SCREENING OF MACHINE LEARNING TECHNIQUES ON PREDICTIVE MAINTENANCE: A SCOPING REVIEW

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ABSTRACT:

Predictive maintenance (PdM) is a set of actions and techniques to early detect failures and defects on machines before they occur, and the usage of machine learning and deep learning techniques in predictive maintenance has increased during the last years. Even with this increase of the literature, there is still a gap concerning the application of such techniques for PdM in the industry, as there are no clear guidelines about which information to use for a PdM system, how to process the information, and what machine learning techniques should be used in order to obtain acceptable results. This scoping review is performed in order to observe the current status on the use of Machine Learning and Deep Learning in predictive maintenance in academia and provide answer to the questions related to these guidelines. For this purpose, a literature review of the last five years is carried out, using those articles that cover information about sources of information used for PdM, the treatment given to such data and the machine learning (ML) methods or techniques used.

The Web of Science: Core Collection database is used as a source of information, specifically the Science Citation Index Expanded (SCIE). The review shows that there are different information sources used for machine learning and deep learning in PdM, depending on the origin of the data and the availability of it, and as well whether the data sets are private or public. Also, we can observe that data used for both training and making predictions does not only use traditional pre-processing techniques, but that about one fifth of the articles even propose new techniques in this field. Additionally, we compare a wide range of techniques and algorithms which are used in Deep Learning - being ANN the most used- and in Machine Learning, being SVM the most used algorithm, closely followed by Random Forest. Based on the results, we provide indications about how to apply ML for PdM in industry.

Keywords: ***machine learning, predictive maintenance, artificial intelligence, deep learning, data processing, data collection***

RESUMEN:

El mantenimiento predictivo (PdM) es un conjunto de acciones y técnicas para detectar tempranamente fallos y defectos en máquinas antes de que ocurran. El uso de técnicas de aprendizaje automático y aprendizaje profundo en el mantenimiento predictivo ha aumentado en los últimos años. A pesar de este aumento en la literatura, todavía existe una brecha en cuanto a la aplicación de tales técnicas en la industria, ya que no existen pautas claras sobre qué información utilizar en un sistema de PdM, cómo procesar la información y qué técnicas de aprendizaje automático se deben usar para obtener resultados aceptables. Esta revisión de alcance se realiza para observar el estado actual del uso del aprendizaje automático y el aprendizaje profundo en el mantenimiento predictivo en la academia y proporcionar respuestas a las preguntas relacionadas con estas pautas. Para este propósito, se lleva a cabo una revisión de la literatura de los últimos cinco años, utilizando los artículos que cubren información sobre las fuentes de información utilizadas para el PdM, el tratamiento dado a dichos datos y los métodos o técnicas de aprendizaje automático (ML) utilizados.

La base de datos Web of Science: Core Collection se utiliza como fuente de información, específicamente el Science Citation Index Expanded (SCIE). La revisión muestra que existen diferentes fuentes de información utilizadas para el aprendizaje automático y el aprendizaje profundo en el PdM, dependiendo del origen de los datos y su disponibilidad, así como si los conjuntos de datos son privados o públicos. Además, podemos observar que los datos utilizados tanto para el entrenamiento como para realizar predicciones no solo utilizan técnicas de preprocesamiento tradicionales, sino que aproximadamente una quinta parte de los artículos incluso proponen nuevas técnicas en este campo. Además, comparamos una amplia gama de técnicas y algoritmos que se utilizan en el Aprendizaje Profundo, siendo las Redes Neuronales Artificiales (ANN) las más utilizadas, y en el Aprendizaje Automático, siendo el SVM (Máquinas de Soporte Vectorial) el algoritmo más utilizado, seguido de cerca por Random Forest. Basándonos en los resultados, proporcionamos indicaciones sobre cómo aplicar el Aprendizaje Automático para Mantenimiento Predictivo en la industria.

Palabras clave: aprendizaje automático, mantenimiento predictivo, inteligencia artificial, aprendizaje profundo, procesamiento de datos, recolección de datos

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1.- INTRODUCTION

Predictive maintenance is a set of actions and techniques taken with the aim of detecting possible failures and defects of machines in the early stages, in order to prevent these failures from manifesting themselves to a greater extent during operation, causing emergency shutdowns and downtime. Its mission is to maintain a certain level of service in the equipment by scheduling revisions at the most opportune time.

Meanwhile current predictive maintenance reduces breakdowns by 70% and lowers maintenance costs by 25% [1], there is still room to improve in this field. Last advances have led to the installation of sensors that collect real-time information on the status of machinery, and here is where machine learning can provide a major advantage: by using the data collected by those sensors and training models which would help to anticipate to the accidents and unforeseen errors.

One of the problems faced by companies that decide to include predictive maintenance within their business is the *lack of a clear process on how to integrate it*. An additional problem we can identify is the *lack of guidelines on how to integrate this maintenance into a workflow together with machine learning algorithms*. While integrating PdM in a company using machine learning may seem a complex task, we can split it in seven stages which usually cover any machine learning project:

1. Collecting data
2. Preparing the data
3. Choosing a model
4. Training the model
5. Evaluating the model
6. Parameter tuning
7. Making predictions

While there is plenty of literature in how to train, evaluate and tune a concrete model once this is chosen, we identify a blank regarding the three initial stages in the scope of predictive maintenance problems. As a result of this situation, we can transform each of these points in key questions to which we would like to provide answers in this paper:

- Q1. What sources of information are commonly used in predictive maintenance?
- Q2. How is the information to be used in predictive maintenance treated?
- Q3. What kind of machine learning methods are used in predictive maintenance?

The relation of sections in which this article covers the contributions and answers to these questions can be seen in Table 1.

Question	Contributions Section	Discussion Section
Q1	3.4	4.1
Q2	3.5	4.2
Q3	3.6	4.3

Table 1. Research questions and discussion.

Due to format requirements, the references used in the different contributions' sections can be provided upon request in a separate document.

Industrial machinery and equipment produce a large amount of information that can be collected through sensors and through the equipment's own records. The question is that, from all this available information, it is necessary *to identify which is the most interesting to perform predictive maintenance tasks*, as well as the relationship of this information with the possible interruptions that may affect the normal operation of the equipment.

Additionally, it is not only important what type of information is selected to perform this task, but also how it will be treated, which will depend largely on how the data is collected, which machine learning models will be used to make the predictions, as well as the required processing of the data in the case that the data set has missing values, due to data loss or any other reason.

Finally, once we have selected and processed the data we want to use, it is important to select the models that perform best for this problem and that offer acceptable levels of accuracy so that the inclusion of predictive maintenance in the organization's business flows will have a positive return on investment for the organization.

This literature review seeks to provide answers to the questions presented, using as a basis the scientific studies carried out during the last five years. Prior to carrying out this systematic review, a search was made for previous reviews that could provide a complete answer to the questions posed. In order to carry on the search of previous reviews, the **Web of Science** platform and **Scopus** were used. Within this search, some relevant articles have been found that partially covers the research questions posed. The first of them, published in 2020 by a team of researchers from the Popular Republic of China, shows a thorough review and road-map of the machine learning techniques applied to fault diagnosis up until 2020 [2], but as we will see in the section 3.1, the amount of literature about this topic in the last two years has bloomed, being the number of publications greater than in the previous ten. Due to that, we considered a more updated review was in need. On the other hand, there is a newer article published in March 2021 by a team of researchers from the National Institute of Technology Warangal in India, while it reviews the most commonly used machine learning algorithms [3], , it does not go into the typology of the data to be collected, or the treatment that should be given to the data to maximize the results of the algorithms. Also, on the research about latest articles which performed previous screening about machine learning techniques applied to predictive maintenance, we found articles about the design of machine learning algorithms based on the data [4], the visualization of classification results [5] or the considerations of fault-diagnosis problems for a concrete field like the airborne electro-mechanical actuators [6], which also analyze the literature about this topic, but in order to give answer to different research questions.

The main objective sought by providing answers to the research questions previously presented is to know what the current state of research regarding the application of machine learning methodologies and techniques to predictive maintenance is, so that it serves as a basis for future research in order to provide a functional and reliable framework for the industry with respect to this topic.

2.- METHODS

2.1.- PROTOCOL

As a search strategy in the SCIE index, we will search for the two main topics which we want to obtain results from:

- Machine Learning
- Predictive Maintenance

Therefore, we will consult the intersection between the literature on both topics:

$$\textit{PREDICTIVE MAINTENANCE} \cap \textit{MACHINE LEARNING}$$

According to the information sources selected, we will mark the SCIE (or SCI-EXPANDED) index as the only search index and according to the exclusion criteria we will only select entries from the last 5 years.

On this basis, the search terms and filters to be used are as follows:

Topic	"PREDICTIVE MAINTENANCE" AND "MACHINE LEARNING"
Time span	Last 5 years
Indexes	SCI-EXPANDED

For the selection process we first perform an additional filtering considering other exclusion criteria:

E1. Discarding results that are not articles.

E2. Discarding results that do not deal with machine learning applications to predictive maintenance.

To discard results based on the exclusion criteria *E2*, the screening of the results with respect to the subject they cover will be done manually based on the content of the abstract of these. This screening consists on a 2-step selection process, where originally two of

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the authors realize a screening with a reduced amount of the same results. Lately, the results of the screening are compared and, in case that the difference between the individual selections is minimal, then a single reviewer continues performing the screening of the remaining articles. On the other hand, if the differences between selected literature is considerable, an internal discussion is carried on aligning the scope of the review.

The goal of this process, even though it may seem redundant at the beginning, is to reduce the resources required to perform the initial screening, as scoping reviews need an agile process in order to be timely and relevant.

Retrieval of information from the articles will be carried out by means of an extraction table containing items that cover relevant information to the research questions previously proposed:

- Article name.
- Article authors.
- Publication year.
- Study Subject. (Table 3)
- Data acquisition method. (Section 3.4)
- Data treatment. (Section 3.5)
- Deep-learning mechanisms used. (Table 4)
- Machine learning mechanisms used. (Table 5)

This retrieval is performed in a cyclical manner, in which an initial reading of all the articles involved is performed in a first iteration and then reviewed in successive iterations over the article list for comparisons or classifications with respect to the different aforementioned items.

The most relevant results from the extraction of each item are offered in this article.

3.- RESULTS

This section deals with the results of the bibliographic and bibliometric review of the selected articles.

As it can be seen in Figure 1, the initial filter applied to the refining tool (*E1*) reduces the amount of analyzed literature from 210 to 179 entries (around a 14.76%), meanwhile the exclusion based on the manual screening of the abstracts (*E2*) concludes with a total of 108 articles, which are the ones covered in this scoping review.

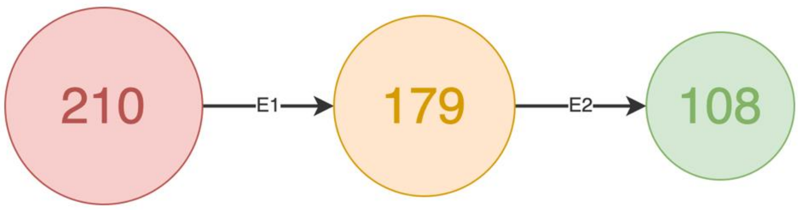

Figure 1. Selection process using the defined exclusion criteria.

First, we write about the bibliometric review, including sections such as publication trends on this topic over the years and which research areas are most involved.

3.1.- PUBLICATION YEARS

As can be seen in Figure 2, there is a clearly growing trend in the publication of articles on this subject, with 2021 being the year with the greatest number of articles.

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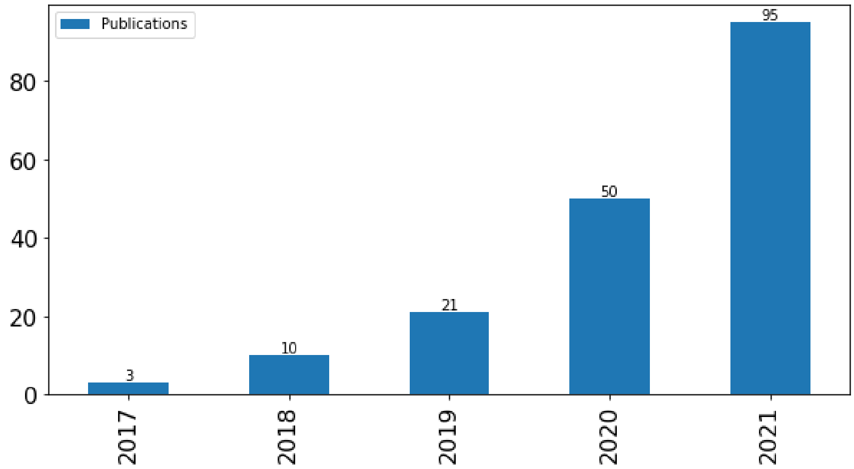

Figure 2. Publications over the years.

The increased interest in the subject from academia reaffirms that the proposal to conduct a review of the related literature will be of great use to future researchers.

3.2.- RESEARCH AREAS

Within the research areas in whose context the articles have been published, we can observe in Table 2 a predominance in the field of **Engineering**, followed by the field of **Computer Science**.

Research Area	Publications
Engineering	120
Computer Science	61
Chemistry	27
Telecommunications	20
Energy Fuels	19
Instruments Instrumentation	17
Materials Science	17
Physics	17
Operations Research Management Science	16
Automation Control Systems	14
Science Technology (other topics)	10
Construction Building Technology	5
Environmental Sciences Ecology	5
Thermodynamics	5
Oceanography	4
Mathematics	2
Nuclear Science Technology	3
Optics	2
Robotics	2

Table 2. Articles by area of research.

As can be seen, the sum of all the articles according to categories is greater than the number of articles reviewed, which is why it should be considered that the articles may belong to more than one research area.

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3.3.- STUDY SUBJECTS

The most important thing when identifying the data sources which have been used in the reviewed studies is to identify the subject of the study. Additionally, it is important to identify whether the predictive models are based on a *specific phenomenon or measurement*, such as the vibration of a part of the machinery [7], or whether *the relationship between a set of measurements*, known or not, is taken into account, such as the relationship between the temperature and the flow of the liquor in the tank of a heat exchanger, such as [8].

In Table 3, we can observe the information related to the subjects of study, as well as the phenomenon they study. This table does not include all the results of the review, since many of them do not contemplate specific study subjects, but rather proposals for frameworks and methodologies when collecting information or applying learning models within a specific field.

Study Subject	Studied Phenomena	No. Articles
Turbofan engine	Miscellaneous	14
Pumping station	Vibration	3
	Temperature	1
	Pressure	1
Wind turbine	Miscellaneous	4
	Vibration	1
	Ultrasonic test	1
	SCADA data	4
Railway	Miscellaneous	3
	Acceleration	1
Rotating machinery	Miscellaneous	4
	Infrared Images	1
Road	Miscellaneous	1
	Images	1
Vehicle (cars)	Miscellaneous	3
Shipping vessel	Miscellaneous	2
Metal cutting tool	Miscellaneous	2
Train	Temperature	1
HVAC installation	Miscellaneous	1
Grinding machine	Bearing fault	1
Heat exchanger	Miscellaneous	1
Bulldozer	Vibration	1
Power shovel	Vibration	1
Backhoe	Vibration	1
Bridge	Deck condition	1
Indoor climate	Miscellaneous	1
Waterjet cutting tool	Miscellaneous	1
Adsorber	Miscellaneous	1
Conveyor motor	Images	1
Heating coiler	Miscellaneous	1
Radial fan	Miscellaneous	1
CEDM	Coil current	1
SOV	AC waveform	1
BLDC motor	Vibration	1
PTU	Shim dimensions	1
APS	Miscellaneous	1
VIA	Vibration	1

Table 3. Study subjects in predictive maintenance.

3.4.- DATA ACQUISITION METHODS

Once we have identified the subjects of study on which predictive maintenance is performed, there is another distinction to consider when we talk about the origin of the sources of information, and this is the method of data collection. Within the articles reviewed, we can make distinctions based on whether the articles use *open or private data sets* for their research. While in the ones which use open sources, the synthetic data sets generated by simulation software are predominant, in the private data sets we can see two different ways of collecting the data: based on automated collection by sensors or human inspections.

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3.4.1.- OPEN DATA SETS

Among the most widely used repositories, the *Turbofan Engine Degradation Simulation Data Set* **offered by NASA's Prognostics Center of Excellence (PCoE)** stands out, as it is used in 14.81% of the total number of articles. This synthetic dataset is generated with the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dynamical model.

3.4.2.- PRIVATE DATA SETS

In articles that use their own data sets, data collection methods can be divided in *data sets based on sensor data*, and *data sets based on human inspections*.

Data sets based on **historical sensor data**: Articles that use historical data, in any format, collected automatically by sensors. These make up the majority of the articles which use private data sets and comprise both data extracted by Big Data from large industries, as well as information collected from sensors in small facilities.

From the articles which use historical sensor data, there are some which, in addition to this data sets for training purposes, use real-time data streams for testing and validate their proposition. These are 8.34% of the cases (9 of the total).

Data sets based on **historical inspection data**: Articles that use historical data collected during routine or extraordinary inspections by humans with specialized knowledge. Items using this procurement method make up a small percentage of the total number of items (4.6%), and all of them involve qualified personnel to perform the inspections and collect the data with which the prediction models will be made.

3.5.- INFORMATION PROCESSING

With respect to information processing, we can observe that 20 of the 108 analyzed articles combine several or propose new techniques for obtaining features and pre-processing the data in order to improve the results of the predictions, this being 18.5% of the total number of articles.

From the remaining 81.5%, only two of them specifically propose the use of raw data in order to avoid the high computational burden of pre-processing [9] - [10].

3.6.- MACHINE LEARNING METHODS IN PREDICTIVE MAINTENANCE

Among all the articles, we can differentiate those that use methods of "deep learning" and neural networks from those that use more traditional architectures of "machine learning". To better identify the differences between these, we are going to make two tables, not only differentiating between them, but also between the mechanisms or algorithms used.

In Table 4, we can see a distribution of the different algorithms and layers used in the articles in which models based on neural networks are proposed.

Deep-Learning Mechanism	References
ANN	23
LSTM	10
CNN	6
O-RBM	1
1-FCLCNN	1
FCN	1
ResNet	1
ESN	1
GOA-based ESN	1
DBN	1
C-DBN based OS-ELM	1

Table 4. Deep Learning mechanisms used in the articles.

In the following Table 5, we can observe the distribution of the used algorithms of machine learning.

Machine Learning Mechanism	References
SVM	16

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Random Forest	13
Decision Tree	8
Linear Regression	5
Naive Bayes	4
SVR	3
KNN	3
XGBoost	3
Decision Forest	3
Gradient Boost	2
LVQ	2
K-Means Clustering	2
Symbolic Regression	2
Boosted Decision Tree	1
DBN	1
BLR	1
Bootstrap Aggregation	1
MLE + CCF	1
Discriminant Analysis	1

Table 5. Machine Learning mechanisms used in the articles.

4.- DISCUSSION

The objective of this review has been to collect, study and synthesize all the literature since 2017 that uses Machine Learning mechanisms in the field of predictive maintenance. We have tried to highlight the typology of data used for predictive models of Predictive Maintenance (sensors, acquisition method, phenomenon to be studied) in section 3.4, as well as the treatment given to the data (transformations, pre-processing by means of data driven techniques, use of raw data in deep learning systems) in section 3.5. Finally, a comparison of the various algorithms used in this literature is made in section 3.6.

To address the results, we will explicitly answer each of the research questions proposed at the beginning of this paper.

4.1.- SOURCES OF INFORMATION IN PREDICTIVE MAINTENANCE

As we have been able to observe, the current literature is characterized by a large use of open data sources, such as the repository on turbofan engine degradation, results from simulation in C-MAPSS, offered by NASA's PCoE.

Most papers using the turbofan engine degradation repository as data sources aim to demonstrate the efficiency of new algorithms and architectures with respect to generic sensor readings.

This data set contains a set of unlabeled measurements from different sensors in different parts of the turbofan engine, so we cannot associate the data source to a specific physical scale or measurement, which leads to pure data-driven prediction models.

For the remaining study subjects listed in Table 3 , we note that for 39 of them (61.90%), *combinations of several physical quantities* have been used or directly *the nature of the measurement is not indicated* to make the predictions, namely in: wind turbines, rails, rotating machinery, roads, transport vessels, cars, HVAC installations, heat exchangers, metal cutting tools, indoor air conditioning, water jet cutting tools, adsorbers, heating coils, radial fans and APS.

Within the physical phenomena most used in isolation to calculate the useful life of machinery we find the **vibration**, used for 7 of the 29 study subjects and in a total of 9 items. This is not uncommon: since 1974 there have been standards - such as ISO 2372 - on the measurement and evaluation of the acceptable vibration level depending on the size of the machinery, the most current being ISO 20816 of 2016. This last standard includes the evaluation of vibration not only in rotating machines, but in any part, rotating or not, of a complete machine.

The existence of the standard ISO 20816 not only facilitates the acquisition of information related to vibration, but also establishes lines of work that allow the transformation of a series of continuous variables, such as the amount of vibration, the dimensions of the machine and the hardness of the support, into categorical variables such as the severity of the vibration, which can be categorized as good, satisfactory, unsatisfactory and unacceptable.

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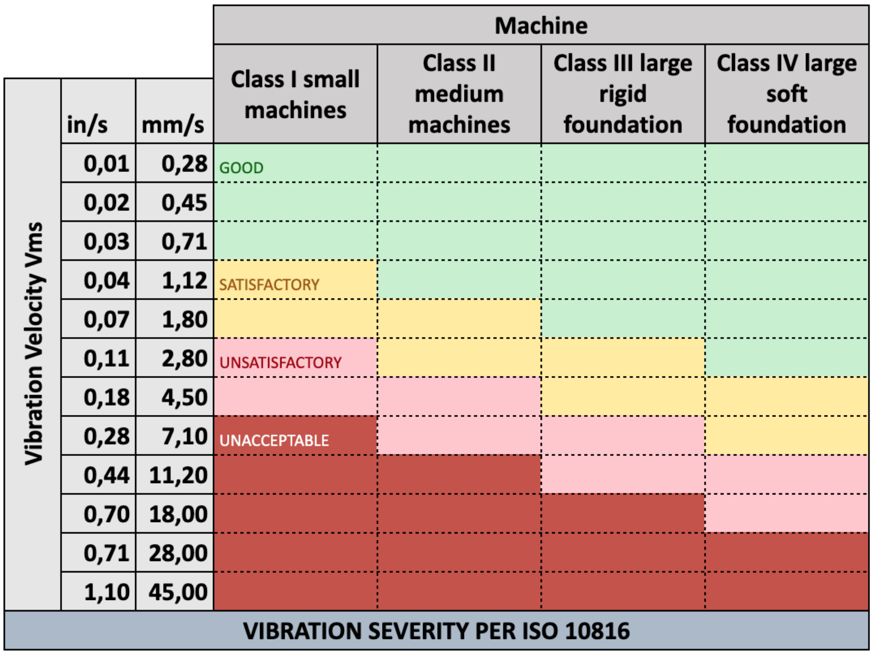

Figure 3. Vibration severity according to ISO 2372 (10816).

Therefore, to give answer to the first question (Q1) **what sources of information are commonly used in predictive maintenance?**, we can say that within the current literature what abounds most is the **use of a combination of sensors without taking into account the measured physical quantities when making the predictions**, whether it is the synthetic data source, such as C-MAPSS, or an application to a real dataset.

In addition, we found that *vibration is the most used physical quantity in isolation*, that means without being in combination with other physical quantities, and that within the articles, these take advantage of the old standardization of vibration severity, as can be seen in Figure 3, for measurements and data pre-processing [11].

4.2.- DATA PROCESSING IN PREDICTIVE MAINTENANCE

Regarding to the treatment of the information, we can see that there is *no specific criterion when performing the feature engineering phase*, although it is true that the vast majority performs a pre-processing of the data before providing them to the model for training.

Among the most innovative and best performing techniques, the one presented by [12], where it uses the advantages of parallel computing for the extraction of spatio-temporal features, which will later serve as input to a one-dimensional convolutional neural network.

In the performance comparison between the model to which the above-mentioned pre-processing is applied and the one that only uses the CNN network, a rather high performance difference is observed taking into account the root-mean-square deviation (RMSE) which is a good measure of accuracy to compare prediction errors of different models.

Another of the most novel techniques in terms of data processing is the Multi-Loss Encoder with Convolutional Composite Features (MLE+CCF) proposed by [13] , where MLE is used to extract features that later serve as input to the artificial neural network.

	FD001	**FD003**
CNN	17.22	15.50
1-FCLCNN-LSTM	11.17	9.99
MLE+CFF	11.57	11.83

Table 6. RMSE of the predictions with the datasets from the Prognostics Data Repository of NASA.

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In Table 6, the proposed model by Peng et al. [12] demonstrates a 35% lower RMSE metric than the CNN model for dataset FD001 and a 35.5% lower RMSE for dataset FD003. On the other hand, although the proposal of Pillai et al. [13] shows promising results, it still falls short of outperforming the model.

In addition, we must also take into account standardized categorical transformations, such as the one performed by Aqueveque et al. following the ISO 2372 standard [11], as well as those that take advantage of the specialized knowledge of experts to carry out transformations and interpretations of the data [14], as part of the information processing.

Even though these last two articles do not use the same dataset, so a comparison is not appropriate, Aqueveque's article makes predictions with a more than acceptable accuracy (around 95%) in vibratory severity predictions, while Ruiz-Sarmiento's article shows a performance (based on the RMSE) of 0.59 in the degradation state prediction after four training sequences using this input from the experts in the information processing phase.

Finally, as an answer to the research question (Q2) **how is the information to be used in predictive maintenance treated?**, we note the presence of *novel proposals* in the literature if we talk about purely *data-driven* data processing, especially when dealing with sensor information whose information sources are mixed and/or of different physical quantities, but also new proposals are introduced such as the use of measurement validation standards or *taking advantage of expert knowledge* to perform characteristic extraction flows and pre-processing.

4.3.- MACHINE LEARNING METHODS IN PREDICTIVE MAINTENANCE

With respect to the use of Machine Learning algorithms and techniques, we can clearly see that prior to 2020 the general trend was towards the use of regression algorithms (mainly SVM} and tree-based decision models (Random Forest, Decission Trees, Gradient Boost, Decision Forest) while in 2020 and throughout 2021, publications using deeep-learning mechanisms such as ANN and RNN predominate.

This change is mainly enhanced by the fact that comparing machine learning models, by using a common dataset, those based on Neural Networks generally perform better. In addition, LSTM networks are suitable for classification, processing and predictions using time series data [15].

	MSE	Normalized MSE	MAE	R^2
LRR	2.307	0.086	1.014	0.916
KRR	1.635	0.059	0.745	0.941
FFNN	1.496	0.054	0.672	0.946
ESN	0.256	0.009	0.173	0.991
LSTM	0.086	0.003	0.097	0.997

Table 7. Regression performance metrics on the test dataset from Bogojeski et al. [16] *for different models.*

In Table 7, we can observe a comparison of the performance of various models for a synthetic data set based on the metrics MSE, normalized MSE, MAE y R^2.

Therefore, based on the work of Bogojeski et al. [16] , we can say that, based on the benchmarking results against their test data set, the Long Short Term Memory (LSTM) model is the one with the best behaviour in comparison to the rest of the models when it comes to performance based on forecast accuracy.

On the other hand, in the work of Chen et al. a performance comparison is made between several models using the metrics MCC and RMSE, which can be observed in Table 8.

	LSTM	RNN	FCNN	DCNN	SVM
MCC Mean	0.8248	0.8221	0.8240	0.8240	0.7738
RMSE Mean (days)	379.8	382.1	387.2	387.2	432.4
Modelling time (s)	259.2	107.5	34.65	43.15	7.263

Tabla 8 Performance metrics of various models for a UK fleet company real-world dataset with one-hot coding from the work of Chen et al. [17]

The MCC metric, mathematically described in appendix A, is commonly represented as *C* and can be interpreted [18] considering that a correlation of:

- C = 1, is that where it exists a perfect agreement,
- C = 0, where the predictions are no better than random, and,
- C = -1, where there is a total disagreement between prediction and observation

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Thus, we can see that, although the training time of LSTM is longer than in the rest of the models, it achieves the highest MCC, with a value of 0.8248 and the lowest RMSE, which is 379.8 days. Conversely, SVM shows the worst performance in this scenario, with a RMSE of 432.4 days and a MCC of 0.7738.

So in order to give an answer to the research question (Q3) **what kind of machine learning methods are used in predictive maintenance?**; based on the literature, and using these previous comparisons as an example, although we cannot categorically state that the LSTM type models will always give the best results, we can state that models based on artificial neural networks have a better performance in predictions oriented to predictive maintenance than those based on simpler regression algorithms, such as Linear Ridge Regression (LRR) or SVM.

Not exclusively centered on the algorithmic, we can also identify that three of the articles make use of **Transfer Learning** due to the scarcity of reliable data and as an approach to reduce the need to labelled examples [19]- [20]- [21].

Transfer learning is a research problem in ML that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. The article of Gribbestad et al. [19] puts this approach into value for Predictive Maintenance and suggest Transfer Learning as a promising research field for reliable prognostics.

5.- CONCLUSION

A review has been carried out on the current use in the academic field of machine learning and deep learning in predictive maintenance. A bibliographic review of the last five years has been performed, based on those articles that cover information on the sources of information used for predictive maintenance, the treatment given to such data and the methods or techniques used. The review has shown that there are different information sources used, which can be classified as joint open data, historical sensor data, historical inspection data and real-time data. Likewise, it has been observed that data processing not only uses traditional pre-processing techniques, but that approximately one fifth of the articles propose new tools. A wide range of techniques and algorithms used in Deep Learning -ANN being the most used- and in Machine Learning, with SVM being the most used algorithm, closely followed by Random Forest.

5.1.- LIMITATIONS

While both **Scopus** and **Web of Science** have been used in the initial research about previous reviews which would cover our research questions, only a single database (**SCIE** index of **Web of Science**) is used during the review process. While we are aware that this is a limitation at the time of conducting a review, since there is a possibility of excluding some unique results from our scope, we also consider that the resulting number of covered articles is enough to create a picture of the current literature and to give an informed response to our research questions, given the characteristics of the index.

5.2.- FUTURE WORK

As mentioned in the objectives, this paper aims to serve as a basis for future research in providing a reliable framework for the industry with respect the usage of machine learning techniques for predictive maintenance.

In alignment to that, taking the results presented on this paper, further questions arise as *what could be the integration of human knowledge in a predictive maintenance pipeline?* or *which process of sensors selection and installation should be considered to retrieve the data?*

Answers to these questions will help on the definition and application of the framework.

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SUPLEMENTARY MATERIAL

Appendix A – Glossary

1-FCLCNN Architecture proposed in the article "A Remaining Useful Life Prognosis of Turbofan Engine Using Temporal and Spatial Feature Fusion" [1] which is made up of a combination of a one-dimensional convolutional neural network and FCN.

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GOA-based ESN	Algorithm proposed in the article "An Improved Grasshopper Optimization Algorithm Based Echo State Network for Predicting Faults in Airplane Engines" [2]
O-RBM	Online Restricted Boltzmann Machine, algorithm based on the architecture of an RBM neural network, with the aim of adapting to data streams.

Appendix B – Acronyms

ANN	Artificial Neural Network
APS	Air Pressure System
BLDC	Permanent Magnet Brush-Less DC
BLR	Bayesian Linear Regression
C-DBN	Convolutional Deep Belief Network
CCF	Convolutional Composite Features
CEDM	Control Element Drive Mechanism
CNN	Convolutional Neural Network
DBN	Dynamic Bayesian Network
ESN	Echo State Neural Network
FCN	Fully Convolutional Network
HVAC	Heating, Ventilation and Air Conditioning
KNN	K-Nearest Neighbor
LSTM	Long Short Term Memory
LVQ	Learning Vector Quantization
MLE	Multi-Loss Encoder
OS-ELM	Online Sequential Extreme Learning Machine
PTU	Power Transfer Unit
ResNet	Residual Neural Network
SCADA	Supervisory Control And Data Acquisition
SOV	Solenoid Operated Valves
SVM	Support Vector Machine
SVR	Support Vector Regression
VIA	Vitros-Immunoassay Analyzer

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Appendix C – Reference Sources for Tables

Study Subject	Studied Phenomena	References
Turbofan engine	Miscellaneous	[3] [4] [5] [6] [7] [1] [8] [9] [10] [11] [2] [12] [13] [14]
Pumping station	Vibration	[15] [16] [17]
	Temperature	[16]
	Pressure	[16]
Wind turbine	Miscellaneous	[18] [19] [20] [21]
	Vibration	[22]
	Ultrasonic test	[23]
	SCADA data	[24] [25] [26] [27]
Railway	Miscellaneous	[28] [29] [30]
	Acceleration	[31]
Rotating machinery	Miscellaneous	[32] [33] [34] [35]
	Infrared Images	[36]
Road	Miscellaneous	[37]
	Images	[38]
Vehicle (cars)	Miscellaneous	[39] [40] [41]
Shipping vessel	Miscellaneous	[42] [43]
Metal cutting tool	Miscellaneous	[44] [45]
Train	Temperature	[46]
HVAC installation	Miscellaneous	[47]
Grinding machine	Bearing fault	[48]
Heat exchanger	Miscellaneous	[49]
Bulldozer	Vibration	[50]
Power shovel	Vibration	[50]
Backhoe	Vibration	[50]
Bridge	Deck condition	[51]
Indoor climate	Miscellaneous	[52]
Waterjet cutting tool	Miscellaneous	[53]
Adsorber	Miscellaneous	[54]
Conveyor motor	Images	[55]
Heating coiler	Miscellaneous	[56]
Radial fan	Miscellaneous	[57]
CEDM	Coil current	[58]
SOV	AC waveform	[59]
BLDC motor	Vibration	[60]
PTU	Shim dimensions	[61]
APS	Miscellaneous	[62]
VIA	Vibration	[63]

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Deep-Learning Mechanism	References
ANN	[37] [5] [64] [22] [54] [59] [51] [46] [44] [8] [16] [62] [65] [66] [67] [68] [69] [70] [9] [71] [32] [72] [73]
LSTM	[74] [31] [52] [36] [4] [47] [75] [76] [77] [78]
CNN	[55] [12] [10] [79] [21] [80]
O-RBM	[11]
1-FCLCNN	[1]
FCN	[31]
ResNet	[31]
ESN	[74]
GOA-b	[2]
DBN	[51]
C-DBN- based OS-ELM	[81]

Machine Learning Mechanism	References
SVM	[15] [50] [8] [58] [82] [16] [37] [70] [63] [32] [68] [34] [83] [40] [84] [85]
Random Forest	[86] [15] [61] [57] [32] [33] [87] [40] [88] [67] [68] [89] [90]
Decision Tree	[15] [8] [37] [77] [19] [32] [87] [40]
Linear Regression	[61] [44] [82] [57] [32]
Naïve Bayes	[50] [8] [56] [91]
SVR	[61] [33] [92]
KNN	[60] [37] [40]
XGBoost	[86] [85] [93]
Decision Forest	[44] [88] [67]
Gradient Boost	[15] [87]
LVQ	[94] [95]
K-Means Clustering	[96] [33]
Symbolic Regression	[57] [97]
Boosted Decision Tree	[44]
Discriminant Analysis	[50]
DBN	[39]
BLR	[44]
Bootstrap Aggregation	[86]
MLE + CCF	[3]

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