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ORIGINAL

Optimization of Fault Prediction by A.I. in Industrial Equipment: analysis of the operating parameters of a Bench Grinder

Optimización de la Predicción de Fallas mediante I.A. en Equipos Industriales: análisis de los parámetros de operación de una amoladora de banco

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ABSTRACT

Predictive Maintenance (PM) plays a crucial role in maximizing efficiency and reducing costs associated with equipment and system maintenance in industrial companies. Recent advancements in Machine Learning (ML) have revolutionized PM by offering accurate and efficient fault prediction and maintenance planning capabilities. This research focuses on monitoring a bench grinder and observing sensors for temperature, current, angular velocity, and vibration under normal operating conditions. The objective is to predict failures based on specific variables related to the machine. To develop the system, a prototype bench was designed to subject the machine to several working scenarios, collecting real-time sensor data. Data clusters were generated for each sensor, collecting 3000 samples over 7 consecutive days without faults and another 7 days with modified bench grinder behavior. Sampling was done at a rate of 1 second. The performance of Decision Trees (DT), Support Vector Machines (SVM), Naive Bayes (NB), and K-Means + Neural Network (NN) algorithms was compared using the confusion matrix metrics. Each algorithm's performance was evaluated for RPM, current, temperature, and vibrations measures. The SVM algorithm showed the highest error for RPM with 43,5 %. In contrast, all algorithms achieved minimal or zero errors for vibrations, indicating excellent performance. These findings demonstrate the potential of ML algorithms in PM for the bench grinder. The results highlight the importance of selecting appropriate algorithms for specific measurements, with vibrations exhibiting the least error across all algorithms and contributes to optimize maintenance activities in industrial settings.

Keywords: AI; Predictive Maintenance; Machine Learning Techniques; Fault Prediction; Bench Grinder.

RESUMEN

El Mantenimiento Predictivo (PM) es fundamental para maximizar la eficiencia y reducir costos asociados con el mantenimiento de equipos industriales. Los avances en Aprendizaje automático (ML) han revolucionado la gestión de mantenimiento al ofrecer capacidades precisas y eficientes de predicción de fallas y planificación. Esta investigación se enfocó en monitorear una amoladora de banco con sensores de temperatura, corriente, velocidad angular y vibración en condiciones normales de operación. El objetivo fue predecir fallos en función de variables específicas relacionadas con el equipo. Para esto, se diseñó un banco prototipo para someter la máquina a varios escenarios de trabajo, recopilando datos en tiempo real. Se generaron conglomerados de datos para cada sensor, recolectando 3000 muestras durante 7 días consecutivos sin fallas y otros 7 días con comportamiento modificado del equipo. El muestreo se realizó a una velocidad de 1 segundo. Se comparó el rendimiento de los algoritmos de Árboles de Decisión (DT), Máquinas de Vectores de Soporte (SVM), Bayes Ingenuo (NB) y K-Medias + Red Neuronal (NN) utilizando las métricas de la matriz de confusión. El algoritmo SVM mostró el mayor error para RPM con 43,5 %. Por el contrario, todos los algoritmos lograron errores mínimos o nulos para las vibraciones, lo que indica un rendimiento excelente. Estos hallazgos demuestran el potencial de los algoritmos ML en PM. Los resultados resaltan la importancia de seleccionar algoritmos apropiados para mediciones específicas, con vibraciones que muestren el menor error en todos los algoritmos y contribuyan a optimizar las actividades de mantenimiento en entornos industriales.

Palabras clave: IA; Mantenimiento Predictivo; Técnicas de Aprendizaje Automático; Predicción de Fallos; Rectificadora de Banco.

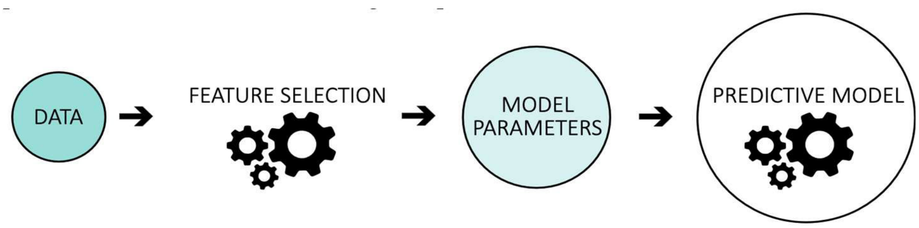
INTRODUCTION

Nowadays, manufacturing processes are of great importance, since they allow the transformation of materials (raw materials) into finished or semi-finished products, which are later destined to different markets. Within this production system, a series of organized elements are involved, such as: materials, specialized personnel, machinery, and technology.(1) According to the production system, manufacturing processes can be classified into products to order, batch production, continuous or chain production.(2) The production of large quantities of products involves the mechanization of the industry, so the maintenance methods of this infrastructure are of vital importance to ensure the continuity of production processes and thus avoid unplanned stoppages of machinery, thus ensuring that these facilities have the highest possible productivity.(3)

Industrial maintenance can be defined as a set of interrelated activities, which are required to achieve optimal operation of facilities, machinery, and equipment, as well as the different workspaces that are part of industrial infrastructures. Industrial maintenance includes the following actions: troubleshooting, repair; adjustment, revision, control and verification, cleaning, among others.(4) According to the activities and their frequency, industrial maintenance can be classified as: corrective, preventive, predictive and improvement.(5)

The main objective of predictive maintenance is to know and report permanently the status and operability of the facilities through the knowledge of the values of certain variables, which are representative of the operation of the machinery. To apply this maintenance, it is necessary to identify the critical physical variables. In the case of motors, these are: temperature, vibration, energy consumption, current.(6) Then, the variation of the data is an indication of problems that may be appearing in the equipment. With this, it can be stated that it is a type of maintenance that requires more technological resources than the others mentioned above, since it requires the use of advanced technology, measurement systems, monitoring, communications,(7) and in certain cases of deep mathematical, physical and technical knowledge.(8)

Since it is required to monitor different variables continuously, this produces large and continuous data streams. Until recently, different techniques based on statistical trends were used or it was also necessary to wait for system failures to occur in order to feed back the mathematical models and their subsequent application.(9) Currently, within the Industry 4.0 environment, cutting-edge technologies such as AI are starting to be used in the field of predictive maintenance, since it allows handling large amounts of data, through which they can identify and understand information, either in the form of numerical values, images, historical data, etc., in order to perform complex calculations and actions with great speed.(10)



Source: Conway J(11)
Figure 1. Machine Learning Process

The process of implementation of AI in modern maintenance systems also involves the process of ML, this is a subset of AI, in which people “train” machines to recognize patterns based on data and make predictions, as shown in figure 1, which fits perfectly with the concept of predictive maintenance, with the advantage that this technology relies on the computational capabilities of microprocessors and algorithms to process large amounts of data in a shorter time, achieving more efficient results.(12)

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Predictive maintenance (PM) and Artificial Intelligence (AI)

In the industry, the study of maintenance techniques is extremely important since in this way the equipment's lifetime can be prolonged, which are used in the manufacture of goods and products. Approximately 80 % of the motors used in the industry are induction,[13] which allows up to 80 % probability of detecting or preventing a fault through a monitoring system, therefore, if it is improves monitoring and fault diagnosis, greatly improves its reliability.

For this reason, monitoring, diagnosing, and controlling operation through the development of applications is extremely important, since on some occasions the motors operate in fault conditions,[14] and it is not possible to detect these anomalies before they cause damage to the equipment or the entire system. It can even cause work accidents.[15]

The maintenance of electric motors has a critical role for efficiency in the industry, thanks to predictive maintenance since it has non-invasive monitoring systems, becoming a priority system for safety in industrial processes, allowing to minimize the consequences of failures due to a bad operation, the steps to carry out a fault detection system are detailed below (figure 2).

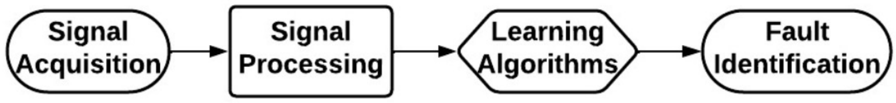

Figure 2. Fault detection flowchart

To predict a fault detection, the application of advanced analytics techniques, such as AI algorithms and statistical methods, is extensively employed. These techniques aim to analyze the collected data and identify identifiable patterns associated with different types of faults. This analytical process entails the utilization of sophisticated computational models and mathematical algorithms to thoroughly scrutinize the data, unveil hidden correlations, and extract valuable insights. By leveraging these advanced techniques, organizations can effectively detect and anticipate faults, facilitating proactive maintenance interventions, optimizing operational efficiency, and ultimately improving overall equipment reliability and performance.

METHOD

The use of AI together with the proposed scheme aims to carry out a correct management of predictive maintenance. A predictive maintenance plan for an induction motor aims to: Minimization of costs, maintenance actions that are carried out based on fault prediction results, the equipment's lifetime is used together with the cost metric (RUL, Remaining Useful Life).[16] Maximization of reliability, the measurements that are used allow us to know the probability that a piece of equipment can be in a normal operating state and that it is operational or not operational.[17] Multi-objective optimization, tries to improve the approach that seeks to optimize the measurements simultaneously, thus allowing a better balance between the objectives.[18]

Within the realm of AI, ML has emerged as a powerful and transformative tool for fault detection, significantly revolutionizing the monitoring and maintenance of industrial systems.[19] To effectively apply ML analysis techniques, several phases can be considered, each playing. a crucial role in the overall process. These phases are outlined below:

The data collection phase involves equipping the bench grinder with sensors and conducting multiple tests to gather a comprehensive dataset. This data serves as the foundation for subsequent analysis. Before using the data in machine learning algorithms, a pre-analysis step is performed to ensure data quality. This involves cleaning and formatting the data to eliminate inconsistencies or errors that could hinder algorithm performance.

During the data analysis phase, thorough examination of the collected data takes place to identify missing values and atypical data points. Statistical methods and visualization techniques are employed to gain insights and extract meaningful patterns. Once the data is prepared, the selected machine learning algorithm is trained using the dataset. The algorithm learns to extract valuable information considering different usage conditions of the bench grinder's emery.

The performance of the trained algorithm is evaluated to measure its accuracy in making predictions. This evaluation assesses the algorithm's effectiveness in detecting faults or anomalies in the bench grinder's operation. Based on the evaluation results, the algorithm with the best performance is selected. This selection is crucial as it determines the algorithm to be deployed for ongoing fault detection and predictive maintenance tasks, ensuring optimal performance in identifying potential issues with the bench grinder.

Machine Learning Algorithms

Among the various ML algorithms, Decision Trees, Support Vector Machines (SVM), Naive Bayes, and Neural Networks have emerged as popular approaches for fault detection. These algorithms belong to the supervised learning methods, as they are quire labeled data for training.[20] Additionally, unsupervised learning techniques such as clustering, particularly k-means clustering, play a vital role in fault detection by identifying groups or clusters exhibiting similar behavior, thereby facilitating anomaly detection and fault classification. Leveraging these diverse ML techniques empowers industries to detect faults effectively, proactively intervene in maintenance, optimize system performance, and minimize costly downtime.[21]

Decision Trees (DT)

It is a tree structure similar to a flowchart where an internal node represents a feature to be analyzed, and each branch represents a decision rule, and each leaf represents a result.

Support Vector Machines (SVM)

SVM are a learning-based method for solving classification and regression problems. For this type of algorithms, training is of vital importance since it is informed with already solved examples so that the results obtained provide an optimal prediction.

Naive Bayes (NB)

It is based on a statistical classification technique called "Bayes Theorem". This algorithm assumes that the predictor variables to be analyzed are independent of each other.[22] This is achieved by calculating the posterior probability of an event given the probabilities of previous events, using the formula shown below.

K-Means

Within the field of unsupervised learning, K-Means clustering has been extremely popular due to its simplicity in implementation and low computational resource consumption. K-Means clustering aims to identify and group data points that exhibit high similarity into classes.[23] This algorithm, known for its efficiency, partitions the data into K clusters, with each cluster represented by its centroid. The algorithm iteratively updates the centroid positions to minimize the within-cluster sum of squares.

Neural Networks

A neural network is a computational representation inspired by the human neuron, utilizing defined and non-linear structures. These networks are composed of interconnected nodes, known as artificial neurons or units, which simulate the information processing capabilities of the human brain.[24] By employing non-linear activation functions, neural networks can capture complex relationships and patterns within the data, enabling them to handle intricate tasks such as image recognition, natural language processing, and fault detection.

Case study

To facilitate the data collection process and ensure accurate measurements, a test bench was developed specifically for this purpose. Specifications of the bench grinder used are show in table 1.

Table 1. Bench grinder specs

Characteristic	Specification
Model No.	MD3215K
Voltage	110 Vac/60 Hz
Power	200 w
Speed	3450 RPM
Wheel	150 mm

The monitoring of a bench grinder was carried out under different operating conditions simulating fault states and normal operation (table 2), with a focus on observing the temperature, current, angular velocity, and vibration sensors.

Table 2. Bench grinder operating conditions

Working Configuration	Details
1	Normal operation
2	Grinder with normal load (3mm stone)
3	Grinder with forced load (2 x 3mm stone)
4	Grinder with forced shaft (metal coupling on the shaft)
5	Grinder with semi-free shaft (loose shaft attachment)

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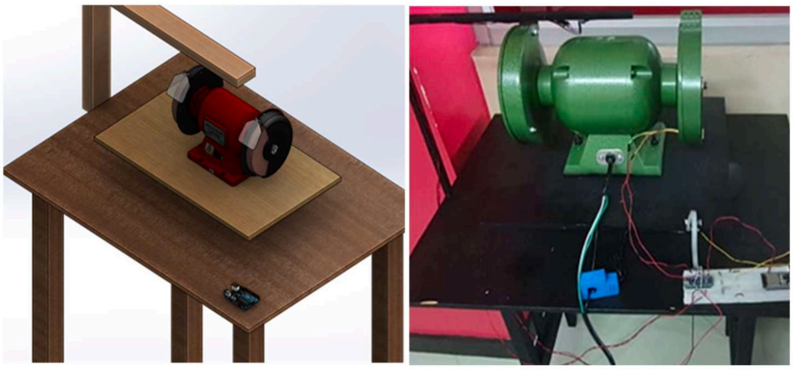
The test bench was designed to subject the bench grinder motor to various types of work, allowing for real-time data acquisition from strategically positioned sensors. The test bench concept and its physical implementation are shown in figure 3. This approach aimed to minimize measurement errors and enable comprehensive analysis of the grinder's performance and potential fault indicators.



a **b**

Figure 3. Developed test bench. a. Bench CAD. b. Bench implementation

By integrating the test bench setup with the sensor data, the investigation sought to gain valuable insights into the grinder's behavior and effectively detect any anomalies or patterns associated with faults.

Sensors

The developed test bench includes a comprehensive set of sensors to monitor and measure the described parameters. These sensors included the MLX90614 infrared sensor, known for its high-resolution temperature measurements with an accuracy of 0,02°C. To capture the electrical behavior, the non-invasive current sensor Sct-013 was utilized, featuring a DC offset of 2,5V to accurately measure the current flow. The encoder FC-03 was employed to capture the angular velocity, while the MPU 6050 IMU sensor with 6 degrees of freedom enabled the measurement of vibration and motion-related data.

Data acquisition architecture

To seamlessly integrate and read data from all these sensors, an Arduino Uno was utilized as a reliable and versatile microcontroller platform. The Arduino Uno effectively facilitated the connection and synchronization of the sensors, ensuring a streamlined data acquisition process. Data acquisition scheme is shown in figure 4.

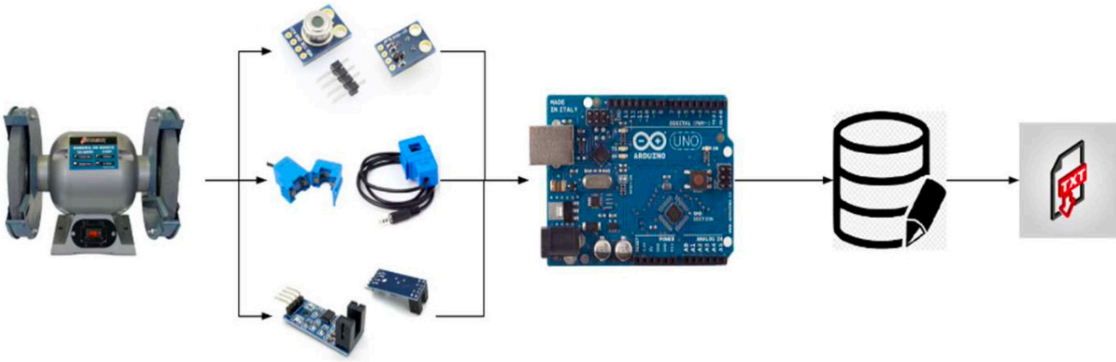


Figure 4. Acquisition general scheme

The acquired data is stored in a local database using a micro-SD module connected to the Arduino development board. Subsequently, this data is extracted and saved with a csv file extension to ensure compatibility and easy access. During the operation of the bench grinder, the sensor signals were processed with a sampling time of 1 second, capturing essential information over the course of one hour. The data of each sensor has been taken for 7 consecutive days in a state of operation without caused failure, then data was taken for another 7 days modifying the behavior of the sensor.

Data preprocessing

Once the data has been obtained, a preprocessing stage was carried out that allows the identification of behavior curves of each type of signal coming from the sensors. In the development of tests, a database

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organized by columns was used, the same ones that contain the record of temperature, vibrations, consumption current and rpm, allowing thus determine if the equipment is failing. A total of 3000 samples from each sensor were collected, each day a local database was generated in a file with a csv extension. A sample of the formatted data can be seen in table 3.

Table 3. Acquired data sample

Sample	Date	Time	RPM	Current (A)	Temperature (°C)	Vibrations
1	21/12/2020	10:00:00	150	0,82	17,6	0,07
2	21/12/2020	10:00:01	350	0,82	18,3	0,05
3	21/12/2020	10:00:02	450	0,82	18,9	0,07
4	21/12/2020	10:00:03	800	0,82	19,6	0,09
5	21/12/2020	10:00:04	1200	0,83	22,1	0,11

The data represents the ground truth of the equipment analyzed, so the duration of the collection of each data set was similar to the time the equipment has been used since it was acquired; therefore, the proposed scheme allows anticipating the feasibility and operation that it may have.

Each set of data had to be grouped according to the performance characteristic. For example, the rpm analysis has two separated files, one of them with data without fault and another file with data with fault. Data with fault (1) and without it (0) were used as input and target values for ML algorithms, respectively. The stored data is then subjected to processing using ML techniques. This data-driven approach not only adds significant value but also enables the identification and prevention of potential problems within the analyzed systems. By harnessing the power of ML, hidden patterns, correlations, and anomalies can be unveiled, providing valuable insights for informed decision-making and optimized maintenance strategies.

ML implementation

For ML algorithms implementation, the following methods were coded using MATLAB ® 2023 Academic Version (25): DT, SVM, NB and a semi-supervised method with K-means and a NN. The training and testing flowchart for each case is shown in figure 5.

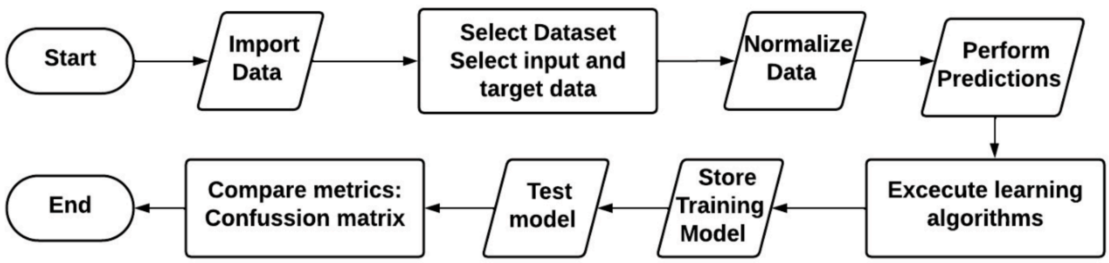

Figure 5. ML implementation flowchart

To determine the best algorithm, the confusion matrix was considered, as well as the performance of each algorithm for each variable to be analyzed.

RESULTS

All ML algorithms implemented previously were trained and tested for each specific feature: RPM, Current usage, temperature, and vibrations. The confusion matrixes obtained in training and validation stages for each case were analyzed for all the features.

RPM

Considering the RPM feature, the confusion matrixes obtained from each implemented ML algorithm are shown in figure 6.

In the confusion matrix of the DT algorithm, when analyzing the absence of faults, it can be observed that 42 data points were misclassified as faults, indicating false positives. Conversely, for the opposite analysis, 31 data points were classified as non-faults despite the presence of faults, indicating false negatives. For the SVM algorithm, it can be observed that for the analysis of non-faults, 2 data points were misclassified as faults. However, for the analysis of faults, the algorithm exhibited erratic behavior as nearly 50 % of the data points

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were misclassified. In the NB algorithm, 118 data points were misclassified, as they were classified as faults in the analysis of non-faults. Additionally, 5 data points in the analysis of faults were not correctly classified. Regarding the NN algorithm, there were 55 misclassified data points when analyzing the absence of faults, and 4 misclassified data points when analyzing the presence of faults.

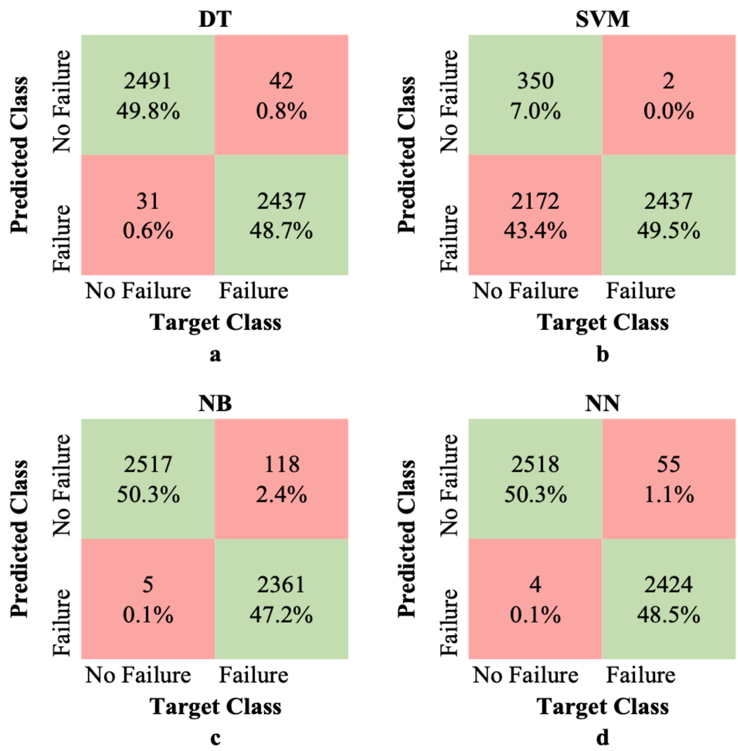

Figure 6. Confusion matrixes comparison for RPM

Current usage

Considering the current usage feature, the confusion matrixes obtained from each implemented ML algorithm are shown in figure 7.

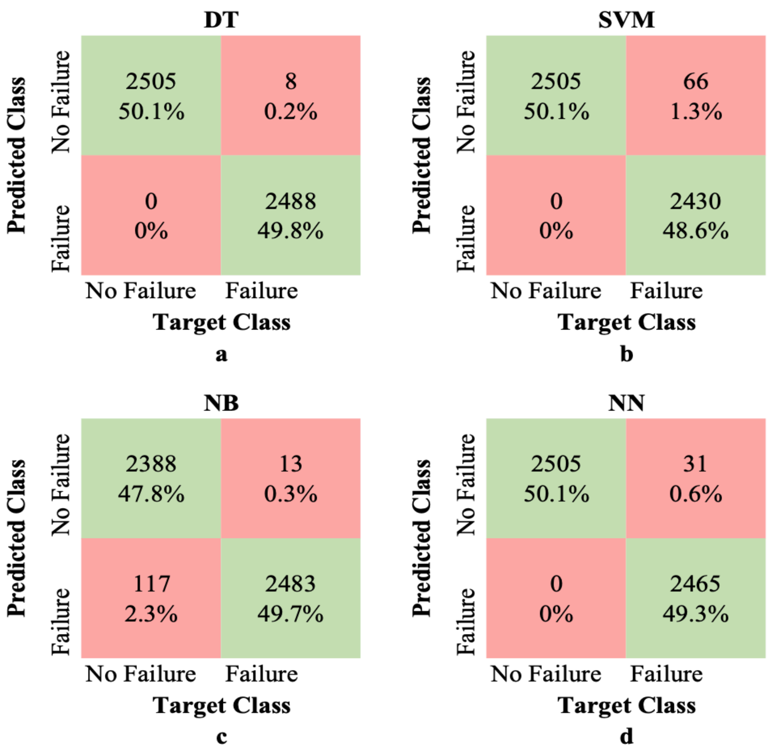

Figure 7. Confusion matrixes comparison for current usage

For the SVM algorithm, in the analysis of data without the presence of faults, 65 instances were misclassified as faults, indicating false positives. However, in the analysis of faults, no errors were observed, suggesting accurate predictions.

For DT algorithm, it can be observed that for the analysis of non-faults, 8 data points were misclassified as faults, indicating false positives. However, for the analysis of faults, no erroneous predictions were made. For NB algorithm, 13 data points were misclassified in the analysis of non-faults, indicating false positives. Additionally, 117 data points in the analysis of faults were not correctly classified, suggesting false negatives. Furthermore, NN algorithm presented 31 misclassified data points when analyzing the absence of faults, indicating false positives. However, in the analysis of faults, no erroneous predictions were made.

Temperature

Considering the temperature feature, the confusion matrixes obtained from each implemented ML algorithm are shown in figure 8.

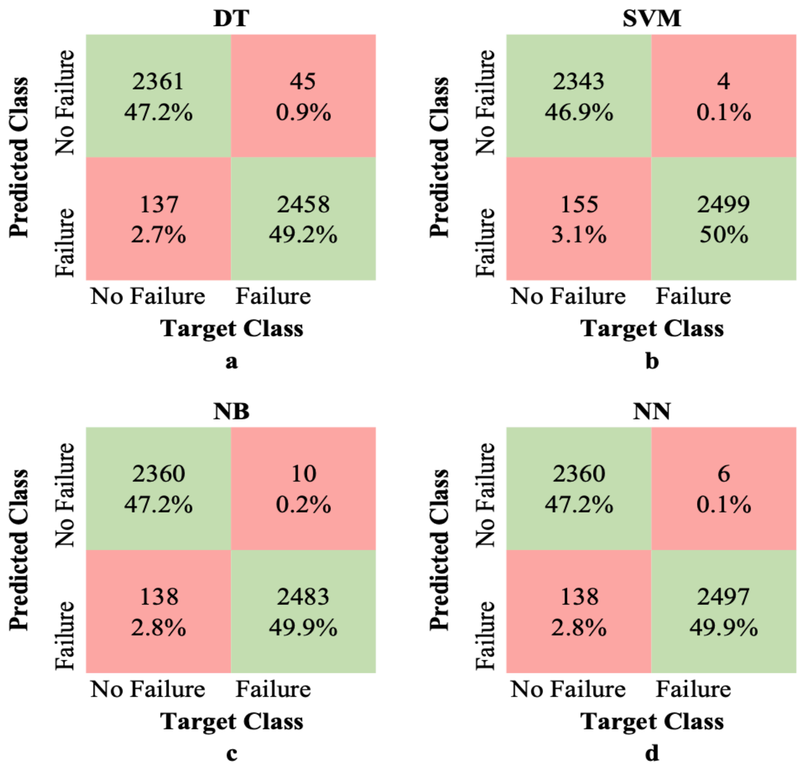

Figure 8. Confusion matrixes comparison for temperature

For the SVM algorithm, in the analysis of data without the presence of faults, 4 instances were misclassified as faults, indicating false positives. However, in the analysis of faults, 185 data points were misclassified, suggesting a high number of false negatives. For DT algorithm, it can be observed that for the analysis of non-faults, 45 data points were misclassified as faults, indicating false positives. However, for the analysis of faults, 137 data points were misclassified as non-faults, suggesting false negatives. For NB algorithm, 10 data points were misclassified in the analysis of non-faults, indicating false positives. Additionally, 138 data points in the analysis of faults were not correctly classified, suggesting false negatives. Furthermore, the NN algorithm presented 6 misclassified data points when analyzing the absence of faults, indicating false positives. Furthermore, 138 data points were misclassified in the analysis of faults.

Vibrations

Considering the vibrations feature, the confusion matrixes obtained from each implemented ML algorithm are shown in figure 9.

For the SVM algorithm, no erroneous behavior was found in the data analysis, indicating accurate predictions. For DT algorithm, no erroneous behavior was found, suggesting accurate predictions. For NB algorithm, no erroneous predictions were made. However, in the analysis of faults, 5 data points were not correctly interpreted. Additionally, in the NN algorithm, no erroneous behavior was found, indicating accu- rate predictions.

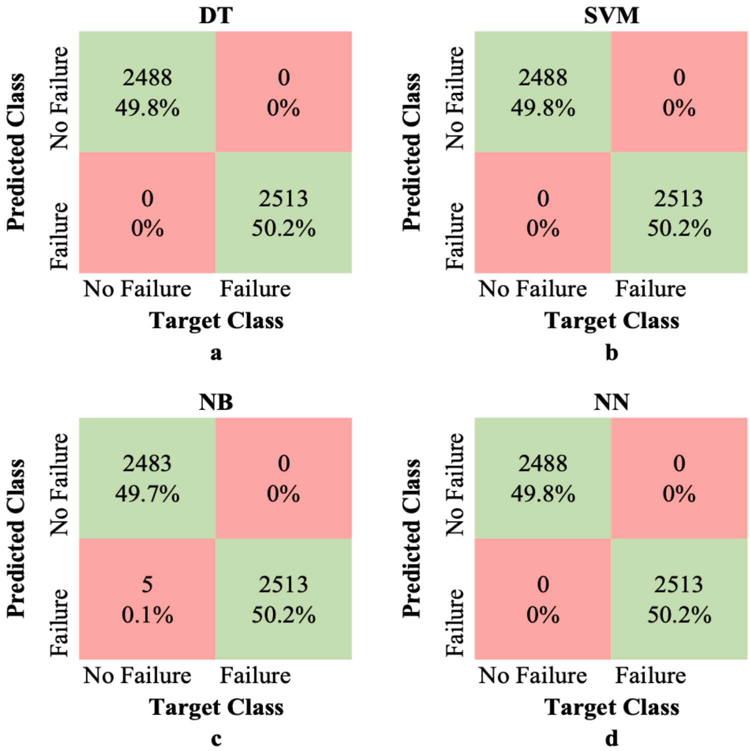

Figure 9. Confusion matrixes comparison for vibrations

CONCLUSIONS

This paper addresses the problem of determining the best algorithm for analyzing data obtained from a bench grinder to minimize production downtime. A predictive maintenance method is implemented using a set of sensors to collect data, which is then analyzed using machine learning algorithms. The performance of DT, SVM, NB, and K-Means + NN algorithms is compared for RPM, current, temperature, and vibrations. The results showed that the SVM algorithm had the highest error rate for RPM, with 43,5 % incorrect predictions. However, all algorithms demonstrated minimal or zero errors for vibrations, indicating excellent performance in that aspect.

In future work, one important direction is the development of an integrated alarm system that incorporates the predictions generated by machine learning algorithms. This integration would enable real-time alerts and notifications, facilitating prompt proactive maintenance actions. Improving the data acquisition process is crucial, and a comparative study of available sensors can help select the most accurate and reliable ones. Exploring advancements in sensor technologies and considering factors like precision, sensitivity, and durability would contribute to more robust and accurate data collection. Additionally, implementing IoT platforms for monitoring sensor signals and algorithmic outputs would enable seamless connectivity, remote monitoring, and management, providing real-time access to data and predictions that facilitate decision-making and optimize maintenance operations.

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