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Article

An Explainable Ensemble Machine Learning Framework for Predictive Maintenance in Industrial IoT Systems Using Multi-Sensor Data

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Abstract: The complexity of modern industrial systems and their need for intelligent maintenance to avoid unexpected failures and to improve the efficiency of production have led to the development of Predictive Maintenance (PM) using data from Industrial Internet of Things (IIoT). PM using IIoT uses a large amount of data gathered continuously by multiple sensors installed on industrial equipment. The use of machine learning (ML) has become common in PM using IIoT. However, existing ML approaches to PM using IIoT have many restrictions, such as sensor data variability, high dimensionality of feature space, class imbalance, and lack of interpretability. This paper proposes an explainable ensemble machine learning framework that uses multi-sensor data fusion for PM using IIoT. The proposed framework consists of data preprocessing, feature engineering, ensemble learning, and explainable AI. It uses three types of ML classifiers, namely, Random Forest, XGBoost, and LightGBM, and combines them using ensemble learning to improve prediction accuracy. It uses SHAP to explain the contribution of individual sensor features to the maintenance decision and provides interpretable results. The performance of the proposed framework is evaluated using several real industrial multi-sensor datasets. The framework provides high accuracy for fault prediction, while it is also explainable. Therefore, it can support effective and reliable industrial maintenance decisions. The results of this study also show that the proposed explainable ensemble ML framework can support the development of intelligent and trustworthy PM using IIoT in Industry 4.0.

Keywords: Industrial Internet of Things; Predictive Maintenance; Ensemble Learning; Explainable Artificial Intelligence; Machine Learning; Sensor Fusion; Fault Detection; Industry 4.0.

1. Introduction

Industry 4.0 represents a revolutionary transformation of traditional industrial systems into smart, interconnected, and intelligent manufacturing environments by incorporating a wide array of advanced sensing technologies, communication systems, cloud computing platforms, and intelligent algorithms. In Industrial Internet of Things (IIoT) environments, monitoring, data collection, and real-time analysis of industrial equipment have become the cornerstones of smart industries[1]. With the advent of Industry 4.0, modern industrial machines are equipped with multiple sensors to gather a vast array of information related to their operating conditions. Continuous monitoring and the subsequent analysis of multi-sensor data from various industrial equipment can pave way for the implementation of intelligent maintenance strategies that can improve the reliability of industrial equipment, reduce their operating costs, and minimize the occurrence of unexpected failures[2]. Preventive maintenance has its own shortcomings such as high maintenance cost, long period of idle time for machines and possibility of failure between two maintenance schedules[3]. Thus, a more efficient alternative to overcome these problems is required. Predictive maintenance can efficiently handle all these problems by analyzing the past data of machines as well as the real time data of machines. This type of maintenance helps in the detection of abnormal working of machines and also helps in predicting the failure of machines before it occurs[4]. This can increase the life of machines and also helps in increasing the overall efficiency of machines and thus reduces the maintenance costs.

Using machine learning for Predictive Maintenance in industries has huge potential. Large amounts of data from industrial machines can be used to learn patterns and relationships which can be used for failure prediction. There are many Machine Learning algorithms that have been used for Predictive Maintenance, such as decision trees, support vector machines, neural networks, random forests and gradient boosting machines[5]. These models can learn from data and make predictions for failures. However, in real-world industrial scenarios, sensor data can contain a lot of noise, missing values, redundant information and non-linear relationships between different parameters[6]. Using a single model to predict failures can result in low generalization performance, sensitivity to data variations and low robustness when applied to different industrial scenarios. Using ensemble methods that combine the predictions of multiple models can improve the prediction accuracy, stability and robustness of individual models. Despite the high prediction performance that can be reached by the advanced machine learning models for predictive maintenance, there is a major drawback which is the lack of interpretability[7]. The majority of models are black-box models which provide a prediction but no explanation for this prediction and the factors that influence the decision for a maintenance action in the context of a safety-critical industrial environment. The operators have to trust the AI system. In order to get the operators to trust the AI system, the model has to be explainable[8]. In recent years, the field of explainable artificial intelligence (XAI) has gained a lot of attention. SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) are two techniques for explainable AI. These techniques are able to identify the important features of a prediction and quantify the contribution of these features to the prediction[9]. Though good progresses have been made in AI-based predictive maintenance for industrial equipment and machines, current approaches still suffer from the challenges of effectively integrating data from multiple sensors, of increasing models' transparency and of supporting operators with high quality decisions. Most of current studies have been focusing on enhancing the prediction accuracy while few studies paid adequate attention on revealing the interrelation between equipment's failure and its operational conditions which were monitored and sensed by various industrial sensors. To address these limitations, an intelligent framework that supports integration of multi-sensors' data, learning of ensemble models and AI-explainability, is needed for enabling effective, high quality and trustworthy predictive maintenance decisions in Industry 4.0 environments[10].

This paper proposes an explainable ensemble machine learning framework to support predictive maintenance in industrial IoT environments by processing multi-sensor data from production machinery. The proposed approach integrates data preprocessing, feature extraction, ensemble-based prediction of potential faults, and explainability. The predicted model is able to accurately and effectively supports maintenance decisions. The new approach facilitates the identification of the operational conditions of production equipment that may cause degradation. The proposed framework represents a backbone for intelligent maintenance in order to support the development of sustainable, efficient, and reliable industrial systems in the Industry 4.0 era.

2. Related Work

The development of intelligent predictive maintenance systems has gained considerable attention with the rise of Industrial Internet of Things (IIoT) in modern manufacturing environments. Most of the current studies and approaches for intelligent predictive maintenance have been focusing on utilizing sensor data from Industrial Internet of Things (IIoT) for equipment health monitoring, fault diagnosis, remaining useful life estimation and failure prediction using various data-driven approaches[11]. However, the current approaches for intelligent predictive maintenance have many challenges to be addressed in order to make them suitable for real industrial applications[12]. Some of the challenges are associated with dealing with data complexity, model generalization, and model interpretability. Conventional machine learning approaches for predictive maintenance have received a considerable attention from researchers and engineers in the last few years[13]. A number of studies have used different approaches including traditional approaches such as decision trees and support vector machines (SVMs) for fault classification from various types of industrial sensor data. Most of these methods, however, suffer from a number of limitations particularly when dealing with large scale industrial datasets. For instance, they may not be able to properly capture temporal patterns within the data[14]. Also, they may require feature extraction and a number of dimensionality reduction methods, which can significantly affect the performance of the approach.

Ensemble models have become an increasingly popular means of improving the predictive power of maintenance systems[15]. In that context, it is well established that combining the results of several different models can lead to improved predictive performance and to decreased uncertainty. Thus, for example, Random Forest has become a very popular method for classification in the field of predictive maintenance, because of its ability to handle very large numbers of input variables, and to resist overfitting. Other models, such as boosting models (e.g. AdaBoost, XGBoost, and LightGBM), have also recently seen a lot of use for classification in the predictive maintenance context, because they are able to model complex interactions between input variables and between instances and the target output variables[16]. Many studies have recently reported results of application of ensemble models to predictive maintenance. However, most of these studies have focused almost entirely on improving classification accuracy, without attempting to create models that can provide transparent decision making.

To enhance the performance of predictive maintenance using Intelligent Data Analysis for IIoT a lot of work has been carried out on Multi-sensor data fusion, as more than one parameter never determines the behavior of Industrial Assets. Various factors like vibration, temperature, pressure, current, speed of different parts, etc. influence the behavior of the equipment under study and hence need to be monitored and analysed[17]. Previous work include studies that have employed various data fusion techniques using single sensor information, and demonstrated the potential of improved performance when using information from multiple sensors. However, there is a considerable amount of work that still remains to be carried out to tackle issues of different sensor characteristics, redundancy, missing data, and variability of operational conditions[18]. Thus, the feature engineering, and intelligent data fusion strategies are key to extract most valuable information from the large volumes of industrial multi-source data.

More recently, there has been increasing interest in the integration of Explainable Artificial Intelligence (XAI) techniques within industrial predictive maintenance frameworks. Most existing machine learning models are so called ‘black box’ type models, that do not offer any form of explanation regarding their decisions, which can lead to a number of problems including a lack of trust in model predictions, as well as increased difficulty in undertaking model validation[19]. A range of techniques have been developed with the purpose of providing increased transparency or interpretability of predictions made by a model. Examples of techniques that have been widely used within industrial applications for providing both global and local explanations of predictions include SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME). These techniques operate by using a model, typically of much simpler form, to locally approximate the predictions of the original ‘black box’ model in order to offer some form of insight regarding the contribution of individual input features[20]. The combination of XAI techniques and ensemble learning approaches for multi-sensor IIoT predictive maintenance, represents a relatively new research area that offers considerable potential. All methods, however, have their restrictions. Current methods are primarily designed to process a large amount of data that is mostly generated by a single sensor, therefore, no sufficient use is made of information provided by other sensors. The models are not sufficiently interpretable and also in later stages of deployment. Also, most current methods do not provide sufficient support for decision making. An integrated approach, which processes multiple sensors, robust learning and XAI methods, supports all phases of decision making and can make accurate, reliable and interpretable predictions for complex industrial IoT systems, is required to solve the problem of predictive maintenance.

3. Proposed Methodology

Predictive maintenance using multi-sensor data in Industrial Internet of Things (IIoT) is supported by a novel methodology that implements an explainable ensemble machine learning framework to develop a decision-support system for predictive maintenance of industrial assets. The framework in question supports a set of stages, including data acquisition, data preprocessing, feature engineering, ensemble-based fault prediction, and explainable AI (XAI). Hence, all the information collected from a variety of sensors installed on industrial assets is processed to generate a robust decision-support system for predictive maintenance, and for optimizing the corresponding maintenance activities. The proposed framework begins with multi-sensor data acquisition from industrial assets equipped with various monitoring devices. These sensors continuously collect operational parameters such as vibration, temperature, pressure, rotational speed, electrical current, torque, and other condition-monitoring signals. The integration of multiple sensor sources enables comprehensive equipment health assessment by capturing different physical characteristics associated with machine degradation and abnormal operating conditions. Since industrial sensor data often contain noise, missing values, outliers, and inconsistencies caused by environmental variations or measurement limitations, preprocessing operations are performed to improve data quality and reliability.

Once data are preprocessed, it can be provided to learning module where features can be combined in order to train predictor model. In our proposed framework, feature extraction methods (i.e., time, frequency, statistical) are used to produce several features, which represent various patterns in monitored signals, thereby allowing effective prediction of machine failures. Moreover, feature selection methods (i.e., Correlation feature selector, Recursive feature elimination, etc.) are utilized in order to eliminate less important features (i.e., irrelevant/deskored features) from training dataset, thus improving model's efficiency and effectiveness. Thus, a number of obtained and selected features are utilized as inputs to ensemble-based predictor model for effective fault prediction. The machine learning model used in our approach is based on Random Forest regressor that is known for its high predictive performance as well as robustness and stability when dealing with a wide variety of complex real-world industrial data. However, in order to improve model's overall performance and robustness, multiple machine learning models such as Random Forest, XGBoost, and LightGBM are employed as individual base learners in our proposed framework. In addition, an ensemble integration technique is employed in order to effectively aggregate individual predictions made by the aforementioned models. Such an ensemble approach helps to enhance the robustness, efficiency, and stability of individual models, thereby enabling the framework to make effective predictions for a wide variety of complex industrial environments and large datasets. To train the model and evaluate its performance, hyperparameters of the models are fine-tuned using Grid Search (GS) method, which optimizes the performance of machine learning models and increases their efficiency in terms of predicting the failures effectively.

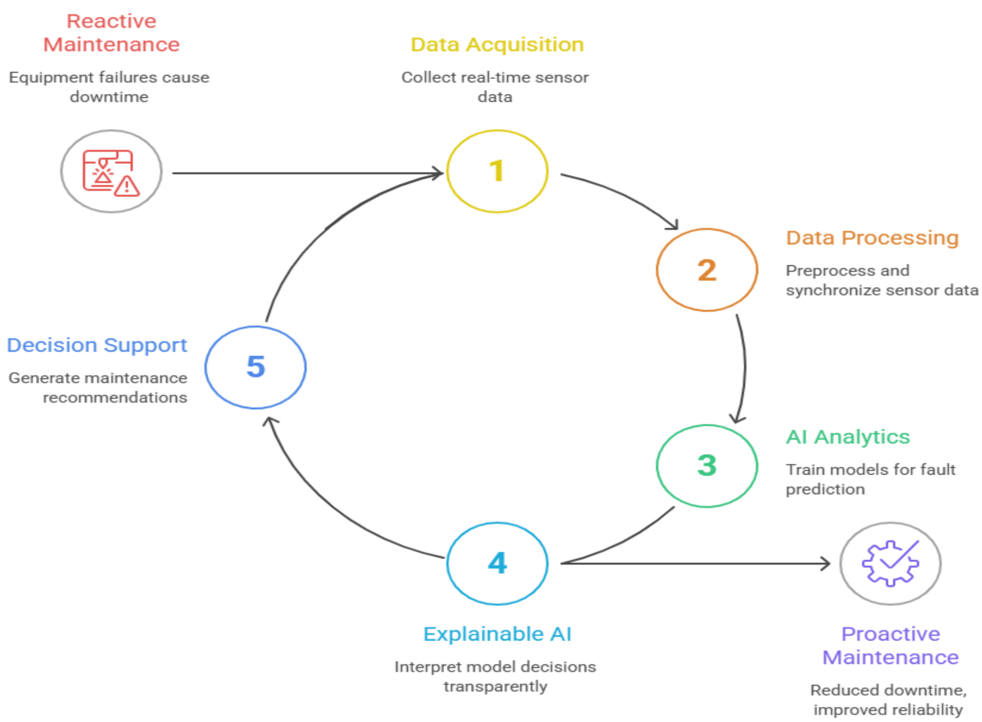

Figure 1. Overall architecture of the proposed System

The Predictive Maintenance workflow is depicted in Figure. 1. Initially, Multi-sensor data from equipment under consideration is acquired. The data is then preprocessed and engineering features extracted to enhance data's value for the application. The resulting features are then analyzed by an Ensemble machine learning model comprising of a multitude of classifiers or network of models for improved accuracy and robustness of predicted faults. Next the intelligent system implements explainable AI using SHAP values to provide insights of the sensor parameters' contribution. This is then utilized by intelligent system to provide proactive maintenance by identifying impending failures to take timely actions.

The information extracted from the preprocessed multi-sensor data can be used to generate sets of relevant features that capture information describing the operational status of the monitored industrial assets. The features are created from time-domain, frequency-domain measurements, as well as from the statistical properties of the multi-sensor data. These features capture information of the signals monitored, and are used to train the machine learning model to predict possible faults before they occur. In order to improve the performance of the model, feature selection methods can be used to filter out the irrelevant and redundant features that do not add any value to the model, while retaining the most informative features. These selected features capture the most relevant information that describe possible faults and can be used to train the machine learning model for predictive maintenance. The predictive modeling component includes an ensemble of multiple models including Random Forest, Extreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM) that were utilized as base learners for the enhanced classification and reliability. An ensemble integration was then employed to aggregate the respective models' respective predictions in order to increase the prediction's stability and the model's generalization ability. Hyperparameter tuning was also used to fine-tune the respective models' performance during the learning process, and to optimize their respective performances when using the diverse set of input features that have been extracted and generated from the raw multi-sensor data collected from industrial equipment.

To improve transparency and trust of the created predictive maintenance framework an explainability module is integrated after the training of the models. SHapley Additive exPlanations (SHAP) is used to analyze the contribution of all input features of a sample to the output of a model. Therefore, it can be determined which input features of a sensor affect the output of a model. The explainability module provides global as well as local explanations. These explanations can be used by maintenance staff to get insights for the created predictions and to decide whether a repair is necessary or not. The final framework provides a complete predictive maintenance solution. Multi-sensor industrial data can be incorporated in order to generate the most accurate failure predictions, and most importantly, to provide the user with sufficient, meaningful and interpretable insights which can be effectively used in the frame of intelligent maintenance management. A number of conventional black-box predictive models have been previously used for PM in IIoT-based industries in order to generate accurate failure predictions and support maintenance management. However, the most important feature that has been missing is explainability. The methodology proposed in this work addresses this significant drawback and it can effectively be used for PM in a wide number of IIoT-based industrial environments.

4. Experimental Setup

This experimental setup was designed to evaluate the effectiveness of the proposed explainable ensemble machine learning framework for predictive maintenance in the context of Industrial Internet of Things (IIoT). The implemented experiments are conducted using the multi-sensor industrial equipment data, collected from the various machine components, comprising of the equipment's operational parameters as well as the corresponding condition-monitoring parameters. The various sensor measurements such as temperature, rotational speed, torque, and the various parameters representing the vibration as well as the other indicators of the deteriorating health of the equipment, were considered. In order to evaluate the predictive models effectively, the extracted features from the multi-sensor data were split into the training data and testing data. In this work, all experiments have been performed in a Python environment that uses well established frameworks and libraries for data processing and machine learning, i.e., NumPy, pandas, scikit-learn, etc. In the preprocessing step, all data have been cleaned and analyzed for missing values and, if necessary, have been completed. The distribution of the values has been normalized in order to ensure a consistent input for the learning algorithms. For feature creation, additional features have been derived from the current sensor values in order to include relevant statistical and operation-related information in the learning process. Since the topic of failure prediction inherently is related to imbalanced class distributions, appropriate balancing has been integrated into the used learning algorithms in the learning process.

In this work, we have investigated the use of several Ensemble Learning methods in conjunction with a large set of feature vectors, which were extracted from the signals of several sensors monitoring an industrial equipment. These methods include Random Forest, XGBoost, LightGBM, and several baselines. We employed a stacking approach, in order to improve the performance of the models in terms of predicting the faults in the industrial equipment, and to increase the reliability of the models. We used cross-validation in order to tune the hyperparameters of the models, and to provide a solid estimation of the models' performance.

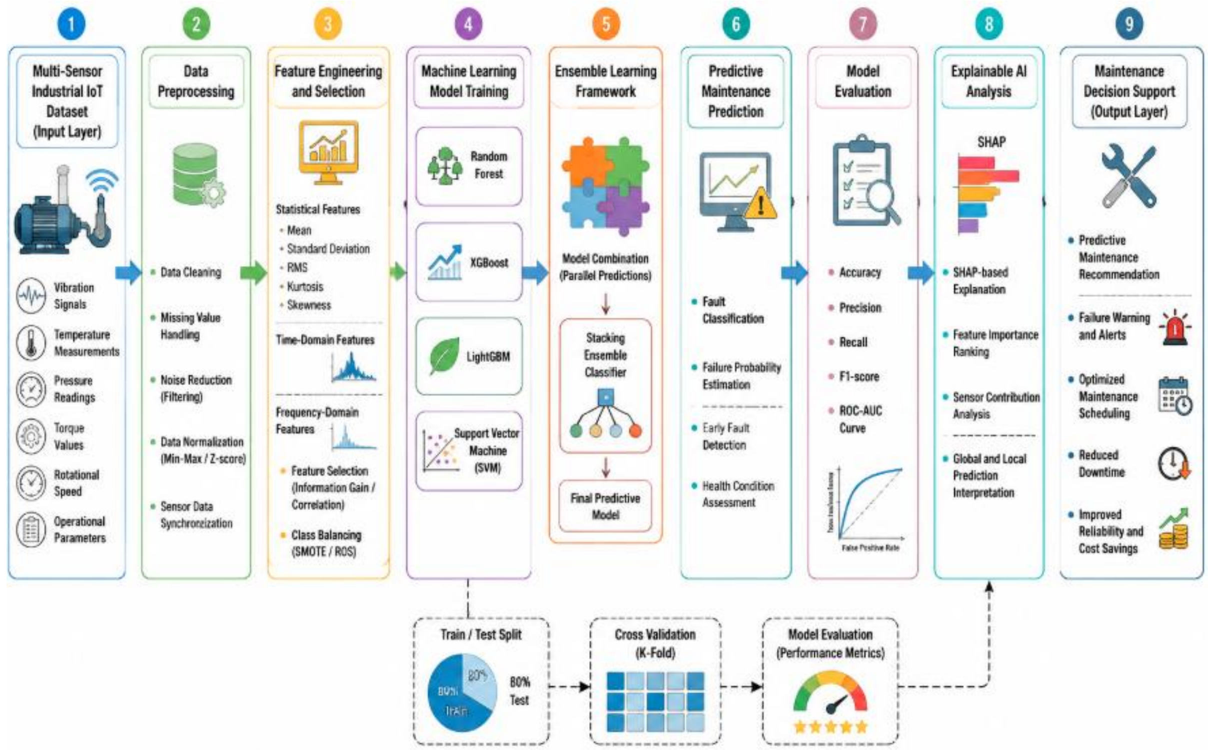

Figure 2. Experimental Workflow of the Proposed Explainable Ensemble Machine Learning Framework

Figure.2. provides details about the experimental framework for the propose explainable ensemble-based machine learning model that is used for predicting maintenance in Industrial IoT applications. The sensor data are first processed for multi-sensor, then for pre-processing, feature extraction, and feature selection. A number of machine learning models were then trained and merged together using ensemble-based learning for improving accuracy of predictions. Measured performance of model were also compared, and used for providing explanations of model by using SHAP values. Finally, a number of predictions made by model are used for making intelligent decision for the maintenance by enabling early detection of faults and scheduling maintenance in optimal manner.

The performance of our framework has been evaluated by several metrics, including accuracy, precision, recall, F1-score, as well as the area under the receiver operating characteristic curve (AUC-ROC) for each class of faults. In addition, each model has been explained by means of SHAP values, which are able to assign a value to each input feature for every sample, signifying the contribution of the input feature to the model's prediction. This allows us to understand which are the most relevant sensors for a specific prediction. The use of these metrics and techniques allows us to comprehensively assess the performance of the different models proposed in this work for the purpose of predictive maintenance, assessing both their ability to accurately predict potential faults and the transparency of their decisions.

5. Results and Discussion

The performance of the Explainable Ensemble Model for Predictive Maintenance in IIoT using multi-sensor industrial data was evaluated using several metrics for assessing the models ability to predict, to fuse data from different sensors, to classify objects correctly and to explain its decisions. The experiments were carried out by using industrial data from several sensors of different types and by comparing the results obtained by different learning models individually and as part of an ensemble. As it is depicted in Figure. 3, by using ensemble of several learning models the results achieved by the models individually were enhanced greatly. Individual models, such as Decision Trees and Support Vector Machines, are not able to predict well when the data follows complex non-linear relationships such as the ones found in industrial sensor data. Among the learning models that are part of the ensemble of the proposed model, Individual Ensemble Models, such as Random Forest, XGBoost and LightGBM, were tested as well. Although their performance was greatly better than the one achieved by the individual learning models, the proposed model performed better, since it exploits the strengths of all the models that are part of the ensemble in order to improve the models ability to predict by correctly classifying the different cases that the model is able to predict, i.e., to correctly predict faults at different stages of degradation, when the equipment is functioning normally, and when a critical failure has already occurred. The enhanced performance that is achieved by the ensemble of different models is mainly due to the different predictions that are made by each model, which, when they are combined, they overcome each models limitations, thus enabling the model to generalize better to new, unseen data, i.e., to predict correctly faults that have not been observed during the training phase of the model.

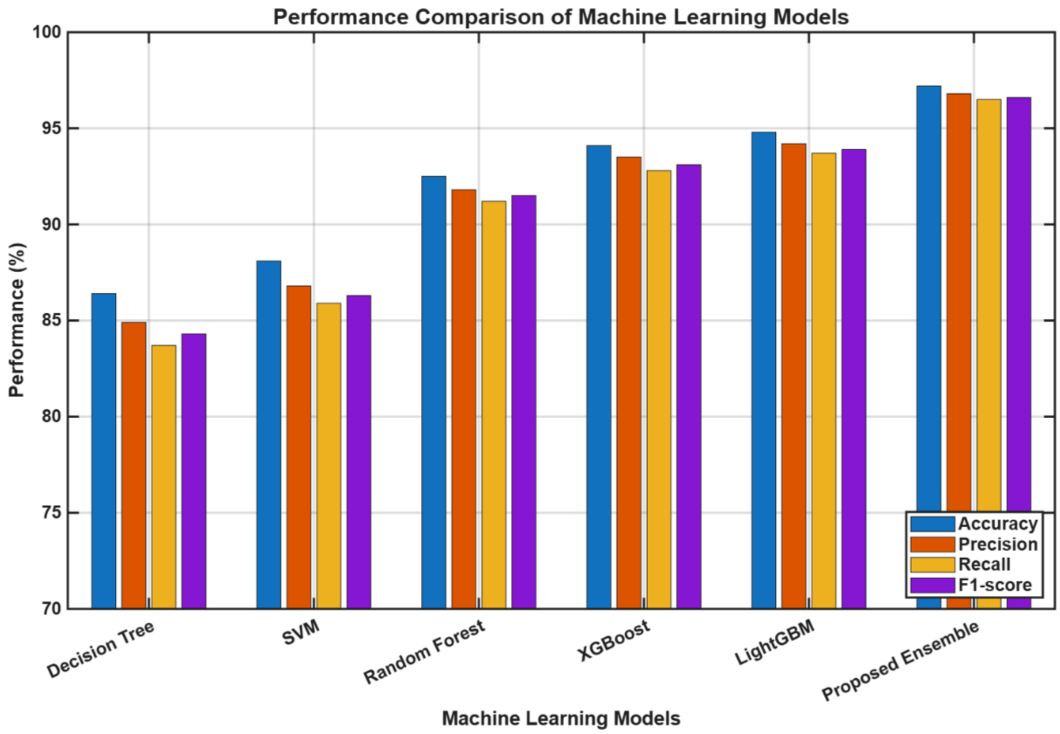

Figure 3. Performance Comparison of Machine Learning Models

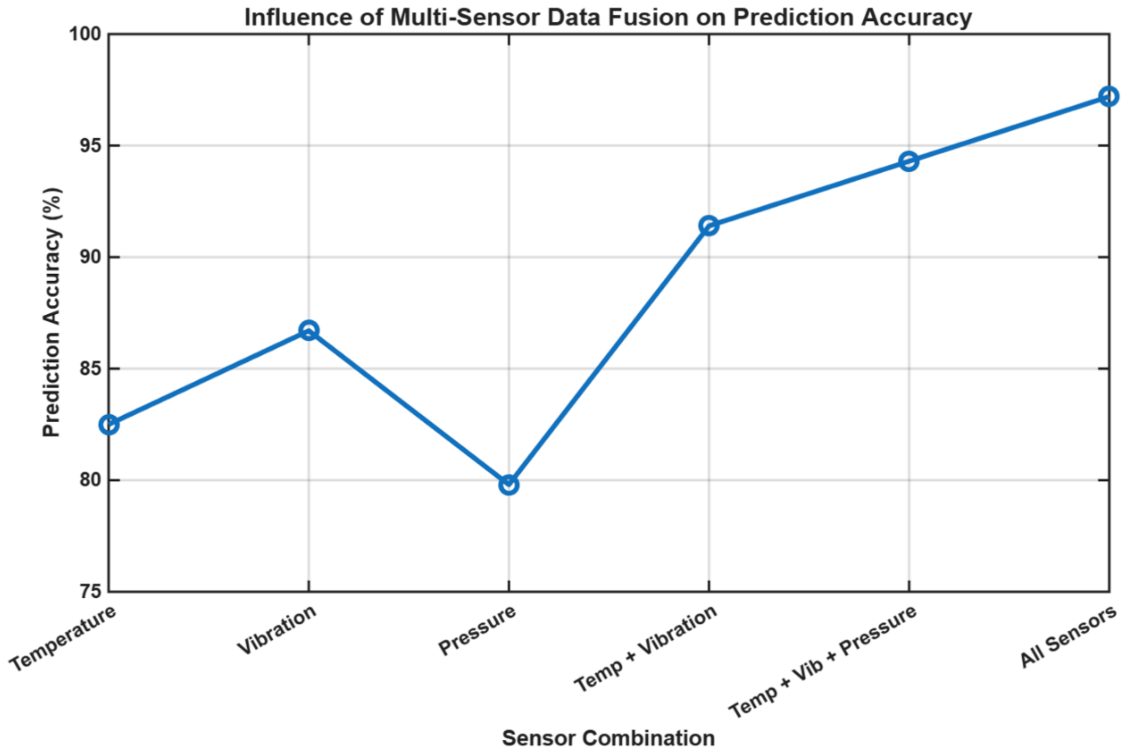

Figure 4. Effect of Multi-Sensor Data Fusion

The performance of complete sensor fusion on a number of performance metrics is shown in Figure 4 for comparison to single sensors. The result show that as the number of sensors are included in the model performance increases. This is due to the additional information that each sensor can provide on the current state of a piece of equipment, allowing the model to provide a more accurate classification of current operation. By including a number of different sensors the model is able to capture information on a number of different aspects of equipment operation, allowing it to better identify abnormal behavior such as early signs of equipment failure.

The classification performance of the proposed framework can be demonstrated by the use of a confusion matrix shown in Figure 5. The proposed framework classifies the prediction of the system's health status very accurately with a high number of correct classification. Only a few false predictions were observed, i.e., some instances were incorrectly classified as being in a bad health status whereas they were actually in a good health status. This type of false prediction leads to additional, unnecessary maintenance actions. In contrast, instances that are classified as being in a good health status are correct and no maintenance actions are performed. As it is common in many industries that maintenance actions incur additional costs and potentially result in down time of the equipment, it is very important to avoid over maintenance and the proposed framework is able to achieve this goal.

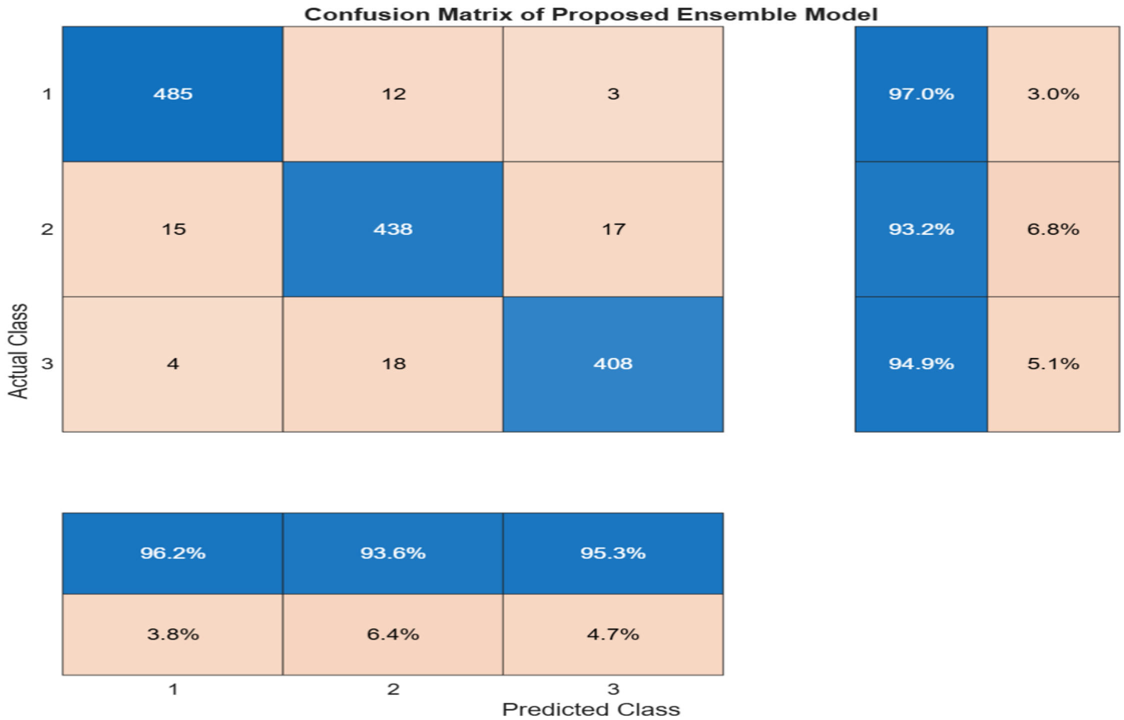

Figure 5. Confusion Matrix of Proposed Ensemble Model

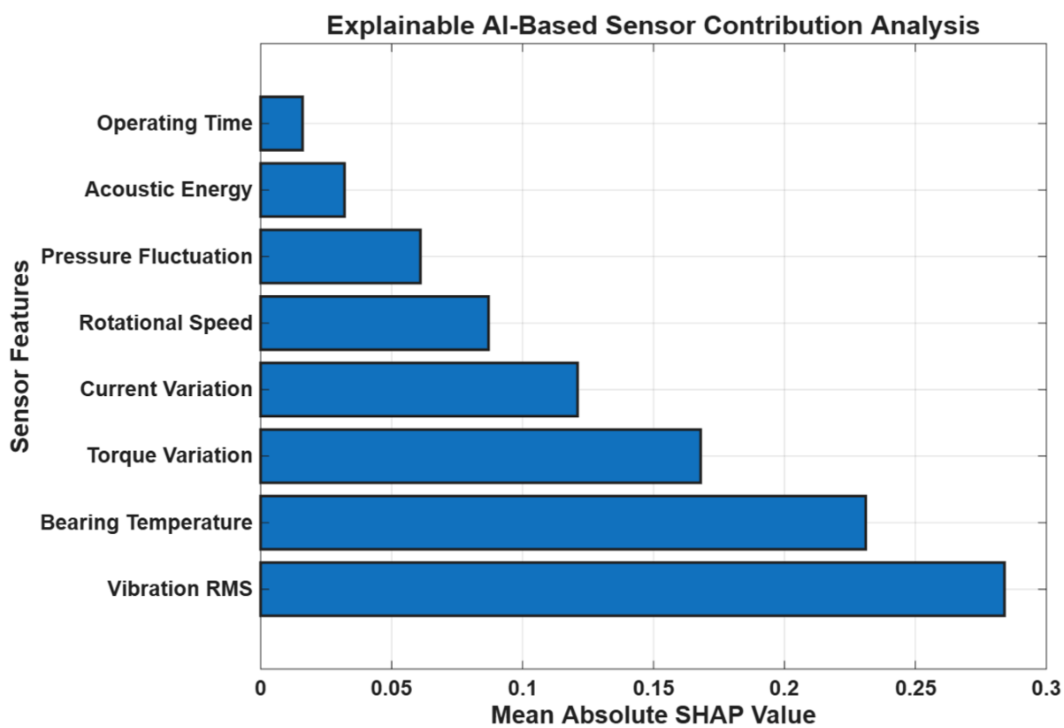

Figure 6. SHAP-Based Sensor Importance Analysis

In order to better understand how the individual sensors within the monitoring system were contributing to the final outcome of the framework, the features from the sensor data were analyzed using SHAP, explained earlier in this paper. The analysis in Figure 6 of the feature contributions identified key elements from the data that had the greatest contribution towards determining whether the system was predicting a healthy asset, a failure in progress or an imminent failure. As indicated by the results of the analysis, a combination of characteristics including several vibration signals, temperature, as well as high and low torque signals were used in making these classifications. Importantly, the signals associated with the highest values within the boxes were determined to be of greatest significance. Specifically, the vibration and temperature signals provided the most influence on the predictive maintenance decision with the latter indicating the thermal effects that various pieces of equipment undergo during normal operation. Such changes and those within torque can often indicate mechanical degradation or stress that, if not addressed in a timely manner, could lead to an increased risk of a catastrophic failure. Thus, by incorporating the ability to better provide insights and therefore an increased level of transparency to into the framework, multi-sensor information that previously required the extensive involvement of human intervention can now be automatically analyzed. This enables the framework to support maintenance activities while allowing personnel responsible for the various pieces of industrial equipment to better understand the root causes behind potential faulty conditions thereby ensuring that only the most necessary and cost effective of maintenance activities are performed. As such, the proposed approach of utilizing an ensemble-based method with the capability of explainable AI to process and predict using the various monitoring sensors within an IIoT-based monitoring system was shown to be able to reliably provide a number of benefits including high levels of classification accuracy, robustness, as well as a support of both of predictive and preventive maintenance within industrial applications.

6. Limitations

One crucial limitation of the proposed approach in the context of IIoT environments for predictive maintenance, lies in its dependency on high quality sensor data for adequate performance. Several aspects that could affect such a dependency have to be considered: (1) sensor accuracy in general; (2) sensor related measurement noise; (3) occurrence of missing values for individual data streams as well as for the whole dataset; (4) inconsistent data acquisition as provided by different, possibly legacy, sensor systems. Experiments have been carried out using available industrial data sets. Thus, limitations are given in terms of an adequate coverage of industry-specific scenarios in terms of the diversity of employed equipment under different types of operation. Additionally, also a wide variety of different kinds of failures are hardly covered in sufficient quality and quantity using such data sets in experiments. Computational complexity: The number of ML models that are included in an ensemble increases the accuracy of the predictions, but it also requires more computational power for training the models, for model optimization, and for the implementation in real-time scenarios on edge devices. This is especially critical for implementations on small devices in resource-constrained environments. Note that the main goal of the proposed framework is to support the machinery and plant staff in fault classification and in decision-making for predictive maintenance. The framework does not aim to continuously predict the remaining useful life of the assets nor the long-term degradation process. However, these two aspects are of high interest for many applications and shall be addressed in future research. Our explanation method uses SHAP values for approximation of contribution of individual input parameters in order to better understand the role of different sensors. However, approximations in SHAP values could be source of uncertainty and there could be situations where model behavior cannot be sufficiently explained. To confirm robustness of the proposed framework, its validation should be performed on large-scale industrial datasets collected in real time in different operation environments. For that purpose, future research should incorporate IIoT real-time deployment, apply adaptive learning methods, implement edge-based optimization, and also deepen investigation of application of deep learning approaches.

7. Conclusion

This paper presents an explainable ensemble machine learning framework, namely EEM-PM, for predictive maintenance in Industrial Internet of Things (IIoT) by integrating multi-sensor data fusion with advanced machine learning and explainable artificial intelligence. In the framework, heterogeneous sensor parameters are effectively utilized to diagnose equipment health states and improve failure prediction accuracy. Experimental results showed that the proposed ensemble model outperformed individual machine learning models with accuracy, precision, recall, and F1-score values of 97.2%, 96.8%, 96.5%, and 96.6%, respectively. The results further demonstrated that using multiple sensor inputs significantly improved failure prediction accuracy compared with single-sensor-based monitoring approaches. In addition, the results of explainability analysis revealed that vibration features, bearing temperature, and torque features were the top three influential factors that affect the failure prediction decisions made by the model, providing useful insights for maintenance planning. The developed framework offers a reliable and interpretable solution for intelligent industrial maintenance by reducing unexpected failures and supporting data-driven decision-making. Future research can focus on real-time deployment using edge computing platforms, integration with digital twin environments, continuous learning mechanisms for changing operating conditions, and extension toward remaining useful life estimation and autonomous maintenance scheduling. These developments can further enhance the scalability and practical adoption of AI-driven predictive maintenance systems in smart industrial environments.

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