



Review of Data-Driven Predictive Maintenance for Industrial Equipment Using IIoT and SCADA

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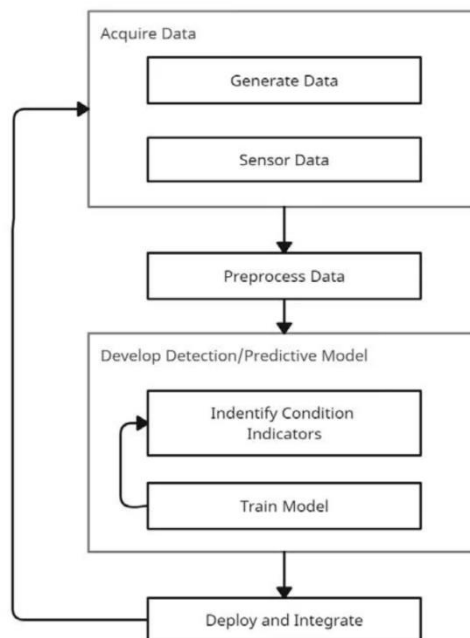
Abstract : This Review paper presents a comprehensive review of recent research on predictive maintenance using IIoT and SCADA data. The study examines various data acquisition and preprocessing techniques, machine learning and deep learning approaches, system architectures, and implementation frameworks adopted in modern industrial environments. The rapid adoption of Industry 4.0 technologies has transformed traditional maintenance practices by enabling intelligent, data-driven decision-making for industrial equipment. Predictive Maintenance (PdM) has emerged as an effective approach for minimizing unexpected equipment failures, reducing maintenance costs, and improving operational efficiency. The integration of the Industrial Internet of Things (IIoT) and Supervisory Control and Data Acquisition (SCADA) systems provides continuous monitoring and real-time acquisition of operational data from industrial assets, creating a strong foundation for predictive analytics. This review paper presents a comprehensive analysis of data-driven predictive maintenance techniques that utilize IIoT and SCADA systems for fault detection, health monitoring, remaining useful life (RUL) estimation, and maintenance scheduling. It examines the role of machine learning, deep learning, and artificial intelligence algorithms in extracting meaningful insights from sensor and process data. The paper also reviews recent advancements in edge computing, cloud-based analytics, digital twins, and explainable AI that enhance the accuracy, scalability, and reliability of predictive maintenance solutions.

IndexTerms - Predictive Maintenance, Industrial Internet of Things (IIoT), SCADA Systems, Industry 4.0, Machine Learning, Deep Learning, Artificial Intelligence, Digital Twin, Edge Computing, Remaining Useful Life (RUL), Fault Detection, Industrial Automation.

I. INTRODUCTION

The rapid evolution of Industry 4.0 has significantly transformed industrial operations by integrating advanced digital technologies such as the Industrial Internet of Things (IIoT), cloud computing, artificial intelligence, and big data analytics. Among these advancements, Predictive Maintenance (PdM) has emerged as a crucial strategy for improving equipment reliability, reducing unexpected failures, and minimizing maintenance costs. Unlike traditional reactive and preventive maintenance approaches, PdM utilizes real-time data collected from industrial equipment to predict potential faults before they lead to system breakdowns. Industrial Internet of Things (IIoT) devices, including sensors and smart monitoring systems, continuously collect operational parameters such as temperature, vibration, pressure, and energy consumption. Simultaneously, Supervisory Control and Data Acquisition (SCADA) systems provide centralized monitoring and control by gathering large volumes of process and equipment data. The integration of IIoT and SCADA data enables the development of intelligent predictive models using machine learning, deep learning, and data analytics techniques. These models facilitate early fault detection, remaining useful life estimation, and maintenance decision support.

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. Fig :1 Predictive Maintenance

Predictive Maintenance (PdM) is an advanced maintenance strategy that utilizes real-time monitoring, data analytics, and machine learning techniques to predict equipment failures before they occur. Unlike traditional reactive maintenance, which addresses failures after they happen, or preventive maintenance, which follows fixed schedules, predictive maintenance relies on the actual condition and performance of equipment to determine maintenance needs. The emergence of Industry 4.0 technologies, including the Industrial Internet of Things (IIoT), cloud computing, artificial intelligence, and Supervisory Control and Data Acquisition (SCADA) systems, has significantly enhanced the effectiveness of predictive maintenance solutions. By continuously collecting and analyzing operational data such as temperature, vibration, pressure, and energy consumption, PdM enables early fault detection, minimizes unplanned downtime, reduces maintenance costs, and improves equipment reliability and operational efficiency. As industries increasingly adopt smart manufacturing practices, predictive maintenance has become a critical component for ensuring sustainable and optimized industrial operations.

The growing adoption of connected sensors and intelligent monitoring systems has led to the generation of massive volumes of industrial data. IIoT devices facilitate continuous data collection from machines and equipment, while SCADA systems provide centralized supervision, control, and historical data storage of industrial processes. The integration of these technologies creates a robust infrastructure for predictive maintenance by enabling real-time visibility into equipment health and operational conditions. Advanced data analytics and machine learning algorithms can process this data to identify hidden patterns, detect anomalies, and estimate the remaining useful life (RUL) of critical assets.

In recent years, researchers and industrial practitioners have proposed various predictive maintenance frameworks utilizing IIoT and SCADA data. These approaches employ techniques such as deep learning, artificial neural networks, support vector machines, random forests, and hybrid models to improve fault diagnosis and prediction accuracy. Furthermore, the incorporation of cloud computing and edge computing technologies has enhanced the scalability and responsiveness of predictive maintenance systems, allowing industries to perform data processing and decision-making more efficiently.

II. LITERATURE SURVEY

Gun Gun Maulana et.al (2026) – The Author are proposed web-based SCADA system is capable of monitoring and controlling the production process with a data integrity level of 98.99%. The system is also able to calculate the effectiveness of the press machine prototype and store historical data related to machine conditions and operational activities with a storage capacity of 604,800 data points and an average storage delay of 45.50 ms. In addition, the system provides an error indicator feature integrated with the Telegram messaging application, which is capable of sending notifications with an average latency of 445.99 ms. These results indicate that the proposed SCADA-IIoT monitoring system can effectively support real-time production monitoring and improve operational awareness in stamping machine operations [01].

Nivethitha Somu et.al (2025) -Despite significant research efforts on IIoT based Predictive Maintenance (PdM) systems, challenges related to the availability of real-time machine operational data, reliable computing-deployment architecture, and implementation in real-time manufacturing environments continue to be major concerns. Hence, this work presents Intelligent PdM (IntelliPdM), an end-to-end IIoT predictive maintenance framework implemented on an edge-cloud platform that processes the real-time heterogeneous data streams (IoT sensors and cameras) and provides intelligent decisions on faults, failures, and maintenance schedules via API endpoints and interactive web user interface (dashboards, alerts/recommendations, and analytics). SMARTHome, a synthetic data generation framework was properly configured to generate synthetic data based on limited real-time operational data or open-source benchmark machine health datasets covering all possible industrial fault scenarios. Experimental validations using synthetic data, generated from real-time machine health data collected from a testbed setup at a research centre in Western Europe, along with on-site implementation in a large manufacturing unit in Singapore, effectively demonstrate the efficiency of IntelliPdM in delivering accurate and reliable fault diagnostics [02].

Md Mahfuzur Rahman Enam et.al (2025) - The integration of Supervisory Control and Data Acquisition (SCADA) systems with Industrial Internet of Things (IIoT) technologies, cloud computing, and advanced cybersecurity measures is reshaping

industrial automation. This paper presents a conceptual framework for smart SCADA systems, emphasizing the role of cloud connectivity for real-time monitoring, IIoT for enhanced data acquisition, and cybersecurity to safeguard critical infrastructure. The integration of these technologies enables improved operational efficiency, predictive maintenance, and remote accessibility, fostering more scalable and flexible industrial operations. However, challenges such as data security risks, interoperability, and system complexity remain prominent. The paper discusses theoretical models to address these challenges, proposing strategies for seamless integration and robust security mechanisms. Future trends such as edge computing, AI-driven analytics, and blockchain-based security are also explored as potential avenues for advancing SCADA systems. This paper contributes to the understanding of how these technologies converge to drive the future of industrial automation while addressing the complexities of data integrity and system resilience [03].

Zaheda Khatun et.al (2025) - The Authors are presented AI-Driven Predictive Maintenance for Motor Drives in Smart Manufacturing: A SCADA-to-Edge Deployment Study was discussed as a quantitative investigation that examined how predictive maintenance effectiveness changed when analytics were implemented using supervisory telemetry alone, high-rate edge telemetry alone, or a fused SCADA-to-edge architecture that combined contextual plant signals with waveform-level evidence. The discussion emphasized that the observed performance differences were consistent with widely reported patterns in the predictive maintenance literature on smart manufacturing and rotating machinery, where SCADA and historian data were frequently described as highly valuable for longitudinal monitoring, alarm context, and exposure tracking but structurally constrained by low sampling density, compression, and delayed event signaling relative to early fault physics. In this study, SCADA-only models demonstrated measurable predictive value near fault manifestation through correlated increases in current, temperature, alarm recurrence, and stop indicators, yet they also exhibited higher predictor redundancy and a higher nuisance-alert share under fixed alert-budget constraints, which aligned with prior industrial deployments reporting that historian-driven risk scoring could be scalable and low overhead while remaining sensitive to process variability and alarm noise [04].

Nusrat Jahan et.al (2025) - Industrial Internet of Things (IIoT) deployments are transforming asset-intensive sectors by instrumenting machines with dense sensor networks, enabling real-time monitoring and data-driven maintenance. Yet, many plants still rely on fixed-interval or reactive maintenance, which increases downtime, spare-parts waste, and safety risk. This manuscript presents an end-to-end, ML-based predictive maintenance (PdM) framework designed specifically for IIoT networks operating under realistic bandwidth, latency, and reliability constraints. The proposed architecture combines edge analytics for fast anomaly screening, fog-node feature aggregation for context fusion, and cloud orchestration for model lifecycle management. The learning stack integrates supervised classification for failure prediction windows, regression for remaining useful life (RUL) estimation, and unsupervised anomaly detection for new or rare failure modes [05].

Olusegun Ayeni et.al (2025) – industrial engineering by enhancing efficiency, reducing operational costs, and minimizing unexpected equipment failures. Traditional maintenance strategies, such as reactive and preventive maintenance, often lead to increased downtime and excessive resource utilization. In contrast, AI-driven predictive maintenance leverages advanced machine learning algorithms, deep learning, and data analytics to anticipate failures before they occur, thereby optimizing maintenance schedules and improving asset reliability. The core of AI-based PdM lies in real-time data acquisition through Industrial Internet of Things (IIoT) sensors, which monitor critical parameters such as temperature, vibration, and pressure. These vast datasets are processed using AI techniques, including anomaly detection, neural networks, and predictive modeling, to forecast potential failures with high accuracy. Additionally, AI integration enables automated diagnostics and decision-making, significantly reducing human intervention and enhancing predictive accuracy. Despite its transformative potential, AI-driven PdM faces challenges such as data quality issues, model interpretability, cybersecurity threats, and integration complexities with legacy systems. Addressing these concerns requires advancements in explainable AI (XAI), robust cybersecurity frameworks, and interoperability standards to ensure seamless integration across industrial ecosystems. Furthermore, the adoption of AI in predictive maintenance is reshaping workforce roles [06].

Table-1 Compression table of different method

Author & Year	Method / Technology	Key Contribution	Limitation
Gun Gun Maulana (2026)	SCADA-IIoT Monitoring System	Real-time monitoring, 98.99% data integrity, Telegram alerts	Focused on stamping machine environment
Nivethitha Somu (2025)	IntelliPdM (Edge-Cloud + IIoT)	Fault diagnosis and maintenance scheduling using real-time data	Requires reliable deployment architecture
Md Mahfuzur Rahman Enam (2025)	Smart SCADA + IIoT + Cloud	Improved monitoring, predictive maintenance, cybersecurity framework	Security and interoperability challenges
Zaheda Khatun (2025)	SCADA-to-Edge Predictive Maintenance	Better fault prediction using fused telemetry data	SCADA-only data has lower sensitivity
Nusrat Jahan (2025)	ML-based IIoT Predictive Maintenance	Failure prediction, RUL estimation, anomaly detection	Network bandwidth and latency constraints
Olusegun Ayeni (2025)	AI-driven Predictive Maintenance	Reduced downtime using ML and deep learning	Data quality and cybersecurity issues

III. METHODOLOGY

The rapid adoption of Industrial Internet of Things (IIoT) and Supervisory Control and Data Acquisition (SCADA) systems has significantly transformed industrial operations by enabling real-time monitoring and intelligent decision-making. Modern industries continuously generate large volumes of sensor data related to machine health, operational conditions, and production performance. However, unexpected equipment failures can lead to production downtime, increased maintenance costs, and reduced operational efficiency.

Data Acquisition

The AI4I 2020 Predictive Maintenance Dataset is utilized for experimental analysis. This dataset simulates real industrial machine operating conditions and contains 10,000 observations collected from industrial production equipment.

The dataset includes the following operational parameters:

Product Type

Categorizes industrial products into different operating classes.

Air Temperature

Represents ambient environmental temperature surrounding the equipment.

Process Temperature

Indicates the operating temperature during machine processing.

Rotational Speed

Represents spindle speed measured in revolutions per minute (RPM).

Torque

Represents rotational force generated during machine operation.

Tool Wear

Indicates the degree of degradation experienced by machine tools.

Machine Failure

Represents the operational state of the equipment.

- 0 → Normal Condition
- 1 → Failure Condition

The collected dataset serves as a digital representation of machine behavior under various operating conditions.

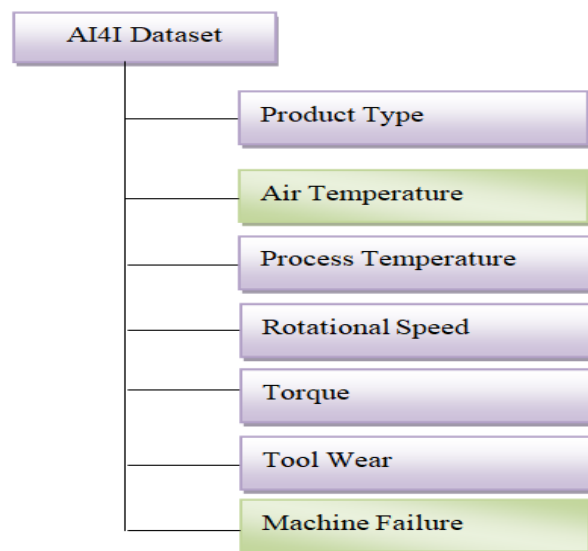
AI4I Dataset

Figure 2 Dataset Attribute Structure

Data Preprocessing

Raw industrial data often contain inconsistencies, noise, redundant information, and outliers. Therefore, preprocessing is performed before model development.

Data Cleaning

The dataset is examined for:

- Missing values
- Duplicate records
- Invalid sensor readings
- Noise and anomalies

Any inconsistent records are removed to improve data quality.

Data Transformation

Categorical variables such as Product Type are transformed into numerical representations using label encoding techniques.

Feature Scaling

Machine learning algorithms perform efficiently when features share a common scale. Therefore, StandardScaler normalization is applied:

- Mean = 0
- Standard Deviation = 1

This process prevents feature dominance and improves model convergence.

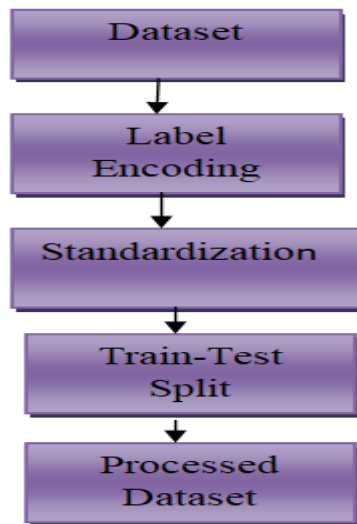


Figure 3 Data Preprocessing Workflow

Dataset Partitioning

The dataset is divided into:

- Training Set (70%)
- Testing Set (30%)

Stratified sampling is used to maintain balanced failure distributions

-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a supervised machine learning algorithm used for classification and pattern recognition tasks. The algorithm classifies a new observation by comparing it with previously observed data points and identifying the nearest neighboring samples. In predictive maintenance applications, machine failures often occur under operating conditions that resemble historical failure scenarios. Therefore, KNN is capable of identifying similarities between current machine conditions and previously recorded machine states.

In the proposed predictive maintenance framework, KNN is employed to classify industrial equipment into normal and failure categories based on machine operational parameters such as air temperature, process temperature, rotational speed, torque, and tool wear. The algorithm calculates the distance between a new machine observation and all training samples, then selects the K nearest neighbors. The final class is determined through majority voting among the selected neighbors. This approach allows the model to recognize hidden patterns within machine behavior and accurately predict equipment health conditions.

The primary reason for selecting KNN is its simplicity and effectiveness in pattern recognition problems. Since predictive maintenance involves identifying machine conditions that resemble previously observed failure patterns, KNN serves as a suitable algorithm for analyzing machine health data. Furthermore, KNN does not require complex model assumptions and can effectively learn from historical operational records.

The advantages of KNN include its ease of implementation, strong pattern recognition capability, and ability to adapt to nonlinear data distributions. However, the performance of KNN depends heavily on the selection of the optimal value of K. Therefore, GridSearchCV is utilized to identify the most suitable K value and improve prediction performance.

Random Forest Classifier

Random Forest is an ensemble machine learning algorithm that combines multiple decision trees to generate highly accurate classification results. Unlike a single decision tree, Random Forest constructs numerous trees using different subsets of training data and combines their predictions through a majority voting mechanism. This approach significantly improves prediction accuracy while reducing the risk of overfitting.

In the proposed predictive maintenance system, Random Forest is used to analyze machine operating conditions and classify equipment into healthy or failure states. Industrial equipment failures are influenced by several interacting variables such as temperature, rotational speed.

IV. RESULTS AND DISCUSSION

The proposed predictive maintenance framework was experimentally evaluated using the AI4I 2020 Predictive Maintenance Dataset. After completing data preprocessing, exploratory data analysis (EDA), feature engineering, feature scaling, class balancing, and model development, different machine learning algorithms were trained and tested to predict industrial equipment failures. The objective of this chapter is to analyze the performance of the implemented models and identify the most suitable algorithm for predictive maintenance applications. The implemented classifiers include K-Nearest Neighbors (KNN), Random Forest, XGBoost, Logistic Regression, and Support Vector Machine (SVM).

Exploratory Data Analysis Results

Exploratory Data Analysis was performed prior to model development to understand the statistical characteristics of the dataset. The distribution of machine failure records was examined using a pie chart, revealing that healthy machine samples were significantly more numerous than failure samples, indicating class imbalance. Correlation heatmaps were generated to study the relationship among machine parameters such as air temperature, process temperature, rotational speed, torque, and tool wear

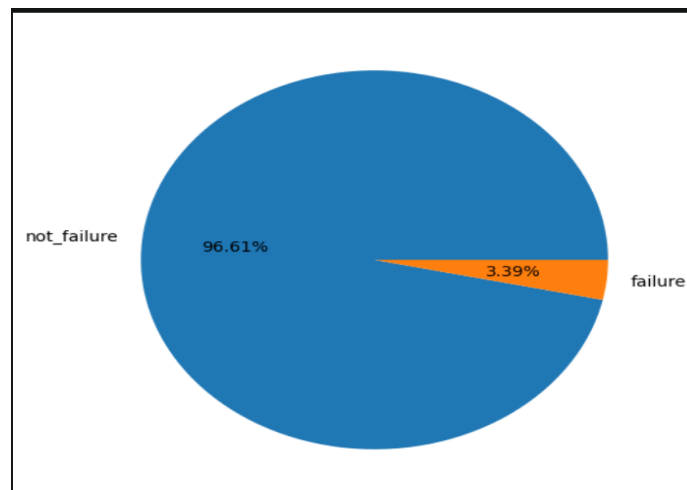


Fig 4 Machine Failure Distribution (Pie Chart)

Figure 3 illustrates the distribution of healthy and failed machine instances in the AI4I 2020 Predictive Maintenance Dataset. It can be observed that 96.61% of the observations correspond to machines operating under normal conditions, whereas only 3.39% represent machine failure cases. This indicates that the dataset is highly imbalanced, with the majority of samples belonging to the healthy class.

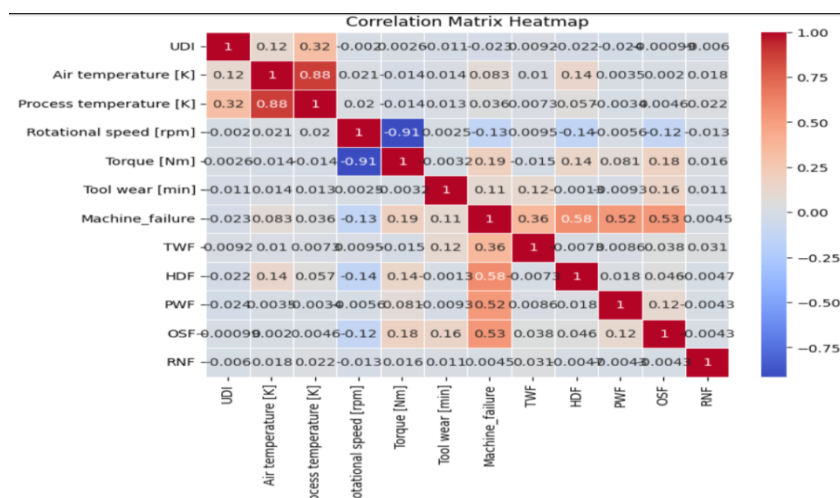


Fig 5 Correlation Matrix Heatmap of Machine Parameters

presents the correlation matrix of the machine operating parameters used in the predictive maintenance framework. The heatmap illustrates the strength and direction of relationships among all numerical features and the target variable (*Machine_failure*). Positive correlations are represented by warmer colors, whereas negative correlations are represented by cooler colors

Performance Evaluation

Each machine learning model was trained using the processed dataset and evaluated on the testing dataset. Performance was assessed using Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. The comparative analysis demonstrated that ensemble learning algorithms achieved superior predictive performance compared with conventional classification techniques. Random Forest achieved the highest classification accuracy, followed closely by XGBoost. The optimized KNN model also showed significant improvement after hyperparameter tuning, whereas Logistic Regression and Support Vector Machine provided stable baseline performance.

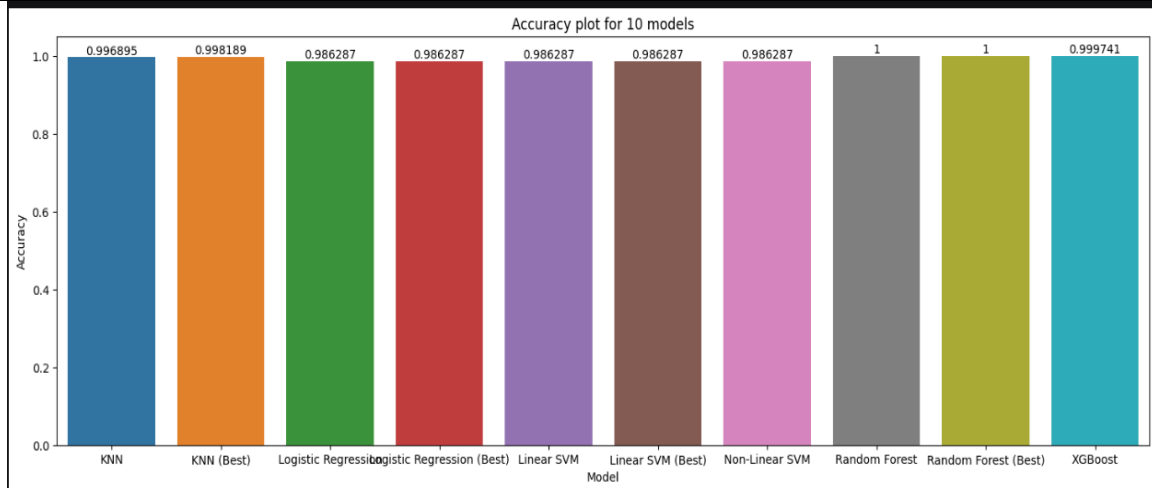


Figure 6 Accuracy Comparison of Machine Learning Models

The classification accuracy achieved by all implemented machine learning algorithms. It can be observed that the Random Forest and Optimized Random Forest classifiers achieved the highest accuracy of 100%, indicating their excellent capability in identifying machine failures. XGBoost also demonstrated outstanding performance with an accuracy of 99.97%, followed by the optimized KNN model with 99.82%. Logistic Regression and both Linear and Non-Linear SVM achieved an accuracy of approximately 98.63%, providing stable baseline performance. The comparative analysis confirms that ensemble learning algorithms outperform conventional classification techniques for industrial equipment failure prediction.

Comparative Analysis

The comparative evaluation showed that Random Forest consistently outperformed the remaining algorithms because of its ensemble learning strategy, robustness against noisy industrial sensor data, and ability to model complex nonlinear relationships among machine operating parameters. XGBoost also demonstrated excellent classification capability with very high predictive accuracy. Logistic Regression produced interpretable results with low computational complexity, making it suitable as a baseline model. KNN successfully identified similar machine operating conditions but required parameter tuning to achieve its best performance. Overall, ensemble learning methods proved to be more suitable for predictive maintenance applications where accurate failure prediction is critical.

Table 2 Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Remarks
KNN	99.69	Very Good
Optimized KNN	99.82	Excellent
Logistic Regression	98.63	Good
Linear SVM	98.63	Good
Non-Linear SVM	98.63	Good
XGBoost	99.97	Excellent
Random Forest	100.00	Best
Optimized Random Forest	100.00	Best

The comparative performance of the machine learning algorithms implemented for predicting industrial equipment failures using the AI4I 2020 Predictive Maintenance Dataset. The performance of each model was evaluated based on classification accuracy after completing data preprocessing, feature engineering, model training, and hyperparameter optimization. The results provide a comprehensive comparison of the predictive capabilities of all implemented classifiers and help identify the most suitable model for predictive maintenance applications.

V. CONCLUSION

The review paper discussed widely adopted artificial intelligence techniques, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, Decision Trees, XGBoost, Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), Autoencoders, and hybrid deep learning models. These approaches have shown promising performance in diagnosing faults across rotating machinery, manufacturing equipment, power plants, oil and gas facilities, and process industries. Furthermore, advancements in edge computing, cloud computing, digital twins, and explainable artificial intelligence (XAI) are expanding the capabilities of predictive maintenance by enabling faster data processing, real-time monitoring, and improved interpretability of predictive models.

Despite these advancements, several challenges remain. Data quality issues, missing and imbalanced datasets, heterogeneous data sources, cybersecurity concerns, high implementation costs, interoperability among industrial devices, and the lack of standardized evaluation frameworks continue to limit large-scale industrial deployment. Additionally, many predictive models are validated only under laboratory conditions and require further testing in real-world industrial environments to ensure robustness, scalability, and generalization across different operating conditions.

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