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Predicción de fallas hacia el mantenimiento predictivo mediante machine learning
Failure prediction towards predictive maintenance using machine learning

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Resumen

Los sistemas de mantenimiento predictivo basados en aprendizaje automático han demostrado su fiabilidad, eficiencia operativa y utilidad para la toma de decisiones informadas. En este trabajo, se evalúa el rendimiento de varios algoritmos de aprendizaje automático supervisado para predecir fallos en maquinaria industrial, utilizando datos de sensores. Se aplican dos enfoques de análisis: uno sin selección de características y otro utilizando el método de Análisis de Componentes de Vecindario (NCA) para reducir la dimensionalidad y resaltar las variables más relevantes para la clasificación. Los resultados principales muestran que el modelo de Análisis Discriminante (DA) logró el mejor rendimiento general, con métricas de precisión (P), exactitud (Acc) y sensibilidad (R) superiores en ambos enfoques. La selección de características utilizando NCA mejora la eficiencia de varios modelos, especialmente KNN y el Clasificador Lineal, reduciendo la complejidad sin comprometer la precisión. The use of classifiers as feature extractors is also explored. Este trabajo demuestra el potencial de los modelos de aprendizaje automático para la implementación en entornos industriales de mantenimiento predictivo.

Palabras Clave: Aprendizaje automático, predicción de fallas, mantenimiento predictivo.

Abstract

Machine learning-based predictive maintenance systems have demonstrated their reliability, operational efficiency, and usefulness for informed decision-making. In this work, we evaluate the performance of various supervised machine learning algorithms to predict failures in industrial machinery, using sensor data. Two analysis approaches are applied: one without feature selection and another using the Neighborhood Component Analysis (NCA) method to reduce dimensionality and highlight the most relevant variables for classification. Discriminant Analysis (DA) model achieved the best overall performance, with superior precision (P), accuracy (Acc), and sensitivity (R) metrics in both approaches. Feature selection using NCA improves the efficiency of several models, especially KNN and Linear Classifier, reducing complexity without compromising accuracy. This work demonstrates the potential of machine learning models for implementation in predictive maintenance industrial environments.

Keywords: Machine learning, failure prediction, predictive maintenance.

1. Introduction

Production systems are affected by degradations and failures caused by operating and environmental conditions. The goal of maintenance plans is to ensure the availability, anticipated performance, and resulting profitability of production systems (Florian *et al.*, 2021). Today, digitization of industrial operations has promoted the implementation of more effective and anticipatory maintenance tactics (Abidi *et al.*, 2022).

Through the analysis of real-time data from integrated sensors in equipment, predictive maintenance (PdM) has become a key technology that helps prevent failures (Belim *et al.*, 2024). Failure prediction is essential in industrial maintenance strategies to prevent unplanned downtime of equipment, machines and processes, as well as to maximise resource use and extend the durability of industrial assets (Tsallis *et al.*, 2025).

In the same way, predictive maintenance has revolutionized the way industries approach asset management. This approach

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depends on the study of past data and the use of sophisticated machine learning (ML) algorithms to find patterns (Çınar *et al.*, 2020; Tadjer *et al.*, 2021). Advances in machine learning have made it possible to create failure prediction models that are more precise and effective. The ability of these algorithms to process large volumes of data and detect subtle patterns in signals from industrial sensors makes them a viable alternative to conventional maintenance methods (Belim *et al.*, 2024).

Several studies have investigated the use of ML techniques in the field of PdM. For example, in (Zheng *et al.*, 2020) an intelligent maintenance scheme is suggested that combines deep learning algorithms with Industrial Internet of Things (IIoT) technologies in order to improve its reliability. In (Serradilla *et al.*, 2022) the authors review deep learning architectures applied to PM, highlighting their effectiveness in anomaly detection and remaining useful life estimation. Within the framework of the feature selection phase, it is of utmost importance to increase the accuracy and efficiency of ML models in failure categorization tasks (Hector y Panjanathan, 2024). Furthermore, the application of deep learning reinforcement algorithms for predictive maintenance in sensor networks has also been reported, evidencing its ability to independently make decisions (Ong *et al.*, 2020).

However, Currently, great interest is reported in the literature regarding the application of machine learning in predictive maintenance, addressing challenges such as feature selection, heterogeneous data integration and adaptive model development (Nacchia *et al.*, 2021). Comparative studies are still necessary to assess how well various algorithms operate in actual industrial settings. Similarly, the main challenges include the heterogeneity and high dimensionality of sensor data, the scarcity of labelled failure data, the imbalance of class, and the need to select relevant features that improve the accuracy of predictive models (Hamaide *et al.*, 2022).

This work presents a paradigm for using sensor data to predict machine failures. Historical data is used to train supervised machine learning models, including Artificial Neural Networks (ANN), Classification Trees (CT), Classifiers Ensemble (CE), Support Vector Machines (SVM), Linear Classifier (LC), Naive Bayes (NB), k-Nearest Neighbours (K-NN) and Discriminant Analysis (DA). Subsequently, a comparative evaluation of the performance of these models in prediction tasks is performed using conventional metrics, considering scenarios with and without the feature selection phase. The two main contributions are the following. First, implementation and analysis of the feature selection phase based on attribute relevance for the failure prediction task. Second, the application of a stack of classifiers as feature extractors to improve the performance o machine learning methods.

2. Machine learning workflow

The supervised machine learning process for machine defect prediction using sensor data is depicted in Figure 1 (Gonzalez-Islas *et al.*, 2021). The workflow is divided into two main stages, including training and testing stages. Data are randomly divided into 80 % for training and 20 % for testing. The division is done in a stratified manner to maintain the proportion of classes in both sets (Kaufmann, 2022).

In addition to the normal workflow shown above, in this article we propose the use of a stacked or cascaded classifier architecture to generate new features.

For this, we use the original features to predict the labels through five classifiers. Subsequently, we combine the predictions of these five classifiers with the original features. For the final prediction, this combined set of features is used. This makes sense, since the classifier that performs the final predictions considers the previous predictions of the other classifiers, which helps improve its performance.

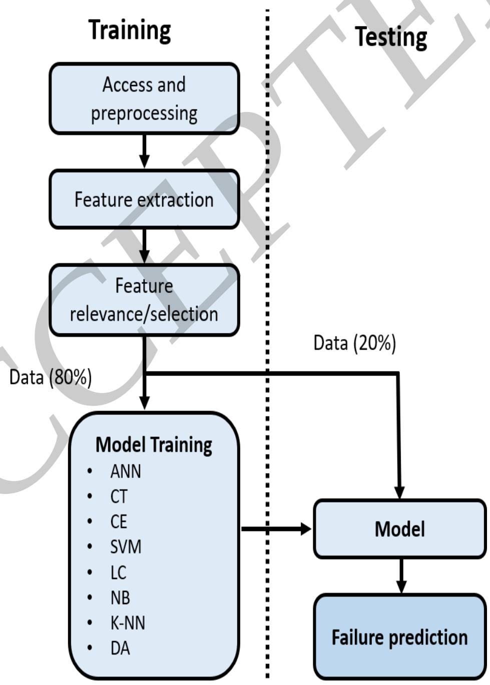

Figure 1: Failure prediction workflow using machine learning.

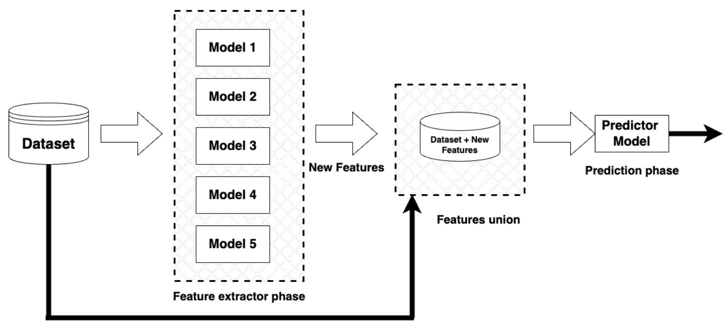

Figure 2: Extendig features trought stacking ML models.

2.1. Access and preproccessing

Accessing data and determining the type of data being handled is the first stage of any machine learning project (Mathworks, 2018). The data used in this study come from sensors installed in industrial machinery (Umer, 2024). This dataset from various machines was collected using sensors, with the objective of predicting machine failures in advance. Various sensor readings are included, as well as recorded machine failures . The dataset has 944 instances, with 9 attributes and 1 binary label for each instance. Of these, 393 instances are with failure diagnosis (label = 1) and 551 instances without failure (label = 0). The attributes correspond to the following feature index.

1. footfall: The number of people or objects passing through the machine.
2. tempMode: The temperature mode or setting of the machine.
3. AQ: Air quality index near the machine.
4. USS: Ultrasonic sensor data, indicating proximity measurements.
5. CS: readings from the current sensor, which indicates the use of electrical current of the machine.
6. VOC: Volatile Organic Compound Level Detected near the machine.
7. RP: Rotational position or RPM (revolutions per minute) of machine parts.
8. IP: Input pressure to the machine.
9. Temperature: The operating temperature of the machine.

Several pre-processing techniques have been used in machine *failure prediction using the Sensor Data* dataset (Umer, 2024) to obtain the data available for machine learning model training. These stages include the removal of duplicate instances, the coding of categorical variables, and the scaling of characteristics (Dhawas *et al.*, 2024).

2.2. Feature extraction

The *Machine Failure Prediction using the Sensor Data* dataset uses several types of feature extraction and selection strategies to enhance the performance of learning models, including: i) derived feature engineering, ii) univariate and multivariate statistical analysis, and iii) bins averaging on temporal sensors. In this work, we have used the features (attributes) provided in the available dataset.

2.3. Feature relevance/selection

In the feature selection stage, two methodological approaches are used to assess the impact of dimensionality on model performance. In the first approach, the full set of attributes available in the dataset is used without applying any reduction or selection method, with the objective of establishing a performance baseline and observing how the model behaves with the full set of information. In the second approach, we implemented the Neighbourhood Component Analysis (NCA) method, a supervised dimensionality reduction technique that assigns weights to each feature based on its relevance to the classification task. This method allows identifying and retaining only those features that are most informative, reducing noise, and potentially improving model generalisation.

2.4. Model training

According to the workflow, the following supervised algorithms in the Statistics and Machine Learning Toolbox (The MathWorks, Inc., 2024) are trained and assessed with each other.

- **Artificial Neural Networks (ANN)**: These models, which may represent complex nonlinear interactions, are modeled after the structure of the human brain. In this case, we use a fully connected feedforward network (Glorot y Bengio, 2010).

- **Classification Trees (CT)**: Models that divide the feature space into homogeneous regions using decision rules. We use a function that returns a fitted binary classification decision tree based on the predictors and the failure label for each instance (Breiman *et al.*, 2017).

- **Classifiers Ensemble (EC)**: These methods combine multiple models (such as Random Forest or Gradient Boosting) to improve accuracy and robustness. For this purpose, a function that uses a classification ensemble model object includes the results of boosting 100 classification trees. For binary classification, the function uses LogitBoost (Zhou, 2025).

- **Support Vector Machines (SVM)**: these models find the hyperplane that maximises the margin between classes. The function trains a support vector machine (SVM) model for binary classification on a low-dimensional predictor dataset (Zhou y Zhou, 2021).

- **Linear Classifier (LC)**: These models assume a linear relationship between the features and the target variable. We use a classification model for two-class learning with sparse predictor data.

- **Naive Bayes (NB)**: Bayes-theorem-based probabilistic classifiers that presume feature independence (James *et al.*, 2013).

- **k-Nearest Neighbours (K-NN)**: This is a method based on similarity, which classifies an instance according to the classes of its nearest neighbours.

- **Discriminant Analysis (DA)**: This technique seeks to find a linear combination of features that best separates classes. Finally, we use a function to fit a discriminant analysis classifier.

2.5. Testing

A methodology based on widely utilized classification measures is used to assess how well supervised machine learning algorithms perform when used to predict machine failure. Initially, the models were trained using a labeled dataset containing sensor data representative of the operational state of different machines. Subsequently, we use the most common metrics such as accuracy (Acc), recall or sensitivity (R), specificity (Sp), precision (P) and F-measure (F) to quantify the effectiveness of each algorithm in the early failure detection task. The equations for calculating each of the metrics are presented below (Gonzalez-Islas *et al.*, 2022).

- accuracy (Acc)

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- sensitivity or recall (R)

$$R = \frac{TP}{TP + FN} \tag{2}$$

- specificity (Sp)

$$SP = \frac{TN}{TN + FP} \tag{3}$$

- precision (P)

$$P = \frac{TP}{TP + FP} \tag{4}$$

- f-measure (F)

$$F = \frac{2PR}{P + R} \tag{5}$$

Where, for this work TP is when a failure is predicted in an instance and it actually exists. TN is when it is predicted that there is no failure in an instance and there is really no failure. FP is when a failure is predicted and it does not exist, and FN is when a failure is not predicted and it does exist. These metrics allowed comparing the balance between false alarms and undetected failures, critical aspects in industrial applications. Furthermore, we use random sampling $k-times$ with the $k = 10$ technique to ensure the robustness of the results and minimise the risk of overfitting. Performance evaluation was carried out using all available attributes and applying feature selection techniques to analyse their impact on the predictive capacity of the models.

3. Results and Discussion

The comparative evaluation of supervised algorithms for machine failure prediction is carried out using five fundamental metrics: accuracy (Acc), recall or sensitivity (R), specificity (Sp), precision (P), and F-measure (F). These metrics enable us to evaluate the models performance in identifying failures, as well as their capacity to prevent false positives. In this section, we discuss the results obtained without applying feature selection techniques. Table 1 summarises the performance of each algorithm for each metric without applying feature selection.

Table 1: Performance of machine learning algorithms without feature selection in failure prediction.

	ANN	**CT**	**CE**	**SVM**	**LC**	**NB**	**K-NN**	**DA**
Acc	0.90	0.87	0.90	0.86	0.90	0.91	0.73	**0.92**
R	0.89	0.84	0.89	0.87	0.90	0.90	0.73	**0.92**
SP	0.89	0.90	0.91	0.85	0.90	0.91	0.72	**0.93**
P	0.86	0.87	0.90	0.87	0.88	0.89	0.69	**0.91**
F	0.88	0.85	0.90	0.86	0.89	0.90	0.71	**0.92**

Discriminant analysis emerged as the most successful model among the algorithms that were evaluated, with the highest overall accuracy (0.92) and consistently high values in all metrics: recall (0.92), specificity (0.93), precision (0.91) and F-measure (0.92). In predictive maintenance systems, where misclassification errors can be expensive, balanced performance of DA indicates that it is very skilled at both failure detection and false alarm minimization.

Furthermore, the Classifier Ensemble algorithm with accuracy (0.90) and balanced precision and recall values (both ≈ 0.90) demonstrates its ability to identify complex patterns in the data. For its part, Naive Bayes (NB) with a specificity of 0.91 and a recall of 0.90, demonstrates that it correctly identifies both positive and negative cases.

ANN, LC, and support vector machines (SVM), with F measure values greater than 0.85, although lower than DA and CE, can be considered intermediate performance algorithms. These models presented a relatively balanced performance, but did not reach the maximum levels observed in the metrics.

In contrast, the K-NN model presents the lowest performance in all metrics: accuracy (0.73), recall (0.73), precision (0.69) and F-measure (0.71). This situation can be attributed to the high sensitivity of KNN to data dimensionality and the lack of feature selection, which limits the ability to generalize.

When working with entire data sets without feature selection preprocessing, algorithms with internal regularisation methods or combinations of classifiers (such as DA and CE) generally perform better, according to the results. This analysis allows us to determine that, in predictive maintenance applications, the use of robust and well-balanced models can significantly improve early failure detection and system reliability.

In general, feature selection not only optimizes the performance of the model, but also improves its efficiency, stability, and explainability, which is fundamental in critical applications such as predictive maintenance. For this purpose, at this stage of the study, a feature selection technique based on Neighbourhood Component Analysis is applied to identify and use only those variables with the highest relevance for the classification task. Figure 3 shows a graphic with the weights of the features vs the feature index of the 9 attributes.

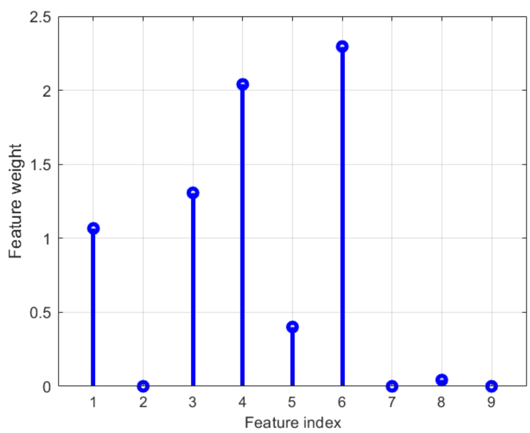

Figure 3: Feature relevance performance using neighborhood component analysis for classification.

If we consider a feature weight (threshold = 0.2), in the selection process, the selected features are: 1,3,4,5 and 6. These index correspond to attributes: footfall, AQ, USS, CS and VOC, respectively. This reduction in feature space made it possible to evaluate how the performance of supervised algorithms changes when irrelevant or redundant attributes are removed. Table 2 summarises the performance of each algorithm for each metric that applies feature selection.

Table 2: Performance of machine learning algorithms with feature selection in failure prediction.

	ANN	**CT**	**CE**	**SVM**	**LC**	**NB**	**K-NN**	**DA**
Acc	0.83	0.88	0.89	0.78	0.91	0.90	0.88	**0.92**
R	0.86	0.86	0.89	0.78	0.89	0.88	0.88	**0.92**
SP	0.81	0.89	0.89	0.81	0.92	0.91	0.88	**0.93**
P	0.82	0.87	0.89	0.81	0.90	0.89	0.86	**0.90**
F	0.83	0.86	0.89	0.75	0.89	0.88	0.87	**0.91**

The results show that the Discriminant Analysis remains the best model for this classification task, even with feature reduction. This model achieved an accuracy of 0.92, a recall of 0.92, and an F-measure of 0.91, which demonstrates its robustness and generalization ability when working with an optimized subset of variables. Similarly, its specificity (0.93) indicates optimal discrimination of negative cases, reducing false positives to a minimum.

The Linear Classifier model also improved its performance with feature selection, achieving one of the best combinations between precision (0.90) and recall (0.89), resulting in an F-measure of 0.89, higher than the result obtained without selection. This behaviour suggests that linear models can eliminate noise and redundancy in the data.

However, the Classifier Ensemble model continued to show similar behaviour, with an F-measure of 0.89 and precision (0.89), demonstrating that the combination of classifiers also has a good performance but still reduces feature spaces. However, Naive Bayes maintained a high and stable performance, which implies that this algorithm can be an effective alternative for binary classification problems with selected features.

On the other hand, the SVM model has an $F = 0.75$, probably because its performance is highly dependent on the structure of the feature space and can be affected when optimal variables are removed. Similarly, the Neural Network model decreased in precision and F-measure compared to its version without selection, which could indicate that this algorithm requires a larger amount of data or attributes to achieve a better representation of the problem.

Finally, it is observed that KNN experienced an improvement compared to when no selection was applied, achieving an F-measure of 0.87 and an accuracy of 0.88, which validates that this algorithm is particularly sensitive to dimensionality and significantly benefits from the reduction of irrelevant features.

When the five classifiers are applied as feature extractors, performance improves. This is shown in table 3. It can be seen that using this type of architecture contributes to the performance of the classification algorithms. Some do not improve significantly, but overall an improvement can be seen.

Table 3: Performance of machine learning algorithms with augmented .

	ANN	CT	CE	SVM	LC	NB	K-NN	DA
Acc	0.91	0.85	0.90	**0.92**	**0.92**	**0.92**	0.89	**0.93**
R	0.90	0.82	**0.91**	**0.91**	**0.92**	**0.91**	0.90	**0.93**
SP	**0.92**	0.87	0.90	**0.92**	**0.92**	**0.92**	0.88	0.91
P	0.89	0.82	0.87	0.89	0.89	0.89	0.85	0.88
F	0.89	0.82	0.89	0.90	**0.91**	0.90	0.87	0.90

4. Conclusions

In this work, we have proposed a machine learning framework for predicting machine failures using a dataset reported in the literature. Evaluation of the performance of the algorithms for the prediction task has demonstrated its effectiveness. The main findings of this work provide a foundation for the design and implementation of ML-based predictive maintenance systems. The application of NCA as a feature selection technique allowed for the improvement or maintenance of the performance of some supervised models, particularly the case of DA, LIN, and KNN.Which implies that for each particular study applying ML and feature selection, it is necessary to perform a specific analysis.

The Discriminant Analysis algorithm is the most consistent and effective in both scenarios - with and without feature selection - achieving the highest values in accuracy, recall, precision, and F-measure. This result highlights the ability of DA to handle both raw data and reduced attribute spaces, making it a robust option for real-world predictive maintenance applications.

Likewise, algorithms such as the Classifier Ensemble, Naive Bayes, and the Linear Classifier also demonstrated competitive performance, especially when feature selection is applied. This technique proved beneficial for most models, improving or maintaining their performance while simultaneously reducing model complexity and computational burden.

However, K-Nearest Neighbours and Support Vector Machines (SVM) showed greater sensitivity to the dimensionality of the dataset, with different results depending on whether feature reduction was applied or not. This implies that these models require more analysis with respect to data pre-processing to ensure their effectiveness.

On the other hand, adding classifiers as an intermediate stage for feature extraction shows an improvement in the overall performance of the methods. The advantages and disadvantages of this approach should be studied in greater depth.

Based on the results obtained, several areas of opportunity remain for future research. In particular, the analysis could be strengthened by incorporating larger and more diverse datasets that encompass various types of machinery, operating conditions, and failure categories. Similarly, investigating unsupervised and semi-supervised methods is very helpful in industrial settings where failure labels are not given. Lastly, real-time systems, which combine industrial monitoring infrastructure (IoT) with trained models to verify their performance in real settings.

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