National Higher School of Technology
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Selecting an appropriate deep learning algorithm for predictive maintenance.

Master's thesis in
Industrial Engineering

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Abstract: Presently, the realm of research is witnessing a burgeoning interest in the utilization of Deep Learning (DL), a branch of machine learning (ML) and artificial intelligence (AI), within the domain of the Industrial Internet of Things. The prediction of failures of industrial equipment before their occurrence, referred to as Predictive Maintenance (PdM), is also a very trendy topic, primarily driven by its potential for cost-savings and numerous advantages over other maintenance types. DL techniques have the potential to provide significant benefices in the context of PdM applications, mainly with highly complex, non-linear, and unlabeled data in real-world scenarios. However, there are a variety of DL algorithms available, and each each possessing distinct characteristics and can be used in different cases. Therefore, choosing the best DL algorithm to resolve PdM issues is not obvious.
This paper aims to improve the performance of PdM by selecting the most suitable DL algorithms. By conducting a comparative study, three deep learning algorithms were chosen, using the criteria commonly utilized in research articles.

Key-words: Industry 4.0, Deep Learning, Neural Networks, Predictive Maintenance, Algorithm Selection.

Contents

1. Introduction

The industry has increasingly focused on artificial intelligence and machine learning methods, because of their ability to design automatic models that handle the massive amount of data currently collected, which is growing exponentially. The research trend of machine learning has switched towards more intricate models, notably deep learning, due to their enhanced accuracy in handling extensive data sets. The advancement of computing power, particularly with the evolution of GPUs, has played a significant role in the development of these methods. As a result, these models have made remarkable progress in various domains such as intrusion detection systems, computer vision, and language processing, consistently achieving state-of-the-art results. [1].
Today, maintenance is a strategic factor to ensure high productivity of industrial systems; however, due to economic pressures, companies are compelled to reduce maintenance's costs, leading to severe implications for long-term reliability. Consequently, it has become crucial for companies to devise suitable maintenance strategies that guarantee efficient operation of production plants in terms of both quality and availability. As a result, the definition and practices of maintenance have undergone significant transformations over time, largely due to substantial contributions from research endeavors [2].

Currently, there is a transition towards the fourth revolution known as Industry 4.0, which is characterized by the integration of cyber-physical systems and the industrial Internet of Things. It involves the utilization of software, sensors, and intelligent control units to enhance industrial processes and meet their requirements. These advanced techniques facilitate automated predictive maintenance functions by analyzing vast volumes of process and associated data through condition monitoring (CM) [3]. Predictive maintenance (PdM) initially conceived in the late 1940s [4], and has become a promising approach, providing solutions for the remaining life of equipment through the prediction of data collected by various sensors on equipment [5]. It has reached critical significance for industries due to the growing intricacy of interactions among various production activities within expansive manufacturing ecosystems. Over time, DL methods have been proposed for PdM. These methods, such as AutoEncoders, Recurrent Neural Networks, Convolutional Neural Networks, and Long Short-Term Memory, aim to predict equipment failures by automatically learning from historical data and estimating the probability of future failures [6].

In this context, numerous DL algorithms are available. Therefore, the research question that guides this study is: What are the best deep learning algorithms to resolve predictive maintenance issues?

With this aim, the article is structured into six sections, starting with an introduction in Section 1, and exploring in Section 2 the concept of Industry 4.0 as the latest technology to evolve industrial domains, Section 3 provides a detailed description of predictive maintenance, including its approaches and the various monitoring techniques employed in PdM. Following thatFollowing that, Section 4 represents the principle of deep learning and has also provided a comparative table between ML and DL, at the end of this section, we cited deep learning algorithms with brief definitions and illustrations. Then Section 5 focuses on the application of DL in PdM, exploring different research experiences in this field. In Section 6, a comparison of DL algorithms is conducted using commonly utilized criteria found in research articles, aiming to identify the most effective algorithms for solving PdM problems. Finally, Section 7 concludes the research work.

2. Industry 4.0

After the introduction of steam power and mechanization of production in industry, 1.0 [7]. The second industrial revolution witnessed the emergence of production and assembly lines, as well as mass production techniques driven by electricity and division of labor [7]. Following that, the third industrial revolution brought about a revolutionary shift with the advent of electronics and Information Technologies (IT). This phase was marked by the utilization of computers, the internet, and industrial robots [7], and the addition of these whole new technologies had a disruptive effect [8]. The Fourth Industrial Revolution is the current era of the industry which is reshaping how industrial companies operate and use new digital technologies and capabilities to create highly digitalized and interconnected smart factories and supply chains consisting of Cyber-Physical Systems(CPS) [7].It was introduced to the public in 2011 at the Hannover Industrial Technology Fair in Germany [9].

Industry 4.0 (4IR) is defined as “the integration of complex physical machinery and devices with networked sensors and software, used to predict, control and plan for better business and societal outcomes” [9], or “a new level of value chain organization and management across the lifecycle of products” [10].

In Industry 4.0, factories are becoming smarter, with the ability to communicate with other machines, monitor and adjust production processes in real time, and even predict and prevent equipment failures before they occur. This is enabling manufacturers to produce goods faster, more efficiently, and with greater customization.

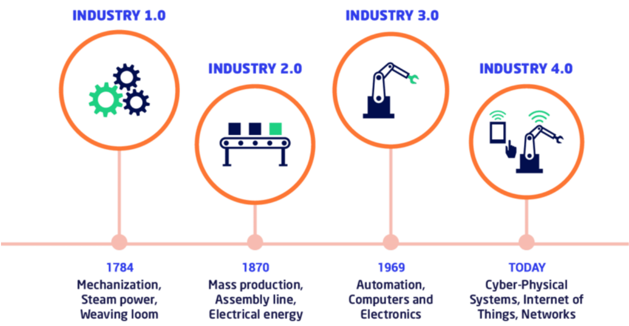

Figure 1: Industry Evolution [7]

3. Predictive Maintenance

Industrial Maintenance was defined by the French Association for Standardization (AFNOR) in 1994 (standard NFX60-010) as “All actions allowing to maintain or restore a property in a state specified or capable of providing a specified service”, this definition was replaced in 2001 (NF EN 13306 X 60-319) with “the combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function” [11]. The activities induced today are of two types: corrective or preventive. Corrective maintenance is scheduled following a failure. However, these activities do not incorporate a preventive aspect. Based on the adage "prevention is better than cure", preventive maintenance is based on predetermined plan implemented proactively [12].

Predictive maintenance is the most recent kind of maintenance that has gotten the attention of researchers and industries. It is defined according to standard NF EN 13306 X 60- 319: start-ups and specialized companies as “conditional maintenance carried out by following extrapolated forecasts from the analysis and evaluation of significant degradation parameters”, it means that one can anticipate and detect the failure before it occurs, thanks to the continuous monitoring [14].

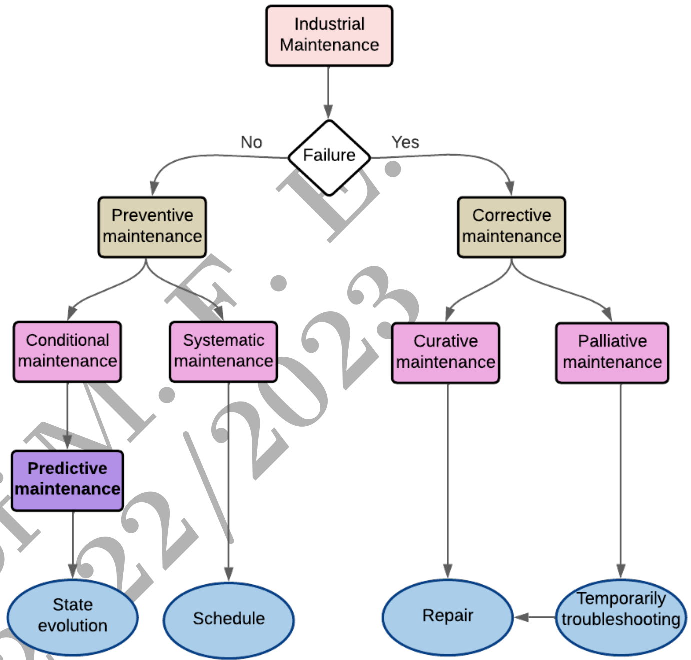

Figure 2: Maintenance types [13]

Many benefits of predictive maintenance compared to corrective and preventive maintenance can be enumerated in table 1:

Advantages of predictive maintenance compared to Preventive systematic maintenance [14][15]
- Decreases the number of breakdowns - Better intervention planning - Decrease in spare parts - Better preparation of response teams - Improved safety
Advantages of predictive maintenance compared to corrective maintenance [17]
- Reduced maintenance costs - Increased equipment lifespan - Better relations between Production and Maintenance departments - Ability to better manage inventory

Table 1: Advantages of predictive maintenance over corrective maintenance and systematic preventive maintenance

3.1. Predictive maintenance monitoring techniques

Monitoring techniques are employed to evaluate the condition of equipment and anticipate the optimal timing for maintenance actions [16].
Various surveillance techniques are used for predictive maintenance, including [18]:

- Vibration analysis: Is used to detect the state of rotating machinery.Technicians can pinpoint potential problems by examining the frequency, amplitude, and phase of vibrations.

- Oil analysis: involves checking the quality of the lubrication oil in the equipment, whereby technicians examine the chemical composition of the oil to identify any possible issues.

- Acoustic monitoring: Involves using microphones to detect abnormal sounds or vibrations in equipment.

- Ultrasonic testing: Uses high-frequency sound waves to detect equipment defects such as leaks, cracks, and corrosion.

- Infrared thermography: Uses thermal imaging cameras to detect unusual thermal occurrences on the equipment.This helps technicians identify potential problems by detecting hot spots.

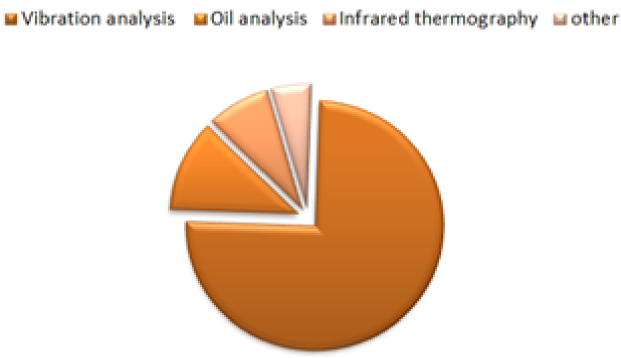

Figure 3: Different Monitoring Techniques [18]

3.2. Predictive maintenance approaches

To apply predictive maintenance, there are several approaches available, which are:

- knowledge-based models
  This type of systems consist of a knowledge base that stores knowledge acquired from experts in a particular field, as well as a rule base that utilizes this knowledge to solve specific problems [20]. They rely on historical failure data as the primary predictive tool [19]. They can be categorized into three types: rule-based, case-based, and fuzzy knowledge-based algorithms [19]. However, one major drawback of this type is its low accuracy, making it less suitable for complex systems but still applicable for simple processes or systems [22].

- Physical-based models
  In this approach, a degrading machine or equipment is described using explicit mathematical representation, aiming to formalize the physical understanding [20]; it requires advanced knowledge in mathematics and physics to be apply effectively [21]. A physical model has the ability to update itself, enhancing its accuracy and quality [20]. However, the main drawback of using a physical model is the challenge of assigning appropriate parameters. Due to the scarcity of extensive and multivariate data needed for parameter assignment, quantitatively characterizing the system behavior becomes difficult [20]. Physics-based models can be divided into several types, including the mathematical model, Hidden Markov model, Probability distribution model, and filter models [19].

- Data-driven based modes
  Data-based models have become much more important in recent years through improved availability of computing power,and the production of large amounts of data coming every day from technical systems [21].For data collection, sensors should be installed at a suitable location.The collected data features are extracted for processing, analysis, and degradation of information hidden in data. The proper algorithm needs to be selected based on corresponding parameters [22].
  Data-driven based models have gotten the attention of many researchers recently due to their numerous advantages and benefits that do not depend on the accuracy of the mathematical and physical models or the development of

a detailed experience rule [19].

Typically, data-driven approaches are categorized into two main groups: machine learning techniques and statistical techniques [20].

Another efficient and emerging approach, anchoring the benefits of various prognostic models currently available, is the "hybrid approach". This approach combines different methodologies to create a hybrid model that exhibits superior predictive capabilities [23].

The current survey gives interest in the models based on the data, specifically deep learning models sub-category of machine learning methods.

4. Deep Learning

Deep learning, a branch of machine learning, employs artificial neural networks to learn from data. These neural networks are specifically crafted to emulate the behavior of human brain biological neurons. They operate by processing data through multiple layers and employ machine learning algorithms to iteratively fine-tune the weights and biases of each layer, ultimately attaining precise predictions or outputs [24].

4.1. Definitions

4.1.1 Artificial Neural Networks ANNs

ANNs are a mathematical representation that draws inspiration from the arrangement and operation of neurons in the human brain. They are composed of interconnected nodes (neurons) that are organized in layers, with inputs and outputs [26]. In ANNs, neurons receive input signals from other neurons and use a non-linear mathematical function to compute their output. This output is then transmit to other neurons in the network through weighted connections. During training , the weights of these connections are adjusted to reduce the error between the network's predicted output and the actual output [25].

ANNs possess an extraordinary capacity to acquire and generalize patterns from data, rendering them highly valuable across diverse domains such as pattern recognition, classification, prediction, and data generation [25]. ANNs have been applied to various fields, such as computer vision, natural language processing, speech recognition, and prediction [26]. They can be designed for various types of inputs, including numerical data, text, and images, and can be trained using a variety of algorithms, such as back-propagation and stochastic gradient descent [26].

4.1.2 Biological neurons

Biological neurons are specialized cells present in the nervous system of living organisms, including humans. Their primary role is to transmit information between cells by utilizing electrical and chemical signals [41].

A biological neuron is composed of a cell body, dendrites, an axon, and synapses. The cell body contains the nucleus and organelles necessary for cell function. Dendrites are short, branch-like extensions that receive input from other neurons or sensory cells. The axon, on the other hand, is a long, slender extension that carries signals away from the cell body to other neurons or to target cells, such as muscles or glands. Lastly, synapses are the junctions between the axon of one neuron and the dendrites or cell body of another neuron [41].

When a biological neuron is activated by an input signal, such as a neuron transmitter released by a nearby neuron, it produces an electrical impulse that propagates along its axon. This impulse can then activate other neurons or target cells at synapses [41].

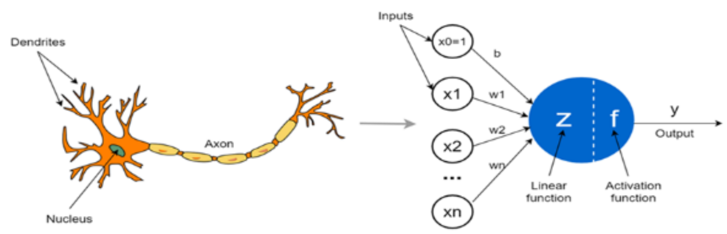

Figure 4: Biological neuron vs Artificial neural [41]

4.2. Deep Learning vs Machine Learning

Although deep learning falls under the category of machine learning, these two approaches exhibit distinct dissimilarities.

Here is a table that outlines a comparison between machine learning (ML) and deep learning (DL):

Characteristics	Machine learning	Deep learning
Human intervention[27] [28][29]	Requires human intervention	Lower need or no need for human intervention
Data type [28]	Need structured data	Operate with both structured and unstructured data
Training time [29] [30] [28]	Fast calculation (seconds to hours)	Slow calculation (days to weeks)
Features extraction [31] [28]	Requires a stage of extracting data by expert	Does not require the features extraction; rather it attempts to learn from raw data by itself
Data requirements[27] [30][28]	Often requires large amounts of training data	Often requires massive amounts of training data
Hardware requirements [27][30][28]	Can run on low-end devices	Necessitates the use of GPUs and thus the high-end system

Table 2: Comparative table between Machine learning and Deep learning

4.3. Deep Learning techniques

Various architectures have been devised for deep learning, each with its unique strengths and weaknesses, tailored to specific tasks. The following are the prevalent deep learning architectures:

4.3.1 Feedforward Neural Networks (FNNs

The first, most common, and simplest architecture is characterized by a series of stacked neurons arranged in layers. Each layer's neurons are connected to all the neurons in the subsequent layer, transmitting their output as input. However, there are no connections between neurons in previous layers or within the same layer. The architecture consists of an input layer, hidden layers, and an output layer [1]. To train the neural network, it is supplied with pairs of input features and target features, which are used to establish the relationship between them. The network achieves this by minimizing the error it produces and mapping the input data to the desired output [1].

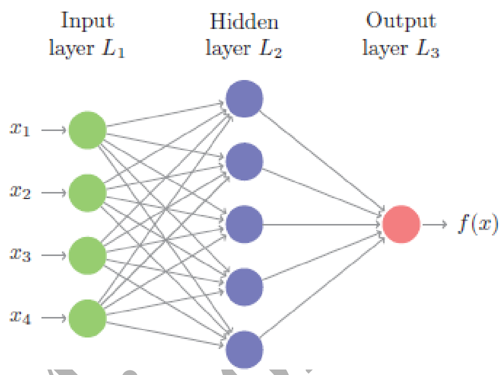

Figure 5: Feedforward Neural Networks architecture [42]

4.3.2 Convolutional Neural Networks (CNNs)

CNN is a type of feedforward network that employs convolutional filters to maintain the connectivity between neurons. It draws inspiration from the visual cortex of animals and finds applications in various domains such as image and signal recognition, recommendation systems, and natural language processing (NLP). The convolutional layer within a CNN is typically linear and is followed by the application of an activation function, which produces non-linear outputs. Subsequently, a max pooling layer may be utilized to reduce the dimensionality of the data. One key characteristic of CNNs is the sharing of convolutional weights, which facilitates easier training [1].

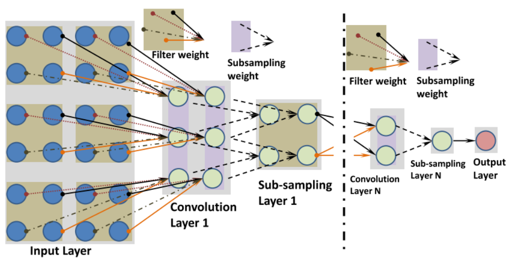

Figure 6: Convolutional Neural Networks architecture [38]

4.3.3 Recurrent Neural Networks (RNNs)

Are a type of neural network that can process sequential data, such as time series or natural language [32]. Contrast to FNNs, RNNs incorporate a feedback loop that allows them to process sequential data by taking into account previous inputs. As a result, they are well-suited for tasks speech recognition, and language translation [33].

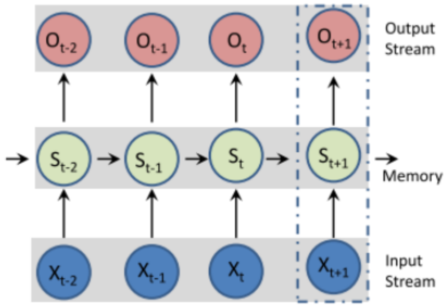

Figure 7: Recurrent Neural Networks architecture [38]

4.3.4 Long Short-Term Memory (LSTM) Networks

LSTMs are derivatives of RNN [48]. They can learn and memorize addictions over a long period. LSTMs thus retain the information stored over the long term. They are especially useful for predicting time series, they remember previous entries. In addition to this use case, LSTMs are also used to compose musical notes and recognize voice [47] [1].

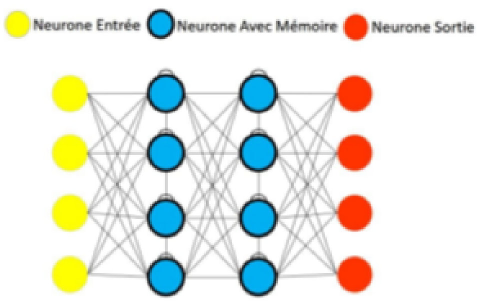

Figure 8: Long Short-Term Memory architecture [40]

4.3.5 AutoEncoders (AE)

AE is based on the concept of singular value decomposition to capture the essential nonlinear features of the input data within a reduced dimensional space. It consists of two parts: an encoder that maps input data to the encoded, latent space, and the decoder, which projects latent space data to the reconstructed space that has the same dimension as input data. The network is trained to minimize the reconstruction error, quantified as the discrepancy between the input and output [1][34].

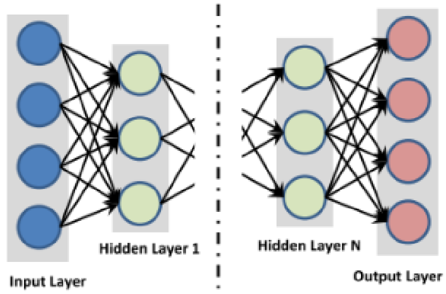

Figure 9: Autoencoders architecture [38]

4.3.6 Generative Adversarial Networks (GANs)

GAN was first proposed by Goodfellow et al [35]. They are a type of DL model that comprise two neural networks: The generator is responsible for producing synthetic data by taking random noise as input, whereas the discriminator is tasked with distinguishing between real and synthetic data by examining both types [36]. Notably, these networks are trained simultaneously [37][35].

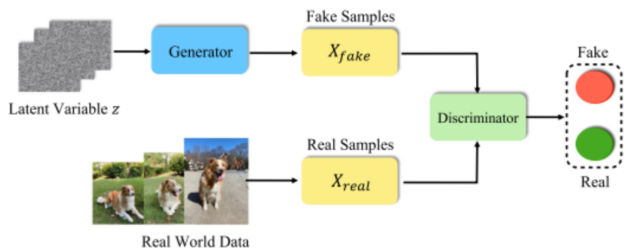

Figure 10: Generative Adversarial Networks architecture [35]

4.3.7 Boltzmann machines restraints (RBM)

RBMs are a type of ANNs algorithm characterized by a two-layer structure comprising a hidden layer and a visible layer. In RBMs, only the hidden and visible layers are connected; however, there is no correlation between the neurons of the same layer. The visible layer receives input data, while the hidden layer extracts relevant features. Moreover, in RBMs, the hidden nodes are self-determining based on certain conditions and do not depend on each other. The weights and biases of the visible and hidden layers are updated iteratively to enable the visible layer to approximate the input data [39] [1] [48].

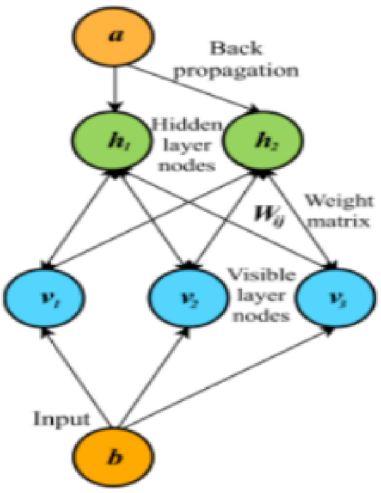

Figure 11: Boltzmann machines restraints architecture [39]

4.3.8 Deep Belief Networks (DBNs)

A DBN can be viewed as a collection of RBMs, combined in a way that each RBM's hidden layer is connected to the visible layer of the subsequent RBM. In DBNs, there are undirected connections only between the top two layers, while directed connections exist towards the lower layers. The initialization of a DBN is achieved using a layer-by-layer greedy learning approach that employs unsupervised learning. Subsequently, the network is fine-tuned based on the desired output [38].

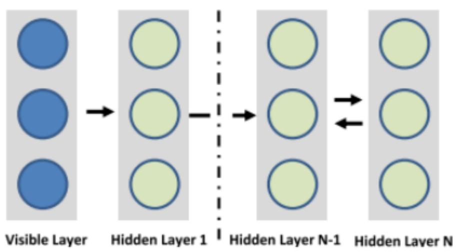

Figure 12: Deep Belief Networks architecture [38]

5. Deep Learning for Predictive Maintenance

As systems require greater levels of reliability, availability, maintainability, and safety, traditional maintenance strategies are losing their effectiveness and becoming outdated. Furthermore, the emergence of Industry 4.0 has created more convenient avenues for implementing predictive maintenance (PdM) on a broader scale [43].

An instance would be the application of intelligent sensors that offer a dependable approach to real-time system monitoring. By leveraging this data, managers can optimize maintenance operations and minimize machine downtimes, ultimately enhancing production flow [43].

5.1. Deployment of predictive maintenance

The suggested predictive maintenance deployment scheme takes advantage of a broad spectrum of emergent technologies, such as IoT, Machine learning (ML), and Deep learning (DL), and involves a series of sequential actions, namely sensors installation, data analysis and processing, data visualization, and decision making, as depicted in the accompanying figure 13.

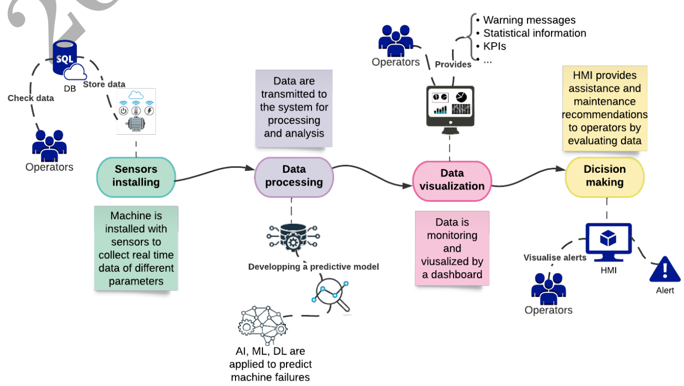

Figure 13: Deployment of predictive maintenance [8]

To initiate predictive maintenance, real-time data from various parameters including temperature, pressure, and vibration are collected through sensors installed on the equipment. These data are then checked, stored in databases, and subjected to data cleaning, transformation, and reduction. The output of this process is utilized in implementing data analysis with ML/DL algorithms to create a predictive model. A dashboard is used to monitor and visualize the outcomes of the preceding stage. Finally, the HMI supports technicians during maintenance interventions by providing guidance and easy access to the equipment's condition [44] [45] [46].

5.2. Related research

Recently, the field of Predictive Maintenance (PdM) has witnessed a surge in the application of deep learning techniques, such as Auto-Encoders (AE), Convolutional Neural Networks (CNN), and Deep Belief Networks (DBN). These models have demonstrated remarkable proficiency in feature learning, fault classification, and fault prediction due to their multi-layer nonlinear transformations [44]. Consequently, the number of research publications in this field has experienced a significant exponential growth [1], as exposed in Figure 14.

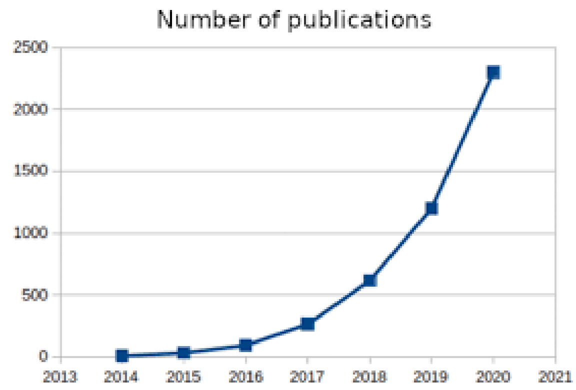

Figure 14: Evolution of a number of publications on deep learning for predictive maintenance in Google Scholar search engine [1]

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In the following table (table 3), we present a literature review of some among various selected research that combines deep learning with predictive maintenance:

Ref	Title	Author(s)	Technique	Description
[49]	Forecasting Appliances Failures: A Machine-Learning Approach to Predictive Maintenance	Fernandes et al	LSTM	develop an LTSM model for predicting severe faults in boilers of the HVAC system
[50]	A recurrent neural network based health indicator for remaining useful life prediction of bearings	Guo et al	LSTM-based RNN	construct an LSTM-RNN-based health indicator to predict remaining useful life (RUL) of bearings.
[51]	Predicting remaining useful life using time series embeddings based on recurrent neural networks	Gugulothu et al	RNN	create an embedded structure that captures machine degradation patterns for time to failure (TTF) estimation.
[52]	A bidirectional LSTM prognostics method under multiple operational conditions	Huang et al	LSTM	developed a method for machine health prognostics under multiple operational conditions
[53]	A data-driven fault detection and diagnosis scheme for air handling units in building HVAC systems considering undefined states	Yun et al	SAE	Conduct a data-driven based model approach for fault detection and diagnosis of FDD of an AHU
[54]	Motor Fault Detection and Feature Extraction Using RNN-Based Variational Autoencoder	Huang & Chen	AE with LSTM	A motor experiment platform were designed to simulate 15 fault scenarios and to collect the time domain vibration signals at 3 different locations.
[55]	A Deep Learning Approach for Fault Diagnosis of Induction Motors in Manufacturing	Shao et al	DBN	A deep learning model based on DBN for induction motor fault diagnosis.
[56]	Deep learning-based fault diagnosis of variable refrigerant flow air-conditioning system for building energy saving	Guo et al	DBN	establish fault diagnosis model based on the DBN model

[57]	A Deep Learning Model for Predictive Maintenance in Cyber-Physical Production Systems Using LSTM Autoencoders	Bampoula et al	AE LSTM	Assess the operational condition of production equipment, using a deep learning method for anomaly detection that is then mapped to different RUL values.
[58]	A semi-supervised approach to fault detection and diagnosis for building HVAC systems based on the modified generative adversarial network	Cheng et al	semi-supervised FDD approach	Use a semi-supervised FDD approach for constructing an HVAC system using modified GAN.
[59]	A novel deep autoencoder feature learning method for rotating machinery fault diagnosis	Shao et al	AE	Presents a methodology of AE optimization for rotating machinery fault diagnosis. The model was applied to fault diagnosis of gearbox and roller bearings.

Table 3: summary of selected articles in the literature on deep learning with predictive maintenance

6. Comparative Study between Deep Learning algorithms

As outlined in figure 15, The key criteria utilized in assessing a DL algorithm, are:

1. Accuracy: is the duration required for the process of training the data. it varies based on the size of the dataset and the algorithm employed [76] [15].

2. Learning time: is the time associated with training the dataset and varies depending on the size of the data and the algorithm we are using [75][15].

3. Prediction time: is the time associated with testing the dataset and varies depending on the size of the data and the algorithm we are using [75][15].

4. Research works: involves gathering articles that employ DL algorithms within the realm of PdM in order to identify the most commonly utilized techniques in this area.

5. Parameterization: Parameters are the buttons to be adjusted during the configuration of an algorithm. These are numerical values that affect the algorithm's behavior [75][15].

6. Memory size: is the capacity required to hold the parameters of the model, including the weights and biases of the various layers, the data and the variables [75][15].

7. Flexibility: refers to a network's capacity to adjust to the patterns within a database. Nonetheless, excessive flexibility may result in noisy learning, leading to the deformation of the classification's inherent characteristics. [75][15].

8. Interpretation facilities: refers to the ability to understand and explain how a model makes decisions or predictions [77][15].

The Mind Map in figure 15, summarizes the criteria for evaluating DL algorithms identified in the state-of-the-art articles.

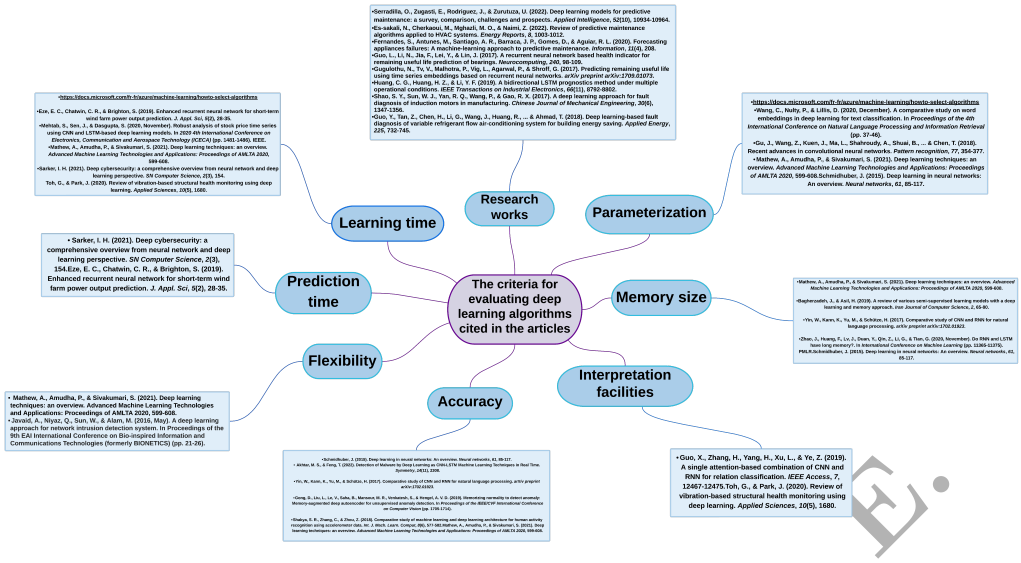

Figure 15: Criteria for evaluating DL algorithms from the state of the art.

Below is a comparative table between the different algorithms

Criteria/Algorithm	CNN	RNN	LSTM	AE	GAN	FNN	RBM	DBN
Accuracy	****	****	****	**	***	**	**	****
Learning time	***	**	**	***	*	**	****	*
Parameterization	**	**	**	****	**	**	****	**
Memory size	***	****	****	**	**	**	**	**
Prediction time	**	****	****	***	***	***	*	**
Flexibility	****	****	****	**	**	**	****	**
Interpretation facilities	**	*	*	*	*	*	*	*
research works	***	***	****	***	**	*	**	**
Score	23	24	25	20	16	15	20	16

Table 4: Comparison between DL algorithms according to criteria
(**** represent the best and * the worst performance))

After assessing the performance of the deep learning algorithms, the ratings are added up to determine which algorithms should be selected:

No	Algorithms	Score
1	Long Short-Term Memory	25
2	Recurrent Neural Networks	24
3	Convolutional Neural Networks	23
4	Autoencoders	20
5	Boltzmann machines rerestraint	20
6	Generative Adversarial Networks	16
7	Deep Belief Networks	16
8	Feedforward Neural Networks	15

Table 5: Algorithm scores in descending order

Based on the previous table, the LSTM algorithm claimed the first position, with the RNN algorithm coming second, followed by the CNN algorithm.

The study's findings suggest that among the various algorithms considered for PdM, these three particularly excel and can be considered the top performers according to the selected criteria and papers.

7. Conclusions

Incorporating automated data-driven predictive maintenance models can enable industrial companies that currently depend on corrective and periodic maintenance strategies to achieve cost optimization.

Predictive maintenance is an important application of ML and DL algorithms that can help organizations in minimizing system failures, enhancing predictability, and boosting system availability. With the rise in industrial data spaces globally, DL solutions have gained popularity for PdM. However, selecting the appropriate architecture for each use case can be challenging due to the numerous factors involved.

The primary aim of this article is to identify an appropriate DL algorithm for PdM, knowing that this selection requires careful consideration of the specific problem and the data at hand. Upon reviewing various DL algorithms, it becomes apparent that each algorithm possesses its own set of strengths and weaknesses with respect to precision, training duration, and comprehensibility.

The study's findings indicate that LSTM achieved the highest score for the set of criteria analyzed, followed by RNN and then CNN. These three DL algorithms are regarded as the most effective for PdM. However, it should be emphasized that the performance of these algorithms is heavily influenced by the quality and quantity of training data. As a result, it is critical to establish a strong data collection and preprocessing plan to achieve the best results.

Future work will be dedicated to setting up an experimental study on the algorithms. This study will involve utilizing either real or simulated data-sets related to PdM. By focusing on the findings in terms of precision, recall, accuracy, or other appropriate performance measures, the most appropriate algorithm for PdM tasks will be selected.

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A. Appendix

Abreviations list:

- **AI : Artificial Intelligence.**
- **ML: Machine learning.**
- **DL: Deep Learning.**
- **PdM: Predictive Maintenance.**
- **GPU: Graphics Processing Unit**
- **CM: Condition Monitoring**
- **IT: Information Technologies.**
- **4IR: Industry 4.0**
- **CPS: Cyber-Physical Systems.**
- **ANN: Artificial Neural Network.**
- **FNN: Feedforward Neural Network.**
- **CNN: Convolutional Neural Network.**
- **NLP: Natural Language Processing**
- **RNN: Recurrent Neural Network.**
- **LSTM: Long Short-Term Memory.**
- **AE: Autoencoders.**
- **GAN: Generative Adversarial Network.**
- **RBM: Boltzmann Machines Restraints.**
- **DBN: Deep Belief Networks.**
- **IoT: Internet of Things.**
- **HMI: Human-Machine Interface.**
- **RUL: Remaining Useful Life.**
- **TTF: Time To Failure.**
- **FDD: Data-Driven Fault.**
- **HVAC: Heating, Ventilation, and Air Conditioning.**
- **AHU: Air Handling Units.**