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PdM-FSA: predictive maintenance framework with fault severity awareness in Industry 4.0 using machine learning

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ABSTRACT

Predictive maintenance contributes to Industry 4.0, as it enables a decrease in maintenance costs and downtime while aiming to increase production and return on investment. Despite the increasing utilization of machine learning techniques in predictive maintenance in industrial systems over the past few years, several challenges remain to be addressed in the implementation of ML, including the quality of the data collected, resource constraints, and equipment heterogeneity. This study proposes an adaptive framework for predictive maintenance in the context of Industry 4.0, specifically in internet of things (IoT) systems, using machine learning (ML) models. In particular, this study introduces PdM-FSA, a new framework based on an ensemble classifier that takes advantage of four widely adopted ML models in the predictive maintenance literature: random forest (RF), support vector machine (SVM), extreme gradient boosting (XGBoost), and k-nearest neighbors (KNN). The performance evaluation results showed that the PdM-FSA framework can perform well for predictive maintenance according to the severity of equipment malfunctions in a smart factory. The results of this study provide significant knowledge to researchers and practitioners on predictive maintenance in the context of Industry 4.0. and enables the optimization of processes and improves productivity.

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1. INTRODUCTION

The term “Industry 4.0” was introduced by the German National Academy of Science and Engineering in 2011 to describe the fourth industrial revolution, with people, machines, and industrial processes intelligently networked [1]. Many technologies drive Industry 4.0, such as artificial intelligence (AI), cloud computing, the internet of things (IoT), cyber-physical systems, edge computing, digital twins, and machine learning (ML) [2], [3]. Through these technologies, Industry 4.0 enables increased productivity and efficiency. It also leads to improved production processes, higher quality products, and greater sustainability. Additionally, it decreases product development costs and shortens lead times [4]. With the widespread use of sensing devices in smart factories, the amount of data generated by production equipment have increased exponentially. These data can be leveraged to provide useful information and gain insights into manufacturing processes, production systems, and equipment. For instance, several studies using ML models in Industry 4.0 have been proposed to enable machines to learn from data and make valuable predictions to anticipate equipment malfunctions [5], [6]. Within the context of Industry 4.0, it is crucial to establish an accurate model for identifying potential machine failures and understanding their specific characteristics. This is primarily driven by the tenet that repairing or replacing an entire malfunctioning machine typically incurs significantly higher costs than replacing a single component.

A good predictive maintenance-based policy enables a decrease in maintenance costs and downtime, and increases production and return on investment [7], [8]. Compared to preventive and corrective maintenance, predictive maintenance relies on historical data collected from sensors and analyzed using algorithms [9]. Although there has been increasing interest over the past few years in the application of ML to predictive maintenance in industrial systems, several challenges remain related to ML implementation, including the quality of the data collected (missing data, dataset size, and outliers), resource constraints, and equipment heterogeneity.

Our analysis of the current state of predictive maintenance is based on related work from 2007 to 2023, identified in various databases. Some limitations have been observed in previous studies on predictive maintenance in Industry 4.0, including low prediction accuracy, small sample sizes, poor data quality, and choice of ML models. To address these issues and accurately forecast equipment malfunctions, this study proposes PdM-FSA, a new framework based on an ensemble classifier that leverages four ML models widely used in the predictive maintenance literature: random forest (RF), support vector machine (SVM), extreme gradient boosting (XGBoost), and k-nearest neighbors (KNN). It adopts a soft voting strategy to combine the predictions from these individual models into a final prediction on whether predictive maintenance is needed, according to the severity of the equipment malfunction, which is classified into three categories: low, medium, and high. The PdM-FSA is designed to help prevent equipment malfunctions accurately by considering the severity of the faults. The problem addressed in this study is formulated in the context of a smart factory composed of various equipment that produce different goods, where sensors monitor the equipment to collect data for predictive maintenance using ML models. The performance of these models is closely related to various factors, such as the size and quality of the dataset, as well as the selection of the ML classifier. Therefore, the research problem involves proposing the right classifier for predictive maintenance that takes into account multiple criteria.

ML in Industry 4.0 has explored various supervised and unsupervised learning models such as SVM, RF, artificial neural networks (ANN), KNN, decision trees (DT), and clustering techniques. However, many of these studies have limitations in prediction accuracy, handling large datasets, computational speed, sensitivity to noise and errors, and accounting for different fault severity scenarios. This study is one of the first to propose an adaptive predictive maintenance framework, referred to as PdM-FSA, that uses an ensemble classifier combining four widely adopted ML models, namely SVM, RF, KNN, and XGBoost. The novelty lies in leveraging an ensemble approach to improve prediction performance while also considering the severity of equipment malfunctions. The framework involves data collection, preparation, and model training/inference steps tailored for fault severity prediction in a smart factory IoT system.

The subsequent sections of this paper are structured as follows. Section 2 provides a summary of some existing studies. The proposed framework is presented in section 3. The performance evaluation results are provided in section 4. Section 5 presents the conclusion, including a summary of key findings and directions for future work.

2. RELATED WORK

machine learning (ML) models are used in various domains, including healthcare, natural language processing, recommendation systems, transportation, and manufacturing, to improve efficiency, accuracy, and support decision-making. The use of machine learning in Industry 4.0 has introduced a number of benefits such as improving product quality and reducing costs through predictive maintenance. This section presents an overview of the existing ML-based solutions for predictive maintenance in Industry 4.0.

Susto *et al.* [10] introduced an ML-based solution for predictive maintenance using multiple classifiers, namely SVM and KNN. These classifiers operate in parallel to identify integral-type faults and optimize the decision process in semiconductor manufacturing. Similarly, Arena *et al.* [11] proposed a novel decision support based on decision trees called classification and regression trees (CART) to identify the conditions under which predictive maintenance using machine learning is more economically profitable than corrective maintenance. The proposed solution helps assess various scenarios based on context-aware information, quality and maturity of collected data, severity, occurrence, and detectability of potential failures, as well as direct and indirect maintenance costs. Ouadah *et al.* [12] proposed a methodology for choosing a suitable supervised-learning algorithm for predictive maintenance. The authors performed a comparative analysis of RF, DT, and KNN algorithms to identify the best algorithm based on criteria such as dataset size and prediction time. Paolanti *et al.* [13] proposed predictive maintenance architecture for a cutting machine, using RF. However, their approach did not investigate different fault scenarios or discuss the quality of the dataset.

Çınar *et al.* [14] performed an extensive analysis of ML models applied in the predictive maintenance of industrial components, focusing on papers published from 2010 to 2020. They reported that predictive maintenance presents significant potential for market growth and that leveraging ML can offer an innovative approach to implementing such maintenance practices. Their findings showed that SVM, RF, and ANN are the most commonly used ML models. Additionally, they identified certain challenges in implementing ML algorithms for predictive maintenance in Industry 4.0, including the identification of the data to be collected and security concerns.

Pagano [15] proposed a predictive maintenance model that uses a combination of long short-term memory (LSTM) neural networks and Bayesian inference in an industrial plant. Potential limitations of this study include noisy data, which may decrease the sensitivity of the model when they are very similar to each other. Abidi *et al.* [16] employed SVM and recurrent neural network (RNN) to develop predictive maintenance model using two datasets. However, their models were not optimized for large datasets and their computational speeds were relatively low.

Amruthnath and Gupta [17] conducted a study to determine the most suitable unsupervised ML models for detecting faults in predictive maintenance using vibration data. They compared the PCA T^2 statistic, hierarchical clustering, k-means, fuzzy c-means clustering, and model-based clustering, based on their prediction accuracy, performance, and robustness. However, it should be noted that their investigation was limited to vibration data and the dataset used was relatively small. Alsina *et al.* [18] used ANN, SVM, RF, and soft computing methods to predict the reliability of 19 industrial components, and found that ML models outperformed traditional approaches when using large datasets.

Carbery *et al.* [19] investigated the application of Bayesian networks (BN) for diagnosing and predicting faults in a large dataset from Bosch. A major drawback of using BN is its computational speed, particularly when handling large datasets. Samatas *et al.* [20] performed an extensive analysis of ML applications in predictive maintenance. Their study found that the production sector is the most dominant industry using predictive maintenance, with ANN, SVM, and RF being the most commonly used models. Teoh *et al.* [21] built a logistic regression model to predict manufacturing equipment health by using real industrial datasets. However, it should be noted that this model is ineffective for nonlinear classes.

The study in [22] implemented a two-phase ML methodology to facilitate the proactive maintenance of low-voltage industrial motors. In the initial phase, three distinct ML models were employed to detect abnormal motor behavior: SVM, backpropagation neural network (BPNN), and RF. In the second phase, SVM was utilized as the most accurate predictive model for identifying individual motor faults that were detected in the first phase. However, one of the limitations of this study was the absence of comprehensive data encompassing every type of motor fault. Wu *et al.* [23] presented a prognostic approach for predicting tool wear using an RF-based method and compared the performance of RF with feed-forward back propagation (FFBP) ANN and support vector regression (SVR) using a dataset consisting of 315 milling tests. The results indicated that RF outperformed FFBP ANN with a single hidden layer and SVR in terms of prediction accuracy.

Alhuqayl *et al.* [24] proposed a methodology to enhance predictive maintenance in industrial environments by integrating ML techniques with the industrial internet of things (IIoT). Their approach leveraged four distinct ML models namely RF regression, gradient boosting regression, SVM, and Elastic Net generalized linear models (GLM), to predict an asset's remaining useful life (RUL) by utilizing a NASA dataset simulating engine deterioration across different operating conditions and failure modes. The authors highlighted the promising performance of the RF regression and gradient boosting regression models in handling complex fault modes and operating conditions. Although their study showed the potential of combining ML and IIoT for improving predictive maintenance strategies, enabling reduced downtime, cost savings, and enhanced operational efficiency in industrial settings, it does not provide a comprehensive comparison with existing predictive maintenance approaches or methodologies.

In summary, several ML models have been proposed for predictive maintenance in Industry 4.0, with most relying on a supervised learning approach [25], [26]. This study is one of the first to propose an adaptive predictive maintenance framework in Industry 4.0, particularly in IoT systems, using an efficient ML-based model to predict when it is necessary to perform maintenance in a smart factory, based on the severity of equipment malfunction. Table 1 presents some recent related works on ML-based predictive maintenance, their strengths, weaknesses, and learning approaches. In summary, most of the supervised ML models share common weaknesses, including memory storage, learning and prediction speeds, and sensitivity to errors in large datasets.

Table 1. Summary of the related work on ML-based predictive maintenance in Industry 4.0

References	ML models	Strengths	Weaknesses	Learning approach
Arena *et al.* [11]	DT	Simple and easy to implement, visualize and interpret.	Poor accuracy and inefficient to solve nonlinear problems.	Supervised
Ouadah *et al.* [12]	RF, DT, and KNN	Perform well with small datasets, predictions closest to reality.	Costly and poor performance with large datasets for RF and DT.	Supervised
Paolanti *et al.* [13]	RF	Higher prediction accuracy.	Require robust datasets.	Supervised
Wu *et al.* [23]	RF	Higher prediction accuracy.	Require robust datasets.	Supervised
Çınar *et al.* [14]	SVM, RF, and ANN	Adapted for large datasets, handle with random, fuzzy and non-linear data.	Require large datasets and have slow learning speed.	Supervised
Amruthnath and Gupta [17]	PCA, Hierarchical clustering, k-means, fuzzy c-means, and model-based clustering	Accurate prediction.	The dataset is relatively small.	Unsupervised
Alsina *et al.* [18]	ANN, SVMs, and RF	Higher accuracy prediction.	Require large datasets and have slow learning speed.	Supervised
Carbery *et al.* [19]	BN	Handle missing data.	Lower computational speed with large datasets.	Supervised
Nikfar *et al.* [22]	BPNN, SVM, and RF	Higher prediction accuracy.	Lack of data, require large datasets.	Supervised
Kamat *et al.* [27]	K-Means	Less computational time.	Sensitivity to the initial placement of the cluster centroids and outliers.	Unsupervised
Bekar *et al.* [28]	K-Means	Easy and simple to implement, efficient and flexible.	Sensitivity to the initial placement of the cluster centroids and outliers.	Unsupervised

3. METHOD

3.1. Problem formulation

The research problem was formulated in the context of a smart factory composed of various pieces of equipment that produce different goods. These pieces of equipment are monitored by sensors to evaluate process performance and machine operations. During operation, the sensors collect data for predictive maintenance using ML models. However, the performance of these models is closely related to several parameters, including the size and quality of the dataset, and the type of ML classifier employed. Therefore, the research problem involves proposing the most suitable classifier for predictive maintenance based on multiple criteria.

3.2. Description of the proposed framework

The main goal of the proposed framework is to provide an efficient ML-based model to adaptively predict when it is necessary to perform predictive maintenance in a smart factory according to the severity of equipment malfunction. The proposed framework involves four steps: i) dataset collection, ii) dataset splitting, iii) data preparation, and iv) model training and inference. Figure 1 presents a high-level overview of the proposed predictive maintenance framework.

3.2.1. Dataset collection

This step involves collecting data from smart-factory equipment using sensors. The collected data include historical data that allow the prediction of necessary maintenance tasks. For the empirical study, we used the AI4I 2020 predictive maintenance dataset, which is a synthetic dataset that represents the real predictive maintenance data that exists in the industry [29]. Table 2 presents the statistics of the dataset.

3.2.2. Dataset splitting

In this step, the dataset is divided into three subsets (datasets 1, 2, and 3) according to the type of failure to devise predictive models that will allow the prediction of whether it is necessary to perform predictive maintenance according to the severity of malfunctioning. Datasets 1, 2, and 3 corresponded to lower, medium, and higher failures, respectively. Dataset 1 consists of 6,000 data points, dataset 2 consists of 2,997 data points, and dataset 3 consists of 1,003 data points.

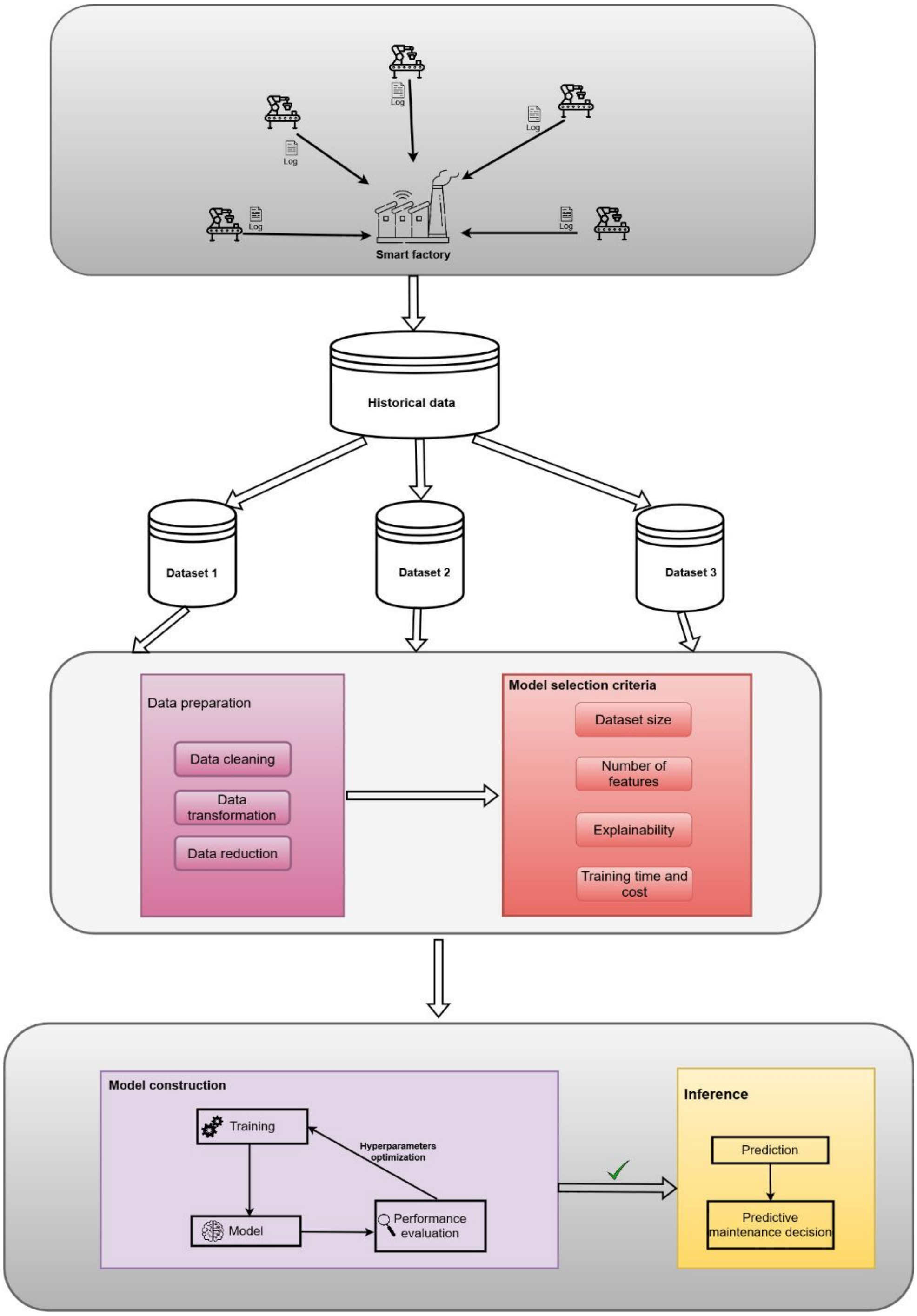

Figure 1. Framework for predictive maintenance

Table 2. Statistics of the dataset

	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure
count	10,000	10,000	10,000	10,000	10,000	10,000
mean	300	310	1538.8	40	108	0.03
std	2	1.5	179.3	10	63.7	0.18
min	295.3	305.7	1168	3.8	0	0
25%	298.3	308.8	1423	33.2	53	0
50%	300.1	310.1	1503	40.1	108	0
75%	301.5	311.1	1612	46.8	162	0
max	304.5	313.8	2886	76.6	253	1

3.2.3. Data preparation

In this step, different actions were performed to ensure that the datasets did not contain missing or invalid values, outliers, or improperly formatted data. The different actions performed include: i) data cleaning to remove missing values; ii) statistical analysis; iii) outlier identification and removal, and iv) features engineering. This produces well-curated data for training an accurate model for efficient predictive maintenance.

3.2.4. Model training and inference

In this step, based on a set of criteria (sample size, explainability, and training cost), some widely used models in predictive maintenance literature were used. These models include SVM, RF, KNN, and XGBoost ML [12], [14]. The specific uses of each model are described below:

– SVM is a supervised learning model used for classification or regression tasks. The SVM finds the optimal hyperplane for regression tasks by using the ε-insensitive loss function, which ignores errors within a certain margin. To perform well, SVM models require some hyperparameters tuning, including the C regularization parameter and gamma (the kernel coefficient).
– RF is a supervised learning model used to perform classification or regression tasks. The RF builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. It operates by constructing multiple trees during training and outputting the mean prediction of the individual trees.
– KNN is another type of supervised learning model used both for classification and regression. The classification or prediction of the grouping of individual data points is determined based on their proximity [30]. To perform well, it is necessary to define the best value for the number of neighbors (n_neighbors), which is a hyperparameter of KNN.
– XGBoost is a supervised learning model designed for ML tasks that requires high accuracy and speed [31]. It is based on decision trees and can be applied solving both classification and regression modeling problems. To run XGBoost, it is necessary to define three types of parameters: general, booster, and task.

To devise an accurate and robust classifier for predictive maintenance, we leverage an ensemble learning model. This ensemble learning model encompasses two or more classifiers to produce the optimal predictive model. In this study, we considered these models to build an ensemble ML model. In this study, a soft voting strategy was adopted. A soft voting strategy combines multiple classifiers to make a final prediction based on the weighted average of the individual predictions. It considers the confidence scores or probabilities assigned by each base model to each class, averages the probabilities, and predicts the class with the highest average probability. This strategy is particularly useful when individual models in the ensemble learning model provide probability estimates for their predictions. Soft voting enhances the overall accuracy and robustness of an ensemble model by considering the confidence of each model in its prediction. Figure 2 illustrates the ensemble learning process used to infer the condition of the equipment for performing predictive maintenance.

In summary, the key methodological aspects covered in this study include: data preprocessing and feature engineering (section 3.2), model selection and training (section 3.2), ensemble model creation using soft voting (section 3.2), performance evaluation metrics (section 4.2), permutation feature importance analysis (section 4.3), and a systematic split of the data by fault severity levels (section 3.2). Sufficient details are provided to enable reproduction of this work. Algorithm 1 presents the steps involved in designing the proposed ensemble-learning model for fault prediction in a smart factory.

Algorithm 1. Training of a predictive maintenance classifier

```
Input: D ▷ historical data for predictive maintenance
            C = {C1, C2, ..., Cn}        ▷ base level classifier
Output: failure prediction (0 or 1)
split D into {D1, D2, ..., Dn} ▷ Splitting is done based on the type of failure
for each dataset in {D1, D2, ..., Dn} do
  remove irrelevant features
if dataset has outlier then
  scale data using Robust scaler
      else
  normalize features between 0 and 1
endif
if dataset is imbalanced then
          resample the dataset
      endif
      Train a Meta level classifier based on C
endif
```

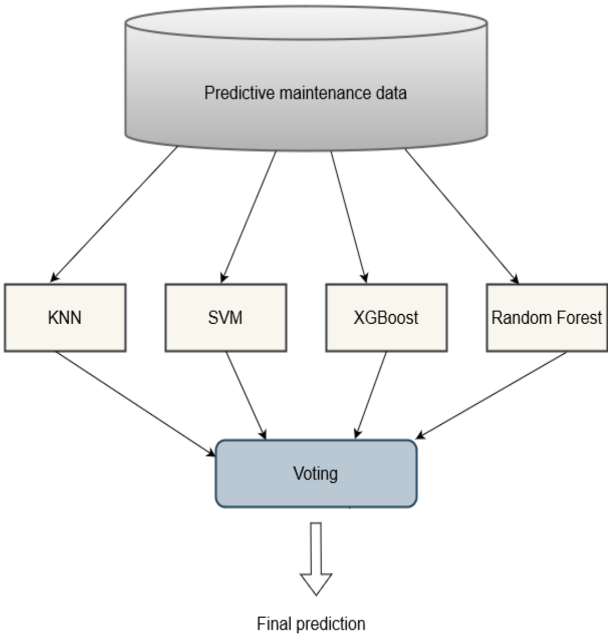

Figure 2. Predictive maintenance based on ensemble learning

4. RESULTS AND DISCUSSION

4.1. Settings of the empirical study

In this empirical study, the classifiers were trained using features extracted from the AI4I 2020 predictive maintenance dataset using Python libraries. During training, hyperparameters were optimized to obtain the most accurate classifier for predicting whether predictive maintenance is required. Table 3 provides the information on the environment used in this study.

Table 3. The environment of the empirical study

Parameter	Value
OS	Windows 10
CPU	Intel Core i7-7500U
RAM	8 Go
Libraries	*sklearn, imblearn, xgboost, numpy, pandas*

4.2. Criteria for performance evaluation

To evaluate the performance of the proposed framework, we considered a number of well-known metrics. These include accuracy, precision, F1 score and Gmean. These metrics are defined as follows:

- Accuracy: Accuracy, as defined by the international vocabulary of metrology (VIM) in [32], is the degree of agreement between a measured quantity value and an actual quantity value of a measurand. This allows for the assessment of the performance of a model on a given dataset.
- Precision: This criterion helps evaluate the ration of true positives to the total number of positives predicted by the model.
- F1 score: this criterion refers to the harmonic mean of precision and recall. The optimal value of the F1 score is 1, whereas the worst value corresponds to 0.
- Gmean: This criterion is useful for evaluating the balance between the classification performance in both majority and minority classes. The best value of Gmean is 1 and its worst value is 0.

4.3. Evaluation of the results

The performance of the different models considered in this study was evaluated. Table 4 presents the results obtained when evaluating the models based on dataset 1 (lower failures). It can be observed that the ensemble classifier (Voting model) provided marginally better results than the other classifiers.

Table 5 presents the results obtained when evaluating the models based on dataset 2 (medium failures). It was observed that the performance of the ensemble classifier was less to that of the XGBoost classifier. Nevertheless, the ensemble classifier (voting model) is somewhat immune to the incorrect prediction of bad models because we adopted a soft voting strategy. Table 6 presents the results obtained when evaluating the models based on dataset 3 (higher failures). These results showed that the ensemble classifier (voting model) provides performance similar to that of the XGBoost classifier.

Table 4. Performance evaluation for ML models based on dataset 1 (Lower failures)

	Accuracy	Precision	F1 score	Gmean
SVM	0.945000	0.968570	0.953573	0.884098
RF	0.973333	0.976446	0.974588	0.876311
KNN	0.931111	0.964717	0.943638	0.863228
XGBoost	0.972778	0.977472	0.974539	0.897634
Voting	0.973889	0.977589	0.975320	0.891031

Table 5. Performance evaluation for ML models based on dataset 2 (medium failures)

	Accuracy	Precision	F1 score	Gmean
SVM	0.956667	0.976659	0.964568	0.837411
RF	0.961111	0.972179	0.965887	0.730926
KNN	0.923333	0.972020	0.943390	0.796952
XGBoost	0.966667	0.976029	0.970556	0.789400
Voting	0.965556	0.974485	0.969355	0.761328

Table 6. Performance evaluation for ML models based on dataset 3 (higher failures)

	Accuracy	Precision	F1 score	Gmean
SVM	0.920266	0.959601	0.937895	0.599000
RF	0.940199	0.956869	0.948045	0.502760
KNN	0.850498	0.960575	0.897645	0.658322
XGBoost	0.943522	0.961720	0.951775	0.607015
Voting	0.943522	0.961720	0.951775	0.607015

Overall, the proposed ensemble classifiers for different categories of predictive maintenance performed well. This performance can also be observed in the confidence interval, which indicates the degree of accuracy of the prediction. Figures 3, 4, and 5 show the 95% confidence intervals for the ensemble classifier for datasets 1 to 3.

However, the accuracy of a predictive model is tied to its input features. To understand how each feature contributes to the prediction of equipment malfunction, we considered the permutation feature importance scores. Figure 6 presents the permutation feature importance scores of the proposed voting classifiers for dataset 1, Figure 7 for dataset 2, and Figure 8 for dataset 3. These results suggest that the number of features during the training can be further reduced.

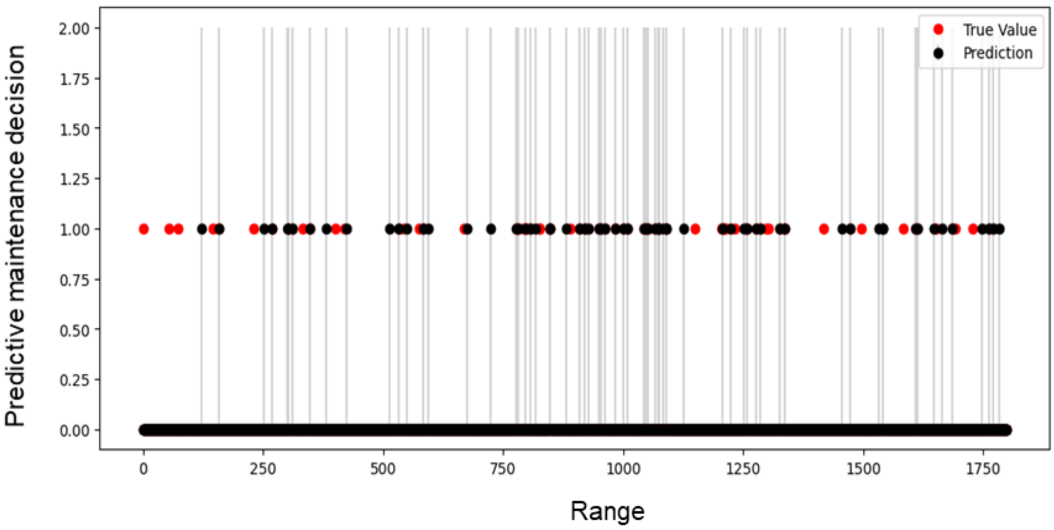

Figure 3. Plot Predicted vs real values with confidence interval - dataset 1

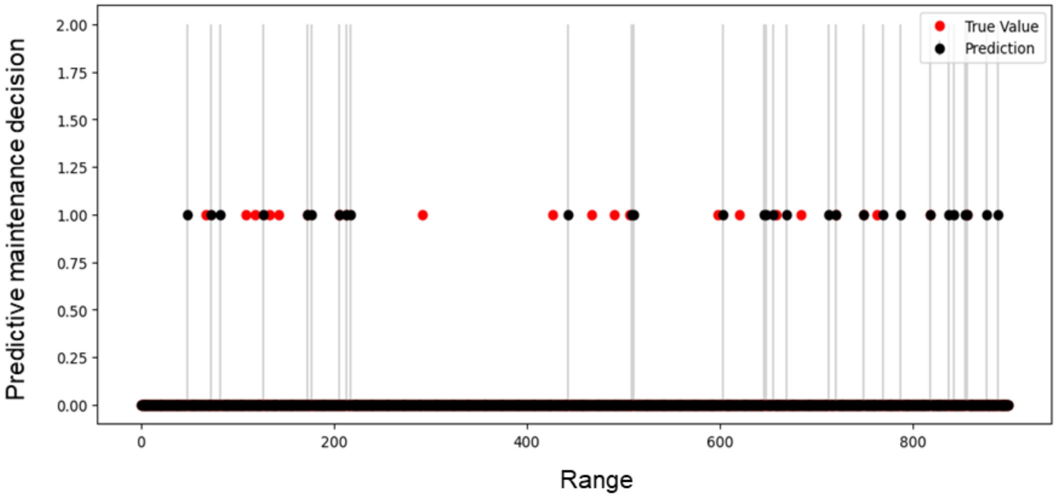

Figure 4. Plot Predicted vs real values with confidence interval - dataset 2

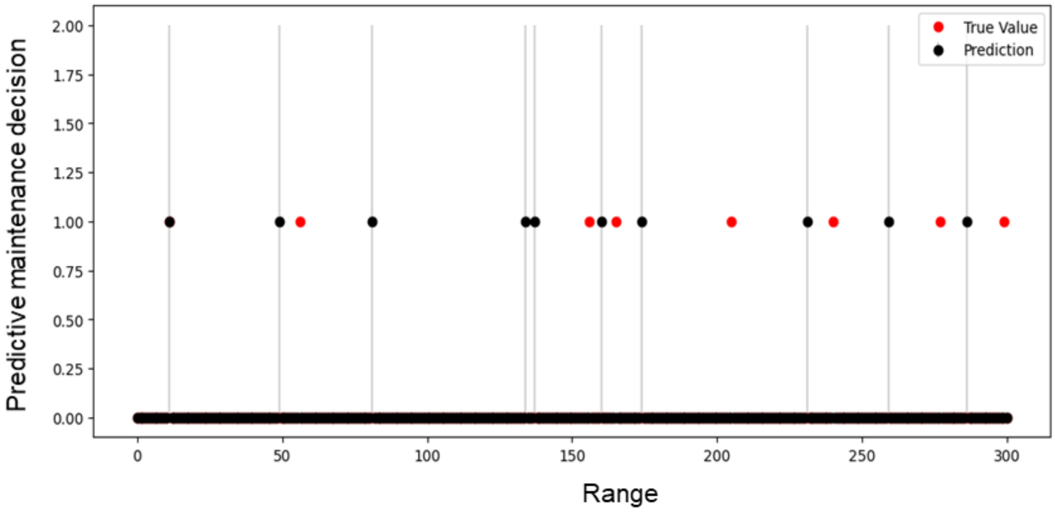

Figure 5. Plot Predicted vs real values with confidence interval - dataset 3

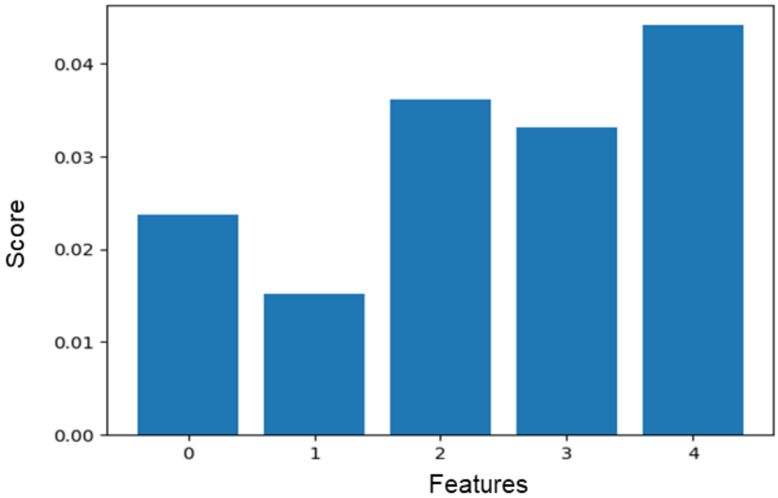

Figure 6. Bar chart of voting classifier with permutation feature importance scores - dataset 1

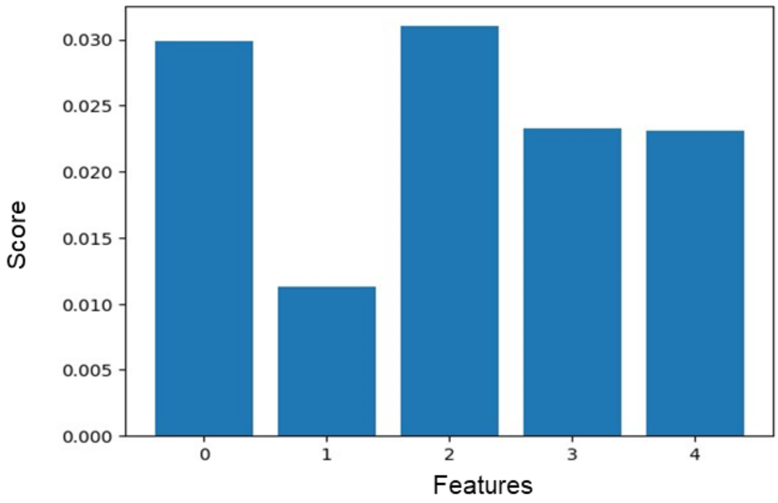

Figure 7. Bar chart of voting classifier with permutation feature importance scores - dataset 2

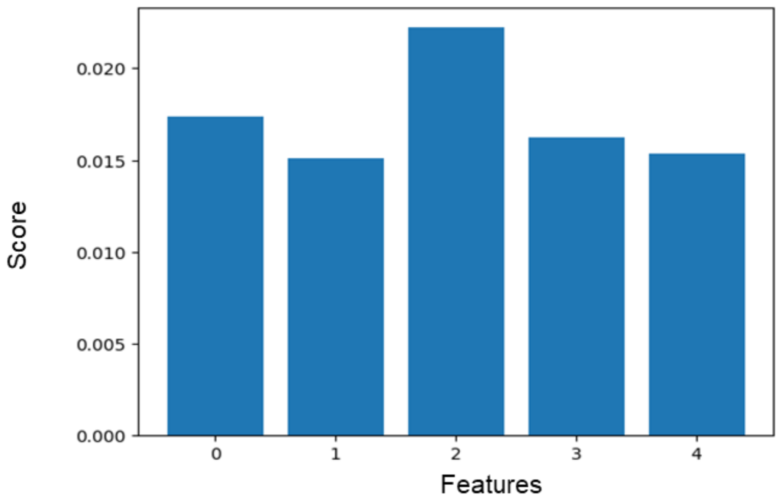

Figure 8. Bar chart of voting classifier with permutation feature importance scores - dataset 3

4.4. Limitations of the study

Limitations are external factors or deficiencies that are beyond the control of researchers and impose restrictions on the technique and processing of study data [33]. This section discusses the constraints associated with the representativeness of the dataset and any potential biases. Although the proposed PdM-FSA framework showed promising results on the AI4I 2020 Predictive Maintenance dataset, it is important to take into account certain limitations. This AI4I 2020 dataset is a synthetic dataset designed to represent the real-world predictive maintenance data. However, as a synthetic dataset, they may not fully capture the complexities and nuances of real-world industrial data. Manufacturing environments can be highly diverse, with variations across different facilities, equipment types, operating conditions, and data collection procedures. The patterns and characteristics present in the synthetic dataset may not be representative of all the possible real-world scenarios. This could limit the generalizability of trained models when deployed in certain manufacturing settings.

5. CONCLUSION

This study aimed to address the problem of maintenance in a smart factory by proposing an adaptive predictive maintenance framework in Industry 4.0, specifically in IoT systems, using machine learning models. This research problem involves proposing the right classifier for predictive maintenance based on multiple criteria. Therefore, this study introduced ensemble classifiers based on four ML models that are widely used in predictive maintenance: SVM, RF, KNN, and XGBoost. The classifiers proposed in this study aimed to accurately detect equipment malfunctions in a smart factory based on their severity. To achieve this, we used the AI4I 2020 predictive maintenance dataset and performed data preparation prior to training our classifiers.

The Voting model outperformed the SVM, RF, KNN, and XGBoost models with regard to the four criteria based on dataset 1 (lower failures). The XGBoost model slightly outperformed the Voting model based on dataset 2 (medium failures). The Voting model presented a similar performance to that of the XGBoost model based on dataset 3 (higher failures). The results of the performance evaluation showed that our classifiers performed well with an accuracy of over 90%. This indicates that these classifiers can be considered for deployment in a smart factory for predictive maintenance.

The study's findings provide useful insights regarding predictive maintenance in Industry 4.0. and enable the optimization of processes and improve productivity. Furthermore, the findings suggest that the performance of the proposed framework can be improved further by reducing the number of features during training. In future research, we plan to reduce the number of features and deploy and evaluate the proposed framework in a real environment. Moreover, we plan to evaluate the performance of the framework on diverse real-world datasets from multiple manufacturing facilities and equipment types. Additionally, techniques such as domain adaptation, transfer learning, and continual learning can be explored to enhance the models' capacity for adapting to new data distributions and mitigate potential biases.

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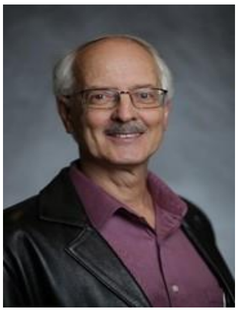

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