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Suresh Babu Rajasekaran
Product Management Lead, NVIDIA, Santa Clara, United States

Correspondence Author;
Suresh Babu Rajasekaran
Product Management Lead, NVIDIA, Santa Clara, United States

Applications of machine learning in manufacturing: Benefits, issues, and strategies

Suresh Babu Rajasekaran

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Abstract
The manufacturing sector now has access to data at a level never before possible. This information could comprise sensor readings from the assembly line, information about the surrounding area, machine tool settings, etc. These data may also take many different forms and have a variety of interpretations. The manufacturing sector and its grip on the expanding manufacturing data repositories have a lot of potential to change in the future thanks to recent developments in some fields. But there are many different machine learning algorithms, concepts, and strategies. This provides a hurdle to the use of these potent technologies for many industrial specialists and may hinder them from taking advantage of the enormous volumes of data that are becoming accessible. After a detailed study, we can say that machine learning (ML) is now a potent tool for many applications in (intelligent) industrial systems and smart manufacturing, and that its importance will only grow in the future. There is a need for cooperation between a number of academic fields, including computer science, industrial engineering, mathematics, and electrical engineering. Both enormous opportunity and substantial risk are generated by this relationship.

Keywords: Manufacturing industry, machine learning's

Introduction

The manufacturing sector now has access to data on a scale that has never been seen before (Chand & Davis, 2010) [14]. These information can have a wide range of forms, connotations, and characteristics, including sensor data from the assembly line, environmental information, machine tool settings, etc (Davis *et al*., 2015) [21]. There are other names for this phenomenon, including Smart Manufacturing (USA), Industry 4.0 (Germany), and Smart Factory (South Korea). The proliferation and accessibility of vast volumes of data are frequently referred to as "big data" (Lee *et al*., 2013) [67]. It is possible to stably improve process and product quality since data is readily available, such as data pertaining to quality (Elangovan *et al*., 2015) [27]. It has been acknowledged, nevertheless, that having too much information may also be troublesome and even detrimental because it might, for example, cause attention to be diverted from the primary problems or causes or result in slow or inaccurate decisions regarding the best course of action (Lang, 2007) [67].

The manufacturing sector and its grip on the expanding manufacturing data repositories have a lot of potential to change in the future thanks to recent developments in some fields. But there are many different machine learning algorithms, concepts, and strategies. This provides a hurdle to the use of these potent technologies for many industrial specialists and may hinder them from taking advantage of the enormous volumes of data that are becoming accessible.

Therefore, the paper tries to offer an overview of the many machine learning fields and propose an overall architecture. It also argues from a manufacturing viewpoint why machine learning is a suitable and promising solution for today's and future difficulties.

The next section provides an overview of the issues that manufacturing is now experiencing. This demonstrates how effective machine learning is as a tool for manufacturers to address these issues directly.

Challenges of the manufacturing domain

The importance of the manufacturing sector cannot be emphasised, despite the fact that it is well-established. Some industrialized economies have seen a decline in the manufacturing sector's share of GDP during the previous few decades.

But in recent years, a lot of initiatives to revitalise the manufacturing sector have been made. Examples include the US and EU programmes "Factories of the Future" (European Commission, 2016) [29] and "Executive Actions to Strengthen Advanced Manufacturing in America" (White House, 2014) [103]. Manufacturing is currently experiencing challenges that are different from those in the past.

There are numerous studies that describe the main challenges that global manufacturing faces. The majority of studies indicate that the following are the primary difficulties: (Thomas *et al*., 2012) [101].

- Using cutting-edge manufacturing methods
- The creation of high-value products is becoming more and more crucial.
- Making use of cutting-edge data management, artificial intelligence, and information technologies.
- Sustainability, both in the methods of production (processes) and in the final goods.
- Flexible and adaptive supply chains and business capabilities.
- Innovation in processes, goods, and services.
- Close industry-research partnership to adopt cutting-edge technology.
- Contemporary manufacturing management techniques.

These important challenges underline the general trend toward increased complexity and dynamicity in the manufacturing industry. The product that will be produced, together with the enterprises' (business) practices and collaboration networks, appear to be getting more complicated on top of the actual production plans (Wiendahl & Scholtissek, 1994) [105]. Given how uncertainty affects the dynamic business climate in which today's manufacturing organisations operate, it is more challenging (Monostori, 2003) [77].

Machine learning techniques are good candidates for addressing some of the most pressing issues facing today's complex industrial systems. These data-driven systems must first be able to recognise highly complex and nonlinear patterns in data from a range of sources and data types in order to forecast, predict, detect, classify, and perform regression. After that, the unprocessed data is converted into feature spaces, or models, which are subsequently applied to the processes.

The sections that follow give a brief overview of the primary benefits and difficulties of machine learning applications in relation to manufacturing, as well as those applications' prerequisites and difficulties. The state of machine learning today is then examined, this time with an emphasis on manufacturing-related applications. A structuring of several machine learning approaches and algorithms is established and provided within that context.

Suitability of machine learning application with regard to today's manufacturing challenges

The terms used are briefly defined prior to determining whether ML is appropriate based on the previously mentioned requirements for a potential solution approach. According to Monostori, Hornyák, Egresits, and Viharos, machine learning can be used to solve a number of NP-complete issues that frequently arise in the field of smart manufacturing (1998).

Due to the availability of massive amounts of complicated data with little transparency as well as the improved usability and capability of ML tools over the preceding two decades, the use of ML approaches has expanded (Larose, 2005) [63]. However, auxiliary factors such potential over-fitting must be taken into account when applying (Widodo & Yang, 2007) [104]. Although it is doubtful given the strength of the algorithms, there are ways to reduce the dimensions if they turn out to be a problem. According to them, the projected results will be less affected by the reduction in dimensionality. Dimensionality is not a practical concern when using ML, and in this case, SVM, hence there is no need to lower dimensionality. This suggests that one might be a little more forgiving when including data from the production that at first looks superfluous but ends up being crucial. As was previously mentioned, this might have an immediate impact on the knowledge gap that is currently present (Alpaydin, 2010; Pham & Afify, 2005) [2, 84].

Manufacturing may be able to employ ML to extract patterns from current data sets that could serve as a foundation for predictions of how the system will behave in the future (Alpaydin, 2010; Nilsson, 2005) [2, 81]. The decision-making of the process owners may benefit from the new information (knowledge), or it may be automatically added to the system to improve it. This means that "the system designer need not anticipate and provide solutions for all likely situations".

ML methods are designed to extract knowledge from data that has previously been collected (Alpaydin, 2010; Kwak & Kim, 2012) [2, 61]. "Storage data only becomes useful when it is assessed and translated into knowledge that we may use, for example, to develop predictions," claims Alpaydin (2010) [2]. Where process checkpoints should be placed may also be affected by this (Wuest *et al*., 2014) [108]. Given the analytical power of ML techniques to extract information from data that was originally deemed to be useless, properly selecting checkpoints may be redundant, even when they make sense in terms of what data are pertinent. It might then be able to recognise more states and gather data on the entire production process. Investigating whether something is advantageous or not is crucial. There are no technical challenges in analysing the additional data because ML can handle high-dimensional data. Data acquisition challenges could still include the ability to gather the data in particular. Finding state drivers in settings with very high dimensionality is not thought to be difficult once the data are available.

Since intelligence and learning are intimately related, as stressed by Monostori *et al*., (1996) [80] learning capability must be a requirement for intelligent industrial systems (1996). Regarding the limitations and difficulties the theoretical product state idea encounters, ML offers compelling arguments. The assessed needs and the aforementioned evaluations suggest that ML approaches are a suitable remedy. The great majority of requirements found are satisfactorily satisfied using ML.

It is necessary to look more closely at the advantages and disadvantages of the different ML techniques in relation to the requirements. There are still a lot of additional problems to be solved, such how ML approaches might handle qualitative data.

The following section highlights the advantages and challenges of machine learning use in manufacturing based on the previously stated needs.

Advantages and challenges of machine learning application in manufacturing

Numerous process optimization, monitoring and control, and predictive maintenance applications in a variety of sectors have successfully used machine learning (ML) (Alpaydin, 2010) [2]. ML approaches can improve quality control optimization in manufacturing systems, particularly in "complex production environments where detection of the sources of errors is hard" (1993). However, it is typically found that ML applications are constrained, concentrating only on a small number of processes as opposed to the entire production system or software (Doltsinis, Ferreira, & Lohse, 2012) [25].

There are many different ML methodology, tools, and techniques available, each with its own advantages and disadvantages. Machine learning has developed into a distinct field of study. This section's goal is to identify a solid machine learning strategy for usage in manufacturing.

Advantages of machine learning application in manufacturing

In the prior sections, one of the general benefits of ML was demonstrated, showing that it can resolve NP-complete issues, which are frequently encountered while dealing with optimization difficulties in intelligent manufacturing systems (Monostori *et al*., 1998) [79]. Because "the majority of engineering and industrial difficulties are data-rich but knowledge-sparse," machine learning (ML) offers a technique to improve domain expertise (Lu, 1990). This section discusses the benefits in an effort to generalize them to all MLs. It is generally acknowledged that ML, by reducing cycle time and scrap, enables resource utilization in a number of NP-hard manufacturing scenarios. The manufacture of semiconductors is a large-scale, intricate process, and machine learning offers strong tools for ongoing quality improvement (Monostori *et al*., 1998; Pham & Afify, 2005) [79, 84].

Some algorithms (like SVM and Distributed Hierarchical Decision Tree) perform better than others when dealing with high dimensionality (Bar *et al*., 2005; Lenca *et al*., 2010) [5, 24]. As was already said, manufacturing may greatly benefit from machine learning algorithms that can handle highly dimensional data. Consequently, one benefit of ML application in production is the capacity to manage huge dimensionality. Another advantage of ML approaches is the enhanced use of algorithms made feasible by (often open source) programmes like Rapidminer. As a result, rapid parameter adjustments may be made to enhance classification performance, and the implementation can be (relatively) easily done in a variety of circumstances.

The ability to learn from the dynamic system and, to some extent, automatically adapt to the changing environment is provided by machine learning algorithms in this situation, given how dynamic, unpredictable, and complicated industrial processes in particular are (Lu, 1990; Simon, 1983) [71, 93]. Adaptation occurs relatively quickly and is nearly always quicker than traditional methods, depending on the ML algorithm. It may be possible to use ML in manufacturing to find patterns in existing data sets that could serve as the basis for forecasts of the system's future behaviour (Alpaydin, 2010; Nilsson, 2005) [2, 81]. The new data could either aid process owners in making wiser decisions or enhance the system as a whole.

Kotsiantis (2007) [59] analyzed a variety of algorithms based on how well they performed in various industrial applications. Every problem is different, and every algorithm responds differently depending on the available data, the processed data, and the parameter choices. In a practical environment, the best algorithm must be compared to a range of alternatives. More information on this is provided in the section that follows.

Challenges of machine learning application in manufacturing

The gathering of pertinent data is a problem that frequently arises with ML applications in manufacturing. Along with accessibility, quality, and substance (do meta-data count, for example?), this is a constraint. The labelling of the accessible industrial data, such as whether or not the data are labelled, significantly affects how effectively ML algorithms perform. Some machine learning (ML) algorithms, for instance, may struggle with high-dimensional data due to the amount of redundant and unneeded information that might affect how well the learning algorithms function (Yu & Liu, 2003) [111]. The majority of currently used machine learning approaches only work with input that has continuous and nominal values (Pham & Afify, 2005) [84]. How much depends on the method itself, parameter values, and other factors. One may argue that getting any data for most manufacturing studies, not just ML applications, is challenging because of things like security issues or a general lack of data collecting during the process. This emphasises the following issue as well as the growing importance of understanding the data while using ML.

Depending on the demands of the method used, pre-processing is frequently necessary after the accessible data have been collected. The results are significantly impacted by the data pre-processing. However, a variety of widely accessible, standardized technologies enable the most popular data normalisation and filtering pre-processing phases. It is also necessary to examine the training data for imbalance. As a result, some algorithms could find it difficult to train. A prevalent issue in industrial practice is the presence or lack of values for specific attributes from the data collection. The use of ML algorithms is hampered by these "missing values." There are numerous useful induction gadgets that could close the gap (Pham & Afify, 2005) [84]. For substituting missing values, each issue and subsequently used ML approach has unique specifications. The original data set is changed when missing values are substituted. The goal of the analysis is to minimise bias and other detrimental elements. Given how widespread this problem is, there are numerous studies and workable solutions (for example, in R) accessible (Graham, 2012) [39].

Choosing the appropriate machine learning method and algorithm is challenging but increasingly crucial (selection of ML algorithm). The multiplicity of cases and its needs which has benefits and drawbacks, despite efforts to explain "generic ML processes," which have both advantages and downsides (Hoffmann, 1990) [47]. There are many different alternative ML algorithms-or at least ML algorithm variants-out there, especially now that the use of ML in manufacturing is garnering more attention from practitioners and academia. Hybrid approaches, which combine multiple algorithms, are becoming more and more well-liked since they are thought to produce better results than "individual" applications of a single algorithm. This makes the situation even more complicated (e.g. Lee & Ha, 2009) [66]. There are several papers available that show how ML techniques work well for specific problems. The test findings are typically kept confidential at the same time. Due to this, it is challenging to examine the findings impartially and objectively and to draw a concluding comparison.

In order to find a suitable method, it is necessary to examine past examples of the algorithms being applied to analogous challenges. In this context, the word "similar" refers to research problems with analogous specifications, such as those in different fields or disciplines.

The interpretation of the findings presents another difficulty. When evaluating the findings, it is crucial to consider the parameters and parameter settings of the chosen method, the "intended outcome," the data, including any pre-processing, and the output format or representation. Certain more exact restrictions may have a major impact on how the results are understood (again, depending on the algorithm of choice). These include, for instance, resilience to over-fitting and bias and variance (thus, the bias-variance tradeoff) (Widodo & Yang, 2007) [104].

Structuring of machine leaning techniques and algorithms

ML has grown through time into a broad and diverse field of study, as was already said. This has sparked the creation of numerous original sub-fields, algorithms, theories, and application domains. The relationships or established structures between the various sections are not universally acknowledged. Different academics opt for various organisational strategies to set up the field. The authors want to group the jobs and easily accessible algorithms in the ML domain of the DM in Figure 1 on the one hand and on the other. This structure emphasises the significance of distinguishing between task (what is the objective) and algorithm for the machine learning (ML) community (how can that goal be accomplished). But the overview in Figure 1 is deficient because it ignores the commonly acknowledged division of ML techniques based on the feedback that is available in supervised, unsupervised, and RL. Monostori (2003) [77] described the three classes as follows:

Unsupervised learning: Since there is no instructor, there is no evaluation [label] of the action. Assisted learning: A teacher provides the appropriate response (label).

Less feedback is provided in reinforcement learning because the teacher simply assesses the action that was selected.

Although the existence of this structure is widely acknowledged, it is still unclear what it involves and to which organisations these three classes actually belong. For example, supervised, unsupervised, and RL were mapped to components of neural networks (NN) in Pham and Afify's (2005) [84] study (Figure 2). Pham and Afify (2005) [84] draw attention to the fact that they exclusively concentrate on supervised categorization learning techniques. This would be in line with Lu's (1990) [71] assertion that supervised and unsupervised inductive learning are two different forms of inductive learning. Others distinguish between active and passive learning, asserting that the former refers to circumstances in which the learner has no control over the training set and the latter refers to learning problems or systems in which the learner "generally used to refer to a learning problem or system where the learner has some role in determining on what data it will be trained" (Cohn, 2011). It is clear that active learning is frequently required to address issues where obtaining labelled training data is challenging (costly and/or time-consuming). Active learners can do better than other learners with less training data since they can sequentially recognise valuable examples (Cohn, 2011) [17]. Active learning has primarily been used in supervised machine learning (ML) applications, but it has also proved successful in several real-world (RL) applications (Cohn, 2011) [17].

For instance, Kotsiantis (2007) [59] only takes into account supervised classification approaches when classifying NN as a learning algorithm under supervised learning. On the other hand, RL and unsupervised learning can both benefit from the employment of NN algorithms (Carpenter & Grossberg, 1988; Pham & Afify, 2005) [12, 84]. When the idea at the top of the hierarchy is viewed as "Supervised ML" rather than the "Machine learning" they first specified, this largely agrees with Pham and Afify's (2005) [84] work.

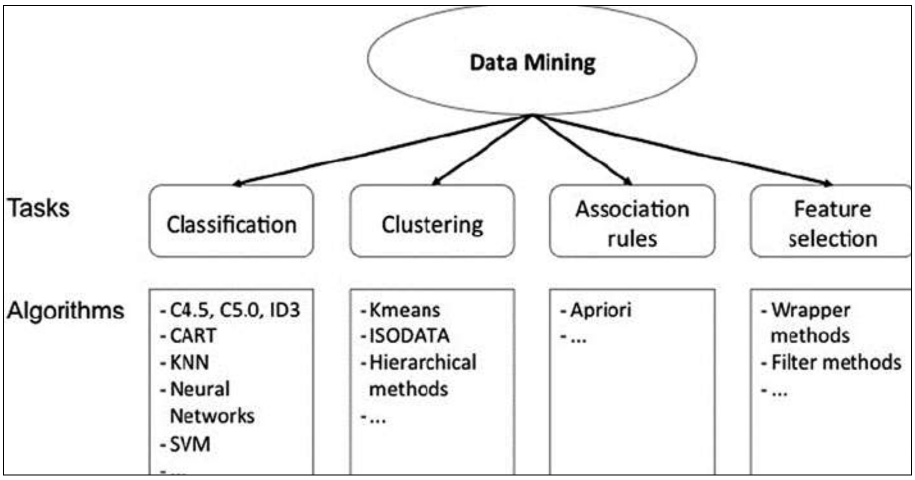

Fig 1: An overview of tasks and main algorithms in DM (Corne *et al.*, 2012) [19].

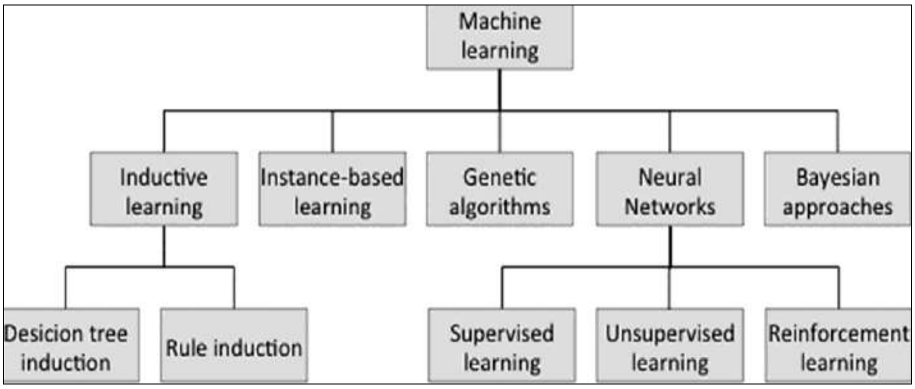

Fig 2: Classification of main ML techniques according to Pham and Afify (2005) [84].

The following is an illustration of how ML approaches and algorithms may be modified and extended:
Figure 3 does not depict all algorithms and method adjustments. The goal is to demonstrate the intricate design and wide range of commonly used and popular ML approaches. When moving farther down the hierarchy, it may not always be easy to choose the main differentiation-supervised, unsupervised, and RL-that is best appropriate for the task at hand. Additionally, it must be remembered that many methods can be integrated to increase classification accuracy (Bishop, 2006) [7]. "Most of the available machine-learning algorithms for producing multiple models may improve greatly on the accuracy of single models," claim Pham and Afify (2005) [4]. That raises the difficulty one must overcome while choosing an appropriate ML algorithm for a specific problem, which hinders comprehension (Pham & Afify, 2005) [84]. Numerous algorithms are useful for both supervised and unsupervised learning, which is another intriguing feature (in adapted form).
Numerous algorithms and combinatory methods have a tendency to be customized for particular tasks. Because of this, it is challenging to compare them, particularly in terms of the problem at hand's categorization power. Chart comparisons like those in Kotsiantis can be used as a first indicator (2007).

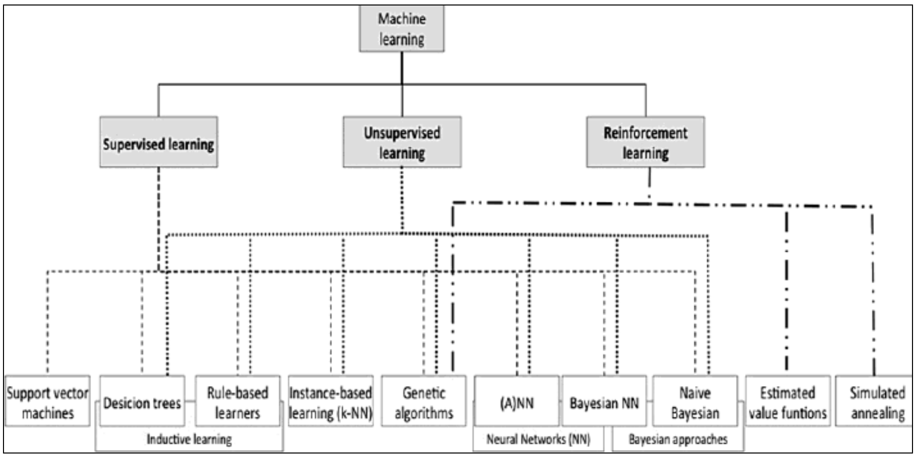

Fig 3: Structuring of ML techniques and algorithms.

A more effective way to choose the best algorithm is to look for similar issues and compare the ML algorithm that was used to solve them with the outcomes. This is a fantastic place to start. A number of approaches can be used, and the outcomes for the targeted problem can be contrasted, once the algorithm has been used to address the issue and preliminary findings are available. The transition is (relatively) easy thanks to contemporary computing platforms that support multiple kernels.
Below is a brief description of each to help you distinguish between supervised machine learning, reinforcement learning (RL), and unsupervised machine learning. Later, more in-depth discussions on supervised machine learning were held since it was found to be the best remedy for the problems and issues that industrial applications faced and because manufacturing data is usually tagged, making expert commentary readily available (Lu, 1990) [71].

Unsupervised machine learning
It's also crucial to research unsupervised machine learning. Unsupervised learning, as contrast to supervised learning, does not receive guidance from a teacher or other expert. Based on factors including the conceptual cohesion of features, the approach is intended to identify clusters from current data (Lu, 1990) [71]. Kotsiantis was the first to put forth the hypothesis that unsupervised learning is most likely to take place when conditions are unlabeled (lack accurate outputs and known labels) (2007). In contrast to supervised learning, which focuses on classification, clustering aims to identify previously unknown classes of objects (Jain *et al.*, 1999) [49]. In its simplest form, unsupervised machine learning is any ML procedure that attempts to learn structure without either a known output [for example, supervised ML] or feedback [for example, RL]. Clustering, association rules, and self-organizing maps are three typical instances of unsupervised learning

(Sammut & Webb, 2011) [89].

Unsupervised methods are becoming increasingly important, especially in the context of Big Data. The main presumption for training the algorithm is that experts who are competent about classifying states can contribute. The manufacturing use is comparable to this (Lu, 1990; Monostori, 2003) [71, 77]. So, the primary emphasis will be on supervised techniques. However, there may still be some benefits to unsupervised learning in manufacturing applications. The first possibility is that expert guidance may not always be available or wanted in the future. Another crucial factor to take into account is realizing hybrid solutions that combine the "best of both worlds," especially in the industrial sector, where the amount of unlabeled data is continually increasing (Kang *et al*., 2016) [53]. Finally, unsupervised techniques can be used to find outliers in industrial data, for instance, and already do so (Hansso *et al*., 2016) [43].

Reinforcement learning

RL is defined as the contribution of the training data from the environment. A numerical reinforcement signal provides information on the system's performance during the specific turn (Kotsiantis, 2007) [59]. The student must figure out for themselves, rather than being told, which activities generate the best results, which is another distinctive trait (numerical reinforcement signal). This sets RL apart from the overwhelming majority of other ML techniques (Sutton & Barto, 2012) [99]. However, other academics claim that RL is "a specific kind of supervised learning" (Pham & Afify, 2005) [84]. To differentiate RL issues from supervised learning issues, however, tagged examples of "good" and "poor" behaviour are not included (Stone, 2011) [96]. RL mimics how individuals learn by simulating a series of contextual interactions (Wiering & Van Otterlo, 2012). RL differs from unsupervised ML in that it exhibits a "reward signal" (Stone, 2011) [96]. In contrast to supervised learning, RL functions best when a trained supervisor is not present. An agent must have the ability to learn from interactions and its own experience in such an uncertain environment. This is when RL can be advantageous (Sutton & Barto, 2012) [99].

It is thrilling and difficult that some acts may not have an immediate effect but instead may manifest later or even during a subsequent additional effort because RL depends on the feedback of activities. RL is typically characterized by stating a learning issue rather than specifying learning methods. Any approach that satisfies that requirement [could be regarded as] a reinforcement learning approach.

The trade-off between exploration and exploitation is a very special challenge for RL. The agent must proactively test new tactics in order to "exploit" the behaviours it has learned to prefer and identify those it must "explore" in order to accomplish the goal (Sutton & Barto, 2012) [99]. According to Gönther *et al*. (2015) [40], there are currently very few examples of RL being successfully implemented in production. Modern industrial applications have access to professional counsel in the great majority of cases. So, even if RL can be used to manufacturing applications, the following mostly focuses on supervised methods.

Supervised machine learning

"Supervised ML," also known as "supervised machine learning," is defined as "learning from examples provided by an experienced external supervisor" in its most basic form. This is partly because (a) expert opinion is readily available and (b) the cases are labelled. One of the most well-known uses of supervised machine learning is in the manufacturing, monitoring, and control sectors (e.g. Pham & Afify, 2005 and Alpaydin, 2010;) [84, 2].

Data processing and teacher setup of the test and training data sets are just two of the processes that make up the usual supervised machine learning approach (Kotsiantis, 2007) [59]. Depending on the circumstance, the pertinent data are located and, if necessary, pre-processed. The training set's definition is essential since it has a big impact on how the classification process turns out. While defining the training data set commonly seems to come first, it is equally crucial to take the requirements of the algorithm selection into consideration. Some algorithms provide a feature known as "kernel selection" that enables the strategy to be changed depending on the particulars of the problem. This demonstrates the flexibility of ML applications and the range of issues they can solve.

Because many algorithms have unique advantages and disadvantages when working with various data sets, data identification and preprocessing are both susceptible to problems (e.g. format, dimensions, etc.). Using the training data set, the algorithm of choice is trained. Typically, 70% of the data set is used for training, 20% is used for assessment (to change parameters like bias), and the remaining 10% is used for testing. In the part that follows, supervised learning algorithms are further discussed because they are now the most popular algorithms for manufacturing applications. In many manufacturing applications, the availability of "labels" based on quality checks is a crucial element.

Supervised machine learning algorithms in manufacturing application

The previously displayed images demonstrate a variety of supervised machine learning algorithms that are available. It's a big job to choose an algorithm that will work for the current industrial research problem. First, to assess how broadly applicable an ML method is to the criteria, more generic comparisons (such those made by Kotsiantis 2007) [59] may be employed. It is unacceptable to select an ML algorithm purely on the basis of such a theoretic and thorough selection, even though the majority of research concerns show the particular characteristics of ML algorithms as well as their modified "siblings." The following phase is a detailed examination of prior uses of ML algorithms on research areas with comparable needs in order to select the best ML method for the situation at hand. The primary factor for the selection process is how well the research topics match the demands that have been identified. The research topics should not be related to one another's field (updating the learning set). To assist the reader in reducing the number of potentially applicable techniques, a concise assessment of the key benefits and drawbacks of the various ML algorithms is provided.

Training a computer to choose a performance function defining the relationship between inputs and outputs (without being explicitly coded) is known as supervised learning in the theory (Evgeniou, Pontil, & Poggio, 2000) [31]. "How well the selected function generalises, or how well it estimates the outcome for previously unobserved inputs," is the primary issue of SLT (Evgeniou *et al*., 2000)

[31]. On the theoretical underpinnings of SLT, other useful algorithms, such as NNs, SVMs, and Bayesian models, are built (Brunato & Battiti, 2005) [10]. The wide range of potential application settings and application tactics is one of the primary benefits of SLT algorithms (Evgeniou *et al*., 2002) [32]. SLT occasionally permits using fewer samples (Koltchinskii *et al*., 2001) [58]. SLT is also superior to other methods for dealing with issues like observer variability (Margolis *et al*., 2011) [74]. Additionally, SLT helps to prevent computational complexity by easing up on some design issues, even though it does not entirely eliminate it (Koltchinskii *et al*., 2001) [58]. However, it is acknowledged that there is limited area for dependent and redundant attributes (Kotsiantis, 2007) [59].

Artificial neural networks, often known as NNs, operate similarly to how the brain does. When converted to a computer or artificial system, the brain's extraordinary abilities, such as vision and speech recognition, may be useful in engineering applications (Alpaydin, 2010) [2]. Parallel processing allows NN to simulate the central nervous system's decentralized "computation". On this NN, the present ML research is dependent (Nilsson, 2005) [81]. One could argue that the use of NN in modern applications is at the representational and algorithmic levels (Alpaydin, 2010) [2]. NN are used for a variety of industrial tasks, such as semiconductor manufacturing, as well as for a variety of issues, such as process control (Wang *et al*., 2005) [102], emphasising their major benefit: their wide use (Pham & Afify, 2005) [84]. "Offers great accuracy in most applications," say Manallack and Livingstone (1999 [72], "but sometimes suffer from over-fitting the training data"). SVM and NN both need a big sample size to obtain the high accuracy, though (Kotsiantis, 2007) [59]. Another issue with NN that is related to high-variance algorithms is over-fitting (again, something like SVMs) (Kotsiantis, 2007) [59].

The SLT outlined previously serves as the theoretical underpinning for SVM, a relatively new and extremely promising machine learning method. Due to its all-around good performance, capacity for high accuracy, and capacity for processing high-dimensional, multivariate data sets, SVM has garnered growing interest in recent years. Cortes and Vapnik (1995) [20] created SVMs. SVM is a "stable and highly accurate intelligent classification technique particularly suited for structure-activity relationship research," according to Burbidge *et al* (2001) [11]. SVM is a useful technique for the STL theoretical framework (Cherkassky & Ma, 2009) [15]. SVMs have a track record of effectively resolving non-linear issues (Li, Liang, & Xu, 2009) [68]. To adapt to different circumstances and demands, SVM can be paired with a variety of kernels, including NNs and Gaussian (Keerthi & Lin, 2003) [54].

Two main theories have demonstrated their ability to forecast the development of the fundamental classifiers. Utilizing sequential ensemble approaches, which feed the output of one base classifier into the next base classifier, is one way to improve the output. Bagging, on the other hand, is the concurrent modification of the underlying classifiers that results in distinct models. A well-known illustration of a bagging strategy is the Random Forest collection of randomly selected tree predictors (Breiman, 2001) [9]. Random Forest first chooses a feature subset at random from the feature space before using a typical split selection technique inside the chosen feature subset.

Application areas of supervised machine learning in manufacturing

Several ML algorithms are available, as was demonstrated in the section prior to this one. Each of them has particular advantages and disadvantages. In a few specific situations, the effective uses of machine learning in industrial systems are highlighted using SVMs, a well-known example of a supervised machine learning algorithm.

Monitoring with SVM is common in the industrial sector (Chinnam, 2002) [16]. SVM is often and effectively utilized in a variety of domains, including defect identification, tool wear, and monitoring tool/machine condition (Azadeh *et al*., 2013) [4]. SVMs have also been effectively used for manufacturing quality control (Ribeiro, 2005) [8].

Image recognition, which includes face and character recognition, is an SVM application field that connects to manufacturing applications (Wu, 2010). Aydaş and Ekici (2010) [13] state that this could be used in manufacturing to recognise (classify) damaged products (for instance, surface roughness). Handwriting classification is one of the additional uses (Scheidat, Leich, Alexander, & Vielhauer, 2009) [91]. Another use of SVM optimization is in time series forecasting (Guo *et al*., 2008) [41].

SVMs are frequently employed in a variety of industries, including manufacturing, image recognition, and the medical sector. SVM has various applications in this field, but the research of cancer stands out. Two other medical use cases are listed by Burbidge *et al*. as medication design and microcalcification detection (El-naqa *et al*., 2002) [28].

Rule extraction, polymer classification, and credit rating are some more uses (Borin *et al*., 2006) [8]. These illustrations from various sectors and optimization issues show how adaptable and widely used the SVM technique is. There are many effective ML applications for manufacturing that are now being employed in industrial applications all around the world, as was demonstrated by the SVM technique.

Conclusion and outlook

This research article emphasises the issues with modern industrial systems, such as their growing complexity, dynamic nature, high dimensionality, and chaotic structures. Below, it was examined what limitations and advantages machine learning has from the perspective of manufacturing before suggesting a structure for the broad topic of machine learning and giving an introduction to its core principles. To categorise the numerous methods and applications, the framework makes a distinction between supervised machine learning, reinforcement learning, and unsupervised machine learning. SVMs, a supervised machine learning technique, are then shown to be beneficial in manufacturing. The evaluation highlights the field's adaptability and wide range of possible uses.

Machine learning will see a sharp growth in its use, particularly in manufacturing, as a result of the quick advancement of algorithms, the availability of data (due, for instance, to affordable sensors and the shift toward smart manufacturing), and the increase in computing power. Currently, supervised algorithms are used in the majority of applications related to manufacturing. The exponential development in data availability brought on by better and more sensor technologies along with more awareness, however, may cause unsupervised techniques (including RL) to become increasingly prominent in the future. There are currently hybrid tactics in use that offer "the best of both worlds." This fits with the current emphasis on breakthroughs utilizing big data. We can safely say that machine learning (ML) is now a potent tool for many applications in (intelligent) industrial systems and smart manufacturing, and that its importance will only grow in the future. There is a need for cooperation between a number of academic fields, including computer science, industrial engineering, mathematics, and electrical engineering. Both enormous opportunity and substantial risk are generated by this relationship.

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