Machine Fault Detection and Classification

Sinan Bayati, Kareema Kilani

CMPE 252, San Jose State University

sinan.bayati@sjsu.edu

kareema.kilani@sjsu.edu

***Abstract*— This report presents a sophisticated predictive maintenance solution for the detection of faults in industrial motors using machine learning techniques. The project aims to classify various motor faults based on vibration data acquired from a laboratory test bench. Multiple advanced approaches, including Long Short-Term Memory (LSTM) models and XGBoost classifiers, were employed to classify different fault types. The findings demonstrate a high degree of accuracy in fault identification, contributing significantly to enhanced system reliability, safety, and maintenance efficiency.**

I. INTRODUCTION

Motors are integral components of industrial systems, serving as the driving force behind machinery worldwide. Unexpected motor failures can result in substantial financial losses, safety hazards, and costly repairs. Traditional fault detection methods rely heavily on manual inspections and scheduled maintenance, which are inherently labor-intensive, non-real-time, and lack the capability to predict specific fault types or evolving patterns. The objective of this project is to develop a machine learning model capable of accurately classifying motor faults using vibration data, thereby facilitating predictive maintenance, minimizing downtime, and improving overall system reliability and safety.

II. PROBLEM STATEMENT

Industrial motors are susceptible to various fault conditions, such as bearing defects and rotor imbalances, which manifest in distinct vibration signatures characterized by different amplitudes and frequencies. Traditional fault detection methods fail to provide the necessary granularity for real-time analysis and predictive maintenance. Consequently, an automated, efficient approach is required to accurately classify motor faults in real time, enabling timely intervention and fault mitigation.

III. OBJECTIVES

The primary objective of this project is to develop a machine learning-based framework for the classification of motor faults using vibration data obtained from a controlled laboratory test bench. Specific objectives include achieving high classification accuracy for diverse fault types in real time, minimizing unexpected operational downtime, and advancing predictive maintenance methodologies to proactively address potential motor failures.

IV. METHODOLOGY

The experimental setup comprises a motor test bench equipped with an array of sensors, including underhang and overhang accelerometers, a tachometer, and a microphone. Data acquisition was performed at a sampling rate of 50 kHz from all channels, yielding high-resolution time-series data for analysis. Different fault conditions were systematically introduced into the system, including normal operation, horizontal and vertical misalignments of varying degrees, rotor imbalances, and bearing faults (cage defects, outer race faults, and ball defects).

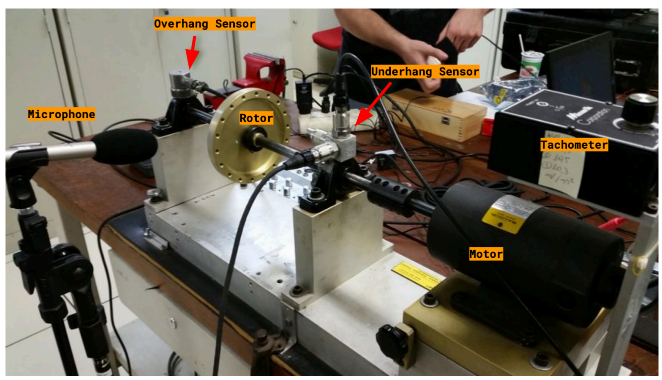

Fig. 1: Experimental Setup

A. Experimental Setup

The experimental setup in figure 1 utilized the SpectraQuest Inc. Alignment/Balance Vibration Trainer (ABVT) Machinery Fault Simulator (MFS). This system is equipped with the following specifications:

- Motor: 1/4 CV DC motor with a frequency range of 700–3600 RPM.
- System Weight: 22 kg.
- Axis Dimensions: Diameter of 16 mm and length of 520 mm.
- Rotor: Diameter of 15.24 cm with a distance of 390 mm between bearings.

B. *Sensors and Data Acquisition*

The setup included an array of sensors to collect as much data as possible while using the minimum amount of needed sensors to capture the full picture:

- Accelerometers:
    - Three Industrial IMI Sensors (Model 601A01) positioned to measure radial, axial, and tangential directions.
    - Sensitivity: ±20% at 100 mV/g (10.2 mV/m/s²).
    - Frequency Range: ±3 dB from 0.27 Hz to 10,000 Hz.
    - Measurement Range: ±50 g (±490 m/s²).
    - One IMI triaxial accelerometer (Model 604B31), covering radial, axial, and tangential directions.
    - Sensitivity: ±20% at 100 mV/g (10.2 mV/m/s²).
    - Frequency Range: ±3 dB from 0.5 Hz to 5,000 Hz.
    - Measurement Range: ±50 g (±490 m/s²).

- Tachometer: Monarch Instrument MT-190 analog tachometer.

- Microphone: Shure SM81, capturing a frequency range of 20 Hz to 20,000 Hz.

- Data Acquisition Modules: Two National Instruments NI 9234 with 4 channels each, sampling at 51.2 kHz.

C. *Fault Scenarios and Data Collection*

Data acquisition was performed at a sampling rate of 50 kHz for each fault scenario, capturing 5-second sequences, resulting in 250,000 samples per sequence. Fault scenarios were systematically introduced to simulate diverse motor conditions:

- Normal Operation: Collected across rotational speeds from 737 RPM to 3686 RPM in increments of ~60 RPM.
- Imbalance Faults: Weights between 6 g and 35 g were added to the rotor. Higher weights (≥30 g) limited the rotation speed to 3300 RPM due to increased vibrations.
- Horizontal Misalignment: Shaft shifts of 0.5 mm, 1.0 mm, 1.5 mm, and 2.0 mm were introduced.
- Vertical Misalignment: Shaft shifts of 0.51 mm to 1.90 mm were applied at incremental steps.
- Bearing Faults: Fault types included outer race, inner race, and ball defects, tested in underhang and overhang positions. Additional weights of 6 g, 20 g, and 35 g enhanced fault detectability.

V. Machine Learning Modeling

To address the task of fault classification, three distinct approaches were employed, each tailored to leverage unique characteristics of the dataset and machine learning techniques. These approaches are described as follows:

A. *LSTM Binary Classification*

The first approach targeted the classification of motor conditions into two categories: normal operation and faulty due to horizontal misalignment (2.00 mm). This binary classification task capitalized on the sequential characteristics of vibration data, employing a Long Short-Term Memory (LSTM) neural network to learn temporal patterns. The LSTM model architecture comprised of:

- A single LSTM layer to capture temporal dependencies in the sequential vibration data.
- A dropout layer to mitigate overfitting by regularizing the model.
- A dense output layer with sigmoid activation to perform binary classification.

The model was optimized using the Adam algorithm, with binary cross-entropy as the loss function and accuracy as the evaluation metric. The training process spanned 10 epochs with a batch size of 32, culminating in a test accuracy of 88.54%.

The dataset was derived from folders labeled Normal and 2.00 mm, each containing 49 CSV files. Each file represented 5 seconds of vibration data sampled at 50 kHz, resulting in 250,000 samples per file. This dataset encompassed a range of motor speeds, ensuring the model's robustness across varying operational conditions. Data preprocessing involved:

1. Structuring raw sensor signals into a DataFrame.
2. Reshaping the data to LSTM-compatible input formats, preserving temporal integrity.

To illustrate the differences between normal and faulty conditions, time-series plots are presented below:

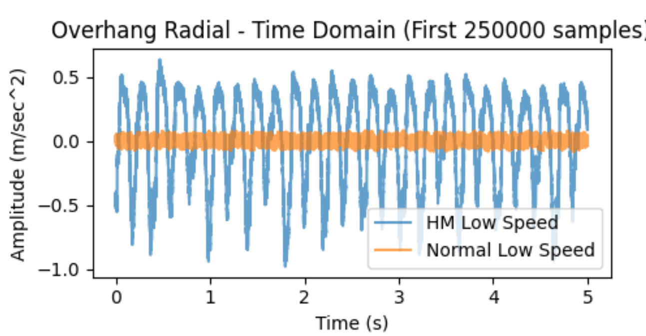

Fig. 2: Horizontal Misalignment vs Normal Operation Time Series overlayed

This visualization emphasizes the distinct vibrational anomalies caused by horizontal misalignment (shown as HM), enabling the LSTM model to identify these patterns effectively.

The LSTM model required approximately 3.5 hours for training, leveraging the complete dataset. Validation was performed on a test set spanning various motor speeds to ensure the model's generalizability.This approach demonstrated that LSTMs could reliably differentiate between normal operation and specific fault states. By learning temporal patterns inherent in the vibration data, the model successfully captured subtle indicators of horizontal misalignment. This work highlights the feasibility of applying sequential neural networks for real-time fault detection tasks in industrial motor systems.

B. LSTM Multi-Class Classification

This approach extended the binary classification method to tackle a more complex task of identifying multiple fault types simultaneously. By leveraging the power of LSTMs to process sequential time-series data, this method focused on capturing subtle distinctions across fault classes. The dataset was carefully constructed to ensure uniform sampling rates and durations, consolidating all fault scenarios into a single structured CSV file. This allowed the model to process consistent input data and learn effectively from the diverse fault types.

This approach not only demonstrated the robustness of LSTM architectures but also provided insights into the scalability of deep learning models for fault classification. A similar LSTM model was employed for multi-class classification of all fault types at a single, consistent operational speed. The output layer utilized softmax activation to address 10 distinct classes. Dataset preparation involved combining all fault scenarios into a single CSV file titled AllMotorFailures_Classified_ SingleSpeed.csv. This file contained 2.5 million rows, representing 250,000 rows per fault type for a 5-second duration at a 50 kHz sampling rate. Training was performed for 50 epochs, resulting in a test accuracy of 96.02%. The total processing time for this approach was approximately 2 hours.

C. XGBoost Multi-Class Classification

The third approach utilized a feature-based methodology, departing from the time-series dependency of the LSTM models. This method focused on extracting features that captured the essential characteristics of vibration signals to enable accurate fault classification. A key aspect of this approach was the generation of 169 features, including the 10 most dominant FFT peaks and their corresponding power values for each sensor channel. With data collected from multiple sensor channels—comprising underhang and overhang accelerometers in radial, tangential, and axial directions, along with microphone signals—this method yielded a rich and high-dimensional feature set. The features encompassed statistical moments such as mean, standard deviation, skewness, and kurtosis, as well as frequency-domain attributes derived from FFT frequencies and power.

- Statistical Features: These include metrics such as:
  - Mean: Represents the average vibration amplitude.
  - Standard Deviation: Captures the spread or variation of the signal.
  - Skewness: Indicates the asymmetry of the signal distribution.
  - Kurtosis: Measures the peakiness or flatness of the signal.
- Frequency-Domain Features: These were derived using Fast Fourier Transform (FFT) and include:
  - FFT Frequencies: Identified dominant frequency components of the signal.
  - FFT Power Spectral Density: Quantifies the signal's energy distribution across frequencies.

The combination of statistical and frequency-domain features enabled the XGBoost model to efficiently capture both time-based and frequency-based characteristics of vibration signals.To provide an intuitive understanding, Figure 3 illustrates an example of FFT spectra for two distinct fault types, showcasing the differences in their frequency components.

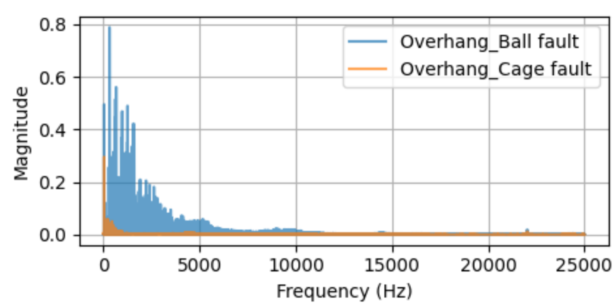

Fig. 3: Overhang Ball vs Cage fault in FFT Spectrum

This feature extraction process yielded a total of 169 features, derived from signals captured by underhang and overhang accelerometers and the microphone. The dataset, titled Train_and_Test_combined_with_tenClasses.csv, was constructed to include data for 10 fault types, including the normal state and also included all speed sweeps in the dataset. This prepared dataset served as input to an XGBoost classifier, achieving a test accuracy of 98.21% and ROC-AUC values nearing 0.999 for each fault type.

The XGBoost model also highlighted the interpretability of its results through feature importance analysis, pinpointing key vibrational attributes that significantly contributed to fault classification. Furthermore, the reduced dimensionality of this approach resulted in rapid training and testing, requiring only a few minutes and reinforcing its practicality for real-time fault detection applications. Below is a visualization of the ROC curves for each fault type, showcasing the model's discriminatory power:

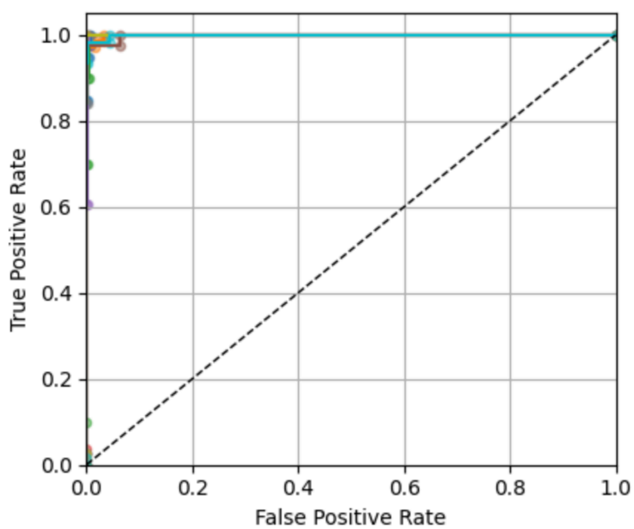

Fig. 4: ROC Curves for Multi-Class Approach

A summary of AUC values for all fault types is presented in the figure and table below:

I. SUMMARY TABLE OF AUC FOR APPROACH THREE

Fault Type	AUC
Horizontal Misalignment	0.999
Imbalance	0.999
Normal	0.999
Overhang Ball Fault	1.000
Overhang Cage Fault	0.999
Overhang Outer Race	0.998
Underhang Ball Fault	1.000
Underhang Cage Fault	1.000
Underhang Outer Race	1.000
Vertical Misalignment	0.999

This high performance can be attributed to the dataset's design, which exclusively recorded data under clearly defined conditions of normal operation or full fault states, with no intermediate states. As a result, the binary-like separation of the data facilitated clear discrimination by the model, explaining the high AUC values. However, it is acknowledged that including transitional states in future datasets could enhance model generalizability in real-world scenarios.

VI. FUTURE WORK

To further improve the performance and applicability of the fault classification model, a two-tower architecture is proposed for future work. This model will combine both time-series data and extracted features in a unified framework. The two-tower model will consist of:

- Time-Series Tower: This tower will process raw vibration time-series data using deep learning architectures, such as LSTM or CNN models, to capture temporal dependencies and patterns inherent in the signal.
- Feature Extraction Tower: The second tower will take as input the pre-computed features, including statistical moments (e.g., mean, standard deviation, skewness, kurtosis) and frequency-domain information, such as FFT peaks and power values. This tower can utilize traditional machine learning techniques or fully connected neural network layers to interpret the feature set effectively.

The outputs from both towers will be combined using a dot product operation to generate a final representation. This combined output will then be fed into a classification layer to predict fault types. By integrating both time-series and feature-based information, the proposed two-tower architecture aims to leverage the strengths of each data representation method.

To validate this architecture, future experiments should involve real-world datasets containing transitional fault states and mixed conditions. This will enhance the model's generalizability and ensure its applicability to dynamic, practical environments.

This approach has the potential to achieve higher accuracy and robustness, particularly when applied to real-world data where fault conditions may not be clearly defined or known in advance. The integration of the two towers will allow the model to generalize better, making it a practical solution for detecting and diagnosing motor faults in industrial environments.

VII. CONCLUSION

This study successfully developed and compared three machine learning approaches for fault classification in industrial motors using vibration data. The results demonstrate the distinct advantages of each approach in identifying motor faults:

- XGBoost Classifier: Achieved the highest classification accuracy of 98.21%, demonstrating the effectiveness of feature-based methods for capturing fault-specific characteristics with reduced computational time.
- LSTM Multi-Class Classification: Attained 96.02% accuracy, showcasing its ability to process sequential time-series data and handle complex, multi-fault scenarios.
- LSTM Binary Classification: Produced an accuracy of 88.54%, highlighting its suitability for detecting specific faults like horizontal misalignment.

While the XGBoost classifier excelled in performance due to its ability to utilize rich, extracted features, the LSTM approaches provided valuable insights into the temporal dependencies inherent in the vibration signals. However, the results also highlight certain limitations:

- XGBoost: Relies heavily on feature engineering, which may require domain expertise and computational preprocessing.
- LSTM Models: Require extensive training time and are sensitive to variations in input data quality.

The high ROC-AUC values achieved by the XGBoost model were attributed to the dataset's design, which captured clearly defined fault states without transitional conditions. Incorporating intermediate fault scenarios in future datasets can further enhance the model's ability to generalize to real-world applications.

This work underscores the significant potential of machine learning-driven predictive maintenance systems to revolutionize industrial motor monitoring. By achieving accurate fault classification, these models can reduce unexpected downtime, enhance operational safety, and optimize maintenance schedules.

Future enhancements, such as the proposed two-tower architecture, aim to combine time-series and feature-based approaches to further improve classification accuracy and robustness. By validating this architecture on real-world datasets, the model can address undefined and transitional fault conditions, paving the way for intelligent, data-driven predictive maintenance frameworks in industrial settings.

REFERENCES

1. MaFaulDa - Machinery Fault Database, http://www02.smt.ufrj.br/681~offshore/mfs/, accessed November 22, 2024.
2. G. Palem, Condition-based maintenance using sensor arrays and telematics, International Journal of Mobile Network Communications Telematics 3 (3) (2013) 19–28.
3. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, Scikit-learn: Machine learning in Python, Journal of Machine Learning Research 12 (2011) 2825–2830.
4. R. M. Singer, K. C. Gross, J. P. Herzog, R. W. King, S. Wegerich,601 Model-based nuclear power plant monitoring and fault detection: Theoretical foundations, in: International Conference on Intelligent Systems Applications to Power Systems
5. P. Guo, N. Bai, Wind turbine gearbox condition monitoring with AAKR and moving window statistic methods, Energies 4 (11) 2077–2093
6. J. Liu, W. Wang, F. Golnaraghi, An enhanced diagnostic scheme for bearing condition monitoring, IEEE Transactions on Instrumentation and Measurement 59 (2) (2010) 309–321
7. .J. P. Herzog, D. Gandhi, B. Nieman, Making decisions about the best technology to implement, Technical report, Smartsignal/GE Intelligent Platforms (2011)