Machine Learning Techniques for Smart Manufacturing: Applications and Challenges in Industry 4.0

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Machine Learning Techniques for Smart Manufacturing: Applications and Challenges in Industry 4.0

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Abstract

The Industry 4.0 is now underway, changing traditional manufacturing into smart manufacturing and creating new opportunities, where machines learn to understand those processes, interact with environment and intelligently adapt their behaviour. Big data and artificial intelligence (AI) make machines in industrial production smarter than before addressing the question of how to build computers that improve automatically through experience. Machine learning (ML), as a subfield of AI, has become the main driver of those innovations in industrial sectors, which provides the opportunity to further accelerate discovery processes as well as enhancing decision making. However, ML algorithms learn directly from the examples, data and experience and are able to figure out how to perform important tasks by generalizing from them. This paper summarizes challenges and future trends of ML applications for smart manufacturing and provides an overview of several ML algorithms (e.g. support vector machine, k-nearest neighbour, neural network etc.) that are able to give the answers to those issues and avoid the potential problems in the future.

Keywords: artificial/computational intelligence, deep learning (DL), industry 4.0, machine learning (ML)

1. INTRODUCTION

The Industry 4.0 lays on the increment of available data sets. Different types of available, large and complex sets of data, namely big data, cannot be processed by using existing conventional technologies. Advanced methods, technologies, algorithms and software must be used in order to collect and extract data from the manufacturing environment [1]–[4]. Big data changes the way decisions are made inside the manufacturing environments based on different scientific areas such as computer science, mathematics and advanced statistics [4]–[6].

The field, that combines together all of these sciences is *machine learning* (ML) [4], [5]. ML is becoming the most important method that is used for predicting and classifying the difficulty solving problems inside the production systems [5]. ML uses increased computing power and various software for gaining the meaningful information and knowledge from the big data, which are collected from the environment, but also, has ability to learn from those data by getting the artificial/computational intelligence [5], [6]. For some specific tasks, ML is able to achieve a higher level of requirements than human. This highlights the importance of the big data from which the information is obtained. However, the balance has to be found. Too much information can lead to delay of the actions or the wrong conclusions of the certain problem and the lack of the information may not lead to problem solving [4]. Another great issue is related to security aspect of the data [7]. Having that issue in mind, ML has to utilize the different techniques and algorithms in order to achieve maximal benefit from the data [4], [6].

The most important techniques that are used for learning, classified by the available feedback, are supervised, unsupervised and reinforcement learning methods [8]. This paper focuses on the challenges and applications that ML faces with in today's manufacturing systems. Also, the accent is put on future trends of ML in manufacturing applications where the primary objective lays behind the utilization of big data in order to accomplish cost efficient, fault-free and optimal quality manufacturing process [9].

2. BACKGROUND

This section presents an overview of the related studies of Industry 4.0 and ML, as well as the ML techniques.

2.1. Industry 4.0 and Machine Learning

The rapid development of technologies interconnected with ICT and internet of things enables the growth of manufacturing which has led to the Industry 4.0 [10]. The implementation of CPS combined with IoT can provide intelligent, flexible systems capable of self-learning which presents the core of Industry 4.0 [1]. In order to achieve intelligent and flexible systems, the big data is required. In knowledge discovery in databases (KDD) of big data, machine learning plays an important role along with data mining, statistic, pattern recognition and other methods [11], [12]. ML, as a part of intelligent system in Industry 4.0, is broadly implemented in various fields of manufacturing where its techniques are designed to extract knowledge out of existing data [13]. The new knowledge (information) supports the process of decision-making or making prediction of manufacturing system. But the end goal of the ML techniques is detection of the patterns among the data sets or regularities that describe the relationships and structure between those sets [4].

2.2. Machine Learning techniques

ML system, that maps an input into an output, needs to be trained in order to learn. The system training is achieved by giving an input data and its corresponding output while determining the structure in the machine so that mapping can be learned [5].

Different researches have different approaches to structure the field of machine learning, but the structure that is most widely used is classified by learning processes, and that is supervised, unsupervised and reinforcement learning, shown in Figure 1 [4], [8], [14].

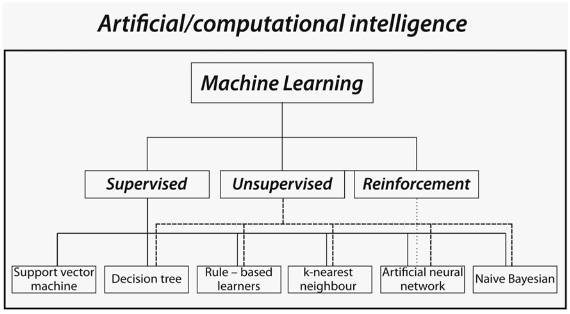

Fig 1. ML techniques and algorithm (adapted from [4]*)*

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The supervised learning is machine learning technique, specified for large amount of input data (training sets), are applied to the systems where the correct response is provided by the knowledgeable expert [4], [5].

In supervised learning, a system is trained with data that has been labelled. The labels categorise each data point into one or more groups. Then the system learns how this training data is structured and uses this to predict in which categories to classify new output data [3]. The final goal of completed supervised learning process is that the outputs are close enough to be useful for all given input sets [15].

The most common supervised machine learning assignments are classification and regression [4], [16]. In classification assignments, the program has to learn how to predict the most likely category, class or label for discrete output values from one or more input data sets [16]. Similar to classification, regression problem, also requires supervised learning techniques. The difference in regression problems is that programs must foresee and predict the value of a continuous output by themselves [17].

According to Wuest et al. [4] as well as Jordan and Mitchell [18], the supervised learning is the most commonly used ML technique, because majority of applications can provide labelled data.

UNSUPERVISED LEARNING

The unsupervised learning represents the intelligent learning where evaluation of the action is not dependent, provided nor supervised, because there is no knowledgeable expert [4], [5], [15], [19]. Unlike supervised learning, the unsupervised learning does not learn from labelled data. Instead of that, it discovers patterns among the data [16].

The assignment of unsupervised learning is to discover groups of related observations of the input data, namely clusters [6]. Such observations within groups have cognation based on some similarly measurements where similar points are grouped together [6], [16]. The main goal of unsupervised learning is to discover the unknown relationships between classes using the clustering analysis [4]. According to Jordan and Mitchell [18] and Hackeling [16] the another unsupervised learning task is dimensionality reduction. It represents the process of discovering the relationships between input data sets and can be used for visualising. Considering that some problems might contain thousands and thousands of input data, problem with big data becomes impossible to visualize [16].

REINFORCEMENT LEARNING

Reinforcement learning presents another ML technique that has focus on learning from experience [4]–[6]. According to report of The Royal Society [6] and Jordan and Mitchell [18], reinforcement learning presents combination of unsupervised and supervised learning techniques, where the information available in the training data is intermediate between supervised and unsupervised learning, while Wuest et al. [4] and Hinton [5] consider it as “a special form of supervised learning”, known as semi-supervised learning.

Reinforcement learning system receives inputs while interacting with manufacturing environments and making sequential decisions in order to maximise future rewards [6]. It addresses assignments where some of the data presents labelled training sets and other data does not [5]. In reinforcement learning, instead of training datasets that indicate the correct output for a given input, the training datasets are presumed to provide only an indication whether an action is correct or not. If an action is not correct, there still remains the problem of finding the correct action [18].

3. ML ALGORITHMS IN MANUFACTURING

This section provides an overview of ML algorithms used in manufacturing processes.

3.1. Support Vector Machine

Support vector machine (SVM), a supervised learning algorithm, is used for linear as well as for non-linear problems, such as classification and regression [5], [16], [20]. SVM was formed based on the idea of creation the flat hyperplane or set of hyperplanes [21]. The hyperplanes divide the high-dimensional or infinite-dimensional vector space into distinguished parts with maximum margin distance between the two nearest training data points of classes [20], [21]. SVM test point of data is said to belong to one class if it is located below the hyperplane, and the other way around [21]. The mapping into an infinite-dimensional vector space is preformed by kernel functions which led to the main goal of SVM and that is fixing the computational predicting problems [21], [22]. The goal of an SVM is to produce a model, based on the training data, that predicts the test point of data where is needed a subset of the training data [5]. In order to achieve the goal, i.e. to achieve prediction of maximum accuracy, SVM requires a large sample size [23].

However, the advantage of SVM is its ability to work with incomplete data as well as the speed of classification. The biggest drawbacks of SVM is slow speed of learning and its lack of explanation ability to humans [23].

3.2. Decision Tree

Decision tree is machine learning algorithm that is easily understandable and humans interpretable due to its graphical representation [5], [24]. The challenging issue is finding an optimal type of decision tree for training data sets. Two types of decision trees are mentioned by Hinton [5]. The first type is classification tree which gives a categorical output, while the second type is regression trees, which gives numerical output. Another disadvantage of decision tree is the inability to solve non-linear problems unlike the SVM algorithm, but it has quite high speed of learning [23]. Decision tree has wide utilization in exploration and prediction problems due to its ability to score so highly on critical features of data mining [25].

3.3. Rule – Based Learners

Rules-based learners, also known as expert systems [5], are considered to be one of the major forms of machine learning in combination with data mining. Also, rule-based learners are used for extraction the information based on statistical significance with the help of “if-then” rules [11]. Although they have application in both, supervised and unsupervised learning, they have the greater utilization in unsupervised learning environments for KDD due to its comprehensibility [23], [25]. As Hinton [5] and Kotsiantis [23] noticed, the drawback of rule-based learners is classification accuracy due to acquisition of the knowledge. However, classification accuracy can be improved by automatic feature construction algorithms and combining different characteristics where the background expert knowledge is used.

Another advantage of the rule-based learners is that the system is able to explain the process how the result was generated where the learning algorithm always methodically checks the entire sets of data [5]. Considering the noise, rule-based learners are resistant to it due to their pruning strategies which avoid overfitting the data [23].

3.4. k-Nearest Neighbour

The k-nearest neighbour (k-NN) is the ML algorithm used for non-linear problems, i.e. classification and pattern recognition that requires computation of distances between sample of data where each input data is labelled of its k closest neighbouring samples [26].

Ismail et al. [25] consider that k-NN as a prediction algorithm, similar to clustering due to its ability to predict and compare similarities of the big data. According to Kotsiantis [23], k-NN algorithm is very sensitive to data values that are missing, noisy, fuzzy, irrelevant and redundant, and the speed of classification is slow. That leads to accuracy in general which is quite low. Also, the k-NN is hard to interpret due to its unstructured collection of training big sets of data. Contrary to that, k-NN has a great speed of learning which makes it one the fastest learning ML algorithms [23]. Figure 4 represents an example of k-NN where the space is divided in four different areas by coloured circle. An empty circle presents a new data, which falls in green area.

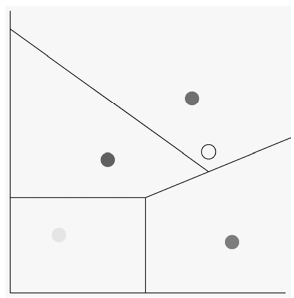

Fig 4. *An example of k-NN algorithm*

3.5. Naive Bayesian

Naive Bayesian (NB) represents ML algorithm, which is defined as a very simple model composed of acyclic graphs. Acyclic graphs of NB model have only one parent and multiple children. The parent represents the unobserved node, while the children are observed nodes [4], [23].

According to Kotsiantis [23], naive Bayesian algorithms are usually less precise that some other ML algorithm that are more sophisticated (i.e. ANN) due to the supposition of independence among children. The opposite of

Kotsiantis opinion, Hastie et al. [15] consider that NB algorithm can often outperform some more sophisticated algorithms due to the fact that it cannot affect the estimation dramatically and that NB has significant advantages over other algorithms.

Naive Bayesian is useful for problems related with classification, regression, clustering and others [27], [28]. Also, it requires little storage space during both stages: training and classification [4]. But the major advantages of the NB classifier are its short computational time for training, fast process of learning and ability of working with big, fuzzy, noisy and incomplete data [4], [23].

3.6. Artificial Neural Network

Artificial neural network (ANN) is ML model that is used for nonlinear classification and regression problems [11], [16], applied in various fields of manufacturing due to the fact that it plays an important role in today's problem solving by parallel processing, where it simulates the decentralized "computation" of the humans central nervous system. The ANN allows an artificial system to perform supervised, unsupervised and reinforcement learning assignments [4]. The challenging task for ANN is achieving the high accuracy where the big data is required. Another issues are related to dealing with overfitting, missing data values, speed of learning and complexity of the models they produce [23].

Similarly to SVM, ANN is capable of handling the high-dimensional data, continuous features and high-variance, but the process of learning is slow [23], [25]. The ANN is good for KDD for hidden patterns or trends due to its abilities of processing which has similarities with human brain [25]. In contrary to that, ANN requires complete records of data to do their work. In other words, the data must not be fuzzy, noisy or incomplete. Another drawback is that the large size of sample is required in order to achieve its maximum prediction accuracy [23]. The example of ANN algorithm is shown on Figure 5, where is presented the layers of which it is constructed. There it can be multiple hidden layers, not just one as presented. However, if there is a greater number of hidden layers with very large dataset, than is talked about deep neural networks (DNN) [29].

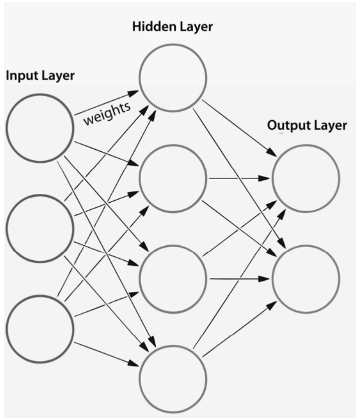

Fig 5. An example of ANN (adapted from [30]*)*

DNNs are based on fundamental concept of ANN. A deep structure of DNN exploits multiple hidden layers with multiple neurons in each layer, a nonlinear activation function, a cost function and a back-propagation [31] algorithm for information-processing in a hierarchical architecture for pattern classification problems [32].

In comparison with ANN architectures, DNNs are able to learn high-level features, which are more complex and abstract, by integrating feature learning [31] and model construction into a single model. That model is created by selecting different kernels or tuning the parameters by end-to-end optimization where the parameters of DNN model are trained jointly without human supervision [33], [34].

4. APPLICATIONS, CHALLENGES AND FUTURE TRENDS OF MACHINE LEARNING

Machine learning techniques bring many improvements inside the manufacturing environments. The conducted review led to identification of application, challenges and future trends of ML which are discussed in the following subsections.

4.1. Application

The application of ML techniques is in constant enlargement over the last couple of decades [35]. Growing application of ML has led to the availability of complex big data that has certain patterns [36], database technologies, computer power [37] and usability of ML techniques [4].

From the perspective of manufacturing, various types of big data sets can be captured, collected, extracted and analyzed in order to improve the traditional manufacturing systems [1], [37]. Finding the knowledge in big data and transforming it into information is done by KDD with the help of ML techniques [1]. According to Escobar Diaz and Morales-Menendez [37], the primary objective of ML applications in combination of big data analytics is the achievement of defect-free and fault-free processes.

Most of the manufacturing issues appertain under classification problems, where the experts of industrial field have to determine a label of the class to specific object or a situation based on the big data set [38]. Problems of classification do not have to be related only to manufacturing but can relate to the entire industry. As Rikalovic et al. [39] mentioned application of machine learning techniques in combination with ANFIS (adaptive neuro-fuzzy inference systems) that rely on expert knowledge has utilization in intelligent decision support system for industrial site classification.

The applications of ML in manufacturing refer to pattern recognition in existing sets of data. That is beneficial for development of foreseeing the future behaviour of the manufacturing system with the end goal of detecting the present behaviour patterns or regularities that describes relations between data [1], [4].

Another advantage of ML application is its ability to further improve the extracted knowledge by learning from results where ML has ability to create new valuable information [4]. As Pham and Afify [38] mentioned in their paper, the supervised ML technique is used for building a qualitative knowledge base where the results of a simulation experiment are used. Also, the supervised learning is employed for investigating the decision-making and process-planning problems in manufacturing [38].

Nowadays, the ML algorithms have wide utilization in different manufacturing areas such as optimization, troubleshooting and quality control [36]. The result of the scientific research has shown that ML techniques is consider to be a powerful tools for permanent quality improvement in a large and complex processes, e.g. semiconductor manufacturing [38].

Machine learning techniques have application in LEAN manufacturing systems as well by using just-in-time (JIT) and kanban tools. The results of implementation of ML into LEAN manufacturing systems show that the neural networks and decision trees represent two most practical algorithms with special abilities for adjusting the number of kanbans in a dynamic JIT manufacturing environments [38].

The ML has many security applications for controlling the access and verification. On the one hand, security application uses pattern recognition along with other methods where the goal is to decide if the given face needs to be classified or labelled as unfamiliar. On the other hand, the goal of verification is to decide whether person is the person he claim that he is while dealing with various conditions, e.g. lighting conditions, facial expressions etc. [35].

The application of ML algorithms such as k-nearest neighbour and naive Bayesian have utilization in building predicting models such as predicting the failure of airplane components before they stop working [38].

Another very important application of ML is related with transparency as “the ability of an organization to unravel and quantify uncertainties to determine an objective estimation of its manufacturing capability and readiness” [40]. The transparency can be achieved as reducing the complexity of the results where ML algorithms evolve the patterns from existing data and extracting the knowledge used for decision-making and giving an approximations about future behaviour [4]. Also, as Lee and Lapira [41] and Lee et al. [42] stated that the increment of transparency in manufacturing environments has a number of advantages, but the application of ML leads to the major cost reduction in every aspect of the transparent manufacturing environment.

4.2. Challenges and future trends

Machine learning is still young scientific field that is growing rapidly due to its practical applications. Having that in mind, one of the major trends is related with the environment in which a ML algorithms operate due to issues of parallelism [43]. ML systems are interconnected with the complex software collections which run on computing platforms and provide a range of algorithms and services to data analysts [43]. Due to that, as mentioned before, trends but also the challenges are related with big data from which knowledge can be extracted [13].

Today, manufacturing is facing an increment of challenges related to complexity and dynamic behaviours [44] while adding the fact that the manufacturing is affected by uncertainty [4]. In other words, the constant enlargement of big data and its availability, high-dimensionality, variety as well as homogeneity represents the main challenges in manufacturing environment because the knowledge cannot be extracted. In order to overcome these challenges, the machine learning techniques and algorithms are used [4]. However, the gathered big data has tendency to contain irrelevant, missing and redundant information which can lead to the impact on the performance of the ML learning abilities [1].

The major concerns related with collecting new kinds of big data, motivated by its economic value, is privacy and security issues since the big data are stored in virtual cloud platforms [28], [43]. The misuse of big data in manufacturing, as well as in entire industry, is in increment, because of the wireless remote control of the physical devices. Therefore, it is possible to take control over the physical machinery if the data is not properly secured [45]. Due to such concerns, the additional researches are needed in order to improve the storage as well as the security of big data. However, sometimes the nature and size of big data does not allow the big data to be located in the single space, but has to be distributed over the distinct physical locations. In order to achieve connection as well as the learning system between the big data from the entire manufacturing environment the communications through wireless devices is required [43].

Another major challenge as well as the future trend is development of the ML algorithms as well as the improvement of existing ones implemented in manufacturing systems that are able to handle various situations and learn from them [1]. As the Wuest et al. [4] consider that the question what ML technique and algorithm to choose is a great issue due to their advantages and disadvantages. Because of that the so called "hybrid algorithms" that present the combination of various ML algorithms, are becoming more and more used in the flexible manufacturing systems [46]. However, the biggest challenge for the development and application of ML algorithms that manufacturing is facing today is finding the human experts in data science and optimization scientific fields having in mind that different skills are required [47].

5. DISCUSSION AND CONCLUSION

This paper provides the preliminary literature overview of the machine learning techniques as a part of intelligent system (i.e. supervised, unsupervised and reinforcement learning) and the mostly used algorithms as well as their advantages and disadvantages within the Industry 4.0. Due to the fact that there can be confusion when it comes to machine learning and statistics, a detailed comparison is given and the differences are presented between these two methods. Also, the application, challenges and future trends of machine learning represent the the main focus of this paper.

The application of ML is closely related to big data without which the development and implementation of ML techniques would not be possible due to the fact that extracting the knowledge is the most important action that lead to the achievement of defect-free and fault-free processes. Also, the further improvement of ML application enable the the learning process where the artificial/computational intelligence plays the most important role. Today, the ML algorithms have wide utilization in different manufacturing areas such as optimization, control, troubleshooting, security and verification where the increment of transparency of the entire manufacturing environment is beneficial for cost reduction without affecting quality of production. Also, ML algorithms have application in semiconductor as well as in LEAN manufacturing environments where the results of the experiment show an improvement in process quality.

Challenges and future trends in machine learning are closely related. All that represents the current challenges also represents the future trends in further research on ML techniques and algorithms. The most challenging assignment as well as the biggest trend is gathering the big data from the manufacturing environments in order to have enough extracted knowledge and information for developing the ML algorithms that are able to learn automatically from patterns and previous behaviour. Sometimes big data can be irrelevant, fuzzy, noisy and redundant which additionally complicates the learning process. Also, because of the fact that the extremely large amount of data is collected, the storage space represents the other challenging issue which leads to privacy, security and economic questions. However, still the biggest challenge and future trend that manufacturing is facing today is reflected in the further development and application of ML algorithms, but also finding the human experts in data science and optimization scientific fields represent another challenging issue. This paper is the initial part of the research, so in future its continuity will contribute to the further exploration and development of ML and its implementation inside intelligent manufacturing environments with focus on Industry 4.0.

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