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Predictive Maintenance of Electromechanical Systems Using Deep Learning Algorithms: Review

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ABSTRACT

Predictive Maintenance (PM) is a major part of smart manufacturing in the fourth industrial revolution. The classical fault diagnosis approach for complex systems such as an electromechanical system is not effective. Taking the advantage of the successful implementations of PM together with Deep Learning (DL) methods replaces the conventional diagnosis methods with modern diagnosis methods. This study intends to aid experts, engineers, and technicians in different electromechanical systems in comprehending how the PM used DL methods to find the multi-fault diagnosis. In this direction, this paper presents a comprehensive review of recent works of DL techniques that are applied to PM for electromechanical systems by classifying the research according to equipment, fault, parameters, and method. To perform the review, 30 papers that are published in proceedings and journals are reviewed within a time window between the years 2016 to 2022. In the context of the electromechanical system, it is observed that motors are the most equipment selected for PM. Moreover, stator winding faults are found to be less selected than bearing for diagnosis of the unhealthy status of the motor. In terms of DL methods, the study reveals that AE, LSTM, and CNN are mostly used. In addition, poorly mixed models of DL methods are also noticed. Finally, finding the optimal design variable of the DL architecture was not widely explored.

1. INTRODUCTION

Predictive Maintenance (PM) is an essential part of smart manufacturing. It reduces outages of companies, cuts maintenance and manufacturing expenses, raises safety, throughput, and equipment longevity, as a result raising total profits [1]. Industry 4.0 and smart technology applications have been connected with PM using Artificial Intelligence (AI) [2]. AI can be considered as a cognitive system that has a two-part knowledge network that comes from a training system and neuron connection comprised of weight that a saving knowledge [3]. The traditional fault diagnosis approach for a complex system such as an electromechanical system is not efficient. Today, the successful implementations of PM together with AI include Machine Learning (ML) and Deep Learning (DL) methods replaces conventional diagnosis strategies with their modern diagnosis scheme for any system that can automatically detect abnormal physical behavior in the early stage [4, 5]. Therefore, PM becomes a powerful maintenance strategy for electromechanical fault prognosis [6]. The current problem of the fault for any electromechanical system is the distinguishing between different types of diagnosis. Forecasting is predicting the event of a fault before it occurs and illustrating its status. Reducing time and cost by PM led to improving revenue by reducing losses caused by equipment stopping suddenly. Besides, another benefit of PM is the ability to find unusual systems work which leads to ensure safe operation in the workplace [7].

Predictive decision utilizes predictive tools to decide when maintenance steps are important before the failure occurs [8]. It depends on real-time monitoring of machines and letting maintenance be achieved when it is required. Currently, DL is one of the most researched subjects and an effective tool for growing intelligent predictive methods in many applications [9]. Numerous types of DL algorithms have been developed and applied to diagnose faults in the electromechanical system. They can be used to recognize the system's weakness based on the dataset that is collected, which can be then extracted automatically from the learning algorithm [10].

Recently, the data-driven diagnosis approach is a very active method and does not need traditional statistical methods. It utilized the availability of big data analysis and employed the historical data of the system to make the system avoid failures more accurately under intelligent monitoring [11]. The basis of the intelligence predictive can be stated as follows: a dataset collected by Cyber-Physical System (CPS) and then transferred by the Internet of Things (IoT) to the monitoring system. After that, data is analyzed automatically. A maintenance decision is then made if there is a possible to have a failure in the system [12].

This study provides a thorough evaluation of recent works of DL approaches that are applied to PM for electromechanical systems.

Unlike other reviews where the majority of them are in general, in this review, the emphasis is only on the incorporation of DL algorithms with PM into different electromechanical systems, more particularly the motor. The purpose of this review is to assist experts, engineering and technicians in electromechanical systems to understand how the PM utilized DL techniques to detect the multi-fault diagnosis. 30 papers published in conferences and journals between the years 2016 and 2022 are considered in this review. These papers are categorized according to equipment, defect, parameters, and method as shown in Figure 1.

The review reveals that the majority of the research selected the CNN and LSTM as the DL algorithm and the bearing of the motor as the defects diagnosis. Poorly applied hybrid strategies between several DL methodologies were observed. In addition, the DL algorithms' optimal design variables can only be determined by experience and trial and error. Trial and error have the disadvantage of taking longer than modern optimization approaches like swarm intelligence.

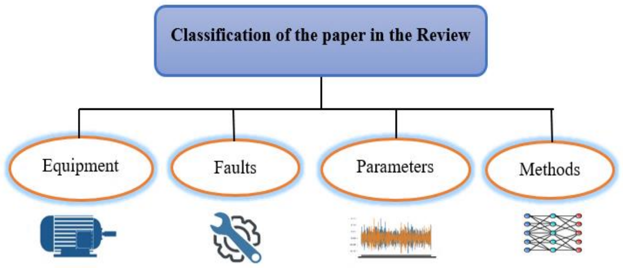

Figure 1. The layout of the review

2. PREDICTIVE MAINTENANCE

The profitability and productivity of any industrial company could be improved by selecting the most suitable maintenance management. For example, a Swedish paper mill company was saved about $0.975 million per year by having an efficient maintenance strategy. The maintenance strategy avoids all unplanned shutdowns and poor quality products [13]. The challenges of maintenance equipment are still the main issues due to several factors including competition, complexity, and cost [14]. The cost of maintenance can be considered an accidental-based cost, which means that the cost of maintenance is difficult to be controlled or planned. This section explains and shows categories of maintenance policies and their performance in any economic industrial company. In general, there are three types of maintenance: corrective, preventive, and predictive.

Corrective maintenance (breakdown maintenance or run-to-failure maintenance) can be defined as a traditional method that performs when failures occur and this will cost the company losses due to the system breakdown. In this way of maintenance, the reason for the fault will be discovered when the equipment stops working. This method is required that the new part of the equipment is always available or quickly brings a piece to be replaced instead of damaged as soon as possible to avoid production losses [15]. On the other hand, preventive maintenance carries out by companies during a fixed time interval and planning continues to change the part no matter if that part is still working or out of function [16]. It aims to reduce faults and degradation of equipment. Here, the routine of the maintenance that is been performed on the equipment may be unnecessary or not sufficient to avoid the breakdown of the machine. Moreover, failures may be happen between periods of the scheduled time of maintenance [17].

Nowadays, the maintenance community has concentrated its studies on Predictive Maintenance (PM). PM utilizes many parameters to predict failure as compared to conventional maintenance. PM performs the actual platform that is required for real maintenance functions. It minimizes the amount of sudden failure. In addition, it reduces the cost and time in routine repairs and decreases the interval between periodic servicing. In fact, PM depends on continuance monitoring of the actual condition of the system. However, PM relies on kinds of technologies for specific real-time monitoring variables including vibration, thermography, current, temperature, ultrasonic, and other non-destructive testing techniques [18].

3. DEEP LEARNING METHODS

Deep Learning (DL) or representation learning (RL) is a part of an Artificial Neural Network (ANN) [19]. The power of getting big data and high-performance computing make DL important and active techniques for solving different issues with high accuracy [20, 21]. DL paradigm consists of a Feed-Forward Neural Network (FFNN) with a single layer or multiple-layer perceptron (MLP) and has one perceptron. In general, these structures contain an input and output layer in addition to numerous hidden layers in multiple-layer [22], if it has one hidden layer called an Extreme learning machine (ELM). It is a type of ANN with a feed-forward neural network [23]. The precision and ability of DL are increased by applying more hidden layers with neurons. However, supervised, unsupervised and hybrid are the general categories of DL. The first type is also known as discriminative learning or classification is used in pattern classification and regression [24].

The popular architectures for this type are Deep Neural Network (DNN), Convolution Neural Network (CNN), and Recurrent Neural Network (RNN). DNNs are feed-forward neural networks with multi-layer. It is been considered as simplest architecture. Each layer has an input to the next layer and the complexity increased in high-level data reaching the output layer [25]. In CNN, the main portion of CNN is minimizing the number of parameters. There are three layers named: convolution layers, pooling layers, and fully connected layers. Convolution layers are using a filter or kernel to extract features from input data to introduce feature maps. The next layer is the pooling layer, this layer is operating on a feature map that comes from previse layer reducing it and taking the data down to choose the characteristics and data filtering. The processing and high-level characteristics of the network are finished in two layers above. The efficient global characteristics are sent to the fully connected layers. CNN's are usually merged in a basic network e.g. image classification [26-28]. Another structure of supervised learning is the RNN. RNN is the best architecture for learning sequences of length and can introduce a single and sequential output. Using a neural sequence model network achieves time series applications with high regularization, such as speech recognition. RNN is very important in visual data processing like image, video, and audio [6, 29]. RNN is a feedback network that permits the information to continue. It can include many immediate identical nodes [7]. LSTM is a type of RNN which introduced to solve gradient vanishing problems in RNN when data with long dependences is used for training [30].

Secondly, unsupervised learning or clustering techniques express the learning approach without using the target information (teacher) in the learning task. A deep auto-encoder

(AE), deep Boltzmann machines (DBM), and Deep Belief Network (DBN) are the popular types of unsupervised learning methods [31]. Boltzmann machines are probabilistic learning. Flat feature representations such as vectors, matrices, and tensors are used frequently in the DBM [32]. There are two parts to the AE network. The first one tries to compact the data input to a comparatively small length description through training. The other part is been used to rebuild the initial input from this small description. The high-level feature of the training is established in a way when the AE tries to derive a compressed description in an easy way to rebuild the initial data with lower loss. AE is used in indexing, searching and feature embedding, and clustering or dimensionality reduction.

Lastly, the hybrid method combines the two above categories for supervised and unsupervised learning to improve them. A hybrid clustering paradigm calm of supervised/classifier learners to pre-process the training data and one unsupervised teacher to teach the unsupervised result or conversely. Moreover, the enhancement of this model can contain two unsupervised, two supervised methods, and one supervised with one unsupervised [33]. For example, a multi-layered perceptron is a standard of DNN are contains a group of layered before the real multi-layered perceptron layers for classification, these layers are used successfully for feature extraction and dimension reduction unsupervised before training and input data filter [34]. Figure 2 illustrates the types of DL networks.

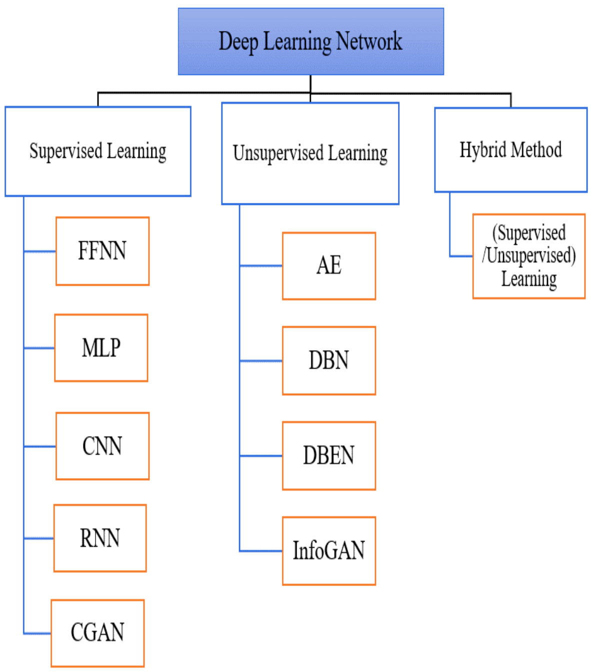

Figure 2. Deep learning architecture

4. PREVIOUS REVIEW ARTICLES

This section gives a brief explanation of the previous review papers in PM using DL methods that have appeared in recent years in different applications. Rieger et al. [35] reviewed the recent trends in the application of DL methods in IoT environments and PM. The study shows that DL methods play an essential role in the industry where several applications are utilized and improved in PM within the IoT environment. This is due to the use of PM applications, and exploring the field of forecasts and real-time processing with DL methods.

Çınar et al. [36] presented a literature on the application of ML in the PM for smart manufacturing. It was noticed that PM has a huge market chance and that ML is an unconventional solution to PM execution. The paper categorized the studies based on the ML algorithms, machinery, and devices used, the way of collecting data, categorization of data, volume, and type. The study presents a comprehensive overview of the most recent developments of ML model employed to PM for industry 4.0 and highlighted the major contributions of these researches. The algorithms of ML and types of sensors in an industry with PM in electrochemical systems were explained by Namuduri et al. [7]. It showed that there will be a rise in the utilization of data from electrochemical and solid-state sensors for PM. This research examined engine failure prediction case studies and DL techniques for PM. It also goes through the industry's existing sensor usage and potential uses for electrochemical sensors in PM.

Fausing and Shaker [37] reviewed the PM of the pump system and thermal power plants based on data-driven models. This study presented the last implementation of PM and provided a structure for developing the PM model, also presented the advantage and limitations of some algorithms in ML. A comparison was given between this field and the area of a pump with heat and power plants. This study reveals that many experimental data-driven approaches have been effectively implemented, but more industrial studies would be helpful for the PM area. Companies and industries considering large-scale applications would gain from studies into the scalability of systems. Here, it will be interesting to look at a technique for automatically maintaining the produced model. Although it offers a specialized grasp of the topic under consideration, this essay can also be utilized to comprehend the PM area as a whole. The paper by Dalzochio et al. [38] provided the challenges of PM in business operations and the use of ML algorithms. This paper focused on recognizing architectures used in reasoning based on ML models and PM in cyber-physical systems. Investigating academic developments in defect prediction is the goal of this study. Concepts like a design support structure and a PM decision support system are taken into account for predicting failures. It is concentrated on platforms for Industry 4.0 and how PM leverages machine learning and logic. This paper focuses on the difficulties in applying ML methods and ontologies in the context of PM and carries out a systematic review of the literature to evaluate scholarly works between 2015 and 2020. Drakaki et al. [2] presented a review of the PM of the induction motor based on the multi-agent system (MAS) with DL methods of early fault detection and diagnosis techniques. The study was been shown that the PM based on MAS with DL methods for induction motor seems to be very promising. Finally, Khan et al. [39] offered reviewed recent trends in the implementation of PM in aircraft engine and hydraulic systems. This research includes a result of system detection depending on forecasting for greater precision before failure occurs. Various ML models are introduced for example DL, NN, logistic regression, and long-short-term method. And recognizing fresh trends and difficulties. Additionally, this work emphasizes the significance of PM and cutting-edge data pre-processing methods for big data sets. Table 1 lists all the recent review papers for the PM based on DL and ML methods in different systems.

Table 1. Attributes of previous review studies

Research	Scope of the work	Year rang	Number of papers reviewed
[35]	Review recent research in the IoT area using DL and PM	(2012-2018)	10
[36]	Review ML techniques that applied to PM for smart manufacturing	(2015-2020)	67
[7]	Review of the electrochemical sensors application in PM based on ML methods	(1985-2019)	19
[37]	Review of recent trends of application of PM in pump systems and thermal power plants based on data-driven models	(1997-2020)	35
[38]	Investigate failure prediction challenges of PM in Business operation and the use of ML algorithms	(2004-2020)	20
[2]	Review of recent trends of application of PM in induction motor based on DL	(2009-2020)	28
[39]	Review challenges of applying PM for aircraft engine and hydraulic systems based on ML methods	(1979-2021)	71
Proposed study	Review recent research of PM based on DL for the electromechanical system	(2016-2022)	30

5. REVIEW METHODOLOGY

5.1 Material collection

In this study, a review has been prepared based on the applications of the DL methods on the PM that applied to the electromechanical system. The time window of this review is between the years 2016 to 2022. The research was using the Google-scholar and Scopus database to search for conferences and articles stored in the English language.

Figure 3 shows the distribution of the papers that is covered by this study based on the published year. The search in this work uses several indexes such as "predictive maintenance", "deep learning approach", "electromechanical system," "motor," and other variety methods of DL including ANN, CNN, LSTM, and AE. For instance, the search phrase formed in this way: "predictive maintenance in an electromechanical system using deep learning approach." It is not a complete survey of all DL methods but the ones that are relevant to this area and the most powerful. It depends on qualitative rather than quantitative data analyses. Figure 4 describes the distribution of publications based on journals.

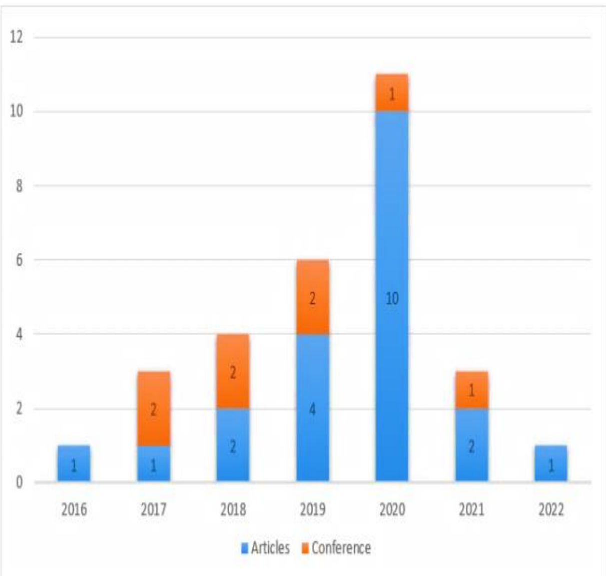

Figure 3. Distribution of publications per year

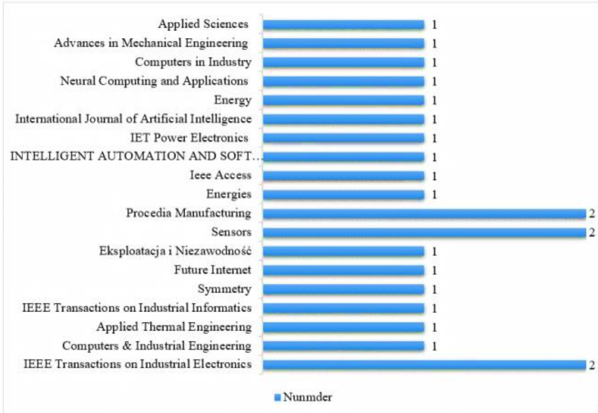

Figure 4. Distribution of publications based on journals

5.2 Descriptive analysis

This section presents the descriptive analysis of the papers that are presented in this review. In general, the papers prove the successful applications of the DL approach in the PM for different electromechanical systems. The motor is considered a major part of any electromechanical system and hence most studies were focused on it. It is found that there are fourteen papers of researches considering the motor as equipment for PM . Six papers are concerned with the rotating machine . Two studies are focused on CNC machines. Finally, eight articles present different systems such as pump, cooling radiator, compressor, elevator system, autoclave sterilizer, worm gearboxes, railcar factories, conveyors system.

In the terms of motor, the paper contains the bearing as the fault. On other hand, stator winding faults have been used in two papers. Moreover, various (operations/conditions) failures are found in different systems like worm gearboxes, compressor, cooling radiator, pump and CNC machine.

ANN, CNN, and LSTM methods were applied in the motor by utilizing the current signal as a parameter for diagnosis prediction. In general, CNN was considered the highlighted method in motor, cooling radiators, and worm gearboxes, especially in rotating machines. ANN and AE approaches use vibration signals in CNC machines. Different electromechanical systems like motor, rotating machine, compressor, and autoclave sterilizer employed RNN-LSTM methods. Table 2 illustrates the different systems with their faults, parameter, and methods in detail with the authors.

Table 2. List of studied papers

Work	Equipment	Fault	Parameters	Method
[40]	Motor	Bearing	Current signal	CNN
[41]	CNC machine	Condition	Vibrations	ANN
[42]	Motor	Operations	Current and voltage signal	ANN/MLP
[43]	Pump	Condition	Multi variables	AE
[44]	CNC machine	Mechanical	Vibrations signal	SAE
[45]	Motor	Operations	Stator currents	ANN
[46]	Motor	Bearing	Vibrations signal	LSTM
[47]	Rotating machinery	Bearing	Vibrations signal	AE+ MLP
[48]	Rotating machinery	Bearing	Vibrations signal	LSTM
[49]	Cooling radiator	Condition	Thermal image	CNN
[50]	Rotating machinery	Degradation image	Infrared image streams	(CNN+LSTM) (LSTM+AE)
[51]	Compressor	Condition	Multi variables	RNN-LSTM
[52]	Elevator system	Movement	Acceleration data	AE
[53]	Motor	Condition	Current signal	EWT-CNN
[54]	Autoclave sterilizer	Pump	NTC thermistors	LSTM
[55]	Worm gearboxes	Operations	Multi variables	CNN
[56]	Rotating machinery	Rotor, bearing	Vibration signals	CNN
[57]	Railcar factories	Wheel bearing	Temperature variation	ANN
[58]	Rotating machinery	Bearing	Accelerometers	CNN
[59]	Motor	Bearing	Current signal	ANN
[60]	Conveyors system	Motor	Multi variables	CNN
[61]	Motor	Bearing	Accelerometer	LSTM+RNN
[62]	Motor	Rotor bar	Torque control	ANN
[63]	Motor	Stator winding	stator currents	ANN
[64]	Motor	Condition	Vibrations signal	ANN
[65]	Rotating machinery	Bearing	Rotation speed, load levels	CNN
[66]	Motor	Stator winding	Multi variables	MLP+LSTM+CNN
[67]	Motor	Operations	Current signal	ANN
[68]	Motor+rotating equipment	Bearing	Vibrations signal	CNN+DNN
[69]	Motor	Bearing	Microphone, accelerometer	DCNN+CNN-LSTM+LSTM

6. DISCUSSION

In order to improve operational efficiency, the industrial operation has developed to allow for more complex manufacturing processes. The "Industry 4.0" is made up of a high level of interaction between production systems, computing systems, and communications. In this context, PM is incorporated into the digital manufacturing. This emerging is crucial due to the sizeable resources and financial assets as well as the requirement for business managers to have a clear understanding on how to utilize this emerging of digital technologies. A strong digital environment is required for PM implementation. This refers to a culture that encourages experimenting with new technologies and places a high value on staff engagement. Industrial management should take into account changes to its management structure, such as the addition of reliability technicians, process technologists, data analysts, and IT specialists, as well as efficient communication methods that combine the skills of the IT organization and the maintenance activity. Effectiveness PM focuses on knowledge and abilities. Manufacturing businesses need to spend in data analytics positions or create new positions that bring capabilities that are complementary to those found in maintenance procedures, including Industry 4.0 professionals and citizen data analysts.

Early machine problem identification, increased machine uptime, extended equipment life, and component optimization are all benefits of proper industrial equipment maintenance. To end this, all of these advantages will result in improved and leaner production processes with lower costs that can be passed directly on other investment. In addition to reduce the cost, the effectiveness of the using the equipment also eliminates the number of resources needed as a factor of sustainability [70].

Electromechanical systems usually come with sensors that gather data about their status continuously [71, 72]. In this regard, the deployment of PM strategies is a desirable approach to act based on factual information rather than preventative recommendations. The ability to characterize a range of behaviors of the system's operational variability is essential in order to enable an effective application and prevent false positives or even false negative results, on other word, the capability of detection the unknown conditions of the asset [72]. The area of computer engineering known as Artificial Intelligence (AI) is dedicated to creating machines that behave similarly to humans. With the initialization of multiple techniques utilizing ANN, the DL had a significant impact on the performance of computing systems in the PM in real-world problems. Intelligent data categorization tasks are a term for several techniques used by computational intelligence systems to diagnose machine faults. Like Binary Classification and Multi-Classification in DL method [73-75]. For moreover the development in DL techniques and entry of the optimal value in PM with production control used together can guarantee the Production system's proper functioning [76].

7. CONCLUSIONS

Nowadays, Predictive Maintenance (PM) takes dynamic decision rules for maintenance. The combination of PM with Deep Learning (DL) algorithms has acquired more attention in smart manufacturing within the context of industry 4. The modern diagnosis fault approach for a complex system such as an electromechanical system becomes an effective way for maintenance. This study introduces a comprehensive review of the recent works of DL techniques that are applied to PM for electromechanical systems by classifying the research according to equipment, fault, parameters, and method. 30 papers were published in conferences and journals which are reviewed within a time window between the years 2016 to 2022.

Many authors consider the motor as critical equipment in electromechanical systems. The observation of the study indicates that the majority of studies choose the bearing of the motor as the faults diagnosis and the CNN and LSTM as the DL algorithm. The hybrid techniques between different DL methods are poorly applied. The optimum value of the design variables in the DL algorithms is only based on experience and trial and error. The drawback of trial and error is time-consuming in comparison with utilizing the recent optimization techniques such as swarm intelligence. As a result, for more accurate dynamic decisions and to enhance the performance of the PM in any system, applying the optimizations method and hybrid different models of DL are needed to be explored in future research efforts.

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NOMENCLATURE

Artificial Intelligence	AI
Artificial Neural Network	ANN
Auto-Encoder	AE
Computer Numerical Control	CNC
Conditional Generator Adversarial Neural Network	CGAN
Convolution Neural Network	CNN
Cyber-Physical System	CPS
Deep Belief Network	DBeN
Deep Boltzmann Machines	DBM
Deep Learning	DL
Deep Neural Network	DNN
Empirical Wavelet Transform	EWT
Extreme Learning Machine	ELM
Feed-Forward Neural Network	FFNN
Info Generator Adversarial Neural Network	infoGAN
Long-Short Term Memory	LSTM
Machine Learning	ML
Multiple-Layer Perceptron	MLP
Predictive Maintenance	PM
Recurrent Neural Network	RNN
Stacked Auto-Encoder	SAE