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Machine Learning Techniques used in Manufacturing

A REVIEW PAPER

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Abstract

Machine learning (ML) has recently become a power-engine, transforming various manufacturing research and applications. The advancement in machine learning creates opportunities to use ML techniques in industries and manufacturing organizations. Machine learning is a way by which a machine can learn from its own experiences. Machine learning analyzes data that are fed to it and finds a general pattern. It is a trial-and-error process and gets better with time and a huge amount of data. Manufacturing processes produce a lot of data which can be analyzed by ML techniques to get new insights, better understand the processes, make better decisions, reduce faults, diagnosis of problems. The broader area and many different algorithms used in ML makes it really difficult to choose a particular model to implement for a particular reason. There are some ML techniques which are used by the industries in manufacturing processes successfully and others are being researched. While different ML techniques have been researched and deployed in manufacturing, many open challenges and questions still remain. In this review paper we will look at these machine learning techniques implemented at different manufacturing organizations and the future trend of using Machine Learning and Big Data in manufacturing plants.

Keywords

Machine Learning, Machine Learning Algorithm, Manufacturing Processes, Big Data

Introduction:

One of the most critical characteristics of today's production is growing sophistication, which is manifested not only in manufacturing systems, but also in the goods to be produced, in processes and company structures (Wiendahl and Scholtissek, 1994). In a changing world, systems work with uncertainty. Artificial intelligence, the latest technological trend, is invigorating many researchers to use it to solve sinuous problems as a mimic of the human brain. Machine learning, which is a subset of artificial intelligence, will make the machine learn from previous knowledge automatically without explicit programming. In artificial intelligence, the ability to replicate human intelligence and understand every aspect of a given conundrum through experience makes machine learning an inescapable operation. While the ramification of machine learning in the early phase did not become obvious, it has now become a sensation. Cutting-edge technology and developments for smart manufacturing are urgently required to meet stringent safety, performance, and sustainability criteria in the modern process industries. At the same time, these needs raise both obstacles and opportunities for the so-called Fourth Industrial Revolution, also referred to as Industry 4.0. The Third Industrial Revolution, which is now nearing its end, originated from the advancement of information technology, while the success of process industries over the past 30 years is primarily attributed to the broad implementation of automated control strategies. It has been widely recognized in the presently occurring Fourth Industrial Revolution that computers should not only be able to relieve people from intensive physical labour, which was a key focus of previous industrial revolutions, but also be successful in taking on intellectual labor and even creating inventions on their own. All manufacturing devices and processes should be " smart 'in process industries so that, as a whole, they can sense the environment intelligently, explore new information, and make logical choices. In addition, machine intelligence could be divided into lower-level intelligence and higher-level intelligence, where lower-level intelligence could physically mimic humans, whereas higher-level intelligence, as an eventual objective to be constantly sought in the future, would go far beyond the human level.

Brief overview of machine learning techniques:

In general, for performing different operations depending on the data, machine learning is divided into two categories: supervised machine learning and unsupervised machine learning. The process is known as supervised machine learning when the target variable is specified, and if it is not given along with the input data, then the process is unsupervised learning. Regression and classification are the procedures under supervised learning, whereas algorithms of clustering and association undergo an unsupervised learning process. Regression is preferred if the input data is continuous and if the input data has a categorical value, the classification process is applied. A simplified machine learning division is given in Fig. 1. Different techniques that have been used in the past two decades have been chosen to present the role and output of machine learning systems in the field of production. SVM, random forest, logistic regression, ANN, Naïve Bayes and genetic algorithm are the techniques considered in the analysis. The efficiency of all approaches is shown by demonstrating the efficiency of machine learning in manufacturing applications. In order to demonstrate its growth in applications and high performance in process modeling and optimization, ANN is given greater importance among all the techniques in the current study.

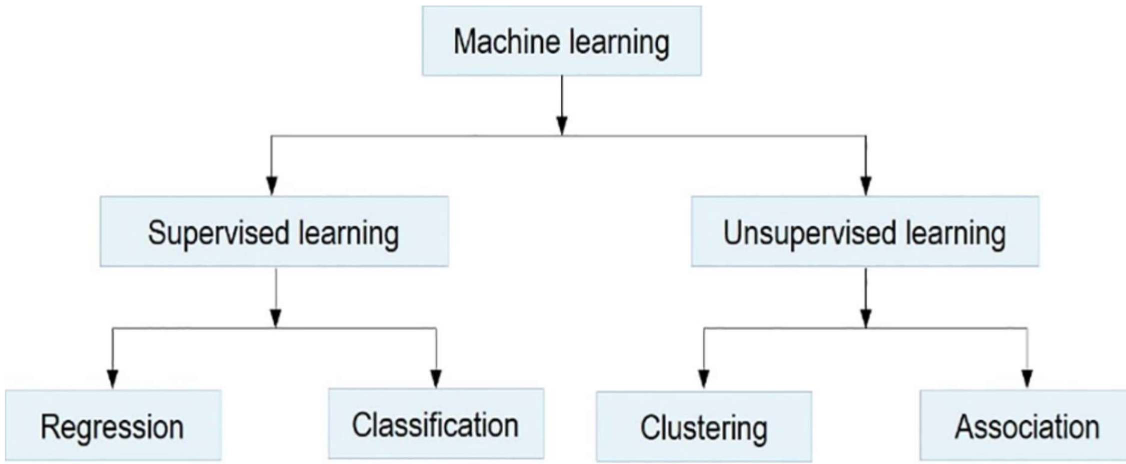


Fig. 1: Machine Learning classification

Intelligent Manufacturing Systems (IMS) are next-generation manufacturing systems that use artificial intelligence (AI) or, in some cases, machine learning to solve problems and make decisions in the unpredictable environment of production (AI). There are two concepts of machine learning, one being machine and the other learning. Machine learning is essentially a methodology by which the machine learns without being programmed directly through its own experiences. In recent years, the field of machine learning has been flourishing.

Learning process can be of different kinds such as (AI):

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised learning can be described as the task of machine learning that predicts an output based on the experience of certain input and output pairs. Unsupervised learning is the process of machine learning that attempts to figure out some pattern from some random data provided. Reinforcement learning provides less program input and is judged on the basis of its behavior (AI). In the majority of instances, the superior is among these three forms of supervised learning.

The training depends on the algorithms on which they are based. There are several algorithms that are linear and non-linear. In the other hand, linear regression, for example, is a linear algorithm, and neural networks are non-linear.

Researchers have attempted to combine numerous machine learning strategies with the manufacturing environment, one of which is the monitoring of instrument condition monitoring (TCM). Neural networks or the Artificial Neural Network (ANN) algorithm display promising results in the development context.

Construction of artificial neural networks are inspired from the working principle of human neuron. Like human neuron, the working principles of neural networks are very hard to visualize. The primary construction of artificial neural network consists of three types of layer. They are:

1. Input Layer
2. Hidden Layer/s
3. Output Layer

Input layer consists of different process variables/parameters. Hidden layer can be single layer or multiple layers and consist of nodes with non-linear functions like ReLU. The final layer is the output layer. The nodes in the output layer depends on how many possible outputs are there. For example, if an ANN is created to detect the numbers shown in the figure between 0-9 than the total output nodes will be 10 because there are 10 possible outputs but the result will be a single digit with the highest possibility on the scale of 0-1.

Use of ANN in tool condition monitoring has shown impressive results. Complexity arises from the choices of input parameters. For monitoring tool wear condition possible parameters are force, torque, temperature, mechanical vibration, acoustic emission etc. Selecting the useful ones from these requires rigorous work, train of the algorithm and test. This problem can be solved using some pre-defined parameters in the algorithm and other parameters to be determined by the algorithm itself. This ANN technique using back propagation method has shown great results in case of pattern recognition.

Performance described in AI: For tool condition monitoring the ANN's job was to classify the tools as sharp tool or worn tool. It was actually a two -class problem as there were two outputs. The algorithm had to identify the tools based on flank wear. If the wear was in between 0-0.2mm than it was sharp and if it was greater than 0.5mm than it was worn. "Depending on the network structure, a classification performance between 96.5% and 98% was reached (AI)."

In smart manufacturing ANN based models are dominant now. These models can easily integrate multiple sensors, process signals, handle uncertainties which make them very attractive choice for manufacturing environment. ANN also has application in non-sensory domains of manufacturing. Neuro-fuzzy approaches can do better in future prospective. [1]

Application of machine learning in manufacturing sector:

In order to present the findings of various machine learning techniques used in the manufacturing sector, articles from different publications are considered and evaluated. Studies performed in manufacturing to equate two or three methods are often tested to illustrate the superiority of one method over the other. At least one or two papers are taken from each year starting from 1995 to 2020 to illustrate the role of machine learning in manufacturing. In the present analysis, several ANN applications are seen to demonstrate their relevance in manufacturing. Maximum error, quality, maximum probability of correct decision (MPCD), area under the curve (AUC), correlation coefficient, sum squared error, average error, and cost function indicate process output.

Few comparative studies on machine learning techniques in manufacturing applications.

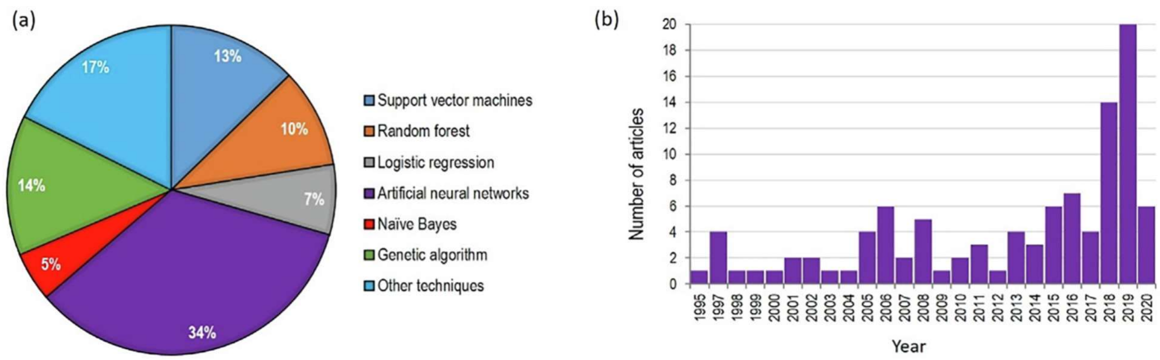
S. No.	Authors [references]	Techniques compared	Performance
1	M. Perzyk et al. [133]	ANN, SVM, RT, CT, and NB	ANN > SVM > CT, RT, NB
2	J. E.R. Dhas et al. [134]	GA, PSO	PSO > GA
3	Z. Li et al. [135]	CART, RF, kNN, SVM	SVM > CART > kNN > RF
4	P. Malaca et al. [136]	ANN, SVM	ANN > SVM
5	B. Das et al. [137]	ANN, SVM, and general regression model	SVM > ANN > Regression model
6	V. Pandiyan et al. [138]	SVM, GA	SVM > GA
7	C.A. Escobar et al. [139]	SVM, LR, NB, kNN, ANN, RF, SVM(RBF)	kNN > SVM(RBF) > ANN > RF > NB > LR > SVM
8	Rosalina [140]	DT, NB, SVM, ANN	DT > NB > SVM > ANN
9	T. Nkonyana et al. [141]	RF, ANN, SVM	RF > SVM > ANN
10	C. Hegde et al. [142]	RF, LR, SVM, GMM, DA	RF > LR, SVM, GMM, DA
11	C. Yang et al. [143]	ANN, NL, DT, SVM, LM, kNN	ANN > NL > DT > SVM > LM > kNN
12	A. Bustillo et al. [144]	MLP, RT, LR, ZeroR	MLP > RT > LR > ZeroR
13	L. Lingitz et al. [145]	RF, bagged RT, SVM, boosted RT, MARS, kNN, Lasso, Ridge, ANN, LM, RT	RF > bagged RT > boosted RT > SVM > LM > MARS > kNN > Lasso > Ridge > ANN > RT
14	Z. Jurkovic et al. [30]	Polynomial Regression, SVM, ANN	Polynomial regression > ANN > SVM
15	L. Xu et al. [146]	ICBR, GPR, Standard CBR, BPNN	ICBR > GPR > Standard CBR > BPNN
16	I. Parviziomran et al. [147]	ANN, RF, SVM	RF > ANN > SVM
17	M. Perzyk et al. [148]	NB, ANN	NBC > ANN
18	D.P. Penumuru et al. [149]	SVM, DT, RF, LR, kNN	SVM > DT, LR, kNN, RF

[2]

Table 1

An output comparison of various machine learning techniques in manufacturing areas can be observed from Table 1. One technique outperformed the other techniques in every post. ANN has outperformed SVM in a few tests, while

ANN has outperformed ANN in a few other SVMs, suggesting that both are competitive with one another. RF and DT have outperformed ANN and SVM in a few situations. Also, the supremacy of kNN and PSO is seen in Table 1. This means that it should be correctly processed to achieve better outcomes, even though the best methodology is selected for the investigation. In manufacturing applications, techniques such as ICBR, GPR, MLP, Lasso, Ridge, MARS, ZeroR, CART, LM and GMM have also played a significant role.

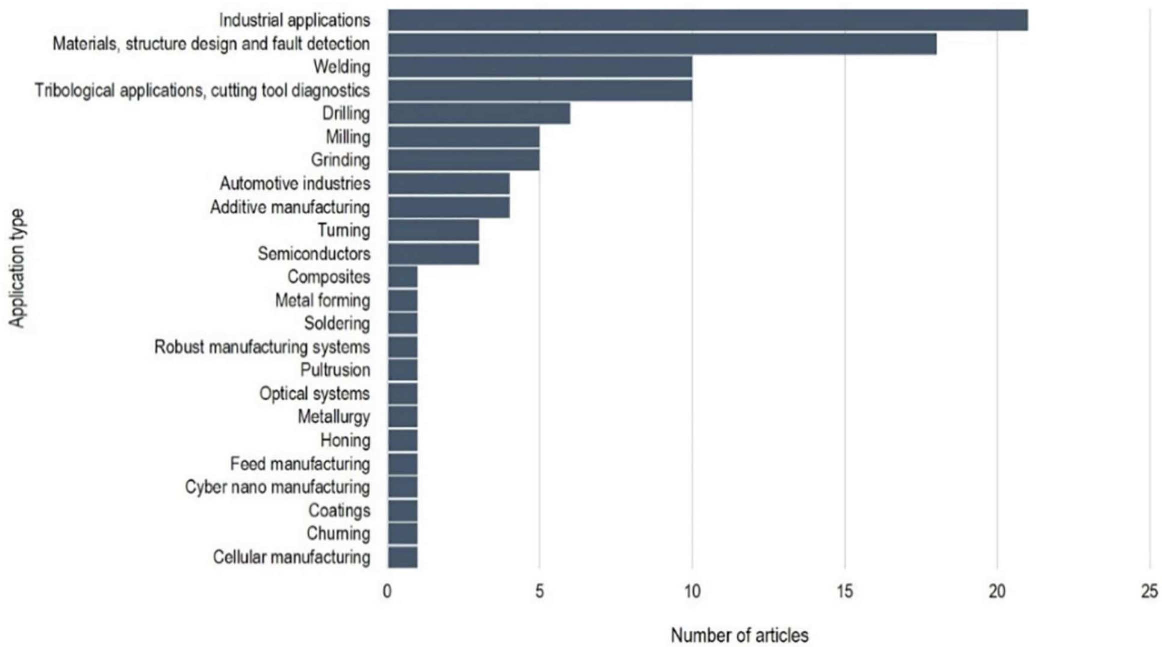


[2]

Fig. 2: Machine learning techniques contribution and year wise distribution of papers considered in the present review.

The number of papers taken to demonstrate the efficiency of each process is given in Fig. 2 (a). It is evident from this that the percentage of papers taken in this study to assess ANN's success (34 percent) across all the techniques is high. The output of SVM, GA, and RF assessment papers is 13 percent, 14 percent, and 10 percent, respectively, suggesting that all three techniques are given equal priority in describing their performances. The proportion of papers assessed for LR and NB is 7 and 5, respectively. From Fig. 2(a), the papers published on the comparison of various machine learning techniques used in production relate to other techniques. With the assistance of studies conducted to compare various machine learning techniques, techniques such as PSO, kNN, DT, NL, GMM, MARS, Lasso, Ridge, Polynomial regression, ICBR, GPR, DA, CART, LM and ZeroR are also seen.

The substantial increase in the application of ANN in various production areas over the past two decades is attributed to a greater number of papers being analyzed to demonstrate the efficiency of ANN. Just in Fig. 2(b) demonstrates the number of papers collected each year to illustrate the success of machine learning in manufacturing. From this, we can observe that the role of machine learning in manufacturing is demonstrated by at least one or two articles taken from each year over the past two decades. More articles are taken from the past five years to demonstrate that in recent years the use of machine learning techniques in manufacturing has steadily increased. Machine learning has been the primary source of research into manufacturing processes for researchers every year for the past two decades.



[2]

Fig. 3: Application of machine learning techniques in different areas of manufacturing.

In various fields of manufacturing, machine learning has found many applications. The production areas covered in the current study to demonstrate the role of machine learning can be observed in Fig. 3. More than 20 different fields have been considered to demonstrate the value of the application of machine learning in the manufacturing sector.

Passive applications: Multivariate statistical process monitoring and soft sensing

It has been widely recognized that activities of modeling can typically be divided into unsupervised learning and supervised learning. Descriptive models are generated in unsupervised learning to define the underlying structure within input data; these are mostly used to describe the distribution of process data in monitoring. A functional mapping between input and output is developed in supervised learning, for both regression and classification, with the prediction accuracy of the output being of particular concern. More research attention has recently been focused on the learning of representation or feature learning. The teaching of representation gives a unified perspective of unsupervised learning and supervised learning. The application of neural networks with piecewise linear units in computer vision is an instance of representation learning.

Due to the large scale and heavy coupling of modern process industries, the effect of a minor failure could be dramatically increased. Therefore, to ensure the safety of manufacturing processes, constant monitoring of the operating status and taking required maintenance steps are vital, since doing so requires a heavy manual workload. MSPM has developed itself as a solution to this conundrum since the 1980s, and a wide range of classic machine learning algorithms have been implemented, demonstrating the intelligence of industrial manufacturing well. In order to construct productive MSPM models, recent attempts have aimed to use prior information that is suited to continuous production processes. Since the settling period of production processes is usually long, certain inertia characteristics are seen in the whole system to be controlled. The underlying states of processes that tend to have slow variability can be defined as this. Slowness has therefore been suggested as a significant attribute for inducing underlying characteristics and thus capturing process dynamics accurately and providing better descriptions.

The history of soft sensing can be traced back to the 1978 technique of inferential control suggested by Brosilow et al. Soft sensing uses easy-to-measure process variables as an intelligent-sensing technology to provide online estimates of difficult-to-measure but relevant indices, such as product quality and other environmental indices. It is worth noting that another growing application of soft sensors is the main performance indicator (KPI) forecast.

It is appropriate to assess certain essential performance indices on the basis of time-consuming experimental tests, and predictive soft sensors can be built to provide real-time estimates of these indices that are useful to assist operators in decision-making. The creation of soft sensors can, in theory, be considered a regression problem, so different supervised machine learning algorithms have been applied.

Active applications: Optimal control and high-level decision-making

Model predictive control (MPC) is a notable and well-established method for advanced control of industrial processes, which is focused on a precisely known mathematical model to explain system behaviors and to schedule optimal control sequences in the near future. In practice, however, the underlying assumption of MPC may be optimal, and there are typically unknowns such as model mismatch, unmeasured disruptions, and random noises. In these cases, the combination of mechanistic models with data analytics and machine learning, which show great potential for dealing with the unknowns, is a promising approach.

Stochastic programming (SP), RO, and distributional RO (DRO) can be grouped into generic optimization techniques under uncertainty; these three approaches have found broad applications in operations of the energy system and supply chain architecture. Data-driven decision-making is a newly emerging framework that combines model-based and data-driven uncertainty optimization systems. This organic convergence of machine learning and mathematical programming contributes to data-driven optimization systems that are inherently more efficient and successful, closing the loop between data analytics and decision support. Scenario programs yield data-driven approximation to classic chance-constrained SPs, where scenarios obtained from past encounters are explicitly adopted to turn chance constraints into a great number of deterministic constraints. Usually, uncertainty sets are built directly based on uncertainty data in data-driven RO. This can be understood as an unsupervised learning task from a machine learning point of view. To this end, however, not all unsupervised learning approaches can be implemented, primarily because the tractability of induced optimization problems needs to be taken into account. The unsupervised learning process, on the one hand, must be efficient enough to accurately capture the distribution of uncertainty; on the other hand, an over-complicated uncertainty set could make it difficult or even intractable to solve the optimization problem. In order to achieve a satisfactory balance between two competing aims, data-driven uncertainty sets must therefore be meticulously devised. A number of unsupervised learning methods, which are dedicated to data-driven constructions of uncertainty sets, have recently been developed based on such motivation.

In the past decade, data-driven DRO has been a common subject in operations research. It can be seen as a combination of

RO and SP; in that it optimizes the worst-case performance on a set of distributions of probability. Ambiguity sets play a key role in data-driven DRO, and are usually calculated based on data analysis. It is normal not to be precisely known in nature for the distribution of uncertainty; such inexactness is referred to as distributional ambiguity. A collection of candidate probability distributions is employed to hedge against distributional uncertainty. To define the complexity, the most used method is to derive first order and second-order moment data from previous data. Based on hypothesis testing, the problem of evaluating
the size of uncertainty sets is formally discussed. DRO has been applied first to process planning and scheduling in process industries and to optimum shale gas supply chain operations. [3]

An outlook on future research directions

- **Process monitoring**

While a variety of methods of feature selection have been used to design process monitoring models, it should be noted that the extracted characteristics must be closely related to prior information customized to process characteristics. Currently, while a large number of process monitoring models are built based on combinations of different methods of extraction of features, nonlinear manifolds and A good process model should usually be not only strong enough to explain process properties, but also allow for simple interpretations that industrial practitioners can easily embrace.

- **Soft sensing**

The output of soft sensors can easily degrade over time because of the time-varying characteristics of industrial processes, requiring a considerable workload to maintain and upgrade the model. Therefore, quality prediction is not merely a problem of regression, and the adaptive mechanism of prediction models, especially in the presence of frequent deviations in operating conditions, should be given more research attention. In addition, the inaccuracy of human-induced laboratory data, such as uncertain time delays, large and varying sampling intervals and the sampling habits of different operators, may also be considered.

- **High-level decision-making**

High-level decision-making is the most critical relative to other applications, as it directly affects the economic benefits and environmental impacts of a process-based manufacturing business. On the one hand, according to the experiences of business leaders, high-level decisions are usually taken under uncertainty, leaving much room for improvement; thus, in the future, more data-driven RO and DRO technologies are expected for decision-making in process industries. On the other hand, in future research, there is value in further improving the quality of the solution and the data-driven RO and DRO computational efficiency. Present DRO methodologies utilize moment data to explain the uncertainty of distributions of probability. In theory, various forms of moment data may be interpreted as the products of basic approaches to data analytics. This situation provides inspiration for the extraction of high-level information such as distribution within high-dimensional feature space, based on which complexity can be further considered, using advanced unsupervised learning methods.

Conclusion:

An increasing amount of data embodying useful data can be obtained and archived in modern process industries. Data analytics and machine learning can help to sense the world, discover
information, and automatically and intelligently make decisions through the use of data. This paper reviews the current status of research in this field and analyzes the information gaps to be filled in, oriented

to data-driven monitoring, prediction, control, and optimization. In particular, we distinguish passive applications from active applications that involve control and optimization of data-driven processes, which include monitoring and soft sensing. For the former, as a major concern, the interpretability of models was suggested, while for the latter, particular attention was paid to functionality.

The following are some of the key points observed from the review:

- Over the past two decades, the use of technology has increased rapidly in production and the method of performing many experiments can be prevented with the assistance of machine leaning techniques in production processes.
- Several articles on the role of ANN in the manufacturing sector have been published in the literature, while articles on other techniques used in the manufacturing sector are comparatively very limited. This demonstrates a greater reliance on the application of ANN in development.
- Increased investigations into factors influencing the performance of manufacturing techniques can lead to improvements in the results of the process.
- The survey focused predominantly on approaches that are used separately rather than hybridized techniques. In the near future, there is also a greater potential for conducting inquiries into hybridized methods used in production processes.

It is possible to foresee the further convergence of more conventional AI and ML strategies with the agent-based approach in the field of intelligent machines, resulting in evolving behavioral systems.

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