applied sciences

MDPI

Article

Overview of Tool Wear Monitoring Methods Based on Convolutional Neural Network

Qun Wang [1,2], Hengsheng Wang [1,*], Liwei Hou [1] and Shouhua Yi [2]

[1] College of Mechanical and Electrical Engineering, Central South University, Changsha 410083, China; 2005313@hnu.edu.cn (Q.W.); lwhou1992@gmail.com (L.H.)
[2] Modern Engineering Training Center, Hunan University, Changsha 410082, China; yishouhua@hnu.edu.cn
* Correspondence: whsheng@csu.edu.cn

Abstract: Tool wear monitoring is of great significance for the development of manufacturing systems and intelligent manufacturing. Online tool condition monitoring is a crucial technology for cost reduction, quality improvement, and manufacturing intelligence in modern manufacturing. However, it remains a difficult problem to monitor the status of tools online, in real-time and accurately in the industry. In the research status of mainstream technology, the convolution neural network may be a good solution to this problem, based on the appropriate sensor system and correct signal processing methods. Therefore, this paper outlines the state-of-the-art systems encountered in the open access literature, focusing on information collection, feature selection–extraction technologies based on deep convolutional neural networks, and monitoring network architecture and modeling methods. Based on typical cases, this paper focuses on the application of the convolution neural network in tool wear monitoring. From the application results, it is feasible and reliable to apply convolution neural networks in tool wear monitoring. Additionally, it can improve the prediction accuracy, which is of great significance for the future development of technology. This paper can be a guide for the researchers and manufacturers in the area of tool wear monitoring for explaining the latest trends and requirements.

Keywords: tool wear; convolutional neural network; network structure; tool condition monitoring

Citation: Wang, Q.; Wang, H.; Hou, L.; Yi, S. Overview of Tool Wear Monitoring Methods Based on Convolutional Neural Network. *Appl. Sci.* **2021**, *11*, 12041. https://doi.org/10.3390/app112412041

Academic Editor: Fabio La Foresta

Received: 19 November 2021
Accepted: 15 December 2021
Published: 17 December 2021

1. Introduction

The rapid development of intelligent manufacturing at a global scale had a profound impact on industrial development and the division of labor. It promoted the formation of various new production methods, industrial forms and business models. Intelligent manufacturing can shorten the product development cycle, reduce resource and energy consumption, reduce operating costs, improve production efficiency, and improve product quality. As typical intelligent manufacturing equipment, the intelligent machine tool is an essential carrier for intelligent manufacturing technology and a powerful tool for automation, intelligence, precision and the environment in the production process. It is an important indicator for measuring national industrialization [1]. The intelligent machine tools make independent decisions on all aspects of the manufacturing process, including monitoring, diagnosing and repairing various process deviations, providing the optimized solution for manufacturing. Moreover, it evaluates and predicts the remaining life of cutting tools, spindles, bearings and guide rails, suggesting the remaining usage life, replacement time and current status [2]. Therefore, the self-perception, self-learning, self-adaptation, and self-optimization of the intelligent machine tool condition created challenges that needed to be overcome [3]. With the development of automation and intelligence in the manufacturing process, online condition monitoring has become increasingly important. Tool wear monitoring has become a critical technology recognized by the global industry. The tool is the end effector of the mechanical manufacturing system, and the tool wear and damage directly affect the entire machining process. The failures caused by tool wear and

tear significantly increase machining costs and maintenance time, reducing production efficiency. Tool condition monitoring employs effective detection methods, feature analysis, and pattern recognition to efficiently and accurately monitor the tool wear condition during the machining process. It provides a basis for subsequent control and processing, thereby reducing the manufacturing losses caused by the tool wear [4]. Effective tool wear monitoring can improve tool utilization, machining accuracy and production efficiency, increase the service life of machine tools, and ensure safe equipment operation, etc. At present, the importance of digital twin technology is increasingly recognized by academia and the industry, and it is recognized as one of the most promising technologies to realize intelligent manufacturing and Industry 4.0 [5–8]. Its purpose is to create a digital object that reflects the actual object behavior, and this technology can be successfully applied to prediction, decision making, and reconstruction [9]. Using neural networks to extract and fuse features of multi-source data in the machining process, and then to monitor tool wear and predict tool life can promote the development of tool digital twin technology [10–12].

The tool wear refers to the deformation or damage of the sharp edge caused by the interaction between the tool and the workpiece during machining. It is a complicated process for monitoring the tool wear condition in order to realize the self-sensing and self-decision in the machining process. A system is nonlinear if its output is not proportional to its input. The inputs of the tool wear monitoring system, such as cutting force, vibration, stress elastic wave, temperature, current, power and workpiece surface quality, are not proportional to wear. Due to the coupling of working conditions, cutting parameters, workpiece material, blade deviation, cutting vibration and other factors, it is difficult to accurately model and predict wear in the cutting process. Tool wear is a very complex nonlinear system [11]. Traditional, supervised learning algorithms formulated various recognition and prediction models for the wear and damage of cutting tools, which achieved recognition outcomes. The deep convolutional neural network automatically learns the feature from the input feature and combines low-level features to form high-level features through a multi-layer convolution kernel [13]. It can accurately approximate continuous, nonlinear functions and exhibits an excellent performance in terms of fault tolerance, adaptability and noise suppression [14,15]. The most basic part of neural network is data information, and the collection of information cannot be separated from sensors, so sensors constitute the most important hardware part of the tool monitoring system [16–18].

This paper mainly studies the tool wear monitoring method based on a convolutional neural network in order to promote the development of mechanical manufacturing and intelligent manufacturing. This process is supported by the published literature. This paper covers the main monitoring methods and the main structure of the monitoring network.

2. Tool Wear Mechanism

The phenomenon that a sharp edge is deformed or damaged due to the interaction between the tool and the workpiece during machining is called tool wear. Tool wear is divided into normal wear and abnormal wear [19]. Normal wear refers to the wear that occurs gradually during the cutting process when the design and use of the tool are acceptable. Additionally, the quality of manufacturing and sharpening meets the requirements. Abnormal wear, namely tool damage, is generally an abnormal failure. It is mainly related to improper use. Here, we mainly discuss and analyze normal wear. As for the mechanism of tool wear, Relevant researchers have carried out much research work [20–24]. Researchers generally believe that tool wear is the result of a mechanical and chemical reaction between tool and workpiece material. Under different working conditions, especially under the condition of high-temperature alloy cutting, the tool wear mechanism mainly includes abrasive wear, adhesive wear, diffusion wear, chemical wear, and so on [25].

Abrasive wear refers to tool loss or tool material loss during cutting friction caused by the extrusion of peeled, hard particles on the tool surface and movement along the surface. Some researchers also believe that work hardening burrs on the surface also cause abrasive

wear when particles flow laterally. This is an important mechanism that is responsible for flank wear, notch wear and nose wear in general [11,12,25,26]. Adhesive wear, also known as bite wear, refers to a form of wear in which metal adhesion occurs locally at the contact surface between the tool and the workpiece; the adhesive part is destroyed in the subsequent relative sliding, and metal chips are pulled down from the tool surface or the tool surface is scratched. Adhesive wear has a great relationship with cutting speed, and the common results are flank wear, notch wear, nose wear, chipping, built-up edge (BUE) and built-up-layer (BUL) formations [24,25,27]. Diffusion wear is caused by the diffusion process of atom transfer from a high-concentration region to a low-concentration region under the influence of a high temperature. The decisive factor is the chemical proximity between a high-temperature tool and working material elements. It has a great influence on coated, ceramic, and CBN cutting tools for high-speed cutting [28–30]. Chemical wear means that at a certain temperature, some elements in the tool material react with some elements in the surrounding medium to form a layer of compound with a low hardness on the surface of the tool, which is taken away by the cutting and workpiece; therefore, tool wear is increased or the tool material is corroded by a medium that causes tool wear. It is not the main wear mechanism [31].

The amount of tool wear increases with the usage time, and the wear speed primarily depends on the cutting conditions. The experiments demonstrated that the tool wear process under different cutting conditions was similar, including three stages: initial wear, normal wear, and sharp wear [32–34].

During the cutting process, tool wear is closely related to changes in the physical parameters of the machine tool operation such as cutting force, vibration, acoustic emission, temperature, current, voltage, power, and resistance. The phenomena or parameter changes related to the machine tool operation can be used as the basis for tool wear monitoring [35]. Therefore, monitoring the changes in the physical parameters can realize tool wear monitoring [36]. For example, the cutting force is a variable of the machining process condition and is very sensitive to the tool wear condition [37]. After the tool is worn, the cutting force and cutting temperature increase, the workpiece machining accuracy and surface quality deteriorate, and vibration and noise occur during machining. This will significantly shorten the tool service life.

3. Common Methods of Tool Wear Monitoring

Tool wear monitoring is divided into two methods of offline direct monitoring and online indirect monitoring [23].

Offline direct monitoring mainly evaluates the tool wear condition via the offline measuring of changes in the tool dimension by visual and optical methods [38]. Before CNC machining, the cutter aligner is used for tool presetting. The tool presetting data difference is comparatively obtained after machining, and the difference is the tool wear amount. However, this method is susceptible to thermal deformation, and its accuracy is low. An improved method is to measure the data after the machine tool is fully heated to thermal equilibrium. For a machine tool equipped with a tool changer, the tool holder and tool are removed together and measured by an external tool detector. The comparison can reduce the thermal deformation impact of the machine tool. There are two shortcomings in the offline direct measurement: (1) Monitoring after shutdown is required. (2) The sudden tool damage during machining cannot be monitored [24]. Therefore, offline monitoring cannot predict the tool wear condition in real time. With the development of the manufacturing industry, especially intelligent manufacturing, the online monitoring of tool wear conditions is increasingly essential.

Online indirect monitoring evaluates the tool wear condition in real-time by monitoring the change of the data related to tool wear. These data can be collected by one kind of sensor or the fusion of information collected by multiple sensors. It implements monitoring when the tool is cutting without affecting the cutting process. It is a nondestructive, simple, sustainable and non-interference monitoring method [17]. Its disadvantage is that the

monitored process features contain a lot of interference information. Compared with the offline direct monitoring method, the indirect online monitoring method is more flexible. It combines the technologies of feature analysis, processing, and pattern recognition to predict the online tool wear condition for achieving intelligent control. Therefore, the research on tool wear monitoring in academia and industry focuses on the indirect online monitoring method [39].

4. Information Data of Indirect Online Measurement on Tool Wear

The information data of indirect online monitoring includes cutting force, vibration, acoustic emission, temperature, current, power, workpiece surface roughness, and multi-information fusion.

4.1. Cutting Force

The cutting force change is closely related to the tool wear/damage conditions during the cutting process. The cutting force information is easy to obtain, and it responds quickly and sensitively to tool wear. The literature [40–43] suggested that cutting force monitoring is a promising method. Machining centers and FMS commonly use the cutting force as information data to monitor tool damage. Nouri et al. [38] proposed a method of tracking cutting force model coefficients to monitor the wear condition of end milling tools in real-time. This method studied the correlation between the cutting force model coefficients and tool wear condition. Altintas et al. [44] established a method for identifying broken cutters in the milling process based on the timing feature of horizontal cutting force. Kaya et al. [45] adopted a rotating dynamometer to collect the cutting force in three directions and the torque of the rotating tool. Wang et al. [46] proposed that the most reliable feature in the cutting process was the cutting force feature, which directly caused the generation of features such as vibration and acoustic emission. Huang et al. [47] used a piezoelectric dynamometer to monitor tool wear conditions in the end-milling operations. Li et al. [48] applied support vector machine regression to realize turning tool condition monitoring based on the cutting force. The results showed that the model had a high prediction accuracy. Zhu et al. [49] created a semi-hidden Markov model considering tool wear continuity index to monitor tool wear. This model reduced the computational cost and improved the recognition accuracy. Hua et al. [50] proposed a method for identifying the milling tool condition based on cutting force features, geometric information, and process information. It is suitable for single-piece and small-batch manufacturing processes, in which the geometry and cutting parameters were constantly changing.

The disadvantage of the cutting force feature is that it is not suitable for processing large workpieces. It is affected by the low stiffness and low-frequency bandwidth of the workpieces. It interferes with the precise motion control of the machine tool spindle and worktable, reducing the rigidity of the machine tool [51,52].

The installation diagram of a cutting force sensor is shown in Figure 1.

4.2. Vibration

Vibration feature monitoring has a low cost, easy assembly, and a periodic shape similar to the cutting force. Thus, it is widely used in tool wear monitoring [53–55]. During the cutting process, the workpiece rubs against the worn side of the cutting edge, causing vibrations of different frequencies. There are two methods for vibration feature monitoring. The first is to divide the amplitude into high and low parts and compare the amplitude of the two parts during cutting. The second is to divide the amplitude into several independent bands and use a microprocessor to continuously record and analyze the bands for monitoring the wear on the tool flank surface. Dang et al. [56] collected the original high-frequency vibration features and performed batch standardization and slice processing. These authors input a hybrid model based on a one-dimensional convolutional neural network and extreme learning machine and output the milling cutter wear condition. Hsieh et al. [57] reported that the vibration acceleration feature change

on the spindle can distinguish different tool wear conditions during micro-milling. Madhusudana et al. [58] used a three-axis IEPE accelerometer mounted on the spindle housing to collect the vibration acceleration feature of face milling. Gao et al. [59] employed a laser vibrometer to collect vibration displacement features to monitor the tool wear in the face milling process and achieve a high monitoring accuracy. Tao et al. [60] analyzed the morphological component characteristics and sparse characteristics of the vibration feature in the high-speed milling process, and extracted the vibration characteristics to monitor the tool wear condition. Cuka et al. [28] proposed that the change in tool wear condition affects the vibration status change during milling. Li et al. [61] confirmed the linear relationship between the milling force with the eddy-current displacement caused by tool holder swing. Additionally, the eddy-current displacement feature was extracted to monitor the milling cutter wear condition. Zhang et al. [62] used an accelerometer to measure the workpiece vibration feature during milling and performed a 5-layer feature decomposition by a wavelet packet to obtain the energy spectrum. Then, it was input into the classic convolutional neural network to realize the recognition of tool wear condition.

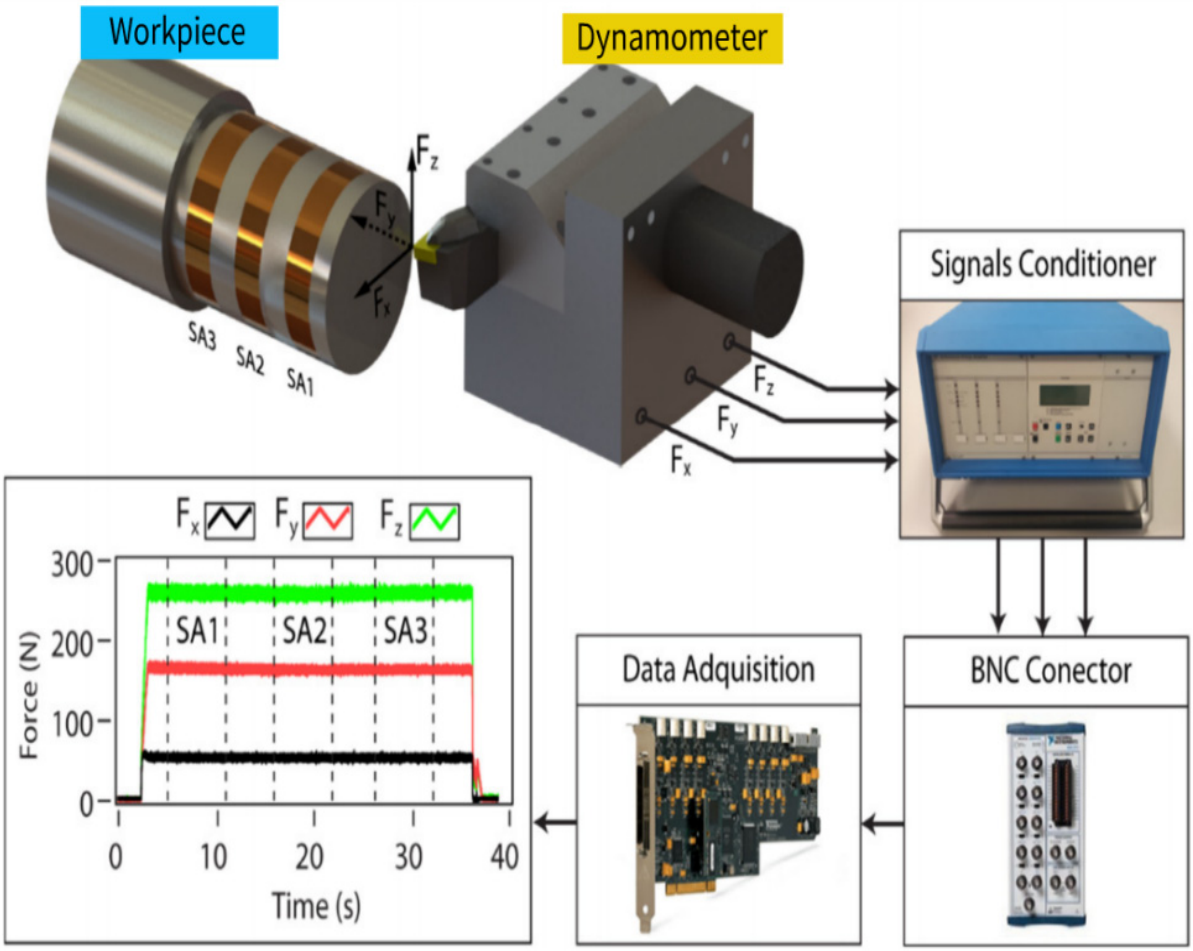

Figure 1. An installation diagram for cutting force sensor (drawn from the literature [43]).

The disadvantage of the vibration feature is that it is limited by the installation position and interference factors (e.g., cutting fluid) during the collection process, which leads to errors, sensor data loss and complex feature filtering [28,38].

The installation diagram of a vibration sensor is shown in Figure 2.

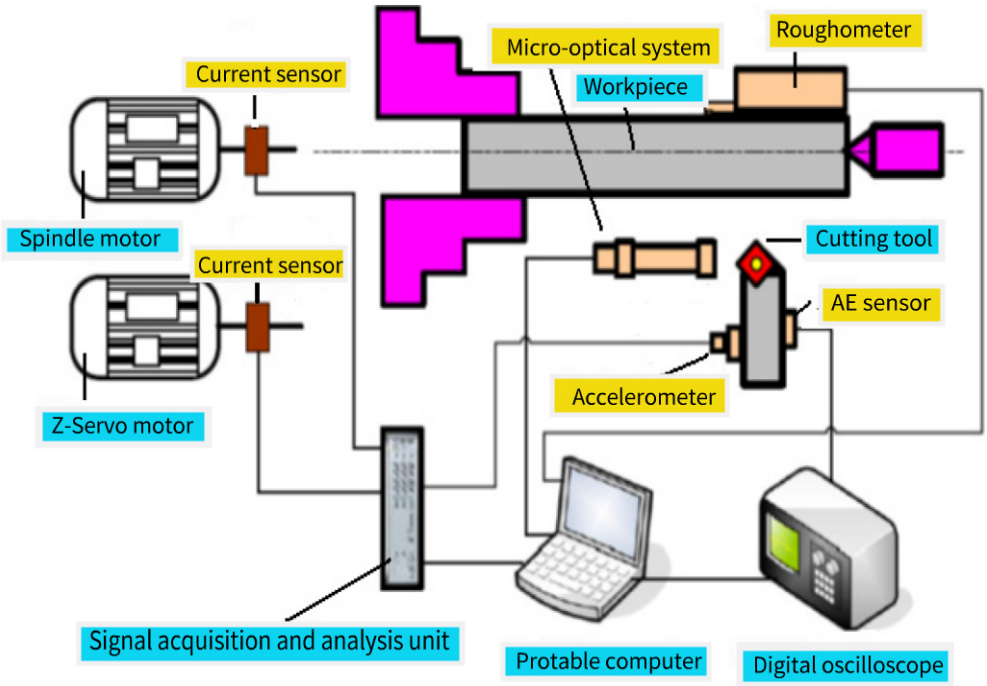

Figure 2. An installation diagram of vibration sensor, current sensor, acoustic emission sensor and surface roughness sensor (drawn from the literature [63]).

4.3. Acoustic Emission

The deformation, fracture and phase change of solid materials cause the rapid release of strain energy, and acoustic emission is the stress elastic wave. Thus, acoustic emission features with a higher amplitude can be monitored when the tool is broken [64–66]. Acoustic emission is not subject to mechanical interference and propagates much higher than the characteristic frequency caused by machining. It has a better sensitivity than force and vibration features. The tool condition monitoring based on acoustic emission is recognized as the most potential monitoring technology [67–70]. Mathew et al. [71] reported that acoustic emission features could effectively reflect changes such as tool breakage and tool chipping. Wang et al. [72] collected the acoustic emission features during milling and identified the tool wear condition through a model of linear-chain conditional random field based on conditional probability. Vetrichelvan et al. [73] suggested that the acoustic emission sensor mounted on the top surface of the tool holder could effectively monitor the crater wear on the tool. Ren et al. [74] argued that the acoustic emission feature was easy to collect and sensitive to the contact between the tool and the workpiece, suitable for tool condition monitoring during micro-milling. Zhang et al. [75] reconstructed the phase space of the acoustic emission feature, extracted the embedding dimension and Lyapunov exponent as the input parameters of the support vector machine. It obtained a high tool wear recognition accuracy. Wu et al. [76] collected acoustic emission features during the life cycle of milling cutters and employed a random forest-based model to predict tool wear condition. The findings suggested that the accuracy of the prediction model is better than that of the artificial neural network and support vector machine. Liu et al. [77] established a monitoring system of tool wear conditions based on the acoustic emission features containing four time-domain characteristic parameters.

The limitation of acoustic emission features is that the other features interfere with the acquisition, extraction, analysis, processing and storage of acoustic emission features during milling, and it is very sensitive to the material properties of the test object [51,78].

The installation diagram of an acoustic emission sensor is shown in Figure 2.

4.4. Temperature

Cutting heat is an essential physical phenomenon in the metal cutting process. Tool wear and damage cause a sudden increase in cutting temperature. There are three main ways to measure cutting temperature. (1) The natural thermocouple composed of the tool and the workpiece measures the average temperature of the cutting zone. The different materials of the tool and the workpiece need to be calibrated. (2) A thermocouple, composed of two metal wires fixed at a point in the tool body, measures the temperature at a certain distance from the tool edge. The method has the problems of time-consuming preparation and a slow response to temperature changes. An infrared thermal imaging camera measures the temperature distribution in the cutting zone, which has the characteristics of a high sensitivity and short response time. However, the instrument is complicated to operate, expensive, and difficult to focus on. Additionally, it is difficult to measure the temperature in the cutting coverage area. Researchers conducted many studies on the relationship between cutting edge temperature and tool wear [79–83]. Korkut et al. [84] developed a method for predicting the temperature of the tool–chip contact area based on a regression analysis and the BP neural network, in order to estimate the tool wear condition accurately. Kulkarni et al. [85] proposed a work–tool thermocouple method to determine the electromagnetic/thermal field feature generated by the interaction between the coating and the workpiece. It suggested that the high temperature at the cutting tool edge has a controlling effect on the wear rate of the cutting tool. Wang et al. [86] established a mathematical model of milling cutter flank wear by obtaining the cutting force and cutting temperature in real time based on determining the wear mechanism.

The cutting temperature depends on the material thermal properties of the workpiece and the tool, and the coolant weakens the correlation between the cutting temperature and the tool wear condition. Therefore, some scholars questioned the feasibility of monitoring methods based on temperature features. Generally, the sensitivity of the temperature sensor is relatively low, and can be easily disturbed by the signal of the environment and affected by the temperature drift of the preamplifier. It is not suitable for measuring small temperature changes.

The installation diagram of a temperature sensor is shown in Figure 3.

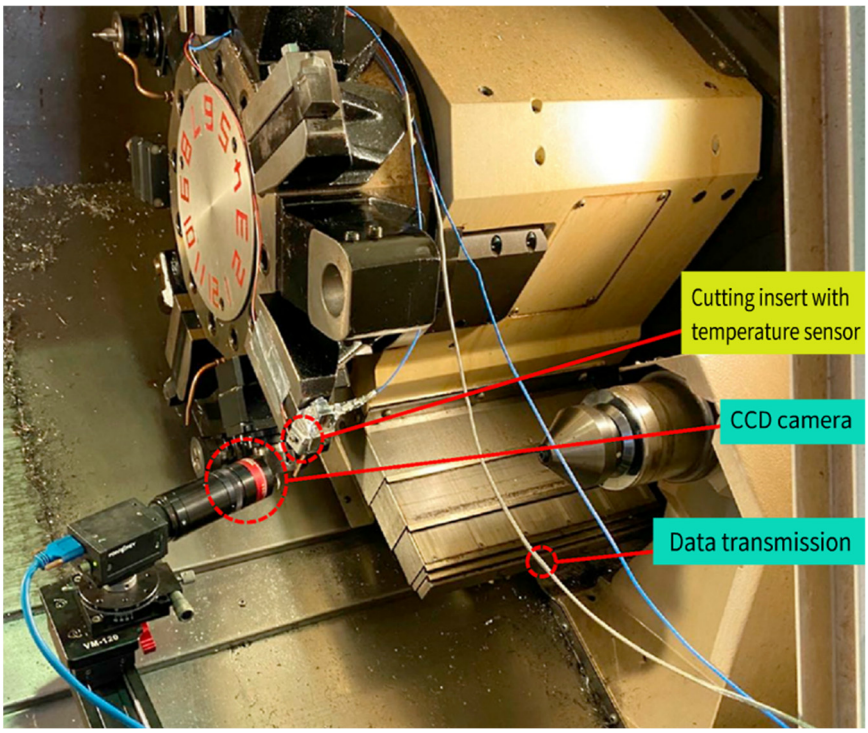

Figure 3. An installation diagram for temperature sensor (drawn from the literature [83]).

4.5. Current

Tool wear causes the cutting torque to increase, and the equipment motor current increases accordingly. As a result, the current can be used for online tool wear monitoring [36,87,88]. Because the sensor installation hardly affects the processing operation, current monitoring is relatively simple and considered the most suitable method for workshop applications [89–92]. Ammouri et al. [88] collected, analyzed, and processed the motor current feature through the current sensor connected to the spindle motor and the X-axis drive motor. Drouillet et al. [93] comparatively found that current and voltage sensors could replace the cutting force sensors for industrial tool wear monitoring. Stavropoulos et al. [94] presented that the current feature has better anti-environmental noise performance and stronger correlation with tool wear, thereby better reflecting the tool wear condition than the vibration feature. Li et al. [95] studied the correlation between the tool wear condition with the input current of the servo motor inverter and monitored the tool wear condition online in real time based on the inverter input side current. Rizal et al. [96] collected the current feature of the motor stator through an instrument to monitor tool wear conditions. The method has the characteristics of convenient operation, high information integration, direct transmission path, suitable feature extraction, free from the influence of the processing environment, cheap, and easy to transplant. This should be a method worth exploring for machine tool applications where the transmission system is closed and available sensors are difficult to install.

The disadvantage of the current feature is that it is greatly affected by noise. It is difficult to detect small features, and high-frequency features are lost due to filtering. The current feature is easily affected by the friction of the mechanical system and the viscous damping of the feed system. Experimental studies indicated that the current is not sensitive to the cutting force changes under high-frequency conditions. The motor current feature is not suitable for monitoring the tool wear condition at high spindle speeds [90,96]. The current sensor should be installed away from the processing area, resulting in reduced sensitivity and reliability.

The installation diagram of a current sensor is shown in Figure 2.

4.6. Power

Spindle power is a comprehensive feature, and related research shows that the change of spindle power is related to tool wear [90]; it can fuse other data information to accurately predict tool wear. Xu et al. [97] found that there was a linear relationship between spindle power and tool wear state. Shao et al. [89] proposed a threshold update strategy for tool condition monitoring. In this study, the classification success rates for turning and drilling are 96% and 93%, respectively. Al-Sulaiman et al. [98] monitors power consumption by electrical features to drill holes and further explain tool wear. Siddhpura et al. [99] studied the relationship between tool wear and extra power input. Drouillet et al. [93] uses neural network (NN) technology to predict the remaining service life of the tool based on the spindle power. It is reported that this method has a low calculation cost and can be used for real-time predictions in the machining process.

At present, the power information data are mainly fused with other information data, to become the supplementary information data of the neural network system, in order to improve the information reliability and help the tool monitoring system achieve good results [26].

The installation diagram of a power sensor is shown in Figure 4.

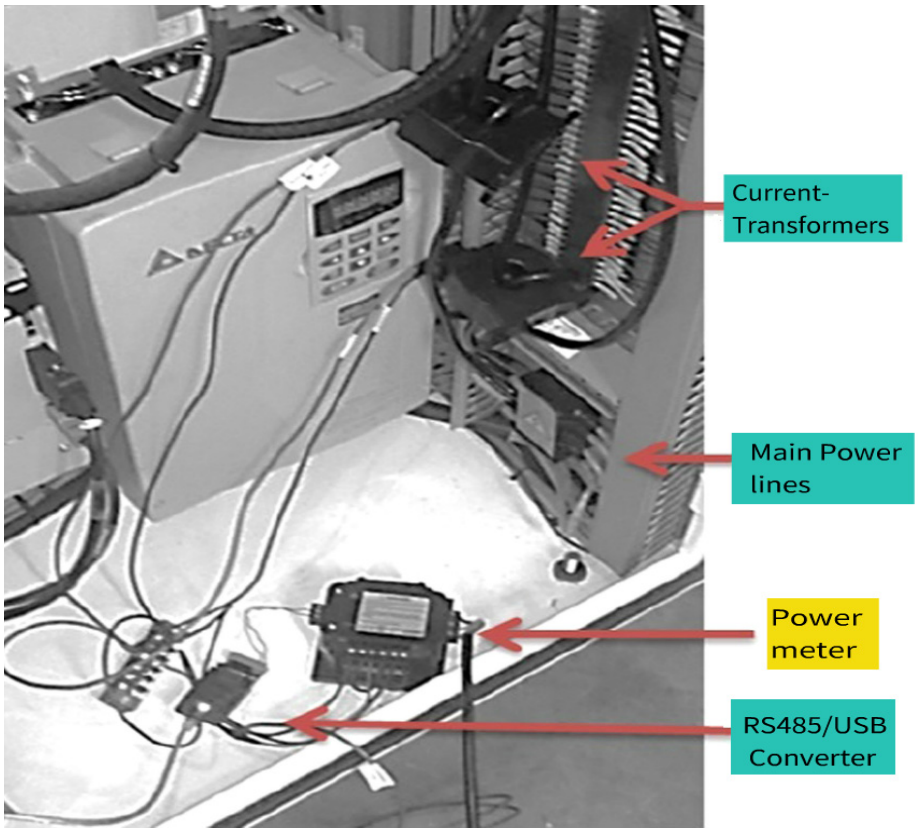

Figure 4. An installation diagram for power sensor (drawn from the literature [100]).

4.7. Workpiece Surface Roughness

In terms of workpiece surface roughness, the surface roughness increases as the tool wear increases or breakages occur. Based on this, the wear or damage condition of the tool can be indirectly inferred. The measurement methods of workpiece surface roughness are divided into two categories. (1) The contact measurement directly obtains the evaluation parameters of surface roughness, which are only suitable for offline measurement. (2) The non-contact optical reflection measurement obtains the relative value of the workpiece surface roughness. Automatic monitoring usually adopts two types: fiber sensor and laser test system [29,101]. Cuka et al. [28] carried out finished turning operations on hardened materials, and measured the flank wear of the tool and the surface finish, which varied with machining time under different machining conditions. Zel et al. [29] developed an online surface roughness recognition system for a lathe based on a neural network and sensor system.

Because the surface roughness feature is mainly used to measure the machined workpiece and cannot be monitored in real time, its application in tool wear online monitoring is limited.

The installation diagram of a power sensor is shown in Figure 2.

4.8. Multi-Information Fusion

Multi-information fusion is a new solution, which can deal with complex practical problems. In industrial applications, this information is accomplished by more than one sensor [102]. Using multiple sensors can compare the information obtained from different resources, and it is easier to determine the status of tools and workpieces [20]. Kuntoğlu et al. [26] studied the fusion of cutting force and acoustic emission feature. Ghosh et al. [27] studied the fusion of cutting force, spindle current, spindle vibration and machining sound feature. Wang et al. [103] studied the fusion of acoustic emission and cutting force features. Cho et al. [104] studied the fusion of cutting force, vibration, acoustic emission and the

spindle power feature. Shao et al. [105] studied the fusion of acoustic emission and sound features. Torabi et al. [106] studied the fusion of cutting force, vibration and acoustic emission features. Lopes et al. [107] studied the feature fusion of acoustic emission and cutting power. According to the results of these studies, these multi-information fusion technologies achieved good results in tool wear monitoring.

The installation diagram of the multi-information fusion of sensors is shown in Figure 5.

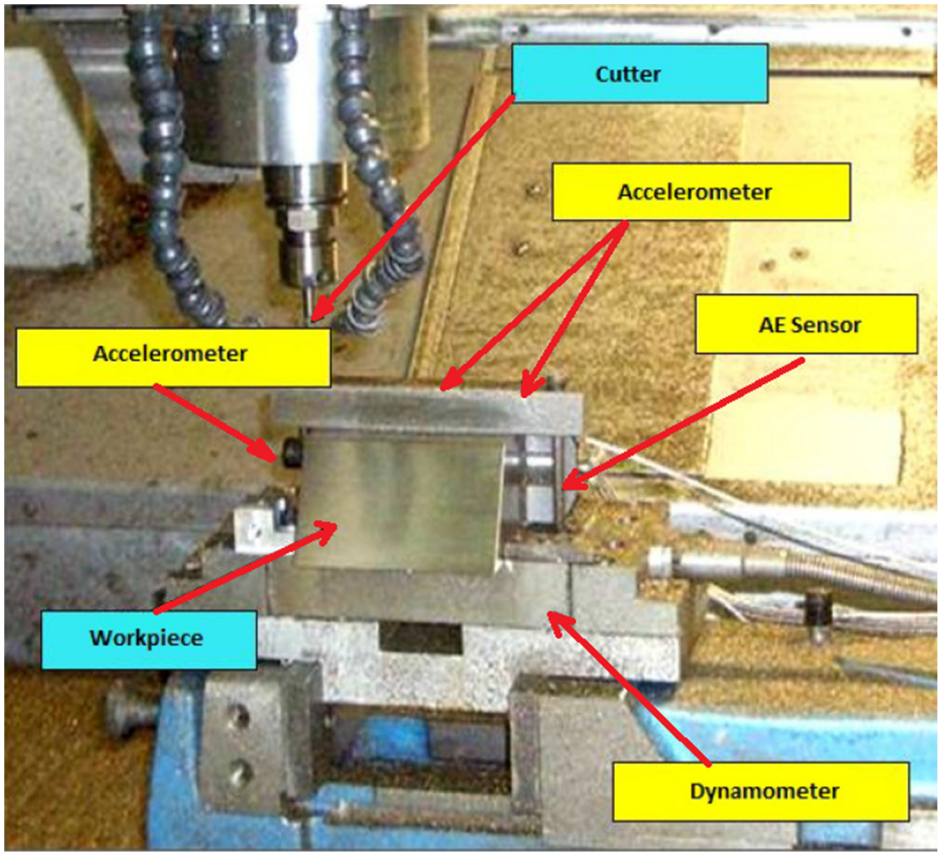

Figure 5. An installation diagram of multi-information fusion of sensors (drawn from the literature [106]).

Scholars conducted a lot of research on the relevant information data of tool wear. Table 1 lists the references, sensors and application environments corresponding to each type of data information in this paper.

Table 1. Research literature and research situation of data information related to tool wear.

Data Information	References	Main Sensors or Tools Used	Main Application Environment and Characteristics
cutting force	[38,41–52]	three-phase dynamometer, dynamometer, strain force sensor, piezoelectric force sensor	applied to turning, milling, drilling, etc., real-time detection, easy to use, widely used, not suitable for processing large workpieces, interference control
vibration	[53–62]	acceleration meter, laser vibration meter, vibration sensor	applied to turning, milling, drilling, etc., real-time detection, sensitive, limited use, easy to lose data

Table 1. *Cont.*

Data Information	References	Main Sensors or Tools Used	Main Application Environment and Characteristics
acoustic emission	[64–77]	acoustic emission sensor	applied to milling, grinding, drilling, etc., real-time detection, sensitive, easy to be disturbed, high requirements for the materials of the test object
temperature	[79–86]	pyrometer, thermocouple, thermal imager	applied to milling, turning, etc., real-time detection, easy to use, low sensitivity, cannot be used in the scene with coolant
current	[36,87–95]	current sensor, hall effect sensor	applied to milling, drilling, etc., real-time detection, difficult to detect tiny features, greatly affected by noise
power	[89,90,93,97–99]	differential power detector, power sensor, current divider	applied to drilling, turning, milling, etc., low cost, easy to use, real-time detection, rarely used alone
workpiece surface roughness	[28,29,101]	roughness probe, roughness meter, laser sensor, infrared sensor	applied to milling, turning, etc., non-real-time detection, limited application
multi-information fusion	[20,26,27,103–107]	multiple sensors	various processing environments; widely used

5. Tool Wear Monitoring Method Based on Deep Convolutional Neural Network

5.1. Deep Convolutional Neural Network

The neural network is a mathematical algorithm model that imitates the behavioral characteristics of animal neural networks for distributed and parallel information processing. Convolutional neural networks (CNNs) are composed of multiple layers of neural networks. Each layer contains many two-dimensional planes with multiple independent neurons. Its essence is a mapping from input to output. It self-learns many mapping relationships between inputs and outputs through the networks and does not require any precise mathematical expressions. The CNNs adopt the idea of a sparse connection and parameter sharing. For example, the one-dimensional time series network and two-dimensional pixel image data are obtained by regularly sampling on the time axis. Unlike the traditional neural network connecting each output feature map with each input feature map, the sparse connection makes each output feature map correlate with the neighboring area of the previous layer feature map. Parameter sharing refers to using the same parameters in multiple model functions; one convolution kernel is required to traverse the entire input image each time. It not only dramatically reduces the number of stored parameters and improves computational efficiency, but also gives the CNNs the characteristics of translation invariance. The CNNs automatically extract features at different levels in the image and perform classification and recognition tasks accordingly. They have a high degree of abstraction and generalization, thereby better reflecting the nature of data. The CNN is considered as one of the best technologies for image content learning, demonstrating the best outcomes in terms of image recognition, segmentation, monitoring, and retrieval [108].

The deep CNNs further reduce the parameter number of the neural network architecture. The low-level features are local, so the convolution window is used for feature extraction. The low-level features (e.g., boundaries) of different image regions are similar, and they share a set of filters. The convolution replaces the full connection for feature extraction, and the low-level features are combined to obtain high-level features with more semantic information. The deep CNNs are generally composed of the input layer, convolutional layer, pooling layer, fully connected layer, and output layer [109]. The LeNet-5 structure of the classic convolutional neural network is shown in Figure 6.

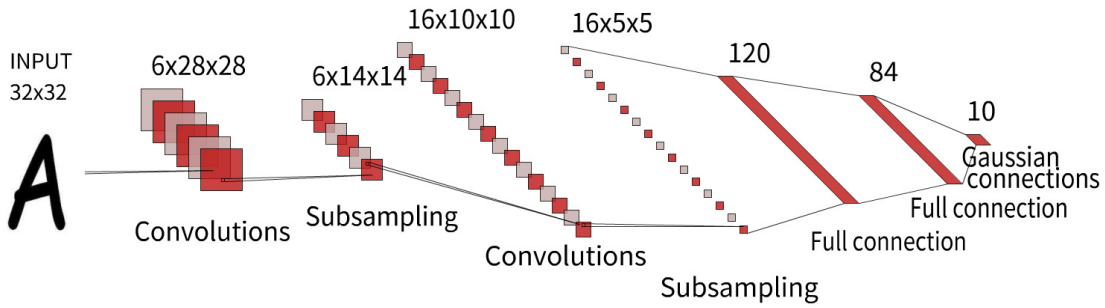

Figure 6. The LeNet-5 network structure (drawn with the permission of Reference [110]. Copyright 2011 IEEE).

Here, the convolutional layer performs a convolution operation, similar to the filter operation in image processing. It is mainly responsible for feature extraction operations, and its output size is related to the input size, the convolution kernel size, the filling value size and the step size.

The pooling layer is an operation to reduce the space in the length and height directions. The calculation formula of the output size is the same as that of the convolutional layer. However, the pooling layer is not filled in most cases. Thus, the output size of the pooling layer is only related to the input size, the convolution kernel size, and the step size.

According to the principle of image local correlation, a small area of the input feature map is selected for feature pooling with the maximum or average value. Consequently, the computational amount is reduced, and it has a certain degree of noise immunity. Finally, the fully connected layer classifies the extracted features and outputs the final result (probability) according to different tasks.

Alex et al. [111] proposed an AlexNet network model consisting of five convolutional layers and three fully connected layers. The network innovatively used the rectified linear unit to solve the gradient divergence and applied the dropout method in the fully connected layer to avoid model over-fitting. Simonyan et al. [112] developed the VGGNet, including network models with varying depths from eleven to nineteen layers. The VGG16 and VGG19 are commonly used, and the model structure adopts the five sets of convolutional layers, the three fully connected layers and the softmax output layer. The difference is more and more cascaded convolutional layers involved in the convolutional layers. The model verified that increasing the depth helps to improve the classification accuracy. Szegedy et al. [113] proposed the GoogLeNet with an inception structure, using a large number of 1×1 convolution kernels. It significantly reduced the parameter number, improved the training speed and promotion ability of the model, and realized the approximation of the dense component to the optimal local coefficient structure. Moreover, two auxiliary classifiers were added to the model to conduct the gradient forward, effectively reducing the phenomenon of gradient disappearance. He et al. [114] proposed the ResNet, which directly transferred input information to output. It converted the direct learning of the target value into learning the residual between the input and the output. To a certain extent, it solved the problem of information loss and reduced learning difficulty. Sang et al. [115] optimized the parameters and training algorithm of the original AlexNet convolutional neural network. The findings suggested that the improved AlexNet convolutional neural network algorithm could better judge the degree of tool wear. Wu et al. [116] employed a convolutional autoencoder to pre-train the network model, combined with the BP and Adam algorithms to fine tune the model parameters, thereby establishing an effective model for tool wear type recognition. Liu et al. [117] selected two features of cutting force and cutting vibration as initial data and used the wavelet packet analysis method to reduce data noise for feature extraction. Then, the entropy result of the monitoring data was calculated as the input of the predictive model. Through training and testing the deep CNNs, the tool remaining life prediction model was finally formulated. Kothuru et al. [118] used CNN to develop a tool condition monitoring model, implementing hyperparameter adjustments to improve prediction accuracy.

With the continuous development of computer hardware and deep learning algorithms, deep CNNs achieved great success in computer vision tasks such as image classification, target monitoring, and image segmentation. Many deep CNN methods were applied to tool wear monitoring. In order to improve the generalization performance of the network, the number of layers of the network can be increased according to the situation, so that the model can mine the tiny information of the machining feature and avoid gradient dispersion. The model operation should facilitate adaptive feature extraction. However, the deeper the network layers, the better; they must be judged according to the actual application. If the data are insufficient, it will lead to problems such as insufficient training and over fitting.

5.2. Acquisition and Preprocessing of Tool Wear Monitoring Feature

In the machining process, sensors are used to collect the information data related to the tool wear. The information is processed and input into the model for evaluating tool wear conditions.

The acquisition and preprocessing of a single-sensor feature are described in Section 3. However, a single-sensor feature has certain limitations for system decision-making. Multiple sensors provide more redundant information, reducing the overall measurement uncertainty. Consequently, the accuracy and resolution of the model system are improved, and a better prediction performance is obtained. Cao et al. [39] employed multiple sensors to collect seven time-domain features of the cutting force and acoustic emission. The cutting force features included the cutting forces (F_x, F_y, F_z) and accelerations (a_x, a_y, a_z) in the three directions. The features were subsampled into 5000 samples to form a tensor of (5000, 7), which was input into the CNNs for evaluating the flank wear condition. Liu et al. [117] selected two features of the cutting force and cutting vibration as initial data, which was processed and input into the prediction model. Through training and testing the deep CNNs, the tool remaining life prediction model was established. Cho et al. [104] indicated that the tool wear monitoring method using feature-level fusion significantly improved the accuracy of tool condition classification. High-precision monitoring was achieved through force, vibration and acoustic emission sensors, correlation feature selection methods, and majority voting machine integration. Torabi et al. [106] applied the proposed clustering method to analyze the wavelet characteristics of force and vibration features. The findings supported that the clustering method can roughly capture the process condition for fault diagnosis and tool wear monitoring. Downey et al. [119] monitored the CNC tool wear condition by fusing the information of the force, vibration, and acoustic emission sensors. Jauregui et al. [120] proposed a cutting force and vibration feature analysis method based on frequency and time-frequency for monitoring tool condition in the high-speed micro-milling. Shankar et al. [121] input the sound pressure and cutting force features to an expert system for monitoring tool wear. Wang et al. [122] developed a multi-scale principal component analysis method based on force and vibration features for online tool wear monitoring during milling.

Adding new features may offset the sensitivity loss of the original feature. Therefore, multi-sensing features can enhance the information richness on the potential wear level. However, more sensor features are not necessarily better. Adding sensors increases the system cost and maintenance difficulty. The more sensors, the greater the impact on the machining process, and the more complex the feature processing. More importantly, too much redundant information reduces decision-making accuracy. It is more effective to select a few feature parameters of critical sensors than to select more parameters [123,124]. How to effectively set a few key feature parameters requires further in-depth study.

5.3. Network Model Structure for Tool Wear Monitoring

According to the actual requirements of tool wear monitoring, the classic network model needs to be modified. Lu et al. [32] borrowed from the residual network design ideas for arrhythmia training proposed by Wu's team. They established the CNNs to predict

tool wear conditions based on information related to cutting force, e.g., spindle load and spindle torque. The network structure is shown in Figure 7. The batch normalization (BN) layer is added to each layer in the model. The rectified linear units (ReLU) behind the BN layer represent the nonlinear transformation of the feature matrix, using the modified linear activation function $f(x) = \max(0, x)$ to operate on all elements in the feature matrix individually. The dimension of the feature matrix remains unchanged after the ReLU conversion. The function increases the network sparsity and improves the representativeness and generalization of the extracted features.

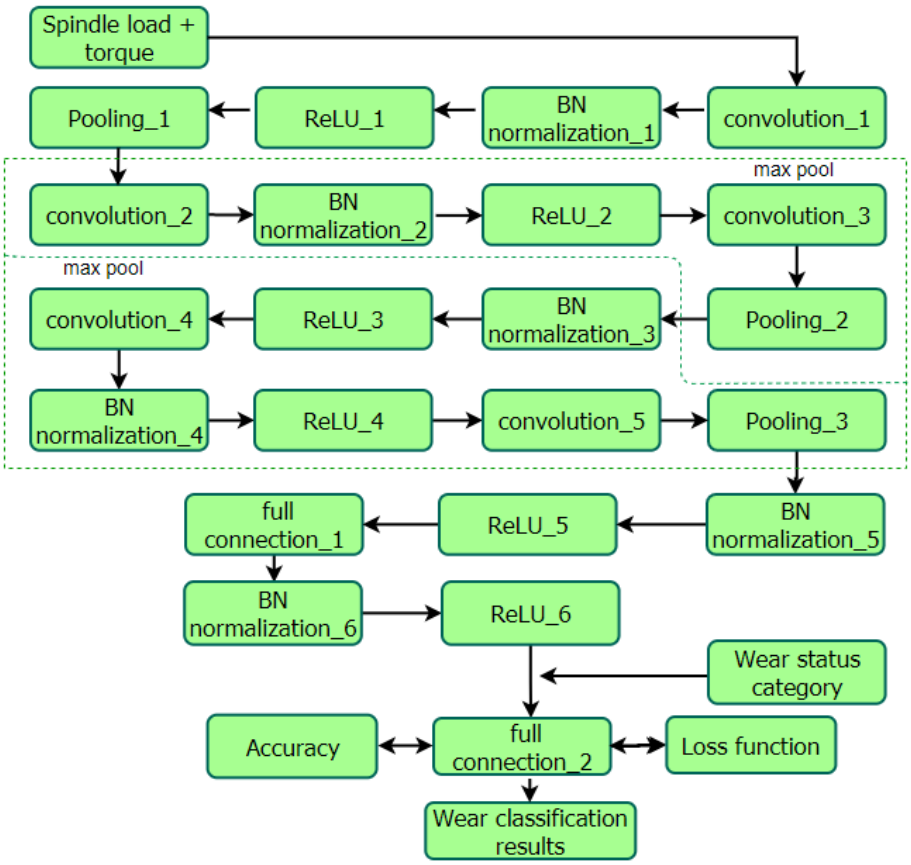

Figure 7. The CNN model structure proposed by Lu et al. (drawn from the literature [32]).

Wang et al. [36] regarded the currents of the three axes as the three input channels of the network. The first convolution layer uses a large convolution kernel of size 21. The size of the subsequent convolution kernel is reduced layer by layer. The step size of all convolutional layers is two, halving the feature map size. The pooling layer is connected to the back of each convolutional layer. The maximum value of the convolution kernel size and step size is two, halving the feature map size again. The channel number in the first convolutional layer is 32. The channel number in each subsequent network layer is increased by two times or remains unchanged. The output size of the last pooling layer is 3×128, flattened into a 384-dimensional vector. Finally, two fully connected layers are connected for classification. The BN layers are added after each convolution operation and before the activation function. To avoid network over-fitting, random dropout technology is applied to the flattening layer after the last pooling layer. During the training process, each neuron output in the hidden layer is set to zero with a probability of $p = 0.5$. As a result, the interdependence between neurons is reduced, thereby decreasing the structural risk. The network structure is shown in Figure 8.

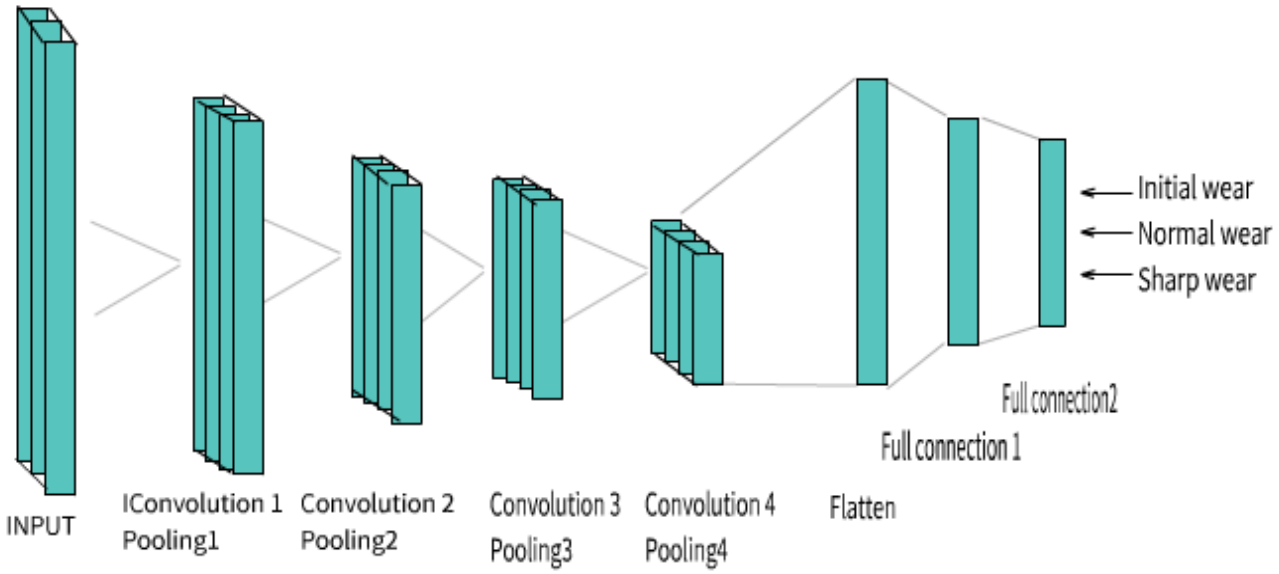

Figure 8. The network structure of tool wear monitoring based on current features proposed by Wang et al. (drawn from the literature [36]).

Zhang et al. [62] improved the training model for ImageNet images proposed by the Caffe team. They used the original vibration feature in the machining process, converted into an energy spectrum by a wavelet packet as the model input. The optimal parameters trained by Caffe were used as the initial model parameters. The output of the original model was modified to three types, which were accurately applied to the monitoring and prediction of tool wear. The modified CNN structure is shown in Figure 9.

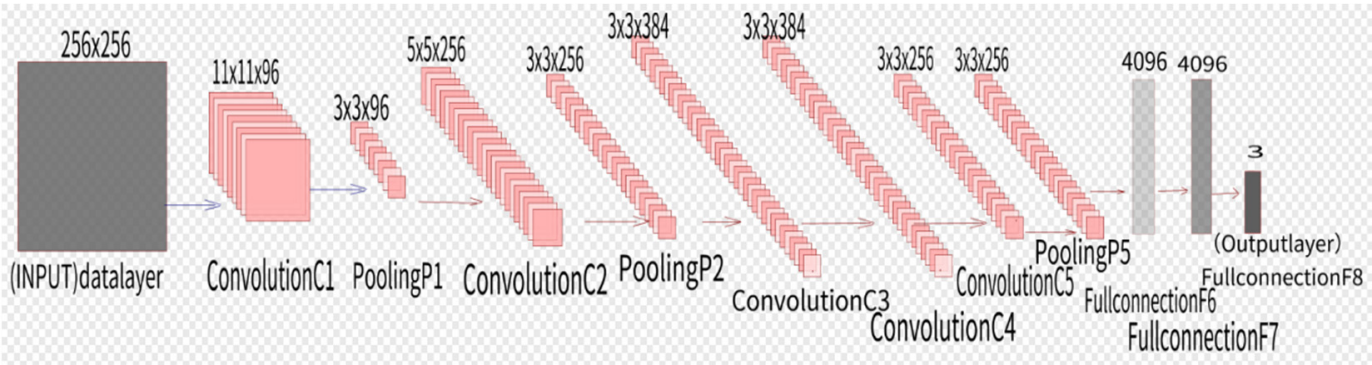

Figure 9. The network structure of tool wear monitoring based on vibration features proposed by Zhang et al. (drawn from the literature [62]).

Wu et al. [116] modified the AlexNet model trained by Caffe, taking the grey-scale wear image with a pixel size of 256 × 256 as an input to divide the tool wear into four types. Consequently, a CNN structure was developed, which could intelligently identify the tool wear type. The convolution kernel size of the C1 convolution layer in the AlexNet model was modified to 14 × 14 × 96. The step size was adjusted to five. The edge expansion parameter was modified to fourteen. Additionally, the final fully connected layer (i.e., output layer F8) was modified to four output types. The modified CNN structure of tool wear type recognition is shown in Figure 10.

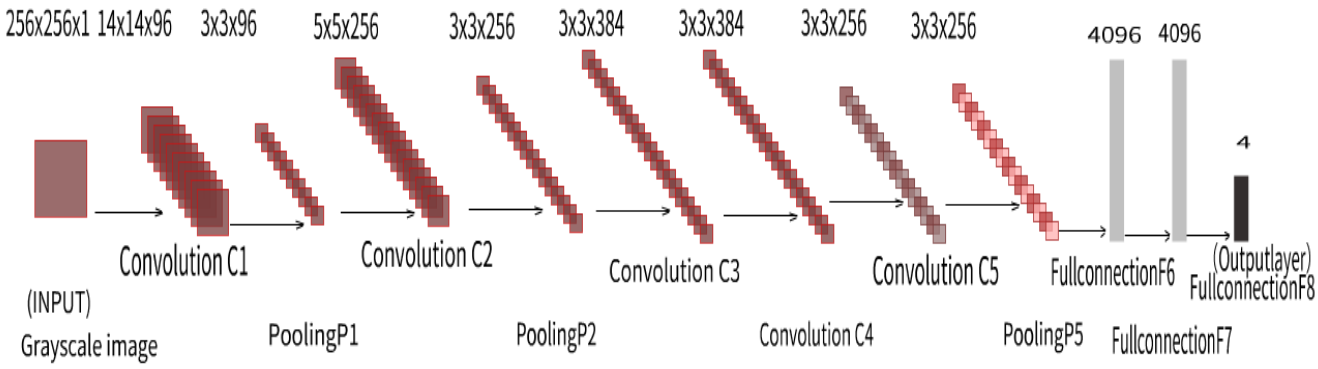

Figure 10. The CNN model structure proposed by Wu et al. (drawn from the literature [116]).

Song et al. [125] used the images of the spindle current clutter to identify the wear condition of the milling cutter and formulated a deep CNN model, as shown in Figure 11. The network model consists of seven layers: an input layer, two convolutional layers, two pooling layers, a fully connected layer, and an output layer. The spindle current clutter feature is normalized and binarized into an image with a size of 140 × 80, used as an input. The convolution kernel sizes of convolution layer I and II are 13 × 15 and 9 × 9, respectively. The convolution step size is 1 × 1. The ReLU function is selected as the activation function. The core size of pooling layer I is 4 × 4, and the step size is 4 × 2. The core size of pooling layer II is 8 × 8, and the step size is 8 × 8. Random pooling is selected for the pooling layers.

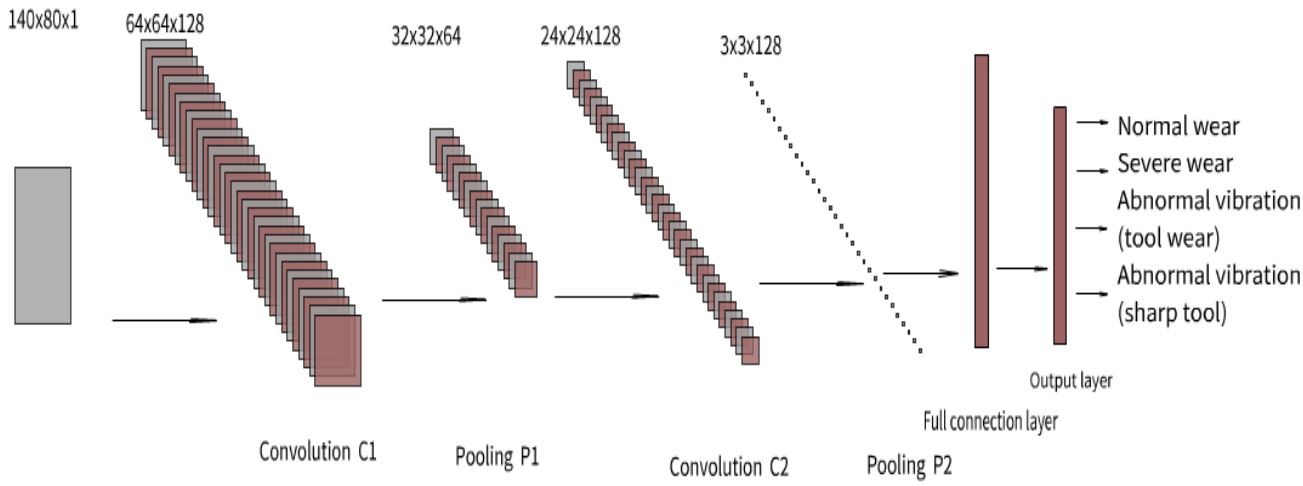

Figure 11. The CNN model structure proposed by Song et al. (drawn from the literature [125]).

Table 2 lists the main characteristics, experimental conditions and experimental results of the above network structure.

5.4. Network Model Training

In the training process of the model, the selection of hyperparameters has a direct influence on the training speed and classification accuracy of the model. Therefore, it is necessary to try different hyperparameters before training, and constantly optimize and select a set of optimal hyperparameters to improve the learning performance and effect [21,22].

Table 2. Main characteristics, experimental conditions and effects of network structure in several typical applications.

Reference	Main Characteristics of Network Structure	Experimental Condition	Experimental Effect
[32]	The model is composed of an input layer, five convolutional layers, three pooling layers, and two fully connected layers. BN normalization layer is added to each layer of the model.	The lathe equipped with Siemens 840dsl CNC system is used to turn aluminum alloy 7109. Cutting speed: 220 r/min. Feed rate: 0.1 mm/r. Cutting depth: 1 mm. The CNC system collects the internal information related to the cutting force such as the spindle load, spindle torque, etc.	The recognition accuracy on the training set is 100%, the verification set is close to 89.9%, the recognition accuracy meets the requirements
[36]	The model is composed of an input layer, four convolutional layers, four pooling layers, one flattening layer, and two fully connected layers. The random dropout technology is applied to the flattening layer.	YG8 spiral milling. CFRP plate (material: QY9611-T700, spindle speed: 10,000 r/min, revolution shaft speed: 720 R/min, feed rate: 1 mm/s) and aluminum plate (material: TC4-DT, spindle speed: 2000 R/min, revolution shaft speed: 720 R/min, feed rate: 0.4 mm/s). Air cooling. Using mik-dji-30a and mik-dji-1a Hall current sensors to collect the current signals during processing.	The tool wear monitoring accuracy of the proposed method is 99.29% and the recall of severe wear stage is 99.60%.
[62]	ImageNet model is adopted and improved. The model is composed of an input layer, five convolutional layers, three pooling layers, and three fully connected layers. The initialization parameters are the best parameters trained by Caffe team, and the output is changed to three types.	The tempered steel (hrc52) was milled on a micro-CNC milling machine with double edge milling cutter (model: seco S550, diameter: 6 mm) covered with multi-layer titanium aluminum nitride coating. Maximum spindle speed: 2500 r/min. Feed rate: 1000 mm/min. A wireless triaxial accelerometer (model: m69) with sampling rate of 1 kHz/channel was used collecting vibration signal in the process of machining.	The prediction accuracy of the output is 98.05%, and the minimum loss function is 0.0353.
[116]	AlexNet model is adopted and improved. The model is composed of an input layer, five convolutional layers, three pooling layers, and three fully connected layers, and the output is changed to 4 types.	Three axis vertical machining center (model: vdl-1000e), indexable face milling cutter (CVD coated carbide tool and PVD coated cemented carbide blade of Sandvik 490R Series). Cutting depth: 0.5 mm. Feed rate: 0.05 mm/Z. Linear speed: 109 m/min. Daheng image industrial digital camera (model: mer-125-30uc) was used to collect tool wear pictures.	The average recognition rate of CNN model after pre training is 96.25%, the recognition accuracy of adhesive wear is 97.7%, and the recognition rate of flank wear is 94.9%.
[125]	LeNeT model is adopted and improved. The model is composed of an input layer, two convolutional layers, two pooling layers, a fully connected layer and an output layer, with 4 types of output.	Milling wear experiments were carried out on DM1007 vertical machining center under seven different working conditions. The self-built system is used to collect the vibration and current signals of the spindle, including the single-phase current signal of the spindle motor and the acceleration signal of the spindle x-direction and y-direction. The sampling frequency is 6.4 KHz.	The experimental results show that the lowest accuracy rate is 87.7%, and the highest is 92.3%.

The next step is to use sample data for training, the sample data are divided into training set data and validation set data [126]. Network model training refers to inputting the training set data into the network to train parameters.

The purpose of network model training is to gradually reduce the loss by adjusting the network parameters, so that the network output is very close to the actual value. The training is guided by the loss function, driving the network parameters to gradually change in loss reduction. The loss function is used to measure the quality of a set of parameters. Before each iteration, it compares the calculated result with the true value to guide the correct the training direction in the current iteration.

The essence of the tool wear neural network is a multi-classification problem. The most commonly used loss functions in neural network classification tasks are the mean square error function and the cross-entropy function.

The mean square error represents the mean square error between the monitored value and the actual value. The cross-entropy represents the gap between two probability distributions [126].

The chain derivation method is used to calculate the gradient of the loss function for each weight. The samples are selected to update the weights in batches, driving the predicted value to continuously approach the actual value.

When training the network using the error backpropagation algorithm based on gradient descent. A large learning rate may cause network oscillations to not converge. A small learning rate may cause a slow convergence and increase training time. The initial learning rate should be set reasonably according to actual conditions.

6. Existing Public Data Set

At present, the data sets of tool wear samples mainly include the NASA data set and PHM data set [127].

National Aeronautics and Space Administration (NASA) introduced a variety of commonly used scientific data sets. The milling data set is packaged into a mat file format, collecting the experimental data of the tool wear on the milling machine at different feed speeds and cutting depths. The data set is provided by the BEST laboratory at the University of California, Berkeley. The New York Society of Forecasting and Health Management (PHM) released the data from the 2010 high-speed CNC machine tool health prediction competition. This data set recorded the relevant information of the high-speed CNC milling machine through the dynamometer, accelerometer and acoustic emission meter. These two data sets were widely used to verify the tool wear monitoring methods based on deep CNN.

7. Challenges and Prospects

7.1. Challenges

From the advances in the tool wear monitoring method based on deep CNNs, many excellent methods emerged. However, many monitoring methods have limitations in practical applications, summarized as follows:

(1) The existing monitoring model is established under fixed cutting conditions. Changes in the cutting process or parameters may cause the recognition model of the tool wear condition to fail. Thus, the model has a weak adaptability and generalization.

(2) In recent years, there many recognition algorithms were applied to the field of tool wear monitoring, for example, fuzzy logic, the hidden Markov model, support vector machine and adaptive network-based fuzzy inference system. However, a single model algorithm is challenging for realizing the high-precision recognition of tool wear conditions [17].

(3) The monitoring performance of the network model depends on the feature data collected by the sensors, and the accuracy of the feature data directly determines the prediction effect. At present, due to the influence of the processing environment, it is difficult for many sensors to collect high-precision feature data [28,38].

(4) Additionally, due to the investment cost and its increase with additional signal acquisition hardware and software equipment, the current situation of sensors used in

the industry, for the most part, is not at a sufficient level. These factors lead to the lack of original information data, which limit the application of neural networks in this field [16].

(5) The performance of multiple sensors may be better than a single sensor. However, using various sensors increases the complexity of noise and feature processing, resulting in reduced monitoring accuracy [101].

7.2. Prospects

With deepening research, the intelligent monitoring method of tool wear will be continuously improved.

(1) With the development of the era of Big Data, the deep convolutional neural network has a stronger ability of feature learning and feature expression. Improving the existing network structure or training the learning algorithm according to actual working conditions, appropriately increasing the number of layers of the network, using larger training data sets, and other methods can improve the adaptability of the network and enhance the generalization ability of the model [128,129].

(2) The convolutional neural network is appropriate for nonlinear mapping, especially for the monitoring condition tool during machining. Combined with the characteristics of deep neural network structures, the deep mining of key feature parameters can enhance the performance of the monitoring model. For example, in the literature [39], a deep convolution neural network is used to mine the hidden, high-dimensional features in processing features, which improve the monitoring accuracy and generalization performance.

(3) With the wide application of the feature processing system, data acquisition and data understanding become more and more important. The proper integration of accurate sensor systems and feature processing methods is of paramount importance in the field. Additionally, with the continuous performance improvement in hardware (e.g., sensors), the information collected will be more accurate and comprehensive. By collecting multiple features at the same time to jointly improve the feature characterization rate, multi-feature fusion can be used as the direction to try to improve the accuracy of monitoring results [16].

(4) Based on cutting-related database analysis, combined with the advantages of different monitoring methods, in-depth analysis of the relationship mechanism between the acquired information data and tool wear, we could obtain a tool wear monitoring model with a better robustness and higher accuracy [130].

(5) Emerging technologies continue to emerge. Tool wear monitoring technology may jump out of its own field and work together with digital twin and other related technologies to promote each other [9,131].

Author Contributions: Conceptualization, Q.W.; methodology, Q.W.; software, Q.W.; validation, Q.W.; formal analysis, Q.W. and H.W.; investigation, Q.W.; resources, Q.W. and H.W.; data curation, Q.W. and L.H.; writing—original draft preparation, Q.W.; writing—review and editing, Q.W. and S.Y.; visualization, Q.W.; supervision, H.W.; project administration, H.W.; funding acquisition, Q.W. and H.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Chen, J.; Hu, P.; Zhou, H.; Yang, J.; Xie, J.; Jiang, Y.; Gao, Z.; Zhang, C. Towards Intelligent Machine Tools. *Engineering* **2019**, *5*, 186–210. [CrossRef]
2. Zhang, R. Overview of Intelligent Manufacturing Equipment Industry. *Intell. Manuf.* **2020**, *7*, 15–17.
3. Ministry of Science and Technology of the People's Republic of China. Special Plan for Scientific and Technological Innovation in the Field of Advanced Manufacturing Technology during the 13th Five-Year Plan Period (Selected). *China Metrol.* **2017**, *12*, 9–20.

4. Siddhpura, A.; Paurobally, R. A review of flank wear prediction methods for tool condition monitoring in a turning process. *Int. J. Adv. Manuf. Technol.* **2013**, *65*, 371–393. [CrossRef]
5. Fei, T.; He, Z.; Liu, A. Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Inform.* **2019**, *15*, 2405–2415.
6. Schleich, B.; Anwer, N.; Mathieu, L. Shaping the digital twin for design and production engineering. *CIRP Ann.-Manuf. Technol.* **2017**, *66*, 141–144. [CrossRef]
7. Kritzinger, W.; Karner, M.; Traar, G. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-Pap.* **2018**, *51*, 1016–1022. [CrossRef]
8. Bazaz, S.M.; Lohtander, M.; Varis, J. 5-Dimensional Definition for a Manufacturing Digital Twin. *Procedia Manuf.* **2019**, *38*, 1705–1712. [CrossRef]
9. Botkina, D.; Hedlind, M.; Olsson, B.; Henser, J.; Lundholm, T. Digital Twin of a Cutting Tool. *Procedia CIRP* **2018**, *72*, 215–218. [CrossRef]
10. Kejia, Z.; Zhenchuan, S.; Yaobing, S. Digital Twin-Driven Tool Wear Monitoring and Predicting Method for the Turning Process. *Symmetry* **2021**, *13*, 1438.
11. Huibin, S.; Junlin, P.; Jiduo, Z.; Rong, M. Tool digital twin model for cutting process. *Comput. Integr. Manuf. Syst.* **2019**, *25*, 1474–1480.
12. Congbo, L.; Xin, S.; Xiaobo, H.; Xikun, Z.; Shaoqing, W. On line monitoring method of NC milling tool wear driven by digital twin. *China Mech. Eng.* **2021**, 1–11. Available online: http://kns.cnki.net/kcms/detail/42.1294.TH.20210519.1545.006.html (accessed on 13 December 2021).
13. Lecun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef] [PubMed]
14. Kalidass, S.; Palanisamy, P.; Muthukumaran, V. Prediction and optimization of tool wear for end milling operation using artificial neural networks and simulated annealing algorithm. *Int. J. Mach. Mach. Mater.* **2013**, *14*, 142–164.
15. Chen, H.-Y.; Lee, C.-H. Deep Learning Approach for Vibration Signals Applications. *Sensors* **2021**, *21*, 3929. [CrossRef] [PubMed]
16. Kuntoğlu, M.; Salur, E.; Gupta, M.K. A state-of-the-art review on sensors and signal processing systems in mechanical machining processes. *Int. J. Adv. Manuf. Technol.* **2021**, *116*, 2711–2735. [CrossRef]
17. Kuntolu, M.; Aslan, A.; Pimenov, D.Y. A Review of Indirect Tool Condition Monitoring Systems and Decision-Making Methods in Turning: Critical Analysis and Trends. *Sensors* **2021**, *21*, 108. [CrossRef] [PubMed]
18. Pimenov, D.Y.; Bustillo, A.; Mikolajczyk, T. Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. *J. Intell. Manuf.* **2017**, *29*, 1045–1061. [CrossRef]
19. Zhiqiang, W.; Hu, G.; Fengzhou, F.; Bing, L. Application of length fractal dimension in identification of wear state of micro-milling cutter. Vibration. *Test. Diagn.* **2016**, *36*, 592–597.
20. Kuntoglu, M.; Saglam, H. Investigation of signal behaviors for sensor fusion with tool condition monitoring system in turning. *Measurement* **2020**, *173*, 108582. [CrossRef]
21. Rong, Z.; Weiping, L.; Tong, M. A review of research on deep learning. *Inf. Control* **2018**, *47*, 385–397.
22. Jun, L.; Yongbao, L.; Youhong, Y. Application of convolutional neural network and kurtosis in bearing fault diagnosis. *J. Aeronaut. Dyn.* **2019**, *34*, 2423–2431.
23. Zhou, Y.; Xue, W. Review of tool condition monitoring methods in milling processes. *Int. J. Adv. Manuf. Technol.* **2018**, *96*, 2509–2523. [CrossRef]
24. Swain, S.; Panigrahi, I.; Sahoo, A.K. Adaptive tool condition monitoring system: A brief review. *Mater. Today Proc.* **2020**, *23*, 474–478. [CrossRef]
25. Ms, A.; Mkg, B.; Itc, D. A state-of-the-art review on tool wear and surface integrity characteristics in machining of superalloys. *CIRP J. Manuf. Sci. Technol.* **2021**, *35*, 624–658.
26. Kuntoğlu, M.; Sağlam, H. Investigation of Progressive Tool Wear for Determining of Optimized Machining Parameters in Turning. *Measurement* **2019**, *7*, 427–436. [CrossRef]
27. Ghosh, N.; Ravi, Y.; Patra, A.; Mukhopadhyay, S.; Paul, S.; Mohanty, A.R.; Chattopadhyay, A.B. Estimation of tool wear during CNC milling using neural network-based sensor fusion. *Mech. Syst. Signal Process* **2007**, *21*, 466–479. [CrossRef]
28. Cuka, B.; Kim, D.-W. Fuzzy logic based tool condition monitoring for end-milling. *Robot. Comput.-Integr. Manuf.* **2017**, *47*, 22–36. [CrossRef]
29. Zel, T.; Karpat, Y. Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks. *Int. J. Mach. Tools Manuf.* **2005**, *45*, 467–479.
30. Lee, S.; Chen, J. On-line surface roughness recognition system using artificial neural networks system in turning operations. *Int. J. Adv. Manuf. Technol.* **2003**, *22*, 498–509. [CrossRef]
31. Wei, D.; Guofang, N. Application of CNN-RNN fusion method in fault diagnosis of rotating machinery. *J. Light Ind.* **2020**, *35*, 102–108.
32. Zhiyuan, L.; Pengfei, M.; Jianglin, X.; Meiqing, W.; Xiaoqing, T. Online tool wear recognition method based on multi-source synchronized signals and deep learning. *China Mech. Eng.* **2019**, *30*, 220–225.
33. Shuai, Z.; Yixiang, H.; Haoren, W.; Chengliang, L.; Xiao, L.; Xinguang, L. Tool wear assessment based on random forest and principal component analysis. *Chin. J. Mech. Eng.* **2017**, *53*, 181–189.
34. Min, Y.; Mei, W.; Yuxia, P.; Maoqin, H. Feature selection method of milling force signal based on improved Drosophila optimization algorithm. *Vib. Impact* **2016**, *35*, 196–200.
35. Bhuiyan, M.S.H.; Choudhury, I.A.; Dahari, M. Monitoring the tool wear, surface roughness and chip formation occurrences using multiple sensors in turning. *J. Manuf. Syst.* **2014**, *33*, 476–487. [CrossRef]

36. Haijin, W.; Zongyu, Y.; Zhenzheng, K.; Yingjie, G.; Huiyue, D. Tool wear monitoring for spiral milling based on one-dimensional convolutional neural network. *J. Zhejiang Univ.* **2020**, *54*, 931–939.
37. Dong, J.; Subrahmanyam, K.V.R.; Wong, Y.S.; Hong, G.S.; Mohanty, A.R. Bayesian-inference-based neural networks for tool wear estimation. *Int. J. Adv. Manuf. Technol.* **2006**, *30*, 797–807. [CrossRef]
38. Nouri, M.; Fussell, B.K.; Ziniti, B.L. Real-time tool wear monitoring in milling using a cutting condition independent method. *Int. J. Mach. Tools Manuf.* **2015**, *89*, 1–13. [CrossRef]
39. Dali, C.; Huibin, S.; Jiduo, Z.; Rong, M. Tool wear on-line monitoring based on convolutional neural network. *Comput. Integr. Manuf. Syst.* **2020**, *26*, 74–80.
40. Javed, K.; Gouriveau, R.; Li, X. Tool wear monitoring and prognostics challenges: A comparison of connectionist methods toward an adaptive ensemble model. *J. Intell. Manuf.* **2018**, *29*, 1873–1890. [CrossRef]
41. Lin, S.C.; Lin, R.J. Tool wear monitoring in face milling using force signals. *Wear* **1996**, *198*, 136–142. [CrossRef]
42. Yan, W.; Wong, Y.S.; Lee, K.S. An investigation of indices based on milling force for tool wear in milling. *J. Mater. Process. Technol.* **1999**, *89–90*, 245–253. [CrossRef]
43. Plaza, E.G.; Lopez, P.J.N. Analysis of cutting force signals by wavelet packet transform for surface roughness monitoring in CNC turning. *Mech. Syst. Signal Process.* **2018**, *98*, 634–651. [CrossRef]
44. Altintas, Y.; Yellowley, I. In-Process Detection of Tool Failure in Milling Using Cutting Force Models. *Trans. J. Eng. Ind* **1989**, *111*, 149–157. [CrossRef]
45. Kaya, B.; Oysu, C.; Ertunc, H. Force-torque based on-line tool wear estimation system for CNC milling of inconel 718 using neural networks. *Adv. Eng. Softw.* **2011**, *42*, 76–84. [CrossRef]
46. Wang, M.; Wang, J. CHMM for tool condition monitoring and remaining useful life prediction. *Int. J. Adv. Manuf. Technol.* **2012**, *59*, 463–471. [CrossRef]
47. Huang, P.; Ma, C.; Kuo, C. A PNN self-learning tool breakage detection system in end milling operations. *Appl. Soft Comput.* **2015**, *37*, 114–124. [CrossRef]
48. Li, N.; Chen, Y.; Kong, D. Force-based tool condition monitoring for turning process using v-support vector regression. *Int. J. Adv. Manuf. Technol.* **2017**, *91*, 351–361. [CrossRef]
49. Zhu, K.; Liu, T. On-line Tool Wear Monitoring via Hidden Semi-Markov Model with Dependent Durations. *IEEE Trans. Ind. Inform.* **2017**, *99*, 69–78.
50. Jiaqi, H.; Yingguang, L.; Changqing, L. Real-time tool condition identification in milling based on cutting force signal-geometry information-process information. *Aviat. Manuf. Technol.* **2018**, *61*, 48–54.
51. Prickett, P.; Johns, C. An overview of approaches to end milling tool monitoring. *Int. J. Mach. Tools Manuf.* **1999**, *39*, 105–122. [CrossRef]
52. Koike, R.; Ohnishi, K.; Aoyama, T. A sensorless approach for tool fracture detection in milling by integrating multi-axial servo information. *CIRP Ann.-Manuf. Technol.* **2016**, *65*, 385–388. [CrossRef]
53. Yesilyurt, I.; Ozturk, H. Tool condition monitoring in milling using vibration analysis. *Int. J. Prod. Res.* **2007**, *45*, 1013–1028. [CrossRef]
54. Sevilla, P.; Robles, J.; Jauregui, J. FPGA-based reconfigurable system for tool condition monitoring in high-speed machining process. *Measurement* **2015**, *64*, 81–88. [CrossRef]
55. Aslan, A. Optimization and Analysis of Process Parameters for Flank Wear, Cutting Forces and Vibration in Turning of AISI 5140: A Comprehensive Study. *Measurement* **2020**, *163*, 107959. [CrossRef]
56. Ying, D.; Weixi, J.; Jiahui, L.; Yun, Z.; Hao, W. Research on the recognition technology of milling cutter wear state based on convolutional neural network. *Mod. Manuf. Eng.* **2021**, *5*, 116–124.
57. Hsieh, W.; Lu, M.; Chiou, S. Application of backpropagation neural network for spindle vibration-based tool wear monitoring in micro-milling. *Int. J. Adv. Manuf. Technol.* **2012**, *61*, 53–61. [CrossRef]
58. Madhusudana, C.; Kumar, H.; Narendranath, S. Condition monitoring of face milling tool using k-star algorithm and histogram features of vibration signal. *Eng. Sci. Technol.* **2016**, *19*, 1543–1551. [CrossRef]
59. Gao, C.; Xue, W.; Ren, Y. Numerical control machine tool fault diagnosis using hybrid stationary subspace analysis and least squares support vector machine with a single sensor. *Appl. Sci.* **2017**, *7*, 346. [CrossRef]
60. Xin, T.; Yunpeng, Z.; Siyu, G. On-line monitoring of tool wear in high-speed milling based on morphological component analysis. *J. Univ. Sci. Technol. China* **2017**, *47*, 699–707.
61. Li, H.; Kan, H.; Wei, Z. On-line monitoring method of milling cutter in complex curved surface machining. Vibration. *Test. Diagn.* **2018**, *38*, 16–23.
62. Zhang, C.; Yao, X.; Zhang, J. Tool wear monitoring method based on deep learning. *Comput. Integr. Manuf. Syst.* **2017**, *23*, 2146–2155.
63. Ambhore, N.; Kamble, D.; Chinchanikar, S.; Wayal, V. Tool Condition Monitoring System: A Review. *Mater. Today: Proc.* **2015**, *2*, 3419–3428. [CrossRef]
64. Chen, X.; Li, B. Acoustic emission method for tool condition monitoring based on wavelet analysis. *Int. J. Adv. Manuf. Technol.* **2007**, *33*, 968–976. [CrossRef]
65. Twardowski, P.; Tabaszewski, M.; Pikua, M.W. Identification of tool wear using acoustic emission signal and machine learning methods. *Precis. Eng.* **2021**, *72*, 738–744. [CrossRef]

66. Chacón, F.; Luis, J.; de Barrena, F.; Telmo, G.A. A Novel Machine Learning-Based Methodology for Tool Wear Prediction Using Acoustic Emission Signals. *Sensors* **2021**, *21*, 5984. [CrossRef]
67. Tansel, I.; Trujillo, M.; Nedbouyan, A. Microend-milling-III. Wear estimation and tool breakage detection using acoustic emission signals. *Int. J. Mach. Tools Manuf.* **1998**, *39*, 1449–1466. [CrossRef]
68. Yen, C.L.; Lu, M.C.; Chen, J.L. Applying the self-organization feature map (SOM) algorithm to AE-based tool wear monitoring in micro-cutting. *Mech. Syst. Signal Process.* **2013**, *34*, 353–366. [CrossRef]
69. Wang, L.; Yang, J.; Zhang, Y. Tool wear state recognition based on stack denoising and self-coding. *China Mech. Eng.* **2018**, *29*, 2038–2045.
70. Shan, G.; Zhenxing, K.; Chang, P. Tool wear recognition method based on cloud theory and LS-SVM. *Vibration. Test. Diagn.* **2017**, *37*, 996–1003.
71. Mathew, M.; Pai, P.; Rocha, L. An effective sensor for tool wear monitoring in face milling: Acoustic emission. *Sadhana* **2008**, *33*, 227–233. [CrossRef]
72. Wang, G.; Feng, X. Tool wear state recognition based on linear chain conditional random field model. *Eng. Appl. Artif. Intell.* **2013**, *26*, 1421–1427. [CrossRef]
73. Vetrichelvan, G.; Sundaram, S.; Kumaran, S.S. An investigation of tool wear using acoustic emission and genetic algorithm. *J. Vib. Control* **2014**, *21*, 3061–3066. [CrossRef]
74. Ren, Q.; Balazinski, M.; Baron, L. Type-2 fuzzy tool condition monitoring system based on acoustic emission in micro milling. *Inf. Sci.* **2014**, *255*, 121–134. [CrossRef]
75. Zhang, D.; Mo, R.; Sun, H. Tool wear condition recognition based on chaotic time series analysis and support vector machine. *Comput. Integr. Manuf. Syst.* **2015**, *21*, 2138–2146.
76. Wu, D.; Jennings, C.; Terpenny, J. A Comparative Study on Machine Learning Algorithms for Smart Manufacturing: Tool Wear Prediction Using Random Forests. *J. Manuf. Sci. Eng.* **2017**, *139*, 071018. [CrossRef]
77. Chengying, L.; Hao, W.; Liping, W. Tool wear state recognition based on PSO optimized LS-SVM. *J. Tsinghua Univ.* **2017**, *57*, 975–979.
78. Zhu, K.P.; Vogel, B. Sparse representation and its applications in micro-milling condition monitoring: Noise separation and tool condition monitoring. *Int. J. Adv. Manuf. Technol.* **2014**, *70*, 185–199. [CrossRef]
79. Young, H.T. Cutting temperature responses to flank wear. *Wear* **1996**, *201*, 117–120. [CrossRef]
80. Dewes, R.C.; Ng, E.G.; Chua, K.S. Temperature measurement when high speed machining hardened mould steel. *J. Mater. Process. Technol.* **1999**, *92–93*, 293–301. [CrossRef]
81. Kim, S.W.; Lee, C.M.; Lee, D.W. Evaluation of the thermal characteristics in high-speed ball-end milling. *J. Mater. Process. Technol.* **2001**, *113*, 406–409. [CrossRef]
82. Brili, N.; Ficko, M.; Klannik, S. Automatic Identification of Tool Wear Based on Thermography and a Convolutional Neural Network during the Turning Process. *Sensors* **2021**, *21*, 1917. [CrossRef]
83. He, Z.; Shi, T.; Xuan, J. Research on tool wear prediction based on temperature signals and deep learning. *Wear* **2021**, *478–479*, 203902. [CrossRef]
84. Korkut, I.; Acır, A.; Boy, A. Application of regression and artificial neural network analysis in modelling of tool-chip interface temperature in machining. *Expert Syst. Appl.* **2011**, *38*, 11651–11656. [CrossRef]
85. Kulkarni, A.P.; Joshi, G.G.; Karekar, A. Investigation on cutting temperature and cutting force in turning AISI 304 austenitic stainless steel using Al Ti Cr N coated carbide insert. *Int. J. Mach. Mach. Mater.* **2014**, *15*, 147–156.
86. Wang, C.; Ming, W.; Chen, M. Milling tool's flank wear prediction by temperature dependent wear mechanism determination when machining Inconel 182 overlays. *Tribol. Int.* **2016**, *104*, 140–156. [CrossRef]
87. Chaohou, W.; Liangling, L.; Han, X. Soft-sensing technology and its application in tool fault diagnosis. *Tool Technol.* **2007**, *10*, 69–71.
88. Ammouri, A.; Hamade, R. Current rise criterion: A process-independent method for tool-condition monitoring and prognostics. *Int. J. Adv. Manuf. Technol.* **2014**, *72*, 509–519. [CrossRef]
89. Shao, H.; Wang, H.; Zhao, X. A cutting power model for tool wear monitoring in milling. *Int. J. Mach. Tools Manuf.* **2004**, *44*, 1503–1509. [CrossRef]
90. Lee, B.Y.; Tarng, Y.S. Application of the discrete wavelet transform to the monitoring of tool failure in end milling using the spindle motor current. *Int. J. Adv. Manuf. Technol.* **1999**, *15*, 238–243. [CrossRef]
91. Jeong, Y.H.; Cho, D.W. Estimating cutting force from rotating and stationary feed motor currents on a milling machine. *Int. J. Adv. Manuf. Technol.* **2002**, *42*, 1559–1566. [CrossRef]
92. Weiwei, S.; Min, H.; Kang, L. Research on tool wear condition monitoring method based on current signal. *J. Henan Univ. Technol.* **2019**, *6*, 77–84.
93. Drouillet, C.; Karandikar, J.; Nath, C. Tool life predictions in milling using spindle power with the neural network technique. *J. Manuf. Process.* **2016**, *22*, 161–168. [CrossRef]
94. Stavropoulos, P.; Papacharalampopoulos, A.; Vasiliadis, E. Tool wear predictability estimation in milling based on multi-sensorial data. *Int. J. Adv. Manuf. Technol.* **2016**, *82*, 509–521. [CrossRef]
95. Kang, L.; Min, H.; Guoxin, W. Design and implementation of tool wear condition monitoring system based on inverter input current. *Modul. Mach. Tool Autom. Mach. Technol.* **2017**, *6*, 90–92.

96. Rizal, M.; Ghani, J.; Nuawi, M. A review of sensor system and application in milling process for tool condition monitoring. *Res. J. Appl. Sci. Eng. Technol.* **2014**, *7*, 2083–2097. [CrossRef]
97. Xu, G.; Chen, J.; Zhou, H. A tool breakage monitoring method for end milling based on the indirect electric data of CNC system. *Int. J. Adv. Manuf. Technol.* **2019**, *101*, 419–434. [CrossRef]
98. Al-Sulaiman, F.A.; Baseer, M.A.; Sheikh, A.K. Use of electrical power for online monitoring of tool condition. *J. Mater. Process. Technol.* **2005**, *166*, 364–371. [CrossRef]
99. Siddhpura, M.; Paurobally, R. A review of chatter vibration research in turning. *Int. J. Mach. Tools Manuf.* **2012**, *60*, 27–47. [CrossRef]
100. Suhaimi, M.A. Trade-off analysis between machining time and energy consumption in impeller NC machining. *Robot. Comput. Integr. Manuf. Int. J. Manuf. Prod. Process Dev.* **2017**, *43*, 164–170.
101. Dutta, S.; Pal, S.K.; Sen, R. On-machine tool prediction of flank wear from machined surface images using texture analyses and support vector regression. *Precis. Eng.* **2016**, *43*, 34–42. [CrossRef]
102. Tm, A.; Ss, B.; Rr, C. Tool condition monitoring techniques in milling process—A review. *J. Mater. Res. Technol.* **2020**, *9*, 1032–1042.
103. Wang, W.; Hong, G.; Wong, Y.; Zhu, K. Sensor fusion for online tool condition monitoring in milling. *Int. J. Prod. Res.* **2007**, *45*, 5095–5116. [CrossRef]
104. Cho, S.; Binsaeid, S.; Asfour, S. Design of multisensor fusion-based tool condition monitoring system in end milling. *Int. J. Adv. Manuf. Technol.* **2010**, *46*, 681–694. [CrossRef]
105. Shao, H.C. Cutting sound signal processing for tool breakage detection in face milling based on empirical mode decomposition and independent component analysis. *J. Vib. Control* **2015**, *21*, 3348–3358. [CrossRef]
106. Torabi, A.J.; Er, M.J.; Li, X.; Lim, B.S.; Peen, G.O. Application of clustering methods for online tool condition monitoring and fault diagnosis in high-speed milling processes. *IEEE Syst. J.* **2016**, *10*, 721–732. [CrossRef]
107. da Silva, R.H.L.; da Silva, M.B.; Hassui, A. A probabilistic neural network applied in monitoring tool wear in the end milling operation via acoustic emission and cutting power signals. *Mach. Sci. Technol.* **2016**, *20*, 386–405. [CrossRef]
108. Amer, M.; Maul, T. A review of modularization techniques in artificial neural networks. *Artif. Intell. Rev.* **2019**, *52*, 527–561. [CrossRef]
109. Wenqi, M.; Huimin, L.; Jianping, W.; Yunshu, G.; Zengkun, W. Vortex beam generation based on spatial light modulator and deep learning. *Acta Opt. Sin.* **2021**, *41*, 79–85.
110. Lecun, Y.; Bottou, L. Gradient-based learning applied to document recognition. *Proc. IEEE* **1998**, *86*, 2278–2324. [CrossRef]
111. Krizhevsky, A.; Sutskever, I.; Geoffrey, H.E. ImageNet classification with deep convolutional neural networks. *Commun. ACM* **2017**, *60*, 84–90. [CrossRef]
112. Simonyan, K.; Zisserman, A. Very Deep Convolutional Networks for Large-Scale Image Recognition. *Comput. Sci.* **2014**. Available online: https://arxiv.org/pdf/1409.1556.pdf (accessed on 13 December 2021).
113. Szegedy, C.; Liu, W.; Jia, Y. Going Deeper with Convolutions. *IEEE Comput. Soc.* **2014**. Available online: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7298594 (accessed on 13 December 2021).
114. He, K.; Zhang, X.; Ren, S. Deep Residual Learning for Image Recognition. IEEE 2016. Available online: https://arxiv.org/pdf/1512.03385.pdf (accessed on 13 December 2021).
115. Hongqiang, S.; Xinjian, Z.; Libing, L. Tool wear detection based on workpiece texture and convolutional neural network. *Modul. Mach. Tool Autom. Mach. Technol.* **2019**, *60–63*, 68.
116. Xuefeng, W.; Yahui, L.; Songze, B. Intelligent recognition of tool wear types based on convolutional neural network. *CIMS* **2020**, *26*, 2762–2771.
117. Shenghui, L.; Renjing, Z.; Shuli, Z.; Chao, M.; Hongguo, Z. Residual life prediction of cutting tools based on deep neural network. *J. Harbin Inst. Technol.* **2019**, *24*, 434–439.
118. Kothuru, A.; Nooka, S.P.; Liu, R. Application of deep visualization in CNN-based tool condition monitoring for end milling. *Procedia Manuf.* **2019**, *34*, 995–1004. [CrossRef]
119. Downey, J.; O'Sullivan, D.; Nejmen, M. Real Time Monitoring of the CNC Process in a Production Environment- the Data Collection & Analysis Phase. *Procedia Cirp* **2016**, *41*, 920–926.
120. Jauregui, J.C.; Resendiz, J.R.; Thenozhi, S. Frequency and Time-Frequency Analysis of Cutting Force and Vibration Signals for Tool Condition Monitoring. *IEEE Access* **2018**, *6*, 6400–64101. [CrossRef]
121. Shankar, S.; Mohanraj, T.; Rajasekar, R. Prediction of cutting tool wear during milling process using artificial intelligence techniques. *Int. J. Comput. Integr. Manuf.* **2019**, *32*, 174–182. [CrossRef]
122. Wang, G.F.; Zhang, Y.; Liu, C. A new tool wear monitoring method based on multi-scale PCA. *J. Intell. Manuf.* **2019**, *30*, 113–122. [CrossRef]
123. Zhou, Y.Q.; Xue, W. A Multisensor Fusion Method for Tool Condition Monitoring in Milling. *Sensors* **2018**, *18*, 3866. [CrossRef]
124. Shen, Y.; Yang, F.; Habibullah, M.S.; Ahmed, J.; Das, A.K.; Zhou, Y.; Ho, C.L. Predicting tool wear size across multi-cutting conditions using advanced machine learning techniques. *J. Intell. Manuf.* **2021**, *32*, 1753–1766. [CrossRef]
125. Song, K.; Wang, M.; Liu, L.; Wang, C.; Zan, T.; Yang, B. Intelligent recognition of milling cutter wear state with cutting parameter independence based on deep learning of spindle current clutter signal. *Int. J. Adv. Manuf. Technol.* **2020**, *109*, 929–942. [CrossRef]
126. Chen, X.; Zhu, R.; Wang, Z. Handwritten Digits Recognition Based on Fused Convolutional Neural Network Model. *Comput. Eng.* **2017**, *43*, 187–192.

127. Palaz, D.; Collobert, R.; Doss, M. Estimating phoneme class conditional probabilities from raw speech signal using convolutional neural networks. *Comput. Sci.* **2013**, 1766–1770. Available online: https://www.isca-speech.org/archive_v0/archive_papers/interspeech_2013/i13_1766.pdf (accessed on 13 December 2021).
128. Al-Saffar, A.; Hai, T.; Talab, M.A. Review of deep convolution neural network in image classification. In Proceedings of the 2017 International Conference on Radar, Antenna, Microwave, Electronics, and Telecommunications (ICRAMET), Jakarta, Indonesia, 23–24 October 2017.
129. Shun, Z.; Yihong, G.; Jinjun, W. Development of deep convolution neural network and its application in the field of computer vision. *J. Comput. Sci.* **2019**, *42*, 453–482.
130. Jun, Y.; Libing, L.; Yanrui, Z.; Zeqing, Y. A review of monitoring methods for tool wear. *Mod. Manuf. Eng.* **2021**, *3*, 152–160.
131. Christiand, K. Digital Twin Approach for Tool Wear Monitoring of Micro-Milling. *Procedia CIRP* **2020**, *93*, 1532–1537. [CrossRef]