National Higher School of Technology
Department of Industrial Engineering & Maintenance

Selecting an appropriate deep learning algorithm for predictive maintenance.

Master's thesis in
Industrial Engineering

LARIBI Hadjer-MELIANI Ouezna,

Advisor:
Prof. BELAYADI Djahida

Academic year:
2022-2023

Abstract: Nowadays, applying Deep Learning (DL), a subset of machine learning (ML) and artificial intelligence (AI) in the field of the Industrial Internet of Things is a growing area of research. The prediction of failures of industrial equipment before their occurrence, which is known as PdM, is also a very trendy topic, especially with its cost-saving potential and many other advantages over other types of maintenance. DL techniques can be beneficial for Predictive Maintenance applications, mainly with highly complex, non-linear, and unlabeled data in the real case. However, there are a variety of deep algorithms available, and each of them represents different characteristics and can be used in different cases. Therefore, choosing the best DL algorithm to resolve predictive maintenance issues is not obvious.

This paper aims to improve the performance of predictive maintenance by selecting the most suitable deep learning algorithm. From a comparative study, we selected three deep learning algorithms, based on the widely used criteria in research articles.

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

Contents

1 Introduction 2
2 Industry 4.0 2
3 Predictive Maintenance 3
4 Deep Learning 5
5 Deep Learning for Predictive Maintenance 8
6 Comparative Study between Deep Learning algorithms 10
7 Conclusions 12
A Appendix 16

1. Introduction

labelsec1

In recent years, the industry has raised attention to artificial intelligence and machine learning techniques due to their capacity 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 to more complex models, such as deep learning, given their greater accuracy in dealing with larger data sets. These methods have evolved due to the increase in computing power and the latter mainly due to the evolution of GPU-s, being deep learning one of the most researched topics nowadays. These models achieve state-of-the-art results in many fields, like intrusion detection systems, computer vision, or language processing [1].
Today, maintenance is a strategic factor to ensure high productivity of industrial systems, but for economic reasons, companies are driven to reduce maintenance expenses, with critical consequences for long-term reliability, and develop appropriate maintenance policies to ensure the efficiency of production plants in terms of quality and availability. As a result, the concept of maintenance itself has evolved considerably over time, thanks to significant contributions of research [2].

Currently, we are transitioning towards the fourth revolution denominated as Industry 4.0, which is based on cyber-physical systems and the industrial Internet of Things. It combines software, sensors, and intelligent control units to improve industrial processes and fulfill their requirements. These techniques enable automated predictive maintenance functions analyzing massive amounts of process and related data based on condition monitoring (CM) [3]. Predictive maintenance (PdM) was first devised back 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 importance for industries due to the increasing complexity of interactions between different production activities in increasingly large manufacturing ecosystems. Over the years, Deep Learning methods have been suggested for PdM. Failure prediction by deep learning methods (e.g., Deep Neural Network, Recurrent Neural Network, Convolution Neural Network, and Long Short Term Memory) estimates the probability of equipment failing through automated learning of system past data [6].

In this context, many deep learning algorithms are available. Hence, the research question of this paper is: What are the best deep learning algorithms to resolve predictive maintenance issues?

With this aim, the article is divided into six sections, starting with an introduction in Section ??, and exploring in Section 2 the concept of Industry 4.0 as the latest technology to evolve industrial domains, Section 3 illustrates a description of predictive maintenance with its approaches and also presents the different monitoring techniques used in PdM. Subsequently, 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 deep learning for Predictive Maintenance and the different research experiences. Later on, in Section 6, we compared deep learning algorithms using the criteria most frequently used in research articles to select the best algorithms to solve predictive maintenance problems, finally, Section 7 presents a conclusion of this research work.

2. Industry 4.0

After the introduction of steam power and mechanization of production in industry, 1.0 [7]. The first production and assembly lines and mass production processes driven by electricity and division of labor were developed in the second industrial revolution [7]. The third industrial revolution was characterized by electronics and Information Technologies (IT), the main drivers of this Industry have been 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 transforming 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 became public in 2011 in Germany [9], at the Hannover Industrial Technology Fair.

Industry 4.0 (4IR) is defined as "the integration of complex physical machinery and devices with net-

worked 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 than ever before.

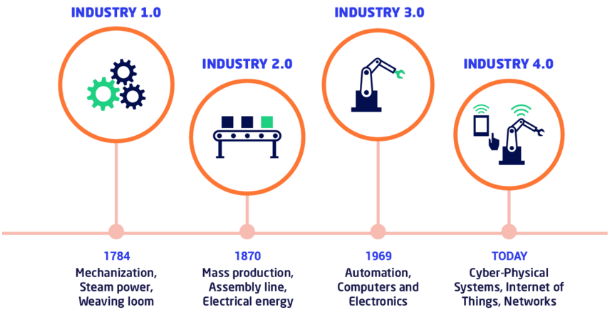

Figure 1: Industry Evolution [7]

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 a plan determined a priori [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].

PdM offers the longest equipment life and reliability, and the most environmentally sound and cost-effective solutions.

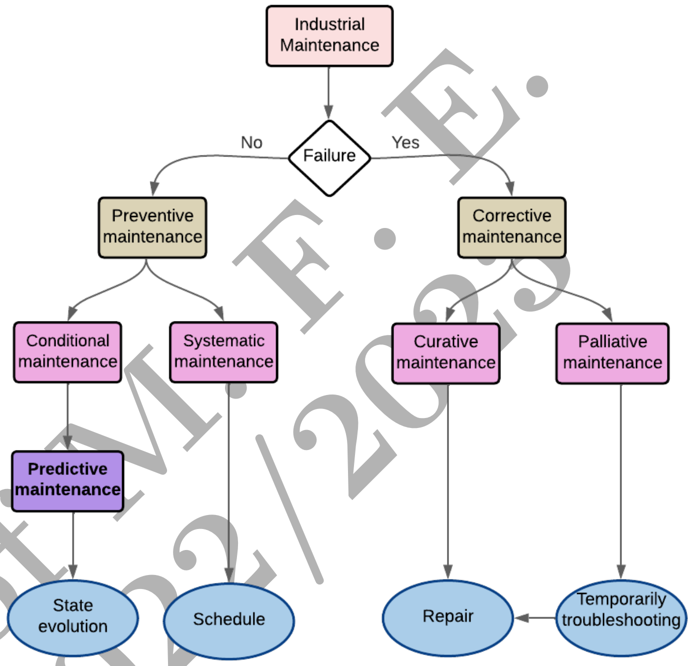

Figure 2: Maintenance types [13]

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 used to assess the state of the equipment and predict when maintenance should be conducted.[16].
Various surveillance techniques are used for predictive maintenance, including [18]:

- Vibration analysis: Is used to detect the condition of rotating machinery. By analyzing the frequency, amplitude, and phase of vibrations, technicians can identify potential issues.

- Oil analysis: Consists of verifying the quality of the lubrication oil in the equipment. By analyzing the chemical composition of the oil, technicians are able to detect potential problems.

- 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 abnormal thermal phenomena on the equipment. By identifying hot spots, technicians can detect potential issues.

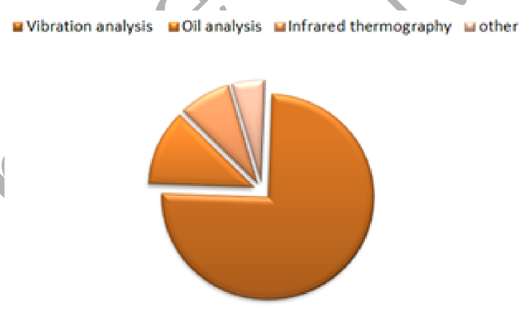

Figure 3: Different Monitoring Techniques [18]

3.2. Predictive maintenance approaches

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

- knowledge-based models

  This type of system consists of a knowledge base that contains accumulated knowledge acquired from domain experts and a rule base for applying acquired knowledge to particular problems [20]. It uses historic failure data as the ultimate predictive tool [19]. This model could be split into three categories: rule-based or case-based algorithms and fuzzy knowledge-based algorithms [19]. The disadvantage of this type is its low accuracy and can hardly be applied to complex systems. Still, applicable for simple processes or systems [22].

- Physical-based models
  This type, use explicit mathematical representation to formalize the physical understanding of a degrading machine or equipment[20]; They require high skills in mathematics and physics of phenomena for the application. [21].a physical model can update itself to improve its accuracy and quality[20]. The main disadvantage of a physical model is the difficulty of assigning appropriate parameters used in the model. Since the massive and multivariate data required for the assignment of parameters are usually not available, it is hard to quantitatively characterize the system behavior [20]. The physics-based models could be divided into; 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].
  Normally, data-driven approaches are classified into machine learning (ML) techniques, and

statistical techniques [20].

Another efficient and emerging approach, anchoring the benefits of various prognostic models currently available, is the "hybrid approach". It's a combination of different approaches that results in a hybrid model with better predictive ability. Hybrid models use an amalgamation of different techniques or approaches for prediction to improve accuracy. [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 is a sub-field of machine learning that uses artificial neural networks to learn from unstructured or semi-structured data. These neural networks are designed to mimic the functioning of biological neurons of the human brain by processing data in successive layers, using machine learning algorithms to adjust the weights and biases of each layer to achieve accurate predictions or outputs [24].

4.1. Definitions

4.1.1 Artificial Neural Networks

ANNs are a mathematical model that is inspired by the structure and function of biological neurons of the human brain. ANNs are composed of interconnected nodes (neurons) that are organized in layers, with inputs and outputs [26]. In ANNs, each neuron receives input signals from other neurons and applies a non-linear mathematical function to these inputs to compute its output. The output of a neuron is then transmitted to other neurons in the network, through weighted connections between them. During training, the weights of the connections between neurons are adjusted to minimize the error between the predicted output of the network and the actual output [25].

ANNs have a remarkable ability to learn and generalize patterns from data, which makes them useful for a wide range of applications, including 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 backpropagation and stochastic gradient descent [26].

4.1.2 Biological neurons

Biological neurons are specialized cells found in the nervous system of living organisms, including humans. These cells are responsible for transmitting information in the form of electrical and chemical signals between cells [41].
Each 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 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. 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 neurotransmitter released by a neighboring neuron, an electrical impulse is generated that travels along the axon. This impulse can then activate other neurons or target cells at synapses [41].

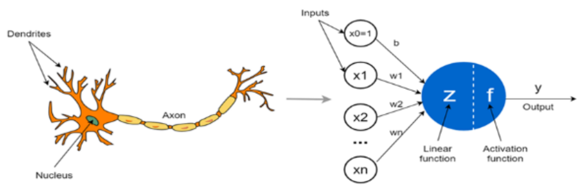

Figure 4: Biological neuron vs Artificial neural [41]

4.2. Deep Learning vs Machine Learning

Although deep learning is a subclass of machine learning, the two approaches represent differences. Here is a table to show 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

There is much different architecture that has been developed for deep learning, and each has its own strengths and weaknesses depending on the specific task at hand. Here is some common deep learning architecture:

4.3.1 Feedforward Neural Networks (FNNs

Is the first, most common, and simplest architecture. It is formed by stacked neurons creating layers, where all the neurons of a layer are connected to all the neurons of the next layer by feeding their output to others' input. However, there are no connections to neurons of previous layers or among neurons of the same layer. The nomenclature for layers is the following: an input layer, hidden layers, and an output layer [1]. The neural network is fed with observations pairing input features and target features, which are used to learn their relation by minimizing the error produced by the network by mapping input data to output [1].

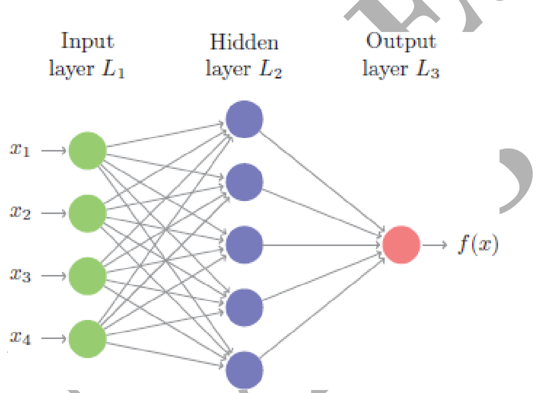

Figure 5: Feedforward Neural Networks architecture [42]

4.3.2 Convolutional Neural Networks (CNNs)

Is a type of feedforward network that maintains neurons' neighborhoods by applying convolutional filters. It is inspired by the animal visual cortex and has applications in image and signal recognition, recommendation systems and NLP among others. The convolutional layer is usually linear and is followed by the application of an activation function to produce non-linear output. After that, a max pooling layer can be used to reduce the dimension. Finally, most architectures have a flattened step to obtain representative features of input data that can be used with other ML or DL networks to perform typical ML tasks. The convolutions' weights are shared, making them easier to train [1].

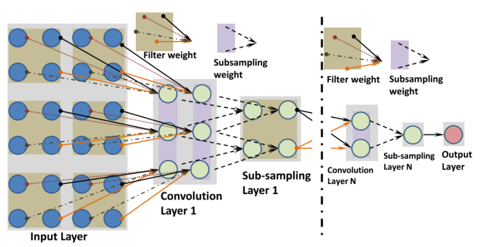

Figure 6: Convolutional Neural Networks architecture [38]

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]. Unlike feedforward neural networks, RNNs have a feedback loop that allows them to process sequential data by taking into account previous inputs. This makes them suitable for tasks such as speech recognition, and language translation [33].

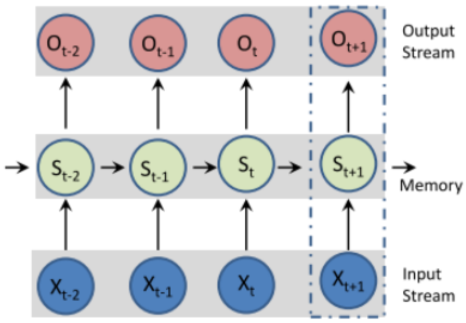

Figure 7: Recurrent Neural Networks architecture [38]

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].

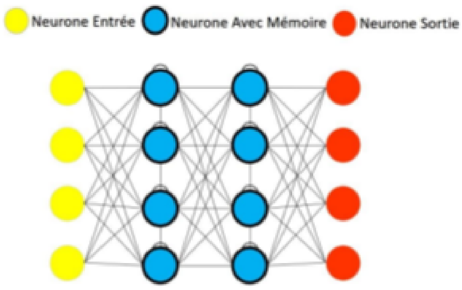

Figure 8: Long Short-Term Memory architecture [40]

4.3.5 AutoeEncoders (AE)

AE is based on the singular value decomposition concept to extract the non-linear features that best represent the input data in a smaller 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, which is the loss between input and output. [1][34].

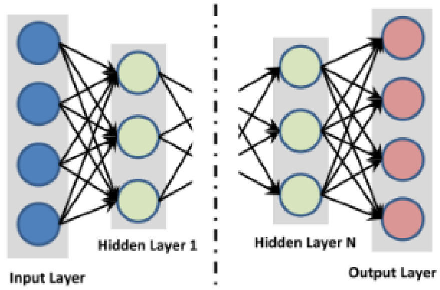

Figure 9: Autoencoders architecture [38]

4.3.6 Generative Adversarial Networks (GANs)

GAN was first proposed by Goodfellow et al [35]. Generative Adversarial Networks are a type of deep learning model that consists of two neural networks: a generator and a discriminator. The generator takes in random noise as input and generates synthetic data, while the discriminator takes in both real and synthetic data and tries to distinguish between them [36].Les deux réseaux sont formés simultanément de manière ludique [37][35].

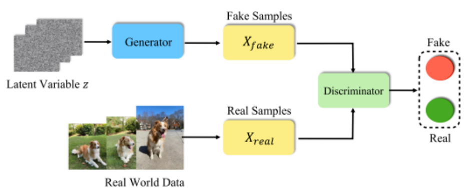

Figure 10: Generative Adversarial Networks architecture [35]

4.3.7 Boltzmann machines restraints (RBM)

Restricted Boltzmann machines (RBMs) are another ANN algorithms that consist of a two-layer networking architecture containing 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 is responsible for input data, while the hidden layer performs feature extraction. Additionally, in RBMs, the hidden nodes are conditionally self-determining and have no interdependency in RBMs.

The offsets and weights of the visible and hidden layers are updated iteratively such that the visible layer can estimate the input data. [39] [1] [48].

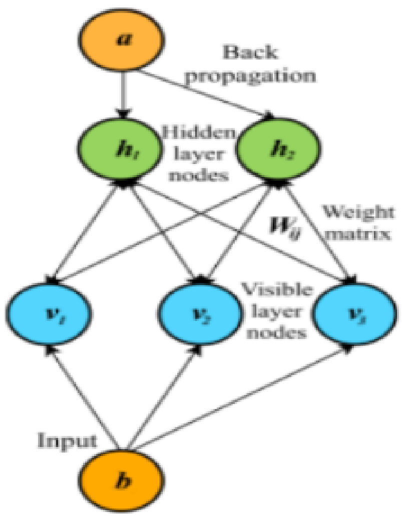

Figure 11: Boltzmann machines restraints architecture [39]

4.3.8 Deep Belief Networks (DBNs)

A DBN can be viewed as a composition of RBMs(Restricted Boltzmann machine) where each subnetwork's hidden layer is connected to the visible layer of the next RBM. DBNs have undirected connections only at the top two layers and directed connections to the lower layers. The initialization of a DBN is obtained through an efficient layer-by-layer greedy learning strategy using unsupervised learning and is then fine-tuned based on the target outputs [38].

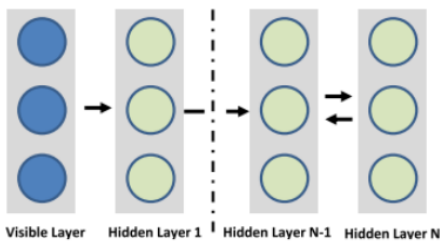

Figure 12: Deep Belief Networks architecture [38]

5. Deep Learning for Predictive Maintenance

Due to the increasing requirement of reliability, availability, maintainability, and safety of systems, traditional maintenance strategies are becoming less effective and obsolete. Besides, the revolution of Industry 4.0 provides more convenient support for the wide development of predictive maintenance (PdM) in practice [43].

For example, the use of intelligent sensors provides a reliable solution for system monitoring in real-time. Having this information, the manager can plan the maintenance activities more effectively to reduce machine downtimes and improve the production flow [43].

5.1. Deployment of predictive maintenance

The proposed predictive maintenance deployment scheme takes advantage of a broad spectrum of emergent technologies, such as IoT, Machine learning (ML), and Deep learning (DL), and includes several steps, namely sensors installation, data analysis and processing, data visualization, and decision making as illustrated in Figure 13.

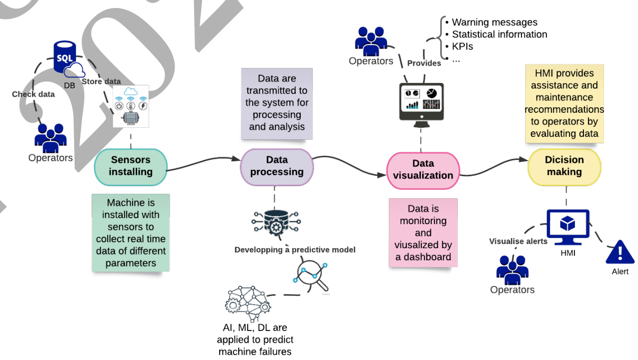

Figure 13: Deployment of predictive maintenance

The functioning of the predictive maintenance starts with the collection of real-time data of different parameters such as temperature, pressure, and vibration...by sensors installed on the equipment; the set of data will be checked and stored in databases. The next step, involves data cleaning, transformation, and reduction. The output of this step will be used in the implementation of data analysis using ML/DL algorithms to perform a predictive model. The result of the previous step will be monitored and visualized by a dashboard. Finally, the HMI is responsible to support the technician during the execution of maintenance interventions, providing guidance and easy access to the machine condition [44] [45] [46].

5.2. Related research

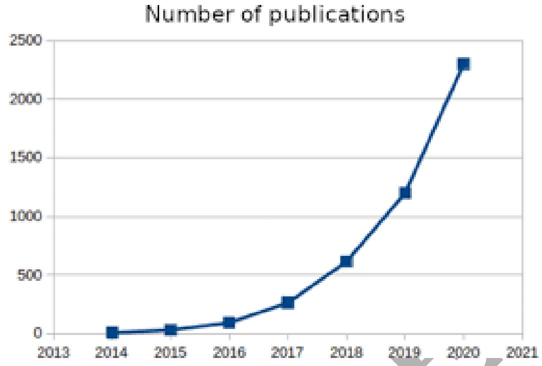

Figure 14: Evolution of a number of publications on deep learning for predictive maintenance in Google Scholar search engine [1]

Recently, deep learning has shown superior ability in feature learning, fault classification, and fault prediction with multi-layer nonlinear transformations. Auto-Encoder (AE), Convolutional Neural Network (CNN), Deep Belief Network (DBN), and other deep learning models are widely applied in the field of PdM [44], and the number of publications in the field has increased exponentially in recent years [1], as exposed in Figure 14.

In the following table (table 3), we present a literature review of 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 and 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

[56]	Deep learning-based fault diagnosis of variable refrigerant flow air-conditioning system for building energy saving	Guo et al	DBN	establish a 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.
[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.
[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.

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

6. Comparative Study between Deep Learning algorithms

As illustrated in figure 15, the most important criteria for evaluating a DL algorithm are as follows:

1. Accuracy: is the percentage of correct predictions of the overall model over the total number of samples used for prediction [76].

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].

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

4. research works: consists of collecting articles that use deep learning algorithms in the field of predictive maintenance to find the most used in this field.

5. Parameterization: Parameters are the buttons that data scientists adjust when they configure an algorithm. These are numbers that affect the algorithm's behavior, such as error tolerance, number of iterations, or variants of the algorithm's behavior. The learning time and accuracy of the algorithm can sometimes depend on the choice of appropriate parameters, algorithms with a large number of parameters require more testing to find the right combination.[75].

6. Memory size: is the space we need to store our data and variables. Researchers are struggling with limited medical bandwidth DRAM (Dynamic Random Access Memory) that must be used by Today's systems for storing huge quantities of weights and activations in DNNs (Deep Neural Networks), GPUs (Graphics Processing Units) and other machines designed for matrix algorithms also suffer from another memory multiplier on the weights and activations of a network of neurons [75].

7. Flexibility: is the ability of a network to adapt to the patterns of the database. However, great flexibility will tend towards noisy learning, which will distort the intrinsic properties of

the classification [75].

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

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

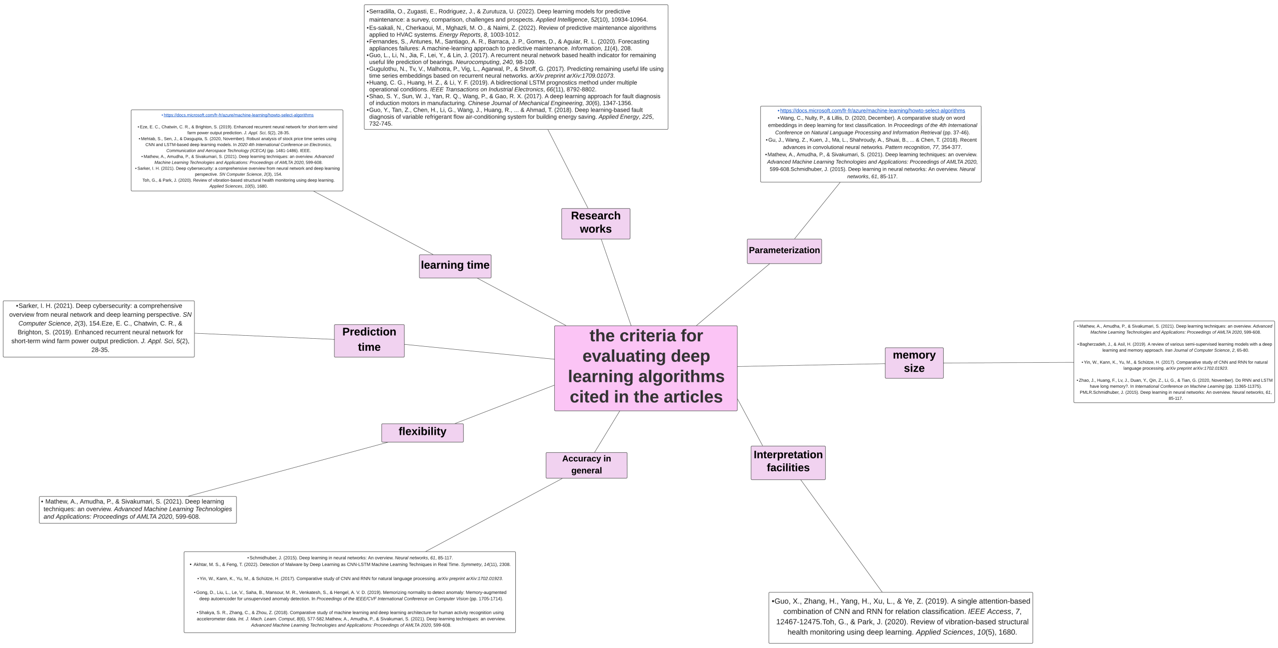

Figure 15: Criteria for evaluating DL algorithms from the state of the art.

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 (**** stars represent the best and * star the worst performance))

From the evaluation of the deep learning algorithms, we sum the stars to denote the algorithms to choose:

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

7. Conclusions

The majority of industrial companies that rely on corrective and periodical maintenance strategies can optimize costs by integrating automatic data-driven predictive maintenance models.
Additionally, predictive maintenance is a critical application of machine learning and deep learning algorithms that can help organizations reduce system failure, improve predictability, and increase the availability of systems. Deep learning solutions have become popular for predictive maintenance due to the growing amount of industrial data spaces worldwide. Choosing the most suitable architecture for each use case complex given the many factors involved.
The main objective of this article is to select a suitable deep learning algorithm for predictive maintenance, knowing that this selection requires careful consideration of the specific problem and the data at hand. After reviewing different deep learning algorithms, it is clear that each algorithm has its strengths and weaknesses in terms of accuracy, training time, and intelligibility.
According to the results of the comparative study, LSTM has the highest score for the set of criteria studied, followed by RNN, and finally CNN. This shows that these three algorithms are the best deep learning algorithms for predictive maintenance. However, it is essential to note that the performance of deep learning algorithms depends heavily on the quality and quantity of the training data. Therefore, it is crucial to have a robust data collection and preprocessing strategy to ensure the best results.

References

[1] Serradilla, O., Zugasti, E., Rodriguez, J., Zurutuza, U. (2022). Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects. Applied Intelligence, 52(10), 10934-10964.

[2] Alaoui Belghiti, A. (2021). Prédiction de situations anormales par apprentissage automatique pour la maintenance prédictive: approches en transport optimal pour la détection d'anomalies (Doctoral dissertation, Université Paris-Saclay

[3] Dusko Lukac. 2016. The fourth ICT-based industrial revolution "industry 4.0" - HMI and the case of CAE/CAD innovation with EPLAN P8. In 2015 23rd Telecommunications Forum, TELFOR 2015. IEEE, 835–838. https://doi.org/10.1109/TELFOR.2015.7377595.

[4] Prajapati, A.; Bechtel, J.; Ganesan, S. Condition based maintenance: A survey. J. Qual. Maint. Eng. 2012, 18, 384–400.

[5] Tiddens, W.; Braaksma, J.; Tinga, T. Exploring predictive maintenance applications in industry. J. Qual. Maint. Eng. 2020, 28, 68–85.

[6] Davari, N., Veloso, B., Ribeiro, R. P., Pereira, P. M., Gama, J. (2021, October). Predictive maintenance based on anomaly detection using deep learning for air production unit in the railway industry. In 2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA) (pp. 1-10). IEEE

[7] Kadir, B. A. (2020). Designing new ways of working in Industry 4.0: Aligning humans, technology, and organization in the transition to Industry 4.0.

[8] Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., Adda, M. (2022). On predictive maintenance in industry 4.0: Overview, models, and challenges. Applied Sciences, 12(16), 8081.

[9] Hermann, M., Pentek, T., Otto, B. (2015). Design principles for Industrie 4.0 scenarios: a literature review. Technische Universität Dortmund, Dortmund, 45.

[10] Maresova, P., Soukal, I., Svobodova, L., Hedvicakova, M., Javanmardi, E., Selamat, A., Krejcar, O. (2018). Consequences of industry 4.0 in business and economics. Economies, 6(3), 46.

[11] FD, X. (2002). 60-000, Norme Française. Fonction Maintenance. AFNOR.

[12] Mattioli, J., Robic, P. O., Reydellet, T. (2018, July). L'intelligence artificielle au service de la maintenance prévisionnelle. In 4ème conférence sur les Applications Pratiques de l'Intelligence Artificielle APIA2018.

[13] MAGHLOUT, H. (2010). Application de l'analyse en ondelettes discrète dans la maintenance prédictive des paliers à roulements.

[14] https://biblio.univ-annaba.dz/ingeniorat/wp-content/uploads/2019/10/Arab-Mustapha.pdf

[15] Ouadah, A., Zemmouchi-Ghomari, L., Salhi, N. (2022). Selecting an appropriate supervised machine learning algorithm for predictive maintenance. The International Journal of Advanced Manufacturing Technology, 119(7-8), 4277-4301.

[16] https://blog.infraspeak.com/condition-monitoring-techniques/

[17] BENCHETTOUH, S. E. (2019). Elaboration d'un système de prédiction des pannes et de planification des maintenances (Doctoral dissertation, UNIVERSITE MOHAMED BOUDIAF-M'SILA-FACULTE MATHEMATIQUES ET DE L'INFORMATIQUE).

[18] Djebili, O. (2013). Contribution à la maintenance prédictive par analyse vibratoire des composants mécaniques tournants. Application aux butées à billes soumises à la fatigue de contact de roulement (Doctoral dissertation, Reims).

[19] Es-sakali, N., Cherkaoui, M., Mghazli, M. O., Naimi, Z. (2022). Review of predictive maintenance algorithms applied to HVAC systems. Energy Reports, 8, 1003-1012.

[20] Cao, Q., Zanni-Merk, C., Samet, A., Reich, C., De Beuvron, F. D. B., Beckmann, A., Giannetti, C. (2022). KSPMI: a knowledge-based system for predictive maintenance in industry 4.0. Robotics and Computer-Integrated Manufacturing, 74, 102281.

[21] Jimenez, J. J. M., Schwartz, S., Vingerhoeds, R., Grabot, B., Salaün, M. (2020). Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics. Journal of Manufacturing Systems, 56, 539-557.

[22] Sayyad, S., Kumar, S., Bongale, A., Bongale, A. M., Patil, S. (2021). Estimating remaining useful life in machines using artificial intelligence: A scoping review. Libr. Philos. Pract, 2021, 1-26.

[23] Gawde, S., Patil, S., Kumar, S., Kotecha, K. (2022). A scoping review on multi-fault diagnosis of industrial rotating machines using multi-sensor data fusion. Artificial Intelligence Review, 1-54.

[24] Chen, J., Ran, X. (2019). Deep learning with edge computing: A review. Proceedings of the IEEE, 107(8), 1655-1674.

[25] Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Umar, A. M., Linus, O. U., ... Kiru, M. U. (2019). Comprehensive review of artificial neural network applications to pattern recognition. IEEE Access, 7, 158820-158846.

[26] Krenker, A., Bešter, J., Kos, A. (2011). Introduction to the artificial neural networks. Artificial Neural Networks: Methodological Advances and Biomedical Applications. InTech, 1-18.

[27] https://levity.ai/blog/difference-machine-learning-deep-learning

[28] https://nixustechnologies.com/deep-learning-vs-machine-learning/

[29] https://www.scs.org.sg/articles/machine-learning-vs-deep-learning

[30] https://www.apriorit.com/dev-blog/472-machine-learning-applications

[31] https://dev.to/bpb-online/machine-learning-vs-deep-learning-what-s-the-difference-2bm7

[32] Gheisari, S., Shariflou, S., Phu, J., Kennedy, P. J., Agar, A., Kalloniatis, M., Golzan, S. M. (2021). A combined convolutional and recurrent neural network for enhanced glaucoma detection. Scientific reports, 11(1), 1-11.

[33] Apaydin, H., Feizi, H., Sattari, M. T., Colak, M. S., Shamshirband, S., Chau, K. W. (2020). Comparative analysis of recurrent neural network architectures for reservoir inflow forecasting. Water, 12(5), 1500.

[34] Makhzani, A., Frey, B. (2013). K-sparse autoencoders. arXiv preprint arXiv:1312.5663.

[35] Cai, Z., Xiong, Z., Xu, H., Wang, P., Li, W., Pan, Y. (2021). Generative adversarial networks: A survey toward private and secure applications. ACM Computing Surveys (CSUR), 54(6), 1-38.

[36] Ye, H., Liang, L., Li, G. Y., Juang, B. H. (2020). Deep learning-based end-to-end wireless communication systems with conditional GANs as unknown channels. IEEE Transactions on Wireless Communications, 19(5), 3133-3143.

[37] Zeng, Q., Ma, X., Cheng, B., Zhou, E., Pang, W. (2020). Gans-based data augmentation for citrus disease severity detection using deep learning. IEEE Access, 8, 172882-172891.

[38] Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., Yang, G. Z. (2016). Deep learning for health informatics. IEEE journal of biomedical and health informatics, 21(1), 4-21.

[39] En, T. Y., Ki, M. S., Hui, N. T., Jie, T. J., Vusoff, M. A. B. M. (2018, December). Predictive Maintenance of a Train System Using a Multilayer Perceptron Artificial Neural Network. In 2018 International Conference on Intelligent Rail Transportation (ICIRT) (pp. 1-5). IEEE.

[40] Bensiah, O. A., Berkane, M. (2020). La Proposition d'une nouvelle approche basée Deep learning pour la prédiction du cancer du sain.

[41] https://towardsdatascience.com/the-concept-of-artificial-neurons-perceptrons-in-neural-networks-fab22249cbfc

[42] https://afit-r.github.io/feedforward-DNN

[43] Nguyen, K. T., Medjaher, K. (2019). A new dynamic predictive maintenance framework using deep learning for failure prognostics. Reliability Engineering System Safety, 188, 251-262.

[44] Ran, Y., Zhou, X., Lin, P., Wen, Y., Deng, R. (2019). A survey of predictive maintenance: Systems, purposes and approaches. arXiv preprint arXiv:1912.07383

[45] Alves, F., Badikyan, H., Moreira, H. A., Azevedo, J., Moreira, P. M., Romero, L., Leitão, P. (2020, June). Deployment of a smart and predictive maintenance system in an industrial case study. In 2020 IEEE 29th International Symposium on Industrial Electronics (ISIE) (pp. 493-498). IEEE.

[46] Jimenez-Cortadi, A., Irigoien, I., Boto, F., Sierra, B., Rodriguez, G. (2019). Predictive maintenance on the machining process and machine tool. Applied Sciences, 10(1), 224.

[47] Rivas, A., Fraile, J. M., Chamoso, P., González-Briones, A., Sittón, I., Corchado, J. M. (2020). A predictive maintenance model using recurrent neural networks. In 14th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2019) Seville, Spain, May 13–15, 2019, Proceedings 14 (pp. 261-270). Springer International Publishing

[48] Khalil, R. A., Saeed, N., Masood, M., Fard, Y. M., Alouini, M. S., Al-Naffouri, T. Y. (2021). Deep learning in the industrial internet of things: Potentials, challenges, and emerging applications. IEEE Internet of Things Journal, 8(14), 11016-11040.

[49] Fernandes, S., Antunes, M., Santiago, A. R., Barraca, J. P., Gomes, D., Aguiar, R. L. (2020). Forecasting appliances failures: A machine-learning approach to predictive maintenance. Information, 11(4), 208.

[50] Guo, L., Li, N., Jia, F., Lei, Y., Lin, J. (2017). A recurrent neural network based health indicator for remaining useful life prediction of bearings. Neurocomputing, 240, 98-109.

[51] Gugulothu, N., Tv, V., Malhotra, P., Vig, L., Agarwal, P., Shroff, G. (2017). Predicting remaining useful life using time series embeddings based on recurrent neural networks. arXiv preprint arXiv:1709.01073.

[52] Huang, C. G., Huang, H. Z., Li, Y. F. (2019). A bidirectional LSTM prognostics method under multiple operational conditions. IEEE Transactions on Industrial Electronics, 66(11), 8792-8802.

[53] yun W-S, Hong W-H, Seo H. A data-driven fault detection and diagnosis scheme for air handling units in building HVAC systemsconsidering undefined states. J Build Eng 2021;35:102111

[54] Huang, Y., Chen, C. H., Huang, C. J. (2019). Motor fault detection and feature extraction using RNN-based variational autoencoder. IEEE access, 7, 139086-139096.

[55] Shao, S. Y., Sun, W. J., Yan, R. Q., Wang, P., Gao, R. X. (2017). A deep learning approach for fault diagnosis of induction motors in manufacturing. Chinese Journal of Mechanical Engineering, 30(6), 1347-1356.

[56] Guo, Y., Tan, Z., Chen, H., Li, G., Wang, J., Huang, R., ... Ahmad, T. (2018). Deep learning-based fault diagnosis of variable refrigerant flow air-conditioning system for building energy saving. Applied Energy, 225, 732-745.

[57] Bampoula, X., Siaterlis, G., Nikolakis, N., Alexopoulos, K. (2021). A deep learning model for predictive maintenance in cyber-physical production

systems using lstm autoencoders. Sensors, 21(3), 972.

[58] Li, B., Cheng, F., Cai, H., Zhang, X., Cai, W. (2021). A semi-supervised approach to fault detection and diagnosis for building HVAC systems based on the modified generative adversarial network. Energy and Buildings, 246, 111044.

[59] Shao, H., Jiang, H., Zhao, H., Wang, F. (2017). A novel deep autoencoder feature learning method for rotating machinery fault diagnosis. Mechanical Systems and Signal Processing, 95, 187-204.

[60] Wang, C., Nulty, P., Lillis, D. (2020, December). A comparative study on word embeddings in deep learning for text classification. In Proceedings of the 4th International Conference on Natural Language Processing and Information Retrieval (pp. 37-46).

[61] Yin, W., Kann, K., Yu, M., Schütze, H. (2017). Comparative study of CNN and RNN for natural language processing. arXiv preprint arXiv:1702.01923

[62] Zhao, J., Huang, F., Lv, J., Duan, Y., Qin, Z., Li, G., Tian, G. (2020, November). Do RNN and LSTM have long memory?. In International Conference on Machine Learning (pp. 11365-11375). PMLR.

[63] Belkin, M., Ma, S., Mandal, S. (2018, July). To understand deep learning we need to understand kernel learning. In International Conference on Machine Learning (pp. 541-549). PMLR.

[64] Bagherzadeh, J., Asil, H. (2019). A review of various semi-supervised learning models with a deep learning and memory approach. Iran Journal of Computer Science, 2, 65-80.

[65] Mathew, A., Amudha, P., Sivakumari, S. (2021). Deep learning techniques: an overview. Advanced Machine Learning Technologies and Applications: Proceedings of AMLTA 2020, 599-608.

[66] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural networks, 61, 85-117.

[67] Sarker, I. H. (2021). Deep cybersecurity: a comprehensive overview from neural network and deep learning perspective. SN Computer Science, 2(3), 154.

[68] Eze, E. C., Chatwin, C. R., Brighton, S. (2019). Enhanced recurrent neural network for short-term wind farm power output prediction. J. Appl. Sci, 5(2), 28-35.

[69] Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., ... Chen, T. (2018). Recent advances in convolutional neural networks. Pattern recognition, 77, 354-377.

[70] Mehtab, S., Sen, J., Dasgupta, S. (2020, November). Robust analysis of stock price time series using CNN and LSTM-based deep learning models. In 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 1481-1486). IEEE.

[71] Toh, G., Park, J. (2020). Review of vibration-based structural health monitoring using deep learning. Applied Sciences, 10(5), 1680.

[72] Akhtar, M. S., Feng, T. (2022). Detection of Malware by Deep Learning as CNN-LSTM Machine Learning Techniques in Real Time. Symmetry, 14(11), 2308

[73] Gong, D., Liu, L., Le, V., Saha, B., Mansour, M. R., Venkatesh, S., Hengel, A. V. D. (2019). Memorizing normality to detect anomaly: Memory-augmented deep autoencoder for unsupervised anomaly detection. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 1705-1714).

[74] Shakya, S. R., Zhang, C., Zhou, Z. (2018). Comparative study of machine learning and deep learning architecture for human activity recognition using accelerometer data. Int. J. Mach. Learn. Comput, 8(6), 577-582

[75] https://docs.microsoft.com/fr-fr/azure/machine-learning/howto-select-algorithms

[76] Kiangala, K. S., Wang, Z. (2020). An effective predictive maintenance framework for conveyor motors using dual time-series imaging and convolutional neural network in an industry 4.0 environment. Ieee Access, 8, 121033-121049.

[77] https://arxiv.org/abs/2103.10689

A. Appendix

List of Abbreviations

- **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.**
- **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.**