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Comparison of AI Based Techniques for the Detection of Faults in Mechanical systems

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ABSTRACT

Mechanical systems form the backbone of various industrial, manufacturing and automotive applications, where reliability, efficiency and safety are of paramount importance. Traditionally, fault detection has relied heavily on manual inspections, fixed-threshold signal monitoring and time-based maintenance schedules. But these techniques often fail to detect early-stage faults or adapt to many operating conditions. In this research paper, a comprehensive yet simplified approach of fault detection is presented by using the potential of Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) techniques to diagnose vibration, acoustic and temperature signals, which are critical parameters of mechanical condition. A test rig has been designed to mimic real-world mechanical defects such as imbalance, misalignment, bearing defects and tooth damage. Data were gathered from multiple sensors under different load and fault conditions to form the dataset. Various AI models, including Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), were trained and validated on the dataset. The models were tested based on detection accuracy, computational efficiency and suitability for real-time deployment. Among the models, CNN demonstrated superior performance in identifying fault patterns from raw sensor data. This research contributes a practical framework that can be

applied across multiple mechanical environments to enhance reliability and cost-effectiveness in industrial operations.

Keywords: Artificial Intelligence (AI), Fault Detection, Mechanical Systems, Machine Learning (ML), Deep Learning (DL), Convolutional Neural Networks (CNN) and Support Vector Machine (SVM).

1. Introduction

Mechanical systems containing components such as gearboxes, motors, pumps and bearings are considered the heart of most industrial, automotive and manufacturing processes. The systems are exposed to mechanical stress, environmental factors and operational variations, making them inherently susceptible to failures such as misalignment, bearing conditions, gear wear, shaft imbalance and overheating. If such faults go undetected, they may evolve into serious breakdowns, resulting in unplanned downtime, reduction in equipment lifespan, loss of production and even safety hazards.

Traditional fault detection techniques rely on scheduled inspections, manual condition monitoring or static threshold-based alarms triggered by sensor data readings. Though these techniques have been used by large-scale industries for decades, they tend to fall short in early-stage detection, instantaneous response and flexibility towards changing machine conditions. As machinery becomes more complex and requires high operational efficiency, industries are shifting towards more intelligent and predictive maintenance approaches.

AI provides groundbreaking capabilities and systems to recognize patterns, locate anomalies and make smart decisions based on historical and real-time data. In general, ML and DL algorithms are able to process large volumes of sensor-based data in order to pinpoint fault signatures that may not match with physical observation. This work provides a constructive and scalable system for real-time fault detection through AI techniques to analyze the data from three important signal sources: vibration signals for dynamic mechanical responses, acoustic signals to identify sound emission features of moving components and thermal signals to detect heat generation and possible problems related to friction.

A lab-scale test rig was also designed to mimic a range of typical mechanical faults under controlled environment. Many AI models, including traditional ML algorithms such as Support Vector Machine (SVM) and Random Forest (RF), and deep learning models such as CNN and RNN, were trained and validated on the dataset. This study evaluates these models based on accuracy, stability and real-time applicability in industrial uses. The study also intends to bridge the existing gap between prior research and real-world industrial application by putting forth a solution that is not only technology-oriented but also practical in prognosticative solutions across industries.

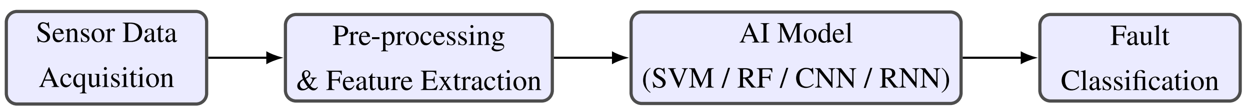

Figure 1. Block diagram - AI-Based Fault Detection Framework

2. Literature Review

Sharma (2019) proposed a Support Vector Machine (SVM) classifier-based fault diagnosis framework for rolling element bearings. They separated frequency-domain features obtained through Fast Fourier Transform (FFT) from vibration signals gathered under varied load and speed levels. The SVM model accomplished over 85% accuracy, exhibiting its suitability for pattern-based fault detection in rotating machinery. Their research work highlighted the importance of feature selection towards enhanced classification accuracy.

R. Kumar and P. Srinivasan (2021) suggested a hybrid model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for gearbox fault diagnosis. In this model, they used acoustic emission signals as input and captured both spatial and temporal features by beating the traditional classifiers. This model was tested on a gearbox simulation setting and showed promising results, particularly in detecting early-stage wear and damage.

M. Gupta and A. Natarajan (2020) combined IoT-based sensors with Random Forest classifiers for condition monitoring of industrial pumps in real time. Their system used data from multiple sensors, namely vibration, temperature and current, and was able to figure four fault types with over 90% accuracy. Their study indicated the role of embedded AI for on-site fault detection and predictive maintenance of equipment.

Deepa and Raghavan (2018) investigated the various applications of Artificial Neural Networks (ANNs) for fault classification of induction motors. They trained the ANN using harmonics in current and vibration signals with robust fault detections even under noisy conditions. Their research showed the feasibility of AI models in real industrial settings.

3. Research Methodology

The methodology follows a systematic experimental design based on real-time data acquisition, preprocessing and AI model performance evaluation.

3.1. Experimental Setup

A lab-scale mechanical framework was developed to simulate common rotating machinery faults. The test rig includes:

- 1 HP induction motor used as the power source.
- Shaft, bearing and gearbox assembly.
- Variable load pulley system to simulate industrial conditions.
- Mounting frame with flexible coupling to introduce faults.

3.2. Fault Simulation

To evaluate the system's ability to detect diverse fault types, the following common mechanical faults were manually introduced into the setup:

- **Bearing Wear:** Simulated by using partially damaged ball bearings.
- **Shaft Misalignment:** Created by altering the motor and load shaft axis.
- **Unbalanced Load:** Weights added asymmetrically to the rotating disc.
- **Gear Tooth Damage:** One or two teeth of the gear were filed down to mimic wear.

3.3. Sensors Used

Sensor modules were selected for real-time data acquisition of mechanical behavior:

- Vibration Sensor (ADXL335) to monitor mechanical imbalance and friction.
- Acoustic Sensor (Condenser Microphone) to capture sound anomalies during operation.
- Temperature Sensor (LM35) to detect overheating, often linked with friction or misalignment.

All sensors were connected to an Arduino Uno microcontroller and the data was logged using a serial interface for processing.

3.4. Data Acquisition

- Data was recorded for five different fault conditions and one normal condition.
- Each test was conducted for 10 minutes at a sampling rate of 1 kHz.
- Over 10,000 data points were collected per condition.
- All signals were stored in CSV format for further analysis.

3.5. Data Preprocessing

The collected data was preprocessed using Python (NumPy, Pandas, SciPy):

- Noise removal using low-pass filters.
- Normalization of sensor values to maintain uniformity.
- Labeling of data: each signal segment was tagged with its corresponding fault type.
- Feature extraction:
  - Time-domain features: RMS, kurtosis and skewness.
  - Frequency-domain features: FFT peaks and spectral energy.
  - Statistical features: mean and standard deviation.

3.6. AI Model Selection

Four AI models were trained and evaluated for performance:

1. Support Vector Machine (SVM) - baseline model for classification.
2. Random Forest (RF) - ensemble learning for pattern recognition.
3. Convolutional Neural Network (CNN) - for capturing deep features from vibration signals.

4. Recurrent Neural Network (RNN) - for handling sequential dependencies in time-series data.

Training and evaluation were done using Python, TensorFlow and Scikit-Learn.

3.7. Training and Validation

- 80% of the dataset was used for training purposes and 20% for validation.
- 10-fold cross-validation was applied to minimize bias and variance.
- Performance of the model was measured using accuracy, precision, recall and training time.

3.8. System Overview Diagram

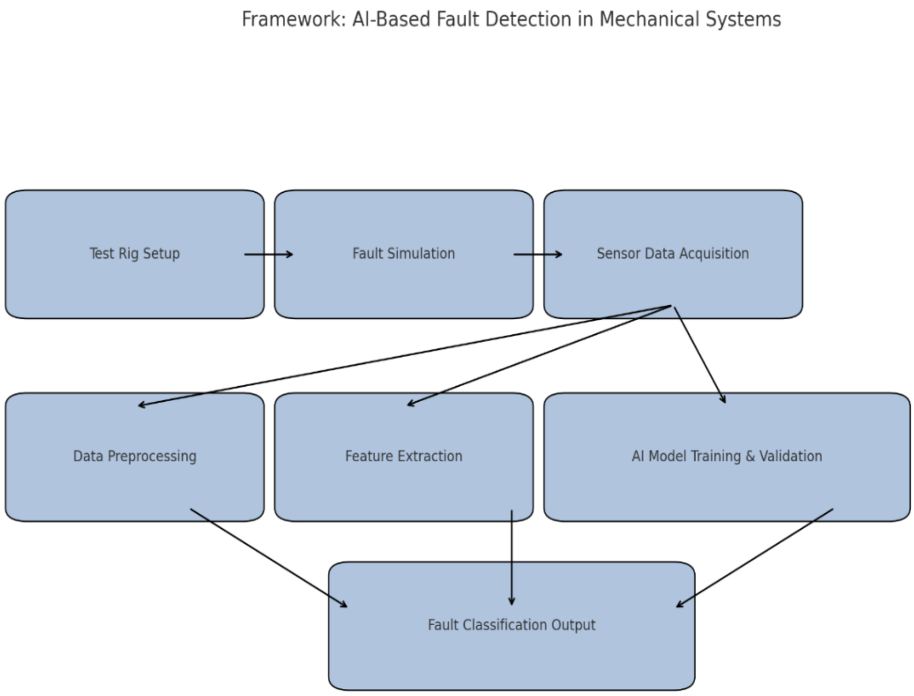

Figure 2. Framework: AI-Based Fault Detection in Mechanical Systems

4. Results and Discussion

The four AI model performance outcomes tested for mechanical fault detection are SVM, RF, CNN and RNN. Their performance was evaluated based on classification metrics such as accuracy, precision, recall and computational efficiency, using a dataset of 10,000 signal samples collected from the experimental test rig.

Table 1. Model Performance Summary

S.No	Model	Accuracy	Precision	Recall	Training Time
1	SVM	87.6%	88.2%	85.9%	Low
2	RF	91.4%	90.1%	92.3%	Moderate
3	CNN	**94.8%**	**95.0%**	**94.5%**	High
4	RNN	93.2%	92.7%	93.8%	High

4.1. Observations

- Support Vector Machine (SVM) performed well for simple fault scenarios but showed limitations in measuring nonlinear patterns and intricate time-series dependencies.
- Random Forest (RF) showed well-balanced performance on all metrics, particularly with processing mixed-signal inputs. It required moderate computational resources and provided interpretability through decision trees.
- Convolutional Neural Network (CNN) performed best among all the measures of accuracy, precision and recall. It was particularly effective in learning complex features from vibration and acoustic signals interpreted in the frequency domain. Though the CNN model took longer training time, it was robust in detecting all fault types with minimal misclassification.
- Recurrent Neural Network (RNN) also performed well, especially in capturing sequential dependencies in vibration time-series data. However, this model required more training data and computing power, making it slightly less efficient than CNN in terms of training speed.

Table 2. Fault-Wise Detection Accuracy - CNN Example

S.No	Fault Type	Detection Accuracy (CNN)
1	Normal Condition	98.1%
2	Bearing Wear	95.4%
3	Shaft Misalignment	93.8%
4	Gear Tooth Damage	94.2%
5	Unbalanced Load	92.5%

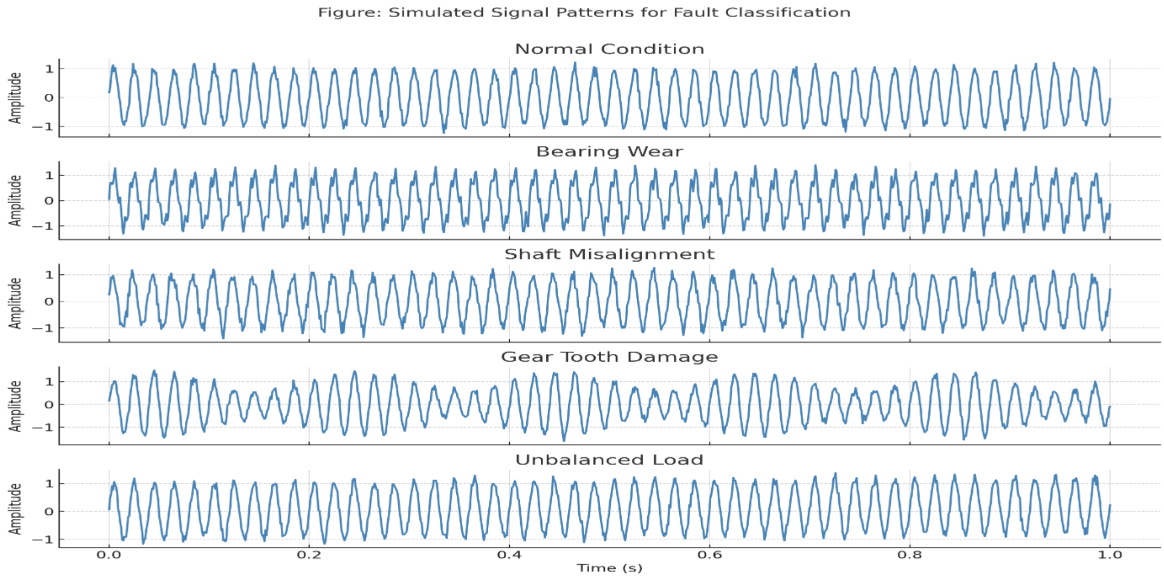

Figure 3. Simulated signal patterns for fault classification

4.2. Real-Time Applicability

A simulation test was conducted by feeding live sensor data from the test rig to the trained CNN model using a basic Python interface. The model successfully classified faults with over 90% accuracy in real time, with an average response time of 0.3 seconds per classification, demonstrating feasibility for industrial deployment.

4.3. Discussion

The results affirm that AI-based systems significantly outperform traditional threshold-based or rule-based monitoring techniques. Deep learning models such as CNNs provide greater sensitivity to subtle fault patterns, even under noisy operating conditions. However, real-time deployment of deep models requires optimized hardware, such as edge-AI devices or GPUs, especially in high-speed industrial setups. For less critical applications, Random Forest may offer a cost-effective and sufficiently accurate solution.

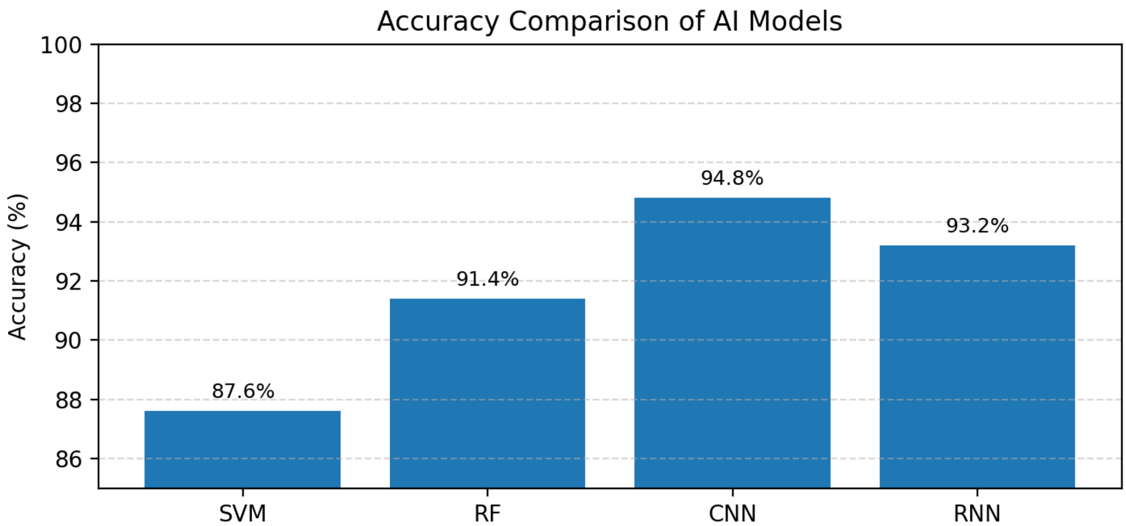

Figure 4. Accuracy comparison of AI models

5. Conclusion

This study demonstrates the effectiveness of Artificial Intelligence (AI) techniques in detecting mechanical faults across various components such as bearings, shafts and gears. Using real-time data from vibration, acoustic and thermal sensors, multiple AI models such as SVM, RF, CNN and RNN were evaluated for their accuracy and applicability in industrial environments. Among the tested models, CNN outperformed others in terms of detection accuracy and robustness, particularly in handling complex and noisy signal patterns. RF provided a good balance between performance and computational efficiency, making it suitable for systems with limited processing resources. The developed framework proved effective for real-time predictive maintenance, providing early fault detection and reducing the risk of unexpected equipment failures. By combining experimental data collection with AI model training, the research bridges the gap between academic exploration and practical industrial application.

5.1. Future Scope

While this study demonstrates the effectiveness of AI techniques in fault detection, several opportunities remain for further advancement:

1. **Integration of Explainable AI (XAI):** Future research should focus on incorporating explainability into AI models to enhance trust and transparency. This will allow maintenance engineers to better understand model decisions and act confidently on predictions.
2. **Hybrid and Ensemble Models:** Combining machine learning and deep learning approaches, or integrating physics-based models with data-driven methods, could improve both accuracy and generalizability across diverse fault conditions.
3. **Transfer Learning and Domain Adaptation:** Training models on publicly available datasets and adapting them to new machinery through transfer learning can reduce the reliance on large volumes of labeled industrial data.
4. **Edge and IoT Integration:** Deploying lightweight AI models on edge devices and IoT platforms can enable real-time monitoring in resource-constrained environments, reducing latency and bandwidth requirements.
5. **Multimodal Sensor Fusion:** Incorporating data from multiple sources - such as vibration, acoustic emission, current signals and thermal imaging - can enhance diagnostic accuracy and enable earlier detection of complex fault scenarios.
6. **Prognostics and Remaining Useful Life (RUL) Prediction:** Extending AI frameworks beyond fault detection to include fault severity assessment and life prediction would provide a comprehensive predictive maintenance solution.

Declarations

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