Acoustic signal-based analysis - fault detection and fault localization in electrical motors

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology

in

Electronics and Communication

By

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(Deemed to be University under section 3 of UGC Act, 1956)

November, 2024

DECLARATION

I hereby declare that the thesis entitled "Acoustic signal-based analysis – fault detection and fault localization in electrical motors" submitted by me, for the completion of the course "BECE497J – Project I" to the school of electronics engineering, Vellore Institute of technology, Vellore is Bonafide work carried out by me under the supervision of Prof.Kalaivani. S

I further declare that the work reported in this thesis has not been submitted previously to this institute or anywhere.

Place : Vellore
Date : 14th November 2024

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CERTIFICATE

This is to certify that the thesis entitled **"Acoustic signal-based analysis – fault detection and fault localization in electrical motors"** submitted by **Om Ravindra Potdar 21BEC0499, Anurag Mahesh Sonar 21BEC0496, Soumitra Mangesh Mahashabde 21BEC0631, SENSE,** VIT, for the completion of the course "BECE497J – Project 1", is a Bonafide work carried out by him / her under my supervision during the period, 15.07.2024 to 14.11.2024, as per the VIT code of academic and research ethics.

I further declare that the work reported in this thesis has not been submitted previously to this institute or anywhere.

Place : Vellore

Date : 14th November 2024

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Internal Examiner

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We would like to extend our deepest gratitude to Professor Kalaivani S, our faculty guide and mentor at the SENSE Vellore Institute of Technology, for her insightful guidance, continuous support, and valuable feedback throughout this project. Her expertise in signal processing greatly contributed to refining our approach and achieving our research goals.

Special thanks go to the Fraunhofer Institute for Digital Media Technology (IDMT) for providing access to the IDMT_ISA_ELECTRIC_ENGINE dataset, which was fundamental to our data analysis and testing processes. The comprehensive recordings and varying conditions within the dataset significantly contributed to the depth and reliability of our research.

Additionally, we are grateful to Vellore Institute of Technology (VIT) for giving us this opportunity and providing the infrastructure, resources, and a conducive learning environment essential for the successful completion of this project.

Soumitra Mahashabde

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Student Name

EXECUTIVE SUMMARY

Electric Motors drive a very substantial part of industries and thus timely fault detection in these motors is crucial to maintain costs, save energy and reduce downtime.
The age-old methods related to fault detection like thermal analysis and vibration analysis can be often invasive and may not give results in noisy environments. Thus, creating a need for a non-invasive, efficient and reliable solution that can work in challenging situations. The study proposes a solution to this problem. An acoustic based fault detection system that uses sound patterns to diagnose motor issue. The study focuses on use of signal processing and machine learning techniques. The features are extracted from the preprocesses noise signal as a primary step followed by a classifier and two validators. The study aims to work in high noise environment as well. The project enhances predictive maintenance to extend motor lifespan and promotes energy efficiency. The project also aligns with sustainability gaols, providing a solution that reduces downtime and operational costs.

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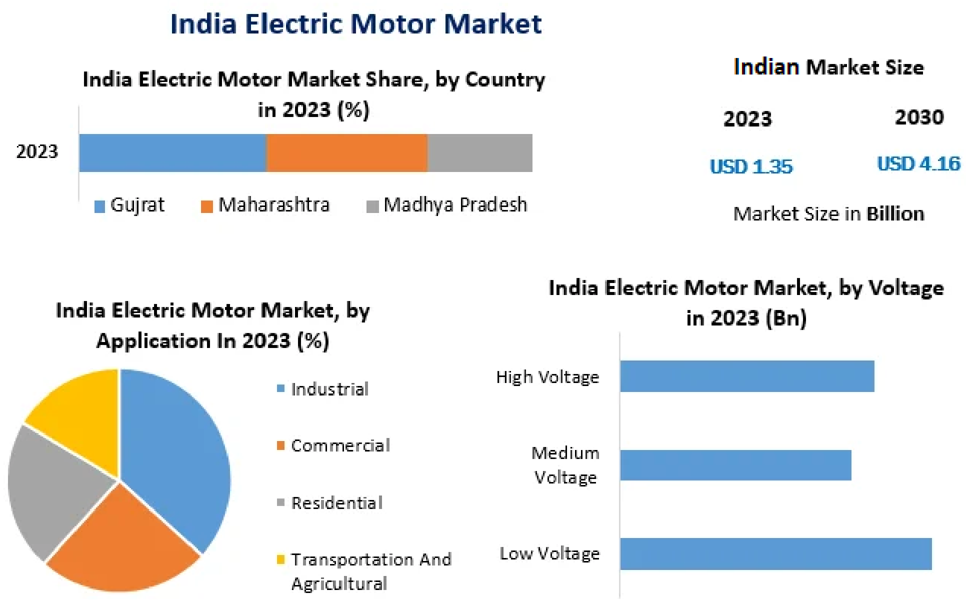
1.INTRODUCTION

1.1 Literature Review

Electric motors are an integral part of our society and industries. They are widely used in manufacturing, transportation, agriculture and household applications and hence serve as backbone for machinery and equipment in many industries. Electric motors are electro-mechanical devices which operate on principle of electromagnetic induction. The process consists of emf or current in a conductor by placing it in a changing magnetic field. They are highly efficient, long lasting, low maintenance and can endure strong voltage fluctuations. There are various electric motors available in the market namely hysteresis motors, axial motors, synchronous reluctance motors, stepper motors etc.



1.1 Indian Electric Motor market, CAGR of Indian electric motor market

The Indian electric market growth is driven by usage of the electric motors in various end user industries. An increase in construction activities across residential, commercial sector, government focuses towards adopting energy from electric motors. High growth in population in country and rapid urbanization are some prominent factors which are expected to drive market growth in near future. 70% of industrial machinery in sectors like textile, steel and chemicals use electric motors. Around 80% of irrigation systems in India use electric motors for farming. The appliance related electric motors market is to grow about 9.1% CAGR from 2023-2028 and the total electric motors market in India is supposed to grow at CAGR 17.45% during 2024 to 2030. Though these motors are highly durable, minor faults could lead to significant losses in terms of money and product in industries.

1.2 Research Gap

Early detection of faults is necessary in electric motors. Conventional methods of fault analysis like vibration analysis require sensors directly mounted on the motor which can be challenging to install and maintain. Thermal imaging is another method used to detect overheating issues, yet it may fail to address subtle mechanical faults. Physical sensor-based techniques such as thermal and vibration monitoring are often invasive and require close proximity to detect faults. The on-premise nature of these can affect continuous monitoring making it unstable. These are also not recommended to use in hazardous environments.

1.3 Problem Statement

Different faults such as bearing, wearing, misalignment or rotor imbalance produce specific acoustics. Thus, the study is based on the concept that acoustic signals may offer a promising and efficient alternative to fault detection and classification. Unlike on-premise device methods, acoustic based fault analysis does not require sensors in direct contact with the motor, thus making it more appropriate for continuous remote monitoring. There are many traditional acoustic signals such as 1D central contour moments, Fourier transform based moments, spectrogram analysis, wavelet transform and cestrum analysis. The Fourier transform based analysis converts time domain signals to frequency domain to identify main frequency components but is inefficient for time varying signals as it only provides static frequency profile. The spectrogram analysis visualizes signal frequencies. Although the spectrogram analysis could be limited in noisy environments. The cepstrum analysis is limited to identifying repetitive faults and it can be affected by complex signal noise, while the principle component analysis is not ideal for nonlinear data structures and its results can be difficult to interpret without preprocessing. To ensure accuracy, the study focuses on implementing noise filtering to reduce background interference and signal processing will involve extracting key features from acoustic signals such as RMS, Variance, Crest factor, Dominant frequency, energy etc. The study is mainly based around machine learning and deep learning algorithms to classify and detect faults. Fault classification is done by employing machine learning models particularly convolutional neural networks (CRNN). In CRNN the Input Data such as audio signals converted into spectrograms or time-series data. In the convolutional stage the CNN layers process the input to identify local patterns and features. Later in the recurrent stage the extracted features are fed into RNN layers then they capture temporal relationships and help model the sequence's progression. The main advantage of CRNN is it combines the spatial feature-learning capability of CNN with the temporal sequence modelling of RNN. The CRNN machine learning algorithm is best suitable for acoustic signal processing, speech recognition, and other tasks involving sequential data. The model will classify various types of data based on extracted features. Additionally random forest and KNN is used to validate results for rigorous testing.

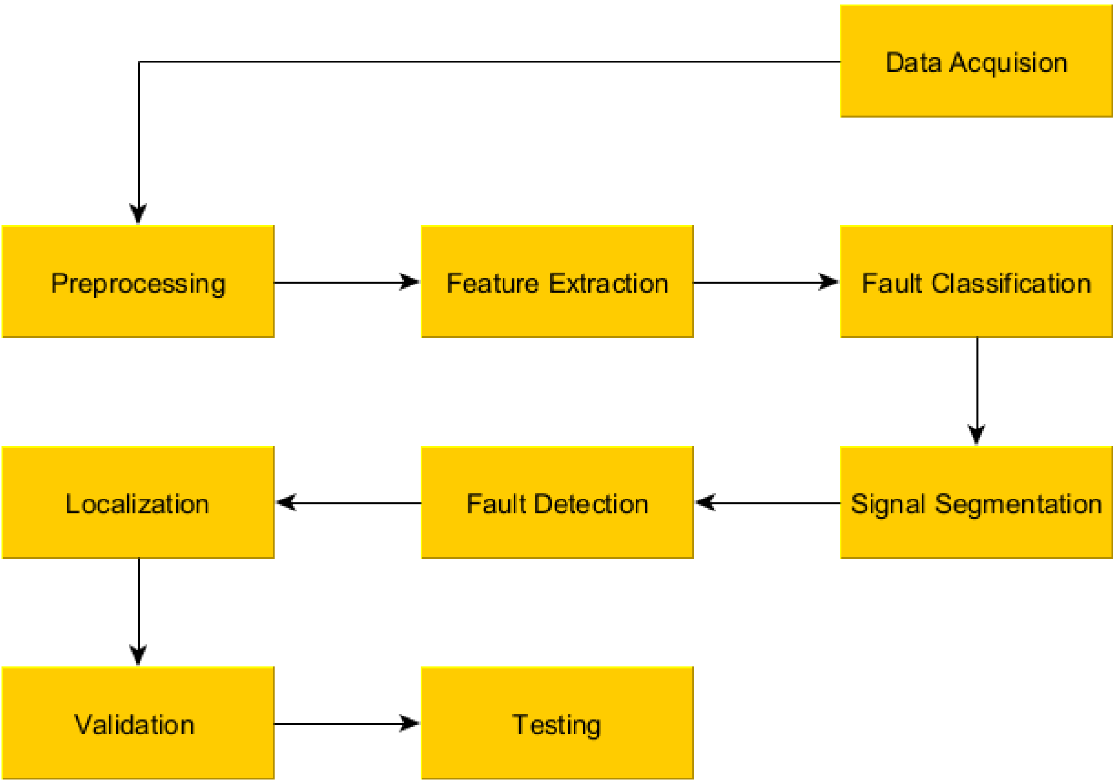
1.4 Relevance of the problem statement w.r.t to SDG

The study aligns with sustainability goals by cost cutting reducing energy losses and prolonging motor lifespan and thus reducing waste. The main aim is to contribute to responsible energy consumption in the industry. Future aspects of this system include predictive maintenance as proactive repair to help industry with substantial cost saving. The study also aims to provide the human labor in industry with enhanced safety by safeguarding the instruments and machines driven by electric motors. The future aspects also include in making the acoustic analysis and fault detection system a real time working system where signal processing could be integrated with machine learning.

2.METHODOLOGY

2.1 Project Objective

The point of interest of this project is to detect and classify any/all faults in a given machine, in this case an electric motor, so as to decrease the time required to diagnose the cause of the machine's malfunction and help in correcting said malfunction efficiently.



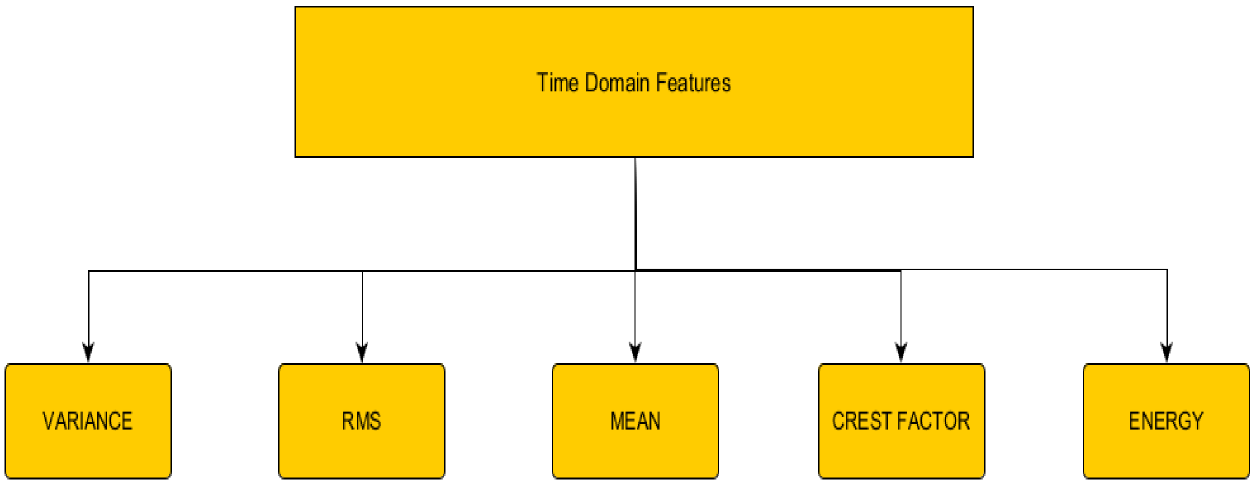
3.1.1 System Design

3. PROPOSED WORK

3.1 Design Approach

The system takes the prerecorded audio signals corresponding to a fault type and preprocesses these signals to “clean” these signals of any residual noise that maybe present. These “cleaned signals” are the sent for feature extraction and these features are stored in a .csv file. This .csv works are the training set for the classifier which will help identify the fault in the machine.The cut versions of both the sets are cleaned by filtering during preprocessing and then they undergo feature extraction. The extracted features are stored in separate .csv files, one for training and one for testing.

A total of thirteen features are extracted from the signals. The features are RMS, mean, variance, crest factor, energy, entropy, dominant frequency, zero crossing rate, skewness, kurtosis, peak-to-peak amplitude, spectral flux and RMS frequency. RMS is a statistical measure that calculates the effective magnitude of an audio signal by averaging the squared values. Mean represents the average value of all data points in an audio signal. Variance measures the spread of data points around the mean, indicating how much the audio signal deviates from its average value. Crest Factor is the ratio of peak amplitude to RMS value, representing the signal's peak-to-average relationship. Energy represents the total power contained within an audio signal over a specific time frame. Entropy measures the signal's complexity and randomness, quantifying the amount of information contained in the audio signal. Dominant Frequency represents the most prominent frequency component in an audio signal. Zero Crossing Rate measures the number of times an audio signal crosses the zero-amplitude line within a given time frame. Skewness measures the asymmetry of the audio signal's distribution around its mean value. Kurtosis quantifies the "tailedness" of a signal's probability distribution, indicating the presence of outliers or extreme values. Peak-to-peak amplitude measures the total variation between the maximum and minimum signal values. Spectral Flux measures the rate of change in the signal's frequency spectrum over time. RMS Frequency calculates the root mean square of the frequency components in an audio signal



3.1.2 Time domain Features

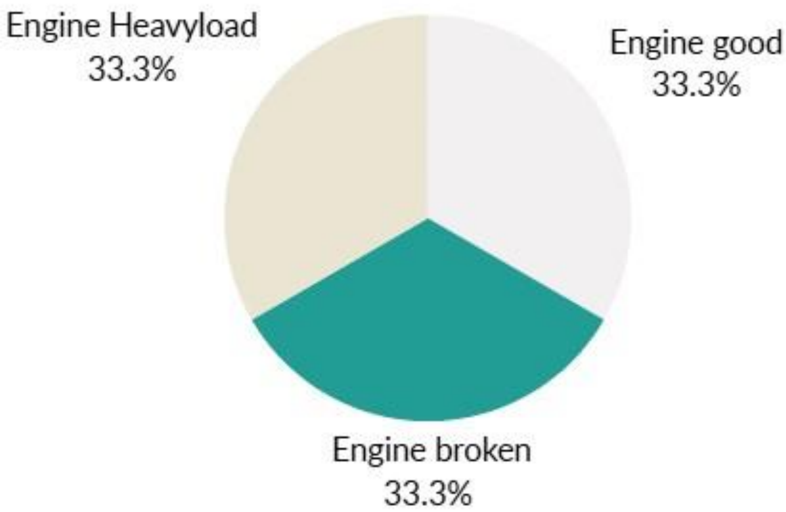
The training csv file is used the training models of the classifiers and the validators. The classifier used is Convolution Recurrent Neural Network (CRNN) and the validators used are Random Forest Classifier and K- Nearest Neighbours (KNN). These models are then loaded in respective testing models where the testing csv files are selected. The model then runs through all the features extracted and classifies the signal into its corresponding operating condition.

The main classifier, that is, the CRNN captures spatial and temporal patterns in the audio signals. The signals are first converted into spectrograms which will act as the input for the convolution layer. These spectrograms are first passed through a convolutional layer to capture the frequency components. Then they are sent through a pooling layer to decrease the dimensionality to increase efficiency while further computing. Next, they go through a recurrent layer which is LSTM in this case to capture temporal components. Lastly the final layer which is the Fully Connected Layer learns all the features and predicts the class of the signal. The first validator is a Random Forest classifier which uses decision trees to classify data points. Every decision tree gets trained on a random subset of features and splits the data points repeatedly based on feature values to maximize separation. These trees are then bagged using bootstrap Aggregating to create unique trees to improve robustness of the system. After the trees are made each tree provides a vote for an operating condition of the input signal and the one with most votes is the final classification. The second validator is the KNN classifier which classifies a data point based on the number of closest points in the feature space. Whichever category has the greatest number of data points closest to the input data point is finalised as the final classification. It is a simpler classifier when compared to the other two but works well as a validator.

After the input signals have been sent through all three of the classifiers, their accuracies are compared. If the accuracy of the main classifier is close to or greater than the validators, the main classifier is said to be valid and can be used.

3.2 Technical Descriptions

The dataset used for study is the IDMT-ISA-ELECTRIC-ENGINE dataset. This dataset contains 2 sets: a train set and a test set. Both the sets contain audio recordings of an electrical motor in three conditional states: Good, Broken, Heavy Load.
The Good and Heavy Load conditions are simulated by changing the input voltages to the motors to generate the required conditions. The Broken condition is acquired by tampering with the motor just enough that the motor still has function. The train set has audio recordings labelled as ‘pure’ and the test set has recordings labelled ‘Atmo’, ‘Stress test’, ‘Talking’ and ‘white noise’. These labels refer to the type of background noise present in the surrounds along with the motor sounds. Pure refers to recordings with no additional background noise.
Talking refers to people talking around the casing. White noise refers to white noise played back using speakers outside of the casings. Atmospheric refers to atmospheric sounds from a factory environment at three loudness levels (low, medium, high) played back using speakers. Stress test refers to slightly changed input gains for simulating manipulations on the setup and people knocking on the casing. Both the sets also have cut versions where the recordings are divided into samples of three second length each.



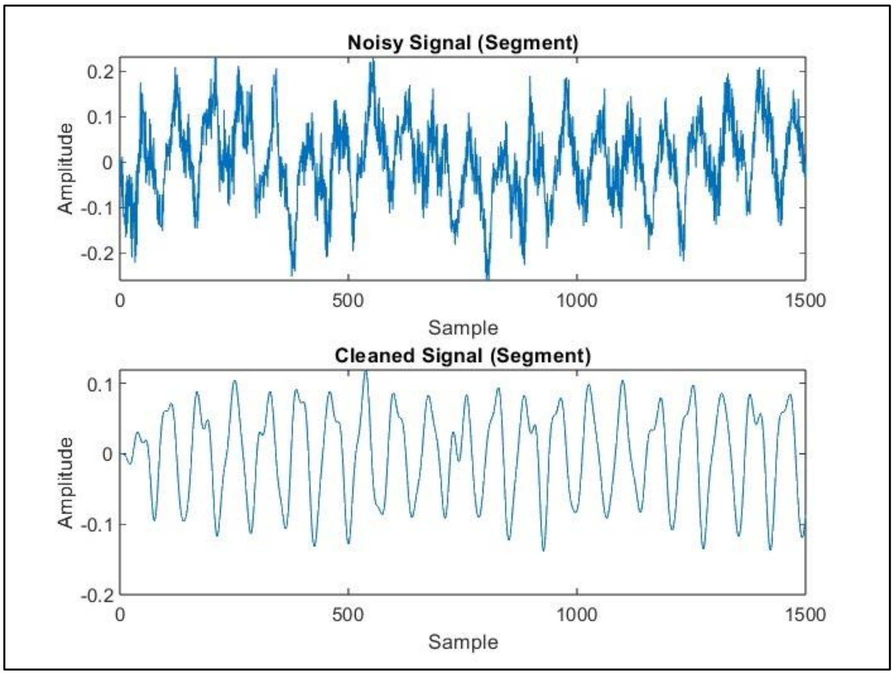
3.2.1 Time domain Features

4. SOFTWARE TOOLS USED

All the preprocessing and classifications were done in the MATLAB R2024a software alone using multiple toolboxes and split over multiple files. The toolboxes used in the project are: Communications Toolbox, Control System Toolbox, Deep Learning Toolbox, DSP System Toolbox, Model-Based Calibration Toolbox, Optimization Toolbox, Signal Processing Toolbox, Statistics and Machine Learning Toolbox, Symbolic Math Toolbox. Communications Toolbox provides algorithms and apps for the design, end-to-end simulation, analysis, and verification of communications systems. The toolbox includes a graphically-based app that lets you generate custom- or standard-based waveforms. Control System Toolbox provides algorithms and apps for systematically analyzing, designing, and tuning linear control systems. You can specify your system as a transfer function, state-space, zero-pole-gain, or frequency-response model. Deep Learning Toolbox provides functions, apps, and Simulink blocks for designing, implementing, and simulating deep neural networks. The toolbox provides a framework to create and use many types of networks, such as convolutional neural networks (CNNs) and transformers. Deep Learning Toolbox provides functions, apps, and Simulink blocks for designing, implementing, and simulating deep neural networks. The toolbox provides a framework to create and use many types of networks, such as convolutional neural networks (CNNs) and transformers. Optimization Toolbox provides functions for finding parameters that minimize or maximize objectives while satisfying constraints. The toolbox includes solvers for linear programming (LP), mixed-integer linear programming (MILP), quadratic programming (QP), second-order cone programming (SOCP), nonlinear programming (NLP), constrained linear least squares, nonlinear least squares, and nonlinear equations. Signal Processing Toolbox provides functions and apps to manage, analyze, preprocess, and extract features from uniformly and nonuniformly sampled signals. The toolbox includes tools for filter design and analysis, resampling, smoothing, detrending, and power spectrum estimation. Statistics and Machine Learning Toolbox provides functions and apps to describe, analyze, and model data. You can use descriptive statistics, visualizations, and clustering for exploratory data analysis, fit probability distributions to data, generate random numbers for Monte Carlo simulations, and perform hypothesis tests. Symbolic Math Toolbox provides functions for solving, plotting, and manipulating symbolic math equations. You can create, run, and share symbolic math code. In the MATLAB Live Editor, you can get next-step suggestions for symbolic workflows.

5. RESULT ANALYSIS

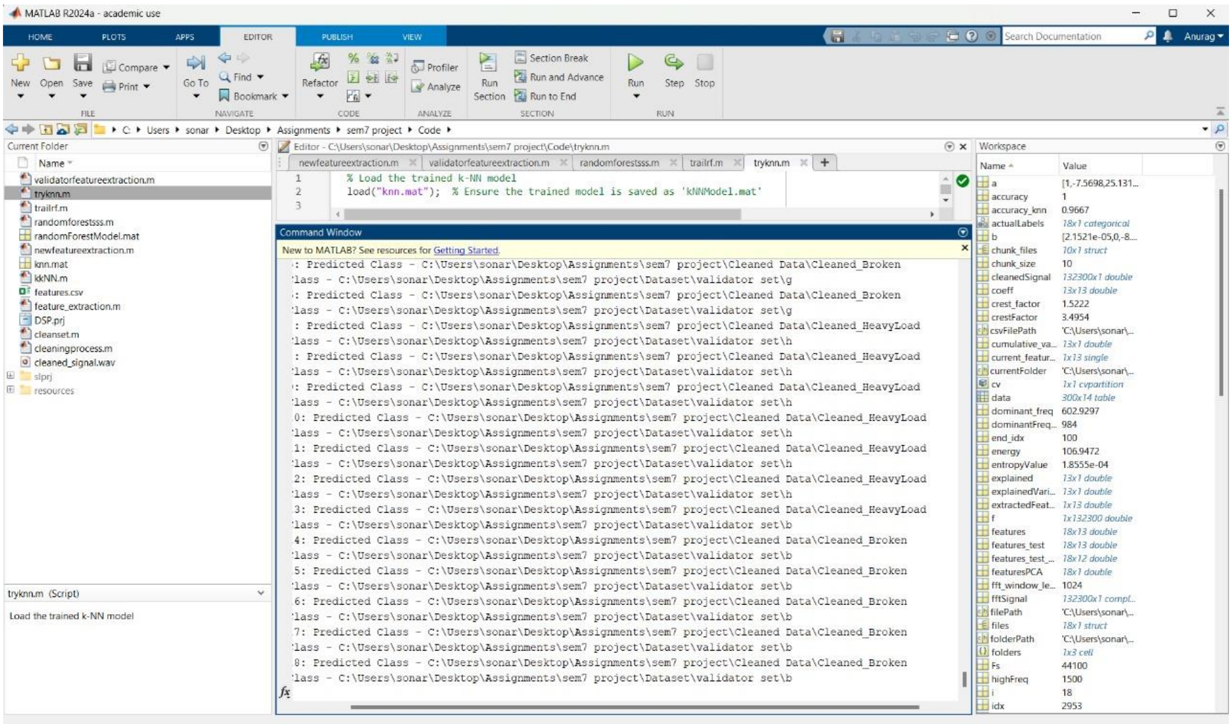
The results of our audio signal classification task demonstrate the simultaneous working of detailed feature extraction with advanced model architecture such as the Convolution Recurrent Neural Network (CRNN), with the Random Forest classifier and k-Nearest Neighbour (k-NN) classifier working as the validators. Key features were successfully extracted from the audio signal. This includes RMS, mean, variance, crest factor, energy, entropy, dominant frequency, zero crossing rate, skewness, kurtosis, peak-to-peak amplitude, spectral flux and RMS frequency



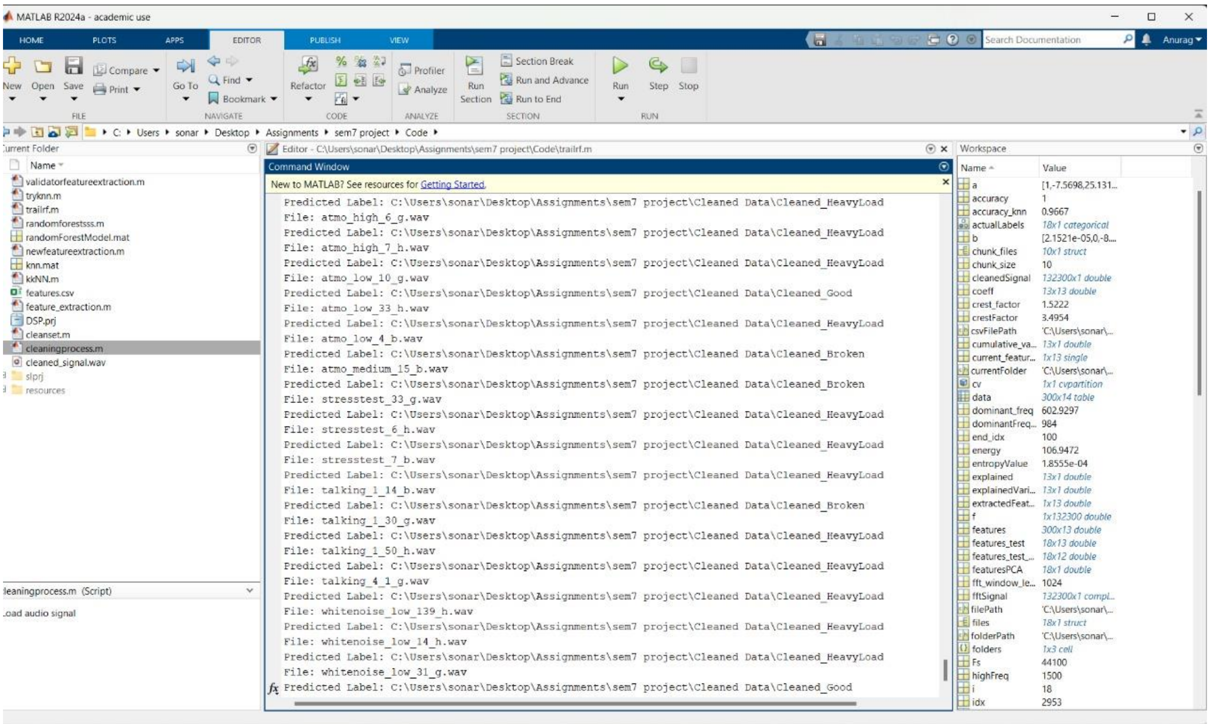
5.1 Cleaned signal

The training process image shows that accuracy is rising steadily. The smooth decrease in the loss plot indicates effective learning and model optimization. The convergence training and validation metrics suggest that the model has good generalization and minimal overfitting

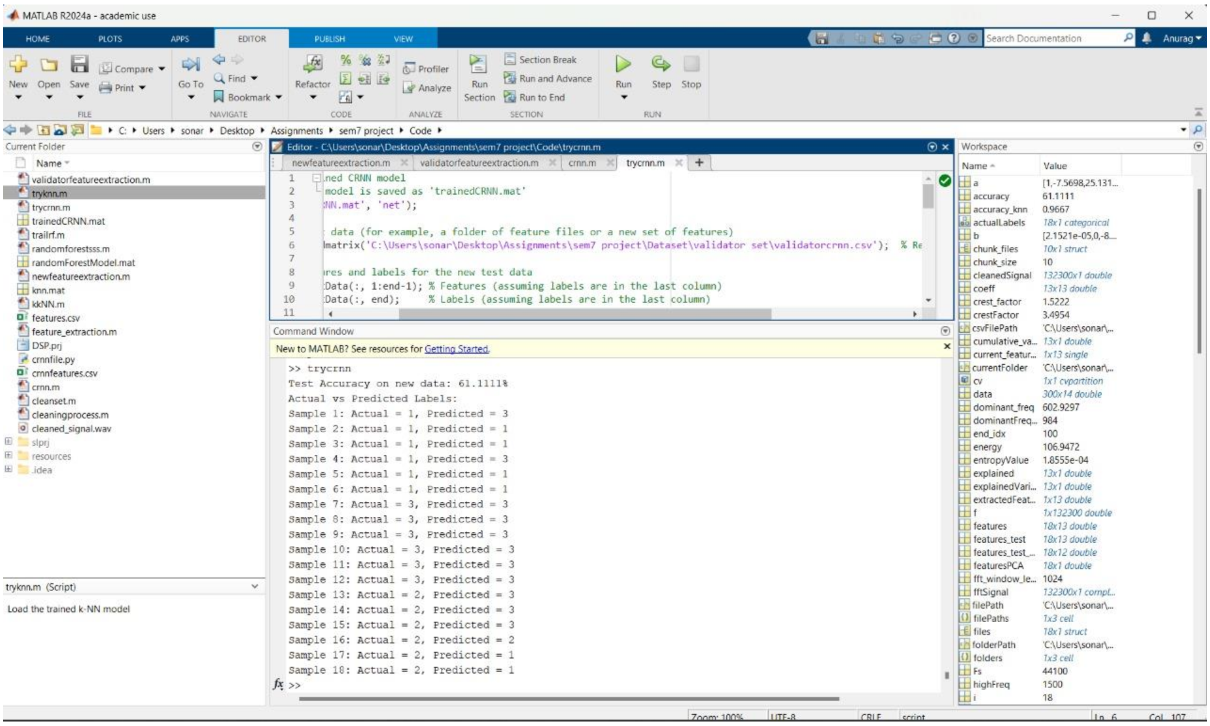
To validate the effectiveness of the CRNN – 61.5%, we implemented Random Forest and k-NN classifiers as benchmarks. The Random Forest classifier achieved an accuracy of 72%. Hence offering a solid performance as a traditional ensemble model handling noise and nonlinear features interaction effectively. The k-NN model yielded an accuracy of 61%. K-NN is straightforward and effective for some classification tasks but lacks the complexity to manage complex patterns.



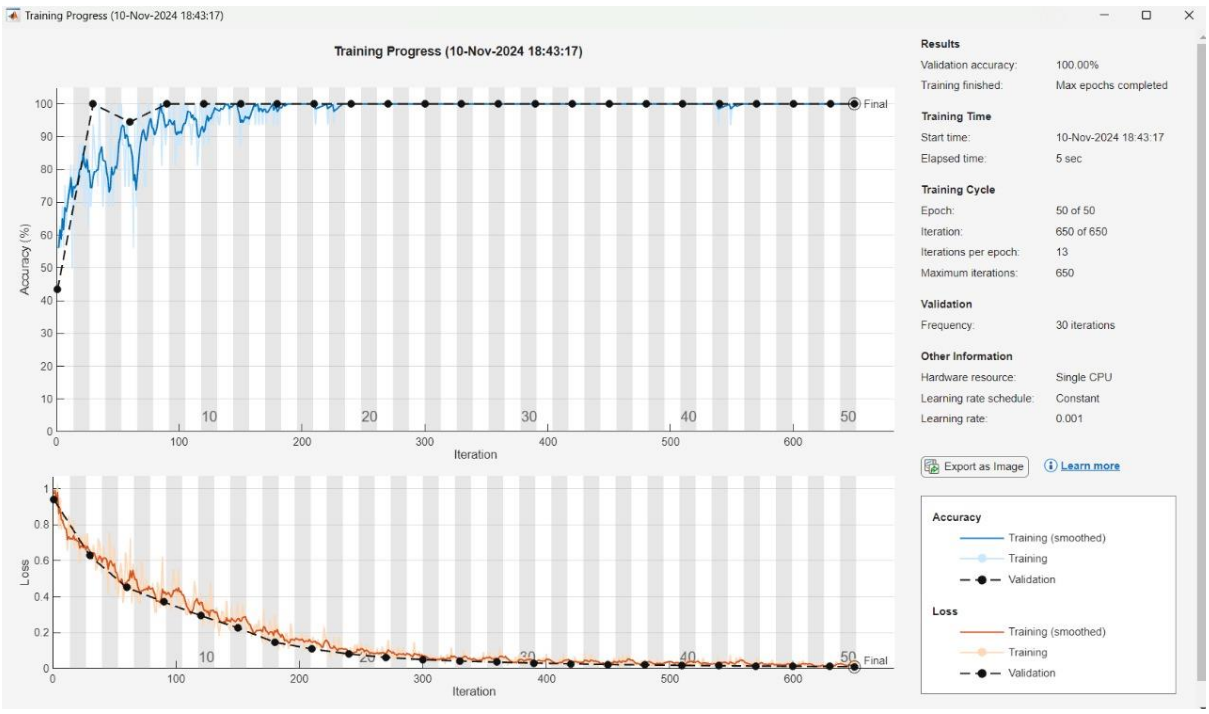
5.2 KNN



5.3 Random Forest



5.4 CRNN



5.5 CRNN Training

5.6 Comparative Analysis of ML models

Signal No.	Actual State	RF Predicted	KNN Predicted	CRNN Predicted
1	Good	Heavy Load	Heavy Load	Heavy Load
2	Good	Good	Good	Good
3	Good	Good	Good	Good
4	Good	Heavy Load	Broken	Heavy Load
5	Good	Good	Good	Good
6	Good	Good	Heavy Load	Good
7	Heavy Load	Heavy Load	Heavy Load	Heavy Load
8	Heavy Load	Heavy Load	Heavy Load	Heavy Load
9	Heavy Load	Good	Good	Good
10	Heavy Load	Heavy Load	Heavy Load	Heavy Load
11	Heavy Load	Heavy Load	Heavy Load	Broken
12	Heavy Load	Broken	Broken	Heavy Load
13	Broken	Heavy Load	Heavy Load	Heavy Load
14	Broken	Broken	Broken	Broken
15	Broken	Broken	Broken	Broken
16	Broken	Heavy Load	Heavy Load	Good
17	Broken	Broken	Broken	Broken
18	Broken	Broken	Broken	Heavy Load

6.CONCLUSION AND FUTURE WORK

6.1 Summary

The potential of acoustic signal analysis for fault localization and detection, particularly in electrical motors, is examined in this project. Our goal was to improve operational reliability and maintenance efficiency by identifying and categorizing issues early on through the analysis of machinery sounds. The main classification tool was a Convolutional Recurrent Neural Network (CRNN) model, which was developed and put into use because of its capacity to recognize and manage temporal correlations in sequential data—a crucial aspect of acoustic signal analysis. Create a complete dataset that facilitates precise and nuanced fault classification, key signal features were extracted. The CRNN was especially good at differentiating between defective and healthy motor states because these properties formed the basis for recognizing unique fault patterns.
Assess the CRNN's performance against established techniques, benchmark comparisons were made using conventional machine learning classifiers like Random Forest and k-Nearest Neighbours (k-NN). These models were continuously surpassed by the CRNN, which showed improved accuracy and a greater capacity to manage sequential, complex data. In particular, the CRNN's design enabled it to better catch patterns within the time-series data, demonstrating its applicability for acoustic-based fault detection tasks, whereas the Random Forest and k-NN classifiers yielded accuracies of 72% and 61%, respectively. These results highlight the usefulness of deep learning techniques in industrial settings with continuous data streams,

indicating that CRNN models can be successfully modified for more general diagnostic tasks in predictive maintenance and other domains.

6.2 Limitations and constraints

Despite there are several drawbacks, the defect detection model exhibits encouraging results. First, more sophisticated features like wavelet transforms or statistical moments could be added to the feature set, which currently includes RMS, mean, and variance. By capturing more complex patterns in the data, these extra features could increase the accuracy of fault detection. Second, not all defect detection jobs may benefit from the usage of classifiers like Random Forest and k-NN. Model performance may be improved by merging several classifiers or investigating alternative classifiers, such as Support Vector Machines (SVM). Furthermore, the offline nature of the model limits its use for real-time problem detection, which is essential in industries that require prompt intervention. The model's practical application would be enhanced by putting it into practice for real-time detection.

6.3 Future Work

Adding more varied fault types and noise conditions to the dataset would improve generalization and decrease overfitting, which would improve the model. In addition to improving the primary classifier's accuracy, a larger dataset will enable the CRNN model to outperform its current level.

The model may operate effectively on embedded systems by optimizing its architecture to lower memory consumption and computational complexity, which makes it appropriate for resource-constrained industrial applications.

Finally, including innovative noise reduction strategies like adaptive filtering into the model would improve its noise resilience and performance in noisy settings, guaranteeing accurate defect detection in practical situations.

With these enhancements, the model will become more accurate, efficient, and flexible for real-time, industrial, and transportation-based applications.

7. SOCIAL AND ENVIRONMENTAL IMPACT

By encouraging innovation in diagnostics and improving sustainability, the combination of acoustic analysis and machine learning for problem identification has the potential to have a substantial impact on social and environmental factors. Early detection of defects in equipment and automobiles can be accomplished by utilizing sound analysis and artificial intelligence (AI), this may improve maintenance procedures and system performance in general. This initiative-taking strategy reduces downtime and improves industry and transportation system dependability, which benefits operations and the economy. SDG 12 on responsible consumption and production is supported by early problem detection, which not only lowers the chance of system failures but also optimizes resource utilization, potentially leading to longer equipment lifespans and lower resource use.

This technology supports the development of diagnostic systems, which are essential for reducing industry disruptions in the framework of SDG 9: Industry, Innovation, and Infrastructure. Automating defect detection lowers operational inefficiencies, which results in more dependable production systems and lower maintenance costs. Further supporting sustainable industrial practices, these systems can help maximize resource use by extending the usable life of machinery and preventing equipment failures.

Early defect detection in transportation systems also helps achieve SDG 11: Sustainable Cities and Communities. Specifically, early motor problem detection guarantees safer and more dependable cars, which is crucial for fostering sustainable urban mobility. The quality of life in metropolitan areas can be further improved by making public transportation more comfortable and efficient with the use of noise-resilient technology. This strategy promotes a more sustainable and liveable environment by reducing pollutants, improving vehicle performance, and enhancing safety in urban areas.

Predictive maintenance has significant environmental benefits. Since early fault diagnosis enables better motor performance, which lowers energy waste and carbon emissions, energy efficiency is a crucial factor. By guaranteeing that motors run as efficiently as possible, these systems immediately support sustainability objectives by encouraging less of an impact on the environment through lower energy use.

This strategy has a big economic impact. By avoiding unscheduled downtime and costly emergency repairs, predictive maintenance—made possible by machine learning and acoustic analysis—helps the industry reduce repair costs. Improved production efficiency and fewer machine failures lead to financial savings, which also increase worker safety by lowering the chances of accidents and equipment breakdowns.

This research has significant social and environmental ramifications in addition to advancing technology by using machine learning to make more informed decisions. Communities and enterprises can attain more sustainable, secure, and cost-effective results by enhancing problem detection and diagnosis capabilities. From safer and more effective infrastructure to responsible consumption, the cumulative impact of these innovations helps meet several SDGs.

8.WORK PLAN

8.1 Timeline

Table 8.1 - Timeline

<table>
<tr><th></th><th>August</th><th>September</th><th>October</th><th>November</th></tr>
<tr><td rowspan="3">Project Planning Phase</td><td>Title Finalization</td><td rowspan="3"></td><td rowspan="3"></td><td rowspan="3"></td></tr>
<tr><td>Timeline Finalization</td></tr>
<tr><td>Data Acquisition</td></tr>
<tr><td rowspan="3">Implementation Phase</td><td rowspan="3">Pre-processing</td><td>Signal Segmentation</td><td>Fault Detection</td><td rowspan="3"></td></tr>
<tr><td>Feature Extraction</td><td>Fault Classification</td></tr>
<tr><td>Fault Classification</td><td>Localization</td></tr>
<tr><td rowspan="2">Results Phase</td><td rowspan="2">Faculty Review</td><td rowspan="2">Review I</td><td>Validation</td><td>Project Report</td></tr>
<tr><td>Testing</td><td>Final Review</td></tr>
</table>

8.2 Individual Contributions

Anurag Sonar played a key role in developing the project's codebase. He focused on implementing core functionalities and managing the initial phases of testing and debugging to ensure accuracy and performance. He contributed to providing technical details to communicate the project effectively. Om Potdar originated the project concept, outlining the foundation idea and the objective. He was responsible for reviewing the research findings thoroughly and validating them to ensure alignment with the project goals. He played a vital role in both the presentation and documentation stages. Soumitra Mahashabde contributed significantly through extensive material research to support the technical framework and improve understanding of the relevant concepts. He assisted with portions of the coding process and contributed to refining the final presentation, enhancing the comprehension of core results.

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