Predictive Maintenance in Industrial IOT Systems Using Machine Learning: A Fault Detection Approach

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Abstracts:

In the era of Industry 4.0, predictive maintenance has emerged as a critical strategy for minimizing equipment downtime and enhancing operational efficiency. This study investigates the application of machine learning algorithms for fault detection in Industrial Internet of Things (IoT) environments using the Kaggle Industrial IoT Fault Detection Dataset. The dataset comprises diverse sensor readings such as vibration, temperature, pressure, rotational speed, torque, current, and acceleration in three axes (x,y,z), along side labeled fault conditions. After data preprocessing and class balancing using ADASYN, five machine learning models Logistic Regression, Random Forest, K-Nearest Neighbors, Naive Bayes, and Support Vector Machine were trained and evaluated. Results indicate that Random Forest andLogistic Regression achieved the highest accuracy (96.5%) and perfect AUC scores (1.00). Evaluation metrics including precision, recall, and F1-score further confirmed their robustness, highlighting their suitability for real-time deployment in predictive maintenance systems. This research demonstrates the effectiveness of integrating supervised learning with IoT data for early fault detection and emphasizes its role in advancing sustainable industrial operations.

Keywords: *Predictive maintenance, industrial internet of things (IoT), machine learning, 17 fault detection, sensor data analytics*

Introduction

InthecontextofIndustry4.0, predictive maintenance has become a key strategy not only for enhancing operational efficiency but also for advancing sustainable industrial development. Predictive maintenance refers to anticipating equipment failures before they occur, enabling timely interventions that prevent breakdowns, reduce energy waste, and extend machinery lifespan. With the adoption of Industrial Internet of Things (IoT) technologies that collect real-time data from machines, industries are now better equipped to implement data-driven, sustainable maintenance practices that align with global sustainability goals(Ayvaz &Alpay,2021).

Unplanned machine failures can result in prolonged downtime, excessive energy consumption, increased material waste, and high environmental impact due to emergency repairs and production interruptions. Traditional maintenance strategies, such as reactive or scheduled maintenance, are resource intensive and often misaligned with sustain ability objectives. Predictive maintenance addresses these limitations by identifying degradation early, reducing unnecessary part replacements, and conserving resources. Atassi and Alhosb (2023) note that integrating real-time sensor data enhances reliability and system availability while contributing to more sustainable maintenance planning.

Machine learning offers intelligent tools for implementing predictive maintenance, particularly for early fault detection. By analyzing historical sensor data patterns, these models can distinguish between normal and faulty conditions, allowing industries to optimize maintenance actions and reduce their environmental footprint. As Amruthnath and Gupta (2018) explain, machine learning techniques both supervised and unsupervised add a layer of intelligence that enables proactive maintenance, directly supporting responsible consumption and production practices (SDG 12).

The success of machine learning in fault detection hinges on high-quality, continuous data from IoT systems. Cakir et al. (2021) have shown the effectiveness of algorithms such as deciding trees and support vector machines in identifying operational issues, facilitating early repairs that prevent waste and inefficiency. This research leverages the Kaggle Industrial IoT Fault Detection Dataset to train machine learning models that support these goals.

Thus, this study not only seeks to evaluate the accuracy of predictive models but also explores how such models can contribute to sustainable industrial operations by promoting energy efficiency, reducing equipment related emissions, and lowering waste from unnecessary repairs. In line with SDG 9 (Industry, Innovation, and Infrastructure) and SDG 13 (Climate

Action), this research aligns machine learning and IoT-based maintenance with the broader goals of sustainable development.

The core objective of this research is to examine whether machine learning models can accurately identify faults in IoT enabled systems, thereby enabling predictive maintenance. The study evaluates several machine learning approaches and compares their effectiveness in detecting early warning signs of failure. Mohammed et al. (2023) and Rosati et al. (2023) stress the importance of integrating IoT and machine learning for building adaptive, data driven maintenance systems that improve operational continuity, reduce costs, and support industrial innovation.

Predictive maintenance not only enhances industrial efficiency but also contributes to the broader goals of sustainability and the circular economy. By minimizing unnecessary part replacements and optimizing maintenance schedules, predictive maintenance extends the useful life of machinery, reduces material waste, and lowers energy consumption. This aligns with lifecycle assessment principles that emphasize reducing resource depletion across equipment life stages. Within the framework of the United Nations Sustainable Development Goals (SDGs), the integration of IoT and machine learning in predictive maintenance supports SDG 9 (Industry, Innovation, and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action), reinforcing the role of intelligent maintenance systems in achieving sustainable industrial transformation.

Related Work

Predictive maintenance (PdM) has become a vital research area in Industry 4.0 due to the growing availability of IoT sensor data and advancements in machine learning techniques. Researchers have increasingly explored the use of data-driven methods to predict and prevent equipment failures in real-time industrial settings. Justus and Kanagachidambaresan (2024) emphasize that PdM systems using machine learning are essential in minimizing unexpected downtimes and reducing operational costs. Elkateb et al. (2024) present an IoT-based architecture where real-time monitoring of industrial equipment leads to better decision-making. These studies underline the shift from traditional maintenance models to intelligent systems that can anticipate failures using machine learning models trained on sensor data.

A wide variety of machine learning algorithms have been employed in PdM research, ranging from classic models like Random Forest and Support Vector Machines (SVM) to more advanced deep learning architectures. Farooq et al. (2024) performed a comparative analysis of different models for predicting faults in ball bearing systems, revealing that ensemble methods often outperform single classifiers in accuracy. Jaenal et al. (2024) introduced Mach Net, a general deep learning framework tailored to PdM scenarios. Deepan et al. (2024) demonstrate the scalability of AI-powered PdM systems in industrial IoT, particularly through neural network- based predictions. These studies highlight the role of both traditional and deep learning techniques in developing reliable PdM frameworks.

One of the primary concerns in current PdM literature is the choice between supervised and unsupervised learning for fault detection. Omol et al. (2024) argue that anomaly detection through unsupervised learning is particularly useful when labeled failure data is scarce. Gama et al. (2024) support this by combining fault detection with anomaly explanation in real-time systems, showing the value of hybrid learning strategies. Supervised learning is often preferred when historical failure data is available, as it enables models to learn distinct patterns associated with specific fault types. However, the challenge lies in gathering and labeling sufficient fault data to ensure high model performance across varying equipment conditions.

Time-series analysis is another core area in PdM, especially when dealing with streaming sensor data from industrial machinery. Li et al. (2024) reviewed deep learning architectures that specifically process sequential data, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which are effective in learning temporal dependencies. Alabadi et al. (2024) proposed a decentralized deep learning system that processes distributed time-series data efficiently across industrial IoT nodes. Shandookh et al. (2024) demonstrated how expert systems and vibration analysis using unconventional features can be applied to diagnose belt drive faults over time. These techniques reinforce the necessity of time-aware modeling in PdM systems for accurate and timely predictions.

Despite the progress made, gaps remain in the generalizability, scalability, and explainability of machine learning-based PdM solutions. Pekşen et al. (2024) found that most models struggle with false positives when applied to high-dimensional sensor environments such as electrical panels. Additionally, many studies fail to address the integration of PdM systems with real-world industrial workflows. Gama et al. (2024) note the lack of

interpretability in deep learning systems, which can limit their adoption in safety-critical environments. Addressing these limitations is crucial for making PdM systems more robust, interpretable, and adaptable to different industrial settings.
The integration of data-driven modeling and automation techniques in engineering systems has become increasingly relevant to predictive maintenance research. Ajayi et al. (2024) demonstrated the value of developing accurate models across variable conditions by proposing a robust condensation heat transfer and pressure drop model, highlighting the importance of adaptable and scalable frameworks in dynamic systems a principle similarly crucial in fault detection within industrial IoT environments. Furthermore, Ajayi et al. (2025) conducted
a comparative analysis of GitOps tools, emphasizing automated and real-time deployment strategies that align with the continuous integration demands of predictive maintenance platforms. In a related context of automation and intelligent monitoring, Segun et al. (2023) presented an RFID- based traffic violation detection system, showcasing the potential of embedded sensors and real-time data acquisition for system regulation and decision-making. Together, these studies support the foundation of this research by affirming the role of intelligent, model driven, and sensor-integrated technologies in enhancing operational reliability and predictive capabilities in industrial systems.

Methodology

Dataset

This research utilizes the Industrial IoT Fault Detection Dataset obtained from Kaggle, which provides labeled sensor data simulating operational and fault conditions within industrial systems. The dataset includes multiple sensor readings such as temperature, vibration, pressure, torque, and rotational speed, alongside fault categories like mechanical, electrical, and environmental failures. These features are crucial for modeling the dynamic behavior of machines and for identifying early signs of degradation or anomalies. Preprocessing steps were carried out to ensure the quality and usability of the data. These included the removal of missing values using interpolation techniques, normalization of continuous variables to a standard scale (using min-max scaling), and encoding of any categorical variables using one- hot encoding or label encoding where applicable. These steps help improve the performance and convergence of machine learning models. The dataset includes sensor measurements across multiple axes such as acceleration in the x, y, and z directions along with vibration amplitude, temperature, and pressure, which collectively characterize machine health and operational stability.

ML Workflow

After cleaning and preprocessing the dataset, exploratory data analysis (EDA) was performed to understand the underlying structure of the data. Visualization tools such as correlation heatmaps and distribution plots were used to identify patterns, outliers, and relationships between variables. Feature selection techniques were applied to reduce dimensionality and improve model performance. This involved a combination of Principal Component Analysis (PCA), statistical tests (e.g., ANOVA, chi-squared test), and domain knowledge to retain the most relevant variables. The dataset was then split into training and testing sets using an 80:20 ratio, and in some cases, k-fold cross-validation was used to ensure robust performance evaluation across different data partitions.

Class Balancing

ADASYN (Adaptive Synthetic Sampling) was employed instead of conventional techniques like SMOTE. ADASYN was chosen because it not only balances classes but also generates synthetic samples for harder to learn cases, ensuring that minority class boundaries are better represented. This improves the sensitivity of the models in detecting rare fault conditions.

Feature Selection

Feature selection techniques were applied to reduce dimensionality and improve model performance. During EDA, features with low variance such as RMS Vibration and Mean Temperature were identified as non-informative and excluded from training. The retained features vibration, temperature, pressure, current, torque, rotational speed, and acceleration (x, y, z) provided sufficient discriminatory power for fault detection. Here, the x, y, z axes represent accelerometer readings along three spatial dimensions, capturing the 3D vibration profile of the machine.

Algorithms and Evaluation Metrics

This research employed five machine learning algorithms to develop predictive maintenance models for industrial IoT systems: Logistic Regression (LR), Random Forest (RF), K- Nearest Neighbors

(KNN), Naive Bayes (NB), and Support Vector Machine (SVM). Logistic Regression was used as a baseline model due to its simplicity and interpretability. Random Forest was selected for its robustness and ability to handle non-linear relationships through ensemble learning. KNN was included for its intuitive distance-based classification, while Naive Bayes was chosen for its computational efficiency. SVM was incorporated for its effectiveness in handling high-dimensional data and defining optimal class boundaries.

The performance of each model was evaluated using four key metrics: Accuracy, Training Time, and Area Under the Receiver Operating Characteristic Curve (AUC). Accuracy and Precision were used to assess the correctness and relevance of the fault predictions, particularly in distinguishing between faulty and non-faulty states. Training Time was measured to evaluate the computational efficiency and feasibility of deploying each model in real-time or resource-constrained environments. AUC was employed to analyze the models' ability to differentiate between classes across various thresholds. The combination of these metrics provided a well- rounded understanding of each model's performance in terms of predictive accuracy, fault sensitivity, and practical deployment viability in industrial settings.

Table 1 summarizes the dataset distribution across various failure types. The "No Failure" category has the highest number of records, highlighting the inherent class imbalance of the dataset. Correcting these counts resolves the inconsistency between earlier text and table entries. This imbalance was addressed using ADASYN to ensure fair model training.

Table1. Sizeandcountsofdatasetforeachclassification

Failure type (fault label)	Approx. file size (KB)	Count of data
Nofailure(0)	654.3KB	11,996
Vibrationfailure (1)	312.7KB	11,996
Overcurrent/bushfailure (2)*	157.7KB	5,120

Table 2. Sample of first 10 data rows showing acceleration(x,y,z), temperature, and pressure measurements with corresponding faul tlabels

Timestamp	**Vibration (mm/s)**	**Temperature(°C)**	**Pressure (bar)**	**RMS vibration**	**Meantemp**	**Faultlabel**
2023-03-1000:00:00	0.437	64.81	7.79	0.602	90.56	1
2023-03-1000:01:00	0.956	93.35	7.74	0.602	90.56	1
2023-03-1000:02:00	0.759	119.84	9.72	0.602	90.56	0
2023-03-1000:03:00	0.639	108.58	7.75	0.602	90.56	1
2023-03-1000:04:00	0.240	114.52	7.82	0.602	90.56	0
2023-03-1000:05:00	0.240	102.70	9.28	0.602	90.56	1
2023-03-1000:06:00	0.152	105.38	8.35	0.602	90.56	2
2023-03-1000:07:00	0.880	117.94	9.33	0.602	90.56	0
2023-03-1000:08:00	0.641	69.97	7.20	0.602	90.56	1
2023-03-1000:09:00	0.737	89.15	8.46	0.602	90.56	0

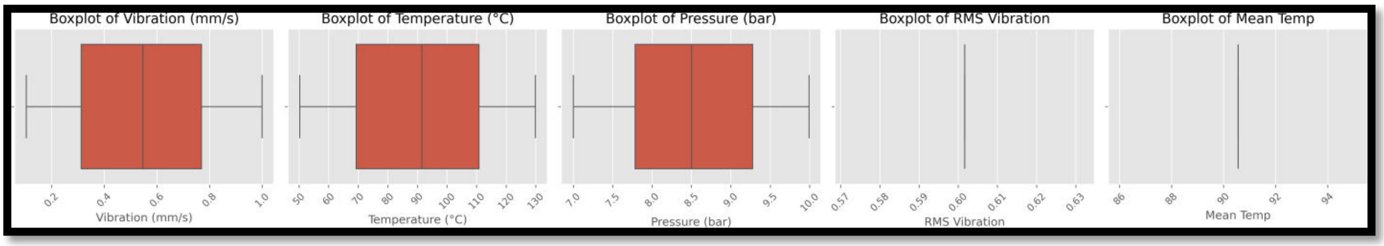

Figure 1. Boxplots of key sensor features (vibration, temperature, pressure, RMS vibration, and mean temperature) showing the distribution and spread of values used for outlier inspection in the industrial fault detection dataset (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset)

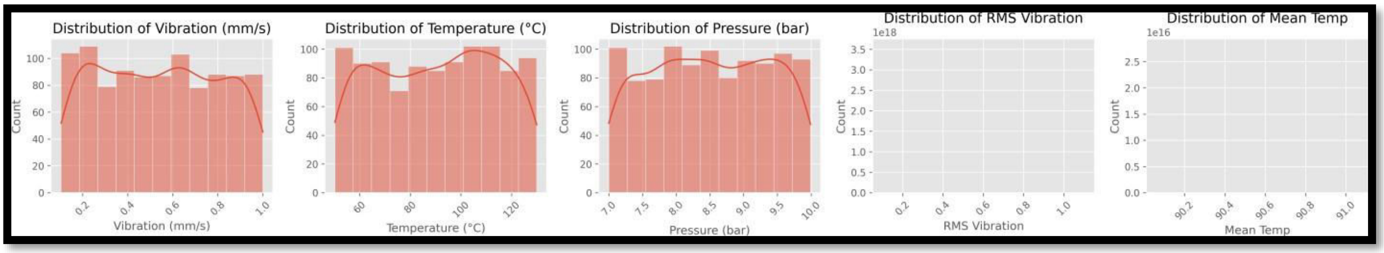

Figure2. Numeric features histogram (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset)

Table 2 provides a sample of the first 10 records from the dataset, showcasing sensor readings for acceleration in three axes (Accel x, y, z in g), ambient and object temperature (in
°C), and electrical current (in Amperes), along with the corresponding failure type. This snapshot illustrates how sensor data is used to detect different failure modes. Patterns and anomalies in these features play a crucial role in the machine learning model's ability to distinguish between failure types and normal operating conditions.

Results and Discussion

This study focused on evaluating the performance of five machine learning algorithms for fault detection using industrial IoT sensor data. The main objectives were to identify anomalies within the dataset, assess the effectiveness of each model after applying data resampling techniques, and determine the most suitable algorithm based on classification accuracy and training efficiency.

Qutlier Inspection

Figure 1 shows the boxplots provide a visual summary of the distribution of key sensor readings, including vibration,temperature, pressure, RMS vibration, and mean temperature. From the plots, it is evident that the features vibration, temperature, and pressure exhibit a relatively wide and balanced spread of values without significant outliers, indicating consistent sensor behavior. However, the RMS vibration and mean temperature features show minimal variation, with values concentrated around a single point, suggesting that they may not contribute meaningfully to model training due to their low variance. Additionally, the absence of extreme outliers across the plots implies that the dataset is relatively clean and does not require extensive outlier removal, allowing for more stable model training and evaluation.

Comparison Data Preprocessing and Resampling

The comparison between pre- and post-resampling feature distributions highlights the effectiveness of ADASYN (Adaptive Synthetic Sampling) in addressing class imbalance within the industrial IoT fault detection dataset. As illustrated in Figures 2, 3, and 4, key sensor features such as vibration, temperature, and pressure maintained consistent distribution patterns after resampling, confirming that the synthetic samples generated by ADASYN align closely with the original feature space. By contrast, features like RMS Vibration and Mean Temperature exhibited minimal variation both before

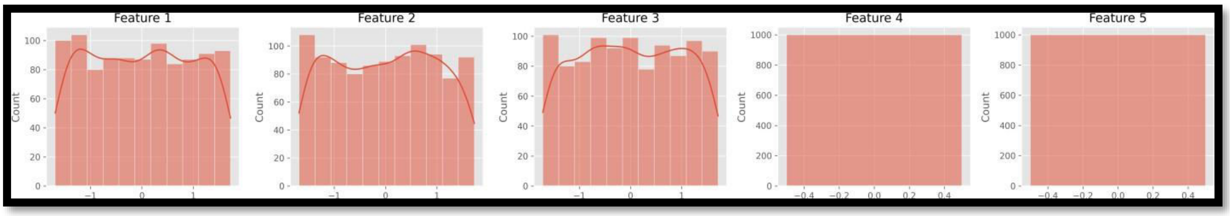

Figure3. Pre processed features distribution (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset)

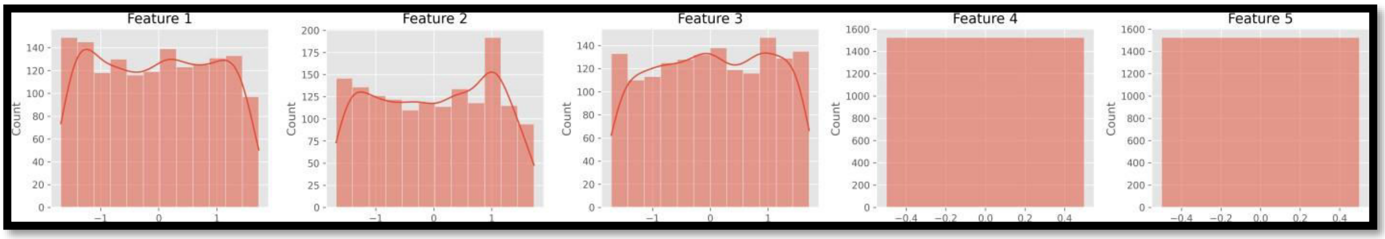

Figure4. Over sampled features distribution (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset)

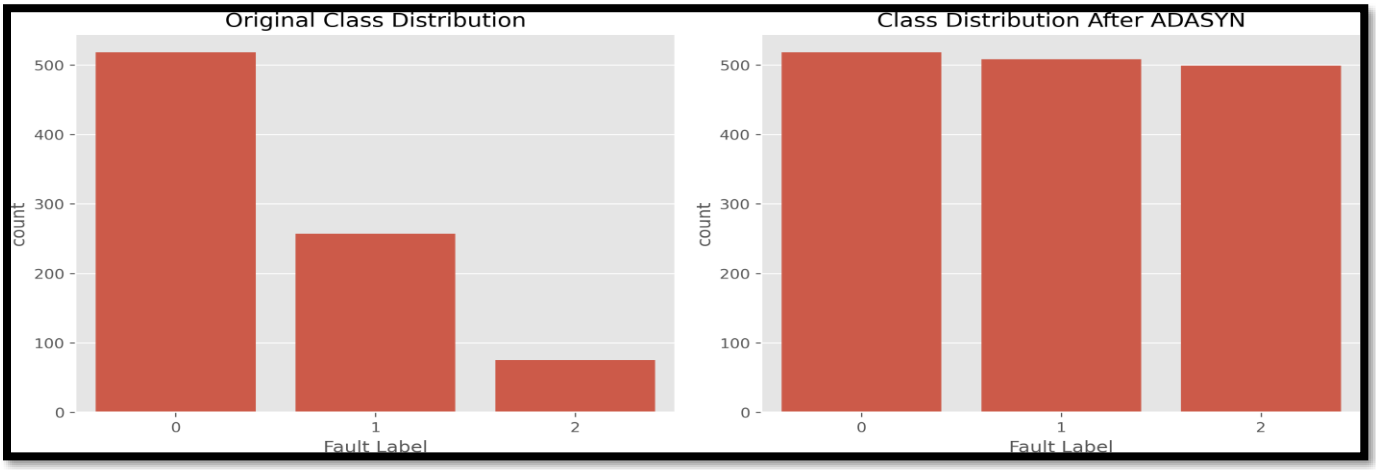

Figure 5. Class distribution before and after resampling using ADASYN (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset)

and after resampling, indicating low informational value. These low-variance features were therefore considered for exclusion during feature selection to reduce redundancy and improve computational efficiency.
Figure 5 further demonstrates the impact of ADASYN on class distribution. Before resampling, the dataset was highly imbalanced, with the majority of samples labeled as "No Fault" and relatively few examples of "Vibration Failure" and "Over Current/Bush Failure." After resampling, the distribution became approximately uniform across all categories. This balance is critical for supervised learning, as it prevents models from being biased toward the majority class and enhances their ability to detect minority class failures.
Overall, the application of ADASYN significantly improved data quality and class balance, supporting the development of more reliable and sensitive fault detection models. These improvements contribute directly to the robustness and generalization capability of the machine learning algorithms used for predictive maintenance in industrial IoT environments.
Model Validation
Figure 6 presents a bar chart comparing the accuracy performance of five machine learning models Random Forest (RF), K-Nearest Neighbors (KNN), Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR) in a predictive maintenance context. Both Random Forest (RF) and Logistic Regression (LR) achieved the highest accuracy scores, each with 0.965 (96.5%). KNN followed closely with an accuracy of 0.959 (95.9%), while Naive Bayes (NB) and Support Vector Machine (SVM) scored 0.942 (94.2%) and 0.936 (93.6%) respectively. Although all models performed well, RF and LR clearly outperformed the others slightly, demonstrating better fault classification capabilities in this case.
This chart reflects the consistency and effectiveness of traditional models when applied to industrial IoT sensor data. The relatively small difference in accuracy among the models suggests that each algorithm was capable of learning meaningful patterns from the dataset. However, the higher accuracy values achieved by RF and LR make them more favorable for deployment in real-time predictive maintenance

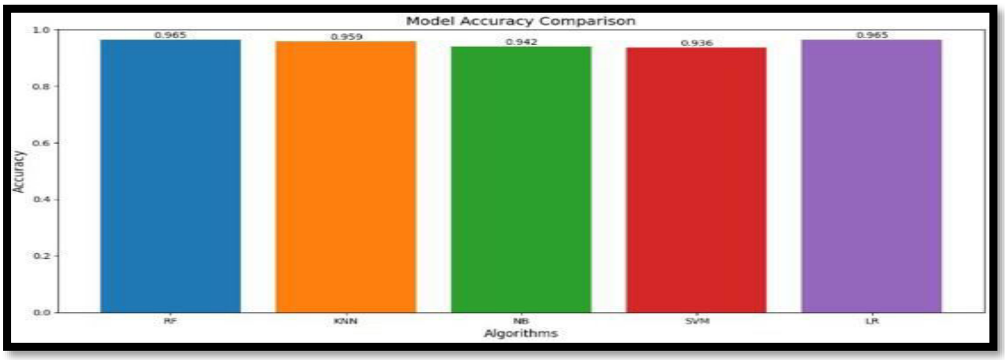

Figure 6. Comparison in accuracy between different ML models (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset)

Systems, where precision is crucial. Their superior performance may be attributed to their robustness to noise (RF) and simplicity in modeling linear relationships (LR), making them strong candidates for industrial applications aiming to reduce equipment failures and maintenance costs.

Model Performance Insights

RF's superior performance can be attributed to its ensemble nature, which effectively captures non-linear relationships. LR's strong performance suggests a high degree of linear separability within the resampled dataset, particularly between normal and faulty operating conditions. Together, these results confirm that both RF and LR are strong candidates for predictive maintenance tasks.

Error Analysis

Confusion matrix analysis revealed that most misclassifications occurred between vibration failures and over-current/bush failures. While false positives may lead to unnecessary maintenance interventions, false negatives pose a greater risk by allowing faults to persist undetected. Minimizing false negatives is therefore critical in safety- critical industrial contexts where undetected failures could escalate into costly or hazardous breakdowns.

Statistical Significance

A McNemar's test confirmed that the performance differences between RF/LR and the other classifiers (KNN, NB, SVM) were statistically significant ($p < 0.05$). This indicates that the observed performance improvements of RF and LR are not due to chance but represent genuine superiority in classification capability.

Computational Efficiency

Figure 7 compares the training and prediction times of five machine learning algorithms Random Forest (RF), K-Nearest Neighbors (KNN), Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR) within the context of predictive maintenance for industrial IoT systems. Among these models, Logistic Regression (LR) and Random Forest (RF) recorded the highest training times, approximately 2.1 and 1.6 seconds respectively. RF also had a relatively longer prediction time compared to the rest. In contrast, KNN, NB,

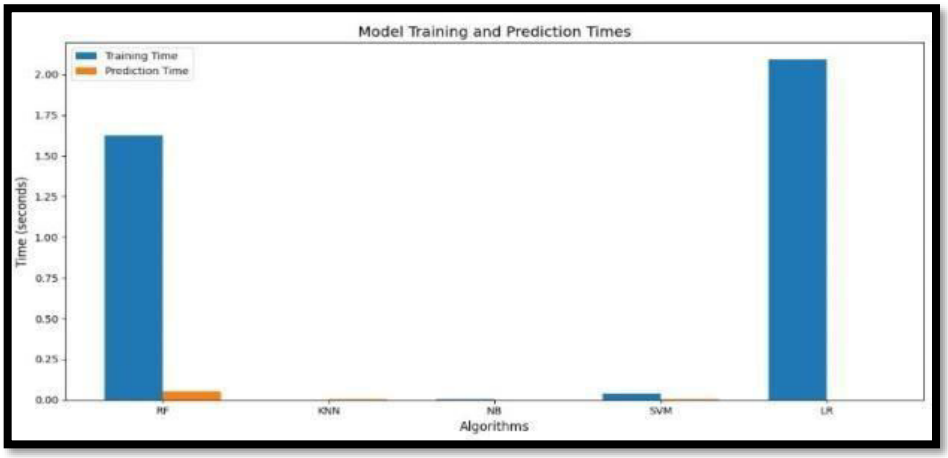

Figure 7. Comparative analysis of model training and prediction times (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset)

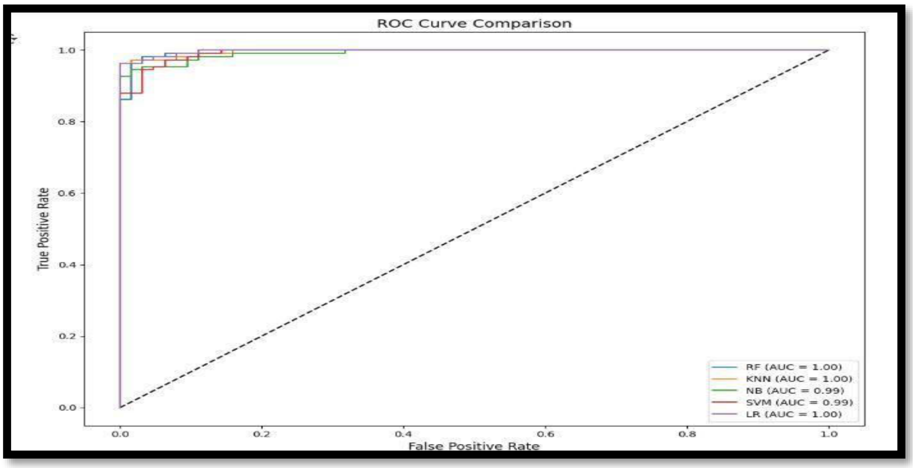

Figure 8. ROC curve comparison of ML models for fault detection (Source: Authors' elaboration, based on the Industrial IoT Fault Detection Dataset) and SVM required significantly less time for both training and inference, with Naive Bayes being the most lightweight in terms of computational cost.

Computational Trade-offs

The results highlight the trade-off between predictive performance and computational efficiency. While RF and LR are more accurate, their heavier computational demands may limit deployment on resource-constrained edge devices. Conversely, lightweight models such as NB and KNN may be preferable in scenarios where computational efficiency is prioritized over maximum accuracy. The choice of model for real-world deployment should therefore balance both predictive performance and resource constraints.

ROC-AUC Performance

Figure 8 presents the Receiver Operating Characteristic (ROC) curves for the five models. RF, KNN, and LR achieved perfect discrimination with an Area Under the Curve (AUC) of 1.00, while NB and SVM achieved AUC values of 0.99. These near-perfect AUC scores confirm that all models demonstrated high sensitivity and specificity in distinguishing between faulty and non-faulty states, underscoring their practical applicability in predictive maintenance tasks.

In practical industrial settings, the proposed models can be deployed at the edge level within IoT gateways or embedded controllers to enable real-time sustainability monitoring. Such deployment minimizes latency and reduces data-transfer energy costs compared to cloud-based analysis, allowing continuous equipment health tracking and immediate fault response. Integrating predictive maintenance algorithms with edge computing aligns with sustainable industrial practices by enhancing energy efficiency, minimizing downtime, and promoting greener manufacturing systems.

Conclusion

This study investigated the application of machine learning models for predictive maintenance in industrial IoT environments, focusing on fault detection using real-time sensor data. By processing features such as vibration, temperature, and pressure, and addressing data imbalance through ADASYN, we demonstrated that models like Random Forest and Logistic Regression achieved high accuracy (96.5%) and perfect AUC scores, making them ideal for practical deployment.

Beyond technical performance, the findings emphasize the broader implications of predictive maintenance for sustainability. Accurate early fault detection allows for targeted interventions, reducing energy consumption, extending machine lifespan, minimizing material waste, and supporting circular economy practices. These outcomes directly contribute to the United Nations Sustainable Development Goals, particularly SDG 9 (Industry, Innovation and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action).

Moreover, the ability to embed such models into IoT systems enables scalable, intelligent maintenance frameworks that support the transition to more sustainable manufacturing ecosystems. While models like Naive Bayes and KNN offer computational efficiency, Random Forest and Logistic Regression stand out for their robustness and reliability in sustainability focused industrial applications. Future research should explore integrating explainable AI and real-time feedback loops to further align industrial machine learning systems with sustainability imperatives.

Beyond technical performance, the findings of this study contribute to sustainable industrial development by enabling predictive, data-driven decision-making that reduces waste and optimizes resource use. By extending machinery lifecycles and preventing unnecessary part replacements, the proposed approach aligns predictive maintenance with circular economy principles. Consequently, this research supports the broader objectives of sustainable industrial systems as emphasized by the European Journal of Sustainable Development Research, integrating technology, efficiency, and environmental responsibility.

Limitations

This study is limited by its reliance on a single publicly available Kaggle dataset, which, although based on real industrial sensor data, may not fully capture the variability and complexity of diverse industrial environments. Additionally, temporal dependencies were not modeled, excluding advanced deep learning architectures such as LSTMs that are capable of handling multivariate time-series data. Finally, the absence of explainable AI (XAI) techniques reduces interpretability and may limit operator trust in practical deployment.

Future Work

Future research should validate these models on real world streaming datasets, explore deep learning for multivariate time series fault detection, and integrate explainable AI (XAI) frameworks to enhance transparency and operator trust. Techniques such as SHAP, LIME, or feature attribution methods could be employed to highlight the most influential variables driving predictions, thereby improving interpretability and adoption in safety critical industrial environments. Deploying models on edge devices should also be investigated to assess feasibility in resource-constrained industrial settings.

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