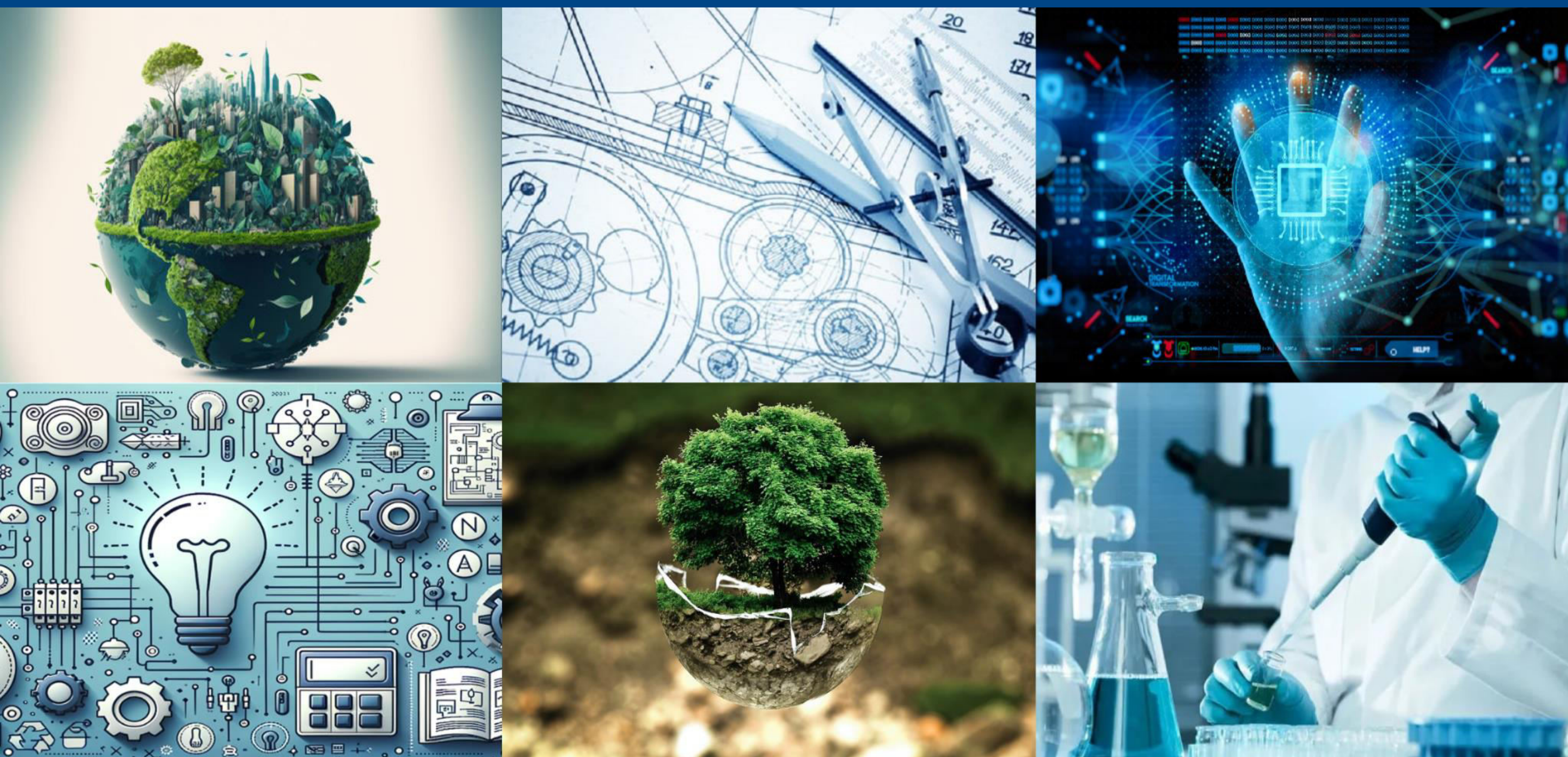
ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 12, December 2025

www.ijmrset.com   ijmrset@gmail.com   +91 6381 907 438   +91 63819 07438

© 2025 IJMRSET | Volume 8, Issue 12, December 2025| DOI:10.15680/IJMRSET.2025.0812034

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Leveraging ML Modelling for Predictive Motor Health Diagnostics for Proactive Operational Resilience

Vikas K S[1], Dr Puja Shashi[2]

PG Student, Dept. of MCA, City Engineering College, Bangaluru, India[1]

Professor & HOD, Dept. of MCA, City Engineering College, Bangaluru, India[2]

ABSTRACT: Industrial motors are most critical components in various applications, and Their unanticipated failure may result in significant financial losses and operational disruptions. Traditional maintenance strategies, such as reactive and preventive maintenance, often fail to optimize motor performance effectively. This project proposes a predictive maintenance approach leveraging machine learning algorithms to analyse motor sensor data and forecast potential failures. The system will collect real-time sensor data, process it using machine learning models, and provide insights through a user-friendly Flask web application. By implementing predictive analytics, businesses can decrease unplanned downtime, decrease maintenance costs, and enhance operational efficiency.

KEYWORD: ML, Random Forest, XG Boost, LSTM, Real-Time Alerts

I. INTRODUCTION

Industrial motors are essential components in many applications, and unexpected motor failures can result in substantial financial losses and operational disruptions. Traditionally, motor maintenance strategies have relied on reactive measures repairing issues after they occur or preventive methods based on scheduled, time-based inspections. However, these conventional methods frequently do not optimize motor performance effectively.

To address these challenges and improve operational efficiency, this project proposes adopting a predictive maintenance strategy. This innovative system applies machine learning algorithms to analyse real-time sensor data gathered from motors, enabling the early detection of potential faults and anomalies.

By implementing the Leveraging ML Modelling for Predictive Motor Health Diagnostics for Proactive Operational Resilience system, organizations can obtain value able insights through predictive analytics. This facilitates proactive maintenance, aiming to reduce unplanned downtime, lower overall maintenance costs, and significantly improve operational resilience by ensuring the continuous and reliable operation of critical industrial assets. The system also offers intuitive visualization and monitoring via a Flask web interface.

II. LITERATURE SURVEY

1. Title: Vibration-Based Anomaly Detection for Induction Motors Using Machine Learning
Authors: Ullah et al. (2024)
Abstract: This study presents a machine learning-based framework for detecting anomalies in induction motors using vibration signals. Statistical and frequency-domain features are extracted and classified using ensemble learning models. The results show improved fault detection accuracy and early warning capability, supporting predictive maintenance and operational reliability.

2.Title: IoT-Enabled Predictive Maintenance Framework for Electric Motor Health Monitoring
Authors: Elkateb et al. (2024)

© 2025 IJMRSET | Volume 8, Issue 12, December 2025| DOI:10.15680/IJMRSET.2025.0812034

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Abstract: The authors propose an IoT-based predictive maintenance system integrating machine learning models for continuous motor health monitoring. Sensor data is processed at the edge to reduce latency and improve real-time fault detection. The framework enhances system availability and supports proactive operational resilience.

3. Title: Fault Diagnosis of Induction Motors Using Deep Learning on Frequency Spectrum Images
Authors: Barrera-Llanga et al. (2025)
Abstract: This paper introduces a deep learning-based fault diagnosis approach using FFT-based spectrum images of motor signals. Convolutional neural networks are employed to automatically learn discriminative features. The proposed method outperforms traditional machine learning techniques in classification accuracy and robustness.

4. Title: Hybrid Deep Learning Framework for Real-Time Induction Motor Fault Diagnosis
Authors: Jakaria et al. (2025)
Abstract: A hybrid CNN–LSTM model is proposed for real-time fault diagnosis of induction motors under varying operating conditions. The model captures both spatial and temporal characteristics of sensor data. Experimental results demonstrate high accuracy and suitability for online industrial applications.

5.Title: Remaining Useful Life Prediction of Induction Motor Bearings Using Machine Learning
Authors: Zulkifli et al. (2025)
Abstract: This research focuses on predicting the remaining useful life of induction motor bearings using machine learning regression models. Current signature analysis is used to construct health indicators for degradation assessment. The approach enables proactive maintenance scheduling and reduces unplanned downtime.

6.Title: Digital Twin-Based Predictive Maintenance for Induction Motors
Authors: Phutane et al. (2025)
Abstract: The authors present a digital twin framework integrated with machine learning models for predictive motor health diagnostics. Real-time sensor data is synchronized with virtual simulations to predict fault progression. The system improves decision-making and enhances operational resilience in industrial environments.

7. Title: Transformer-Based Motor Fault Diagnosis Using Multi-Sensor Data
Authors: Huang et al. (2025)
Abstract: This study explores transformer-based deep learning models for fault diagnosis in electric motors using multi-sensor data. The approach effectively captures long-range dependencies and nonlinear patterns. Results indicate superior generalization performance across varying load and speed conditions.

III. METHODOLOGY

Existing Problem
The current approach to motor maintenance primarily follows three strategies:
1. Reactive Maintenance: Repairs are performed only after a failure occurs, leading to costly downtime.
2. Preventive Maintenance: Maintenance schedules are based on predefined time intervals rather than real-time motor health, potentially resulting in unnecessary servicing.
3. Manual Monitoring: Technicians periodically inspect motors, which is time-consuming and prone to human error.

Disadvantage of the existing system include:
• High maintenance costs due to frequent inspections and unnecessary servicing.
• Unplanned downtime leading to production losses.
• Inefficient utilization of maintenance resources.

Proposed solution
The proposed solution features an ML-powered web platform on Flask, leveraging Random Forest and Gradient Boosting models for motor health forecasting. It processes past and live sensor data on vibrations, current, and heat to

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

accurately predict faults and lifespan. Sophisticated data cleaning fills voids and sharpens input quality. A clean dashboard displays motor status (healthy, at-risk, failed) with simple visuals and alerts. This setup drives timely fixes, smarter choices, and robust industrial uptime.

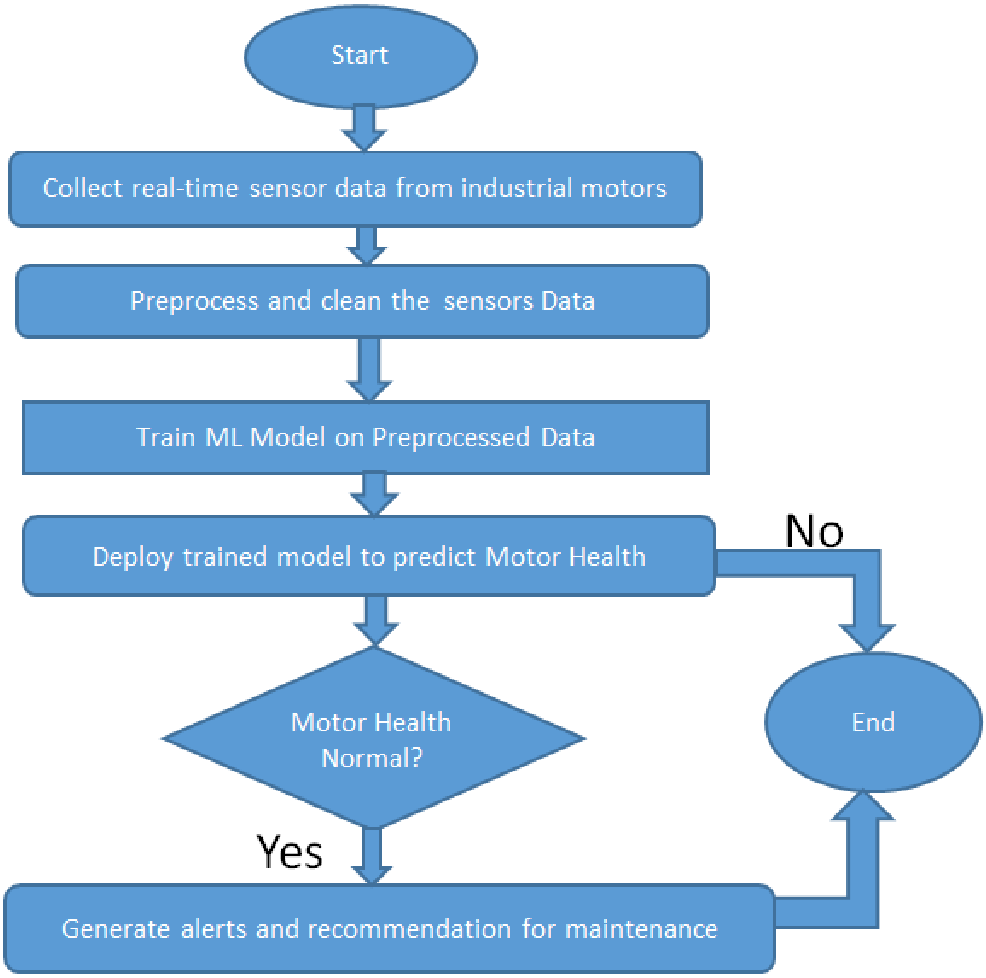


Fig 1: Proposed Methodology of Motor Health Diagnostics

The proposed methodology for motor health diagnostics follows a module pipeline:

1.Data Collection Module: Real-time ingestion of motor sensor data (temperature, vibration, current, voltage) at 1-10 Hz sampling rate using IoT gateways and MQTT protocol.
2. Data Preprocessing Module: Cleaning and normalization using Pandas and scikit-learn handling missing values via forward-fill, removing outliers using IQR/Z-score methods, and applying MinMax scaling to range.
3.Feature Engineering Module: Extraction of time-domain features (RMS, Peak, Skewness, Kurtosis), frequency-domain features (FFT, Spectral Centroid, Energy), and statistical features using SciPy, and Pandas. This converts raw sensor signals into 20-30 meaningful features for model training.
4.Train-Test Split: Chronological 70-15-15 split maintaining temporal order (critical for time-series data) to prevent data leakage.
5.Model Training Module: Implementation of multiple algorithms—SVM (baseline), Random Forest, XG Boost, LSTM, and CNN-LSTM—trained on historical motor sensor data to learn fault patterns.

6. Model Evaluation Module: Performance assessment using Accuracy, Precision, Recall, F1-Score, and ROC-AUC metrics on test data.
7. Hyper parameter Tuning: Grid search with cross-validation to optimize model parameters and select the best-performing architecture.
8. Model Deployment: Serialization and containerization of the best model for production readiness.
9. Real-Time Prediction & Inference: Live deployment of the trained model on incoming sensor streams to classify motor health as Normal/Warning/Fault with confidence scores.
10. Flask Web Application & Dashboard: Interactive web interface displaying real-time sensor data, motor health status, prediction confidence, historical trends, and alert logs.
11. Alert & Notification System: Generation of alerts (Normal/Warning/Fault) with actionable recommendations sent via email, SMS, and dashboard notifications.

This end-to-end pipeline enables proactive motor maintenance by detecting degradation before Catastrophic failure occurs.

IV. SYSTEM DESIGN

The platform is structured as a web-driven solution for forecasting motor condition via Flask and ML techniques. It comprises four key elements: data acquisition, refinement stage, forecasting core, and visualization frontend. Sensor readings—including vibrations, electrical current, heat levels, and rotational force from motors are gathered live and archived in sturdy storage for evaluation. The preparation unit filters out irregularities, fills data gaps, and crafts predictive variables for defect spotting. The ML core deploys proven algorithms such as Random Forest and Gradient Boosting to assess motor status, predict breakdowns, and project operational lifespan for timely safeguards. The Flask frontend enables effortless user engagement, displaying vital stats, fault warnings, and forecasts through a clear dashboard. This layered setup facilitates simple enhancements, expansion, and dependable health checks to avert disruptions in essential systems.

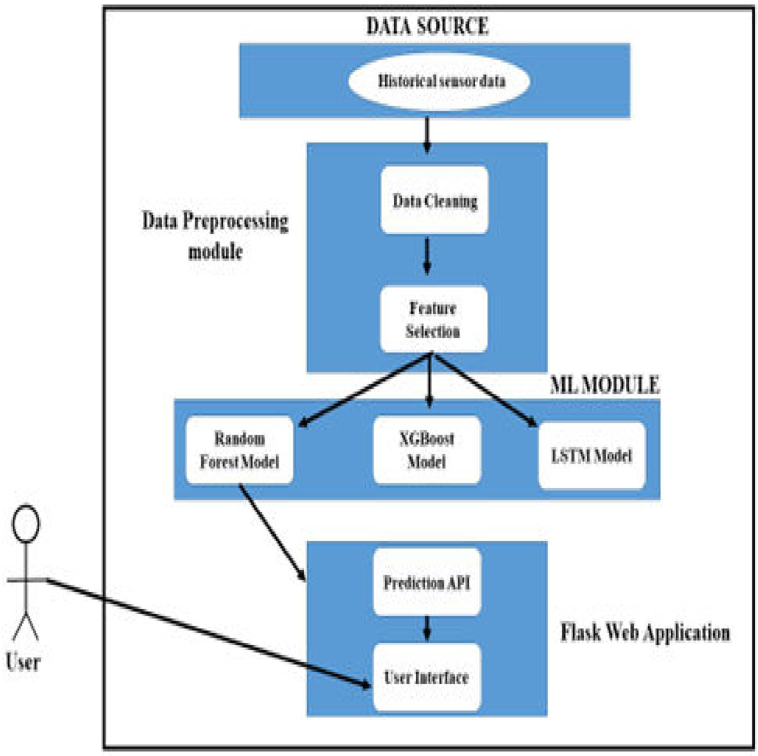


Fig 2: System Design Motor Health Diagnostics

© 2025 IJMRSET | Volume 8, Issue 12, December 2025| DOI:10.15680/IJMRSET.2025.0812034

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

V. SYSTEM ARCHITECTURE & DESIGN

Reliable motor health predictions and proactive maintenance are enabled by the system's multi-layered architecture. Historical motor sensor data (temperature, vibration, current, voltage) is gathered from industrial datasets and routed to the data preparation layer for cleansing, outlier removal, missing value imputation, and normalization. Post-processing, the machine learning prediction layer applies XG Boost, Random Forest, LSTM, and CNN-LSTM algorithms to detect fault patterns and generate precise health classifications (Normal/Warning/Fault).

Trained models deploy via a Flask-powered backend that processes real-time sensor streams and delivers instant diagnostics with confidence scores. The presentation layer, built with HTML, CSS, JavaScript, and Bootstrap, visualizes motor status, trend charts, prediction histories, and alert notifications. Its modular structure supports scalability, low-latency inference, superior fault detection accuracy, and operational resilience for industrial equipment.

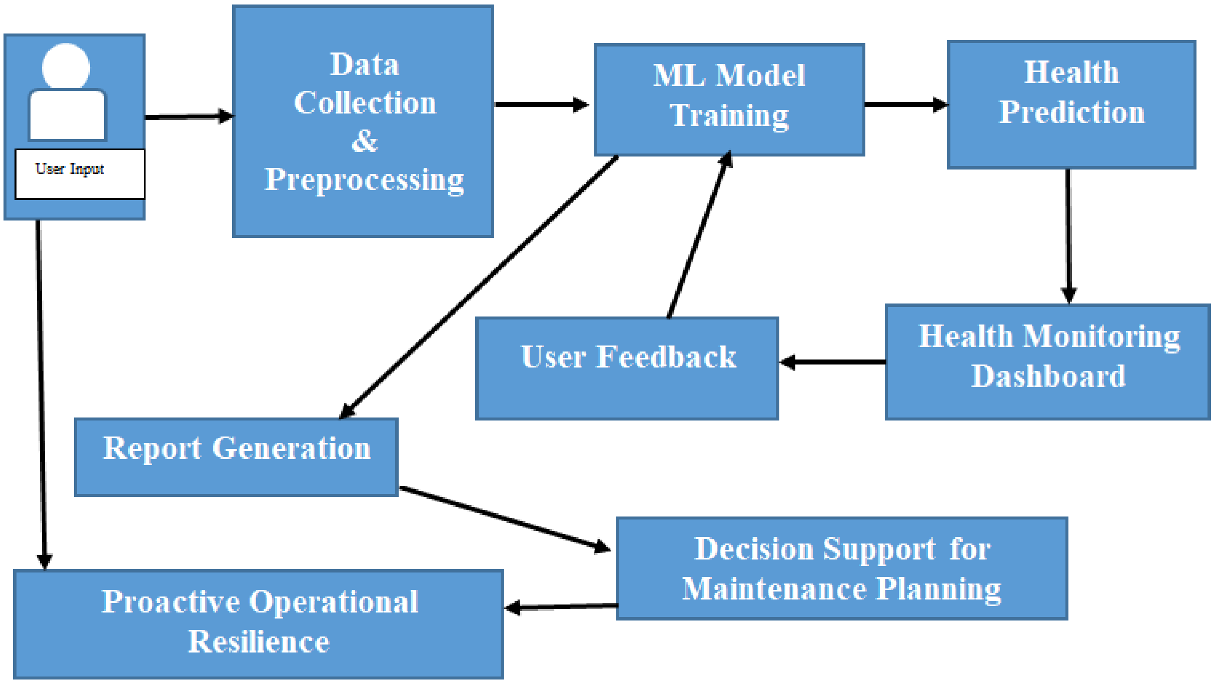


Fig 3. System Architecture of Motor Health Diagnostics

VI. IMPLEMENTATION

The project employs Python, machine learning models, and the Flask framework for deployment. Sensor data on motor vibrations, current, temperature, and torque is first loaded into the system. It undergoes cleaning to eliminate outliers and gaps, ensuring higher prediction precision. Fault detection and health scores are then computed by training Random Forest and Gradient Boosting on the refined data. The top model is chosen and preserved for reuse. Lastly, this model powers a Flask web app, offering an intuitive interface where users access predicted motor conditions and alerts effortlessly.

© 2025 IJMRSET | Volume 8, Issue 12, December 2025| DOI:10.15680/IJMRSET.2025.0812034

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

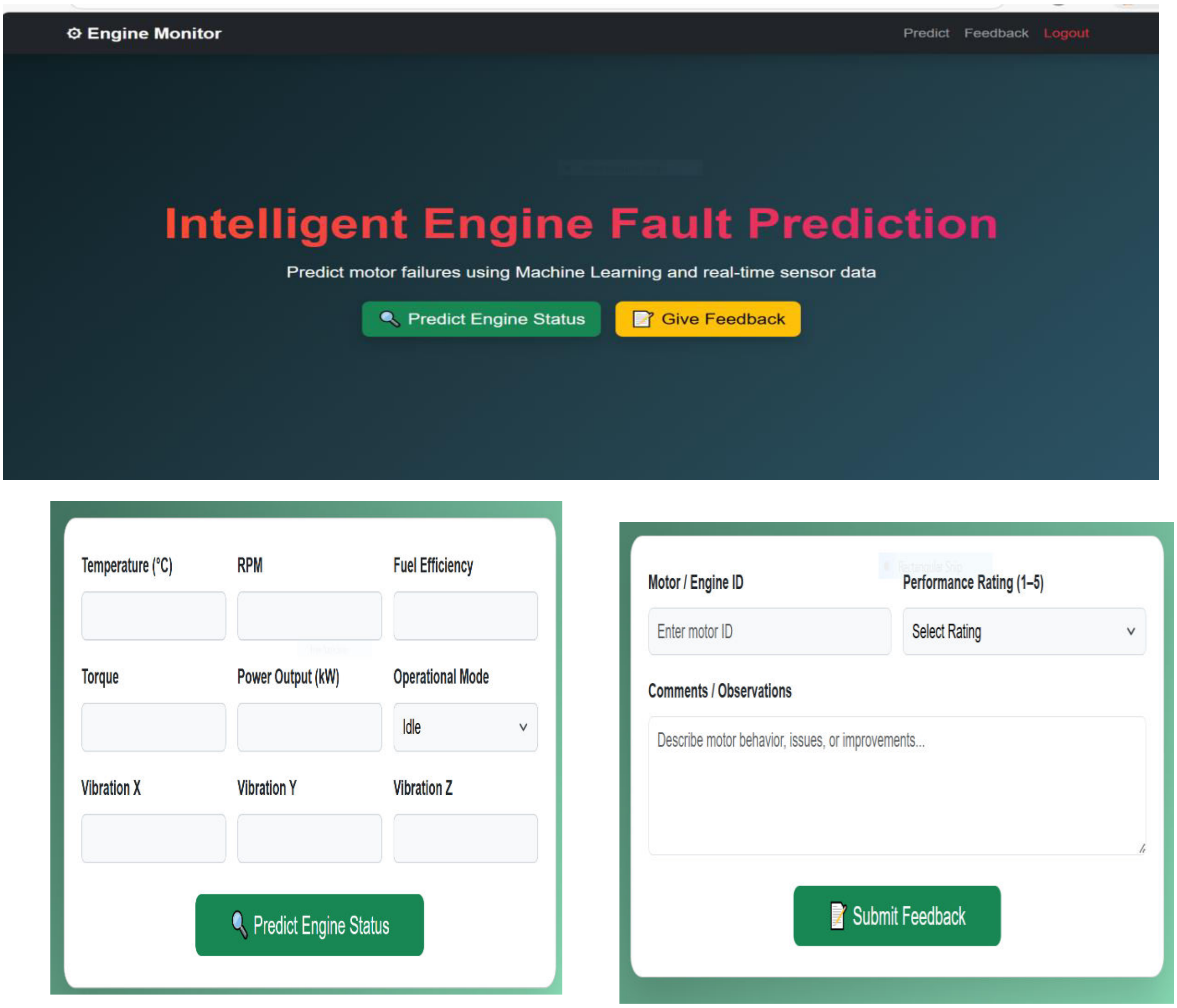


Fig 4. Snapshot of Predictive Motor Health Diagnostics

VII. RESULTS & DISCUSSION

The developed Leveraging ML Modelling for Predictive Motor Health Diagnostics for Proactive Operational Resilience system was evaluated by providing varied sensor inputs, user details, and alert mechanism to user. It consistently processed the data, matched it with the internal knowledge base, and generated meaningful recommendations within seconds. For mild conditions, the system suggested industrial-based motor health care, whereas urgent or high-risk cases to motor triggered alerts message for user. The built-in severity scoring helped users quickly understand the seriousness of their motor health status.

Test outcomes showed that the of machine learning processing enabled accurate interpretation of user-entered collected sensor data. The interface was simple to operate, and the dashboard presented results in a clear, well-organized manner. The use of lightweight and optimized technologies allowed smooth operation even on devices with limited resources, ensuring accessibility in different environments.

System performance relies heavily on the accuracy and detail of motor condition inputs from users or sensors. Poorly captured data like erratic vibration levels, absent temperature logs, or variable load reading can sometimes yield general rather than targeted predictions. Future improvements should prioritize broader datasets covering diverse conditions, failure modes, and uncommon breakdowns. Strengthening pre-processing steps, feature derivation, and

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

model handling of time-series sensor patterns will boost forecast reliability and detail. The system meets its goal of rapid, precise, and accessible motor diagnostics. Early anomaly spotting supports preventive actions, fortifying operations against disruptions. Its flexible structure fits varied industries, from major factories to smaller setups.

VIII. CONCLUSION

Development of an ML-powered predictive maintenance tool for electric motors offers a smart upgrade over outdated maintenance methods. It uses live data from sensors tracking vibration, heat, power draw, and electrical levels to spot motor issues early and forecast breakdowns before they halt production. Moving from fix-after-failure or scheduled checks to analytics-led predictions cuts unexpected outages, trims expenses, and boosts system dependability.

Adding a Flask web dashboard makes it even more effective, with easy-to-use charts, instant oversight, and automatic notifications tailored for factory settings. Key components—like cleaning input data, building ML models, and ongoing forecasting—deliver precise analysis and smart choices. In essence, the project highlights how fusing sensors, data processing, and AI can craft a sturdy upkeep system. Looking ahead, upgrades like deeper neural networks, IoT links, cloud expansion, and handling multiple motors could turn it into a full-scale tool for managing industrial gear. This boosts machine uptime and fuels ongoing tech upgrades across sectors.

REFERENCES

1. **Zhao, J., et al. (2024)-**Deep learning-based fault diagnosis for rotating electrical machines: A comprehensive review.
2. **Hamani, K., et al. (2025)-**Advancements in induction motor fault diagnosis using data-driven and deep learning techniques.
3. **Barrera-Llanga, K., et al. (2025)-**Fault diagnosis of induction motors using deep learning on Fourier spectrum images.
4. **Ullah, I., et al. (2024)-**Vibration-based anomaly detection for induction motors using machine learning.
5. **Jakaria, J. M., et al. (2025)-**Hybrid deep learning framework for real-time fault diagnosis of induction motors.
6. **Huang, K., et al. (2025)-**Motor fault diagnosis using fine-tuned large models for electric vehicle motors.
7. **Elkateb, S., et al. (2024)-** IoT-enabled machine learning framework for predictive maintenance of electric motors-Journal of Industrial Information Integration.
8. **Thomas, K., et al. (2025)-**A multi-sensor dataset for fault diagnosis of three-phase induction motors.
9. **Ali, U., et al. (2025)-**Multimodal machine learning for induction motor fault diagnosis using vibration and current signals-IEEE Sensors Journal.
10. **Zulkifli, N. Z., et al. (2025)-**Remaining useful life prediction of induction motor bearings using machine learning-Machines, MDPI.
11. **Lei, Y., et al. (2023)-**Health index construction and RUL prediction for rotating machinery using deep learning-Mechanical Systems and Signal Processing.
12. **Carvalho, T. P. et al. (2023)-**Machine learning and Industry 4.0 for predictive maintenance and operational resilience- Computers & Industrial Engineering.
13. **Zhang, W.et al. (2024)-**AI-driven predictive maintenance for resilient industrial systems- IEEE Transactions on Industrial Informatics.

INNO SPACE
SJIF Scientific Journal Impact Factor

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर
NISCAIR

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

| Mobile No: +91-6381907438 | Whatsapp: +91-6381907438 | ijmrset@gmail.com |

www.ijmrset.com