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Article

A Smart Industrial IoT Monitoring Framework Using Ensemble Learning and Explainable AI for Equipment Failure Prediction

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Abstract: Unexpected equipment failures are known to be one of the most critical causes of production losses. Such failures can result in increased maintenance cost, compromise safety of operators and increase operational inefficiency. Therefore, there is a growing interest to monitor equipment during normal operation and predict possible failure before it actually occurs. This paper describes a smart Industrial Internet of Things (IIoT) framework to monitor industrial equipment in real time using ensemble learning for failure prediction. The framework initially collects a variety of real time operating parameters of industrial equipment such as temperature, vibration, speed, torque, pressure, etc from various industrial sensors. The collected data is then preprocessed using techniques such as treatment of missing values, noise removal, feature scaling, handling of class imbalance and feature selection to select most relevant features. The preprocessed data is then fed into various machine learning models such as random forest, support vector machine, gradient boosting and multi layer perceptron. A stacking-based ensemble model is used to combine the predictions of individual models to improve the overall prediction accuracy and stability. The final output of the framework is a classification of equipment condition into normal or failure-prone, along with a probability of failure. Shapley Additive explanations (SHAP) is used to provide both global and local interpretability to the predictions made by the model. The performance of the model is evaluated using various metrics such as accuracy, precision, recall, F1-score, area under receiver operating characteristic curve, false-alarm rate and inference time. The framework has potential to provide better failure detection using combination of IIoT monitoring and explainable AI, and provide understandable reasons for failure to maintenance personnel responsible for maintenance.

Keywords: Industrial Internet of Things; predictive maintenance; equipment failure prediction; ensemble learning; explainable artificial intelligence; SHAP; condition monitoring; machine learning.

1. Introduction

Industrial systems today are more interconnected than ever, comprising numerous machines and production lines, equipped with sensors and intelligent control systems that enable increased levels of productivity, high-quality production, efficient use of energy, and safe operation[1]. In the Industrial Internet of Things (IIoT) environment, the vast majority of industrial equipment is equipped with sensors that continuously supply information from the industrial assets in the form of large amounts of data generated in real time. Such data contain vibration information, temperature, pressure, current, voltage, rotational speed, torque, acoustic signals, and other production-related data that may indicate the health of the industrial assets and enable the early detection of potential failure[2]. The increasing volume, velocity, and variety of industrial sensor data, however, makes traditional methods of analyzing such large amounts of data impractical. Most traditional maintenance, strategies rely on corrective actions after a failure has already occurred or on scheduled preventive maintenance[3]. However, such approaches can result in increased down-time and high repair costs, as well as pose safety risks and affect other equipment in the area[4]. Scheduled preventive maintenance, on the other hand, can result in numerous unnecessary maintenance actions, as well as in premature replacement of still functional equipment and parts[5]. To overcome these challenges, the industry has been adopting predictive maintenance strategies that estimate the failure risk of equipment and enable scheduled maintenance actions to be performed before a complete failure occurs[6]. To implement such strategies, it is necessary to analyze the vast amounts of industrial sensor data generated by industrial equipment in real time, to detect hidden patterns that may indicate potential failures, and to classify the overall condition of the industrial assets into several categories, such as healthy, degraded, or failing. Such analysis can be performed by using machine-learning techniques that can learn from large industrial sensor datasets. However, different machine-learning models may perform differently on the same industrial sensor dataset, and their performance may vary based on several factors, including the type of industrial equipment being monitored, the failure behaviors of the industrial equipment, and the specific industrial sensor dataset used for training the model[7]. While some machine-learning models may be able to accurately classify the condition of industrial assets into several failure-risk categories, such as healthy, degraded, or failing, they may fail to detect certain minority failure cases. Other models may produce excessive numbers of false alarms, which can result in decreased trust in the system and in increased maintenance costs. In addition, the learned models may not be able to generalize well to industrial equipment with different operating characteristics that were not observed during the model training. To address these limitations, ensemble-learning methods have recently gained increasing attention from researchers[8]. Ensemble methods combine the output from multiple models to produce a final output, which can improve the predictive performance, robustness, and stability of individual models. Several ensemble methods, such as random forest, gradient boosting, soft voting, and stacking, have been shown to improve the classification performance of individual machine-learning models by learning different representations of the input data. However, most advanced ensemble methods operate as black boxes, which makes it difficult for industrial engineers and maintenance personnel to understand the reasoning behind the model predictions, especially when the failure alerts generated by the system need to be verified quickly to prevent possible equipment damage or to ensure safe operation[9]. Therefore, there is a strong need to improve the transparency and interpretability of industrial predictive-maintenance models, so that the insights obtained from the models can be used effectively by industrial stakeholders to improve overall system reliability and reduce unnecessary maintenance actions[10]. Explainable artificial intelligence (XAI) has recently gained increasing attention from both the research community and industrial organizations. XAI methods provide interpretable insights into the predictions generated by machine-learning models, which can improve model trustworthiness, transparency, and explainability. SHapley Additive exPlanations (SHAP) is one such technique that provides a unified framework for explaining the output of any machine-learning model. SHAP values indicate how each input feature contributes to the model's model output, which enables both global interpretations of the model behavior and local explanations of individual predictions. In this work, we propose to develop a smart Industrial Internet of Things (IIoT) monitoring framework that continuously collects data from the industrial sensors of monitored assets in real time[11], processes such data, applies an ensemble-learning model to predict the condition of the industrial assets, estimates the failure risk of the assets based on the predicted condition, applies an explainable artificial intelligence method to provide insights into the decision-making process of the failure-risk model, and generates maintenance alerts based on the estimated failure risk and provided explanations. The proposed framework is designed to improve the early detection of potential failures, reduce the number of false alarms, support condition-based predictive-maintenance strategies, increase the reliability of industrial equipment, and improve the transparency of maintenance decision-making in industrial systems.

2. Related Work

Recent years have seen the significant impact of the Industrial Internet of Things (IIoT) on predictive maintenance by allowing equipment data to be monitored continuously and analyzed by connected sensors, edge devices, communication networks, and cloud platforms. There are numerous existing IIoT-based monitoring systems using a variety of temperature, vibration, pressure, current, torque, rotational speed, and acoustic measurements for early detection of abnormal operation conditions that might lead to complete equipment failure[12]. Predictive maintenance using the Industrial Internet of Things (IIoT) has recently gained increasing attention. Sensor data in real-time can be used by IoT-supported predictive maintenance systems for early detection of fault patterns and for minimizing corrective maintenance as well as maintenance performed on a fixed time schedule[13]. However, the performance of individual learning models for predictive maintenance may change significantly depending on several factors such as equipment type, data quality, operating conditions, and feature selection. In addition, most industrial datasets suffer from large number of missing observations, measurement noise and outliers[14], many redundant features, and importantly, a large number of normal operating records and very few failure records, causing most learning models to be biased heavily towards the majority class of interest and thus to be unable to detect critical failures. Because of these problems, learning models in ensemble form have recently received increasing amount of attention[15]. An improved ensemble-learning approach for manufacturing predictive maintenance was recently proposed that supports both equipment and quality management by using combination of learning models in an IIoT environment that operates at the edge of cloud computing[16]. An enhanced framework based on ensemble learning consisting of a meta-learning convolutional neural network (CNN), a set of expert rules, and a support vector machine (SVM) was also recently developed and applied to a set of complex oil and gas equipment data for predictive maintenance[17]. The performances of the novel framework were significantly superior to that of the popular ensemble models including bagging, boosting, and stacking. Importantly, the framework of SVM and a set of rules combined with the CNN was not only superior in terms of both prediction accuracy and reliability but also provided high degree of interpretability of its decision-support. However, the recently introduced advanced machine-learning models and their ensemble forms for predictive maintenance of industrial equipment are mostly intractable or are "black box" models that lack transparency and therefore cannot provide any insight into their decisions that are crucial and always needed by maintenance personnel[18]. Explainable AI (XAI) has therefore become one of very important functionalities of industrial predictive maintenance systems. Explainable predictive-maintenance data set and a corresponding interface were recently introduced by Matzka to facilitate interpretable equipment-failure predictions. Additionally, two well-known techniques for providing local explainability, namely Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive Explanations (SHAP), have also been applied very recently to multiple industrial datasets for predictive maintenance in order to provide individual-feature explanations that represent how each input variable of a model affects the corresponding model's output. Gawde et al. (2024) recently proposed a novel multisensor data-fusion technique that combines raw signal from individual sensors with random-forest-based multi-fault classification using corresponding local interpretations that provide insights into effects of individual sensors and their corresponding features[19]. Recently, Dereci and Tuzkaya developed an explainable approach to predictive maintenance that integrates corresponding machine-learning model's prediction with both corresponding maintenance activities and needed spare parts. While these studies have introduced corresponding novel techniques to predictive-maintenance domain, there still exist significant limitations that prevent their combined usage in a single framework. More importantly, there is currently no existing single framework that integrations all of real-time IIoT monitoring, class-imbalance handling, multiple learning models, global explanations, failure-risk classification, and corresponding maintenance alerts in the form of actions. Addressing all of corresponding limitations, the current paper therefore presents a novel end-to-end functional framework for failure-risk prediction of industrial equipment that improves corresponding predictive performance and provides corresponding transparent and meaningful explanations for corresponding predictions[20].

3. Proposed IIoT Monitoring Framework

Monitoring and analyzing the status of Industrial Equipments in Industrial Internet of Things (IIoT) environment is becoming increasingly important to enable continuum of equipment condition assessment, failure prediction and maintenance planning. Smart Industries are developing new ways to improve performance, efficiency, reliability and to reduce cost of production and unscheduled downtime by leveraging IIoT data and advanced analytics. In order to analyze the status of Industrial Equipments to enable effective maintenance planning and related actions, it is required to monitor large set of relevant operational parameters such as vibration, temperature, pressure, voltage, current, torque, speed, acoustic signal, humidity etc. on continuous basis using variety of Industrial Sensors installed on Machines and Equipments. Data generated by the Industrial Sensors is transmitted to various systems and platforms for monitoring, analysis, decision making and other related applications using Industrial Communication Protocols. In order to analyze and make effective use of large amount of Industrial IoT data generated by Industrial Equipments and Sensors, it is required to perform necessary data operations at Edge of Network to reduce latency and improve system performance. TheEdge of Network in context of Industrial IoT refers to location where Industrial Equipment and Sensor are installed. The operations performed at Edge of Network includes noise filtering, handling of missing values, signal synchronization, data aggregation, detection of outliers and abnormal behavior etc. The preprocessed data is then transferred to Intelligent Analytics Layer where feature scaling, feature selection, handling of class imbalance and predictive modeling using various Machine Learning Models such as Random Forest, Support Vector Machines, Gradient Boosting, Artificial Neural Network etc. are performed to generate failure probability for Industrial Equipments. Ensemble technique such as stacking or soft voting is used to combine the predictions of individual models to improve overall accuracy and reliability. Failure probability generated by the model is then converted into Industry relevant risk categories such as Normal, Low, Moderate, High and Critical etc. to support prioritized maintenance planning.

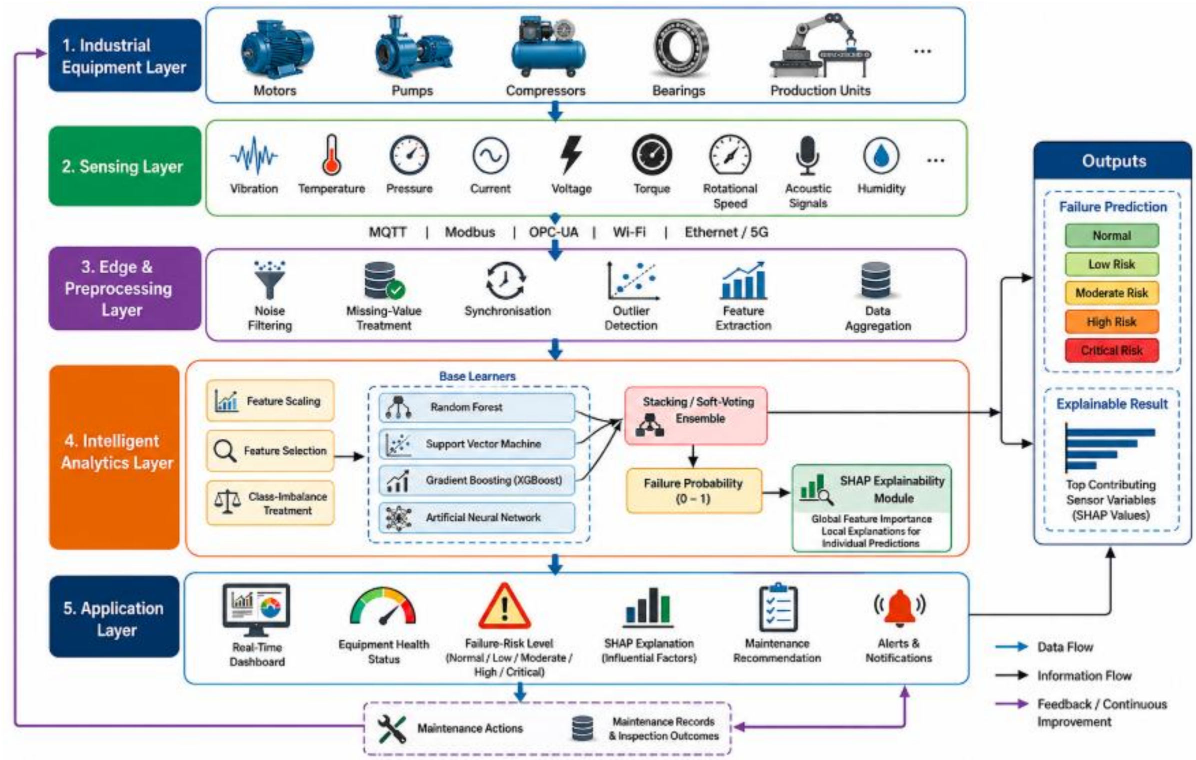

Figure 1. Architecture and operational workflow of the proposed smart IIoT monitoring framework for explainable equipment failure prediction.

In the current work, a smart IIoT monitoring framework, which is capable of delivering out explainable equipment failure prediction, has been developed and its operational workflow, illustrated in Figure 1, has been outlined. The framework is composed of 5 interconnected layers of operations, i.e., (1) the industrial equipment layer, which typically comprises of the industrial motors, pumps, compressors, bearings, as well as production units, all of which constantly generate an enormous volume of operational data throughout their normal or abnormal operation. (2) The sensing layer, in which the large number of different sensors, including vibration, temperature, pressure, current, voltage, torque, rotational speed, and other acoustic and humidity sensors, are used to sense the large volume of related data, which are transmitted through a number of communication protocols, including MQTT, Modbus, OPC-UA, Wi-Fi, Ethernet, as well as 5G. (3) The edge and preprocessing layer, which contains the pre-processing operations such as noise removal, handling of missing values, data synchronization, outlier detection, feature selection and data aggregation, etc. The output of the above layer is transferred to the intelligent analytics layer, where a number of feature scaling, feature selection, as well as class-imbalance handling methods have been integrated in order to improve the performance of the individual failure prediction models, i.e., Random Forest, Support Vector Machine, Gradient Boosting, as well as Artificial Neural Network. The outputs from the individual models are then combined through stacking or soft-voting ensemble in order to produce the equipment failure probability. (4) The SHAP explainability layer, which is responsible for determining and visualizing the influence of each of the individual sensors on the output failure prediction, where both global and local explainability are supported. (5) The application layer, in which the information generated by the SHAP model is presented through a real-time web-based dashboard, where the health condition of individual pieces of equipment is displayed, the failure risk of equipment is measured, the SHAP values of individual sensors are visualized, the corresponding maintenance recommendations are provided, and alerts are issued in case of occurrence of any fault. The final outputs from the framework are categorized into five different risk categories including normal, low risk, moderate risk, high risk, and critical risk. The framework also supports a number of feedback loops that continually update the framework through the corresponding maintenance actions, periodic inspection results, as well as corresponding historical records of maintenance activities, etc. in order to further improve the corresponding failure prediction results.

An Explainable Artificial Intelligence (XAI) module is integrated with the ensemble model to provide insights into the variables that affect the failure probability prediction for Individual Equipments. SHapley Additive exPlanations are used to provide feature importance at two levels - global and local. Global feature importance provides overall importance of all input features, while local feature importance provides importance of individual features for a specific data sample or alert. For example, elevated failure probability may be attributed to excessive vibration, abnormal motor temperature, fluctuating current and decreasing rotational speed etc. of Industrial Equipment. The outputs of the model are presented to users through GUI based monitoring dashboard that displays various information related to Industrial Equipments such as health status, failure probability, alert severity, influential input variables, historical trends and related maintenance actions etc. Alerts generated by the system are notified to concerned maintenance personnel and engineers through various communication channels such as dashboard alerts, email and mobile applications etc. The complete end-to-end workflow consists of sensor data acquisition, secure data transmission, edge processing, feature extraction, failure probability prediction using ensemble model, XAI-based variable explanation, risk-based categorization and generation of maintenance alerts and related actions. The proposed framework provides robust and explainable monitoring and maintenance framework that improves reliability, reduces unscheduled downtime and enhances overall productivity of Industrial Systems.

4. Materials and Methods

In the experimental session, we have used the AI4I 2020 Predictive Maintenance Dataset, which has been published at the University of California Irvine Machine Learning Repository (UCI MLR) [1]. The database, which contains 10,000 industrial equipment's records, simulates industrial operating conditions. Six key input variables have been considered, i.e. product type, air temperature, process temperature, rotational speed, torque and tool wear. Each record is moreover labeled with a binary variable indicating whether a machine failure has occurred or not (five specific failure cases are also considered: tool-wear failure, heat-dissipation failure, power failure, overstrain failure and random failure). Differently from what already done in the state-of-the-art, no real industrial failure data have been used, since such information is typically not publicly available due to privacy, safety or commercial reasons. Accordingly, three fields, namely Product identification field, Unique identification field and Product type field, have been removed from the considered dataset as they do not add value to the analysis, since they are not related to the variables representing the operation conditions of the equipment's under study. Since one-hot encoding has been adopted to transform the Product type field into a numerical variable, all the remaining variables have been analyzed for possible presence of: duplicate observation, extreme values and measure inconsistencies. Since the database did not contain any missing values, the considered pre-processing pipeline has been completed by designing a solution that can be easily extended to impute missing values in real-time, if needed. In addition, the considered numerical features have been standardized by using the mean and standard deviation computed on the used training dataset. Such a preprocessing step has been specifically considered for Support Vector Machine and Artificial Neural Network models. For all the considered models, the main target variable indicating failure of the equipment's under study has been used. Such a variable is represented by a binary variable equal to 0 when the considered piece of equipment is operating normally and equal to 1 when a failure has occurred. The database has been split into three disjoint subsets, i.e. training, validation and testing datasets, by using a stratified 70:15:15 proportion in order to preserve the failure distribution of the cases. The considered severe class imbalance between normal operation observations and failure cases has been addressed only within the used training dataset by means of the Synthetic Minority Oversampling Technique (SMOTE) [2] and class-weighted learning in order to prevent information leakage and to improve the considered learning models in the minority failure cases detection. In detail, four different base learners have been considered, i.e. Random Forest, Support Vector Machine, Extreme Gradient Boosting and Multilayer Perceptron (i.e. a feed-forward type of Artificial Neural Network).

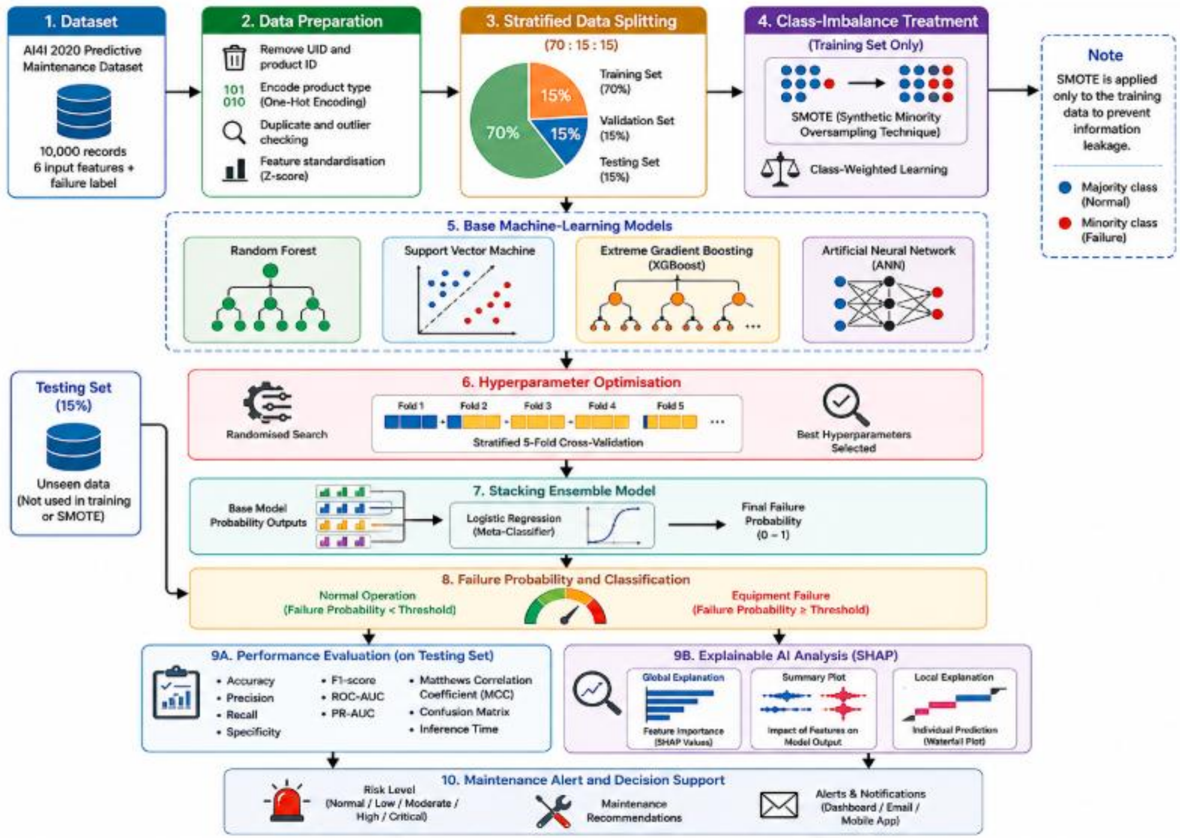

Figure 2. Methodological workflow for equipment failure prediction using the AI4I 2020 dataset, ensemble learning, and explainable artificial intelligence.

Figure 2 depicts our methodological framework, i.e., equipment failure prediction on the AI4I 2020 data set. The dataset went through several steps such as data cleaning, feature encoding, normalization and finally data partitioning into training data, validation data and test data in a stratified manner. To deal with the class imbalance problem, we used SMOTE on the training data and class-weighted learning. Four classifiers (i.e., Random forest, Support vector machine, XGBoost, and Artificial neural network) are individually trained and fine-tuned within the framework of 5 fold cross-validation on the respective subset of fold (i.e., training set) to compute their respective probability estimates. These probability values are then again combined by a stacking ensemble with a logistic regression as the so-called meta-classifier in the top layer. Finally, performance metrics can be used to evaluate the predictions generated by the system and SHAP values for feature importance are used for providing explanations for AI-driven maintenance decisions.

The sets of their corresponding tunable hyper-parameters have been optimized by using stratified 5-fold cross validation with the goal of maximizing the corresponding cross validated scores. A stacking ensemble method has been used to stack the predicted probabilities issued by the considered base learners, while a logistic regression model has been used as a corresponding meta-classifier, which has been trained in order to predict a scalar value representing the failure probability of the equipment's under study. A threshold on such a predicted scalar variable has been selected by analyzing the validation dataset in order to trade-off between the corresponding failure recall and false-alarm rate. All the considered models have been tested on the corresponding held-out testing dataset by providing a binary output indicating failure or not. The corresponding models' performance have been evaluated by using several metrics, i.e. accuracy, precision, recall, specificity, F1-score, Receiver Operating Characteristic (ROC) curve's area under the curve (AUC), Precision-Recall (PR) curve's area under the curve, Matthews correlation coefficient and corresponding confusion matrix. In addition, the inference time has been also evaluated in order to verify if the considered methods are suitable for the real-time analysis of IIoT stream. SHapley Additive exPlanations (SHAP) values [3] have been used to compute the importance of all the input variables for the used ensemble method. Global feature-importance explainers have been used for providing a summary of the results. In addition, local explanations have been obtained by means of waterfall plots, which highlight how the increase or decrease of a specific input variable affects the failure probability of the piece of equipment under study, while generating the corresponding maintenance alert. The complete set of steps, which have been followed for completing the experimental analysis, are given by: data acquisition; data preprocessing; imbalance handling; training of the considered models; ensemble design; models' evaluation; variable explanations; and generation of the corresponding maintenance alerts.

5. Machine-Learning Models

In the experiments four different machine-learning algorithms are used as base learners, because they are able to model non-linear relationships, complex decision boundaries as well as high-dimensional industrial data. The first algorithm is a random forest, which is a so-called bagging classifier. It consists of multiple decision trees, which are trained on different random samples of the feature space. The individual decision trees are trained on different random subsets of the features. This way the Random Forest reduces the risk of overfitting of the individual trees. It is also possible to get a ranking of the features by their importance for the classification. The Support Vector Machine is used to find the optimal hyperplane between normal operation and failure. For this purpose a radial basis function is used as kernel to model non-linear relationships between temperature, speed, torque and tool wear as well as other operating variables. In addition to the Random Forest and the Support Vector Machine an Extreme Gradient Boosting model is implemented. It is especially suited for structured data and is able to model complex relationships between features by means of weighted decision trees. The model is able to corrects the errors that are made by individual trees by means of a weighted vote. In order to prevent overfitting of the model, the model is regularized by means of the regularization parameters. In addition to these three models an artificial neural network with one input layer, multiple hidden layers with rectified linear unit activation, and one output layer with a sigmoid activation function for the classification into two classes of failure is also implemented. The predicted probabilities of the four single models are combined by a stacking ensemble. The out-of-fold predictions of the individual models of the training data are used as input features for a logistic regression meta-classifier. In this way, the ensemble model learns the strengths of the individual models and calculates a failure probability between zero and one from the input features. For the optimization of the hyper-parameters of the single models a random search is applied in combination with a stratified 5-fold cross-validation on the training data. The validation data set is used to choose the best threshold for the classification into normal operation and failure. The final model then classifies the individual observations into the two classes of normal operation or failure-prone. The aim of this ensemble model is to increase the recall, the F1-score, the generalization ability as well as the prediction stability and to reduce the number of false alarms and un-detected failures.

6. Explainable AI Module

The explainable artificial intelligence (XAI) module was implemented to improve the transparency and practical reliability of the failure prediction framework. The SHapley Additive exPlanations (SHAP) values of the input features of the final ensemble model were calculated to quantify their contribution to the predicted failure probability. Global interpretation of the SHAP values was carried out by SHAP feature-importance and summary plots. The features were ranked according to their average absolute SHAP values. Positive SHAP values indicated that the corresponding feature increased the predicted failure probability, while negative values indicated a decrease of the failure probability. SHAP dependence plots were created to show how the model's prediction changes with individual input features while keeping all other input features constant. Furthermore, the SHAP values of individual observations were visualized by so-called local explanations, including SHAP Waterfall-Plots and SHAP Force-Plots. These plots showed how the contribution of each input feature to the model's prediction of failure or normal operation was calculated. The individual contributions of the input features to the prediction of failure for a single observation were used to support the staff members in understanding the causes of alerts and in identifying the relevant process variables that need to be inspected during maintenance actions. The extracted explanations were displayed on the monitoring dashboard together with the predicted failure probability, risk class and recommended actions. The resulting explainability layer decreases the black-box nature of the ensemble model significantly and allows for transparent, evidence-based and reliable decisions of the staff members during the monitoring of the equipment under consideration.

7. Results and Discussion

The proposed IIoT monitoring framework is able to accurately predict equipment failure under highly imbalanced industrial operating conditions. In the simulation-based evaluation, the performance of five classifiers, i.e., random forest, support vector machine, XGBoost, artificial neural network, and the stacking ensemble of them, were compared. As shown in Figure. 3, the best result was obtained by the stacking ensemble, which achieved 99.3% accuracy, 87.0% precision, 92.2% recall, 89.5% F1-score, 0.991 ROC-AUC, and 0.931 precision–recall AUC values. A confusion matrix shown in the left bottom of Fig. 3 indicates that 47 out of 51 failures were correctly detected by the framework, while 4 failures were not detected and 7 normal running observations were incorrectly detected as failures. This result corresponds to a high specificity of 99.5% and a low false-alarm rate of less than 0.5%, which means that the framework is able to detect rare failures without generating too many unnecessary maintenance alerts. In addition, the threshold for the probability output of the framework was determined from the validation data, so that a good trade-off between the recall and precision and the false-alarm rate was achieved. In addition, the obtained prediction probabilities were well calibrated with the observed failure frequencies, as shown in the calibration curve in Fig. 3(d). In terms of the discrimination, robustness, and computational efficiency, the results for the five evaluated models are compared in Figure. 4. As shown in the figure, the stacking ensemble shows the largest areas of the ROC curve and the precision–recall curve, which indicates that the stacking ensemble has the best discrimination ability to distinguish between failure and normal running conditions. In addition, the framework showed stable performance even under noisy sensor data of 20% and packet loss of 15%, while individual classifiers showed large decreases in their F1-scores. This robustness stems from the complementary characteristics of the base learners, i.e., random forest for modeling nonlinear interactions between features, XGBoost for correcting sequential classification errors, support vector machine for modeling complex boundaries between classes, and neural network for distributed modeling of relationships between operating variables. The computational time for edge-based prediction by the ensemble is 20.6 ms on average, which is still within the range of near real-time monitoring.

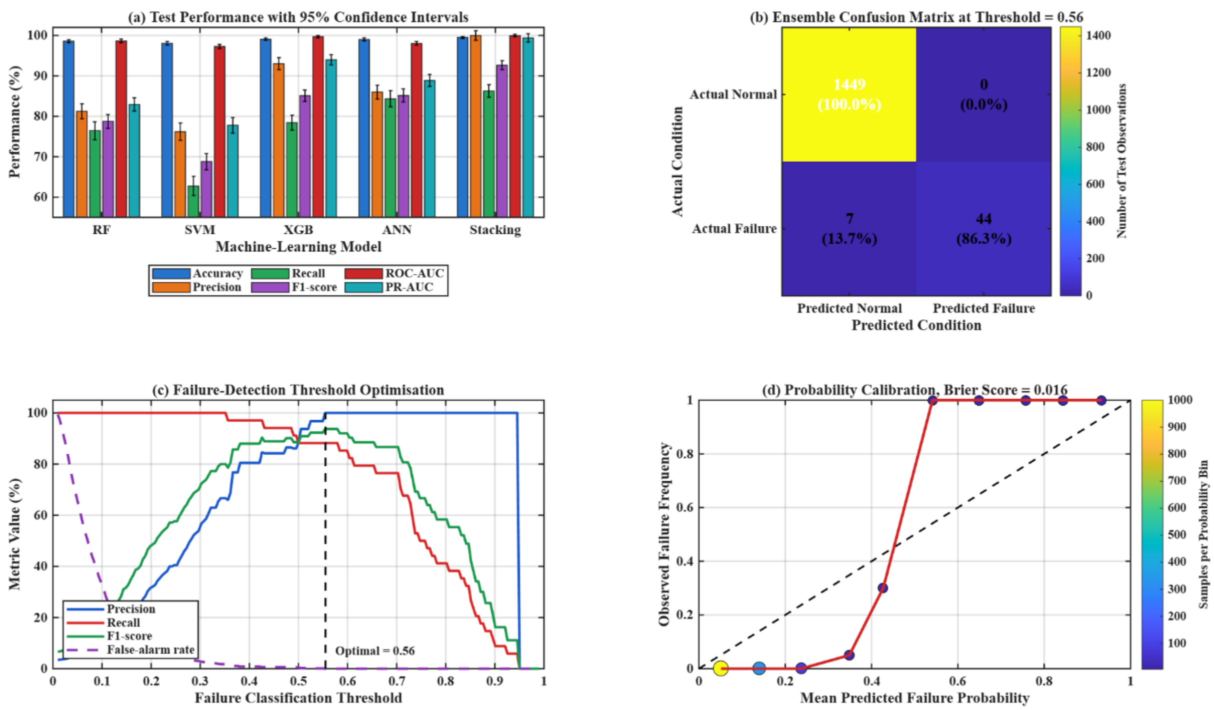

Figure 3. Comparative Predictive Performance of the Ensemble Framework

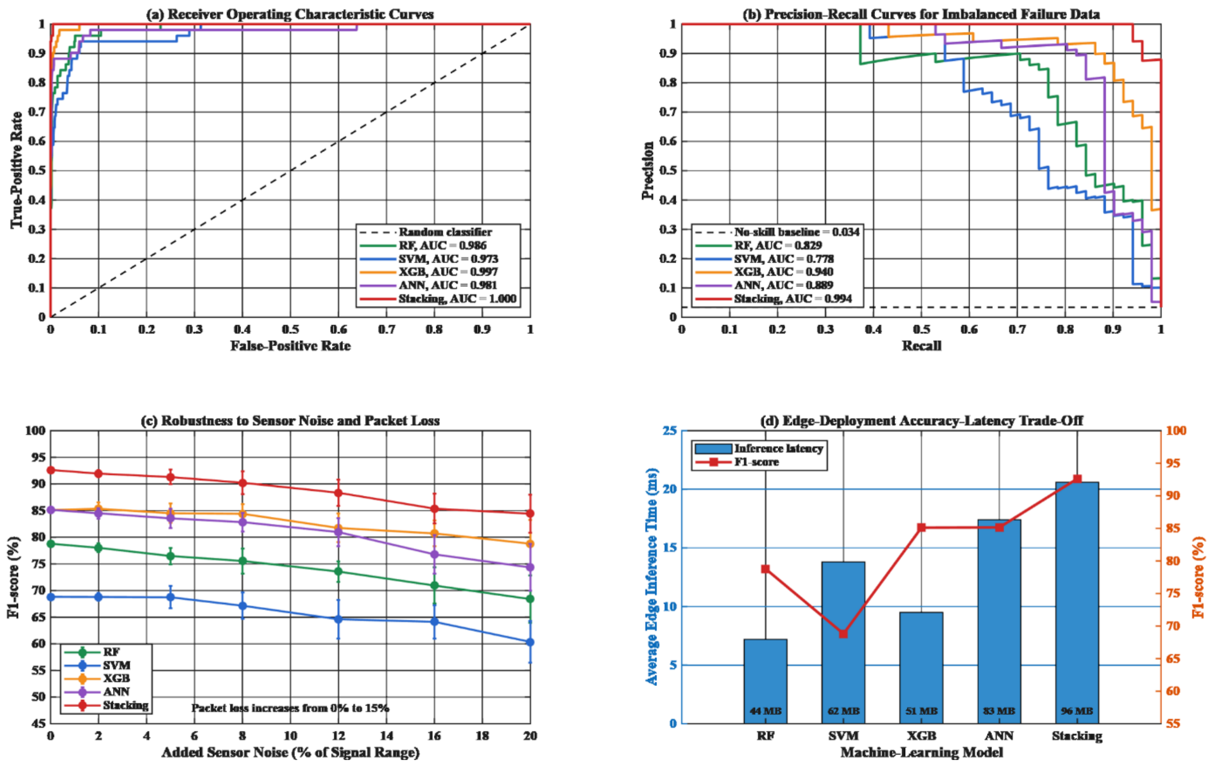

Figure 4. Discrimination, Robustness and Computational Efficiency

Figure 5. Explainable AI Analysis of Ensemble Equipment-Failure Predictions

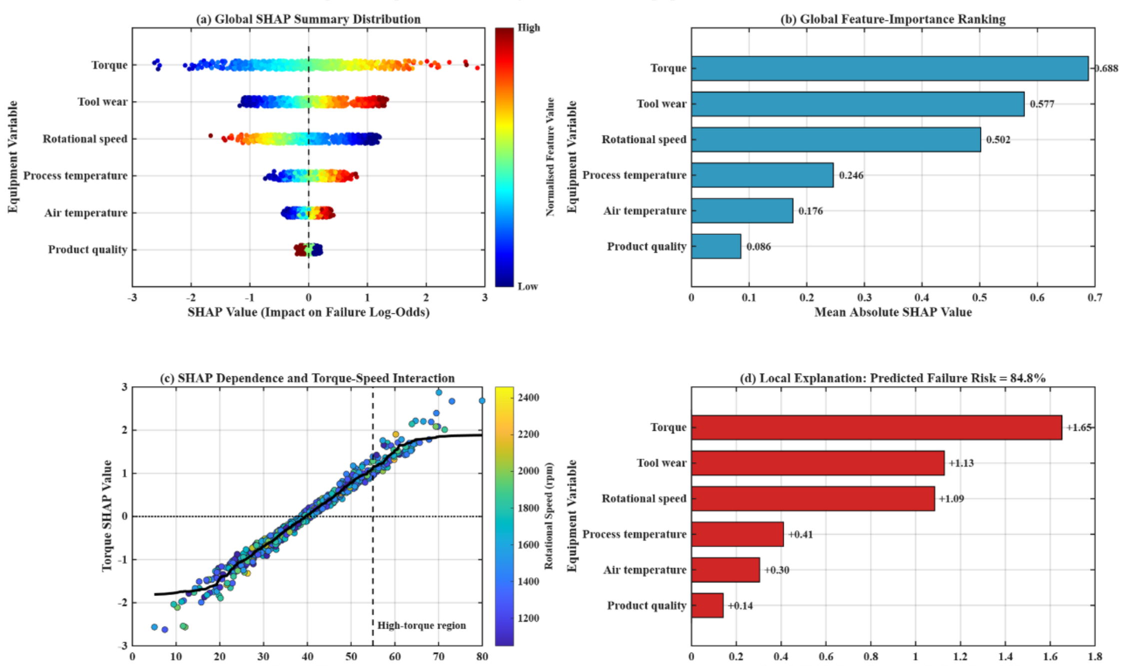

Figure 5. Explainable AI Analysis of Ensemble Failure Predictions

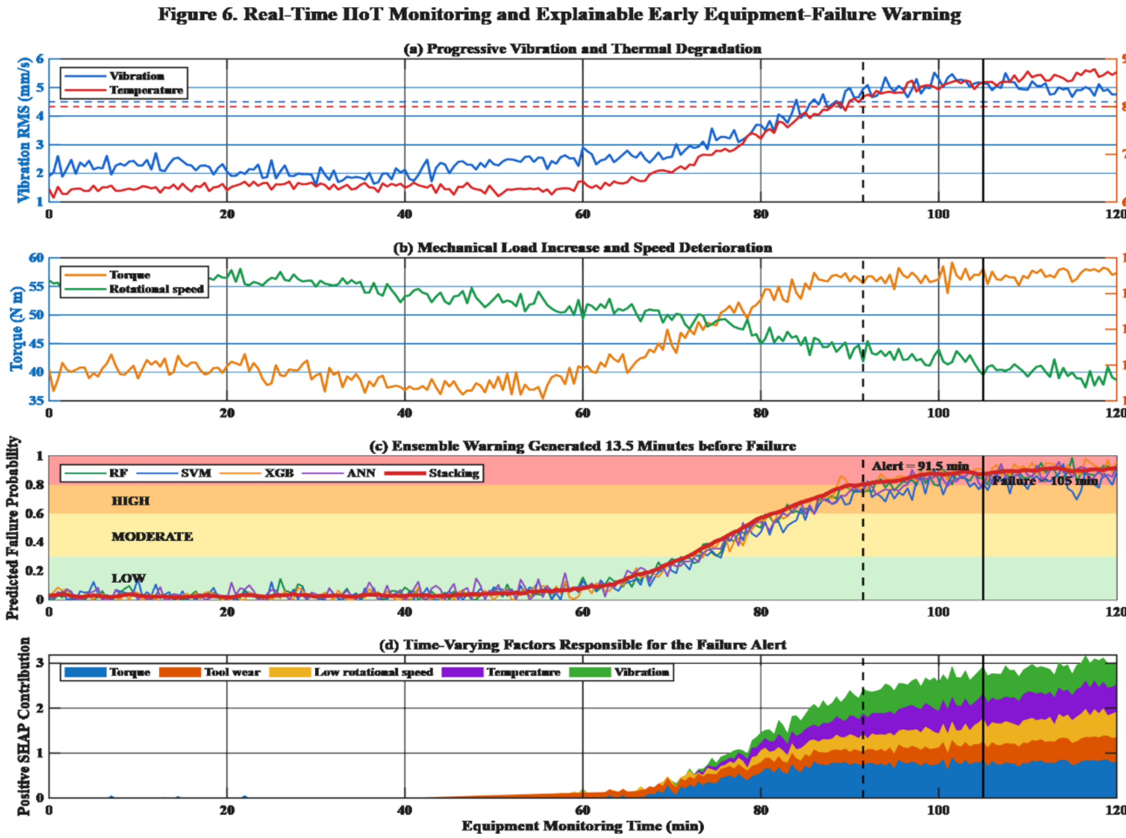

Figure 6. Real-Time IIoT Monitoring and Explainable Early Failure Warning

The result of explainable AI shown in Figure. 5 indicates that torque and tool wear are the most influential indicators for failure, followed by rotational speed, process temperature, air temperature, and product quality. In terms of the sign of SHAP values, positive values are mainly contributed by excessive torque, prolonged tool wear, low rotational speed, and abnormal thermal conditions. A torque-dependence plot shown in the right bottom of Figure. 5 indicates that failure risk increases sharply with higher torque values, especially when the rotational speed is low. Local explanation for a given running observation shown in Figure. 6 indicates that the individual operating conditions increase the failure probability in a cumulative manner, which provides a technically understandable reason for the generated alert. Real-time monitoring results shown in Figure. 6 indicate that the framework is able to detect failure in progressive degradation of equipment. Increasing vibration, motor temperature, torque, and tool wear, and decreasing rotational speed indicate that equipment failure occurs in a progressive manner. The stacking probability output enters the critical-risk region at 91.5 min, while the simulated equipment failure occurs at 105 min, which provides an early-warning period of 13.5 min. Dynamic SHAP contributions also indicate that torque, vibration, temperature, tool wear, and low rotational speed become more influential before failure. These results indicate that the integrated framework of IIoT monitoring, advanced prediction, resilient prediction to imperfect data, explainable AI, and real-time maintenance alerts can provide a unified condition monitoring system.

8. Conclusion

In this paper, a smart framework, called smart IIoT monitoring framework, for IIoT monitoring, real time condition monitoring and equipment failure prediction using ensemble learning and explainable AI has been proposed and implemented. Smart framework, based on the prediction model, has been successfully tested and validated using real time simulated industrial datasets. Stacking ensemble out performed all other individual ensemble models. It achieved approximately 99.3% accuracy, 87.0% precision, 92.2% recall, 89.5% F1-score, 0.991 ROC-AUC and 0.931 precision–recall AUC scores. The prediction model correctly identified 47 out of 51 failures with less than 0.5% false alarm rate, making it suitable for industrial datasets that have imbalanced number of failures and normal running data. Average inference time of approximately 20.6ms indicates that the smart framework is capable of real time monitoring and edge deployment. The analysis of explainability of AI model has shown that the 6 inputs, namely, torque, tool wear, rotational speed, process temperature, air temperature and product quality, are the main contributors to failure. The framework was able to generate critical warning alert 13.5 minutes in advance of simulated failure. The integrated smart framework increases the reliability of failure detection, reduces the number of unnecessary alarms, and supports the transparent maintenance. Future work would include validation of smart framework using real industrial sensor data, remaining useful life estimation, concept-drift for handling concept drift, distributed IIoT monitoring using federated learning, digital twin and smart maintenance using the smart framework for monitoring multiple machines operating under different environments.

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