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MACHINE LEARNING ALGORITHMS FOR PREDICTIVE MAINTENANCE: A SYSTEMATIC LITERATURE MAPPING

Algoritmos de Machine Learning usados en mantenimiento predictivo: un mapeo sistemático de literatura

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ABSTRACT

Predictive maintenance is a practice that industrial companies can apply to their processes thanks to technologies such as artificial intelligence and the Internet of Things. Machine Learning algorithms are used in many fields to make predictions or classifications. Predictive maintenance is an area of research that provides new practices, strategies, or methodologies. As a relatively new field, the methodologies are still scattered and there is little information on the maturity of the algorithms. To provide a solid foundation, a systematic literature review is presented to give engineers and researchers an overview of machine learning algorithms used in predictive maintenance. The results obtained show some growth in recent years, demonstrating the interest in this area of research. However, most of the contributions in this field can be summarized as concept proofs and it is still difficult to obtain a prototype that can be validated as a complete and certified system. This paper describes the main machine learning algorithms used in predictive maintenance according to their type of use and supervision, analyses their input and output parameters, and determines their maturity.

Keywords: Machine Learning, Predictive Maintenance, Systematic Literature Mapping, PdM.

RESUMEN

El mantenimiento predictivo es una práctica que gracias a tecnologías como la inteligencia artificial e internet de las cosas permiten que las empresas industriales lo puedan aplicar en sus procesos. Los algoritmos de Machine Learning son utilizados en muchos campos y sirven para realizar tareas de predicción o clasificación. El mantenimiento predictivo es un campo de Investigación que aporta con nuevas prácticas, estrategias o metodologías. Al ser un campo relativamente nuevo las metodologías aún se encuentran dispersas y existe poca información sobre la madurez de los algoritmos. Para proporcionar una base sólida, se presenta un mapeo sistemático de literatura con el objetivo de ofrecer a ingenieros e investigadores una visión general de los algoritmos de Machine Learning usados en mantenimiento predictivo. Los resultados obtenidos muestran un crecimiento en los últimos años demostrando un interés en este campo de investigación. Sin embargo, la mayoría de las contribuciones en este campo se pueden resumir como pruebas concepto y aún resulta difícil obtener un prototipo para que sea validado como un sistema completo y certificado. En este artículo se describen los principales algoritmos de Machine Learning usados en mantenimiento predictivo de acuerdo al tipo de uso y su supervisión, además, se analizan los parámetros de entrada y las salidas de los mismos y por último se determina su nivel de madurez.

Palabras Clave: Machine Learning, Mantenimiento Predictivo, Mapeo Sistemático de Literatura, PdM.

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I. Introduction

The world is currently experiencing a new industrial revolution called 'Industry 4.0', thanks to advances in technologies such as artificial intelligence, the Internet of Things (IoT) or big data [1]. To ensure digital transformation, a new approach is needed that combines physical and digital systems. The integration of these two systems will result in a large amount of data from different parts of a factory, which must be processed to extract information [2].

The use of IoT architectures generates a large amount of data [3]. Much of this data includes events and alarms that occur on the production line of a factory. By processing and analyzing this data, information about the production process can be easily obtained. This is important for decision making, maintenance tasks, fault detection, cost reduction and improving operator safety [4].

The above benefits are closely related to internal processes in the manufacturing industry. It is necessary to implement strategies to identify possible failures in critical machinery in order to avoid unplanned shutdowns that affect production [5]. For example, [6] proposes the monitoring of an oil refinery's compressed gas system, using Industrial Internet of Things architectures to obtain data from specific machines and then using machine learning algorithms to obtain predictions of the machine's current state. A system to perform predictive maintenance tasks is proposed by [7], which is able to obtain a health index of the machinery of an entire factory. A predictive maintenance model uses neural network algorithms to determine the remaining life of a machine and supports maintenance scheduling in a factory [8]. A method can use quantitative and qualitative analysis to apply machine learning techniques to predict failures, thereby aiding maintenance decision making and reducing the costs associated with these tasks [9].

Several nomenclatures can be found in the literature to describe maintenance strategies. However, in this paper we consider the classification proposed by [10]. They classify maintenance strategies as shown below:

Corrective maintenance: this type of maintenance is carried out to repair a machine after a fault has occurred.

Preventive maintenance: this is carried out at regular intervals according to a maintenance schedule, even if the machine has not yet failed.

Predictive maintenance: this type of maintenance attempts to predict a future failure before it occurs in order to plan maintenance tasks and reduce costs.

Fig. 1 gives an overview of the types of maintenance. Although corrective maintenance is the simplest strategy, it requires stopping production to correct the fault, which increases maintenance costs. Preventive maintenance is effective in preventing breakdowns, but increases costs by performing unnecessary maintenance when the machine is in optimal condition. Predictive maintenance uses data on specific machine quantities and a history of failures. It can also use statistical approaches and machine learning algorithms. Therefore, predictive maintenance has several advantages, such as maximizing machine uptime and reducing maintenance tasks and associated costs [11].

Predictive maintenance uses machine learning, an application of artificial intelligence, as its main tool. This approach is the most optimal because several machine learning algorithms have recently emerged that are highly accurate and easy to implement. In addition, machine learning is also capable of handling large amounts of data and extracting hidden relationships from dynamic environments such as industrial environments [12]. Therefore, machine learning can serve as a powerful tool in predictive maintenance tasks, although it is highly dependent on the algorithm used. Therefore, the aim of this paper is to present a systematic literature review that presents the main machine learning algorithms used in predictive maintenance. This paper provides a useful background on the main machine learning algorithms, as well as their main applications and maturity levels, and will help future research work.

The paper is structured as follows: Section II presents a background with several concepts of the different machine leaning algorithms Section III presents the planning and execution of the systematic literature mapping. Section IV presents a description of the main machine learning algorithms used, while section V presents the types of input data and outputs produced by the algorithms, as well as their maturity. Section VI presents a related work and finally, section VII presents the contributions and conclusions of this paper.

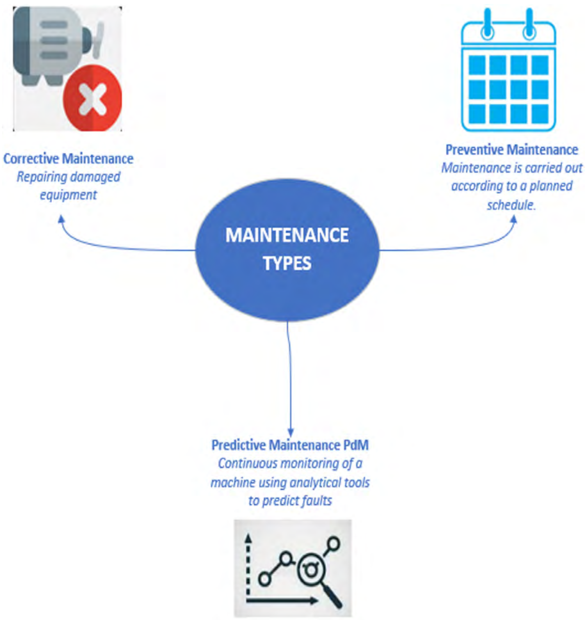

Fig. 1: *Overview of types of maintenance*

II. Background

It is important to have some concepts, so here is a brief description of some that were considered important after the systematic mapping:

- Machine learning: is a branch of artificial intelligence that allows machines to learn without being programmed. This allows machines to make predictions, classify or identify patterns [13].
- Supervised algorithms: they base their learning on a set of previously labelled data, so that the value of their target attribute is known [14].
- Unsupervised algorithms: they base their learning on an unlabeled data set, or no target value or class is known. It is used for clustering tasks [14].

Regression: aims to predict a numerical result [15].

- Classification: aims to predict a categorical outcome [15].
- Linear regression: is a supervised machine learning algorithm. It is a data analysis technique that predicts the value of unknown data using another related and known data value [16].
- Decision tree: is a supervised, non-parametric machine learning algorithm. It has a hierarchical tree structure consisting of a root node, leaf nodes and internal nodes. It can be used for regression or classification tasks [17].
- Random forest: is a popular machine learning algorithm used for classification or regression. It is a set of decision trees [18].
- Support Vector Machines: is a supervised machine learning algorithm that allows finding the optimal way to classify among several classes. It can be used for both regression and classification. It is based on the principle of separating two classes by means of a hyperplane called a support vector [19].
- Neural Networks: is a type of supervised machine learning algorithm that aims to simulate the behavior of the human brain. It can be defined as a network of interconnected nodes. They can be used to perform classification or regression [20].
- K-means: is an unsupervised machine learning algorithm that attempts to form clusters of data with similar characteristics [21].
- K-nearest neighbor: is a supervised non-parametric machine learning algorithm. It is based on the distance from one data to another and classifies objects based on the classes of the nearest neighbors. This algorithm is designed to perform classifications, although it can also be applied to regressions [22].
- Long short-term memory: This is a type of recurrent neural network. The output of the last stage feeds the current stage. It is specifically designed to handle sequential data. It is used for classification or regression [23].
- Autoencoder: is a machine learning technique that attempts to reconstruct the input data from the output to eliminate errors or outliers [24].

III. Related works

Machine learning algorithms used in predictive maintenance is an area that is currently being researched and exploited. Some literature review works have already emerged from this field. Carvalho et al, focuses on describing four important algorithms such as random forest, neural networks, support vector machine and k-means, in addition, it also mentions the type of equipment where these algorithms can be used, the year in which this research is conducted is 2019 [25].

Machine learning algorithms can be used to perform regression or classification. Classification is an important task and supervised or unsupervised algorithms can be used. Saranavan et al, provide a literature review where they focus on those supervised machine learning algorithms to perform classifications, revealing methodologies, advantages and disadvantages [26].

Another approach is to compare machine learning algorithms used in predictive maintenance, Silvestrin et al, provides a comparison of convolutional neural networks with time series, finding significant differences in the use of convolutional neural networks [27]. Industry 4.0 is the new industrial revolution that the world is currently experiencing, which is why Serradilla et al, in their literature review, provide models of machine learning architectures that can be used in predictive maintenance tasks to ensure reproducibility and replicability in different environments. Following the Industry 4.0 line, Drakaki et al. provide an insight into the main machine learning algorithms used in predictive maintenance of induction motors, focusing on machine learning architectures and techniques [28].

Focusing on more specific applications, there are several works, the most notable of which is that of Olesen et al. It identifies new trends and challenges that can be solved by using predictive maintenance and machine learning in pumping systems and thermal power plants [29].

Of the works described above, none focuses on classifying the algorithms or analyzing the types of input data required by the machine learning algorithm to be used and the output produced by the algorithm. Similarly, no work focuses on providing a maturity level for machine learning algorithms used in predictive maintenance.

IV. Systematic Literature Mapping

A systematic literature mapping SLM can provide an overview of the area of interest. This method identifies, appraises and interprets information relevant to a particular area, problem or phenomenon of interest [30]. A systematic literature review is a secondary study that aims to critically evaluate research with a similar scope. The methodology proposed by [31] is used to carry out SLR.

A. Scope of the Study

The main objective of this study is to provide an overview of the state of the art of machine learning based data analysis algorithms used in predictive maintenance. To successfully achieve this goal, the following research questions have been proposed:

- RQ 1. What types of machine learning algorithms are used in predictive maintenance?
    - RQ1.1 What are the algorithms?
      A classification of all the algorithms found will help the reader to have a better understanding to find similarities or differences that will help to improve predictive maintenance.

- RQ 2. What input data does the machine learning algorithm use?
  Identifying the input and output parameters is important as it will help to better understand how the algorithms used in machine learning work.
    - RQ 2.1 What types of data does the machine learning algorithm use?
      Knowing whether the data used in machine learning is synthetic or real data is important for predictive maintenance applications.
    - RQ 2.2 What input parameters are required for this type of data?

- RQ 3. What is the output of the algorithm? It is important to know the type of output the algorithm produces to use it for predictive maintenance tasks.

- RQ 4. What is the maturity of the algorithms used?

It is important to know the maturity level of the algorithms in order to know which ones are most commonly used in predictive maintenance tasks.

B. Study Identification

A database-driven search approach was used in this study, with Scopus as the main search database:

1) **Search String**
The choice of keywords to construct the search string was based on common terms used in the literature and terms related to this work (for example, PdM or ML). Some of the terms suggested by [32] were used to find synonyms. Table 1 shows the search string used.

The search string was validated by an expert in the field. The expert provided 10 relevant items, and the search string found 9 of them, that is the string contains 90% of the items provided by the expert.

A search was performed on 5 October 2023 and 6019 items were found.

TABLE I
Search String Used

((((predictive AND (maintenance or monitoring)) or PdM)) AND (“machine learning” or ML) AND (algorithm OR model OR strategy OR technique))

2) **Inclusion and Exclusion Procedure**
The inclusion and exclusion process consists of two phases: an automatic phase and a manual phase. The automatic phase uses the Scopus functions, which values are listed in Table II, while the manual phase uses the CADIMA software [33]. A flowchart of the inclusion and exclusion procedure is shown in Fig. 2.

The manual phase was carried out on 2349 articles after removing duplicate articles with a CADIMA proprietary function using the inclusion and exclusion criteria in Table III. Before starting the manual phase, a pilot phase was carried out between the principal investigator and the expert with a set of 10 randomly selected articles to standardize the inclusion and exclusion criteria. The title and abstract of each article were read and marked as included or excluded. To ensure inter-rater reliability, the Krippendorff alpha coefficient was set at 0.8, which is an accepted value in most studies [34]. At the end of the pilot study, a Krippendorff alpha coefficient of 1 was obtained.

TABLE II
Inclusion Criteria Used in Scopus

Filter	Values
Research Field	Engineering Computer Science
Type of document	Conference article Journal article
Language	English

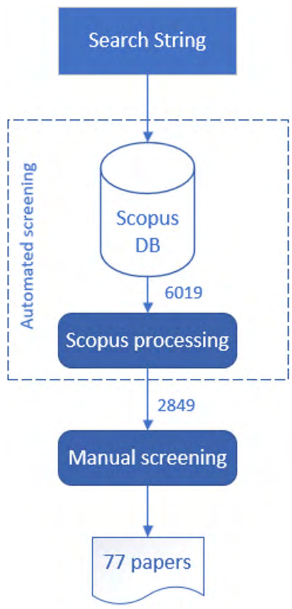

Fig. 2: *Inclusion and exclusion procedure*

The manual inclusion and exclusion process consisted of 3 iterations carried out by the principal investigator. In the first iteration, the title was read and 502 articles were included for the next iteration. In the second iteration, the abstract was read, including 116 articles. In the third iteration, the conclusions were read, including 77 articles.

For the coding and information extraction phase we have a set of 77 articles. Fig. 3 shows the percentage of articles included in each iteration. The articles included are presented in Appendix A.

Four labels were used to classify articles in the manual inclusion and exclusion phase. These labels are:

Included: the article meets all the inclusion criteria and none of the exclusion criteria.

Excluded: the article meets the exclusion criteria or none of the inclusion criteria.

Unclear: the investigator is in doubt as to whether the article should be included or excluded.

Secondary: the article is a secondary or tertiary contribution.

TABLE III
Inclusion and Exclusion Criteria

Criteria Type	Values
Inclusion (all must be met)	The article must be related to predictive maintenance.
	The article must be related to data analysis based on machine learning.
	The article should contain information about the machine learning algorithm used.
	The article must contain information about the input and output parameters as well as the data used in the machine learning model used.
	The article must be a primary contribution.
Exclusion (none can be fulfilled)	The article is a secondary or tertiary contribution.

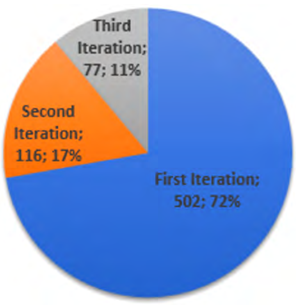

Fig. 3: *Articles included in each iteration*

V. Results

Fig. 5 shows the number of articles published between 2014 and 2023 using the exclusion and inclusion criteria presented in this paper. This confirms that predictive maintenance is a technique that has been used in papers since 2014. On the other hand, it can be observed that the interest in this field of research has increased in recent years, reaching a peak between 2021 and 2023. This effect is related to the amount of data generated by industrial equipment and the latest advances in machine learning algorithms.

The small number of works in the field of predictive maintenance is due to the complexity of implementing efficient strategies in production environments [39]. On the other hand, the number of machine learning algorithms is limited because data science is still a relatively new field of study and there are still no defined methodologies for obtaining historical maintenance and failure data in industrial environments.

A. RQ. 1. What types of machine learning algorithms are used in predictive maintenance?

The articles reviewed fall into two main categories: use and type of supervision. Most articles report the use of supervised machine learning algorithms and for use in regression (data prediction). This is because the datasets used are labelled and categorized, which makes it easier to make a prediction or classification.

On the other hand, there is little work using unsupervised machine learning algorithms, as they only aim to find patterns of possible failures for future use in maintenance task planning. Unsupervised algorithms are more prone to failure when making predictions or classifications. Of the selected papers, those using unsupervised algorithms are only used in regression tasks.

Fig. 6 shows the proportion of papers using supervised and unsupervised algorithms and whether they are also used for regression or classification.

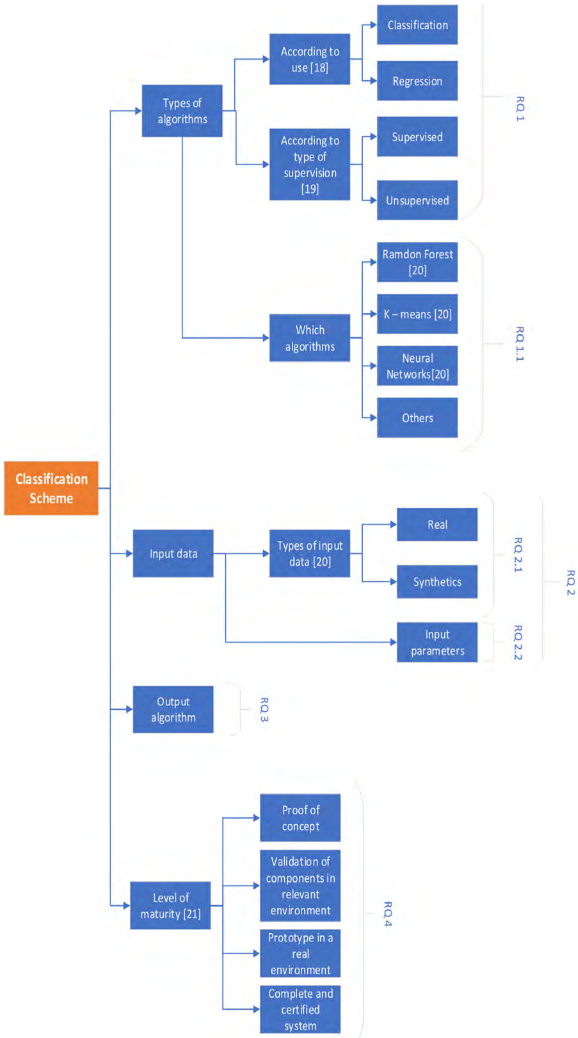

Fig. 4: *Classification Scheme used*

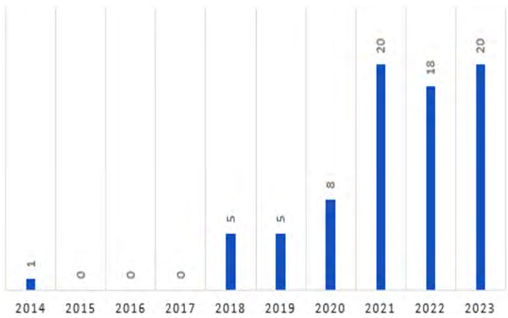

Fig. 5: *Classification Scheme used*

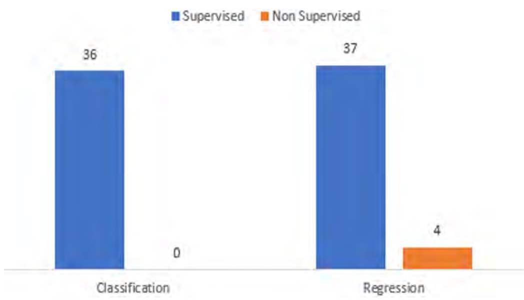

Fig. 6: *Papers per type and use and supervision*

In more than 50% of the selected papers, machine learning algorithms are used for regression, since one of the main objectives of predictive maintenance is to estimate the remaining useful life (RUL). On the other hand, the algorithms using classification try to provide a state of health of the machine or equipment by classifying it in categories proposed by each author.

Table IV summarizes the types of algorithms according to their use and type of supervision in the articles studied.

RQ. 1.1. What are the algorithms?
The papers consulted use a range of machine learning algorithms that can be applied to predictive maintenance tasks. These algorithms range from those with a relatively simple mathematical basis, such as linear regression, to the more mathematically complex variants of artificial neural networks.
The authors do not use a single algorithm in their work but use several to test the accuracy and error results of their main contribution. The most used algorithms for supervised models are:

- Linear regression
- Decision tree
- Random forests
- Support vector machines
- Neural Networks
- K-Nearest Neighbour
- Gradient Boost
- XGboost
- Adaboost
- Long term memory
- Autoencoder

The choice of these algorithms depends very much on the practical application and the data obtained. For example, if you have a dataset with a lot of outliers, a robust algorithm to use is Decision Trees, while a vulnerable one is Adaboost.

On the other hand, the most used algorithms in unsupervised models are:

- K-means
- Neural Networks

- Principal Component Analysis

In general, the k-means algorithm is the most used in unsupervised models because it can group the data into clusters to find possible relationships.

Fig. 7 shows the proportion of machine learning algorithms used in predictive maintenance.

TABLE IV
Types of algorithms proposed on the studied papers

Algorithm Type		Papers studied
According to type of supervision	Supervised	ID1, ID5, ID12, ID30, ID32, ID34, ID41, ID42, ID61, ID70, ID83, ID87, ID93, ID100, ID103, ID109, ID127, ID137, ID140, ID144, ID148, ID153, ID156, ID158, ID165, ID169, ID172, ID173, ID188, ID191, ID197, ID206, ID208, ID219, ID232, ID240, ID245, ID249, ID250, ID254, ID272, ID283, ID291, ID294, ID310, ID325, ID334, ID343, ID356, ID357, ID375, ID378, ID396, ID406, ID410, ID417, ID425, ID429, ID431, ID435, ID444, ID448, ID454, ID460, ID463, ID471, ID477, ID483, ID489, ID494, ID499, ID501, ID502
	Unsupervised	ID16, ID20, ID157, ID215,
According to use	Regression	ID1, ID16, ID20, ID30, ID32, ID34, ID42, ID83, ID87, ID100, ID109, ID127, ID137, ID140, ID153, ID156, ID157, ID158, ID165, ID169, ID173, ID215, ID219, ID245, ID250, ID254, ID272, ID294, ID310, ID334, ID356, ID406, ID410, ID417, ID425, ID429, ID431, ID435, ID444, ID448, ID502
	Clasification	ID5, ID12, ID41, ID61, ID70, ID93, ID103, ID144, ID148, ID172, ID188, ID191, ID197, ID206, ID208, ID232, ID240, ID249, ID283, ID291, ID325, ID343, ID357, ID375, ID378, ID396, ID454, ID460, ID463, ID471, ID477, ID483, ID489, ID494, ID499, ID501

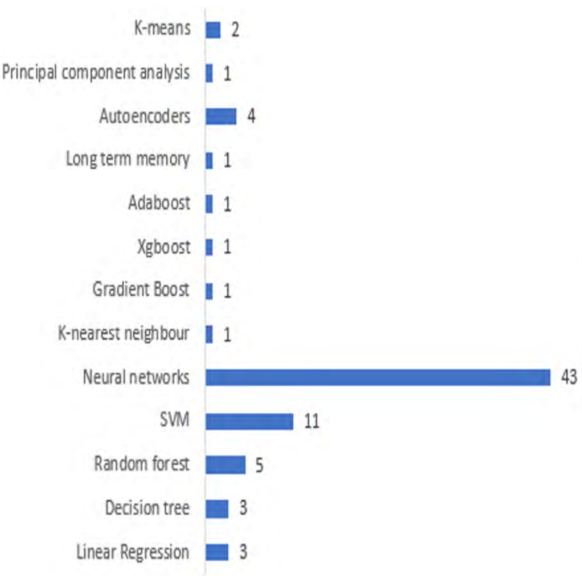

Fig. 7: *Machine Learning algorithms*

TABLE V
Algorithms proposed on the studied papers

Algorithms	Papers Studied
Linear regression	ID12, ID100, ID431
Decision tree	ID103, ID29, ID429
Random forests	ID32, ID34, ID41, ID156, ID245
Support vector machines	ID70, ID83, ID127, ID144, ID165, ID191, ID272, ID356, ID375, ID396, ID460
Neural Networks	ID1, ID5, ID30, ID42, ID61, ID87, ID93, ID109, ID140, ID148, ID158, ID169, ID172, ID173, ID188, ID206, ID209, ID232, ID249, ID250, ID254, ID283, ID294, ID325, ID334, ID343, ID357, ID378, ID406, ID410, ID417, ID435, ID444, ID448, ID454, ID463, ID471, ID477, ID483, ID489, ID494, ID499, ID501, ID502
K-Nearest Neighbour	ID240
Gradient Boost	ID191
XGboost	ID137
Adaboost	ID156
Long term memory	ID310
Autoencoder	ID16, ID157, ID208, ID425
K-means	ID16, ID20
Principal Component Analysis	ID215

Table V summarizes the algorithms used on the studied papers.

B. **RQ 2.** *What input data does the machine learning algorithm use?*

To better understand the input data that a machine learning algorithm uses, the research question has been divided into two sub-questions. The first sub-question focuses on the types of data, while the second sub-question focuses on the input parameters required by machine learning algorithms.

1) **RQ 2.1.** What types of data does the machine learning algorithm use?

According to the classification scheme in Figure 4, data can be divided into real and synthetic data. Real data are those obtained from the monitored machines that have not been subjected to any outlier elimination or filtering process. Synthetic data, on the other hand, are those that have undergone various processes to protect their information, as they may belong to a machine of a critical process in an industry.

Moreover 72% of the articles consulted use real data obtained from different machines in real or laboratory scenarios, although they are also obtained from public repositories such as the Bearing Data Center of Case Western University Bearing, while the remaining 28% of the articles use synthetic data mainly obtained from public repositories such as NASA's CMAPSS and also from machines present in industries that do not reveal their name for reasons of confidentiality.

Table VI summarizes the types of data used in studied papers.

Fig. 8 shows the proportion of data types used in the selected articles.

TABLE VI
Types of data on the studied papers

Type of Data	Papers studied
Real	ID1, ID5, ID16, ID20, ID30, ID34, ID42, ID61, ID70, ID83, ID103, ID109, ID127, ID140, ID144, ID148, ID153, ID156, ID157, ID165, ID172, ID188, ID191, ID197, ID206, ID208, ID215, ID232, ID240, ID249, ID254, ID272, ID291, ID294, ID310, ID325, ID334, ID343, ID357, ID375, ID378, ID396, ID406, ID410, ID417, ID425, ID429, ID431, ID435, ID444, ID448, ID454, ID460
Syntethic	ID12, ID32, ID41, ID87, ID93, ID100, ID137, ID158, ID169, ID173, ID219, ID245, ID250, ID283, ID356, ID463, ID471, ID477, ID483, ID489, ID494, ID499, ID501, ID502

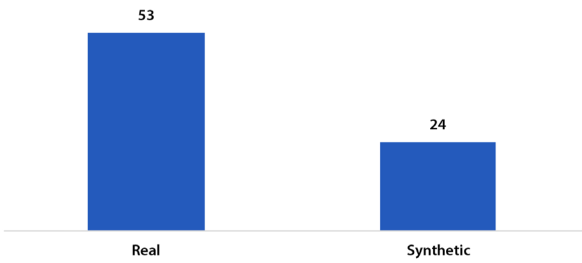

Fig. 8: *Types of Data Used in Papers*

1) **RQ 2.2.** What input parameters are required for this type of data?

The input parameters used in machine learning algorithms are highly dependent on the application and the machine being monitored. For example, when monitoring an induction motor, data such as current, voltage or power, as well as vibration or temperature, are used to estimate remaining life or classify a possible failure. Another component susceptible to failure and found in many machines is the bearing, and data such as vibration, temperature and radial load are usually obtained.

Some works also use historical failure data as input parameters to avoid certain failures, component degradation levels and failure patterns. The choice of input parameters depends very much on the components and variables that can be measured and controlled in the machinery to be monitored.

C. **RQ 3.** What is the output of the algorithm?

The main objective of predictive maintenance is to anticipate an eventual failure, so the main outputs of the machine learning algorithms are the remaining useful life and a failure classification.

The prediction of the remaining useful life is performed using regression algorithms. Depending on the measured variables or input parameters of the algorithm, the accuracy can increase or decrease.

The classification of failures according to pre-defined categories is useful for scheduling possible maintenance tasks. It is also possible to determine the state of health of the machine according to the measured variables at a given time.

Fig. 9 shows the ratio of the outputs of the algorithms obtained in the systematic mapping, while Table VII summarizes the Outputs of the algorithms.

D. **RQ 4.** What is the maturity of the algorithms used?

Although machine learning algorithms already have very concrete applications that are accessible to the public, the level of maturity in predictive maintenance is still very low. Most papers focus on interpreting the data obtained to test different performance metrics in controlled environments or laboratories. More than 90% of the papers selected in this study are only proof of concepts.

The papers that have been carried out in a relevant environment represent 10% of the total number of papers selected. Although the breakthrough to relevant environments has been made, no prototypes have been developed for testing in a real environment, nor have the necessary qualifications for a complete system been achieved.

Fig. 10 shows the proportion of maturity of machine learning algorithms used in predictive maintenance, while Table VIII summarizes the algorithm maturity ratio

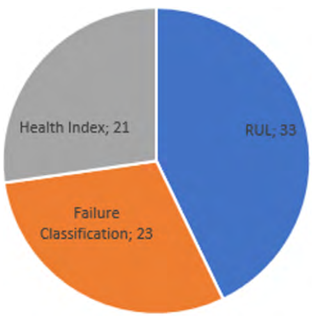

Fig. 9: *Outputs of The Algorithm*

TABLE VII
Outputs of the algorithms on the studied papers

Output	Papers Studied
Remaining useful life RUL	ID1, ID16, ID30, ID32, ID42, ID61, ID83, ID87, ID100, ID109, ID137, ID140, ID153, ID156, ID157, ID158, ID165, ID169, ID173, ID215, ID219, ID245, ID250, ID406, ID410, ID417, ID425, ID429, ID431, ID435, ID444, ID448, ID454,
Faulire classifi-cation	ID5, ID12, ID20, ID70, ID103, ID144, ID148, ID188, ID191, ID197, ID206, ID232, ID240, ID249, ID283, ID291, ID325, ID396, ID460, ID463, ID471, ID477, ID483
Health index	ID34, ID41, ID93, ID127, ID172, ID254, ID272, ID294, ID310, ID334, ID356, ID343, ID357, ID375, ID378, ID489, ID494, ID499, ID501, ID502

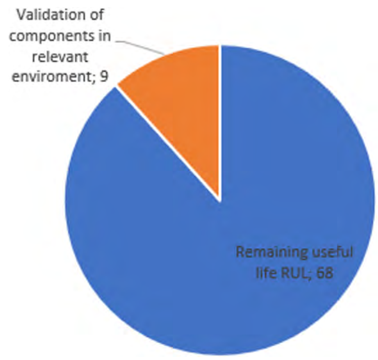

Fig. 10: *Algorithm Maturity Ratio*

VI. DISCUSSION

There is no doubt that predictive strategies are increasingly being used in industrial maintenance. By using predictive strategies, they reduce the costs associated with unplanned downtime and can maximize their production. Although there is still no defined methodology for data collection and processing, progress has been made in this area, especially since 2014, and the last three years have seen exponential growth in these topics.

Machine learning emerged in the 90s with the aim of giving computers intelligence. In this field, there are already defined methodologies, strategies and algorithms capable of solving specific problems, which have been tested in relevant environments and some form complete certified systems. Today, with technological advances, it is relatively easy to implement a machine learning algorithm for either prediction or classification, and there are specialized frameworks and software for this type of task.

Today, the transition from Industry 3.0 to Industry 4.0 has led to the emergence of new paradigms. Artificial intelligence is one of the main enablers of Industry 4.0, which, together with other technologies such as the Internet of Things, can create a new dimension of work that combines the operational and administrative parts of companies. In this way, both vertical and horizontal integration will be achieved, providing companies with competitive tools.

The relationship between predictive maintenance and machine learning is extremely important, as PdM is a product of ML. With the large amount of data generated in today's factories, it is possible to generate predictive or classification models with acceptable, albeit improvable, accuracies.

Machine learning algorithms can be classified according to the type of monitoring and the use of monitoring, a classification widely accepted by different authors. It is difficult to add new fields, as the current ones are sufficiently broad and can easily include other subcategories that we would like to propose.

The algorithms proposed in the works related to predictive maintenance have very solid mathematical and statistical bases. Some algorithms have advantages and disadvantages, such as noise immunity or susceptibility to outliers. From the review of the papers, there is a tendency to use hybrid approaches that combine several algorithms to provide robustness. Such hybrid algorithms still need to improve their methodologies in order to be implemented ubiquitously and with relative ease. On the other hand, these approaches represent new lines of research for future work that have a solid foundation.

Although several literature reviews have been carried out, most seek to establish a taxonomy or classification of algorithms so that the reader can have a broad vision and do not focus on a particular application. However, this work provides the author with a specific vision of machine learning algorithms in the field of predictive maintenance. In addition, the level of maturity of the algorithm analyzed in the field can be measured, which is important for implementation in the field. real life of this type of applications.

Talking about input data would be very broad, as predictive maintenance can be applied to many machines, but the most common application is for induction motors, although there are other machines such as turbojet engines, gearboxes or wind generators. However, there are other approaches, such as monitoring specific machine parts such as gears or bearings, which are components with high mechanical wear due to the working conditions they are exposed to. It is important to use real data wherever possible to create models that have real accuracy and can be extrapolated to other applications. It is also necessary to consider sharing knowledge with the scientific community, so it is suggested to use real rather than synthetic data sets.

Regarding the outputs of the algorithms, the most common in predictive maintenance is to estimate the remaining useful life, to have a classification or to obtain the health index of the machine. However, other outputs can be obtained, for example by using supervised algorithms to find relationships between the data obtained from the machine. The prediction of remaining useful life can be improved by using more data and more variables to obtain estimates with an acceptable margin of time before damage to the machine occurs.

Finally, the level of maturity of all the works consulted is still insufficient to obtain a complete and certified system. However, some works have been tested in relevant environments such as factories. This type of contribution can be used as a basis for designing a prototype and validating it in real conditions before any necessary certifications are obtained.

VII. CONCLUSIONS

The main results of a systematic literature review were presented to review the state of the art of machine learning algorithms used in predictive maintenance. An overview of algorithms and predictive maintenance has been provided so that researchers can further develop this area of research with new contributions. While for engineers and technicians, the maturity of the algorithms is provided for future developments leading to certification of a complete system.

This field of research is in constant development, as can be seen in the growing number of articles published in recent years. Most contributions attempt to use an algorithm that is tested against other algorithms to measure its metrics such as accuracy or error. Machine learning has now become a highly researched and developed topic in various fields, although it is still at a low level of maturity in predictive maintenance.

This work can serve as a theoretical basis for the generation of hybrid algorithms that are much more robust, with higher accuracy and lower error. Consideration should also be given to the generation of new methods to assist in the collection and processing of data from industrial machines. Finally, the topic should be further developed to reach a level of maturity that allows industrial companies to adopt this type of technology.

VIII. Referencias

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IX. Appendix

LIST OF STUDIED PAPERS

ID	Reference	Authors	Year
1	Evaluating time series encoding techniques for Predictive Maintenance	De Santo, A.; Ferraro, A.; Galli, A.; Moscato, V.; Sperlì, G.	2022
5	Logistic-ELM: a novel fault diagnosis method for rolling bearings	Tan, Z.; Ning, J.; Peng, K.; Xia, Z.; Wu, D.	2022

12	Data Science Application for Failure Data Management and Failure Prediction in the Oil and Gas Industry: A Case Study	Arena, S.; Manca, G.; Murru, S.; Orrù, P.F.; Perna, R.; Reforgiato Recupero, D.	2022
16	Fault detection and diagnosis for industrial processes based on clustering and autoencoders: a case of gas turbines	Barrera, J.M.; Reina, A.; Mate, A.; Trujillo, J.C.	2022
20	Predicting Bearings Degradation Stages for Predictive Maintenance in the Pharmaceutical Industry	Juodelyte, D.; Cheplygina, V.; Graversen, T.; Bonnet, P.	2022
30	Remaining Useful Life Estimation of Cooling Units via Time-Frequency Health Indicators with Machine Learning	Rosero, R.L.; Silva, C.; Ribeiro, B.	2022
32	Simulation for predictive maintenance using weighted training algorithms in machine learning	Jittawiriyanukoon, C.; Srisarkun, V.	2022
34	Real-Time Induction Motor Health Index Prediction in A Petrochemical Plant using Machine Learning	Khrakhuean, W.; Chutima, P.	2022
41	Selecting an appropriate supervised machine learning algorithm for predictive maintenance	Ouadah, A.; Zemmouchi-Ghomari, L.; Salhi, N.	2022
42	On the Importance of Temporal Information for Remaining Useful Life Prediction of Rolling Bearings Using a Random Forest Regressor	Bienefeld, C.; Kirchner, E.; Vogt, A.; Kacmar, M.	2022
61	A recurrent neural network method for condition monitoring and predictive maintenance of pressure vessel components	Halliday, C.; Palmer, I.; Joyce, M.; Pready, N.	2022
70	Remaining Useful Life Estimation Using Fault to Failure Transformation in Process Systems	Arunthavanathan, R.; Khan, F.; Ahmed, S.; Imtiaz, S.	2022
83	Estimation of Remaining Useful Life (RUL) of BLDC Motor using Machine Learning Approaches	Sree, R.D.; Jayanthy, S.; Vigneshwaran, E.E.	2022
87	Predictive Maintenance Algorithm Based on Machine Learning for Industrial Asset	Alfaro-Nango, A.J.; Escobar-Gomez, E.N.; Chandomi-Castellanos, E.; Velazquez-Trujillo, S.; Hernandez-De-Leon, H.R.; Blanco-Gonzalez, L.M.	2022
93	RNN-Autoencoder Approach for Anomaly Detection in Power Plant Predictive Maintenance Systems	Santoso, B.; Anggraeni, W.; Pariaman, H.; Purnomo, M.H.	2022
100	Predicting Remaining Useful Life of Wind Turbine Bearing using Linear Regression	Jellali, A.; Maatallah, H.; Ouni, K.	2022
103	Predictive Maintenance of Hydraulic System using Machine Learning Algorithms	Yugapriya, M.; Judeson, A.K.J.; Jayanthy, S.	2022
109	An Artificial Intelligence Neural Network Predictive Model for Anomaly Detection and Monitoring of Wind Turbines Using SCADA Data	Amini, A.; Kanfoud, J.; Gan, T.-H.	2022
127	Predictive maintenance of abnormal wind turbine events by using machine learning based on condition monitoring for anomaly detection	Chen, H.; Hsu, J.-Y.; Hsieh, J.-Y.; Hsu, H.-Y.; Chang, C.-H.; Lin, Y.-J.	2021
137	Remaining Useful Life Prediction of Equipment Based on XGBoost	Jia, Z.; Xiao, Z.; Shi, Y.	2021
140	Integrating physics and data driven cyber-physical system for condition monitoring of critical transmission components in smart production line	Song, L.; Wang, L.; Wu, J.; Liang, J.; Liu, Z.	2021
144	Application of machine learning to a medium gaussian support vector machine in the diagnosis of motor bearing faults	Lin, S.-L.	2021
148	IIoT Solution for predictive monitoring based on vibration data from motors using Microsoft Azure machine learning studio and Power BI	Ferreira, R.H.M.S.; de Figueiredo, L.O.; Lima, R.B.C.; Silva, L.A.P.; Barros, P.R.	2021
153	Predictive Analytics of Machine Failure using Linear Regression on KNIME Platform	Pakhir, E.A.; Ayuni, N.	2021
156	Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time	Ayvaz, S.; Alpay, K.	2021
157	An applicable predictive maintenance framework for the absence of run-to-failure data	Kim, D.; Lee, S.; Kim, D.	2021
158	Two stage deep learning for prognostics using multi-loss encoder and convolutional composite features	Pillai, S.; Vadakkepat, P.	2021
165	Intelligent Predictive Maintenance Model for Rolling Components of a Machine based on Speed and Vibration	Ahmad, B.; Mishra, B.K.; Ghufran, M.; Pervez, Z.; Ramzan, N.	2021
169	Remaining Useful Life Prediction of Bearings Using Ensemble Learning: The Impact of Diversity in Base Learners and Features	Shi, J.; Yu, T.; Goebel, K.; Wu, D.	2021
172	A deep learning model for predictive maintenance in cyber-physical production systems using LSTM autoencoders	Bampoula, X.; Siaterlis, G.; Nikolakis, N.; Alexopoulos, K.	2021
173	Remaining useful life (Rul) prediction of equipment in production lines using artificial neural networks	Kang, Z.; Catal, C.; Tekinerdogan, B.	2021
188	A Novel Approach for Incipient Fault Diagnosis in Power Transformers by Artificial Neural Networks	De Andrade Lopes, S.M.; Flauzino, R.A.	2021

191	A Combination of Fourier Transform and Machine Learning for Fault Detection and Diagnosis of Induction Motors	Duc Nguyen, V.; Zwanenburg, E.; Limmer, S.; Luijben, W.; Back, T.; Olhofer, M. Limmer, S.; Luijben, W.; Back, T.; Olhofer, M.	2021
197	Motor classification with machine learning methods for predictive maintenance	Kammerer, C.; Gaust, M.; Küstner, M.; Starke, P.; Radtke, R.; Jesser, A.	2021
206	Machine Learning Based Predictive Maintenance System for Industrial Chain Conveyor System	Goh, K.W.; Chaw, K.H.; Yong, J.C.E.; Koh, Y.S.; Dares, M.; Su, E.L.M.; Yeong, C.F.	2021
208	Bearing Fault Detection Using Comparative Analysis of Random Forest, ANN, and Autoencoder Methods	Kamat, P.; Marni, P.; Cardoz, L.; Irani, A.; Gajula, A.; Saha, A.; Kumar, S.; Sugandhi, R.	2021
215	Fault Detection of Smart Grid Equipment Using Machine Learning and Data Analytics	Sarita, K.; Kumar, S.; Saket, R.K.	2021
219	Automatic Remaining Useful Life Estimation Framework with Embedded Convolutional LSTM as the Backbone	Zhou, Y.; Hefenbrock, M.; Huang, Y.; Riedel, T.; Beigl, M.	2021
232	On-line fault diagnosis of rolling bearing based on machine learning algorithm	Sun, J.; Yu, Z.; Wang, H.	2020
240	EEMD assisted supervised learning for the fault diagnosis of BLDC motor using vibration signal	Shifat, T.A.; Hur, J.-W.	2020
245	Experimental analysis of machine learning algorithms used in predictive maintenance	Sahasrabudhe, N.; Asegaonkar, R.; Deo, S.; Umredkar, S.; Mundada, K.	2020
249	Wind power forecasting of an offshore wind turbine based on high-frequency SCADA data and deep learning neural network	Lin, Z.; Liu, X.	2020
250	A Hybrid Cyber Physical Digital Twin Approach for Smart Grid Fault Prediction	Tzanis, N.; Andriopoulos, N.; Magklaras, A.; Mylonas, E.; Birbas, M.; Birbas, A.	2020
254	Advanced Predictive Maintenance with Machine Learning Failure Estimation in Industrial Packaging Robots	Koca, O.; Kaymakci, O.T.; Mercimek, M.	2020
272	Failure Prediction of Aircraft Equipment Using Machine Learning with a Hybrid Data Preparation Method	Celikmih, K.; Inan, O.; Uguz, H.	2020
283	Predictive model for the degradation state of a hydraulic system with dimensionality reduction	Quatrini, E.; Costantino, F.; Pocci, C.; Tronci, M.	2020
291	Predictive Maintenance of Air Conditioning Systems Using Supervised Machine Learning	Trivedi, S.; Bhola, S.; Talegaonkar, A.; Gaur, P.; Sharma, S.	2019
294	The Prediction of Remaining Useful Life (RUL) in Oil and Gas Industry using Artificial Neural Network (ANN) Algorithm	Fauzi, M.F.A.M.; Aziz, I.A.; Amiruddin, A.	2019
310	A deep learning approach for failure prognostics of rolling element bearings	Sadoughi, M.; Lu, H.; Hu, C.	2019
325	Intelligent fault diagnosis for rotating machines using deep learning	Sumba, J.C.; Quinde, I.R.; Ochoa, L.E.; Martínez, J.C.T.; Vallejo Guevara, A.J.; Morales-Menendez, R.	2019
334	Robot fault detection and remaining life estimation for predictive maintenance	Pinto, R.; Cerquitelli, T.	2019
343	Fault Analysis and Predictive Maintenance of Induction Motor Using Machine Learning	Kavana, V.; Neethi, M.	2018
356	Prediction of Remaining Useful Lifetime (RUL) of turbofan engine using machine learning	Mathew, V.; Toby, T.; Singh, V.; Rao, B.M.; Kumar, M.G.	2018
357	Transformer Fault Condition Prognosis Using Vibration Signals over Cloud Environment	Bagheri, M.; Zollanvari, A.; Nezhivenko, S.	2018
375	Increasing production efficiency via compressor failure predictive analytics using machine learning	Pandya, D.; Srivastava, A.; Doherty, A.; Sundareshwar, S.; Needham, C.; Chaudry, A.; Krishnalyer, S.	2018
378	Predictive maintenance strategy of running fault based on ELM algorithm for power transformer	Wu, Q.; Yang, X.; Deng, R.	2018
396	Fault diagnosis of automobile gearbox based on machine learning techniques	Praveenkumar, T.; Saimurugan, M.; Krishnakumar, P.; Ramachandran, K.I.	2014
406	Machine Learning for the Detection and Diagnosis of Anomalies in Applications Driven by Electric Motors	Ferraz, F.; Romero, R.; Hsieh, S.	2023
410	Neural Networks Detect Inter-Turn Short Circuit Faults Using Inverter Switching Statistics for a Closed-Loop Controlled Motor Drive	Oner, M.; Sahin, I.; Keysan, O.	2023
417	An Approach to Predicting the Residual Life of an Electric Locomotive Traction Motor	Sidorenko. V.; Kulaginm M.	2023
425	Optoelectronic sensor fault detection based predictive maintenance smart industry 4.0 using machine learning techniques	Zhu, C.; Shao, S.	2023
429	A Robot-Operation-System-Based Smart Machine Box and Its Application on Predictive Maintenance	Chang, Y.; Chai, Y.; Li, B.; Lin, H.	2023

431	Improving Reliability of 2 Wheelers Using Predictive Diagnostics	Vijaykumar, S.; Sabu, A.; Pradhan, D.; Shrivardhankar, Y.	2023
435	Remaining Useful Life Estimation Using Fault to Failure Transformation in Process Systems	Arunthavanathan, R.; Khan, F.; Ahmed, S.; Imtiaz, S.	2023
444	Tool remaining useful life prediction using bidirectional recurrent neural networks (BRNN)	De Barrera, T.; Ferrando, J.; García, A.; Badiola, X.; de Buruaga, M.; Vicente, J.	2023
448	Remaining cycle time prediction with Graph Neural Networks for Predictive Process Monitoring	Duong, L.; Travé-Massuyès, L.; Subias, A.; Merle, C.	2023
454	Remaining Useful Life Estimation for Railway Gearbox Bearings Using Machine Learning	Beqiri, L.; Bakhshi, Z.; Punnekkat, S.; Cicchetti, A.	2023
460	An IoT and Machine Learning-Based Predictive Maintenance System for Electrical Motors	Mohammed, N.; Abdulateef, O.; Hamad, A.	2023
463	A machine learning based predictive maintenance algorithm for ship generator engines using engine simulations and collected ship data	Park J.; Oh, J.	2023
471	Vibration Signal-Based Diagnosis of Wind Turbine Blade Conditions for Improving Energy Extraction Using Machine Learning Approach	Sethi, M.; Sahoo, S.; Dhanraj, J.; Sugumaran, V.	2023
477	LSTM-Based Condition Monitoring and Fault Prognostics of Rolling Element Bearings Using Raw Vibrational Data	Afridi, Y.; Hasan, L.; Ullah, R.; Ahmad, Z.	2023
483	Multivariate Time-Series Classification of Critical Events from Industrial Drying Hopper Operations: A Deep Learning Approach	Rahman, M.; Farahani, M.; Wuest, T.	2023
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499	Anomaly detection in the temperature of an ac motor using embedded machine learning	Ismail, E.; Ahmad, M.	2023
501	Early detection of tool wear in electromechanical broaching machines by monitoring main stroke servomotors	Aldekoa, I.; del Olmo, A.; Sastoque-Pinilla, L.; Sendino-Mouliet, S.; Lopez-Nova, U.; del Lacalle, L.	2023
502	Remaining useful lifetime prediction for predictive maintenance in manufacturing	Taşcı, B.; Omar, A.; Ayvaz, S.	2023