FAULT CLASSIFICATION USING ACOUSTIC SIGNAL IN ELECTRIC MOTORS

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Introduction

- Fault detection in electric motors is vital to ensure efficiency and prevent breakdowns.
- Acoustic signals are used as a non-invasive method to identify motor faults, such as bearing defects.
- Fault classification is performed using Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNN) and so on for high accuracy.
- The approach is robust, working effectively even in noisy industrial environments.
- Provides a practical, efficient solution for real-time fault diagnosis in electric motors.

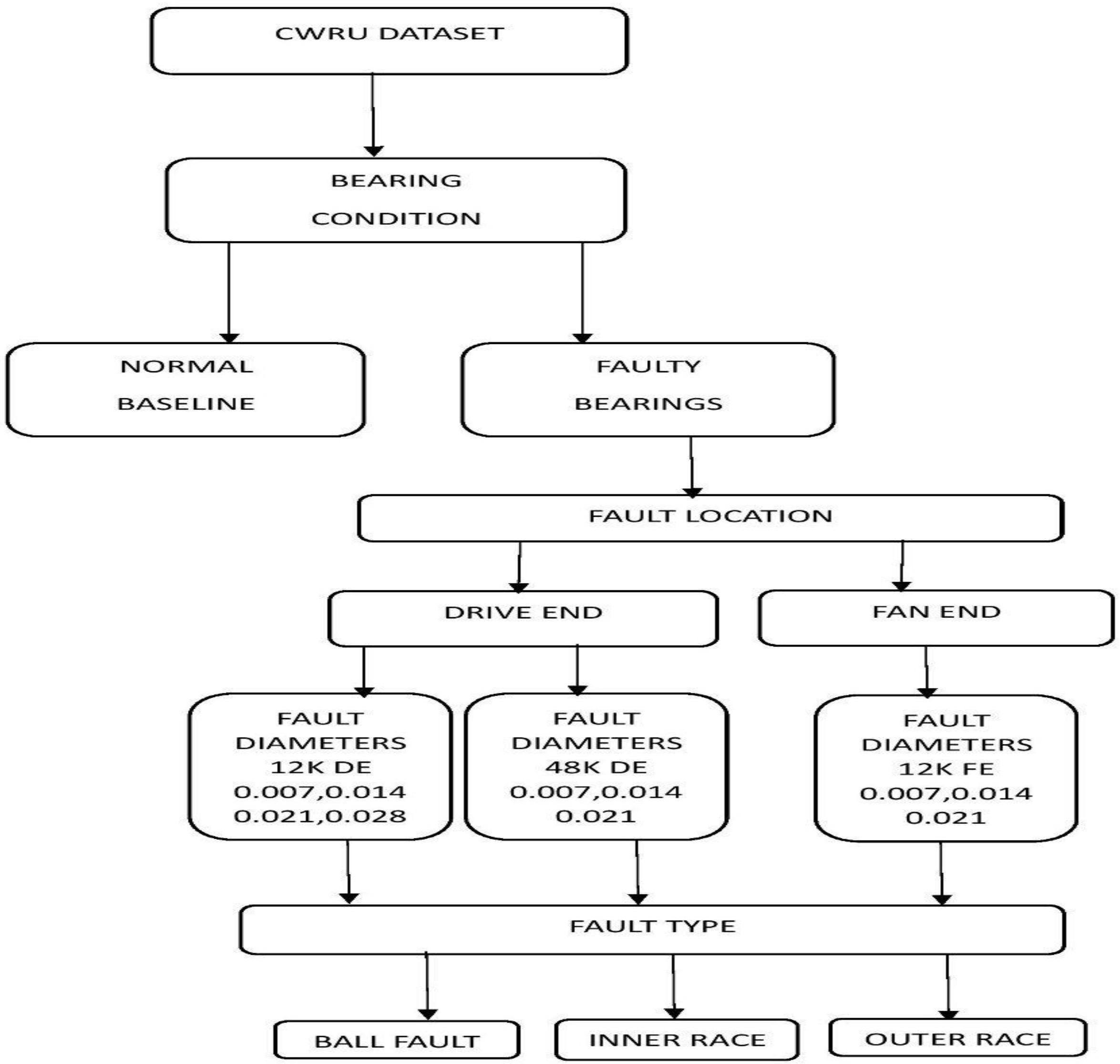
Literature survey

S.No.	Title and Author	Inferences
1)	Bearing Fault Classification Based on Convolutional Neural Network in Noise Environment Qinyu Jiang, Faliang Chang, and Bowen Sheng	• The paper proposes a noise-resistant method for bearing fault classification using Convolutional Neural Networks (CNNs). • It employs Spectral Kurtosis (SK) filtering to reduce noise and extracts features like Mel-frequency cepstral coefficients (MFCC) and delta cepstrum. • These features are transformed into 2D matrices for CNN-based classification. The method achieves high accuracy even in noisy environments, making it effective for industrial fault diagnosis.
2)	Detecting of the Rolling Bearing State Based on Acoustic Signal and the k-NN Classifier Dorota Gil, Marcin Grochowina, and Lucyna Leniowska	• The paper proposes a method to detect rolling bearing conditions using acoustic signals and the k-NN classifier. Features were extracted via FFT, and bearings were classified into "good," "special attention," and "bad" categories. • The method showed high accuracy, especially at low speeds, where classification was 100% accurate. This approach offers a reliable, non-invasive solution for monitoring rolling bearings, particularly effective for low-speed applications.
3)	Audio Data-driven Anomaly Detection for Induction Motor Based on Generative Adversarial Networks Jaehoon Shim, Taesuk Joung, Sangwon Lee, and Jung-Ik	• The paper introduces an unsupervised anomaly detection method for induction motors using audio data and a GAN-based model (GANomaly). • By analyzing mel-spectrograms of audio signals, the model identifies anomalies like front and rear bearing faults based on reconstruction errors. It achieves high accuracy (92.52%) and an AUROC of 0.9822, offering an effective solution for detecting untrained motor faults in industrial settings.

Problem statement & Project objectives

- To develop a deep learning model to find fault in the system with
  - higher efficiency
  - lower computational power
  - lower Latency

Dataset Flowchart



Dataset Flowchart

Data was collected for normal bearings, single-point drive end and fan end defects. Data was collected at 12,000 samples/second and at 48,000 samples/second for drive end bearing experiments. All fan end bearing data was collected at 12,000 samples/second.

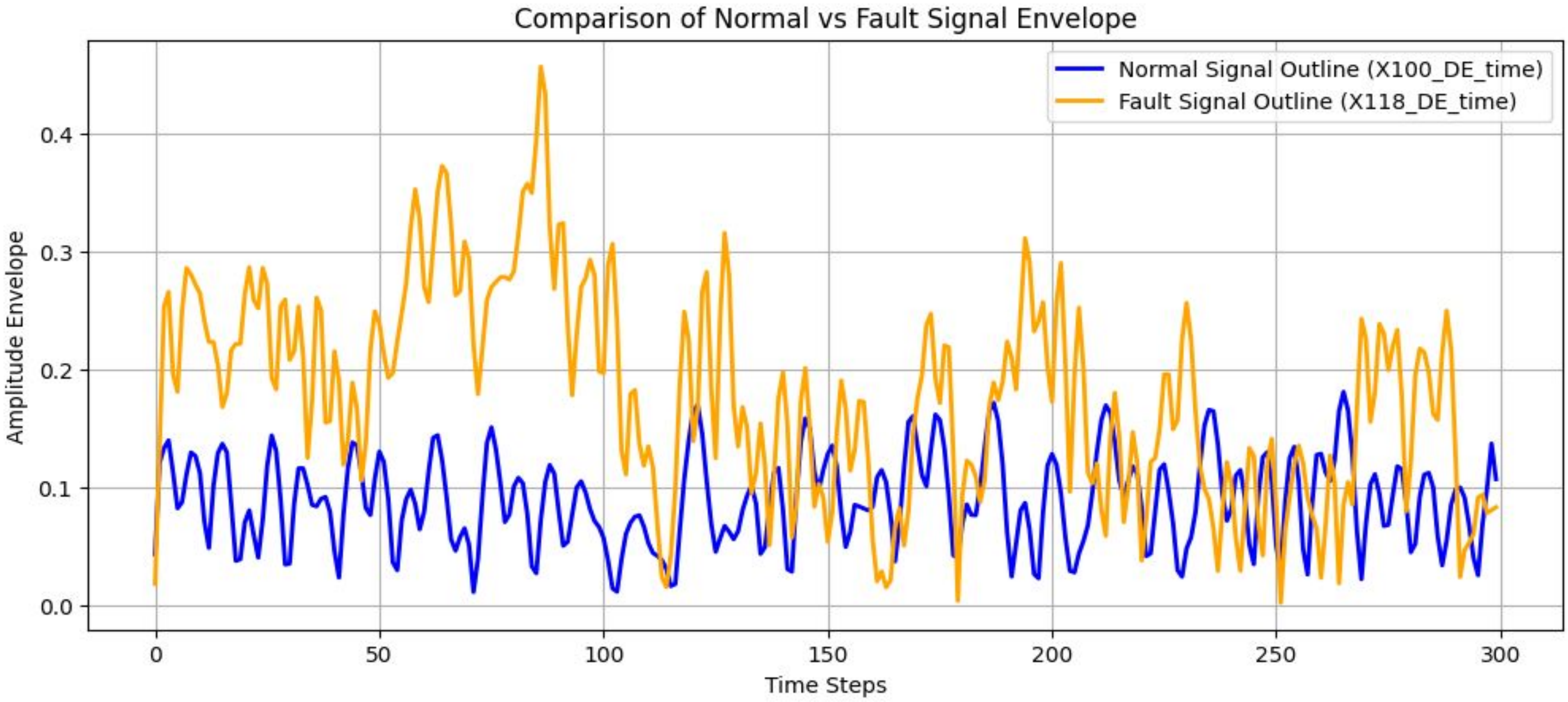
Data files are in **Matlab** format. Each file contains fan and drive end vibration data as well as motor rotational speed. For all files, the following item in the variable name indicates:

DE - drive end accelerometer data
FE - fan end accelerometer data
BA - base accelerometer data
time - time series data
RPM - rpm during testing

Click the below link to continue:

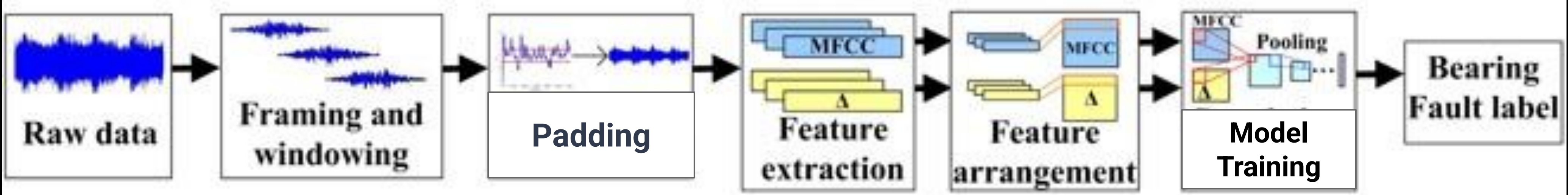
The Dataset is converted to MFCC numpy from MAT files as a step in data preprocessing

https://engineering.case.edu/bearingdatacenter/download-data-file

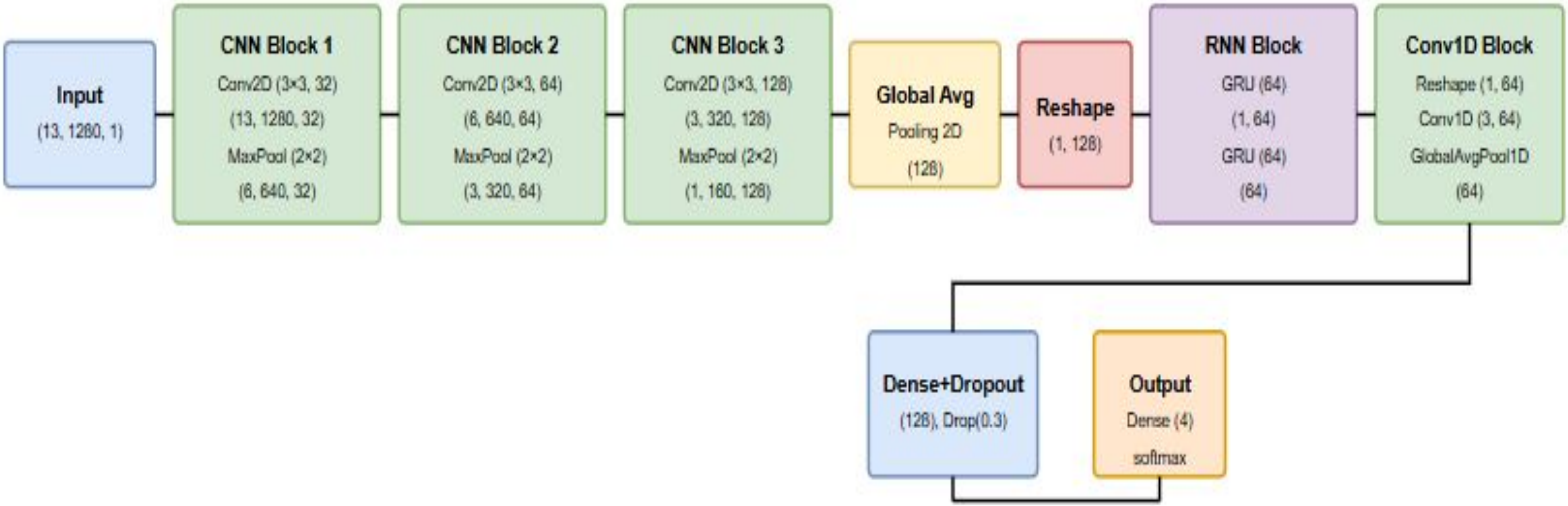


Comparison of Normal vs Fault Signal Envelope
Normal Signal Outline (X100_DE_time)
Fault Signal Outline (X118_DE_time)
Amplitude Envelope
0.0
0.1
0.2
0.3
0.4
0
50
100
150
200
250
300
Time Steps

System block diagram



Model Architecture



Current Progress

- Data contains time-series segments,features extracted manually.
- The dataset contains 3 types of faults related to bearing defects.
- Standardized features using StandardScaler to improve model performance.
- Implemented Support Vector Classifier (SVC) for fault classification.
- Computed Confusion Matrix and Classification Report for performance analysis
- **Evaluated accuracy - 84%**
- SVC is effective in handling high-dimensional feature spaces, making it ideal for time-series feature classification
- SVC requires manually extracted statistical features and increases processing latency, SVC sensitive to noisy and non-stationary signals.

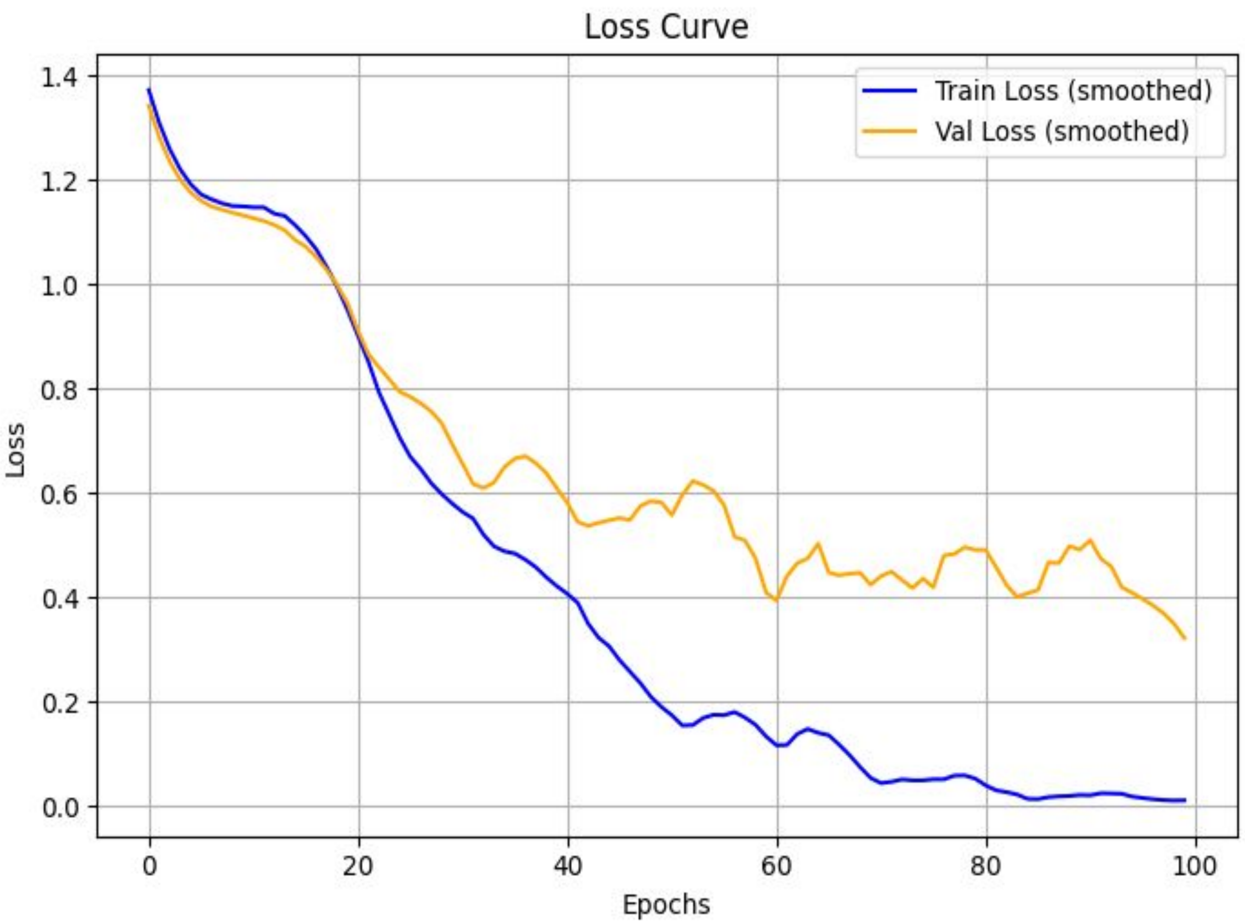
Current Progress

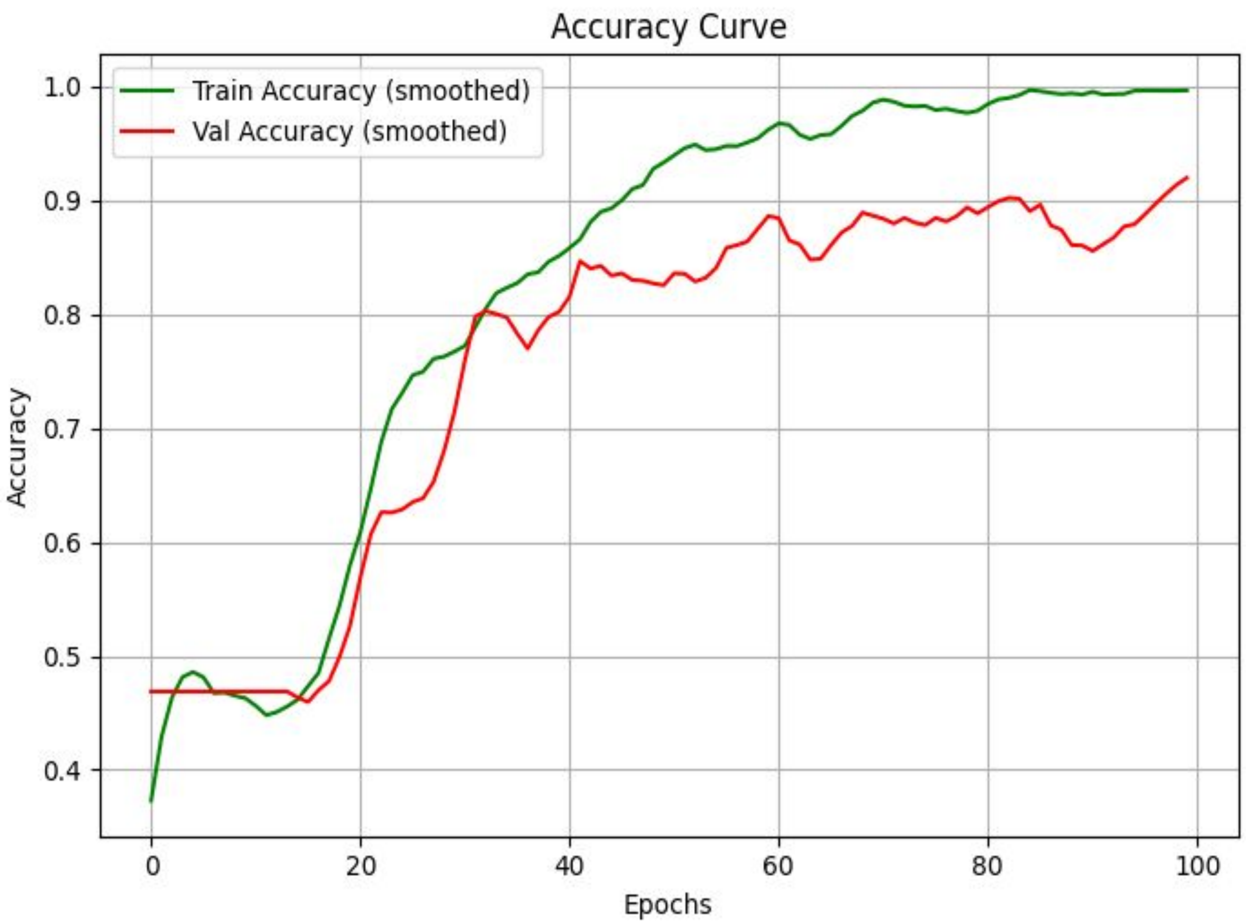
	Only CNN	Only RNN	Hybrid CNN + RNN
Layers	Conv2D Layers = 5 with Pooling	Bi-LSTN Layers = 3 with Dropout	Conv 2D Layers = 3, GRU Layers = 2, Conv1D Layers = 1
Accuracy	89%	81%	**93.75%**
Total Parameters	15,707,342 (252.01 MB)	2,423,886 (9.25 MB)	**528,206 (2.01 MB)**
Trainable Parameters	2,235,780 (84.00 MB)	807,108 (3.08 MB)	176,068 (687.77 KB)
Average Inference Time	82.0391 ms	77.1271 ms	**65.6799 ms**

Model Summary

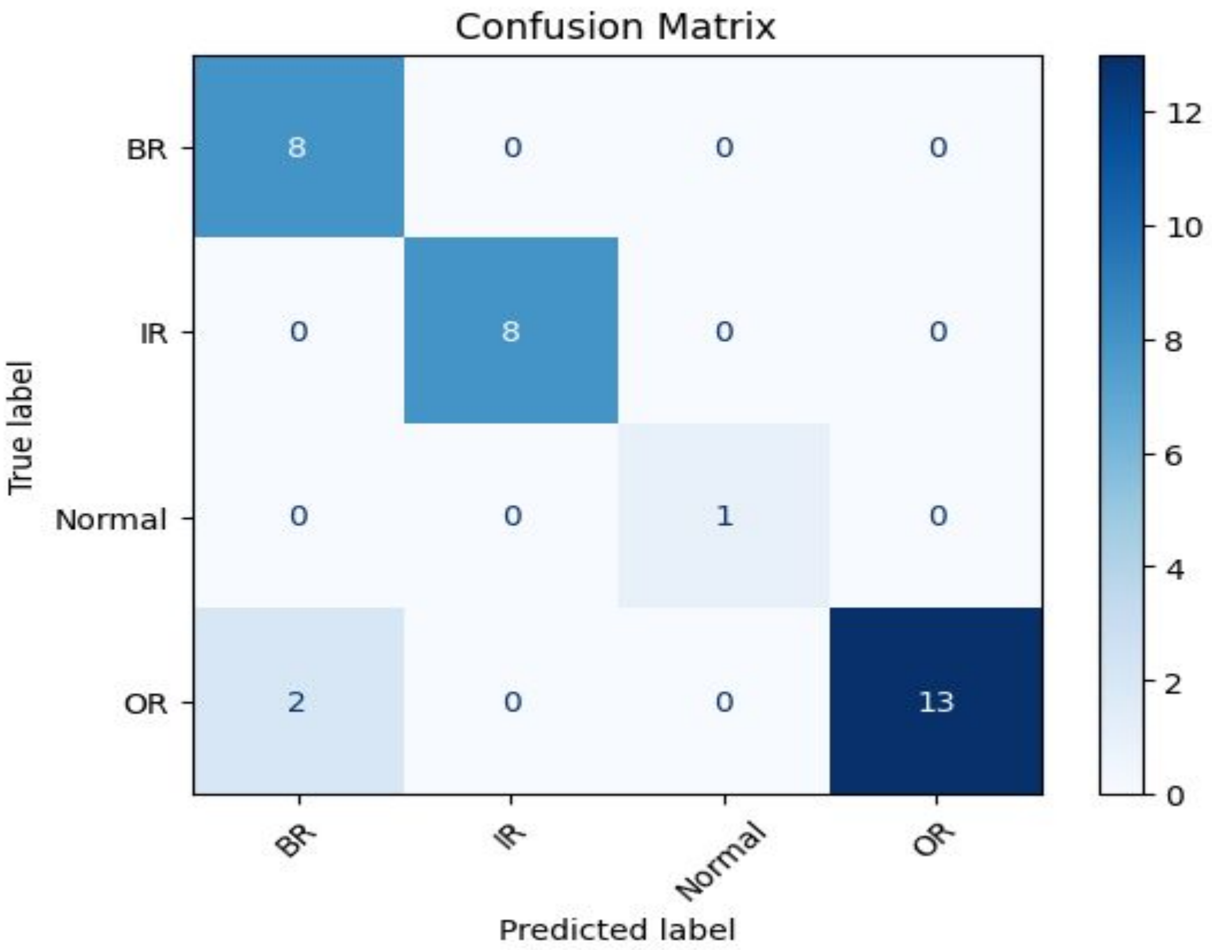
Layer (type)	Param #
Conv2D	320
MaxPooling2D	0
Conv2D	18,496
MaxPooling2D	0
Conv2D	73,856
MaxPooling2D	0
GlobalAveragePooling2D	0
GRU	37,248
GRU	24,960
Conv1D	12,352
GlobalAveragePooling1D	0
Dense	8,320
Dropout	0
Dense	516
Total params:	**528,206 (2.01 MB)**

Results of the Model





Confusion matrix



Classification Classes:

BR - Ball Race
IR - Inner Race
OR - Outer Race
Normal

Future Works:

- Planning to do raw audio augmentation in the audio files to improve the accuracy and robustness of model.

QUANTIZATION

- Converts high-precision (FP32) weights to lower precision (FP16 or INT8) for smaller memory usage and faster execution.
- Reduces inference latency on hardware like TPUs, edge devices.
- INT8 is ideal for real-time applications, while FP16 balances speed and accuracy.use significantly less energy, which is crucial for battery-powered and IoT devices.

APPROXIMATION

- Reduces redundant computations in convolution layers using techniques like depthwise separable convolutions.
- Uses simplified activation functions (e.g., replacing expensive functions like exp with piecewise linear approximations

Conclusion

This project successfully demonstrates that **acoustic signals**, when processed using deep learning techniques, can be a **reliable and non-invasive method** for identifying faults in electric motors. By converting raw vibration data into MFCC features and applying **hybrid CNN + RNN architectures**, we achieved high classification accuracy while maintaining **low computational complexity** and **fast inference times**.

Key takeaways:

- The **CNN + GRU + Conv1D** model achieved **93.75% accuracy** with significantly fewer trainable parameters and the **lowest latency**, proving suitable for **real-time deployment**.
- Techniques like **quantization (INT8/FP16)** and **model approximation** further optimized performance for **edge devices** and **resource-constrained environments**.
- The approach is **robust against noise**, making it viable for real-world industrial applications.

References

1.Bearing Fault Classification Based on Convolutional Neural Network in Noise Environment.
https://ieeexplore.ieee.org/document/8723023

2.Audio Data-driven Anomaly Detection for Induction Motor Based on Generative Adversarial Networks.

https://ieeexplore.ieee.org/document/9947652

3.Detecting of the rolling bearing state based on acoustic signal and the k-NN classifier.

https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8936710

Thank You!