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Survey on Machine Learning Applied to CNC Milling Machining

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Abstract

CNC milling is one of the most critical manufacturing processes for metal-cutting applications in different industry sectors. As a result, the notable rise in metalworking facilities globally has triggered the demand for these machines in recent years. Simultaneously, emerging technologies are thriving owing to the digitalization process on the advent of Industry 4.0. For this reason, a review of the literature is essential to identify the current Artificial Intelligence (AI) technologies that are being applied in the milling machining process. A wide range of Machine Learning (ML) algorithms have been applied recently, and the accuracy of each model depends on the input data and preprocessing of raw data. Some ML methods have attracted increasing attention, such as Artificial Neural Networks and all the Deep Learning methods. The most significant factor that ensures the performance of the implemented models is the choice of appropriate input data. Therefore, in this survey, we also attempted to describe the types of input data (e.g., the physical quantities measured) used in the

ML algorithms. Therefore, in this review, we also describe the types of data (e.g., physical quantities measured) used in the algorithms. Additionally, choosing the most accurate and quickest ML methods considering each Milling Machining Challenge are also analyzed. Considering this fact, we also address the main challenges being solved or supported by ML methodologies. This study yielded eight main challenges in Milling Machining, eight data sources used, and 164 references.

Keywords: Machine learning, Deep Learning, milling process, quality prediction

1 Introduction

Today, the search for digitalizing of all manufacturing processes, especially on production lines, to monitor all processes and predict any failure or error during the manufacturing process is vital.

As a result, in the concept of Industry 4.0, the entire manufacturing process is moving from traditional methods to digitalized manufacturing processes. The main reason for the transformation of the manufacturing process is the high number of parts due to the malfunction of equipment and operator errors. Digitalization makes it possible to optimize the process and reduce errors in manufacturing processes. In addition, digitalized manufacturing can minimize the number of rejected parts during milling owing to non-conformities.
Furthermore, the development of sensors and digital measurement equipment makes it possible to monitor the quality of the produced part and the cutting tool's health. This study attempts to address these two challenges and find the best way to monitor and improve the quality of the produced part and milling machine cutting tools.
Machining is a word describing the process in which the material is removed from the workpiece, and it is the most critical manufacturing process [1]. One of the main advantages of machining compared to other operations is that it usually requires further operations before the product is completely ready. In addition, machining operations can be applied to different material types such as polymers, wood, ceramics, composites, and exotic materials.
Milling machining is a manufacturing process that machines flat and curved surfaces or machines on vertical or irregular surfaces by moving the workpiece in the direction opposite to that of the rotating cutting tool. Traditional milling machines can be classified as knee-type, cutter-containing, milling ram-type, manufacture or bed type, and planer-type. The components of traditional milling machines consist of self-contained electric drive motors, reciprocating coolant systems, variable spindle speeds, and a power-operated adjustable worktable feeding the workpiece. However, with the invention of CNC milling machines, the milling process can perform complex operations faster, more accurately, and consistently.

Artificial Intelligence has had a significant impact on the manufacturing process and has facilitated the transition to intelligent manufacturing in recent years. Furthermore, manufacturers have urgency in predictive systems to calculate the time of failure of a machine or a component. By innovating cutting-edge devices such as modern sensors and rapidly enhancing big data, IOT, and digital twins, it becomes easier to implement frameworks for online prediction systems in smart manufacturing especially, in CNC machining. Consequently, predictive machine learning approaches, one of the best and most reliable prediction methods, have been increasingly applied to machinery prognostics and maintenance management. It is transforming legacy manufacturing systems into intelligent manufacturing systems. It creates data-driven services to mitigate the main challenges of these operations.
Considering the many variants of ML applications in the milling processes, a survey is needed and helpful to understand and utilize the best machine learning models. This paper provides a survey of state-of-the-art machine learning applications utilized in the milling process. Section 2 describes the milling operations and machines. Section 3 presents the primary challenges in this context. Section 4 discusses the extracted data and the primary means of obtaining it. Also, an introduction to machine learning definition is presented in section 5. In Section 6, the application of Machine Learning in the milling processes is discussed. Section 7 provides a comprehensive overview of the paper, discussing the challenges faced in milling machining, machine learning models utilized, input parameters considered, and pre-processing methods applied. Finally, the highlighted conclusions as well as proposed future works are described in section 8.

2 Milling Machining

In milling, the workpiece is shaped and sized by moving a rotating tool with specific cutting edges. This tool is usually attached to a holder, which is connected to the spindle. The spindle controls the rotational speed, torque, and power of the tool. To manipulate the tool and workpiece, multiple axes are employed to adjust the relationship between the tool, holder, spindle, and workpiece [2].
The cutting process is performed by feeding the workpiece to the rotating cutter. Among the factors affecting the milling process, spindle speed, table feed, cut depth, and cutter rotation account for the most significant factors. A high-quality product is only produced when each set of cutting parameters is set to their optimum amounts and is well balanced.
The cutting tool used in the milling process is known as a mill. Additionally, the cutting edges are named teeth, which can be an extension of the mill or attach to the mill body. It has been discovered that chip sizes produced in the milling process are short. Consequently, the mill's material and geometric should be designed to stand against repetitive force and thermal shocks[3].
Two types of milling processes, peripheral and face milling, are based on the

orientation of the mill with respect to the workpiece surface, as illustrated in Figure 1.

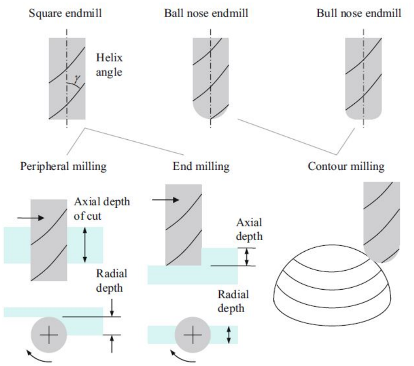

Figure 1 Example milling applications and tool geometries [2]

3 Challenges on Milling Machining

The milling machining is one of the most critical manufacturing processes, and tackling the challenges has a vital role in this regard.
One of the most challenging unwanted phenomena during milling is the machine tool chatter. Mill chatter vibrations can cause self-excited oscillations of the mill and workpiece. Chatter phenomena might lead to poor quality of the finished surface, inaccurate dimensions of the product, and chipping of the mill, which might damage the mill and workpiece [4]. The most common approach to ensuring the stability of the cutting process is to predict the stability lobe diagram (SLD) and determine the process parameters that can lead to an unstable cutting process.
Tool wear significantly affects the milling process efficiency. For instance, tool wear might affect dimensional accuracy, material removal rate, and tool life, which can lead to the technical and economic efficiency of the milling process. In addition, excessive tool wear in the milling process leads to cutting heat, cutting force, and friction between the tool and the machining surface. Moreover, the cutting, tool, cooling lubrication, and parameters of the processed materials account for the most influential factors leading to tool wear in the milling process [5].
Surface roughness (Ra) is an arithmetical mean height that indicates the average of the absolute value along the sampling length, indicating the deviation from the requirement of a product affecting the product's functionality and integrity. Additionally, revealed that the cutting speed and feed per tooth are the most critical factors affecting tool life and machined surface roughness.
Machine tool accuracy has attracted significant attention in recent years.

Table 1 Challenges in milling machining Process

Challenges	Description
Chatter detection	Chatter is a self-excited vibration that can arise in the machining process at specific combinations of cutting. parameters, depth of cut, and spindle speed. This phenomenon affects the surface finish resulting in strong vibrations of the cutter.
Tool Wear Monitoring	A tool monitoring system analyzes machine data from many devices to determine the health, lifespan, and remaining utility of a tool. Monitoring the health and lifespan of a tool is more difficult to perform than machine condition monitoring.
Surface Roughness Prediction	Surface roughness is a measure of the average texture of a part's surface, in this case, after CNC machining. There are different parameters used to define surface roughness. One of the most ubiquitous of these is Ra (Roughness average), which is derived from the differences between heights and depths on a surface.
Thermal Errors Predictions of Machine Tool	Thermal error is one of the main sources of machining errors in machine tools. Being a key component of the machine tool, the spindle will generate a lot of heat in the machining process and thereby result in a thermal error itself. Real-time measurement of thermal error will interrupt the machining process. Therefore, this paper presents a machine learning model to estimate the thermal error of the spindle from its feature temperature points.
Combine FEM with Machine Learning	In machining, specific cutting forces and temperature fields are of primary interest. These quantities depend on many machining parameters, such as the cutting speed, rake angle, tool-tip radius, and uncut chip thickness. The finite element method (FEM) is commonly used to study the effect of these parameters on the forces and temperatures.
Energy Consumption Prediction	Energy consumption in machining contributes a significant part to manufacturing costs and produces a great environmental impact critical assessment of energy consumption in a machining system. Energy consumption usually is classified at the process, machine, and system levels.

The most significant factors affecting machine tool accuracy include thermal errors, tool wear, chattering, geometric and kinematic errors, and cutting force-induced errors [6]. The thermal expansion of the milling machine components causes the displacement of the machine tools and workpieces. Error compensation is the most effective method for addressing this challenge. Error compensation examines the effect of each heat-source temperature of a machine tool on the thermal error by utilizing analysis, statistics, and induction.
A high energy consumption rate can significantly affect the environment and sustainability, especially in manufacturing. Many types of research and strategies have been applied to minimize the energy consumption in the manufacturing process. Reducing energy usage in the milling machining process has a crucial role. The most significant factors for reducing the energy consumption and power in the milling process are spindle speed(N), feed rate ((Vf), and depth of cut(d)[7].
In conclusion, to enhance the accuracy of geometry and eliminate nonconformity in milling, it is crucial to address the aforementioned challenges also shown in Table 1 by employing various techniques. One of the most promising approaches is the application of machine learning.

4 Sensors, Data and AI framework in Milling

There are two types of milling process monitoring, direct (offline) and the other one is indirect (online) monitoring.

The offline monitoring usually uses a fiber optic sensor or CCD camera, electric resistance, displacement, and acoustic emission, which can measure the dimensional changes in cutting tools and machined parts with high accuracy. However, utilizing optical sensors in the machining atmosphere can lead to the distortion of optical gadgets. Also, to utilize a direct monitoring method during the milling process, the operation should be interrupted, which is not practical in the production line.

Another way to monitor the milling process is an indirect method (online). In this method, the signals sourced from external sensors such as vibrations, temperature, cutting force, acoustic emission, and internal CNC machine signals such as Spindle and Servo Motor Current usually took advantage.

In [8] (Bernhard Sick) mentioned that the data collected in the direct method is less accurate than the sensors used in the indirect method., but one of the advantage of them is that they are easy to install and real-time monitoring without any interruption in the production line, which is a significant. However, the accuracy of data collected in the direct method versus the sensors used in the indirect method can vary depending on several factors. In direct monitoring, real-time data is collected directly from the milling process using sensors attached to the machine. This can provide highly accurate and precise measurements of parameters such as cutting forces, tool wear, and surface finish. On the other hand, indirect monitoring involves analyzing data collected after the milling process has completed. This data can include measurements of the machined part's dimensions, surface quality, and tool condition. While indirect monitoring may not provide real-time feedback, it can still offer accurate information about the overall process performance and the quality of the final product. Ultimately, the accuracy of the data depends on the quality and calibration of the sensors used in both direct and indirect monitoring methods. It is essential to select reliable sensors and ensure proper calibration to achieve accurate measurements in either approach.

As shown in Table 2, a range of seven sensor types are employed, including a Dynamometer, Piezoresistive MEMS strain gauge, piezoelectric accelerometer, AE transducer, Hall Effect and inductive sensor, microphone, and thermometer. Each of these sensors is designed to measure specific physical quantities.

Compared to the traditional method of measuring tool wear, this approach involves continuous monitoring of machining processes using sensing devices. The goal is to quantify process performance or gather information for process optimization [10].

In contrast to the conventional method of tool-wear measurement, the approach is that the machining processes are continuously monitored via sensing

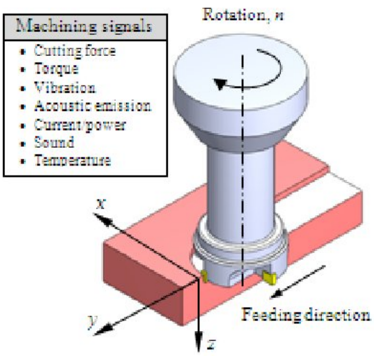

Figure 2 Sensor utilized in milling process [9]

Table 2 Sensor Used in Milling Machining

Physical Quantities	Description	Sensors
Cutting force	The force sensor used four strain gauges attached to the sides of the tool holder to estimate the cutting forces. The force controller is designed to adjust the feed rate because a fast change in the feed rate could damage the cutting tool.	Dynamometer
Torque	Piezoresistive MEMS strain gauge structure consists of several metal-wire resistances with different resistance capacities. These metal wire resistances should organize an independent Wheatstone circuit bridge.	Piezoresistive MEMS strain gauge
Vibration	The piezoelectric accelerometer is the most common type used in the vibration sensing of machining operations. Its transducer has the highest frequency response and range for dynamic events.	The piezoelectric accelerometer
Acoustic Emission	An AE Transducer is made up of a case, damping material, electrical lead, piezoceramic element, couplant layer, and wear plate.	AE transducer
Current/Power	Generally, the current signal is measured by a Hall Effect and an inductive sensor. The current conductor passes through a magnetically permeable core that concentrates its magnetic field. The Hall effect device is mounted in the core at a right angle to the concentrated magnetic field.	Hall Effect and an inductive sensor
Sound	A microphone is the receiver's device that translates sound vibrations in the air into electronic signals or write them onto a recording medium. The microphone enables a wide variety of audio recording devices.	microphone
Temperature	The inferred thermometer measures the temperature of an object without coming into contact with it using both emissivity and radiation as a means of measurement. Emissivity is a coefficient that indicates how well an object emits infrared radiation compared to a theoretically perfect black body. This radiation is used by the sensor to calculate the object's temperature	Thermometer

devices to quantify the process performance or provide information for process optimization. Finally, the choice between direct and indirect monitoring depends on your specific needs and priorities. If you require immediate feedback and real-time adjustments, direct monitoring would be more suitable. However, if you're focusing on long-term process improvement and statistical analysis, indirect monitoring can provide valuable insights. It's also worth noting that a combination of both methods can be used to achieve the most accurate and comprehensive monitoring of the milling process.

A sensor, being a type of transducer, is a device that converts a physical property into a corresponding electrical signal by detecting and transforming various physical phenomena. As it mentioned the most significant physical quantities deployed in the indirect methods are the cutting force, torque, vibration, acoustic emission, motor current or power, temperature, sound, etc. Subsequently, the received signals, typically in the form of time series data, are fed as inputs into the intelligent monitoring framework, as further described (refer to Figure 3)

4.1 Sensor Choice and Data Challenges

The initial phase of the monitoring system involves selecting the appropriate sensors and addressing the associated data challenges. In this context, Table 2 highlights the utilization of seven sensor types in the milling process, including Dynamometer, Piezoresistive, Piezoelectric, Inductive, Microphone, and Thermometer sensors. There are different challenges in choosing a specific type of sensor, such as the machining conditions, the distance between installation locations of sensors, the frequency range of machining, and the presence of cutting fluid and dust. However, there are four types of challenges related to data. For instance, The Internet of Things can tackle many problems and make it more accessible to use the data collected from different resources for monitoring and predicting purposes. The first challenge is related to the data size, that is, whether the data size is large or small. There is a rule mentioning that the number of samples should be ten times bigger than the number of parameters used in the deep learning approach [11]. In addition, high-dimensional data can be a challenge for implementation in machine learning models. It was revealed that the size of the data, whether small or large, can drastically affect the machine-learning architecture.

4.2 Data pre-processing and Feature Engineering

The signal pre-processing significantly affects the intelligent model's performance and enhances its accuracy. Different pre-processing approaches exist, such as signal-segmentation, de-noising, wavelet transformation, amplification, and normalization, to decompose the signals into their high and low-frequency components before the feature selection step.

It also revealed that feature engineering could significantly affect the monitoring-predicting system performance leading to many types of research to find the best technique. The most verified feature selection techniques include correlation, chi-square, and ANOVA filtering. The other widely utilized feature extraction is the wrapper technique, such as step-wise selection, backward elimination, and forward selection; the other is embedded methods, such as a random forest. However, there needs to be in-depth research on optimal feature extraction in milling condition monitoring. Therefore, the selection of optimal feature extraction usually refers to other literature or selects the feature extraction method by trial and error. Furthermore, another approach in this regard is applying data fusion methods to small-size data collecting in early-stage machining data, then calculating the range of data and generating synthetic data [12]. Consequently, prominent and sufficient data size is required for a fully automated feature engineering approach.

4.3 Choosing Machine Learning model

The selection of the most accurate and simultaneously fast machine learning model depends on the monitoring purpose, based on which one may select a model for regression, classification, or clustering. The most widely used models for decision-making in the machining processes in ascending order are artificial neural networks (ANNs), fuzzy models, neuro-fuzzy (ANFIS) models, and Bayesian networks. Recently, a growing interest has been observed in using Deep Learning decision-making models. The model selection mainly depends on the size and complexity of the acquired data and the level of pre-processing (such as de-nosing and feature extraction.) performed on the raw data.

4.4 Monitoring-Prediction Purposes

Intelligent systems have been primarily used for tool condition monitoring (TCM), including tool wear classification, flank wear prediction, chatter detection, and tool temperature monitoring. Not only Tool Condition Monitoring can be applied in intelligent systems, but also surface roughness, waviness, and chip condition (chip formation, size, breakage, dust emission, etc.), machining environment monitoring (e.g., airborne dust emission), and process condition monitoring (process fault, variation, state, etc.) is another primary purposes of establishing the intelligent monitoring systems. The monitoring purpose defines the type of intelligent decision-making model (e.g., using classifiers for tool wear detection vs. regression-based models for flank wear prediction). Figure 3 shows that the intelligent monitoring framework in milling machining processes consists of 6 sections. In the first section, the most applicable sensors, such as accelerometers, dynamo meters, and microphones, should be selected. After that, the sensors will obtain data types, such as Acoustic Emission, Vibration, Cutting Force, and Temperature. The next step is the pre-processing of data, including signal segmentation, de-nosing, wavelet transform, amplification, and normalization. Then, the feature engineering process including the feature selection methods such as filtering, wrapper, and time-frequency domain, apply to the received data. Furthermore, the Machine Learning and/or Deep Learning models should be selected in the next step in order to implement a prediction, monitoring, or anomaly detection framework. Furthermore, one of the most significant sections of the intelligent monitoring framework is the governing model for predicting/monitoring, such as the prediction of chatter stability diagram, tool condition monitoring, surface roughness prediction, the prediction of cutting tool deflection caused by thermal loads, the prediction of cutting force and other mill parameters using finite element analysis data, the prediction of machining time and cost and finally the prediction of CNC machine energy consumption.

5 Machine Learning

Machine learning (ML) significantly impacts the manufacturing industry in the concept of the Industry 4.0 paradigm. In the Industry 4.0 paradigm context, it has been highly recommended to utilize more intelligent sensors, devices, and machines to enable smart factories to receive data online and apply ML to predict or monitor the primary challenging purpose. This section sheds more

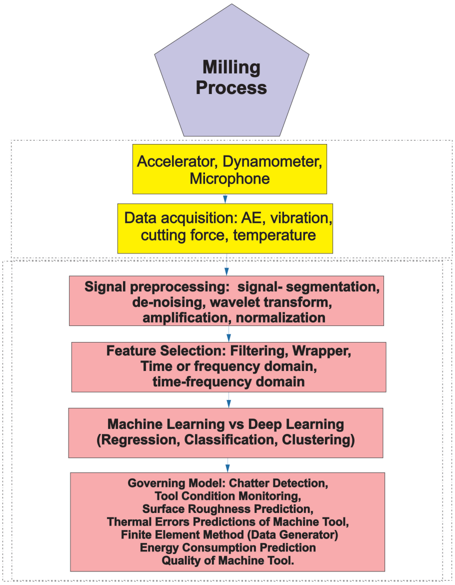

Figure 3 Intelligent Monitoring Framework

light on both the concept of ML and the most used ML methods in the milling machining process.

5.1 Basics Concepts

Machine learning is a branch of artificial intelligence (AI) that focuses on developing algorithms and models that enable computer systems to learn and make predictions or decisions without being explicitly programmed. In other words, it's about teaching machines to learn patterns and extract insights from data, allowing them to improve their performance over time through experience. By using statistical techniques and algorithms, machine learning algorithms can automatically analyze and interpret vast amounts of data to identify patterns, make predictions, or solve complex problems. The ultimate goal of machine learning is to create intelligent systems that can autonomously learn from data and adapt to new situations, making them more efficient and effective in various domains. Predictive methods can be divided into two categories: regression and classification methods. Detecting anomalies or outliers can be seen as a binary classification problem, meaning it involves only two classes. To predict anomalies or outliers, you can employ supervised, unsupervised, or even semi-supervised methods. An unsupervised method utilizes unlabeled data to construct models, and clustering is a commonly used unsupervised method for outlier detection. On the other hand, supervised methods rely on labeled data to train models. One-class and binary classifiers are examples of supervised methods frequently used for outlier detection. Additionally, there are semi-supervised methods that utilize both labeled and unlabeled data to train models.[13]

Regression is a predictive task at assigning a quantitative value to a new, unlabeled object, given the values of its predictive attributes.[13] Generally, regression can be divided into two main theories. The first theory admits that regression is forecasting and prediction which is widely utilized. The other regression theory defines it as determining the causal relations between the independent and dependent variables. For instance, regressions alone show only relations between a dependent variable and a fixed data set collection of different variables. [14]

Moreover, another method primarily utilized in ML approaches is classification. Classification is a predictive task where the label assigned to a new, unlabeled object, given the value of its predictive attributes, is a qualitative value representing a class or category. [13]

Also, another approach widely utilized in different data problems is the Clustering technique. Clustering is an ML method that partitions data sets into different groups.[15].

Different causes can lead to outliers appearing in the data sets, such as mechanical faults and human errors, which could be important information for monitoring and predicting the data by experts. (Barnett and Lewis,1994) defined the outlier as an observation that appears to be inconsistent with the remainder of that data set [16]. In other words, Outlier Detection is any process that finds the outliers of a data set; those items that do not belong.[13]

5.2 Main Methods/Models

5.2.1 Neural Networks

Artificial neural networks (ANNs) are connected computer systems based on the nervous system. In this artificial neuron system, each neuron is connected to other neurons to get a value, and then, the activation function applies to the weighted sum, shown in Equation 1.

$$Output\$equal = \sum(Weights * Inputs) + Bias \tag{1}$$

5.2.2 Deep Learning

W.J. Zhang et. al [17] presented a definition of deep learning as below:

Deep Learning is a class of machine learning algorithms that: (1) Use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input. (2) Learn multiple levels of representations corresponding different levels of abstraction; the levels form a hierarchy of concepts, which can be observed in Figure 4.

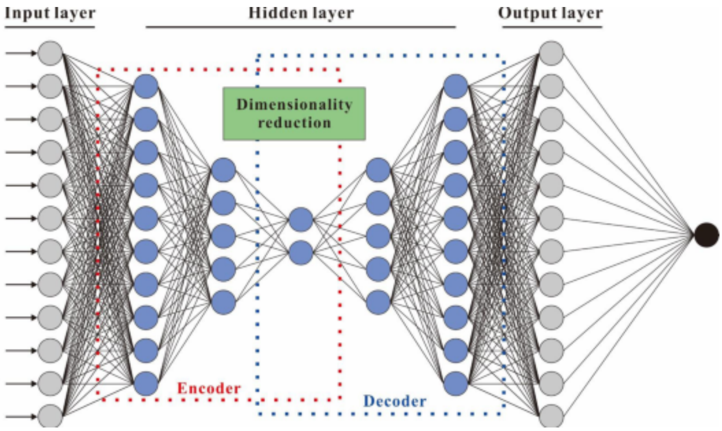

Figure 4 Deep Neural Network (Auto Encoder)[18]

The main difference between conventional Machine learning and Deep Learning is that the conventional Machine learning models are typically shallow, or in some ANN models, they are limited to two hidden layers which can be observed in Figure 5.
In deep learning applications, usually, the feature engineering steps are minimal. In other words, manual feature extraction and selection are built-in. However, it is highly required to employ feature engineering in Machine learning approaches. Comparing two models regarding Data Size, Deep Learning results in high performance when working with big data; however, ML gains high accuracy and performance when it deals with small and medium-sized data. Also, Deep Learning is suitable for industry-scale data size, which has high-dimensional data like data collected by sensors and images. However, ML has a challenge working with high-dimensional data sizes, and feature selection is required. On the other hand, ML has difficulty in interpretation but is less challenging than deep models. Also, ML models are less computationally expensive than to deep learning models. The most utilized Deep Learning approaches in AI-based manufacturing processes are autoencoders, deep belief networks, convolutional neural networks, and recurrent neural networks.

5.2.3 Decision Trees

In some cases, there is a need for a predictive model which should be easy to understand. One of the most straightforward models to interpretable is flowchart models in the format of a tree. Decision trees usually are utilized in frameworks that require a decision-maker. In the same format in machine learning, a Decision tree induced the decision by creating a tree-like hierarchical structure in which each node of the structure represents a predictive attribute.[13]

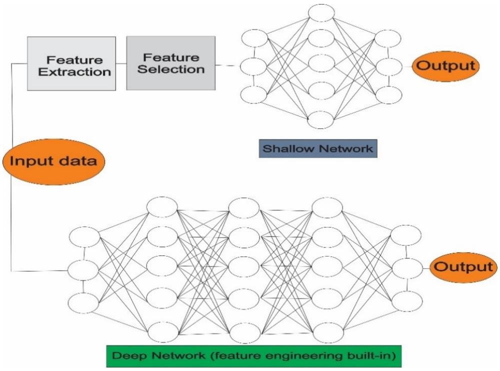

Figure 5 Deep learning VS Conventional Machine Learning

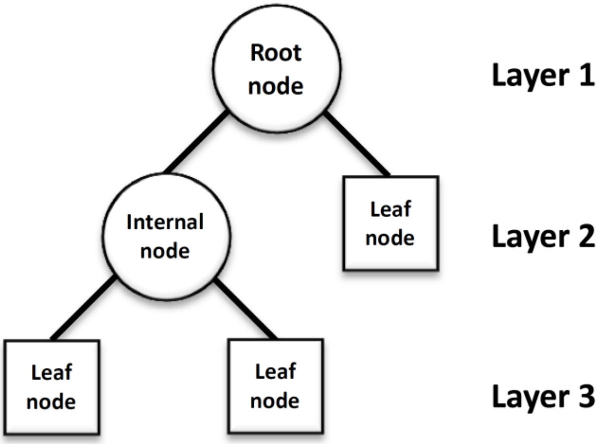

Figure 6 Illustration of a Decision Tree.[19]

5.2.4 Support Vector Machines

The support-vector machine is a machine learning method utilized in both classification and regression. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high dimensional feature space. In this feature space, a linear decision surface is constructed. Special properties of the decision surface ensure the high generalization ability of the learning machine [20].

It is considered that the training set of n points $\{\mathbf{x}_i, y_i\}$ $i = 1, \ldots, n$ where $y_i \in \{-1, 1\}$ is the class of the point x_i. It desires that by using two classes as $y_i = 1$ and $y_i = -1$, constructing a classifier hyperplane that can map x_i's into higher dimensional space so that the two different classes of points can divide. The proposed hyperplane should specify the maximum margin maximizing the distance of the hyperplane and nearest points from both groups.

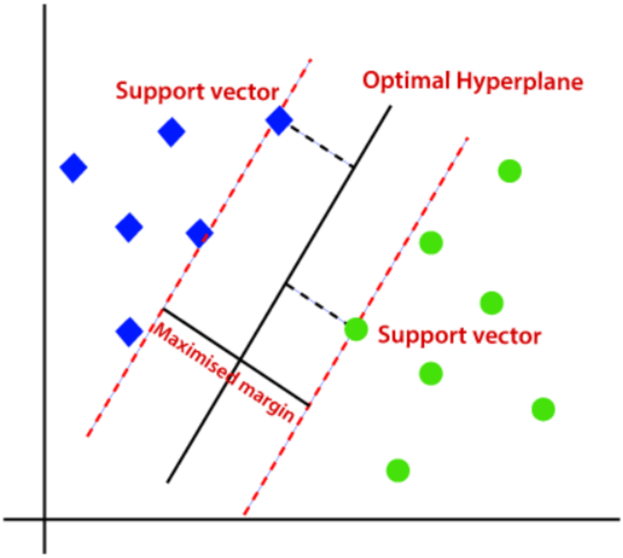

Figure 7 Illustration of a Support Vector Machine.

The hyperplane equation in linear cases illustrates in equation 2:

$$\mathbf{x}_i\mathbf{w} + b = 0 \tag{2}$$

The Support Vector Machines method expects to obtain two parallel hyperplanes separating data, and the distance between these two parallel hyperplanes must be maximized, as demonstrated in the equations 3.

$$\mathbf{x}_i\mathbf{w} + b = +1, \mathbf{x}_i\mathbf{w} + b = -1 \tag{3}$$

The distance between the two hyperplanes $\frac{2}{w}$ can be calculated as shown in equation 4:

$$d_+ + d_- = \frac{\text{1-b}}{\|w\|} + \frac{\text{-1-b}}{\|w\|} = \frac{2}{\|w\|} \tag{4}$$

It means that the $\|w\|$ should be minimized as it is always positive. Furthermore, the constraints illustrating in equations 5, 6, 7 for every $i \in (1, n)$, x_i and y_i, should be satisfied at the same time.

$$\mathbf{x}_i\mathbf{w} + b \geq +1, \quad \text{if } y_i = +1 \tag{5}$$

$$\mathbf{x}_i\mathbf{w} + b \leq -1, \quad \text{if } y_i = -1 \tag{6}$$

$$\mathbf{x}_i\mathbf{w} + b \leq -1, \quad y_i = -1 \equiv \; y_i(\mathbf{x}_i\mathbf{w} + b) - 1 \qquad \geq 0, \quad \forall i \tag{7}$$

6 Machine Learning Applied to Milling Machining

Machine Learning has a significant impact on advancing manufacturing and process monitoring systems and has a crucial role in transitioning toward the Industry 4.0 concept. Also, ML has concentrated on concepts such as multi-sensor utilization and data-driven methods after revealing the hidden patterns in high dimensional data [21](Lee J, 2018). The remainder of this chapter assumes the use of indirect methods as described in Section 4.

The milling machine monitoring framework mostly applies by utilizing high-tech sensors and artificial intelligence models to predict the wearing of cutting tools and avoid non-conformities and surface quality in the product. Also, it might lead to chatter and dimension accuracy of the machined products and excessive heat production in both cutting tools and machined parts. The different sensors, such as acoustic emission, vibration, power, and temperature, collect large amounts of data using them for developing predictive models.

Then, preprocessing applies to the data, such as amplification, filtering, labeling, and noise reduction, which is a highly significant to achieve accurate results in monitoring of the tool. For instance, if the raw data does not correctly denoising, it might significantly affect the prediction model's accuracy. Another essential step in the ML framework is data labeling, in which datasets must be entirely or partly labeled consistently, otherwise, the learning process could be impaired. Also, Fast Fourier transform (FFT), and wavelet transform (WT) are among the most applied methods, according to this review. However, the FFT method is localized in the frequency domain, but the WT is localized in the time-frequency domain. The predictive machine learning models are usually used for predicting items mentioned below: 1. Chatter stability prediction 2. Tool Wear Monitoring 3. Surface Roughness Prediction 4. Thermal errors Predictions of Machine Tool 5. Energy Consumption

6.1 Chatter Detection

Chatter is a self-excited vibration of parts in the milling process. It usually happens across a range of cutting processes and impacts efficiency and quality in production processing [22].
(Y. Altinta, 1995) in [23] developed a prediction model to predict the chatter phenomena by utilizing an analytical predictive model whose goal was to predict the dynamic cutting force coefficients and the chatter-free axial depth of cuts and spindle speeds without any digital iterations.
Furthermore, [24](Yesilli, et al., 2019) utilized topological features of data

simulating cutting tool vibrations and four machine learning algorithms including TF: Template Functions, SVM: Support Vector Machine, LR: Logistic Regression. Since the deviation of accuracies for featurization methods was low, the machine learning algorithm result can be reliable. Finally, it was revealed that topological features of data were appropriate descriptors for chatter recognition in milling, and by using this method, there is no need for manual preprocessing not only for non-noisy data sets but also for time series with noise.

Another research conducted by (Chen, et al., 2019) [25] used an intelligent chatter detection method based on image features and the support vector machine. After that, the FFT method was applied to identify the dominant frequency bands that divide the time-frequency image of the short-time Fourier transform into several sub-images. The dominant frequency bands identified from the average FFT were used to divide the STFT images to increase the signal-to-noise ratio and the sensitivity of image features.

Furthermore, (Batihan Sener, 2021) [26] also established an intelligent monitoring framework for detecting chatter by applying a deep convolutional neural network (DCNN) and vibration data used for training the neural network. Considering chatter's nonlinear and dynamic specifications, continuous wavelet transform (CWT) was used. Then, the images were utilized for training and testing the developed DCNN. Although the shuffling approach is a common way for testing and training datasets, in this research, the cutting parameters were applied as scalar inputs to fully connected layers which led to high accuracy and performance of the DCNN method. Also, using cheap accelerometer sensors makes them more accessible in industries.

Another chatter prediction for the machining of Titanium alloy was made by (Zacharia, et al., 2020)[27]. Firstly, the vibration signals were captured by accelerometer sensors, then the features were extracted, and a decision tree algorithm was utilized in selecting the dominant features. Chatter is predicted by three different machine learning methods, including Decision Tree (DT), Artificial Neural Network (ANN), and Support Vector Machines (SVM). Finally, it was observed that the efficiency of the ANN approach was the best compared to the other methods.

Additionally, (Shi, et al., 2020)[28] established a prediction system for the chatter identification by using the Reinforced k-Nearest Neighbors method under different cutting conditions, such as the rotating speed and the cutting depth. The signal segmentation and normalization method was applied at first, and then, the t-SNE method was used for feature extraction purposes. Next, the RkNN method was utilized for chatter identification purposes, and at the end, signals obtained from different sensors in the milling experiments validated the model.

Also, (Li, et al., 2020) [29] established an online chatter detection and chatter severity levels identification. They applied the angular synchronous averaging (ASA) method for data preprocessing. The multiscale permutation entropy (MPE) and multiscale power spectral entropy (MPSE) were extracted, and

Laplacian score (LS) methods were used to select the optimal sensitive scales. Next, a sliding window was applied to divide the signal into frames (Overlapping). Online chatter selection was established by calculating the permutation entropy (PE) and power spectral entropy (PSE) for each frame. Finally, a trained gradient tree boosting (GTB) classifier was applied to automatically calculate the chatter severity levels to establish an intelligent diagnosis.
(Tran, et al., 2020)[30] establish a novel approach based on deep CNNs. In the proposed approach, the cutting force signals convert to two-dimensional images, and then, the time-frequency image of the force signal was applied to a CNN model.
[30] establish a novel approach based on deep CNNs. In the proposed approach, the cutting force signals convert to two-dimensional images, and then, the time-frequency image of the force signal was applied to a CNN model.

Moreover, (Peng, 2015) [31] utilized the cutting force as the monitoring signal, and then wavelet energy entropy theory was used to extract the feature vectors. A support vector machine was established for pattern classification based on the feature vectors gained from the experimental cutting data. After that, it combines with the dynamic cutting force simulation model, and the stability lobes diagram (SLD) is established. Finally, the results were tested and validated by experimental data as well as zero-order analytical (ZOA) and semi-discretization (SD) methods.
Additionally, (Jaydeep Karandikar, 2022) in [32] introduced a novel approach for preventing the chatter phenomena in milling machining utilizing a closed loop controller. The closed loop controller applied in this research work consisted of an architecture for monitoring the machine state taking advantage of MT Connect(MT Connect is a standardized framework in the manufacturing industry that facilitates the retrieval of valuable process information from computer-controlled machine tools). Then, the next stage is developing an intelligent monitoring framework. In this work, a Bayesian Machine Learning method is utilized to learn the stability boundary by taking advantage of test results and a model for choosing the test parameters. In the future work section of this paper it is proposed that an online feedback controller (digital twin) must be implemented to update the G-code inputs for each defined loop. To be more specific, the CNC machine parameters instantly update to prevent chatter phenomena and cutting tool wear simultaneously, optimizing the surface roughness of the product and energy consumption of the CNC machine.
Additionally, the same authors in other research applied a novel ML method called active learning in [33] to identify the stability process map in machining using the time domain simulations. Then, the results illustrated the decrease in time-domain simulations required for identifying the stability process. Finally, one of the most recent studies conducted by Tony Schmitz et al. [34] presented an approach for identifying milling stability. This approach incorporates both physics-based models and stability predictions. In this regard, the binary result obtained from the experimental test was labeled as

stable or unstable according to their frequency content and chatter frequency when an unstable result and user risk tolerance were obtained. After that, the probabilistic Bayesian machine learning with adaptive, parallelized Markov chain Monte Carlo sampling to update the probability of stability with each machine test. Finally, the results revealed that the applied algorithm converged rapidly to optimize milling parameters for maximum metal removal rate utilizing all available information.

6.1.1 Chatter Detection focuses on deep learning

Deep learning methods have shown their strong potential for monitoring and predicting chatter phenomena in recent years. A research conducted by [35] (Postel, et al., 2020) in which a hybrid approach was applied to improve the stability limits of milling operations. It combined the knowledge gained studying of the various dynamic behaviors of the tool holder-tool assemblies with the resulting stability lobe diagrams. Through the use of deep neural networks, the approach was able to perform practical simulations with varying cutting conditions. Also, clamping lengths, spindle speeds, and axial and radial engagement parameters utilized as the inputs and stabilities of the simulated cut were the output of the Neural Network.
Also, (Denkena, et al., 2020)[36] applied a Support Vector Machine and Artificial Neural Network methods to predict the Stability lobe diagrams of the milling process. The acceleration and sound signals are utilized as input for the machine learning algorithms.
Additionally, Deep Neural Networks were utilized by (Yichao Dun, 2021)[37], and proposed an unsupervised method named the auto-encoder approach to diagnosing milling stability according to massive unlabeled measured dynamic signals. When signals were distributed more, the results were more accurate and reliable.
Furthermore, (Yang Fu, 2015)[38] utilized deep belief networks to build a feature space for monitoring cutting tools. In this research, three types of machine learning methods, including the DBN with a BP output neuron network (NN) containing only one hidden layer and support vector machines (SVM) compared, and the result showed that the DBN gained high accuracy.
Finally, (Rui Zhao, 2016)[39] also applied deep LSTMs to predict the actual tool wear by taking advantage of raw signals obtained from sensors. Finally, the comparison of results with experimental data revealed that the deep LSTM achieved accurate results compared to other baseline methods.

6.2 Tool Wear Monitoring

It has been revealed that monitoring tool wear conditions and calculating the Remaining Useful Life of cutting tools play a crucial role in automatic metal-cutting manufacturing processes. Estimating the tool wear status accurately can lead to the optimum time of utilization of the cutting tool and, in

the end, leads to enhancing the product quality and reducing downtime and costs [40]. One research using machine learning models for monitoring the tools wear of cutting tools was done by (Rodolfo E. Haber, 2003)[41]. This research established an intelligent supervisory system for predicting tool wear under actual cutting conditions. The Machine learning model utilized was an artificial neural network that could predict the process output.
Additionally, (N.Ghosh, 2007) [42] proposed a neural network-based sensor fusion model for tool condition monitoring (TCM). Then, utilizing the methods of signal level segmentation for temporal registration, feature space filtering, outlier removal, and estimation space filtering were applied to extract signals of cutting forces, spindle vibration, spindle current, and sound pressure level. Finally, the neural network was validated by data obtained from the laboratory and industrial tests.
Another application of Machine Learning for establishing a tool condition monitoring system was made by (Dazhong Wu, 2016)[43]. They utilized the Random Forest as well as the PRF (Parallel Random Forests) method using the MapReduce framework and took advantage of Amazon Elastic Compute Cloud. The data was obtained using sensors for cutting force, vibration, and acoustic emission signal channels. Then feature extraction was done, including Maximum, Median, Mean, and Standard Deviation. The performance of different Random Forest Algorithms was measured by utilizing mean squared error, R-square, and training time.
Finally, by doing experimental tests, it was revealed that for a limited number of training data, random forests predict more accurately. However, PRF showed better performance for a large amount of training data.
Furthermore, the most popular machine learning approaches, including Artificial Neural Networks (ANNs), Support Vector Regression (SVR), and Random Forest (RFs), were utilized by (Dazhong Wu, 2017) [44] to predict the tool wear in milling operations. First, the statistical features were extracted from cutting force signals, vibration signals, and acoustic emission signals, and the performance (mean squared, R-squared, and training time) of each one of the Machine Learning algorithms was validated on the data-set collected from 315 milling tests. It was revealed that although the run time for training of Random Forest was more than Feed Forward Back Propagation Artificial Neural Networks (ANNs) and Support Vector Regression (SVR) algorithms, the Random Forest generated more accurate results compared to the one hidden layer FFBP ANNs and SVR methods.

(Shen, et al., 2021)[45] developed a data-driven predictive model in which the data pre-processing, including cutting detection, signal segmentation, and measurement interpolation applied, and then, three feature extraction techniques, namely, time domain, frequency domain, and time-frequency domain were investigated. Next, the key features were selected. Different regression algorithms such as Random Forest (RF), Gradient Boosting Regression, Neural Network and Linear Regression, and Support Vector Regression were applied to predict the tool wear values.

Moreover, (Lei et. al) [46] proposed a novel ITD-based KELM method for detecting tool wear conditions in the milling machining process. In this sense, the vibration signals were utilized as input of the machine learning approach, and the results revealed that ITD-based KELM methods obtain more accurate results compared to ITD-based SVM, EEMD-based KELM, and VMD-based KELM. It was concluded that ITD is more suited for analyzing non-stationary tool vibration signals and can detect tool wear conditions more effectively.

(Cheng, et al.) [47] utilized a generalized multi-class support vector machine (GenSVM). Then, multidimensional feature extraction was applied in the time domain, frequency domain, time-frequency domain on the domain statistical analysis, power spectrum analysis, and complete ensemble empirical mode decomposition with adaptive noise, respectively. Then, a Pearson correlation coefficient was applied to pick up the useful features.

(Li, et al., 2019) [48] utilized the extended convolutive bounded component analysis (ECBCA) to process multivariate audio signals to distinguish a set of source signals from a set of mixed signals. Then, the multivariate synchro squeezing transform (MSST) was used to characterize multivariate audio signals with time-varying oscillatory properties. Next, the adaptive kernel principal component analysis (AKPCA) was utilized to transform the denoised signals into a feature space. Experimental tests were done, and audio signals using multi-channel microphones were collected and used for training and validating the predictive model. The results revealed that the ECBCA-MSST method could extract the significant features of source signals representing the dynamic response of the cutting tool during the milling operation. Furthermore, the AKPCA method enhanced the accuracy of the predictive model by reducing the dimensionality of the extracted features.

(Zhou, et al., 2020)[49] established a tool-tipping monitoring approach for the milling process of titanium. Then, the singularity analysis method was applied to characterize the variation of vibration waveforms quantitatively with the Holder Exponent (HE) index. The probability density distribution and statistical analysis were employed to extract effective HE features from the HE indexes to correlate with the different cutting parameters. Next, the mutual information method was adopted to rank the discriminability of HE statistical parameters. Finally, several machine learning applications such as Decision Tree (DT), Support vector machine (SVM), k-Nearest Neighbor (KNN), and Ensemble Learning (EL) were implemented utilizing the selected HE indicators to classify data into different label groups and compare the accuracy of them. Finally, the results revealed that the Support Vector Machine model could provide accurate estimation results.

6.2.1 Tool Wear Monitoring focuses on deep learning approaches

Many researchers have advocated finding a more accurate solution for tool wear monitoring, and it was revealed that deep learning is alternatively more accurate in most cases compared to the shallow ML methods, and there is no need for a feature engineering step. Based on the survey, the most concerning challenge in milling machining was dedicated to tool condition monitoring compared to other Machining challenges such as chatter detection, surface roughness prediction, energy consumption, and thermal error detection.

One of the most accurate and utilized deep learning approaches in tool condition monitoring based on the survey is Auto-encoder (AE). Auto-Encoder is an unsupervised method to monitor the wear state of a milling cutter by tracking an error sequence generated by reconstructing monitoring signals.

One of the most recent Auto-Encoder applications in tool monitoring was made by [50], in which an inferential anomaly detector for tool wear monitoring on the machining process applied in which the power or the force signals utilized as input into the Deep Learning model. In this research, the anomaly detector utilized a physics-based model, Auto-Encoder, decision trees, and other neural networks for incremental error correction. Then, CUSUM statistics based on a physics-based and hybrid model applied and mislabeled the change in operating conditions and gave a false alarm. Finally, it was revealed that all four features, including the width of cut, depth of cut, feed rate, and spindle speed, were mandatory for establishing an accurate model.

Also, in [51], a Bayesian optimized discriminant analysis model was used to classify and monitor the mill (the cutting tool) into three user-defined categories. In this research, a data acquisition (DAQ) module designed in the house was used, and the hyper-parameter tuning has been incorporated using Bayesian optimization search.

The next research accomplished by (Jianming Dou, 2019) [49] established a tool tipping monitoring approach for the milling process. The singularity analysis method based on wavelet transform was used to characterize the Holder Exponent index of vibration variations. After that, the statistical analysis and density distribution were applied to extract the effective HE features for correlating with different tool conditions. Finally, the Support Vector Machine (SVM) model was applied to the selected HE features which resulted in the highest training and classification accuracy performance compared to other Machine learning models.

Moreover, (Chuang Sun, 2019) [52] utilized a Deep Transfer Learning method, including three transfer strategies with weight transfer, feature transfer learning, and weight update, using run-to-failure data. Consequently, in this work, first, a Stacked Auto-Encoder trained by run-to-failure data

containing the Remaining Useful Life information of the mill under an off-line process. Then, the trained is transferred to a new tool under operation for on-line Remaining Useful Life prediction, which results showed high performance of the Deep Transfer Learning method compared to the other methods.
In research conducted by (Tim von Hahn, 2021) [53], the tool wear of the mill by utilization of the disentangled-variational-autoencoder was predicted, and end-to-end deep learning method. A temporal convolutional neural network was applied for the architecture of the Beta-VAE, and an anomaly detection technique was applied to make final predictions.
Another application of Auto-encoder was made by (Antoine Proteau, 2020) [54] using a VAEC method for data obtained in a milling machining process in which a two-step training methodology, both unsupervised and supervised, used for predicting the cutting operation label.
Also, (Jiayu Ou, 2021) [55] utilized a new deep learning algorithm to enhance the performance of the monitoring framework and its ability to deal with the huge amount of data. In this work, a stacked denoising autoencoder (SDAE) was utilized. The main reason for choosing the SDAE was its ability to reduce the dimension of origin data. Then, an online sequential extreme learning machine (OS-ELM) was established for intelligent recognition of tool wear states.

Moreover, the Tool Wear Condition Monitoring framework utilizing the Auto Encoder was established in another work by (Luis Enrique Escajeda Ochoa, 2019)[56] in which a Mel Frequency Cepstrum Coefficients (MFCC) and Auto Encoder (AE) were used as a nonsupervised method to detect the features of the signals. By using the AE in the form of an SSAE neural network, significant parameters indicating the sparsity, regulation, and impact of the sparsity regularizer were encountered to find the optimal network and avoid the under-fitting and over-fitting.
Additionally, the auto-encoder method, which does not need label data, was used by (Jonggeun Kim, 2020)[57] in which the cutting force signals were extracted from the spindle motor. Three Auto-Encoder methods, including CFSAE using raw data, false negative rate (FNR) FSAE and FSAENR utilize featured data employed in this research.
(Jianming Dou, 2020)[58] used a well-structured Stacked Auto-Encoder (SAE) model that can adaptively extract the features of the signal without the need for supervision of the empirical label. Also, in this research, three-phase current signals were utilized as input of deep learning networks instead of traditional force and vibration signals.
Furthermore, (Jiayu Ou, 2020)[59] employed a stacked sparse auto-encoder (SSAE) neural network combining an order analysis (OA) model and a Soft-Max classifier can better extract the features of tool wear. Additionally, a novel multi-dimensional stacked sparse autoencoder model (MD-SSAEs) with feature fusion was employed by (Chengming Shi, 2019))[60]. In this research, the MD-SSAEs were designed to model more valuable features and validated by experimental results with high accuracy compared to traditional methods.

According to Figure 9 the convolutional neural network (CNN) can be considered as the most utilized deep learning method for Tool wear monitoring and one of the most applied methods in other milling challenges. The convolutional neural network (CNN) class of artificial neural network has become dominant in various computer vision tasks, attracting interest across various domains, including different Manufacturing processes [61]. Convolutional Neural Network (CNN) allows the researcher to import the images of the tool directly or apply the signals obtained from external and internal sensors, such as sound, vibration, and Current signals, as an input of a neural network. A pre-processing technique such as a wavelet transform method should be applied to the mentioned signals before using them in the CNN Method.
CNN consists of a convolution layer, a pooling layer, and a fully connected layer between the input layer and the output layer, as shown in Figure 8.

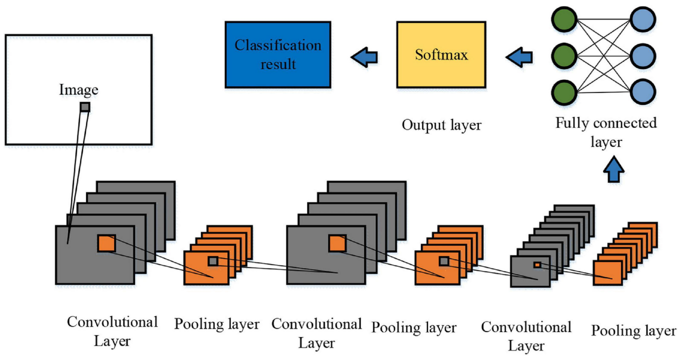

Figure 8 Illustration of a Convolution Neural Network [62]

One of the researches on applying convolutional neural network (CNN) in tool wear monitoring was made by (Xincheng Cao, 2019)[63]. It was based on 2-D CNN and derived wavelet frames (DWFs). Furthermore, the frequency band of the high signal-to-noise ratio was extracted via derived wavelet frames and then folded into a 2-D matrix to train the CNN.

Furthermore, (Harshavardhan Mamledesai,2020)[64] utilized the concepts of computer vision, a convolution neural network (CNN), and transfer learning (TL) to teach the machines the visualization of conforming component-producing tool and non-conforming component-producing tool. (Hui Zheng, 2019)[65] developed a CNN network and used cutting force signals and then time-frequency analysis for feature extraction applied to the images used as input into CNN. Moreover,(Xingwei Xu, 2020)[66] 1-D CNN was utilized for extracting features from raw data, and the residual block with the dilated convolution and a fully connected layer was also developed for the prediction of tool wearing. Then, the trained model accuracy was validated by comparing the ML predicted values and experimental results.

Moreover, (Xin-Cheng Caoa, 2019)[67] established an intelligent tool wear framework using vibration signals. A proposed framework combining derived wavelet frames (DWFs) and convolutional neural networks (CNN). Firstly, DWFs decompose the original signal into frequency bands in order to pronounce the tool wears. Then, the reconstructed sub-signals were stacked into a 2-D signal matrix for matching into CNN structure, then the 2-D CNN recognized features from a multi-scale 2-D signal matrix. Another application of CNN in tool wear monitoring was made by (Zhiwen Huang, 2019)[68] in which a deep convolutional neural network (DCNN) model in milling operation for enhancing the performance of prediction was applied. In this work, multi-domain (including time-domain, frequency domain, and multi-domain) features were extracted from multi-sensory signals as health indicators of tool wear condition. Next, the DCNN model is implemented for predicting the tool wear states using the extracted features and real-time tool wear.

Also, with the development of a charge-coupled device (CCD) image sensor as well as deep learning algorithms, the identification of wear types of high-temperature alloy is now possible. In this regard, (XuefengWu, 2019)[69] implemented a convolutional neural network (CNN) model to automatically identify the wear types of high-temperature alloy tools in the face milling process. This research applied the convolutional automatic encoder (CAE) to train the network model. The backpropagation algorithm combined with stochastic gradient descent (SGD) was used for fine-tuning the model's hyperparameters.

Also, another application of CNN in tool wear monitoring during the milling machining process was established by, (Kaiyu Song, 2020)[70] in which an online tool wear state monitoring framework was established. This work used the spindle current clutter signal (SCCS) and LeNet-WSRMC network design based on the DCNN in extracting the signal image.
Additionally, (Giovanna Mart ́ınez-Arellano, 2019) in [71] proposed a tool wear classification utilizing combining imagining process as an encoder and Convolutional Neural Network. The combined method is capable of working directly on the raw data, and there is no need for statistical pre-processing or filter methods, which is crucial when dealing with a large amount of data that holds complex evolving features. As mentioned, the imaging process serves as an encoding procedure of the data received by sensors which means that the original times series could be re-created without any loss of information. Then, off-the-shelf deep learning was implemented, and the manual selection of features was consequently avoided, making this a unique approach when working with many datasets.

Furthermore, (ZHIWEN HUANG, 2019)[72] used a novel multi-sensory data-driven tool wear predicting method based on reshaped time series convolutional neural network (RTCNN) in which the reshaped time series layer was implemented for illustrating the multi-sensory raw signals after that convolutional and pooling layers to learn distinctive characteristics of tool wear directly from multi-sensory raw signals.

(Xingwei Xu, 2021)[73] implemented a multi-scale feature fusion for developing parallel convolutional neural networks for tool monitoring of cutting tools utilized in in-cylinder engine production. Furthermore, it has been revealed that utilizing heterogeneous sensors is challenging. For this reason, a systematic methodology was applied to combine signal denoising, feature extraction, feature optimization, and deep learning-based prediction.

(Xiaoyang Zhang,2021)[74] utilized the CNN model to monitor the tool wear during the milling process. To be more precise, in this research, the intelligent monitoring framework can be divided into three steps. First, signal denoising was carried out using a Hampel filter-based method. Second, the feature extracted from heterogeneous sensors in the time and frequency domains was optimized utilizing designed recursive feature elimination and cross-validation (RFECV)-and Isomap-based methods. Finally, the convolutional neural networks (CNN) algorithm was applied to optimized features to implement tool wear prediction.
Also, one of the most promising research was conducted by (Han, Te, et al. 2019) [75] for intelligent fault diagnosis of CNC machines, in which a novel DACNN integrates the adversarial learning framework into a convolutional neural network. It was revealed that the proposed model not only inherits the benefits of deep models but also makes the feature illustration more robust and enhances the condition under limited training data.
In other research, a combination of the CNN method and Long short-term memory is applied to resolve the problems with the CNN. In this research, a two-layer BLSTM network and a one-layer ULSTM network were designed to denoise and encode the temporal information containing the past and future contexts of the time step and long-term dependencies in local features. Then, the CNN-SBULSTM network was proposed to compute the milling tool's remaining useful life (RUL). Finally, experimental results verified the validity and feasibility of the integrated model.
(Ou, et al., 2021) [55] enhanced the ability to deal with massive data samples by introducing a novel deep learning algorithm and an unsupervised method named stacked denoising autoencoder (SDAE). Next, the online sequential extreme learning machine (OS-ELM) algorithm was applied to indicate the tool wear states in a short run time. This method was able to extract signal features with no need to utilize many complex algorithms such as empirical mode decomposition (EMD), and variational mode decomposition (VMD).
Also, (Ma, et al., 2021)[76] established a convolutional bi-directional long short-term memory network and a convolutional bi-directional gated recurrent unit as a novel predictive model based on the force signals, then they compared it with the commonly used predictive model. Then, the model's performance, including the mean absolute error and root mean square error, revealed that the proposed CNN+BILSTM and CNN+BIGRU prediction models were

more accurate compared to CNN+GRU and CNN+LSTM models.

Another research carried out by (Cheng, et al., 2019) [47] proposed a multi-sensory data-driven health degradation monitoring system. The schema used multi-sensory signal preprocessing and feature extraction, PCC-based feature selection, and SVM-based health state identification. Then, the multi-sensory signals were collected and preprocessed. Next, time-domain features were extracted based on TDSA, PSA extracted frequency-domain features, and IEFs in the time-frequency domain were extracted via CEEMDAN. Moreover, PCC was used to pick up features and was able to the degradation process of machining tools from massive extracted features.

Also, (Zhou, et al., 2020)[77] presented a novel TCM method for milling processes based on a two-layer angle kernel extreme learning machine (TAKLM), and binary differential evolution (BDE) was applied. The TAKLEM could improve inherent feature extraction, and there is no need for presetting the kernel function or optimizing its hyperparameter. Finally, the performance of the mentioned method was verified on two experiments (one open-access benchmark TCM data set and one TCM experiment) by comparison to the KELM-BDE, PCC-TAKELM, and mRMR- based methods. The result showed that the TAKLM method prediction was more accurate compared to the other methods.

(Zheng, et al., 2019) [65] developed a hybrid information model based on LSTM for tool condition monitoring purposes. The LSTM was developed to extract temporal features and use them accompanied by process information for feeding into a nonlinear regression model. The regression model was designed with two fully connected layers and a linear regression layer to obtain the tool wear prediction. After comparing the prediction results with experimental results, it was revealed that the LSTM-based model could predict tool wear more accurately than LR, SVR, MLP, and CNN.

Additionally, (Sun, et al., 2020)[78] presented a novel deep learning-based approach for real-time tool condition forecasting (TCF). By leveraging the most recent historical vibration (VB) data, the Long Short-Term Memory (LSTM) network was able to predict tool conditions. Additionally, the Residual Network (ResNet)-based TCF model has been integrated to facilitate real-time TCF.
(Li, et al., 2020) [79] developed a highly efficient convolutional neural network (CNN)-based anomaly detection technique for detecting tool breakage by analyzing the spindle current. This method not only identifies instances of tool breakage but also offers an opportunity to detect such breakages in computer numerical control (CNC) machines by analyzing the spindle current. Finally, it was concluded that the anomaly detection method is more suitable for the problem of positive and negative sample imbalance.

Next, (Xia. et al) [80] proposed a temporal convolutional network (TCN) for predicting the tool wear of machine tools. Dilated casual convolution and residual connections were utilized to establish an enhanced structure and increase the performance of the training gradient for the sequential model. It was revealed that TCN could contribute to more accurate results compared to the traditional convolutional neural network (CNN) and long short-term memory (LSTM) network.

Another deep learning approach utilized for predicting and monitoring the condition of machine tools was the recurrent neural network. (Wennian Yu et al.)[81] proposed a technique consisting of two steps. The first step is a bidirectional recurrent neural network auto-encoder applied to the high-dimensional data collected by sensors and converted to low-dimensional embeddings, creating one-dimensional health index values. Then, the test health index was compared with the degradation pattern, and finally, the remaining useful life (RUL) was estimated.

Also, (Jinjiang Wang et al.)[82] developed a deep heterogeneous GRU model consisting of an intermediate layer to predict the long-term relationship. Then, experimental data validated it. Finally, it was concluded that the local feature extraction method could integrate the domain knowledge into the Bi-Directional GRU model. Also, the local feature extraction method can integrate expertise/domain knowledge into a Bi-Directional GRU model to enhance feature learning. The proposed method resulted in better accuracy in terms of RMSE and MSE compared to traditional multivariate regression prediction methods. Additionally, [83] established a health monitoring system utilizing health index estimation and RUL in which an RNN Encoder-Decoder (RNN-ED) trained in an unsupervised manner to learn fixed-dimensional representations or embedding to capture machine behavior. Finally, the health of the machine is estimated by comparing the recent embedding and the existing set of embeddings. Moreover, a novel transformed-based neural network model was proposed by [84]. The structure of the transformed learning was upgraded, for example, a multi-layer LSTM was applied to improve the ability to capture position information in the TBNN model. Furthermore, in this research, three submodels were employed to extract the features received from the raw signals processed into three types of temporal feature data.

6.3 Surface Roughness Prediction

Surface roughness prediction and estimation intelligent framework mostly use two types of Machine Learning categories including the classification and the regression approaches. Considering the regression prediction methods, one of the most renowned algorithms can be considered the Artificial Neural Network.

In the research conducted by (Lin Yung-Chih, 2020)[85] an online surface roughness recognition system was introduced in which the cutting parameters and spindle tool vibration were the inputs for the Artificial Neural Network model. The predictive model can be the base for developing an online surface roughness recognition system and cutting parameters, spindle tool vibration account as input of ML systems to predict the surface roughness.
Also, (Chen et al. 2020) [86] took advantage of a back-propagation neural network to predict the surface roughness in CNC end milling. The sensitivity analysis for input features (spindle speed, feed rate, cutting depth, and milling distance) by ANOVA was investigated. The study compared linear regression and BPNN (Backpropagation Neural Network). The experimental findings confirm that the BPNN outperforms linear regression, as it achieves a lower RMSE (Root Mean Square Error) and a higher R2 (R-squared). Furthermore, in order to monitor the surface quality of the machined parts, different Machine Learning applications were applied in the classification of the design for the surface quality level. The (Lu, et al. 2019) in [87] applied the theory of Support Vector Machines (SVM) to predict the surface roughness of Inconel718 in micro-milling. The SVM prediction model is implemented using MATLAB and incorporates three cutting parameters: spindle speed, cutting depth, and feed speed. Experimental tests are conducted to validate the accuracy of the model, resulting in an average relative error of 13.5 percent. The findings demonstrate that the developed SVM prediction model effectively captures the intricate non-linear relationship between micro-milling Inconel718 surface roughness and the cutting parameters. The model exhibits high accuracy in predicting both the value and variation of surface roughness in micro-milling Inconel718.

6.3.1 Surface Roughness Prediction using deep learning

Deep learning approaches have been widely used to predict the milled parts' surface roughness. Especially, Convolutional Neural Networks are one of the more accurate methods for monitoring and predicting surface roughness, what attracted the attention of many researchers in recent years. (Achmad P. Rifai, 2020) investigated a Convolutional Neural Network in which the feature engineering part was eliminated, which is one of the greatest advantages of utilizing deep learning methods [88].

Also, (Christopher Kantzos, 2019) utilized a Convolutional Neural Network (CNN) to predict stress concentrations and surface roughness. It is worth mentioning that stress concentration accounts for one of the critical factors leading to initiating the crack in the machined parts. In this research, the image of the surface of the machined part and especially its height map of surface images result in quite accurate predictions [89].

(Peng Wang, 2019)[90], established a convolutional neural network model. In this work, the image of the surface of the cutting tool and its wear were

utilized as input to the model to identify surface roughness and wear severity. Finally, the obtained results fed into a recurrent neural network for discovering the relationship between the tool condition degradation and power profiles and the effect of tool wear on machined surface roughness.
Furthermore, (Binayak Bhandari,2021)[91], utilized the Design of an Experiment with the method called the Taguchi orthogonal array to design some experiments for calculating the surface roughness as an object and spindle speed, feed rate, and depth of cut, cutting speed, and machining duration as different factor levels in DOE method. After designing the experiments, the surface roughness measured was categorized into four classes: fine, smooth, rough, and coarse, based on the roughness value Ra. After that, images of the machined part surface were fed into the CNN model for surface roughness class prediction, and the most accurate results were obtained by RAdam optimizer. Additionally, (Bhandari, 2021)[92], utilized different Deep learning methods, including Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN), Long short-term memory (LSTM). In these classification models data obtained from sound and force sensors were used as input data.
Furthermore, (Wan-Ju Lin, 2019)[93] utilized three models, namely, Fast Fourier Transform-Deep Neural Networks (FFT-DNN), Fast Fourier Transform Long Short-Term Memory Networks (FFT-LSTM), and one-dimensional convolutional neural network (1-D CNN) for prediction of surface roughness.

Also, (Donthu Tejakumar, 2020) [94] used Deep Neural Network keras modeling for accurately constructing a correlation between the surface image characteristics and the actual surface roughness.
Finally, (Jianbo Yu, 2020)[95] applied a knowledge-based deep belief network (KBDBN). It utilized both the symbol rules and classification rules with the deep network. It was revealed that utilizing a KBDBN-based predictive method is not only effective in the discovery of both symbolic rules and classification rules for process control but also illustrates better performance compared to other machine learning models such as SVM, ANN, Logistic Regression, and DNNs (deep belief network, stacked auto-encoder).

6.4 Thermal Errors Predictions of Machine Tool

The temperature variation of the machine tools due to different factors, such as machine internal heat generation or heat exchange with the ambient atmosphere, causes thermal deformation. Moreover, [96] (Makoto Fujishima, 2019) used a deep learning algorithm named Bayesian dropout to predict the thermal displacement. The mentioned method utilized the ambient temperature change and cutting heat generation by spindle rotation or axes movement. Finally, the results revealed that the Bayesian dropout method achieves high performance and accurate results.

Also, a thermal prediction model using a Deep Neural Network was developed by [97] (Yang Tian, 2020) for predicting the thermal error modeling of

heavy-duty machine tool-foundation systems. In this work, a self-organizing dropout mechanism for unsupervised training was applied, and then a regularization improved transfer function was developed to prevent co-adaptation of the feature detectors and reduction of the less significant weights of the process. Next, the acquired data from heavy-duty machine tools were used to establish a thermal error predictive model. Finally, the accuracy of the thermal error prediction model was validated by thermal error experiments.
Additionally, (Zhaolong Li)[98] utilized the BP Neural Network Optimized by Beetle Antennae Search Algorithm. In this research, the temperature and axial thermal drift data of the motorized spindle at different speeds were used to find the most sensitive temperature points in which a fuzzy clustering and grey relational analysis. Finally, the BAS (Beetle antennae search algorithm)-BP (Backpropagation) neural network was established to predict the machining process's thermal error. Also, different Machine learning methods such as Back Propagation Neural Networks (BP-NN), multiple regression analysis (MRA), and the CNN model, including the input layer, feature extractor, fully connected layer, and output are applied to predict the thermal error by (Peiwen Li, 2020)[99]. The four models were tested on the data of the machine tool, and the result revealed that the CNN method predicts better performance and high accuracy compared to other approaches.

Moreover, (Pu-Ling Liu, 2021)[100] used the thermal error modeling method based on bidirectional long short-term memory (BiLSTM) deep learning. Although thermal error exists in all three axes of the machine coordinate system, only the z-direction was considered in the modeling process. Finally, BiLSTM was compared with the other approaches, such as Feed Forward Neural Network, Recurrent Neural Network, and BiRNN deep learning network, and the result revealed that the best performance was achieved for the model which was composed of one BiLSTM layer, two feed-forward networks (FNN) layers, and one max-pooling layer.

Another research utilized the improved particle swarm optimization (IPSO) to optimize the Back Propagation Neural Network (Bo Li, 2019)[101]. In this study, a Self-Organizing Feature Map (SOM) and statistical correlation analysis were utilized to explore the correlation between the thermal sensitive points and the thermal error of the spindle. Finally, by comparison of two methods GA (Genetic Algorithm)-BP (Back Propagation) and IPSO-BP accuracy, it revealed that the accuracy of IPSO-BP was higher than GA-BP accuracy.
In the following research work, a support vector regression (SVR) optimized by the whale optimization algorithm (WOA) was established by (Zheyu Li, 2021)[102] in order to model the thermal error in which the STI matrix (synthetical temperature information (STI) is established by combining the temperature value information, the temperature shape information, and the relationship between temperatures and errors) was first constructed. Then the STI matrix and the optimal number of clusters were applied for fuzzy C-means

clustering (FCM), and the correlation coefficient was applied to select the sensitive points. Then, the S-WOA-SVR model was verified at different speeds and compared with other methods, such as the SVR model optimized by the WOA based on the (T-WOA-SVR) clustering method and the SVR model optimized by the Genetic Algorithm (GA) based on STI (S-GA-SVR). The results revealed that the S-WOA-SVR model achieved higher accuracy and robustness than the T-WOA-SVR model and the S-GA-SVR model.

6.5 Machining Time and Cost Prediction

Other significant challenges in CNC machining are the machining time and the product's final cost. Machining plays a critical role in producing a wide range of products utilized in different industry sectors, such as automotive parts, plastic molds, and gears. These services' costs highly depend on machining time which can be drastically affected by the machining strategy and parameters. In this sense, machine learning can predict the machining time leading to minimizing the time and cost of producing the parts.
The first factor that can significantly affect the machining time is selecting a suitable machining strategy and cutting tool, revealed by [103]. Furthermore, the type of feature in the machined part is another factor that can determine the cost of the machining process. In [104] an artificial neural network was applied for feature recognition.

Also, another research that applied ANN to establish a relationship between the number of features and the cost of the part was done by (Ning et al.) in [105]. On the other hand, some researchers applied ANN to predict the machining time directly. For instance, (Mostafa R. A. Atia et al) in [106] used eight parameters, including the workpiece, machines, and tools parameters which, after preprocessing, were used as the input for the artificial neural network. The results showed that the ANN implementation reduced the machining time and, consequently, the cost entailed by the machining time. Furthermore, (Blaž Florjanič et al.) in [107] applied an artificial neural network in which different process parameters, including Part envelope length (mm), Part envelope width (mm), Part envelope height (mm), Part surface area (mm), Part volume (mm3), Nominal part thickness (mm), Part material, Envelope volume (mm3), Part complexity/Cavity detail, Overall dimensional tolerance requirements of the part, Mould length(mm), Mould width (mm) used as input for the ANN. Artificial intelligence tools for estimating manufacturing cost were also studied in [108], and the comparison of different types of ANN for predicting the machining time was made in [109].
Additionally, another application of milling machining is in producing the gears which has a critical role in different industries sections. In order to estimate the machining times of gears by ML, a huge dataset is required which needs a long duration and a large number of test periods. Utilization of Machine Learning for predicting the machining time and optimizing the milling process parameters can significantly reduce the material, labor force, and time losses.

In general, it leads to enhancing production planning by applying the intelligent production systems requiring Computational Intelligence (CI) criterion in manufacturing process simulation. The CI methods for simulation of the manufacturing process have a key role because of their capacities for predicting the complex manufacturing process [110, 111].
Moreover, "Extreme learning machine (ELM) is a training algorithm for single hidden layer feedforward neural network (SLFN), which converges much faster than traditional methods and yields promising performance" [112].

Also, (Gurgenc et al. 2019) utilized the ELM for predicting the machining times of the cycloidal gears in CNC milling machines[113]. In this study, the ELM based on the CI algorithm was modeled by taking advantage of results obtained from experimental tests. To be more precise, in ELM model parameters such as the cutting sensitivity of the hypocycloidal profile (Betas), cutting sensitivity of the epicycloidal profile (Phis), feed rate of the end mill cutter (F), tooth number of the gear (Z), tooth addendum roulette radius (re), tooth dedendum roulette radius (rh) and cutting depth (hn) accounted as input, and machining times (te) were considered as the output of ML models. Then, the results obtained from the ELM model were compared to feed-forward and back-propagation-based ANN algorithms. By comparing both CI methods, the ELM model converged much faster and was more accurate compared to the ANN model.

6.6 Energy Consumption Prediction of CNC Machine

CNC Machines working on the shop floor are rarely optimized for minimization of energy consumption, as no clear guidelines exist in operating procedures, and high production rates and finishing quality are requirements with higher priorities. However, there has been much attention to applying more energy-efficient process designs due to new regulations and increases in energy charges. An example of applications of Machine learning methods for predicting the energy consumption of CNC machines was done by [114] (Dimitrios Pantazis, 2019) in which the response surface methodology (RSM) utilized for optimizing the energy consumption in cutting operations. Then, the hidden Markov method was applied to extract the features from time-series power data through sequential segmentation, clustering, and simple filtering of the power signals.
Additionally, (Chen, et al., 2019) [115] utilized the gradient boosting regression tree (GBRT) method for predicting the energy consumption of milling machines and validated it by experimental results. Firstly, the energy consumption model was applied for each component under the unload condition. Then, the model of milling energy was established based on the gradient boosting regression tree (GBRT) algorithm. After that, the enhancement of each processing parameter on energy consumption was analyzed, and the model was verified by the experimental milling data, which showed the model's high accuracy.
(Markus Brillinger, 2021) [116] developed different algorithms such as decision

trees, random forest, and boosted random forest. Then, the real production data was used for training the algorithm. The result revealed that the Random Forest Algorithm could achieve higher accuracy than other models. Furthermore, (Jianhua Cao, 2021) [117] developed a CNC milling energy consumption prediction method based on program decomposition and IPBPNN. Firstly, the automatic parsing algorithm did the extraction and classification of the parameters of the CNC program. Then, the relationship between the CNC command parameters and energy consumption was discovered by using a parallel neural network.

Additionally, (Raunak, Bhinge, et al. 2014) established a Gaussian Process (GP) regression model to predict a machine tool's energy consumption. In the GP model, some parameters, including feed rate, spindle speed, depth cut, cutting direction, and cutting method defined as input and energy consumption of the CNC machine, were set as the model's output. Then, different energy consumption models were established to compare the energy consumption of the different operations for machining a specific part. In the end, an uncertainty analysis was performed to establish the confidence bounds [118].

6.7 Utilizing Finite Element Method as a data generator for ML frameworks

The Finite Element Method (FEM) could be an alternative approach for simulating the machining process for obtaining input data for the ML framework. FEM is cable of predicting some parameters for which there is no objective analytical approach or requires expensive sensors to measure in the machining process. Consequently, in some cases, FEM can be applied to tackle the mentioned challenges. (Mekarthy et al., 2022) applied a FEM model for the chip formation of orthogonal machining during milling process simulation [119]. Then, the generated data by FEM simulation was selected for input features of the Artificial Neural Network approach to predict the cutting forces as well as the temperature of the cutting tool for different cutting parameters, including the rake angle, uncut chip thickness, and cutting speeds. Furthermore, (Bingxiao Peng, 2019) in [120] used a Deep Neural Network, and in order to obtain the training set, both experimental orthogonal cutting as well as a 2D finite element simulation were performed under different cutting parameters, tool geometries, and tool wear conditions. Another combined approach of ML and FEM was done by (Charalampous, 2021) in [121] for predicting cutting forces during the milling. In this study, a series of machine learning algorithms were applied, such as the SVR, k-nearest neighbor, polynomial regression, and random forest. The result revealed that the SVR algorithm achieved the best performance. Further application of combined ML and FEM was made by (George K 2021)[122].

(Feng, Jilu, et al.2020) also applied a combination method of Kriging surrogate models and finite element simulations for establishing equivalency between milling positions and dynamic parameters. In this research, the new method used both the regenerative chatter and Kriging models to calculate the depth of cut. Finally, the regenerative chatter and Kriging results were compared to the experimental results, which showed a relatively good accurate result [123].

7 Discussion

A general overview of the research, including the milling machining challenges, machine learning models, input parameters, and pre-processing methods for each research, has been illustrated in table 7. Also, in this survey, the most recent progress in Machine Learning models applied in monitoring/predicting the different types of challenges in the milling machining process is investigated.
Tool wear monitoring/prediction in the machining process has a critical role in predicting and monitoring the condition of the cutting tool, leads to producing the machined part with high geometrical accuracy with no chatter trace, high quality of surface, and in general, avoiding the non-conformities during the machining process.
In order to establish the decision-maker system for tool wear prediction/monitoring intelligent framework, usually supervised learning algorithms including regression and classification are used. Considering the classification algorithms, it was revealed that the accurate results obtained by utilizing the Kernel extreme learning machines (KELM) approach and its improvements, such as ITD-based KELM, compared to other approaches such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs). On the other hand, regression algorithms such as ANN, LSTM, and SVR are also considered some of the most significant applied machine learning approaches in tool wear monitoring.
Additionally, in recent years, deep learning methods have been widely utilized to predict and monitor the cutting tool condition in the milling process. It was illustrated that Auto Encoder is considered one of the fundamental approaches among the unsupervised deep learning approaches for monitoring and predicting the tool wear in the milling process. Furthermore, other deep learning approaches, such as SVMs, KELMs, CNNs, and LSTMs, rely on accurate labeling of big data acquired from different conditions of the milling machining process. As shown in Figure 9, the pie chart illustrates the distribution of the ranges of Machine Learning methods applied in Tool Condition Monitoring and Remaining Useful Life estimation reviewed in this survey.

Another significant challenging occurrence in milling machining is the chatter phenomenon. Machine learning approaches can accurately predict/monitor, and a recent paper presented by [32] tried to prevent the chatter. As shown in Figure 10, a wide range of regression and classification models was implemented, such as ANN, SVM, CNN, and Auto-Encoder methods for predicting the chatter and excessive vibration. Furthermore, surface roughness prediction of machined products in the milling machining process has a crucial role

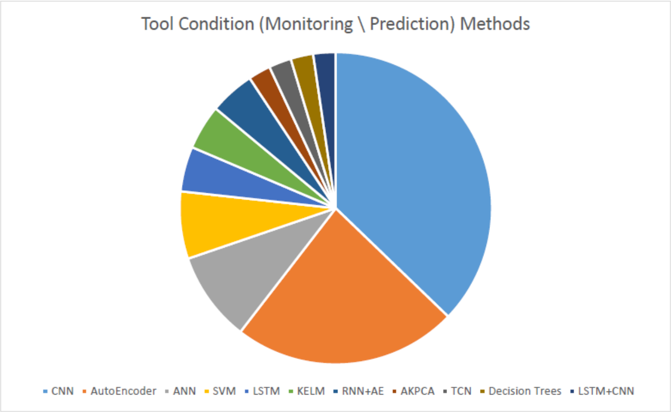

Figure 9 Tool Condition (Monitoring/Prediction) Methods

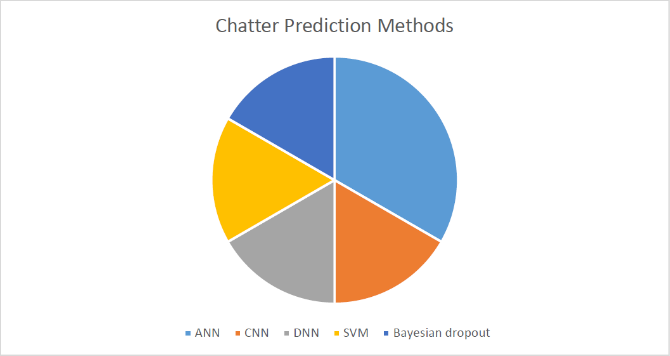

Figure 10 ML Methods used for predicting Chatter

in changing the quality of the finished surface according to the defined requirements. In this regard, enormous research dedicated to utilizing Machine Learning methods is shown in Figure 11. Furthermore, the tool deflection caused by thermal forces can drastically affect the geometry accuracy and surface roughness of the produced part; consequently, it is highly recommended to predict the thermal error deflection of the cutting tool. The temperature variation of machine tools due to many causes, such as heat generation by CNC machines or exchanging heat with the ambient atmosphere, leads to thermal deformations. Consequently, predicting the deflection of machine tool has a crucial role in preventing nonconformists during the manufacturing process, and Machine learning, in particular, play a crucial role in this regard. The following pie chart illustrates the proportion of Machine learning methods applied in each paper as the most accurate models in Thermal Deflection of cutting tools that can be observed in Figure 12.

Moreover, predicting the energy consumption of CNC machines is an effective means to realize the lean management of CNC machine tool's energy

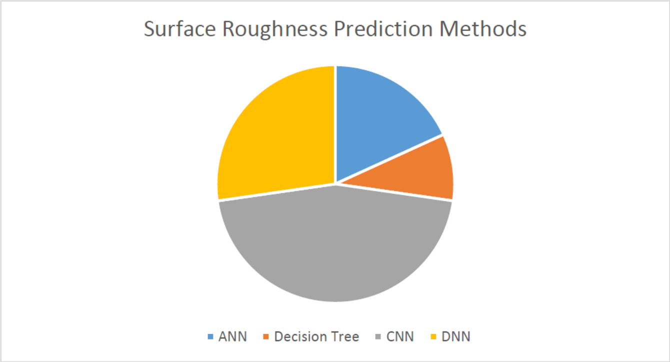

Figure 11 ML Methods used for predicting Surface Roughness

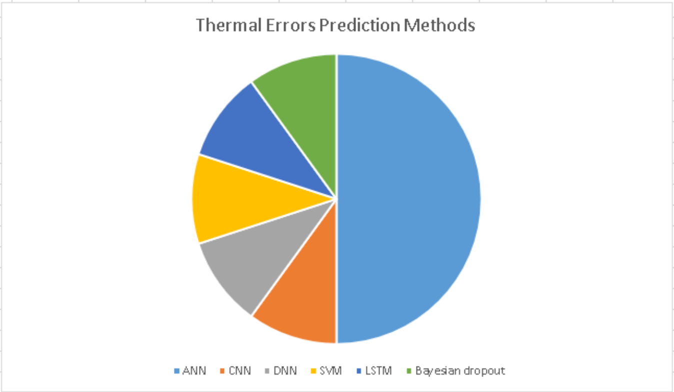

Figure 12 ML Methods used for predicting Thermal Error

consumption and achieve the sustainable development of the manufacturing industry. A wide range of Machine Learning methods is utilized for this purpose, which can be observed in Figure 13.

On the other hand, most Deep Learning methods, including DMLPs, CNNs, and LSTMs, depend on the precise labeling of Big Data collected from a wide range of operational conditions. This can be done by combining Deep Learning methods with unsupervised techniques, such as k-means clustering, and releasing the adaptability of Deep Learning techniques, allowing them to update their training during routine operational monitoring continuously. Alternatively, CNN-based architecture can be combined with k-means clustering to create a semi-supervised architecture that can handle unlabeled new data after pretraining.

On the other hand, machine learning approaches have some drawbacks as well. For instance, an Artificial Neural Network, as one of the most utilized machine learning models in predicting/monitoring the milling process, is capable of modeling nonlinear and complex data structures. Also, it can model

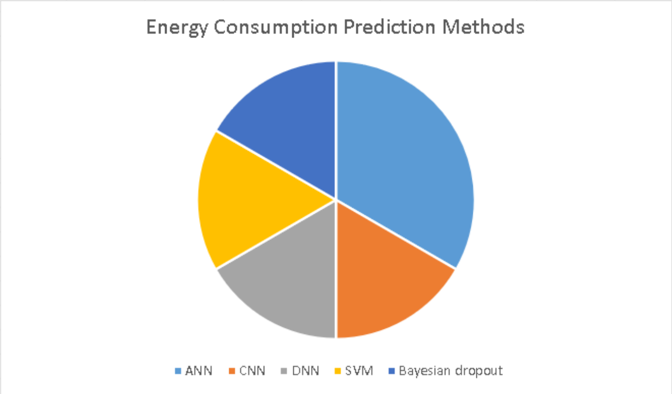

Figure 13 ML Methods used for predicting Energy Consumption

datasets with incomplete and noisy signals received from the sensors. Additionally, one of the key features of ANN is requiring minimal prior knowledge of data for predicting the result.

Moreover, Support Vector Machines are another most used Machine learning method, according to the Figure 10, which is capable of handling nonlinear data sets by taking advantage of kernel functions. Additionally, SVM also has good generalization with small training data.

However, the main drawback of using SVM is selecting suitable kernel functions and their hyperparameters. Also, SVMs are quite expensive and cable of a slow learning speed which for large datasets results in a slow convergence rate.

Furthermore, Using an autoencoder for fault detection and monitoring involves employing an artificial neural network model that is trained to reconstruct its input data. The key idea is to train the autoencoder on normal, fault-free data, and then use it to reconstruct new data samples. When a fault or anomaly occurs, the reconstructed output will deviate significantly from the original input. By comparing the original input data with the reconstructed output, the autoencoder can effectively identify deviations or abnormalities indicating the presence of faults or anomalies. This approach allows for the detection and monitoring of faults in various systems, such as manufacturing processes, industrial machinery, or even complex datasets. Autoencoders provide a powerful technique for fault detection and monitoring as they can learn complex patterns and relationships in the data. By leveraging their ability to capture the underlying structure, autoencoders can accurately identify deviations from normal behavior, enabling proactive maintenance and timely detection of faults, ultimately optimizing the operational efficiency and reliability of systems. In [58] a robust SAE (Sparse Autoencoder) model, was aimed to extract signal characteristics and train the model without relying on empirical labels. It was also examine the model's reconstruction performance for cutting signals. Building upon this, an automatic online tool wear state identification strategy was developed to monitor milling processes. In real-time, the SAE model reconstructs the subsequent signal segment, allowing to record the mean reconstruction error (MRE) sequence associated with tool wear. The SAE model was continuously trained and updated using the current signal segment. In [54] a variational autoencoder technique to address an industrial machining problem. Our proposed model was built upon a two-step training process and a two-dimensional latent space. Unlike principal component analysis, which would require 24 components to capture 90.0 percent of the variation, our two-dimensional latent space exhibits superior dimension reduction capability. Furthermore, our model demonstrates remarkable accuracy in classifying cutting operations solely based on sensor data obtained from a CNC machine, achieving an impressive 99.24 percent. Not only does our suggested model excel in classification, but it also serves as an efficient visual process monitoring tool. It effectively detects early changes in a machining process, even identifying defects caused by a minuscule increase of less than 1 percent in signal energy. This is a significant improvement compared to conventional monitoring methods. Another significant section for establishing an accurate, intelligent monitoring system in the milling process is the sensors' selection and installation, which can significantly affect ML results accuracy. Depending on the application, different sensors will be utilized. For instance, sound sensors (microphones) or industrial cameras may be suitable for acquiring data during the milling process, although their implementation in an actual industrial environment may find several drawbacks. For example, cameras need to be positioned correctly and have a clean environment. Not only are they accounted as expensive sensors, but also, the measurement may be influenced by dust. Image quality may be influenced by floor vibrations or the final print's shape.

Moreover, since the actual image quality will result in high-dimensional input data, more complex algorithms will be needed to be used. In consideration of CNN applications, although the image could be used, a first filtering and data reduction phase should be implemented to reduce the computational time required.

Despite their great ability in chatter recognition, sound sensors require an important phase of signal treatment typically developed for each application, and the actual microphone disposition may generate several issues in the actual practical application. Dynamometers may have limitations when it comes to the dimensions of the workpieces. Additionally, they are also expensive and may hinder the stability of milling machines. The positioning of the sensors is crucial for accurate measurements. For this reason, embedded sensors have been widely utilized for measuring the cutting force and torque, such as strain gauges [124], [125], piezoelectric polyvinylidene fluoride (PVDF)[126], [127], semi-conductive strain gauge, fiber Bragg grating, surface acoustic wave [128], capacitive sensor [129], and piezoresistive microelectromechanical systems (MEMS) [130], [131].

Integrating accelerometers in the Tool Condition Monitoring sensor nodes is quite a simple task. Researchers usually pick a commercial piezoelectric sensor [124] or MEMS sensor [132] with appropriate bandwidth and mount it.

As the tool holder has a rotating axis, in terms of cost, weight, and volume, MEMS sensors are superior to piezoelectric ones, but their signal-to-noise ratio and bandwidth are limited. Moreover, different placements of bonding the thin film wireless sensors, including on the tool [126], [133], under the inserts [134], on a reduced diameter of the tool holder [135], or on an integrated flexible body [130], illustrated in Figure 14.

Conversely, acquiring signals is considered a significant module of the intel-

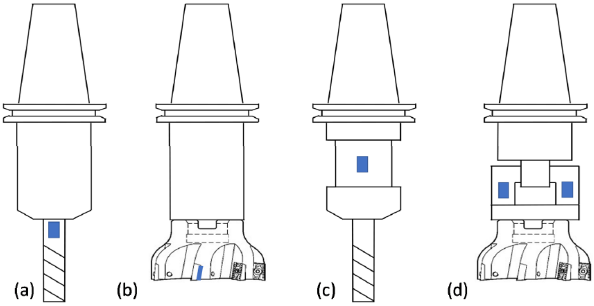

Figure 14 Various concepts of thin film placements as indicated by the blue spots: (a) on the tool [126], [133], (b) under the insert [134], (c) on a reduced diameter of the tool holder [135], and (d) on an integrated flexible

ligent monitoring framework system. The acquired signals usually contain noise and non-stationary elements [136]. Additionally, data are collected at a high-increasing rate with extremely high dimensions, which require massive storage and very high computational resources. The main purpose of signal processing is to filter useful information and eliminate unwanted data[137]. One way to tackle this problem is to use dimensionality reduction techniques for selecting the most significant features. As it was mentioned, the nature of manufacturing signals contains noise, consequently applying multi-sensory systems such as using both microphone and vibration sensors for obtaining high- and low-frequency components.

8 Conclusion and future works

This survey gave an overview analysis of the latest application of machine learning in milling machining processes with promising results. Data-driven methods have advanced monitoring processes by incorporating machine learning techniques to develop intelligent systems to monitor or predict health status. Machine learning in general, and deep learning in particular, have significantly impacted feature engineering and expert decision-making by enabling

Purpose	**Methods**	**Type of Data**	**Preprocessing**	**Ref**
Chatter stability lobes prediction	SVM and Gradient Boosting	simulated oscillations of the milling tool data	Carlsson Coordinates	[24]
Chatter stability lobes prediction	SVM	Vibration Signals	average FFT	[25]
Chatter stability lobes prediction	ANN, SVM, DT	Speed RPM, Depth of Cut	N/A	[138]
Chatter stability lobes prediction	Reinforced k-NN	Sound Signals, Vibration	Statistical Methods	[28]
Chatter stability lobes prediction	Gradient Tree Boosting	Radial depth of cut , Axial depth of Cut, Cutting speed,Spindle Speed	ASA, Laplacian score	[29]
Chatter stability lobes prediction	SVM (radial basis function kernel)	Vibration signal	Wavelet packet transform, wavelet energy entropy theory, normalization	[31]
Chatter stability lobes prediction	ANN, kernel interpolation (KI)	Acceleration Sensors and a Microphone	N/A	[36]
Chatter stability lobes prediction	Deep Neural Networks and transfer learning	simulated data from analytical stability models	N/A	[35]
Chatter stability	Auto-Encoder	Dynamic Signal	hybrid clustering method based on both density metric and distance metric	[37]
Chatter stability	Deep Belief Networks	Vibration Signal	MFCC and wavelet method	[38]
Chatter stability	LSTM	Force, Vibration	N/A	[39]
Chatter Detection Method	Deep Convolution Neural Networks	Vibrations	continuous wavelet transform	[26]
Chatter stability lobes prediction	convolutional neural network (CNN)	Vibration acceleration Signal	Continuous Wavelet Transform (CWT), Resizing the Images	[30]
Chatter stability	CNN- weight and bias optimize by An improved magnetic bacteria optimization	Image Data	N/A	[139]
Tool Wear Prediction	Neural Network	Feed Rate, Process Parameters, Depth of Cut	N/A	[41]
Tool Wear Prediction	Random Forest	Accelerometer, AE, Dynamometer	N/A	[43]
Tool Wear Prediction	RF, ANN, SVR	Force ,Vibration, AE	Statistical Features	[44]
Tool Wear monitoring	RF, Gradient Boosting Regression, ANN, Linear Regression and SVM	depth of cut, cutting speed, feed rate	time domain, frequency domain time-frequency domain	[45]
Detect tool wear conditions in the milling process	KELM	Vibrations	ITD, CC Analysis based on PR	[46]
Tool Wear Classification	SVM	Sound	WPT, ECBCA-MSST, and APKA	[48]
Tool Condition Binary Classification	SVM	Vibrations	WTMM, and HE index MI	[49]
Optimized Tool Wear Condition Classification	OS-ELM	Current	SDAE	[55]
Tool Wear Condition Monitoring	TA-KELM	Vibrations, Forces, Current, Sound	TD, FD, and WPT BDE	[77]
Tool Wear Regression Prediction	ANN	Vibrations, AE, Forces, Spindle Current, and Process Parameters	LSTM	[140]
Tool Breakage Classification	CNN-AD	Current	TD, FFT, and WPT	[79]
Tool Wear Prediction	SSAE	Currents	OA based on FFT	[59]
online monitoring method for tool wear	Auto-Encoder	signals consist of the force and vibration	N/A	[58]
Remaining Useful Life Prediction	Auto-Encoder	run-to-failure data, cutting tool in an off-line process	N/A	[52]
Tool Wear Monitoring	Auto-Encoder	UC Berkeley milling data set	N/A	[54]
Tool Wear Monitoring	Auto-Encoder	physical data (vibration)	N/A	[55]
Tool wear state	Auto-Encoder	three current signals of the spindle of CNC machine tool	N/A	[55]
Tool Wear Monitoring	Auto-Encoder	Accelerometer, Dynamometer, Acoustic Emission	N/A	[56]
Tool Diagnosis	Auto-Encoder	Cutting Force Data	N/A	[57]
Tool wear monitoring	Auto-Encoder	Force, Vibration Signals	N/A	[58]
Tool wear monitoring	Auto-Encoder	Cutting Signal	N/A	[59]
Tool wear monitoring	Auto-Encoder	Image Data	N/A	[141]
Tool wear monitoring	Auto-Encoder	vibration Signals	FFT and WPD	[60]
Tool Monitoring	CNN	Images of cutting tool	N/A	[142]
Tool Monitoring	CNN		Derived Wavelet Frames	[63]
Tool Monitoring	CNN	Image Data, Insert Condition	N/A	[64]
Tool Monitoring	CNN	cutting force signals	the time frequency analysis	[65]
Tool Monitoring	CNN	vibration data	1D CNN	[66]
Tool Monitoring	CNN	machine spindle vibration signals	N/A	[67]
Tool Monitoring	CNN	vibration and acoustic signals	Temporal Feature Extraction, Data Normalization	[29]
Tool Monitoring	CNN	cutting force and vibration	time-domain, frequency domain and time–frequency domain	[68]
Tool Monitoring	CNN	Image Dataset	N/A	[69]
Tool Monitoring	CNN	the clutter signal of spindle current	signal segmentation, signal fitting, clutter signal extraction, clutter signal normalization and image binary	[70]
Tool Monitoring	CNN	Force, Vibration, AE	N/A	[71]
Tool Monitoring	CNN	3-D Forces, Vibrations, AE, Microphone	N/A	[72]
Tool Monitoring	CNN	Cutting Force Signals, vibration Signals, Acoustic Emission Signals	CNN	[73]
Tool Monitoring	CNN	Current , Vibration, AE, Tool Wear Measurement	Hampel filter, Time-Frequency domains, REFCV	[74]
Tool Wear Monitoring and RUL Prediction	SBULSTM + FC layers + Regression layer	Vibrations, Current, and PLC signals	CNN	[143]
Tool Wear Classification	BLSTM	Forces	CNN	[76]
Tool Wear Monitoring Classification	GenSVM	Vibrations, AE, and Current	TD, FD (FFT), and CEEMDAN PCC	[?]
Tool Wear Classification	LSTM + ResNet	Vibrations, AE, and Forces	Convolutional Layer	[78]
Surface roughness prediction	Knowledge-Based Deep Belief Network (KBDBN)	The vibration signal, process parameters	N/A	[95]

Purpose	Methods	Type of Data	Preprocessing	Ref
Surface roughness prediction	The Deep Forest	Forces and load signals	N/A	[144]
Surface roughness prediction	K Nearest Neighbours, Random Forest	vibration data	FFT, Statistical Methods	[145]
Surface Roughness Prediction	ANN	Cutting Parameters(Speed, feed, rate)	N/A	[85]
Surface roughness prediction	BpNN	Cutting Depth, Spindle Speed, Feed Rate, Milling Pitch	N/A	[86]
Surface roughness prediction	BpNN	Material, cutting material, coating, tool diameter, cutting speed, feed rate, depth of cut, entry/exit angle, average chip thickness, etc.	N/A	[146]
Surface roughness prediction	SVM (radial basis function kernel)	Spindle speed, depth of cut, feed speed	Normalization	[87]
Surface roughness prediction	Multiple linear regression (MLR)	Speed, feed, depth of cut, flank wear, vibration	Statistical features PCA	[147]
Surface Roughness Prediction	CNN	The digital image of surface textures		[88]
Surface Roughness Prediction	CNN	surface images, mechanical data	N/A	[89]
Surface Roughness Prediction	CNN	Optical Images of Milling Tool Wear and Workpiece surface roughness	N/A	[90]
Surface Roughness Prediction	CNN	Image Data	N/A	[91]
Surface Roughness Prediction	CNN	Sound, Force	Mel-Spectrogram and Mel Frequency Cepstral Coefficients (MFCCs) audio Feature Extraction	[92]
Surface Roughness Prediction	(FFT-DNN), (FFT-LSTM), (1-D CNN)	Vibration Signals	N/A	[93]
Surface Roughness Prediction	Knowledge-based deep belief network		N/A	[95]
Combined FEM and ML: cutting forces and maximum tool temperatures	ANN	rake angle, uncut chip thickness and cutting speeds	N/A	[119]
Combined FEM and ML: cutting forces	Deep Neural Network (DNN)	cutting parameters, tool geometries and tool wear conditions	N/A	[120]
Finite Element—Machine Learning The Optimal Feed, cutting speed, depth of cut	Multi-Layer Perceptron (MLP)	classifierforce in the x direction, force in the y direction, power,temperature	N/A	[122]
Prediction of Cutting Forces Using Machine Learning and Finite Element Analysis	SVR, KNN, PR, RF	Cutting Speed, depth of cut, feed rate	N/A	[121]
A hybrid approach to predict the cutting forces under consideration of the tool wear	DNN	Orthogonal Cutting Tests, 2D FEM chip formation	N/A	[148]
Thermal Error Prediction	DNN	Temperature	N/A	[97]
Thermal error modeling	NN	Temperature	N/A	[149]
Thermal Error Modeling	BNN	Temperature	N/A	[98]
The Thermal Error ModelingDeep Transfer Learning	BP NN, CNN, Match Rating Approach(MRA)	Temperature	N/A	[99]
Thermal error modeling	BiLSTM deep learning, FFNN, RNN, and BiRNN	Temperature	N/A	[100]
Thermal error modeling	particle swarm optimization (IPSO) optimize back propagation (BP) neural network and GA-BP NN	Temperature	N/A	[101]
Thermal error modeling of spindle	support vector regression (SVR) optimized by the whale optimization algorithm (WOA)	Temperature	N/A	[102]
Thermal displacement prediction	DNN with Bayesian DropoutThe sensor failures to test the robustness of the model	Temperature	N/A	[96]
Predict the thermal drift	pretrained coefficients for the CNN initialization: CNN-FT (fine-tuning)based on four different working conditions	Temperature	N/A	[150]
The thermal error prediction	the CNN approach a Domain Adaptation Module	Temperature	N/A	[99]
Energy Consumption Prediction	RF	Spindle Speed, Length of tool path, Feed rate determination, Internal machine variables	Mathematical Transformation	[116]
Energy Consumption Prediction	RF	Power Signal	Gaussian Mixture Hidden Markov model (GMHMM)	[114]
Energy Consumption Prediction	parallel neural network		N/A	[117]
Energy consumption of a five-axis MT	Gradient Boosting Regression Tree (GBRT) model	Spindle speed, feed rate	N/A	[115]
Detect workpiece surface defects	CNN	data from a laser beam and simulated data	N/A	[151]
Detect edge inconsistencies from images			N/A	[152]
Flatness deviation prediction	RF Ensemble, the Synthetic Minority Over-Sampling Technique	the tool's life, average drive power and flank wear	N/A	[153]
The diameter,roundness and other quality parameters	RF	Torque values and speed statistical time–domain features	N/A	[154]
Flatness classification prediction in honeycomb cores	Linear kernel	The force signal and the PCA for feature reduction	the time–domain and requency–domain(based on FFT) features	[155, 156]

automated feature selection, processing of big data and large dimensions, and avoiding the redundancy of the sensors. It also facilitates optimal data fusion and the development of intelligent hybrid models that can be used for descriptive analytics for product quality control, diagnostic analytics for failure assessment, and predictive analytics for predicting failures. Despite its enormous potential, a data-driven industrial approach still poses challenges, especially in terms of the size and quality of data collected.

Small data challenges should be explored by practicing data fusion methods and comparative studies between machine learning and deep learning. The concept of fusion at different sensors, functionality, and decision levels must be evaluated and compared.

The difference between lab-scale results and real-industrial conditions should be emphasized by examining process uncertainty and applying cloud computing. Incremental and transfer learning can be pivotal in bridging the lab-to-industry gap. Intelligent monitoring systems must focus on capturing big data to understand the power of data-driven methods fully. Additionally, the critical role of feature engineering should be recognized by developing an attitude that integrates feature selection and expert decision-making to better reveal hidden patterns in data for intelligent monitoring.

Though much progress has been made in Intelligent machining research, especially for the milling process, still the following challenges should be tackled: The concept of deep learning, its possibilities, and its limitations were explored and compared to machine learning models. Comparative studies should be carried out between different deep basic models and more complex hybrid models. There is a demand for fastening the network, avoiding delays creating a more secure network against attacks, and enhancing the reliability of monitoring systems. In order to tackle the mentioned challenges in [157], a cloud-based manufacturing monitoring framework was introduced. Furthermore, it was investigated that utilizing a computing layer can lead to reducing the response latency of the monitoring system. Also, (Taiyong Wang et al. 2020) in [158] utilized a fog computing architecture including three layers containing edge computing, fog Computing, and a cloud computing layer utilizing the data received from milling machining sensors. It was proven that using the fog computing layer can solve the problems concerning an online monitoring framework.

Additionally, heterogeneous data in manufacturing usually contain irrelevant and redundant information, which these data curation leads to a wide range of challenges for machine learning and all the intelligent monitoring framework. The prospective future research direction related to data quality enhancement could be the convergence of different correlated-based prediction models, such as machine tool health status and individual process status. Furthermore, another significant challenge is whether the trained ML method for one specific CNC Machine can be utilized for any other machines or have the same accuracy or performance on the other CNC machines, which is known as transferability. This challenge usually happens due to the dependency of the model on the training data, which means if the value changes for any reason, the AI reacts sensitively and outputs different results. Even when the trained ML model of machining is performed on the same workpiece on the same machine tool, ML usually only guarantees the same performance because of sensor data that change their values for each machining condition, dynamics, and other environmental factors. In order to enhance the transferability of the AI model, two approaches include data-level solutions and algorithm-level solutions. The data level solution can be tackled by applying data scalings such as normalization or standardization etc. [159]. On the other hand, at the algorithm level, several approaches that make the Machine learning model quickly adapt to similar domains with a small amount of data have been applied. This type of approach is called transfer learning, and several studies are dedicated to proposing the transfer learning method [160, 161].

Another recommendation for future research in advancing the ML applications in Manufacturing and especially in the Machining process, the prospective research direction is utilizing real-time processing of large volumes of data is applied by introducing the 5G and 6G high-speed internet to enhance the amount of data communicated between the machine tools to sensors, sensors to computers, computers to cloud, and clouds to machine tools again. Also, implementing a preventing intelligent monitoring system in which an online feedback controller is applied to set the input CNC machine parameters to prevent the main challenges in milling machining, such as chatter and surface roughness, and perform automated optimal machining control by feeding it back to the machine tool [32, 162].

Finally, some other future research directions for applying ML in milling process has listed bellow:

ML algorithms can be employed to dynamically adjust machining strategies based on real-time feedback. This includes automatically adapting cutting parameters to changing conditions such as material variations, ensuring consistent quality and performance.

- Sensor Data Fusion: Investigate techniques to fuse data from multiple sensors, such as force sensors, temperature sensors, vibration sensors, and tool condition monitoring systems. ML algorithms can be applied to analyze the combined sensor data in real-time, enabling the identification of optimal machining parameters and adaptive strategies.
- Online Tool Wear Prediction: Develop ML models that can predict tool wear in real-time. By analyzing sensor data and historical tool wear patterns, ML algorithms can learn to anticipate tool degradation and adjust machining parameters, such as cutting speed or feed rate, to maintain optimal performance and extend tool life.
- Adaptive Cutting Parameters: Explore ML algorithms that can dynamically adjust cutting parameters based on real-time feedback. By continuously analyzing sensor data, ML models can adaptively optimize parameters such as cutting speed, feed rate, and depth of cut to achieve the desired machining outcomes, such as surface finish, accuracy, or tool life.
- Intelligent Tool Path Optimization: Investigate ML approaches to optimize tool paths dynamically. By integrating real-time sensor data with ML algorithms, machining paths can be adjusted on the fly to avoid areas of high tool wear, reduce vibrations, or optimize material removal rates. Reinforcement learning techniques can be employed to iteratively optimize the machining path based on real-time feedback.
- Feedback Loop Optimization: Explore ways to optimize the feedback loop between the machining process and the ML algorithms. This can involve developing adaptive learning algorithms that can quickly adapt to changes in machining conditions, sensor data, or tool wear patterns. Efficient data collection, model retraining, and deployment strategies can be investigated to enable seamless integration of ML-based adaptive machining strategies.

- Hybrid modeling techniques: Combining ML with physics-based models can lead to more accurate simulations and predictions of milling processes. This integration enhances the understanding of complex interactions between cutting forces, tool geometry, and material behavior, aiding in process optimization.

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- Data-Driven Model Calibration: Develop techniques to calibrate physics-based models using ML algorithms. ML can be employed to learn the parameters and variables that are difficult to measure directly, improving the accuracy and reliability of the physics-based models. This calibration process can leverage historical data from milling processes and combine it with the physics-based model to refine and enhance its predictions.
- Integration of ML in Physics-Based Simulations: Explore methods to integrate ML algorithms directly into physics-based simulations. ML techniques can be used to augment or enhance the physics-based models by learning complex relationships or capturing non-linearities that may be challenging to model explicitly. This integration can provide more accurate and efficient simulations of milling processes.
- Physics-Informed Learning: Investigate techniques that incorporate physics-based constraints into ML models. By imposing physical laws and constraints as part of the learning process, ML models can learn from limited data while still preserving the underlying physics. This can lead to more robust and interpretable models that are capable of making accurate predictions in complex milling scenarios.
- Transfer Learning and Domain Adaptation: Explore methods to transfer knowledge and insights gained from one milling process to another. ML algorithms can be trained on data from one milling machine or material and then adapted to a different scenario, allowing for quick adaptation and improved predictions. This can reduce the need for extensive data collection and expensive simulations for each specific case.
- Real-Time Monitoring and Optimization: Explore AI techniques to continuously monitor the milling process and make real-time adjustments to optimize performance. This can involve analyzing sensor data, such as vibrations, temperatures, and cutting forces, to detect anomalies and optimize milling parameters accordingly..
- Uncertainty Quantification: Develop techniques to quantify and propagate uncertainties in hybrid modeling approaches. Incorporating uncertainty estimation from both ML algorithms and physics-based models can provide more reliable predictions and facilitate decision-making in milling processes.

ML can be leveraged to enable collaborative robots, or cobots, to work alongside human operators in milling processes. ML algorithms can enable cobots to learn from human expertise, adapt to changing conditions, and improve overall productivity and safety.some perspective research directions can be accounted as:

- Adaptive Path Planning: Develop AI algorithms that enable Cobots to adaptively plan their paths based on real-time feedback from the milling process. This can involve optimizing the milling routes to improve efficiency, reduce errors, and enhance surface finishes. Reinforcement learning techniques can be employed to optimize the milling parameters based on the desired outcomes and constraints.
- Machine Learning for Collision Avoidance: Research can focus on training machine learning models to identify potential collision scenarios and develop algorithms to dynamically adjust the robot's movements to avoid them. This can involve using computer vision techniques to analyze the milling environment and anticipate potential obstacles.
- Human-Robot Collaboration: Investigate ways to enhance the collaboration between human operators and Cobots during milling tasks. AI can play a role in understanding and adapting to the intentions and actions of human operators, ensuring safe and efficient collaboration.
- Real-Time Monitoring and Optimization: Explore AI techniques to continuously monitor the milling process and make real-time adjustments to optimize performance. This can involve analyzing sensor data, such as vibrations, temperatures, and cutting forces, to detect anomalies and optimize milling parameters accordingly.
- Cognitive Assistance: AI can be leveraged to provide cognitive assistance to human operators, such as intelligent tool selection, error detection, and process optimization recommendations. This can significantly improve the overall milling process by combining the strengths of humans and Cobots in a collaborative manner.

ML can enhance the development and utilization of digital twin models for milling machines. By coupling ML algorithms with virtual replicas of the physical milling system, real-time monitoring, performance prediction, and optimization can be achieved.

- Anomaly Detection and Fault Diagnosis: Develop ML algorithms that can detect anomalies and faults in the milling machine's operations. By analyzing sensor data from the physical milling machine and comparing it to the digital twin model's predictions, ML techniques can help identify deviations and diagnose potential issues. This can enable proactive maintenance and optimize machine performance.
- Predictive Maintenance: Investigate ML techniques that can predict the maintenance needs of milling systems. By analyzing historical data from both the physical machine and the digital twin model, ML models can learn patterns and predict when specific components or systems may require maintenance, thereby minimizing downtime and optimizing maintenance schedules.

- Optimization and Control: Explore ML algorithms to optimize milling process parameters and control strategies. By coupling ML techniques with the digital twin model, it becomes possible to identify optimal cutting parameters, speeds, feeds, and toolpaths for maximizing productivity, surface quality, and tool life. Reinforcement learning algorithms can be used to iteratively improve the milling process based on feedback from the physical machine.
- Data-Driven Model Calibration: Develop ML-based approaches for calibrating and refining the digital twin model using real-time sensor data from the physical milling machine. By continuously updating and refining the model based on actual operating conditions, the accuracy and reliability of the digital twin can be improved.
- Integration of Simulation and Real-Time Data: Investigate techniques to combine real-time sensor data from the physical milling machine with simulation models in the digital twin. ML techniques can be used to bridge the gap between simulated and real-world data, allowing for more accurate predictions and performance optimization.

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Declarations

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