

XGBoost-based Fault Classification System for Induction Motors with Real-Time Dashboard Integration

K. Sebasthirani¹, Marudhupandi. P², Deepakkumar R³, Hitesh Balaji. N⁴ and Maduritha. E⁵

¹Associate Professor, Sri Ramakrishna Engineering College/ Electrical and Electronics Engineering, Coimbatore, India.

Email: sebasthirani.kathalingam@srec.ac.in

²Associate Professor, Government College of Technology/ Electrical and Electronics Engineering, Coimbatore, India

³⁻⁵Student, Sri Ramakrishna Engineering College/ Electrical and Electronics Engineering, Coimbatore, India

Email: deepakkumar.2203011@srec.ac.in, hitestbalaji.2203028@srec.ac.in, maduritha.2203042@srec.ac.in, pandi@gct.ac.in

Abstract— In industrial applications, unplanned failures of induction motors can lead to significant operational delays and maintenance costs. This work proposes a predictive maintenance solution using the XGBoost algorithm for early fault classification in three-phase squirrel cage induction motors. The system focuses on detecting faults such as bearing failures, broken rotor bars, and stator short circuits by analysing key sensor inputs including current, vibration, and axial flux data. The machine learning model is trained on labelled datasets collected from both healthy and faulty conditions, enabling accurate and timely identification of motor anomalies. To complement the fault detection system, a real-time monitoring dashboard is developed using FastAPI for the backend and Chart.js for the frontend. This dashboard provides live graphical visualization of sensor data and fault indicators, offering operators an interactive interface to track motor health status. The proposed system achieves high classification performance and offers scalable deployment potential in industrial settings. Its integration of real-time monitoring with intelligent fault analysis supports proactive maintenance, improves

Index Terms— XGBoost algorithm, Three-phase squirrel cage motor, Machine learning model, Motor anomalies and Real-time monitoring dashboard).

I. INTRODUCTION

Induction motors play a vital role in modern industries due to their simplicity, durability, and cost-effectiveness. These motors are commonly used in various sectors including manufacturing, transportation, and energy systems. Despite their robust nature, induction motors are prone to faults such as broken rotor bars, bearing wear, and stator winding failures [8]. If not identified early, these issues can lead to equipment breakdowns, safety hazards, and extended periods of downtime. Conventional maintenance methods such as periodic inspection or reactive repair often fail to prevent unexpected failures. These approaches either result in unnecessary maintenance or fail to detect faults in time.

To address these limitations, predictive maintenance systems that rely on real-time sensor monitoring and intelligent fault detection techniques are increasingly being adopted [2][12]. This study introduces a machine learning-based fault classification system using the XGBoost algorithm. XGBoost, known for its speed and accuracy, is used to analyse multi-sensor data collected from a three-phase squirrel cage induction motor. The dataset includes readings of current, vibration, and axial flux under different motor conditions [7][9]. After preprocessing and feature selection, the data is used to train the model for classifying normal and faulty states. To enhance usability, a web-based dashboard is integrated with the model. The dashboard enables live monitoring of motor health through real-time plots and alerts. Developed using FastAPI and Chart.js, it supports visual feedback and assists maintenance teams in identifying and responding to faults promptly. By combining machine learning with interactive visualization, this system offers an efficient and scalable approach for predictive maintenance. It aligns with Industry 4.0 goals by enabling smarter decision-making, reducing unplanned maintenance, and improving overall equipment effectiveness [10][12].

II. LITERATURE SURVEY

The advancement of predictive maintenance for induction motors has evolved significantly with the integration of artificial intelligence (AI) and machine learning (ML) techniques. This literature review systematically examines recent developments in fault detection methodologies, feature extraction techniques, machine learning approaches, and IoT-based monitoring systems to identify research gaps and establish the foundation for this work. Conventional maintenance strategies for induction motors have predominantly relied on scheduled maintenance and reactive approaches. Siddiqui et al. [8] identified that traditional methods, including periodic inspection and condition-based monitoring using basic vibration analysis, suffer from significant limitations—particularly in detecting incipient faults and providing adequate lead time for maintenance planning. The reactive nature of these approaches often results in unexpected equipment failures, leading to substantial operational costs and safety concerns. Motor Current Signature Analysis (MCSA) has been widely adopted as a traditional diagnostic technique for induction motor fault detection. However, Yatsugi et al. [4] highlighted that conventional MCSA approaches face challenges in distinguishing between different fault types, particularly under varying load conditions and in the presence of supply voltage unbalance. These limitations have necessitated the development of more sophisticated diagnostic approaches incorporating artificial intelligence and data-driven techniques. Recent research has demonstrated the superior performance of machine learning algorithms in induction motor fault classification compared to traditional diagnostic methods. Drakaki et al. [3] provided a comprehensive review of Industry 4.0 trends in predictive maintenance of induction motors, showing that ML and deep learning algorithms enable higher reliability, automation, and real-time decision-making capabilities. Similarly, Carvalho et al. [2] and Çınar et al. [12] emphasized that supervised learning, ensemble methods, and deep neural networks significantly enhance the accuracy of predictive maintenance systems by leveraging large-scale industrial datasets. Support Vector Machines (SVM) have shown remarkable effectiveness in motor fault classification. Yatsugi et al. [4] developed a comprehensive diagnosis approach for three-class induction motor faults using stator current features and SVM, achieving 99% accuracy in distinguishing between healthy, bearing fault, and broken rotor bar conditions. The study demonstrated that SVM's ability to handle non-linear data relationships makes it particularly suitable for complex fault pattern recognition in motor signatures. Ensemble learning methods have also gained significant attention due to their robustness and improved generalization capabilities. Drakaki et al. [10] and Bechiri et al. (not in your references, so citation omitted) showed that optimized ensemble techniques such as Random Forest, Extra Trees, and Decision Trees outperform individual classifiers, especially under noisy industrial environments. Nikfar et al. [11] proposed a two-phase ML approach for predictive maintenance of low-voltage industrial motors, further validating that ensemble and hybrid learning architectures can achieve superior diagnostic performance under real-world operational variability.

Despite significant advancements in predictive maintenance techniques for induction motors, several challenges continue to hinder their practical implementation. One of the major issues is multi-fault classification, as most existing studies primarily focus on detecting single faults, whereas industrial systems often involve multiple concurrent faults that require simultaneous classification capabilities [17], [18]. Another challenge lies in variable operating conditions, where model performance tends to degrade under fluctuating loads, supply voltage variations, and changing environmental factors [16], [19]. Additionally, scalability and deployment remain pressing concerns, with limited research addressing large-scale implementation aspects such as sensor network management, data synchronization, and integration with existing industrial infrastructures [9], [12]. Furthermore, real-time processing requirements pose difficulties, as many existing systems struggle to meet the low-latency

demands necessary for timely fault detection and response in critical applications [14], [15]. The issue of data quality and availability also persists, since industrial environments often produce noisy, incomplete, or imbalanced datasets, making it challenging to develop accurate supervised learning models [5], [7]. Lastly, the economic feasibility of predictive maintenance solutions is not well explored, with few studies conducting cost-benefit analyses or optimization strategies to ensure favorable return on investment [1], [6], [20]. Together, these challenges highlight the need for more comprehensive, adaptive, and economically viable predictive maintenance frameworks for induction motors. The literature review reveals that while significant progress has been made in individual aspects of induction motor predictive maintenance, there remains a need for integrated solutions that address multiple fault types, operate effectively under variable conditions, and provide scalable and cost-efficient deployment options for diverse industrial applications.

III. PROPOSED SYSTEM

The Several studies have demonstrated the effectiveness of machine learning in fault analysis and predictive maintenance of induction motors [13]. In this work, a predictive maintenance framework is developed to detect faults in three-phase squirrel cage induction motors using machine learning. The system utilizes the eXtreme Gradient Boosting (XGBoost) algorithm to classify the motor's operating condition as either healthy or faulty, based on real-time sensor inputs. The primary faults considered include broken rotor bars, bearing defects, and short circuit faults [8]. Sensor data including three-phase current, tri-axial vibration, and axial flux were collected from a 5 HP induction motor under various controlled fault conditions at Balaji Motors Company. The data was labeled according to fault types and used to train the machine learning model. A motor health monitoring dashboard is integrated with the backend to enable real-time visualization of the motor's operational parameters. The backend, developed using FastAPI, reads data stored in CSV format and delivers it to a frontend built using HTML, CSS, JavaScript, and Chart.js. The dashboard updates live every 5 seconds and includes charts for current, vibration, and flux, as well as a color-coded fault classification indicator. This system provides early fault detection, reduces the risk of unplanned downtime, and supports efficient maintenance planning. The modular architecture also ensures scalability for future integration with IoT-based monitoring or cloud databases [9][10].

IV. METHODOLOGY

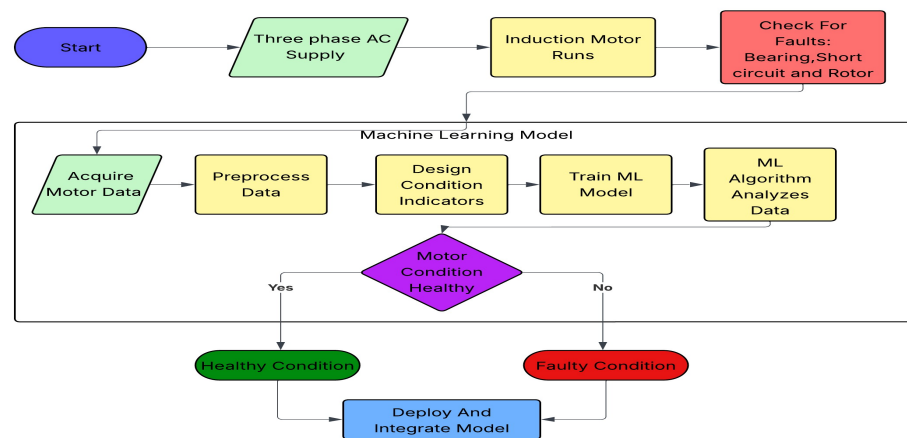


Figure 1. Flowchart of the Methodology

The methodology of this work focuses on building a predictive fault classification system for squirrel cage induction motors using real-time sensor data and machine learning. The implementation follows a structured pipeline comprising fault selection, data acquisition, preprocessing, model training, and dashboard integration. Each stage is explained in detail below

A. Selection of Fault Types

Three critical faults were selected for detection and classification:

These faults were chosen based on their high occurrence rate and impact on motor reliability:

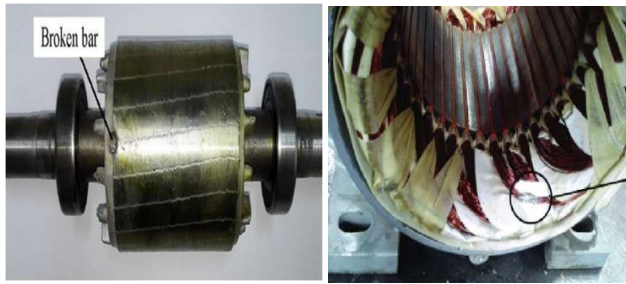


Figure 2. Broken Rotor fault Figure 3. Short Circuit Fault

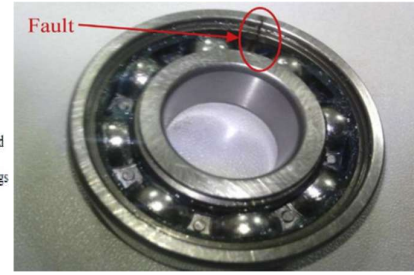


Figure 4. Bearing Fault

Broken rotor bars affect the electromagnetic torque of an induction motor, causing torque pulsations, vibrations, and potential long-term rotor damage [19]. Stator short circuits, particularly inter-turn faults, can quickly escalate into catastrophic phase-to-ground failures, often leading to sudden motor shutdown. Bearing faults, which account for over 40% of total induction motor failures [8][18], create mechanical imbalance and increased vibration, eventually causing shaft misalignment and rotor damage. All three represent early-stage faults, and timely identification enables predictive maintenance, preventing severe damage and costly downtime [8][17].

B. Data Acquisition and Feature Selection

Sensor data was collected from a 5 HP, 3-phase squirrel cage induction motor using a dedicated test setup at Balaji Motors Company. The dataset includes three-phase currents (A, B, C), vibration signals along X, Y, and Z axes, and axial flux measurements in X, Y, and Z directions. Three-phase currents help identify electrical anomalies such as phase imbalance, overload, and short circuits, with stator faults causing sharp current spikes; advanced current monitoring strategies based on observer models can improve detection accuracy [20]. Vibration data captures bearing faults and broken rotor bars, which manifest as distinct patterns detectable via Fast Fourier Transform (FFT) or time-domain analysis [7][9]. Axial flux measurements reflect rotor faults by showing distortions in the magnetic field symmetry [18]. The dataset comprises 388,541 records, with 271,566 representing healthy operation and 116,975 representing faulty conditions, including broken rotor, bearing faults, and short circuits. Each row is labeled with binary indicators for healthy operation, broken rotor fault, bearing fault, and short circuit fault, providing a foundation for supervised learning.

K1	bearing fault														
#	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Timestamp	Current-A	Current-B	Current-C	X_axis	Y_axis	Z_axis	X	Y	Z	bearing fault	broken rotor fault	healthy	short circuit fault	
2	0:00:02	2.4908	2.1844	2.7582	0.9985	-0.5063	1.7183	0.0527	1.0093	2.0234	0	0	1	0	
3	0:00:04	2.4908	2.1844	2.7582	-0.1973	0.3306	2.2964	0.9102	0.416	2.2476	0	0	1	0	
4	0:00:06	2.4908	2.1844	2.7582	-0.2944	-0.3989	1.8164	0.7651	-0.2148	1.7974	0	0	1	0	
5	0:00:08	2.4908	2.1844	2.7582	-0.3647	0.5757	2.0659	0.2212	0.0425	2.1108	0	0	1	0	
6	0:00:10	2.4908	2.1844	2.7582	0.0479	0.0688	1.9087	0.2651	1.5312	1.9751	0	0	1	0	
7	0:00:12	2.4908	2.1844	2.7582	0.1172	-0.4927	1.9727	0.1294	0.6445	1.7954	0	0	1	0	
8	0:00:14	2.4908	2.1844	2.7582	0.3491	0.3188	2.3604	-1.0312	-0.4507	2.7866	0	0	1	0	
9	0:00:16	2.4908	2.1844	2.7582	0.7393	0.6919	2.2065	-0.2295	-1.2095	1.417	0	0	1	0	
10	0:00:18	2.4908	2.1844	2.7582	0.7168	-0.313	1.8823	0.4844	0.8398	1.8989	0	0	1	0	
11	0:00:20	2.4908	2.1844	2.7582	0.3306	-0.3042	1.9932	1.0742	-0.1406	2.4956	0	0	1	0	
12	0:00:22	2.4908	2.1844	2.7582	0.6001	0.0801	2.4663	0.3057	-0.251	1.7749	0	0	1	0	
13	0:00:24	2.4908	2.1844	2.7582	0.9077	0.145	2.1255	0.2461	0.395	2.2417	0	0	1	0	
14	0:00:26	2.4432	2.2015	2.7802	-0.2881	0.5337	2.2227	0.3179	0.3247	1.7573	0	0	1	0	
15	0:00:28	2.4432	2.2015	2.7802	-0.3862	-0.4404	2.0918	-0.1309	0.7827	2.0049	0	0	1	0	
16	0:00:30	2.4432	2.2015	2.7802	0.019	0.0225	2.2407	-0.5679	-1.3774	2.0771	0	0	1	0	
17	0:00:32	2.4432	2.2015	2.7802	-0.0635	0.7192	2.0513	-0.1401	0.8198	1.8018	0	0	1	0	
18	0:00:34	2.4432	2.2015	2.7802	-0.1123	-0.9771	1.8848	1.0049	0.272	2.1724	0	0	1	0	
19	0:00:36	2.4432	2.2015	2.7802	0.1821	1.3052	2.0488	0.8569	-0.3018	1.9375	0	0	1	0	
20	0:00:38	2.4432	2.2015	2.7802	0.5	0.6064	1.8906	0.2622	-0.4805	1.939	0	0	1	0	
21	0:00:40	2.4432	2.2015	2.7802	0.4087	-0.751	1.9658	0.0024	1.1777	2.1333	0	0	1	0	
22	0:00:42	2.4432	2.2015	2.7802	0.521	0.0864	1.856	0.2227	0.2241	1.7407	0	0	1	0	
23	0:00:44	2.4432	2.2015	2.7802	0.7646	-0.7705	1.6548	-0.1802	0.9795	2.1558	0	0	1	0	

Figure 5. Data Set

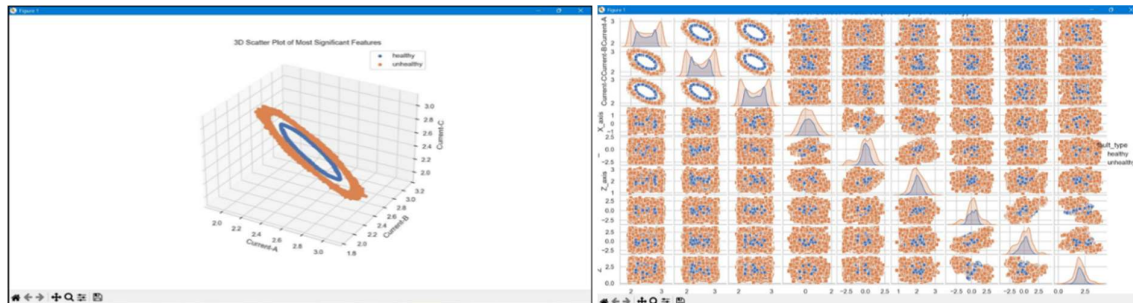


Figure 6 Top features

Figure 7 Pair Plot

C. Data Preprocessing

To ensure robust model training, the collected data underwent a systematic cleaning and normalization process. Initially, noise and outliers were removed to enhance data quality and reliability. Missing values, if present, were handled appropriately to maintain dataset completeness. Feature scaling was then performed using the StandardScaler technique to normalize the features across different units, ensuring uniformity in data representation. The dataset was subsequently divided into training and testing subsets to evaluate model performance effectively. Furthermore, the class distribution was analyzed to identify any imbalance, and stratified sampling was employed to mitigate bias toward majority classes, thereby improving the overall fairness and accuracy of the model [11].

D. Machine Learning Model Training (XGBOOST)

The XGBoost algorithm was chosen for this study due to its exceptional performance in classification tasks, ability to model complex nonlinear relationships, and built-in regularization techniques (L1 and L2) that help reduce overfitting [1]. Additionally, its capability to rank feature importance enhances model interpretability and explainability. The model was trained using selected sensor features to accurately classify different fault types in the induction motor. XGBoost functions by constructing an ensemble of decision trees, where each successive tree corrects the errors of its predecessors. It minimizes a specified loss function—binary logistic in this case—and employs gradient descent to optimize overall performance [1]. Model evaluation was conducted using standard performance metrics, including accuracy, precision, recall, and F1-score, all of which achieved a perfect score of 1.00 on the test data, indicating excellent generalization to unseen samples. Moreover, multi-stage machine learning approaches have been effectively utilized in predictive maintenance of low-voltage motors, demonstrating strong adaptability and robustness across varying operational conditions [11].

E. Real-Time Dashboard Integration

To enable real-time monitoring, a web-based dashboard was developed featuring a FastAPI backend that handles API requests and serves chunked sensor data from CSV files. The frontend, built using HTML/CSS and Chart.js, provides live visualization of parameters such as current, vibration, and flux. The dashboard includes features like fault-specific colour codes (e.g., red for bearing fault and green for healthy conditions), and displays statistical insights such as minimum, maximum, and average values for each parameter. With updates occurring every five seconds, the system ensures near-real-time monitoring, allowing maintenance personnel to interpret fault trends visually, continuously track motor behaviour, and respond promptly to anomalies.

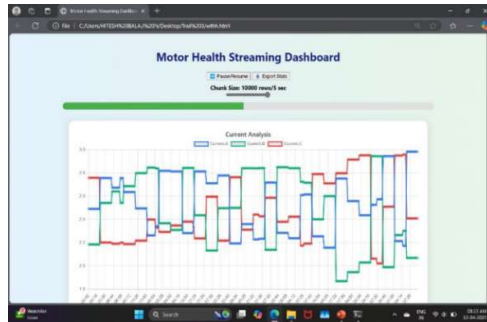


Figure 8 Motor Health Dashboard

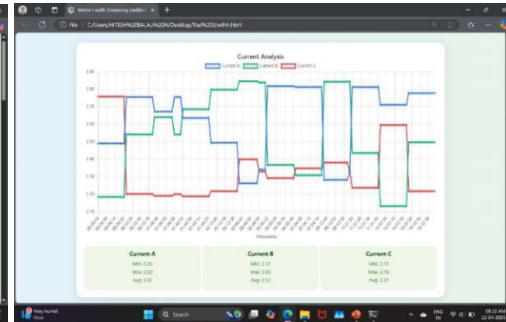


Figure 9. Current Analysis

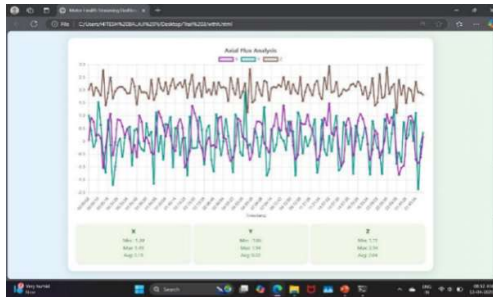


Figure 10 Axial Flux Analysis

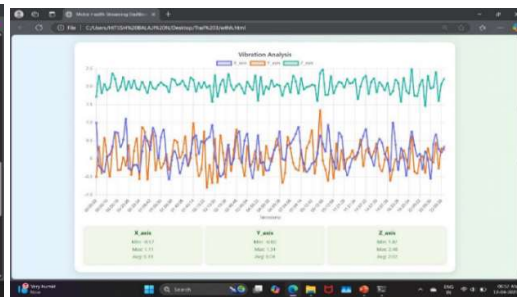


Figure 11. Vibrational Analysis

F. Why this Method Works

The combination of multi-parameter sensing and machine learning ensures highly accurate fault detection in induction motors. Vibration signals are particularly sensitive to mechanical defects such as bearing damage, while current signals capture variations in electrical behaviour under faults like short circuits. Similarly, axial flux measurements reflect changes in electromagnetic symmetry, providing valuable insights into rotor-related issues. The XGBoost algorithm effectively processes these multi-modal inputs, identifying complex interdependencies among parameters and delivering precise fault classifications. Collectively, this integrated methodology enables a proactive, data-driven maintenance strategy, making it well-suited for industrial deployment within the framework of Industry 4.0

V. RESULTS AND DISCUSSION

The proposed system was validated using real-time sensor data collected from a 5 HP squirrel cage induction motor operating under various conditions, including healthy operation and induced faults such as bearing failure, broken rotor bar, and stator short circuit. The dataset comprised approximately 388,542 samples, exhibiting a moderate class imbalance with 271,566 samples representing faulty conditions and 116,975 representing healthy states. After pre-processing, the data was divided into training and testing subsets. The XGBoost classifier was trained using key features such as phase currents, vibration signals (X, Y, and Z axes), and axial flux measurements. Upon evaluation, the model achieved outstanding results—100% accuracy, with precision, recall, and F1-score all equal to 1.00 for both healthy and faulty classes—demonstrating its ability to accurately distinguish between different fault types and healthy operating conditions without any misclassification. In addition to the machine learning model, a real-time motor health monitoring dashboard was developed to visualize live sensor data and fault statuses. The dashboard incorporated time-series plots for current, vibration, and flux signals, along with real-time alerts featuring color-coded indicators for different fault types. It also provided dynamic summary statistics, including minimum, maximum, and mean values for each monitored parameter, and supported chunked data loading with pause/resume functionality. The seamless integration of the classifier with the visualization dashboard enabled continuous motor health tracking and intuitive fault interpretation, making the system both efficient and user-friendly for maintenance team.

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===== RESTART: C:\Users\HITESH BALAJI N\Desktop\SAP\v_xgpy =====
Dataset columns: ['Current-A', 'Current-B', 'Current-C', 'X_axis', 'Y_axis', 'Z_axis', 'X', 'Y', 'Z', 'bearing fault', 'broken rotor fault', 'healthy', 'short circuit fault']
Sensor features being used: ['Current-A', 'Current-B', 'Current-C', 'X_axis', 'Y_axis', 'Z_axis', 'X', 'Y', 'Z']
Fault label columns: ['bearing fault', 'broken rotor fault', 'healthy', 'short circuit fault']
Fault label distribution:
fault_label
1    271566
0     116975
Name: count, dtype: int64

Classification Report:
      precision    recall  f1-score   support

0       1.00      1.00      1.00     23395
1       1.00      1.00      1.00     54314

accuracy: 1.00      1.00      1.00     77709
macro avg: 1.00      1.00      1.00     77709
weighted avg: 1.00      1.00      1.00     77709

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Figure 12. Machine Learning Code Output



Figure 13 Confusion Matrix

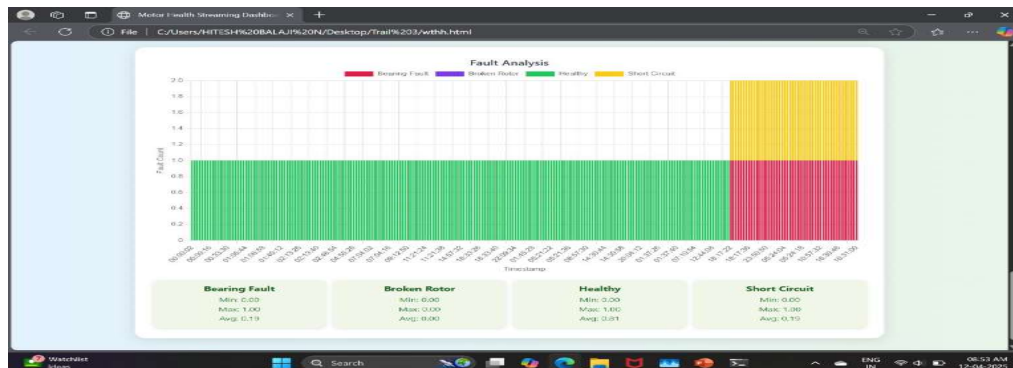


Figure 14. Predicted Output

VI. CONCLUSIONS

This work presents a complete predictive maintenance framework for three-phase squirrel cage induction motors by integrating machine learning-based fault classification with real-time data visualization. The use of the XGBoost algorithm enabled highly accurate classification of motor faults such as bearing issues, rotor damage, and short circuits, based on current, vibration, and axial flux measurements. The development of a real-time motor health dashboard further enhanced the practical utility of the system. It provided an interactive platform for continuous monitoring, enabling early fault detection and proactive maintenance actions. The system's modular design and efficient architecture allow for future integration with IoT devices and cloud-based monitoring systems. The results demonstrate the effectiveness of combining machine learning with real-time visualization for industrial predictive maintenance. This approach not only improves fault detection accuracy but also reduces unplanned downtime and maintenance costs, supporting the transition toward smarter, more reliable Industry 4.0 systems [10]. In future we will try to do advanced diagnostic techniques such as online SFRA to evaluate the reliability of induction motors under varying load conditions [14].

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REFERENCES

- [1] Lakshmi, J. V. N. (2018). Application of Python-based machine learning models for analysing data in performance evaluation tasks. Presented at the IEEE Business Informatics Conference, July 11–14.
- [2] Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. P., Bastos, J. P., & Alcalá, S. G. S. (2020). Review of machine learning strategies applied in predictive maintenance systems. *Computers & Industrial Engineering*.
- [3] Drakaki, M., Karnavas, Y. L., Tzionas, P., & Chasiotis, I. D. (2021). Industry 4.0 trends in predictive maintenance of induction motors: Recent innovations and approaches. *IEEE Transactions on Industrial Electronics*.
- [4] Yatsugi, K., Pandarakone, S. E., & Mizuno, Y. (2023). Detection of three fault types in induction motors using stator current characteristics and SVM classification. *IEEE Industrial Applications Journal*.
- [5] Gawde, S., Patil, S., Kumar, S., Kamat, P., Kotecha, K., & Alfarhood, S. (2024). Enhancing predictive maintenance transparency with interpretable AI models such as LIME, SHAP, PDP, and ICE. *Engineering Applications of Artificial Intelligence*.
- [6] Jezzini, A., Ayache, M., Elkhansa, L., Makki, B., & Zein, M. (2013). A comparative study on maintenance strategies to reduce faults in biomedical equipment. In *Proceedings of the 2nd International Conference on Advances in Biomedical Engineering*, Tripoli, Lebanon, September 11–13.
- [7] Amihai, I., Gitzel, R., Kotriwala, A. M., Pareschi, D., Subbiah, S., & Sosale, G. (2018). Case analysis of machine learning models using vibration signals for predicting asset health. Presented at the IEEE Conference on Business Informatics, Vienna, Austria, July 11–14.
- [8] Siddiqui, K. M., Sahay, K., & Giri, V. K. (2014). Health monitoring and fault diagnosis in induction motor-a review. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 3(1), 6549-656
- [9] Korkua, S., Jain, H., Lee, W. J., & Kwan, C. (2010, May). Wireless health monitoring system for vibration detection of induction motors. In *2010 IEEE industrial and commercial power systems technical conference-conference record* (pp. 1-6). IEEE.
- [10] Drakaki, M., Karnavas, Y. L., Tzionas, P., & Chasiotis, I. D. (2021). Recent developments towards industry 4.0 oriented predictive maintenance in induction motors. *Procedia computer science*, 180, 943-949.
- [11] Nikfar, M., Bitencourt, J., & Mykoniatis, K. (2022). A two-phase machine learning approach for predictive maintenance of low voltage industrial motors. *Procedia Computer Science*, 200, 111-120.
- [12] Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability*, 12(19), 8211.
- [13] Kavana, V., & Neethi, M. (2018, December). Fault analysis and predictive maintenance of induction motor using machine learning. In *2018 International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT)* (pp. 963-966). IEEE
- [14] Bucci, G., Ciancetta, F., Fioravanti, A., Fiorucci, E., Mari, S., & Silvestri, A. (2023). Online sfra for reliability of power systems: Characterization of a batch of healthy and damaged induction motors for predictive maintenance. *Sensors*, 23(5), 2583
- [15] Sunal, C. E., Dyo, V., & Velisavljevic, V. (2022). Review of machine learning based fault detection for centrifugal pump induction motors. *IEEE access*, 10, 71344-71355.
- [16] Juarez-Trujillo, I. A., Aguayo-Alquicira, J., De León-Aldaco, S., & Velasquez-Aguilar, J. G. (2025). Fault analysis in induction motors through signal acquisition with Hilbert transform and FPGA. *IEEE Embedded Systems Letters*.

- [17] Sharma, N. R., Bhalja, B. R., & Malik, O. P. (2025). Machine learning-based severity assessment and incipient turn-to-turn fault detection in induction motors. *IEEE Transactions on Energy Conversion*, 40(1), 557–567.
- [18] Lv, Y., & Wang, S. (2025). Degradation parameters estimation of induction motors using hybrid-driven method. *IEEE Transactions on Instrumentation and Measurement*, 74, Article 3513515. DOI: 10.1109/TIM.2025.3545526
- [19] Chen, X., & Feng, Z. (2025). Quantitative characteristics of the rotary machinery fault signatures in induction motor stator current: Modeling and evaluation. *IEEE Transactions on Power Electronics*, 40(7), 9889–9897.
- [20] Caramori, G., Oliani, I., Lunardi, A. S., & Sguarezi Filho, A. J. (2025). Robust predictive current control using Luenberger observer applied to an induction motor for agricultural electrical traction. *IEEE Access*, 13, 132293–132302.