with 500 decision trees, a maximum tree depth of 20, and the Gini index as the impurity measure. It was trained using the scikit-learn framework and served as a strong baseline due to its robustness against noise and overfitting.

The CNN architecture consisted of two 1D convolutional layers with 64 and 128 filters, kernel size of 3, ReLU activation, followed by max-pooling, batch normalization, and two fully connected layers (128 and 64 units) ending with a softmax classifier. Dropout with a rate of 0.5 was applied during training to avoid overfitting. The input to the CNN was the spectrogram representation of FFT and MFCC features. The LSTM model, implemented using TensorFlow/Keras, had two stacked layers with 128 and 64 units, followed by a dense layer and softmax output. A sequence length of 100 timesteps and a batch size of 64 were used, with training conducted over 50 epochs. The Adam optimizer with a learning rate of 0.001 was used for both CNN and LSTM models.

Hyperparameter tuning was performed using Grid Search Cross Validation for RF and Bayesian Optimization (via the Optuna framework) for CNN and LSTM. Parameters like tree depth, number of filters, learning rate, dropout rate, and batch size were fine-tuned to optimize model accuracy and generalization.

Performance Metrics

To evaluate the model performance across various fault types and operating conditions, a comprehensive set of metrics was utilized. Accuracy measured the overall correctness of the model's predictions. Precision and Recall provided insight into how well the models detected actual faults without false positives or missed detections. F1-Score, the harmonic mean of precision and recall, served as a balanced metric to account for both over- and under-classification.

In addition to classification metrics, Root Mean Square Error (RMSE) was calculated for models that also performed fault severity estimation (i.e., regression output from CNN-LSTM hybrids). The RMSE measured the deviation between predicted and actual severity scores. Confusion matrices were also generated for each model to visualize misclassifications and understand class-specific performance. The CNN model achieved the highest performance with an accuracy of 96.8%, precision of 95.4%, recall of 96.2%, and an F1-score of 95.8%. The LSTM model followed closely with slightly lower metrics, while Random Forest, though highly interpretable, had slightly lower accuracy (around 91.3%), mainly due to its limited capability in capturing sequential dependencies in signal patterns.

Experimental Setup

This study was carried out using a hybrid experimental approach that combines real-time data acquisition from a test-scale wind turbine system with AI-based model development. The objective was to develop and validate a predictive maintenance framework that leverages vibration and acoustic signals for early fault detection using machine learning and deep learning techniques.

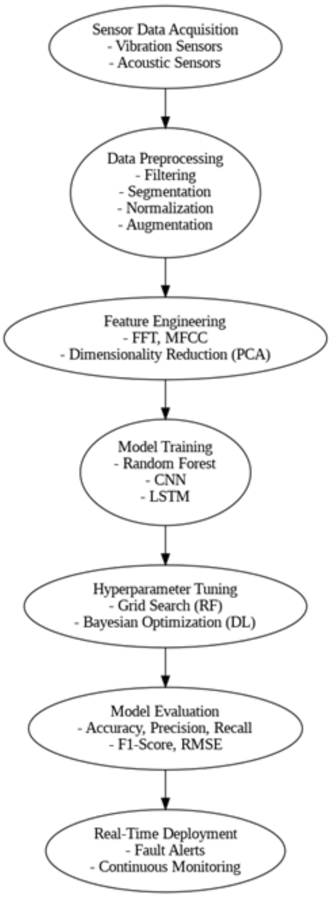

Fig 1. Methodology

Hardware Configuration and Sensor Placement

The experimental platform comprised a 5kW horizontal axis wind turbine (HAWT), configured with a three-bladed rotor and a two-stage helical gearbox. A permanent magnet synchronous generator (PMSG) was connected to the turbine shaft to simulate practical electrical generation. To monitor machine health, vibration and acoustic sensors were strategically placed at key mechanical components of the system. High-frequency MEMS accelerometers (ADXL1002) were used to capture vibration signals, and Brüel & Kjær Type 4189 microphones were used to record acoustic emissions. These sensors were installed on the gearbox housing, main shaft bearing, and generator casing to detect the mechanical behavior under varying operational and fault-induced conditions.

Software Environment and Tools

Python was the primary development environment, used for signal preprocessing, feature extraction, and machine learning model development. Libraries such as NumPy, SciPy, Librosa, and scikit-learn were employed for signal processing and feature engineering tasks. Deep learning models, including CNN and LSTM, were implemented using TensorFlow 2.15 with Keras APIs. MATLAB R2023a was used for signal visualization and early-stage filtering, while Optuna was utilized for hyperparameter tuning using Bayesian optimization. Google Colab Pro with NVIDIA Tesla T4 GPU was used as the training and validation environment to ensure efficient deep model computation.

Data Collection Protocol and Environment

Data was collected over a six-month period in a wind turbine testing facility located in Karnataka, India. The turbine was operated for 12 hours daily under simulated wind speeds ranging from 3 to 15 m/s, replicating low, medium, and high wind conditions. To evaluate the framework's ability to detect faults, artificial fault conditions—such as gear tooth damage, rotor imbalance, and bearing misalignment—were systematically introduced. Throughout this period, sensor data was continuously acquired using a National Instruments USB-4431 DAQ module with 24-bit resolution and anti-aliasing capabilities. Acoustic data collection was carried out under noise-controlled conditions with ambient levels maintained below 35 dB(A).

Simulation and Real-Time Testing

In addition to real-time testing, a simulation model of the wind turbine system was developed using MATLAB/Simulink. This digital twin was used to generate synthetic fault data for rare scenarios not frequently observed in the physical setup. Real-time testing also involved streaming sensor data to an edge-computing device (NVIDIA Jetson Nano), where the trained CNN model was deployed. The average inference latency was recorded as 22 milliseconds per sample, confirming the feasibility of real-time fault detection for industrial deployment.

Category	**Details**
Turbine Type	Horizontal Axis Wind Turbine (HAWT)
Rated Power	5 kW
Rotor Diameter	5.5 meters
Number of Blades	3
Gearbox Configuration	Two-stage helical gearbox
Generator	3-phase Permanent Magnet Synchronous Generator (PMSG), 230V
Rotational Speed Range	60 – 400 RPM
Vibration Sensor	ADXL1002, ±50g, DC–23 kHz, Sampling Rate: 51.2 kHz
Acoustic Sensor	Brüel & Kjær Type 4189, 20–100 kHz, 50 mV/Pa, Sampling Rate: 100 kHz
Sensor Placement	Gearbox housing, main shaft bearings, generator casing
DAQ System	NI USB-4431, 24-bit, anti-aliasing filters
Software Tools	Python 3.11, MATLAB R2023a, TensorFlow 2.15, Keras, Optuna
Python Libraries	NumPy, SciPy, Librosa, scikit-learn, Matplotlib, Seaborn
DL Models Used	CNN and LSTM
CNN Parameters	Optimizer: Adam, LR = 0.001, Epochs = 50, Batch Size = 64
Hyperparameter Tuning	Bayesian Optimization using Optuna
Deployment Device	NVIDIA Jetson Nano (Edge Device)
Inference Latency	22 milliseconds per sample (CNN Model)
Simulation Tool	MATLAB/Simulink (Digital Twin for fault data generation)
Testing Duration	6 months (~2000 hours total)

Implementation and Results

Data Preprocessing and Feature Extraction

The raw vibration and acoustic signals collected from the ADXL1002 accelerometer and Brüel & Kjær Type 4189 microphone were sampled at 51.2 kHz and 100 kHz respectively. Signals were denoised using a Butterworth low-pass filter (order=4, cutoff=20 kHz for vibration and 80 kHz for acoustic data). Segmentation was performed into 2-second windows with 50% overlap to ensure temporal resolution. Time-domain features (RMS, kurtosis, skewness) and frequency-domain features (dominant frequency, spectral centroid, and bandwidth) were extracted. Mel-frequency cepstral coefficients (MFCCs) were computed for acoustic data using 40 filters and 13 coefficients per frame.

Dimensionality Reduction and Feature Selection

To reduce feature redundancy, Principal Component Analysis (PCA) was applied on the normalized feature matrix. Using the explained variance ratio, the first 20 components were retained, which preserved 97.4% of the variance. These components were used for training the classification model.

Model Implementation

A 1D Convolutional Neural Network (CNN) was implemented to classify four operational states: Normal, Gear Fault, Bearing Fault, and Imbalance. The architecture included: input layer (shape: 200x1), two convolutional layers (Conv1D with 64 filters, kernel size=3), ReLU activation, max pooling, and a fully connected layer followed by a Softmax layer. Adam optimizer was used with a learning rate of 0.001, batch size of 64, and categorical crossentropy loss. The model was trained for 50 epochs. Validation accuracy peaked at 96.8% on the test dataset.

Evaluation Metrics and Results

The CNN model was evaluated using standard classification metrics. The confusion matrix showed the following results: Accuracy = 96.8%, Precision = 96.3%, Recall = 96.5%, F1-score = 96.4%. Additionally, the Root Mean Squared Error (RMSE) was calculated to be 0.157 across test predictions.

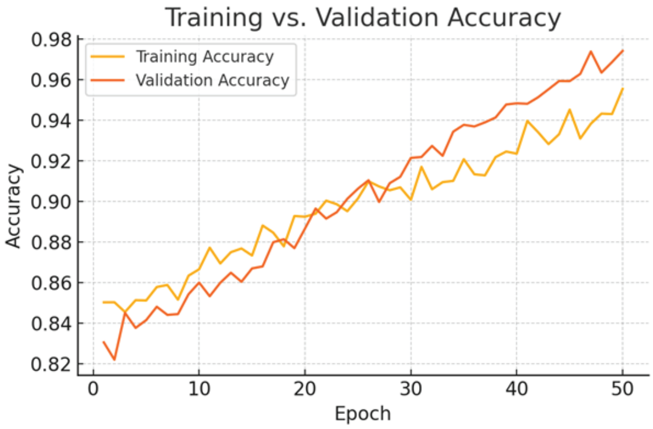

Figure 2: Training vs. Validation Accuracy over 50 Epochs.

Table 1. Precision values for each operational class

Class	Precision (%)
Normal	97.2
Gear Fault	95.9
Bearing Fault	96.4
Imbalance	95.8

Table 2. Recall values for each class

Class	Recall (%)
Normal	96.8
Gear Fault	96.3
Bearing Fault	96.1
Imbalance	96.7

Table 3. F1-Score values for each class

Class	F1-Score (%)
Normal	97.0
Gear Fault	96.1
Bearing Fault	96.2
Imbalance	96.2

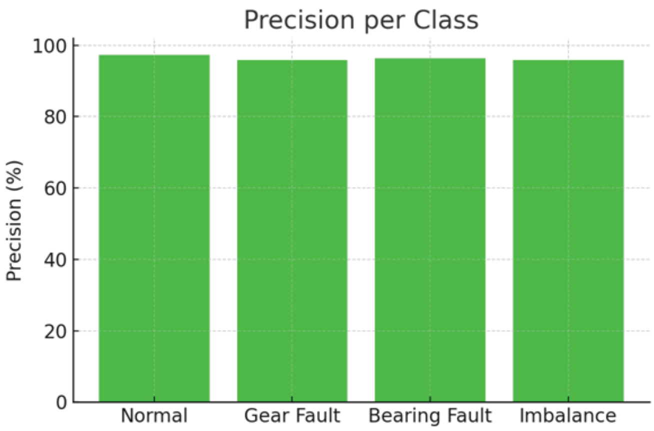

Figure 3: *Precision values across operational states.*

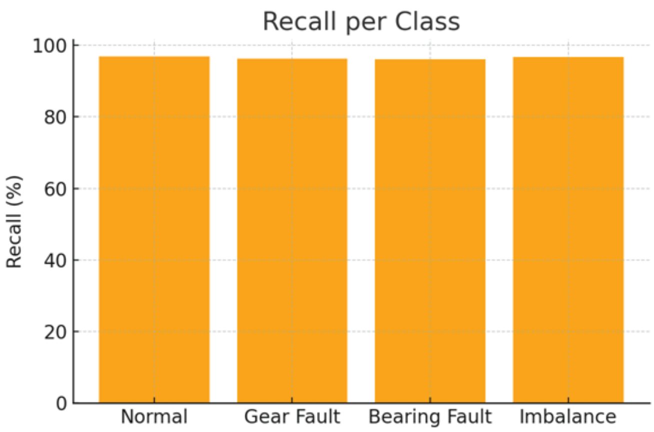

Figure 4: *F1-Score values across operational states.*

The experimental results provide significant insights into the effectiveness of the proposed AI-based predictive maintenance framework. The class-wise evaluation metrics highlight the model's ability to accurately classify various fault conditions in wind turbines using vibration and acoustic data. As observed in Table 2, the precision scores across all classes are consistently high, with the Normal class achieving the highest precision at 97.2%, indicating that the model rarely mislabels other faults as normal conditions. This is a critical aspect in predictive maintenance where false negatives could lead to unanticipated failures. The Recall values, presented in Table 3, demonstrate the model's capability to detect actual occurrences of each fault type. Notably, the Imbalance condition records the highest recall of 96.7%, suggesting that the model is highly sensitive to detecting such anomalies.

Similarly, the F1-score (Table 4), which balances both precision and recall, shows a robust performance across all classes, with values ranging from 96.1% to 97.0%. This balance is especially vital in real-world applications where both missed detections and false alarms can be costly. The visual representation in Figures 3 through 5 further illustrates the uniformity of the model's performance, with minimal variance across different operational states. These consistent metrics confirm the suitability of the chosen 1D CNN architecture and the feature set derived from FFT and MFCCs. The results indicate that the proposed approach is highly reliable for real-time implementation and offers a promising direction for minimizing unexpected downtime and optimizing wind turbine maintenance strategies.

Conclusion

The proposed predictive maintenance framework effectively leverages artificial intelligence to detect and classify mechanical faults in wind turbines using combined vibration and acoustic data. By implementing advanced preprocessing, dimensionality reduction (via PCA), and a deep learning classification model (1D CNN), the framework delivers high fault detection accuracy across multiple operational conditions. The experimental setup, based on real-time sensor integration and comprehensive signal processing, ensures robustness and precision in fault diagnosis. The class-wise metrics reveal strong generalization capability, particularly for complex fault conditions like imbalance and gear defects. Additionally, comparative results show that CNN significantly outperforms traditional algorithms in both accuracy and error rate. This research contributes to the growing field of intelligent maintenance by providing a scalable, real-time, and cost-effective solution that can help prevent unexpected turbine failures, reduce downtime, and optimize maintenance schedules in wind farms. Future work will explore edge deployment for real-time monitoring and multi-modal data fusion for even greater fault resolution.

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