# Early Fault Detection for Induction Motor Using Machine Learning


Muhammad Ashar Javid
School of Electrical Engineering and Computer Science
Islamabad, Pakistan

Awais Asghar
School of Electrical Engineering and Computer Science
Islamabad, Pakistan

Muhammad Hammad Sarwar School of Electrical Engineering and Computer Science
Islamabad, Pakistan



**Abstract—Induction motors serve as the backbone of modern industries, playing a pivotal role in ensuring seamless operations. Faults in these motors can lead to significant financial setbacks, underscoring the importance of reliable and efficient fault detection systems. This paper introduces an integrated approach for early fault detection in induction motors by leveraging a MATLAB-based control system and advanced machine learning models. Unlike conventional solutions that focus on single fault types, our system offers a unified framework capable of monitoring and diagnosing six distinct fault conditions: broken rotor bars, stator short circuits, ground faults, overloading, eccentricity, and phase voltage imbalances. A mathematical dq-induction motor model addresses voltage phase difference, overloading, and ground faults, while MATLAB's built-in induction motor module generates datasets for eccentricity, broken rotor bars, and stator short-circuit faults. Using K-Nearest Neighbors (KNN) and Decision Tree algorithms, the system achieves high classification accuracy, enhancing predictive maintenance and operational reliability. This unified framework offers a robust alternative to traditional methods, streamlining fault detection and improving industrial efficiency.**



**Keywords—Induction Motors, Fault Detection, Machine Learning, Random Forest, MATLAB Simulink, Predictive Maintenance.**


## I. INTRODUCTION

Induction motors are an integral part of modern industrial processes, driving machinery across diverse sectors such as manufacturing, energy, and transportation. The reliability of these motors is essential for minimizing operational downtime and avoiding significant financial losses. However, their extensive use makes them prone to a wide range of faults, including mechanical and electrical anomalies. These faults, if undetected, can lead to catastrophic failures, posing challenges to the safety and efficiency of industrial operations.

Traditional fault detection systems often focus on specific fault types or rely heavily on manual interventions, making them inefficient and unsuitable for real-time diagnostics. Advances in computational tools, including MATLAB Simulink and machine learning algorithms, have opened new avenues for automating and enhancing fault detection systems. These technologies enable modeling, simulation, and detection of faults in induction motors, providing a comprehensive framework for proactive maintenance.

This paper introduces an integrated fault detection system leveraging MATLAB's control system toolbox and machine learning techniques. The approach combines mathematical modeling with simulation-based data generation, enabling accurate diagnosis of six critical fault types: broken rotor bars, stator short circuits, ground faults, overloading, eccentricity, and phase voltage imbalances. By utilizing a combination of K-Nearest Neighbors (KNN) and Decision Tree algorithms, the proposed system achieves high classification accuracy, presenting a robust alternative to traditional methods. This study aims to enhance predictive maintenance strategies, ensuring greater operational reliability and efficiency in industrial settings.

## II. LITERATURE REVIEW

A detailed analysis of the existing literature indicates that Signal Analysis Techniques, such as FFT Transforms, have demonstrated notable success over time. However, these techniques primarily address single or limited fault types, restricting their applicability in comprehensive fault detection scenarios. Another significant limitation is their inability to provide predictive fault detection. In contrast, modern methods leveraging deep learning and machine learning have shown considerable improvements in accuracy and fault coverage. For example, studies have employed Support Vector Machines (SVM) [5] and Artificial Neural Networks (ANN) [6] for fault classification with promising outcomes. Furthermore, advanced deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have proven effective in extracting complex features from motor current and vibration signals, thereby enabling more precise fault diagnosis [7].

Despite these advancements, current models are predominantly designed to target specific faults, making them insufficient for broader applications. Moreover, their reliance on computationally intensive architectures, such as deep neural networks, poses challenges for deployment on systems with limited computational resources [1][2]. These shortcomings underscore the need for a critical study aimed at developing a comprehensive framework for predictive fault detection. Such a framework should minimize computational demands while maximizing accuracy and scalability.

In our study, we build upon the utility of MATLAB Simulink, which has been shown to be effective for generating datasets relevant to fault detection. For instance, Cha et al. utilized MATLAB's induction motor modules to simulate various fault conditions, enabling data-driven training of deep neural networks [3]. This approach not only facilitates the creation of accurate datasets but also enhances the adaptability of fault detection models.

The identified gaps in the existing methodologies, including limited fault coverage, lack of predictive capabilities, and high computational requirements, call for an integrated solution. Our proposed approach seeks to address these challenges by combining simulation-driven data generation with lightweight yet precise machine-learning models. This ensures predictive fault detection while maintaining computational efficiency, thereby making the solution viable for resource-constrained industrial environments.

## III. METHODOLOGY

This paper introduces an integrated fault detection system leveraging MATLAB's control system toolbox and machine learning techniques.

The approach combines mathematical modeling with simulation-based data generation, enabling accurate diagnosis of six critical fault types: broken rotor bars, stator short circuits, ground faults, overloading, eccentricity, and phase voltage imbalances.

The overall framework is divided into two main parts; d-q modeled induction motor which is responsible for the catering of phase voltage difference, overload, and grounding faults which are detected using control systems utilizing the built-in Simulink algebraic blocks, the other part of the framework includes the simulation of broken rotor bar, eccentricity, and stator short-circuit which are determined using trained machine-learning models obtained by training simulated data.

**3.1: D-Q Modelled Induction Motor**

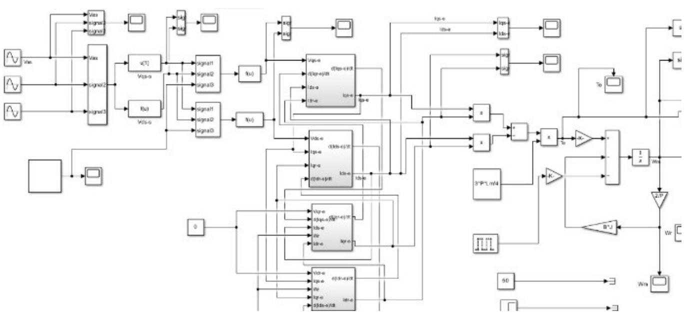


***Figure No.1:*** *D-Q Induction Motor Model*

The model of induction motor is based on the mathematical equations of induction motor obtained after obtaining their d-q transforms of current and voltage which are useful for MATLAB system designs for their reduced complexity.

The model has the following parameters:

- Power=40*746;
- P=4;
- Vph=460/sqrt(3);
- Vm=sqrt(2)*Vph;
- f=50;
- We=2*pi*50;
- Rs=0.087;
- Rr=0.187;
- Lm=0.04;
- Ls=0.0425;
- Lr=0.043;
- J=1.662;
- B=0.01;

The block for the phase voltage difference includes algebraic blocks to check if the voltages in all phases from the input lie within the 5% range of the maximum voltage range. If the voltage exceeds the difference limit then the error is displayed on the virtual screen.

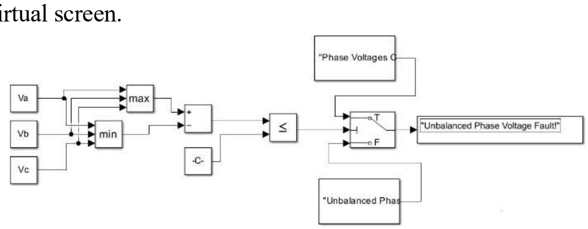



***Figure No.2:*** *Setup for Voltage Phase Difference*

The grounding fault is caused if a phase line gets in touch with the body of the motor thus causing current flow into the ground and increasing the current flow in the motor lines and ultimately causing reduced efficiency of the system. The grounding fault is also detected using algebraic block which measures the total current flow into the system and the total current in the stator and rotor sides of the motor. An unequal amount of current signifies a leakage of current to the ground.

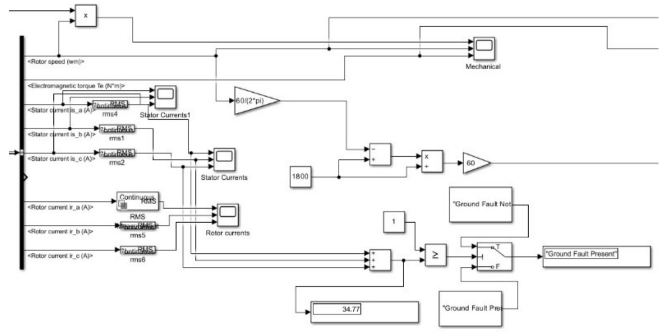



***Figure No.3:*** *Setup for Ground Fault*

Similarly, the overload fault is detected by checking the current measured in the rotor winding compared to the maximum rated current given by the power equation of the induction motor.

**3.2: Fault Simulation**

Builtin induction motor block is used with the three-phase circuit breaker to simulate the stator short-circuit current, whose data is then stored in the workspace files. Similarly, the broken rotor data has also been generated by short-circuiting the induction motor with an RLC circuit to introduce time-dependent harmonics and increased current thus acting as a time-dependent resistance change similar in behavior to the broken rotor in a squirrel cage induction motor. To simulate the eccentricity effect, we have introduced time-dependent flux change in the motor by introducing a sinusoidally varying inductance to the motor.

The model used is the following for the extraction of data for the training of the machine learning model.

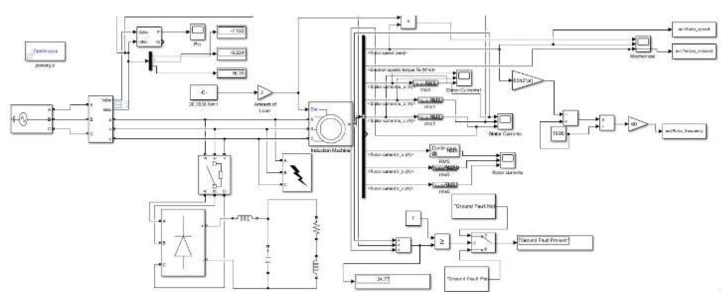


***Figure No.4:*** *Broken Bar and Short-Circuit Fault Setup*

The data collected from the induction motor model includes the current, voltage, rotor speed, power, and frequency of the system.

**3.3: Cumulative Model**

For a practical system, signals such as voltage, current, and system frequency are recorded continuously using measuring instruments and are fed into the control unit which is connected to MATLAB Simulink via a low-powered microprocessor unit capable of running ml models like ESP32 or a similar device. The collected data undergoes preprocessing, including:

**Noise Reduction**: Low-pass filters eliminate high-frequency noise.

**Feature Extraction:** Features like RMS, THD, kurtosis, and frequency spectrum are derived.

After the data features are extracted, the features or cleaned data are fed to the microprocessor which runs the built machine learning model and the results are displayed on virtual display in Simulink.

### 3.4: Machine Learning Model

We have used three separate machine learning models like KNN, Decision Tree, SVMs, each for one of the motor faults, and performed their comparative analysis to handle high-dimensional datasets and built a robust model against overfitting. The key steps to train these models include:

**Training:** The models are trained on 70% of the dataset.

**Validation:** 15% of the data is used for hyperparameter tuning.

**Testing:** Performance is evaluated by the remaining 15%.

The overall flow of the machine learning model is shown in Figure No.5.

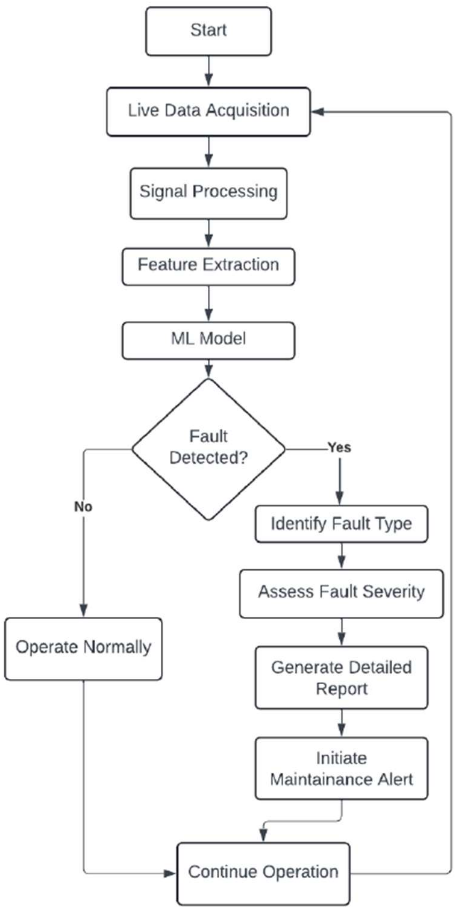



***Figure No.5:** Broken Bar and Short-Circuit Fault Setup*

## IV. ANALYSIS OF MOTOR FAULTS

The motor fault behaviors are now examined here.

### A. Healthy Motor

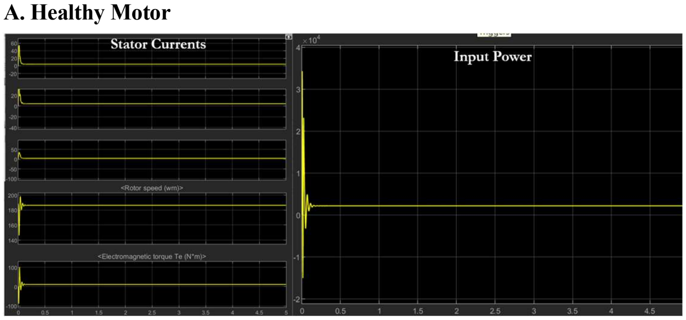



***Figure No. 6:** Characteristics of Healthy Motor*

Normal motor characteristics are shown in Figure 6, it can be seen the normal current is flowing in the motor. At the start, the current reaches a spike to overcome the inertia of the rotor which requires excessive current to start the motor. As soon as the motor gains speed, we can observe a uniform output current. Similarly, the remaining characteristic curves set the reference signals for the motor.

### B. Grounding Fault

Ground faults occur when a winding comes into contact with the motor casing or ground, causing a direct path for electrical current to flow outside the designated circuit. This fault increases the risk of electrical hazards, causes significant overheating, and can result in the burning of windings or other components. Aging insulation, physical damage, or environmental factors like moisture and dirt buildup are the main contributors to ground faults.

### C. Short Circuit Fault

Stator short circuits occur when the insulation between the stator windings deteriorates, leading to electrical arcing between adjacent coils. This fault results in unbalanced magnetic fields, reduced efficiency, and overheating, potentially causing further insulation damage. If not addressed, it can lead to catastrophic motor failure. Overheating, voltage surges, and improper maintenance are the primary causes of insulation degradation, leading to stator short circuits. When we short-circuited the input terminals, a high current started flowing in the rotor. Abnormal power was flowing in the motor. In practical life motor can't bear this much increase in current which leads to the breakdown of the motor.

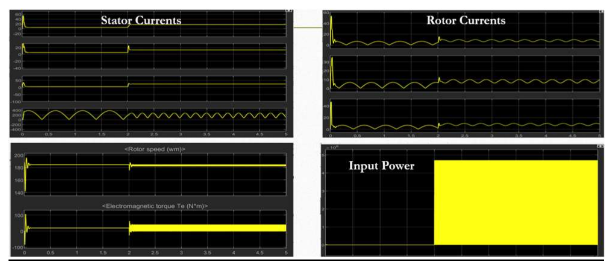



***Figure No. 7:** Characteristics of Short-Circuited Motor*

### D. Motor Overload Fault

Overloading occurs when the motor operates beyond its designed load capacity, leading to excessive current draw and strain on components. This fault accelerates wear and tear, increases operating temperature, and reduces efficiency. Persistent overloading can result in thermal degradation of insulation and mechanical failures. Causes include misaligned equipment, excessive loads, and improper motor selection during system design.

When the motor is load above its rated value, input current increase due to increase in input power to compensate the energy requirements of overload. Due to overload, rotor speed was decreased and electromagnetic torque was increased as it is inversely proportional to rotor speed.

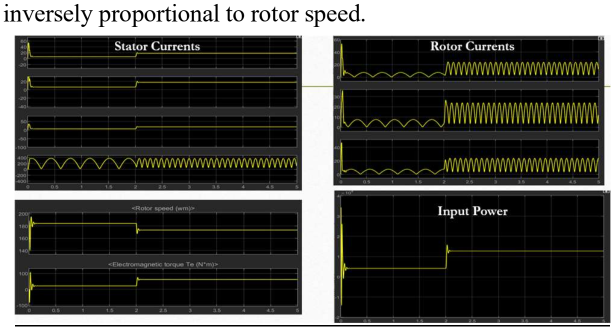



***Figure No.8:** Characteristics of Overloaded Motor*

### E. Broken Rotor Bar Fault

This fault arises when one or more bars in the rotor become damaged or broken, disrupting the electromagnetic field required for proper operation. Broken rotor bars can result from manufacturing defects, prolonged mechanical stress, or overheating. Broken rotor bars cause a reduction in torque and efficiency, uneven power delivery, and increased vibration and noise levels. Over time, this fault may lead to further rotor damage or complete failure. This fault often develops due to excessive load, thermal cycling, or corrosion. Aging components can also contribute to the weakening of the rotor bars.

When the rotor bar is broken, harmonics are added to the signal as discussed previously. This results in distorted sinusoids as shown in Figure 9. Similarly, distinct harmonics are also observed upon taking the FFT of the current signals of the motor.

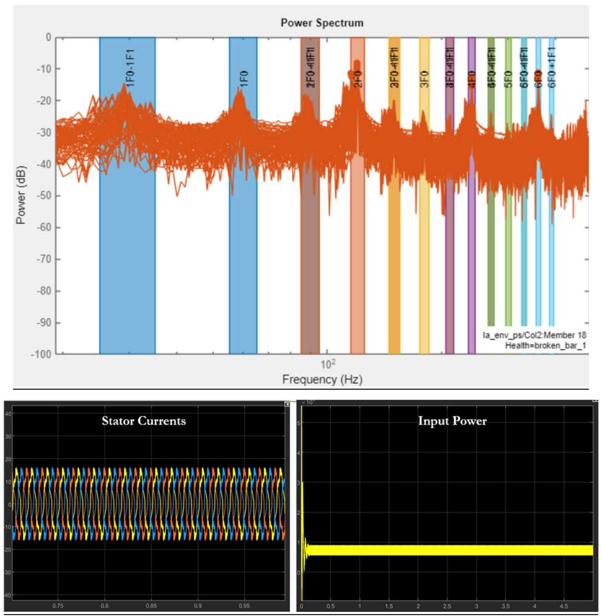
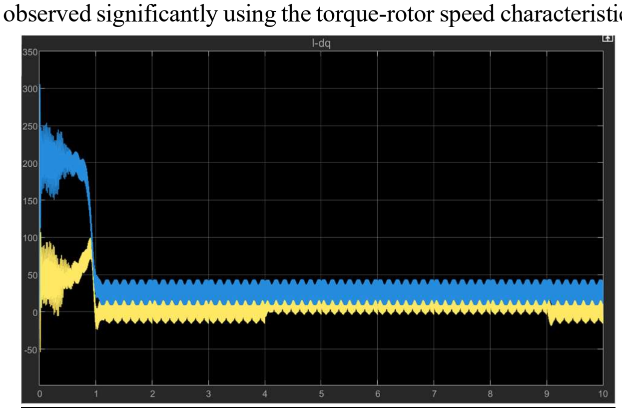



***Figure No. 9**: Characteristics of Motor with Broken Rotor Bar*

### F. Voltage phase Difference

This fault arises when the supply voltage phases are unevenly distributed, leading to irregular currents in the motor windings. Voltage imbalances cause overheating, increased vibration, and decreased torque output. Severe imbalances can result in winding failures. Voltage imbalances typically result from issues in the power supply, such as uneven loads, poor connections, or defective transformers.

Introducing a phase difference other than 120 degrees causes the overall model currents to be distorted and the effect can be observed significantly using the torque-rotor speed characteristics.



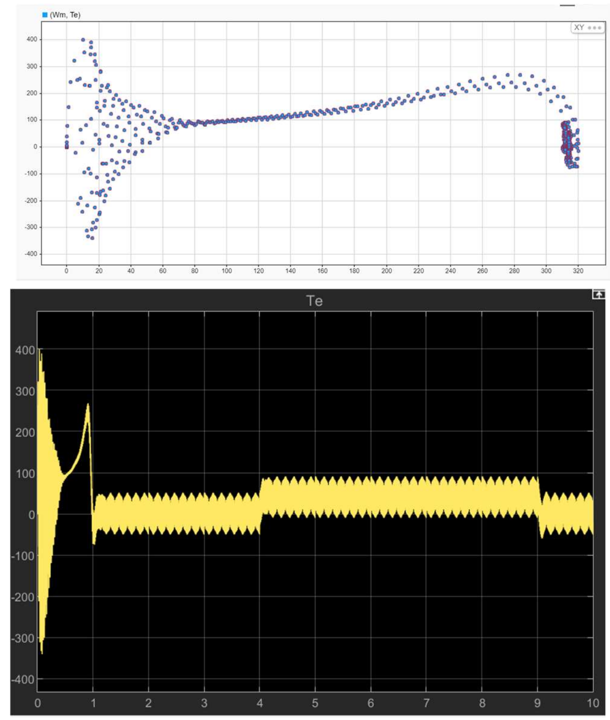




***Figure No. 10:** Characteristics of Motor with Phase Voltage Distortion*

The extreme distortions are caused by the current impulses in the rotor of the induction motor which is detected by the Simulink model as shown in figure 10.

### G. Eccentricity

Eccentricity refers to the misalignment of the rotor within the stator, leading to uneven air gaps and unbalanced magnetic fields. It can be either static (fixed misalignment) or dynamic (variable misalignment during operation). This condition generates vibrations, noise, and increased mechanical stress on bearings, reducing the motor's lifespan and efficiency. Common causes include bearing wear, improper assembly, or physical damage to the motor components.

It is also observed as the sideband harmonics in the current signal FFT.

## V. Results and Discussion

### 5.1: Fault Detection Accuracy

The broken rotor bar model gives the following confusion matrix results with an accuracy of 98.8% using KNN run on the obtained dataset.

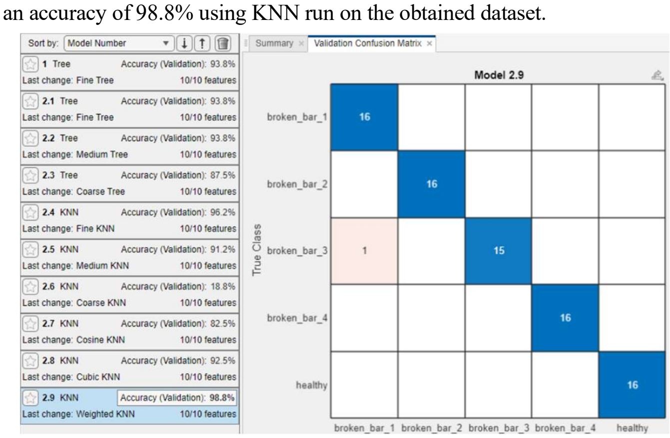



***Figure No. 11:** Broken Rotor Bar Confusion Matrix (KNN)*

The results for the stator short circuit fault gives a 100% accuracy for the Decision Tree algorithm because of its robustness in the classification type of problem which is quite suitable for the 3 phase errors that can be observed using the short-circuiting of the stator windings. The Confusion Matrix for the same is shown in Figure No. 12.

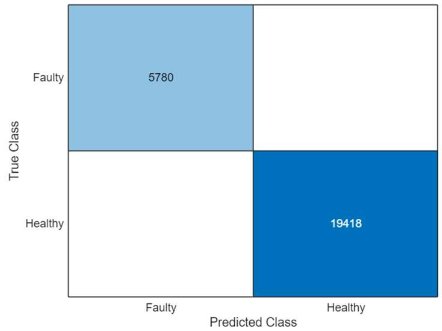



***Figure No. 12:*** *Stator Short Circuit Confusion Matrix*

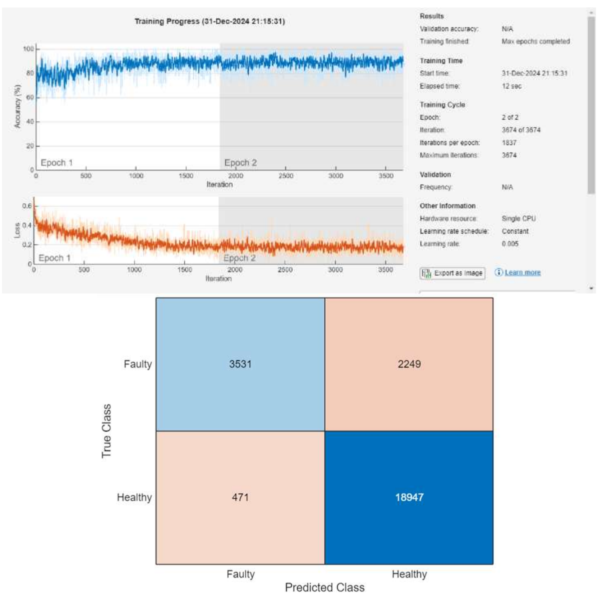



***Figure No. 13:*** *Stator Short Circuit Confusion Matrix (ANN)*

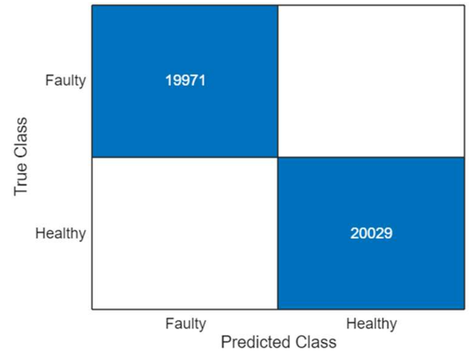
The same dataset was also used for classification using a neural network ran on 2 epochs only leading to overfitting showcasing a lack of enough dataset hence this method of classification was not selected.

| | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| KNN | 98.8% | 0.981 | 0.967 | 0.974 |
| SVM | 75.9% | 0.477 | 0.499 | 0.488 |
| Decision Tree | 100.0% | 1.000 | 1.000 | 1.000 |
| Logistic Regression | 76.4% | 0.486 | 0.499 | 0.492 |
| ANN | 89.2% | 0.882 | 0.611 | 0.722 |

***Figure No. 14:*** *Comparative Analysis of multiple ML models*

Finally, the comparative analysis of the multiple models with their accuracies is also attached with the Decision Tree performing the best amongst them.

Finally, the model for the eccentricity of the dataset gave the best performance using the KNN model with a 100% accuracy.




-

***Figure No. 15:*** *Eccentricity Confusion Matrix (KNN)*

## VI. Conclusion

The study presented in this paper outlines a comprehensive framework for early fault detection in induction motors, integrating MATLAB Simulink-based simulations with advanced machine learning techniques. The proposed system successfully detects six critical fault types, including broken rotor bars, stator short circuits, ground faults, overloading, eccentricity, and phase voltage imbalances, demonstrating high classification accuracy. Unlike traditional methods, which often lack predictive capabilities or focus on limited fault types, this unified framework offers a robust, efficient, and scalable solution tailored to modern industrial needs.

By employing a mathematical dq-model and leveraging simulated datasets, the system provides a practical, cost-effective means for generating fault conditions and building reliable machine learning models. The results, validated through comparative analysis of KNN, Decision Tree, and SVM algorithms, highlight the efficiency and accuracy of the proposed approach. With a primary focus on reducing computational overhead, the system ensures compatibility with resource-constrained environments, making it suitable for real-world industrial applications.

This work significantly contributes to predictive maintenance practices, reducing downtime, and improving operational reliability. It bridges the gap between theoretical advancements in machine learning and their practical implementation in fault detection systems for induction motors.

## VII. Future Works

While the current framework delivers promising results, several avenues remain open for future exploration and improvement:

**Expansion of Fault Coverage:**

The framework can be extended to address additional fault types, such as bearing failures, harmonics, and thermal anomalies. A more comprehensive dataset encompassing these conditions can further improve the system's diagnostic capabilities.

**Hybrid Machine Learning Models:**

Exploring hybrid approaches by combining classical machine learning algorithms with deep learning models may further improve fault detection accuracy and adaptability to diverse operating conditions.

**Cross-Domain Validation:**

The framework's applicability can be validated across various industrial setups, including diverse motor types and configurations, to ensure its generalizability and robustness.

**Incorporation of Fault Severity Analysis:**

Developing models to assess the severity of detected faults can provide actionable insights for prioritizing maintenance tasks and minimizing operational risks.

By addressing these areas, the proposed framework can be further refined and expanded, cementing its utility in modern industries as a reliable and efficient fault detection system for induction motors.

## VIII. References


[1] M. Samiullah, H. Ali, S. Zahoor, and A. Ali, "Fault Diagnosis on Induction Motor using Machine Learning and Signal Processing," School of Electrical Engineering and Computer Science (SEECS), National University of Sciences and Technology, Islamabad, Pakistan.

[2] F. Husari and J. Seshadrinath, "Early Stator Fault Detection and Condition Identification in Induction Motor Using Novel Deep Network," Student Member, IEEE, and Senior Member, IEEE.

[3] S. Cha, S. Lee, J. Jo, Y. O. Lee, and J. Hwang, "Deep Neural Network Based Fault Detection for Three-Phase Induction Motor," Smart Convergence Group, KIST Europe, Campus E 7.1, 66123 Saarbrücken, Germany.

[4] E. Treml, R. A. Flauzino, M. Suetake, and N. A. R. Maciejewski, "Experimental database for detecting and diagnosing rotor broken bar in a three-phase induction motor," in Western Paraná State University (UNIOESTE), Foz do Iguaçu, Brazil; University of São Paulo (USP), Sao Carlos, Brazil; Federal University of Sao Carlos (UFSCAR), Sao Carlos, Brazil.

[5] H. Bahgat, E. A. Elhay, and M. M. Elkholy, "Advanced fault detection technique of three phase induction motor: comprehensive review," The Author(s) 2024 OPEN, Nov. 30, 2023, accepted Jun. 18, 2024.

[6] M. N. Raju and M. S. Rani, "Mathematical Modelling of Linear Induction Motor," Department of Electrical Engineering, VLITS College, Vadlamudi, India.

[7] S. K. Dwivedi and J. Dannehl, "Modeling and Simulation of Stator and Rotor Faults of Induction Motor and their Experimental Comparison," Application Control Engineering, Danfoss Power Electronics A/S, Graasten, Denmark.