Received February 19, 2020, accepted March 15, 2020, date of publication March 23, 2020, date of current version April 6, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2982800

An Intelligent System for Grinding Wheel Condition Monitoring Based on Machining Sound and Deep Learning

CHENG-HSIUNG LEE[1], JUNG-SING JWO[1,2], HAN-YI HSIEH[3], AND CHING-SHENG LIN[1]
[1]Master Program of Digital Innovation, Tunghai University, Taichung City 40704, Taiwan
[2]Department of Computer Science, Tunghai University, Taichung City 40704, Taiwan
[3]Department of Computer Science and Information Engineering, National Taipei University of Technology, Taipei 10608, Taiwan

Corresponding author: Cheng-Hsiung Lee (hsiung@thu.edu.tw)

ABSTRACT Immediate monitoring of the conditions of the grinding wheel during the grinding process is important because it directly affects the surface accuracy of the workpiece. Because the variation in machining sound during the grinding process is very important for the field operator to judge whether the grinding wheel is worn or not, this study applies artificial intelligence technology to attempt to learn the experiences of auditory recognition of experienced operators. Therefore, we propose an intelligent system based on machining sound and deep learning to recognize the grinding wheel condition. This study uses a microphone embedded in the grinding machine to collect audio signals during the grinding process, and extracts the most discriminated feature from spectrum analysis. The features will be input the designed CNNs architecture to create a training model based on deep learning for distinguishing different conditions of the grinding wheel. Experimental results show that the proposed system can achieve an accuracy of 97.44%, a precision of 98.26% and a recall of 96.59% from 820 testing samples.

INDEX TERMS Grinding wheel wear, intelligent system, machining sound, audio signals, deep learning.

I. INTRODUCTION

Since maintenance costs of manufacturing plants account for the majority of total operating costs, how to reduce maintenance costs has become a topic of concern in the manufacturing industry. Depending on the specific industry, maintenance costs may be not. In the case of steel, pulp and paper, and other heavy industries, maintenance costs account for 60% of total production costs [1]. Recently, tool condition monitoring and fault diagnosis as part of machine maintenance management has gradually received attention, because wear tools will directly affect the surface finish and geometrical accuracy of the finished workpiece [2], [3].

Numerous studies have been developed tool wear monitoring systems using available and suitable sensors [4]. Related sensors used to the monitoring of machining operations can be divided into direct methods, such as an optical device of scanning electron microscope (SEM) and indirect methods, such as cutting force, acoustic emission, spindle motor, vibration, temperature, and machining sound [5]. Although direct methods have a high spatial resolution and good accuracy, they often require interrupting machining processes and have a strict demand on the environment [6], and most can only be used as laboratory techniques [7]. Because of the limitations of practical applications, indirect methods more suit for applying to wear monitoring systems.

In indirect methods, some researchers start to collect the maximum amount of information from multiple sensors for monitoring states of tools or machines due to different kinds of sensors can reveal specific features of interest [5], [8]–[12]. Although the use of multiple sensing systems could compensate for the limitations of a single sensor when collecting signals [5], the results of the mixed feature analysis cannot effectively reflect the current states of the detected objects due to interference between the signals. Furthermore, the number of sensors used may be directly related to on-site operation efficiency and cost, because the fewer the number of used sensors in the factory area, the lower the maintenance cost, and the less complexity of signal analysis too, which will promote operational efficiency [13]. Unlike other single

The associate editor coordinating the review of this manuscript and approving it for publication was Zhigang Liu.

sensors that only detect single-point problems of machines, machining sound represents the full picture of the machine's operating state. Machining sound usually reflects the working condition of the machine. Because when there is a problem with the machine, the machining sound will be different, many experienced operators can initially diagnose a machine just by listening to its machining sound [14]. To this end, this study applies the artificial intelligence (AI) technique to attempt to learn the experienced operators' experiences which used variations in sound to judge the attrited condition of tools.

Grinding is known to be most complicated among major machine operations including milling, drilling, and turning [15]. Grinding is a metal removal process, which used to fabricate workpiece material to specific dimensions and surface precision. Currently, the decision of dressing interval for grinding wheel wear is typically roughly determined by a skilled operator. However, grinding wheel wear might already happen before dressing process, which usually causes grinding quality problems. On the contrary, if dressing process is carried out ahead of wheel wear, the grinding efficiency is definitely reduced and the abrasive materials are wasted at the same time [6]. Furthermore, wheel wear may lead to grinding burn and bad surface quality, even serious accidents. Therefore, a grinding wheel wear monitor system is desired in intelligent manufacturing to increase machining efficiency.

Two common acoustic-based sensors for monitoring grinding wheel wear are acoustic emission (AE) [16] and microphone [17], respectively. To distinguish different states of grinding wheel condition, Liao *et al.* [18] extracted features from AE signals collected at 1 MHz in grinding alumina with a resin-bonded diamond wheel and applied an adaptive genetic clustering algorithm. Then, Warren Liao *et al.* [15] presented a wavelet-based unsupervised grinding wheel condition monitoring methodology. The features is extracted from AE signals based on discrete wavelet decomposition by following a moving window approach, and then applied a clustering algorithm to obtain clustering result. The test results indicated that the proposed methodology can achieve on average 97% clustering accuracy for the high material removal rate condition (12.7 μm depth of cut), 86.7% for the low material removal rate condition (10.2 μm depth of cut), and 76.7% for combined grinding conditions. The size of the dataset for all the above experiments is 30 records, respectively. Yang and Yu [6] proposed a wavelet and support vector machine based grinding wheel wear monitoring system to classify sharp and worn wheels by AE sensor. The experimental results showed that classification accuracy could reach up to 99.39% with a cut depth of 10 μm for 40 records of sharp condition and 70 records of worn condition and 100% at the cut depth of 20 μm for 80 records of sharp conditions and 20 records of worn condition by SVM classification. In their experiment, half records of each data set for different cut depth were taken out for training and the other half for testing.

Although laboratory and industrial test-rig experiments have shown that an AE sensor is possible to detect the change in wear rate, if an AE sensor is used in an actual operating environment, more factors may need to be considered. In general, AE sensors are not suitable for machining process monitoring because the capacitive type displacement sensors of AE are very sensitive to sensor position and surface mounting [19]. AE sensors have high sensitivity to small changes in wear rate, but sometimes this is part of normal operation during machine operation and is not necessarily related to impending failures [20]. This will make the analysis process of tool wear more complicated. Furthermore, AE sensors are primarily used in detecting tool breakage and not wear, because the breakage phenomenon causes an imminent peak in the AE signal [21]. In addition to the limitations of inherent physical characteristics of AE sensors for detecting the tool wear condition was mentioned above, in cost consideration, AE sensors belong to more expensive sensing devices compared with another acoustic-based sensor, a microphone. Based on the above reasons, this study replaces the AE sensor with a microphone to collect machining sound during the grinding process.

Recently, deep learning (DL) architecture is becoming an efficient pattern recognition network structure with the potential to overcome current obstacles in intelligent fault diagnosis [22]. This technique also has attracted the attention of researchers in the field of tool wear monitoring [23] because it made great achievements in the classification and recognition of large dataset images [24]. Because deep convolutional neural networks (CNNs) are widely used in solving high dimensional and intricate nonlinear problems [12], and specifically designed for variable and complex signals and have shown remarkable success in various applications in the past few years [25], we developed an intelligent system based on CNNs to recognize different conditions of grinding wheel during grinding process.

The remainder of this paper is organized as follows. Section 2 provides the experimental setup and procedure in this study. Section 3 presents an intelligent system to automatically monitoring the conditions of the grinding wheel during the grinding process from continuous machining sound. Section 4 describes the classification method used in this study, and experimental results and analysis and conclusions are presented in Section 5 and in Section 6, respectively.

II. EXPERIMENTAL SETUP AND PROCEDURE

The grinding tests were performed on G50150 model automatic surface grinder machine using the wheel (32A46J12V) to grind carbon steel materials (S45C). The workpiece has a dimension of 700 mm in length and 500 mm in width. The grinding parameters were as follows: grinding velocity: 20 m/s, wheel speed: 1800 rpm, feed velocity: 5 mm/min, depth of cut: 10 μm. The acoustic signals during grinding process were collected at 44,100 samples per second (sampling rate: 44.1 kHz) by a microphone mounted on the side face of the wheel guard. After that, the collected acoustic signals were real-time analyzed and estimated by Raspberry Pi 3 for the following preprocessing, feature

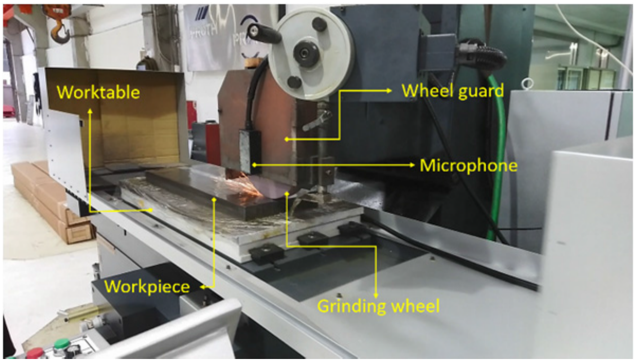


FIGURE 1. The experimental equipment layout of the grinding machine in this study.

extraction, and classification operations. A schematic diagram of the experimental setup is shown in Figure 1.

Prior to data acquisition, the carbon steel materials were ground several times to stabilize the grinding wheel. Then the recording equipment was turned on to collect signals in the steady state. All new grinding wheels are used in our experiment. The machining sound collection in the grinding process starts from the new grinding wheel until the grinding wheel wears. According to the operator's experience to determine whether the grinding wheel is worn based on the grinding sound and sparks.

III. INTELLIGENT GRINDING WHEEL CONDITION MONITORING SYSTEM

The framework of the proposed intelligent system for grinding wheel condition monitoring is shown in Figure 2, where the dotted area is a training process. After collecting machining sound during the grinding process by a microphone device, a mechanism that audio normalization and automatic detection of target signals from machining sound is described in Section 3.1. In Section 3.2, a feature extraction method is proposed to find the most discriminating feature for improving classification accuracy. Finally, to effetely detect the worn condition of the grinding wheel, the deep learning technique adopted in this study is discussed in Section 4.

A. PREPROCESSING

The machining sound in the grinding operation is mainly composed of two parts, one is the target signals that the grinding wheel and workpiece actually contact and another is the idle signals that grinding wheel away from the workpiece, respectively. The purpose of the preprocessing method is to automatically segment the target signals from continuous machining sound during the grinding process. According to the parameters setup of the grinding machine, the length of the target signal is nearly one second, as shown in Figure 3.

Figure 3 shows the machining sound for 16 seconds. It can be clearly seen that the idle signal between the two target signals has a lower amplitude due to the idling of the grinding wheel. In the following experiments, the target signal that nearly one minute represents one sample data. The critical steps in preprocessing are described as follows.

Step 1 Audio Normalization: First of all, the raw audio signals in grinding operation is processed by the procedure of audio normalization for adjusting audio recordings collected from different days to bring the amplitude to a target level. Figure 4(a) shows the audio signals of machining sound after audio normalization with one minute. Note that a

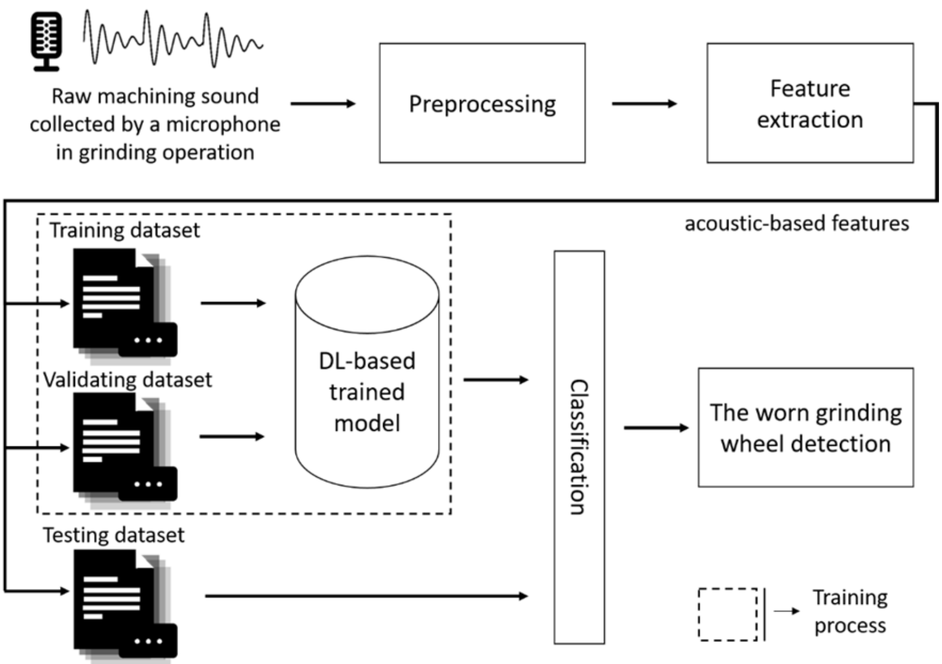


FIGURE 2. The framework of the proposed intelligent system for grinding wheel condition monitoring.

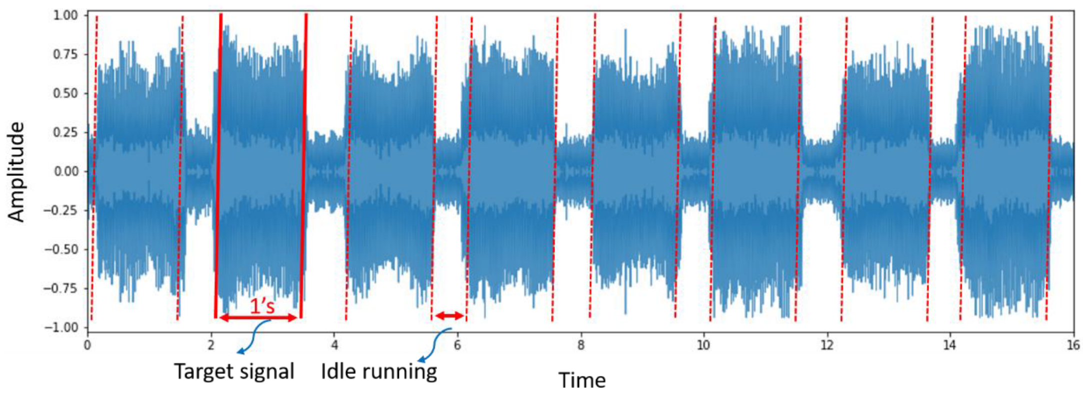


FIGURE 3. Machining sound during the grinding operation in the time domain.

one-minute audio record will be produced 2,646,000 data points (60s 44.1kHz = 2646000).

Step 2 *Absolute Value Processing:* Figure 4(b) shows the result that absolute value processing of raw audio signals after audio normalization. We use the symbol $|S_M|$ to represent it, where $|\cdot|$ is absolute value operation and S_M represents the signals of machining sound after processing by *Step 1*.

Step 3 *Threshold Value Decision:* To separate target signals from continuous machining sound, we design an adaptive threshold value. Before analyzing signals, a one-minute audio signal in the grinding operation is collected and the average amplitude value is calculated every tenth of a second. In other words, a one-minute audio file will produce 600 averages (2646000 / 4410 = 600), as shown in Figure 4(c). Finally, the average result for 600 values obtained from the above step will be as the adaptive threshold value, T, which is defined as follows:

$$T = \frac{\sum_{i=1}^{n} avg \left|S_{M_i}\right|}{n}, \tag{1}$$

where $avg\,|S_{Mi}|$ represents the average amplitude value of the i-th specific tenth of a second in a one-minute audio file and n is 600.

Step 4 *Target Signal Detection:* In the final step, if the amplitude value of the audio signal for a particular period during the grinding process is greater than the threshold value (T), the signal will be marked target signal (1), otherwise, it will be marked the idle signal (0), as shown in Figure 5. To effectively analyze the machining sound in the grinding operation, target signals that nearly one second period will be preserved. The determination of the target signal length is related to the grinding parameters and the size of the workpiece. According to our experimental settings and the confirmation of the field operator, the target signal is about one second. For consistency of experimental data, the target signal will be discarded, if it's length below 0.8s.

B. FEATURE EXTRACTION AND ANALYSIS

In this section, we attempt to find the most discriminating feature for effective monitoring of the grinding wheel states. A signal in time domain can be transformed to frequency domain by Fourier transform. The details of derivation of Fourier transform can be found in [26]. By spectrum analysis, we can observe the variations of magnitude at different frequencies during the grinding process. Figure 6 shows two different spectrums, which are processed by fast Fourier transform (FFT) for the one-second target signal from the sharp and worn grinding wheels, respectively.

From the comparison of two spectrums, we can find that there is a higher magnitude for the worn grinding wheel in the range between 300 Hz to 500 Hz. The reason is that the worn grinding wheel has a large frictional force when it contacts the workpiece, there will cause a resonance sound of low frequency. The focused frequency band is determined by convergence tests from multiple testing sets in this study. In addition, data acquisition for tool wear monitoring during the grinding process is inevitably disturbed by the noise of the operating environment. To emphasize the critical feature and reduce moderately the interference of ambient sound in the factory field, this study preserves the critical feature that 300 Hz to 500 Hz frequency segment and then sets the magnitudes of other frequency segments to 0. Subsequently, inverse FFT (iFFT) will be applied to transform the frequency segment which processed by the above step to the time domain. Finally, the audio signals in the time domain which only preserves the critical frequency segment will be used as the most discriminating feature to discriminate different conditions of the grinding wheel.

IV. CLASSIFICATION

In recent years, AI has attracted great attention from many researchers and has shown promising results in machinery fault identification applications. DL has become a very popular research topic in the field of AI [27], and it provides an effective way to learn features automatically at multiple levels of abstraction, allowing to learn complex input-to-output functions directly from data, without depending on feature extraction methods, which can be of great benefit for industrial rotating machinery fault diagnosis [28].

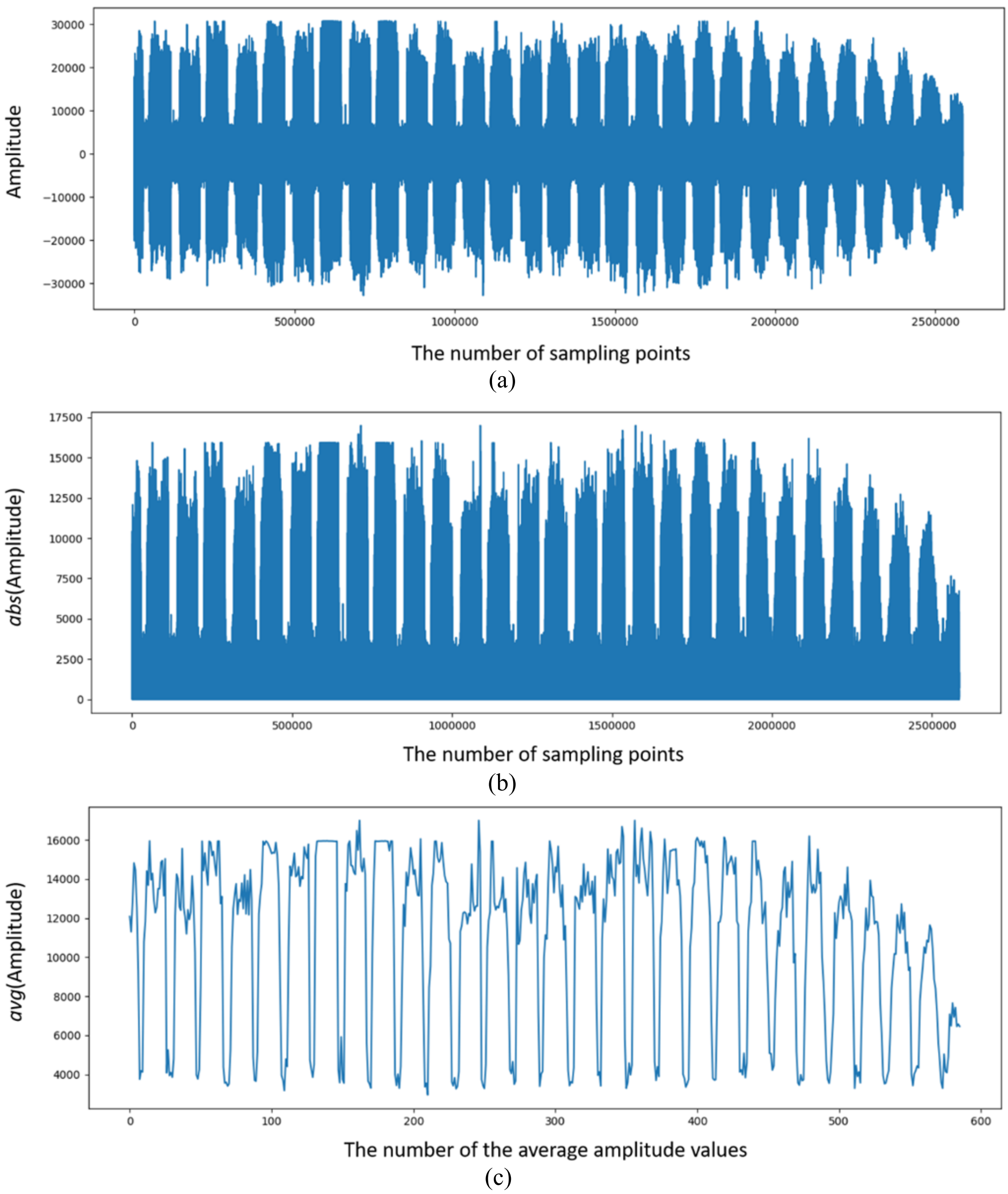


FIGURE 4. The illustration shows the output result of each phase of the critical steps in preprocessing.

Zhao *et al.* [29] also shown that DL has accelerated its application and shown its superiorities in monitor machine health.

DL solves the central problem in representation learning by expressing simpler representations to enable the computer to build complex concepts out of simpler concepts [30]. The CNNs are one of the many popular models in deep learning, which can serve as an efficient feature extractor for the classification tasks [31], [32]. CNNs are a specialized kind of neural network for processing data that has a known grid-like topology. Take time series data as an example, it can be regarded as a one-dimensional (1D) grid sampled at fixed time intervals, and for image data, which can be thought of as a 2D grid of pixels [33]. Currently, CNNs are becoming more widely used in audio-related tasks, including environmental sound classification [34], speech recognition [35] and sound event detection [36]. To the best of our knowledge, no former works addressing the use of CNNs to recognition audio features, which in turn can detect grinding wheel wear, for the occasion of which this study was realized.

Three architectural ideals of CNNs are combined to ensure some degree of shift, scale, and distortion invariance: local filters, shared weights and spatial or temporal subsampling

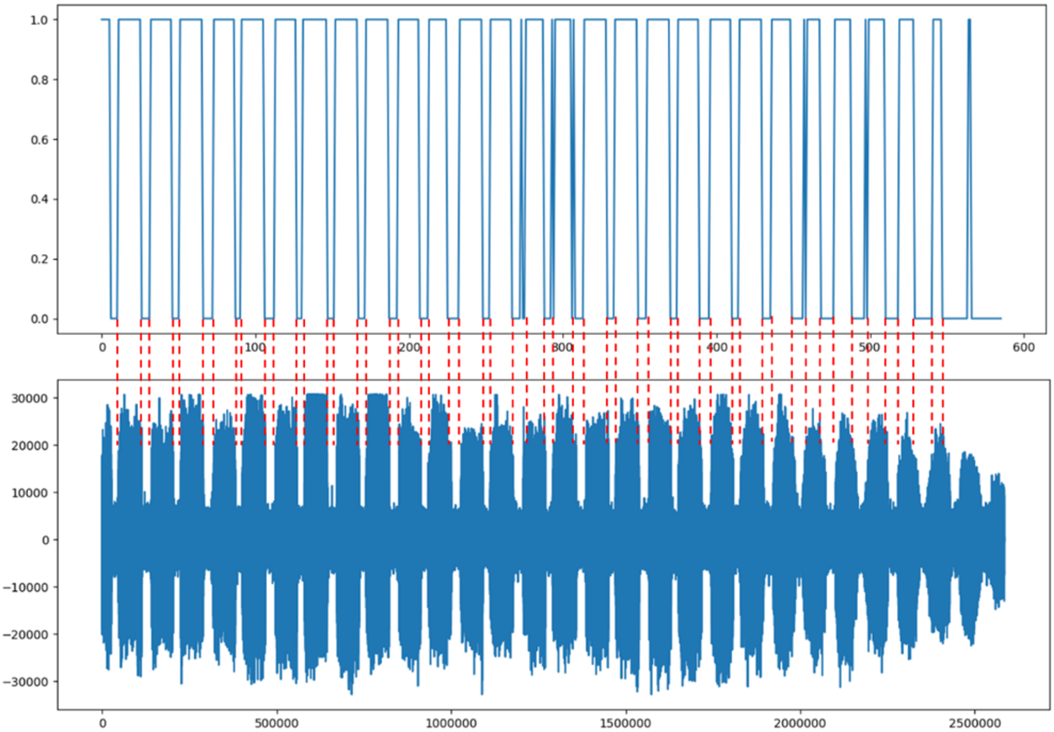


FIGURE 5. The automated detections of target signals from continuous machining sound in grinding operation. The red-dotted line is the auxiliary line, which corresponds to the detected target signals from raw audio signals in grinding operation (Figure 4(a)).

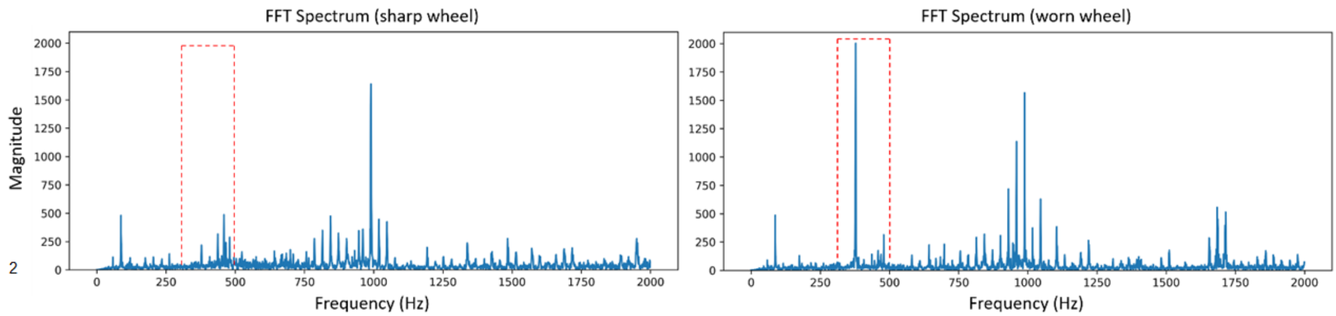


FIGURE 6. The two FFT spectrums of machining sound during the grinding process with the sharp and worn grinding wheels. The red dotted line represents the range between 300 Hz to 500 Hz.

(pooling) [33]. The details of the CNNs method can be found in [33], [34], [37]. Since the features adopted in this study are sequences of audio signals, the 1D CNN is briefly introduced as follows.

An input sequential acoustic-based feature with a duration of one second is assumed to be $\mathbf{x} = [x_1, x_2, \ldots, x_n]$, where n denoted the length of the sequence. Here, n is 44100 because the sampling rate used in this experiment is 44.1 kHz. In convolutional layers, the convolutional operation can be defined as multiply operation between a 1D filter kernel $\mathbf{w}$, and a concatenation vector $\mathbf{x}_{i:i+ks-1}$, which can be expressed as [38]

$$\mathbf{x}_{i:i+ks-1} = x_i \oplus x_{i+1} \oplus \cdots \oplus x_{i+ks-1}, \tag{2}$$

where ks is the size of filter kernel, $\mathbf{x}_{i:i+ks-1}$ represents a 1D window of ks length sequential data points starting from the ith point, and $\oplus$ is the concatenate symbol used to connect sequential data points of specific range into a longer embedding. The general formulation of the 1D forward propagation from convolution layer $l-1$ to determine the input of a point (neuron) k at layer l, $\mathrm{x}_{\mathrm{k}}^{\mathrm{l}}$, which is defined as

$$x_k^l = f\left(\mathbf{w}^T \mathbf{x}_{i:i+ks-1}^{l-1} + b_k^l\right), \tag{3}$$

where $\mathrm{b}_{\mathrm{k}}^{\mathrm{l}}$ is the scalar bias of the kth neuron at layer l, $f(\cdot)$ is the non-linear activation function, and $*^T$ denotes the transpose of a vector *. Note that the output $\mathrm{x}_{\mathrm{k}}^{\mathrm{l}}$ can be considered as the local learned feature by convolution operation between the filter kernel $\mathbf{w}$ and the corresponding subsequence $\mathbf{x}_{i:i+ks-1}$ at layer $l-1$. Since, in CNNs, the convolutional layer is to extract different features from

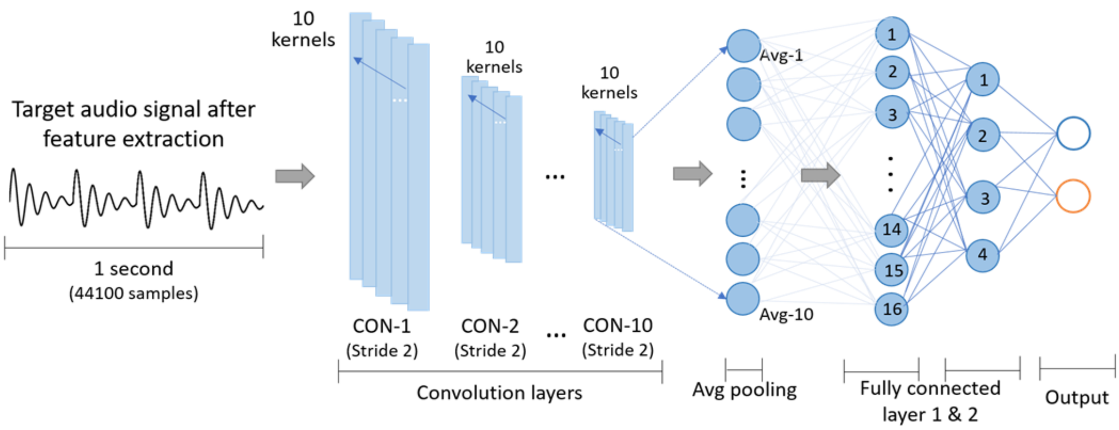


FIGURE 7. The proposed CNNs model architecture.

the input local samples through multiple filter kernels with specific filter length ks, the feature vector $\mathbf{X}^{lj}$ can be obtained as follows by sliding the jth filter kernel from the first neuron to the last neuron at layer l.

$$\mathbf{X}^{lj} = \left[x_1^{lj}, x_2^{lj}, \ldots, x_{N-ks+1}^{lj}\right], \tag{4}$$

where N is the total number of neurons at layer l. In the CNNs architecture used in this study, the ranges of l and j are from 1 to 10, because the audio signals were fed into the ten consecutive 1D convolution operations with 10 different filter kernels for obtaining discriminative features.

To better understand the proposed CNNs model architecture, it is possible to refer to Figure 7. In this architecture, the target signal after preprocessing and feature extraction methods will be processed by 10 consecutive 1D convolution operations (from CON-1 to CON-10) with 10 different filter kernels of 1×3 size and the stride size is set to 2. Then, a pooling layer is applied to the feature vectors generated by the convolution layer. In general, the pooling stage is able to extract the most significant local information from each feature vector. In this study, the average-pooling function will be applied to each filtered feature filtered by 10 different filter kernels to descript representative characteristics of machining sound in grinding operation because of average-pooling and max-pooling are widely used [38]. After average-pooling stage, the feature vector of 1×10 size will be fully connected 16 and 4 neurons in sequence in fully connected layers. The fully connected layer is a traditional multilayer perceptron, and the neurons in it are all connected to the neurons in the previous layer.

Finally, a sigmoid function will be applied to compute the final classification probabilities as the output result in the last layer. In this study, the rectified linear units (ReLU) function [24] is applied as the activation functions of the convolutional, pooling and fully connected layers, because the ReLU can effectively overcome deficiencies of gradient disappearance and slow convergence in the training process [12]. To further improve the performance of classification, the training process uses the back-propagation algorithm to minimize the loss function, which can be expressed as

$$L = \frac{1}{2N} \sum_{i=1}^{N} \left\| \hat{y}_i - y_i \right\|^2, \tag{5}$$

where N is the total number of training samples, and $\hat{y}_i$ and y_i represent the predicted grinding wheel wear value and the actual grinding wheel wear value for the training sample i, respectively.

V. EXPERIMENTAL RESULTS AND ANALYSIS

In this paper, there were 1803 target signals are detected and segmented automatically from the machining sounds collected during the grinding process with cutting depth of 10 μm by the proposed preprocessing method. Each target signal segmented by the preprocessing method is nearly a one-minute duration, which regards as one sample in the following experiment. Those acquired target signals after feature extraction are divided into training, validating, and testing datasets. The purposes of training and validating datasets is that learning and finding the relationship between the proposed acoustic-based features and real-time the conditions of grinding wheels. There were 820 testing samples (sharp cases: 410, worn cases: 410) in the testing dataset used to test the classification performance of the proposed intelligent grinding wheel condition monitoring system. Table 1 shows the number of samples for different grinding wheel conditions used in three datasets.

TABLE 1. Description of experimental datasets.

Dataset	Training datasets	Validating datasets	Testing datasets	Total datasets
Sharp	311	169	410	890
Worn	329	174	410	913

TABLE 2. Cross-relations between test and actual results.

Confusion matrix (P, positive; N, negative)		Actual results: Sharp	Actual results: Worn
Test results	Sharp	TS	FS
	Worn	FW	TW

To quantitatively evaluate the overall performance of the proposed intelligent system for recognizing grinding wheel conditions in grinding operation in this study, the following four measurements are adopted, including accuracy, precision, recall, and the area under receiver operating characteristic (ROC) curve. Let TS, TW, FS, and FW represent "true sharp", "true worn", "false sharp", and "false worn", respectively, in the confusion matrix as shown in Table 2.

The definitions for the above measurements are listed below [39].

$$\text{Recall} = TS/(TS + FW), \tag{6}$$

$$\text{Precision} = TS/(TS + FS), \tag{7}$$

$$\text{Accuracy} = (TS + TW)/(TS + TW + FS + FW). \tag{8}$$

The test result of a sharp condition is either sharp (TS) or worn (FS). On the other hand, the test result of a worn condition is either sharp (FW) or worn (TW). In this study, we regard the sharp grinding wheel as the sharp condition and the worn grinding wheel as the worn condition.

Recall, also known as a true sharp rate (TSR), represents the probability of classifying the grinding wheel as sharp state given it is truly sharp in this study. Precision, also known as precision rate, is the proportion of all sharp test results which are truly sharp grinding wheel. The accuracy is the proportion of both true sharps and true wear in all test results. It is the overall correct classification rate of all test results. In addition, we also calculate the area under the ROC curve (abbreviated as AUC) [40] to reflect the classification performance.

In our experimental results, the TS, TW, FS, and FW are 396, 403, 7, and 14, respectively. The accuracy is 97.44% ((396+403)/820), and the results of precision and recall are 98.26% (396/(396+7)) and 96.59% (396/(396+14)), respectively. In the cases of misjudgment, there were 7 worn samples misclassified as the sharp state, and there were 14 sharp samples misclassified as the worn state. It is worth noting that in the actual situations, we are more concerned about the misjudgment of the wear grinding wheel because compared to the misjudgment of the sharp grinding wheel, the loss caused by the manufacturing site is greater. The AUC is 0.99, as shown in Figure 8, which false sharp rate is FS/(FS+TW).

Table 3 summarizes the previous studies for grinding wheel condition monitoring. For an acoustic-based sensor, Liao *et al.* [18] can achieve 76.7% accuracy with cutting depth of 10 μm. Next year, Liao *et al.* [15] proposed another method and reported their method had an accuracy of 86.7% with cutting depth of 10.2 μm. To improve the effectiveness of grinding wheel monitoring, Liao [41] analyzed different feature extraction methods and combined feature selection methods. Their method using AR coefficients as the features can achieve 93.14% accuracy for 320 testing samples. The proposed method by Yang and Yu [6] indicated that their

TABLE 3. Summary of previous studies on grinding wheel monitoring with acoustic-based sensor.

Reference	Sensor (s)	Depth of cut	Classification	Number of testing samples	Test results
Lezanski (2001) [8]	AE, vibration and Forces	2, 5, 10μm	Neuro-fuzzy model	18	83.3%
Liao et al. (2006) [18]	AE	10 μm	HMM-based clustering method	---	76.7%
Liao et al. (2007) [15]	AE	12.7 μm	Adaptive genetic clustering	30	97.7%
		10.2 μm		30	86.7%
Subrahmanya & Shin (2008) [44]	AE, Power and accelerometer	---	LS-SVM	---	97.42%
Liao et al. (2010) [41]	AE	Not available	Clustering + feature selection methods	320	93.14%
Yang & Yu (2012) [6]	AE	10 μm	SVM	55	99.39%
		20 μm		50	100%
Devendiran & Manivannan (2013) [42]	AE	10 μm	Decision tree	---	96.70%
		20 μm			98.95%
		30 μm			99.15%
Our method	Microphone	10 μm	Deep learning	820	97.44%

Note: The notation '---' represents unavailable or not provided.

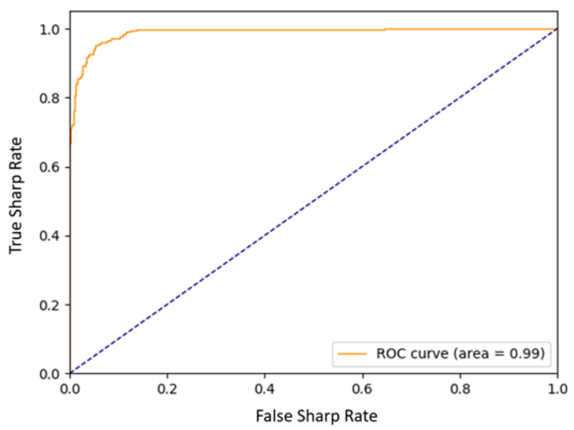


FIGURE 8. The ROC curve of classification result using the proposed acoustic-based features.

method can reach up to 99.39% accuracy for 110 testing records (sharp: 40, worn: 70) as a depth of cut is 10 μm. Furthermore, Devendiran and Manivannan [42] showed that the classification accuracy could reach up to 96.70% with cutting depth of 10 μm, 98.95% with cutting depth of 20 μm and 99.15% with cutting depth of 30 μm. In general, if the depth of cut is increased, the area of the chip-tool contact will increase approximately [43], which will cause changes in the grinding sound will be more significant. However, they did not further explain how many training and testing samples used in the experimental results. For multiple sensors, Lezanski indicated that the method achieved 83.3% accuracy from 18 testing samples for different parameters of cutting depth. Subrahmanya and Shin reported their method can achieve 97.42% accuracy. From a summary of Table 3, it appears that our proposed method is competitive compared to the previous studies on the same grinding condition of the depth of cut, whether used multiple sensors or not.

It is worth noting that our used the number of testing samples is up to 820 (sharp: 410, worn: 410). In addition, we attempt to select affordable an acoustic-based sensor, microphone to collect machining sound during grinding operation for two grinding wheel conditions (sharp vs. worn). It can be known from the preliminary experimental results that this study successfully developed an intelligent system for grinding wheel condition monitoring based on machining sound and deep learning. Complete experimental analysis of real-time monitoring of grinding wheel wear is not in the scope of this paper.

VI. CONCLUSION

This study has developed an intelligent system based on machining sound and deep learning for grinding wheel condition monitoring. From experience, the variation in machining sound is very important for the field operator to judge whether the grinding wheel is worn or not. To this end, an acoustic-based sensor, microphone, embedded in the grinding machine to collect audio signals during the grinding process. In feature extraction, we attempt to find the most discriminated feature from spectrum analysis to distinguish different conditions of the grinding wheel, and then the features will be input the designed CNNs architecture to create a DL-based training model. To test the performance of classification for the proposed intelligent system, we use 820 audio records with a length of one second as testing samples. Experimental results show that the proposed method can achieve an accuracy of 97.44%, a precision of 98.26%, a recall of 96.59%, and AUC is 0.99. In the future, we will continue to collect more data for different grinding parameters, and consider on-site environment factors to strengthen the stability and robustness of the system.

We would like to emphasize the following points to highlight the main contributions of this paper.

1) We successfully propose an intelligent system based on machining sound and deep learning to recognize the grinding wheel condition effectively.
2) Compared with previous studies related grinding wheel wear monitoring, we use a large number of testing samples, which is sufficient to show that the proposed method is represented in the effectiveness of classification results and can be competitive compared with previous studies.
3) In the previous studies based on the acoustic-based sensors, most of them used more sensitive and expensive sensors, AE. In this study, we successfully used a microphone as a collection device to collect machining sound during the grinding process on site.
4) The results of this research are indirectly confirmed that AI technique can lean auditory experiences of field operators to judge the attrited condition of tools by variations in sound during the machining process. It is hoped that this study can provide another indicative reference to tool wear monitoring.
5) One of the key issues in the monitoring of grinding wheel conditions is the online industrial application. For example, as mentioned in the pre-processing stage of this research, how to separate the target signals and the idle signals from the continuous machining sound. Unfortunately, such kind of efforts has been rare in previous related studies.

REFERENCES

[1] R. K. Mobley, "Impact of maintenance," in *An Introduction to Predictive Maintenance*, 2nd ed. Burlington, MA, USA: Butterworth-Heinemann, 2002, pp. 1–10.

[2] V. P. Astakhov, "The assessment of cutting tool wear," *Int. J. Mach. Tools Manuf.*, vol. 44, no. 6, pp. 637–647, May 2004.

[3] E. Jantunen, "A summary of methods applied to tool condition monitoring in drilling," *Int. J. Mach. Tools Manuf.*, vol. 42, no. 9, pp. 997–1010, Jul. 2002.

[4] F. Jia, Y. Lei, J. Lin, X. Zhou, and N. Lu, "Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data," *Mech. Syst. Signal Process.*, vols. 72–73, pp. 303–315, May 2016.

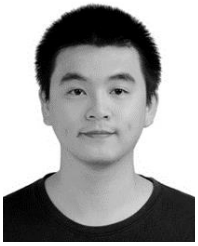
[5] P. Stavropoulos, A. Papacharalampopoulos, E. Vasiliadis, and G. Chryssolouris, "Tool wear predictability estimation in milling based on multi-sensorial data," *Int. J. Adv. Manuf. Technol.*, vol. 82, nos. 1–4, pp. 509–521, Jan. 2016.

[6] Z. Yang and Z. Yu, "Grinding wheel wear monitoring based on wavelet analysis and support vector machine," *Int. J. Adv. Manuf. Technol.*, vol. 62, nos. 1–4, pp. 107–121, Sep. 2012.
[7] R. Teti, K. Jemielniak, G. O'Donnell, and D. Dornfeld, "Advanced monitoring of machining operations," *CIRP Ann.*, vol. 59, no. 2, pp. 717–739, 2010.
[8] P. Lezanski, "An intelligent system for grinding wheel monitoring," *J. Mater. Process. Technol.*, vol. 109, pp. 258–263, Feb. 2001.
[9] T. P. Banerjee and S. Das, "Multi-sensor data fusion using support vector machine for motor fault detection," *Inf. Sci.*, vol. 217, no. 25, pp. 96–107, Dec. 2012.
[10] Y. Lei, J. Lin, Z. He, and D. Kong, "A method based on multi-sensor data fusion for fault detection of planetary gearboxes," *Sensors*, vol. 12, no. 2, pp. 2005–2017, Feb. 2012.
[11] K. Kannan, N. Arunachalam, A. Chawla, and S. Natarajan, "Multi-sensor data analytics for grinding wheel redress life estimation—An approach towards industry 4.0," *Procedia Manuf.*, vol. 26, pp. 1230–1241, Jun. 2018.
[12] Z. Huang, J. Zhu, J. Lei, X. Li, and F. Tian, "Tool wear predicting based on multi-domain feature fusion by deep convolutional neural network in milling operations," *J. Intell. Manuf.*, pp. 1–14, Aug. 2019.
[13] N. Seemuang, T. McLeay, and T. Slatter, "Using spindle noise to monitor tool wear in a turning process," *Int. J. Adv. Manuf. Technol.*, vol. 86, nos. 9–12, pp. 2781–2790, Oct. 2016.
[14] J. Lin, "Feature extraction of machine sound using wavelet and its application in fault diagnosis," *NDT & E Int.*, vol. 34, no. 1, pp. 25–30, Jan. 2001.
[15] T. Warren Liao, C.-F. Ting, J. Qu, and P. J. Blau, "A wavelet-based methodology for grinding wheel condition monitoring," *Int. J. Mach. Tools Manuf.*, vol. 47, nos. 3–4, pp. 580–592, Mar. 2007.
[16] N. Ding, C. L. Zhao, X. C. Luo, and J. Shi, "An intelligent grinding wheel wear monitoring system based on acoustic emission," *Solid State Phenomena*, vol. 261, pp. 195–200, Aug. 2017.
[17] A. Hosokawa, K. Mashimo, K. Yamada, and T. Ueda, "Evaluation of grinding wheel surface by means of grinding sound discrimination," *JSME Int. J. C, Mech. Syst., Mach. Elements Manuf.*, vol. 47, no. 1, pp. 52–58, 2004.
[18] T. W. Liao, G. Hua, J. Qu, and P. J. Blau, "Grinding wheel condition monitoring with hidden Markov model-based clustering methods," *Machining Sci. Technol.*, vol. 10, no. 4, pp. 511–538, Dec. 2006.
[19] W. Hundt, D. Leuenberger, and F. Rehsteiner, "An approach to monitoring of the grinding process using acoustic emission (AE) technique," *CIRP Ann.*, vol. 43, pp. 295–298, Jan. 1994.
[20] J. Z. Sikorska and D. Mba, "Challenges and obstacles in the application of acoustic emission to process machinery," *Proc. Inst. Mech. Eng. E, J. Process. Mech. Eng.*, vol. 222, no. 1, pp. 1–19, Feb. 2008.
[21] J. C. Principe and T. Yoon, "A new algorithm for the detection of tool breakage in milling," *Int. J. Mach. Tools Manuf.*, vol. 31, no. 4, pp. 443–454, Jan. 1991.
[22] X. Li, W. Zhang, and Q. Ding, "A robust intelligent fault diagnosis method for rolling element bearings based on deep distance metric learning," *Neurocomputing*, vol. 310, no. 8, pp. 77–95, Oct. 2018.
[23] Y. Fu, Y. Zhang, Y. Gao, H. Gao, T. Mao, H. Zhou, and D. Li, "Machining vibration states monitoring based on image representation using convolutional neural networks," *Eng. Appl. Artif. Intell.*, vol. 65, pp. 240–251, Oct. 2017.
[24] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. 25th Int. Conf. Neural Inf. Process. Syst. (NIPS)*, Dec. 2012, pp. 1097–1105.
[25] X. Li, Q. Ding, and J.-Q. Sun, "Remaining useful life estimation in prognostics using deep convolution neural networks," *Rel. Eng. Syst. Saf.*, vol. 172, pp. 1–11, Apr. 2018.
[26] L. Marple, "Computing the discrete-time 'analytic' signal via FFT," *IEEE Trans. Signal Process*, vol. 47, no. 9, pp. 2600–2603, Sep. 1999.
[27] N. N. An, N. Q. Thanh, and Y. Liu, "Deep CNNs with self-attention for speaker identification," *IEEE Access*, vol. 7, pp. 85327–85337, May 2019.
[28] R. Liu, B. Yang, E. Zio, and X. Chen, "Artificial intelligence for fault diagnosis of rotating machinery: A review," *Mech. Syst. Signal Process.*, vol. 108, no. 4, pp. 33–47, Aug. 2018.
[29] R. Zhao, R. Yan, J. Wang, and K. Mao, "Learning to monitor machine health with convolutional bi-directional LSTM networks," *Sensors*, vol. 17, no. 2, pp. 273–290, 2017.
[30] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
[31] L. Eren, "Bearing fault detection by one-dimensional convolutional neural networks," *Math. Problems Eng.*, vol. 2017, pp. 1–9, 2017.
[32] R. Huang, Y. Liao, S. Zhang, and W. Li, "Deep decoupling convolutional neural network for intelligent compound fault diagnosis," *IEEE Access*, vol. 7, pp. 1848–1858, 2019.
[33] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proc. IEEE*, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.
[34] M. Valenti, S. Squartini, A. Diment, G. Parascandolo, and T. Virtanen, "A convolutional neural network approach for acoustic scene classification," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Anchorage, AK, USA, May 2017, pp. 1547–1554.
[35] O. Abdel-Hamid, D. Li, and Y. Dong, "Exploring convolutional neural network structures and optimization techniques for speech recognition," in *Proc. INTERSPEECH*, Lyon, France, Aug. 2013, pp. 3366–3370.
[36] Q. Kong, Y. Xu, I. Sobieraj, W. Wang, and M. D. Plumbley, "Sound event detection and time-frequency segmentation from weakly labelled data," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 27, no. 4, pp. 777–787, Feb. 2019.
[37] O. Abdel-Hamid, A. R. Mohamed, H. Jiang, L. Deng, G. Penn, and D. Yu, "Convolutional neural networks for speech recognition," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 22, no. 10, pp. 1533–1545, Oct. 2014.
[38] X. Li, W. Zhang, Q. Ding, and J. Q. Sun, "Intelligent rotating machinery fault diagnosis based on deep learning using data augmentation," *J. Intell. Manuf.*, vol. 31, pp. 433–452, Nov. 2018.
[39] P.-L. Lin, P.-W. Huang, C.-H. Lee, and M.-T. Wu, "Automatic classification for solitary pulmonary nodule in CT image by fractal analysis based on fractional Brownian motion model," *Pattern Recognit.*, vol. 46, no. 12, pp. 3279–3287, Dec. 2013.
[40] A. P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," *Pattern Recognit.*, vol. 30, no. 7, pp. 1145–1159, Jul. 1997.
[41] T. Warren Liao, "Feature extraction and selection from acoustic emission signals with an application in grinding wheel condition monitoring," *Eng. Appl. Artif. Intell.*, vol. 23, no. 1, pp. 74–84, Feb. 2010.
[42] S. Devendiran and K. Manivannan, "Condition monitoring on grinding wheel wear using wavelet analysis and decision tree C4.5 algorithm," *Int. J. Eng. Technol.*, vol. 5, no. 5, pp. 4010–4024, Jan. 2013.
[43] R. G. Silva, K. J. Baker, S. J. Wilcox, and R. L. Reuben, "The adaptability of a tool wear monitoring system under changing cutting conditions," *Mech. Syst. Signal Process.*, vol. 14, no. 2, pp. 287–298, Mar. 2000.
[44] N. Subrahmanya and Y. C. Shin, "Automated sensor selection and fusion for monitoring and diagnostics of plunge grinding," *J. Manuf. Sci. Eng.*, vol. 130, no. 3, pp. 0310141–03101411, Jun. 2008.

CHENG-HSIUNG LEE received the B.I.M. and M.I.M. degrees in information management from the Chaoyang University of Technology, in 2002 and 2004, respectively, and the Ph.D. degree in computer science and engineering from the National Chung Hsing University, Taichung City, Taiwan, in 2013.

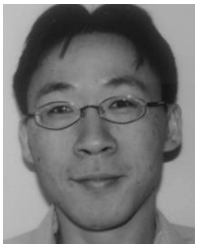
From September 2017 to July 2018, he was a Postdoctoral Research Fellow with the Center of Intelligent and Innovation Manufacturing System, Tunghai University, Taiwan. He is currently an Assistant Professor with the Master Program of Digital Innovation, Tunghai University. His current research interests include machine learning, big data analytics, computer vision, and smart manufacturing.

JUNG-SING JWO received the B.E. degree in mechanical engineering from National Taiwan University, Taiwan, in 1984, and the M.S. and Ph.D. degrees in computer science from The University of Oklahoma, Norman, OK, USA, in 1991. He has served as the Director of Board of Governors, Software Engineering Association of Taiwan (SEAT), from August 2014 to July 2017. He is currently a Professor with the Department of Computer Science and the Chair of the Master Program of Digital Innovation, Tunghai University, Taiwan. He is the author of three books, and holds 12 software patents. His main research interests are business AI, smart manufacturing, software engineering, and user experience design.



HAN-YI HSIEH received the B.E. and M.S. degrees in computer science from Tunghai University, Taichung City, Taiwan, in 2013 and 2017, respectively. He is currently pursuing the Ph.D. degree in computer science with the National Taipei University of Technology, Taipei, Taiwan.

Since 2018, he has been a Research Assistant with Software Engineering and Technology Center, Tunghai University. His research interests include the machine learning, digital image processing, and digital signal processing.



CHING-SHENG LIN received the B.S. and M.S. degrees in applied mathematics from National Chung Hsing University, Taiwan, in 1998 and 2001, respectively, and the Ph.D. degree in computer science from the State University of New York at Albany, in 2016.

He was a Postdoctoral Research Fellow with Tunghai University, Taiwan, in 2018. He is currently an Assistant Professor with the Master Program of Digital Innovation, Tunghai University. His research interests include natural language processing, artificial intelligence, and machine learning.