

Laser machining process monitoring using stethoscope and neural networks

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ABSTRACT

This paper presents a novel in-situ monitoring technique and deep learning models for laser machining process condition identification and quantification using acoustic wave. Laser machining is a thermal process that removes atoms from a workpiece and generates short pulses induced by the interaction between the laser and target material. Short pulses were collected using a digital stethoscope placed on a 525 μm -thick silicon substrate. The proposed use of stethoscope allows real-time monitoring, analysis, and control of the laser machining process, thereby facilitating accurate pattern parameters (depth, width, and surface microparticulate debris around the heat-affected zone). In this study, the neural network models were implemented for the qualitative and quantitative identification and classification of laser-machined surfaces. Specifically, several signal processing methods (fast Fourier transform, short-time Fourier transform, log scaling, and downsampling) were applied to the time-series stethoscope data. Subsequently, neural network models were developed to predict the pattern parameters (depth, width, and surface debris). Convolutional neural networks, fully connected layers, and a stacking ensemble network were integrated to improve the prediction performance. The developed model successfully predicted the presence of debris with 99.63 % accuracy and estimated the depth and width of the pattern with errors of 43.26 and 4.47 μm , respectively. This neural network model can be used to prevent machining beyond material boundaries by automatically estimating the laser pattern dimensions and minimizing the surface microparticulate debris.

1. Introduction

Laser machining for cutting, welding, joining, peening, corrosion removal, etc., has been widely used for a few decades because the laser machines various materials, such as metals, non-metals, and even bio cells, by adjusting the intrinsic laser parameters and properties (wavelength, pulse duration, iterative rates, power, polarization, incident angle, beam spot, etc.) [1–6]. Recently, laser micromachining has enabled three-dimensional (3D) fabrication with micrometer-level dimensional accuracy, creating variable shape and size features using various materials.

As the desired feature size decreases and its geometry becomes more complicated, the laser machining process requires tighter tolerance in terms of part accuracy and precision, feature size, surface quality,

throughput, and in-process control. Laser machining processes have evolved by combining other machining processes such as jet machining, turning, drilling, and milling [5,7,8]. These machining processes are difficult to incorporate with feedback or monitoring systems for process quality because of the limitations of the machining environment [9–11], and machining performance is mostly evaluated by post-processing using measuring instruments such as optical microscopes and surface profilometers. Recently, infrared imaging has enabled the visualization of the thermal distribution of the laser-induced area, the so-called melted pool [12,13]. However, it has a low bandwidth to capture rapid temperature changes during the phase changes of the material. Therefore, improving the monitoring capability of the laser-machining process has the potential to predict and diagnose laser-machined regions.

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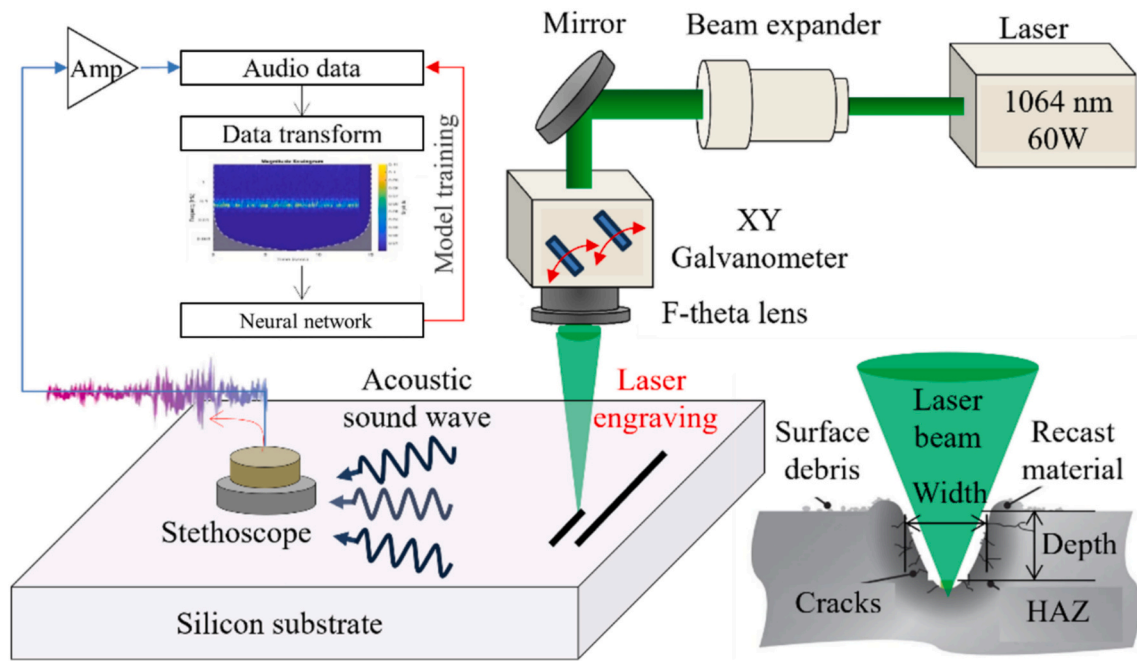


Fig. 1. Schematic of the laser machining experiment testbed.

Acoustic wave-based approaches for process control and monitoring in various machining applications have been widely studied over the past few decades [14–18]. This technology continues to evolve with the development of machine learning and enables smart and digital manufacturing, allowing the characterization, classification, and quantification of manufactured parts, systems, and processes [19–22]. Machine learning models can be adapted for all machining applications in smart manufacturing. For example, a machine learning-based classifier using acoustic data was used to classify tool conditions into six stages for milling machines [23]. Multichannel audio data were acquired and used as input for the classification process. Subsequently, various signal processing techniques (e.g., wavelet and adaptive kernel principal component analyses) were applied to the acoustic signals. The statistical and energy features were then extracted. They performed classification using a CART decision tree, random forest, support vector machine, and k-nearest neighbor algorithms. Kvinevskiy et al. [24] developed a classifier to detect the occurrence of chatter in CNC milling machines, which degrades machining quality. First, they obtained a short-term Fourier transform (STFT) of the audio data. Subsequently, the STFT results are compressed by training the autoencoder. The latent variables of the autoencoder were used as the input of the support vector machine. Hat et al. [25] proposed a classification model to distinguish the four states of the paragon cutter of a CNC machine. Vibration signals were acquired by an accelerometer, and the acoustic signals were preprocessed using fast Fourier transform (FFT) and principal component analysis. Subsequently, a support vector machine, k-nearest neighbors, and a convolutional neural network (CNN) were used as classifiers of the cutter status.

Unlike in the case of mechanical tool-based machining processes, such as milling, drilling, grinding, and turning, the machining performances of laser machining processes are often difficult to predict because the laser-matter interaction varies with materials, defects, surface conditions, and even environmental conditions. Therefore, laser machining processes require in-process monitoring to maintain the parts or systems at the highest quality and condition. The laser itself can be monitored and controlled by its internal feedback sensor systems. However, there are few studies on the in-process prediction of the quality of laser-machined parts.

In this study, to overcome current limitations and challenges in the

laser machining process, the acoustic waves produced during laser machining were analyzed to classify the laser machining performance indicators (width, depth, and presence of surface debris) using neural network models. The 60 W pulse laser (wavelength 1064 nm) was used for patterning on the 525 μm -thick Si wafer. A digital stethoscope was placed on the wafer substrate, and acoustic waves were collected during the laser–matter interaction; a neural network model, which can monitor laser machining, was developed using the acoustic wave data.

The remainder of this paper is organized as follows: Section 2 describes the experimental setup of laser machining and the processing results (i.e., line patterns created by various laser powers and corresponding acoustic signals). Section 3 describes the signal processing, debris prediction model, and pattern depth/width estimation model developed in this study. Section 4 describes the classification accuracy of the debris-prediction model and the error of the depth/width estimation models. Section 6 presents potential future work related to this study, and provides a concise summary and the conclusion of the study.

2. Experiment

2.1. Experiment plan

A laser incident on a substrate may produce acoustic waves in two ways: the thermoelastic effect (induced by thermal expansion) and the ablation effect (induced by vaporizing the substrate material) [26]. The ablation effect becomes dominant in high-power laser-machining applications, and the laser pulses generate a thermal gradient, leading to thermoelastic-acoustic wave generation in the material [27]. The laser pulse-induced acoustic wave in the substrate could be a clue to understanding the laser–material interactions, monitoring laser machining processes, and evaluating machining performance, such as part quality.

In this study, the laser engraving test bed (Fig. 1) equipped with a long pulse Nd:YAG laser (60 W, 1064 nm), optic components, and a galvanometer were used to machine the $\phi 4$ inch silicon substrate. A digital stethoscope was placed on the silicon substrate, and acoustic waves were collected at a sampling frequency of 48 kHz during laser machining. The engraved patterns (depth and width) and other effects (surface debris, recast material, cracks, and heat-affected zone (HAZ)) are highly dependent on the incident laser conditions such as power,

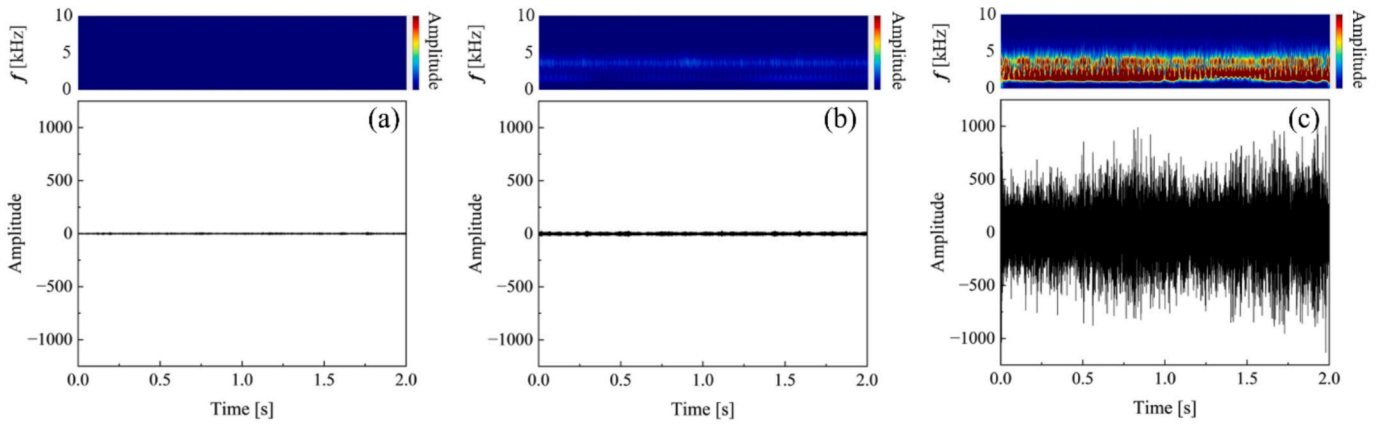


Fig. 2. Comparison of acoustic wave amplitudes according to the environment: (a) anechoic chamber, (b) laser engraving machine with the power on, and (c) laser engraving condition (18 W case).

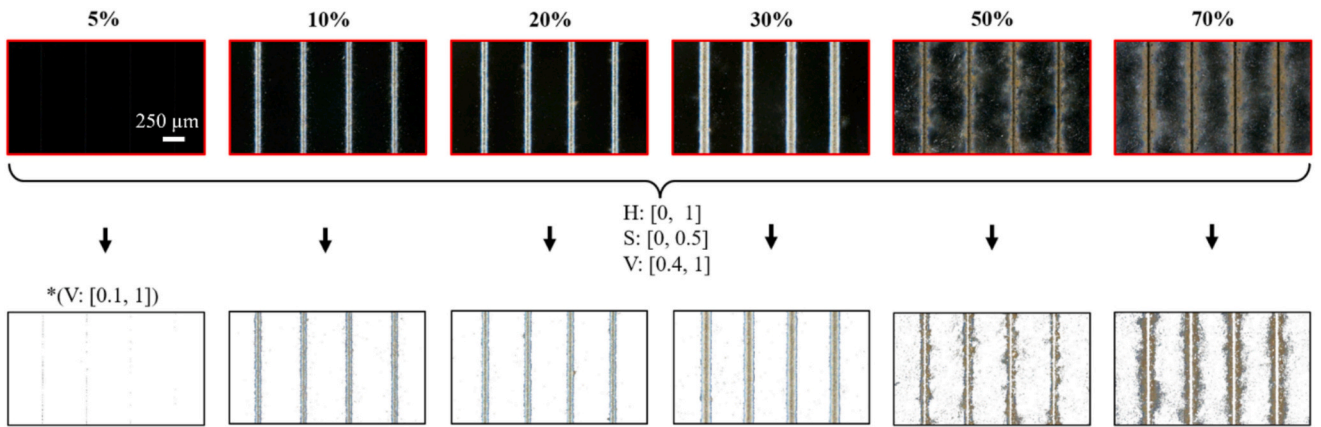


Fig. 3. Laser machining results and surface debris featurization.

focus spot size, pulse duration, and scanning rate, etc. Because this study focuses on the characterization of the relationship between the laser machining processes and the induced acoustic waves, rather than the laser machining process characterization or optimization, the acoustic waves were collected during the process using the digital stethoscope under various laser power conditions (5 %–70 % of the 60 W laser power) incident on the substrate, while other laser conditions remained constant. The pattern width, depth, and presence of surface debris were considered as performance index parameters related to the acoustic

wave data. As shown in Fig. 1, the acoustic waves were saved as audio data and converted into time–frequency domain data. The neural network model was then trained to classify and quantify the laser machining performance.

To validate the use of a stethoscope in this study, the acoustic waves were collected under three different environmental conditions (anechoic chamber, laser engraving machine, and during laser machining process), as shown in Fig. 2. No significant noise signals were observed using the digital stethoscope. Although low-amplitude noise

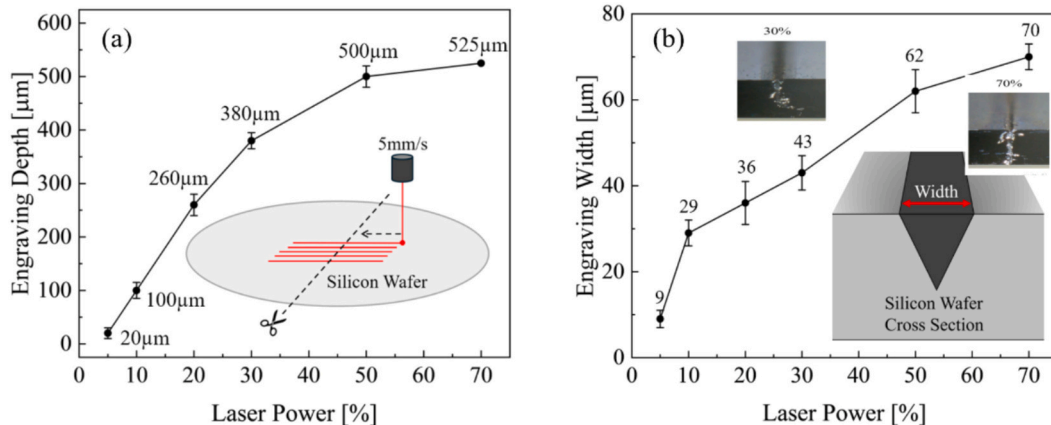


Fig. 4. Laser pattern according to the laser power conditions: (a) depth and (b) width.

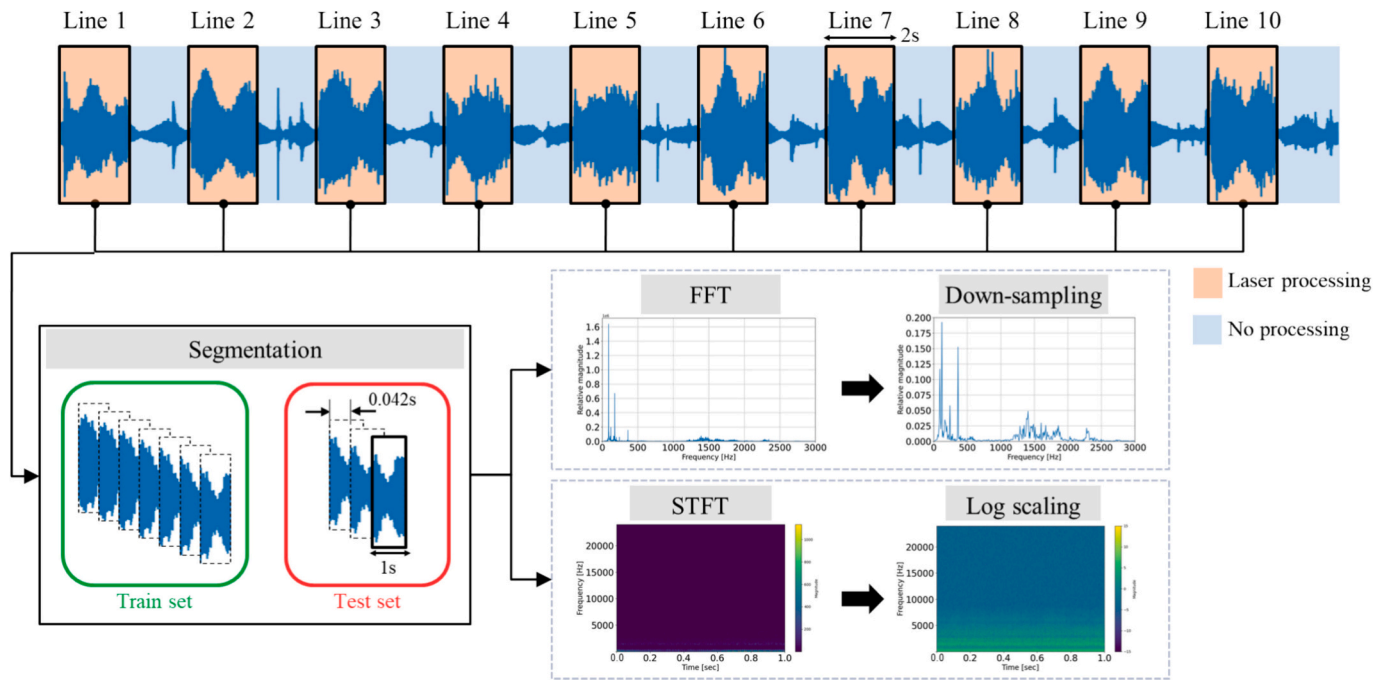


Fig. 5. Signal preprocessing for neural networks.

signals were observed in the laser engraving machine with the system powered on, during laser machining these signals (Fig. 2b) were negligible compared to the amplitude of the acoustic wave (Fig. 2c). These validation test results indicate that the digital stethoscope used in this study is effective for collecting acoustic waves in a laser machining environment and during its operation.

2.2. Laser machining

Six different conditions (5 %, 10 %, 20 %, 30 %, 50 %, and 70 %) of the 60 W long pulse laser power were considered for laser machining. The laser engraved 10 of the 10 mm long line patterns on the 525 μm -thick silicon substrates with a 500 μm interval for each laser power case. The laser scan rate was set to 5 mm/s in all cases. Laser-engraved patterns were not observed in the 5 % power case, and the 50 % and 70 % cases showed excessive laser machining, creating a large HAZ around the patterns.

HAZ is characterized by hue, saturation, and value or brightness (HSV) color space transformation, which has gained significant attention in various image processing applications since it was first introduced in 1978 [28]. This method is an alternative representation of the red, green, and blue (RGB) color model and offers better colorimetric analysis and perception than the RGB color space model. In particular, this method has recently been applied to defect metrology and inspection based on computer vision techniques and AI [29–31]. The HSV values of the surface debris in the HAZ were determined previously, and the microscopic images were filtered using surface debris HSV masking. As shown in Fig. 3, surface debris was observed in 50 % and 70 % cases, and no significant surface debris was observed in the other cases.

The depths (Fig. 4a) and widths (Fig. 4b) of the laser-engraved patterns were measured using high-resolution optical microscopy. Each value was measured ten times and averaged. As shown in Fig. 4, the pattern depth and width increased with the laser power, and the silicon substrate was engraved up to the bottom layer in the laser power of 70 % case.

2.3. Data acquisition

The utilization of a stethoscope enabled intricate data acquisition in sound generation during laser machining processes, and the sensing capability of a stethoscope captured the miniscule acoustic properties generated during laser machining on the silicon wafers. The digital stethoscope placed on top of the wafer surface served as a sensitive observer of the sound of the silicon material excited by the laser beam. To ensure optimal contact and reliable signal acquisition, an additional weight was applied to press the digital stethoscope firmly against the Si wafer substrate. The stethoscope was connected to a personal computer via an audio auxiliary cable to record acoustic signals in real time and store them in a 16-bit WAV file format.

Owing to the limited number of bits in the digital device, the amplification of incoming acoustic signals in the digital stethoscope was carefully adjusted to avoid quantization errors. If the signal is not adequately amplified, weak or quiet sounds may not be effectively captured, leading to a loss of detail in the digitized signal. The digital stethoscope was configured in wideband mode without any filtration, with a sampling frequency of 48 kHz, allowing the recording of acoustic signals across a broad frequency range. The recorded WAV files provided dynamic-acoustic interaction data between the laser beam and silicon material during machining.

3. Analysis with deep learning model

3.1. Preprocessing

The data used for training were the acoustic signal data for six laser power levels (i.e., 5 %, 10 %, 20 %, 30 %, 50 %, and 70 %) of the 60 W long pulse laser power. Time-series acoustic signals were acquired during the machining process at a sampling frequency of 48 kHz. The laser line patterning process, each lasting 2 s, was repeated 100 times at each power level. The signals between the end of one laser process and the beginning of the subsequent process were removed from the dataset, as shown in Fig. 5. Each process interval was then cropped using a sliding window with a length and shift of 1 and 0.042 s, respectively. This segmentation produced ten signal segments per patterning process.

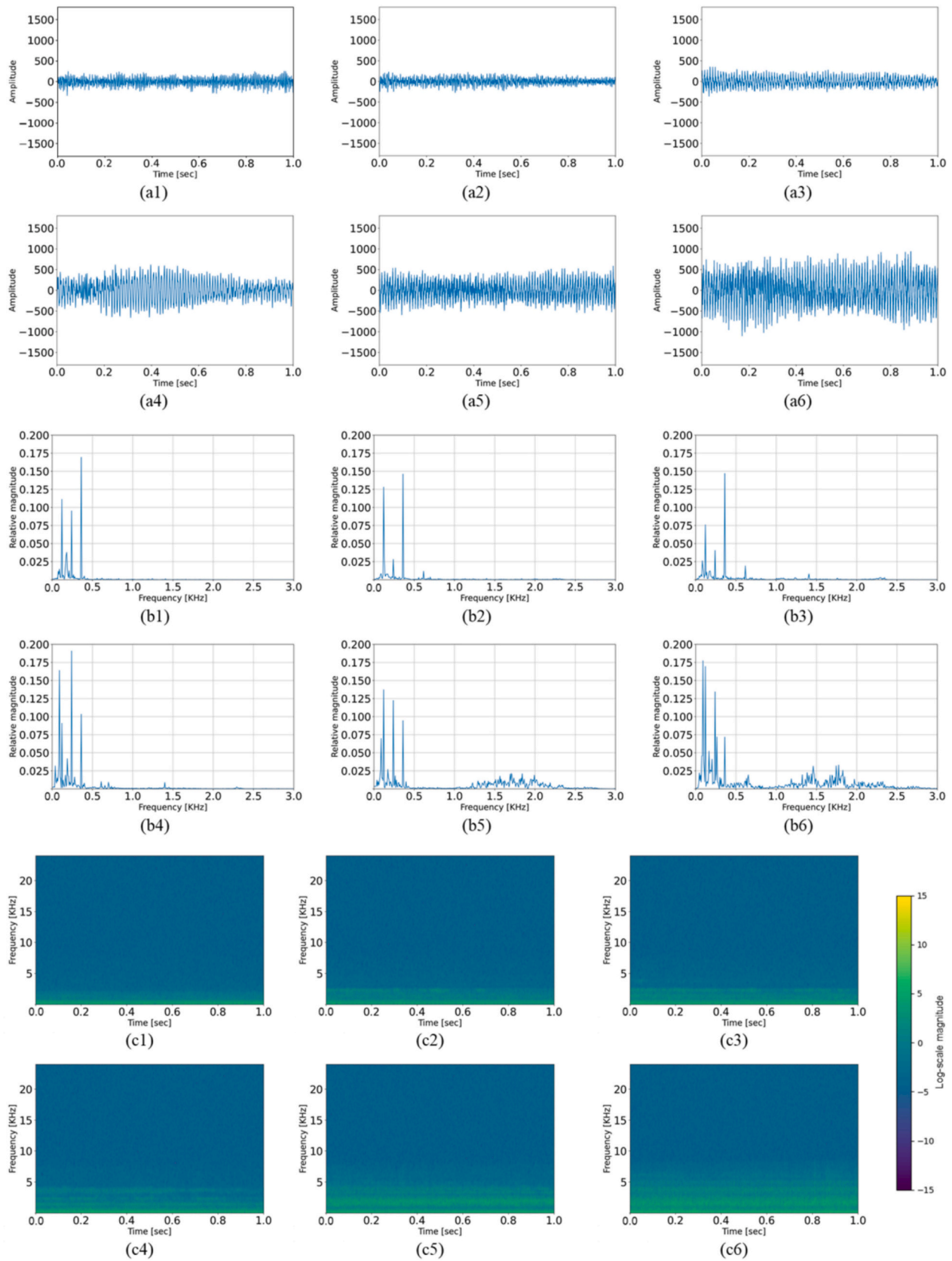


Fig. 6. Exemplar preprocessing results (a1–a6) acoustic time-series data of 5 %, 10 %, 20 %, 30 %, 50 %, and 70 % laser powers, respectively, (b1–b6) FFT results, (c1–c6) STFT results of the power levels.

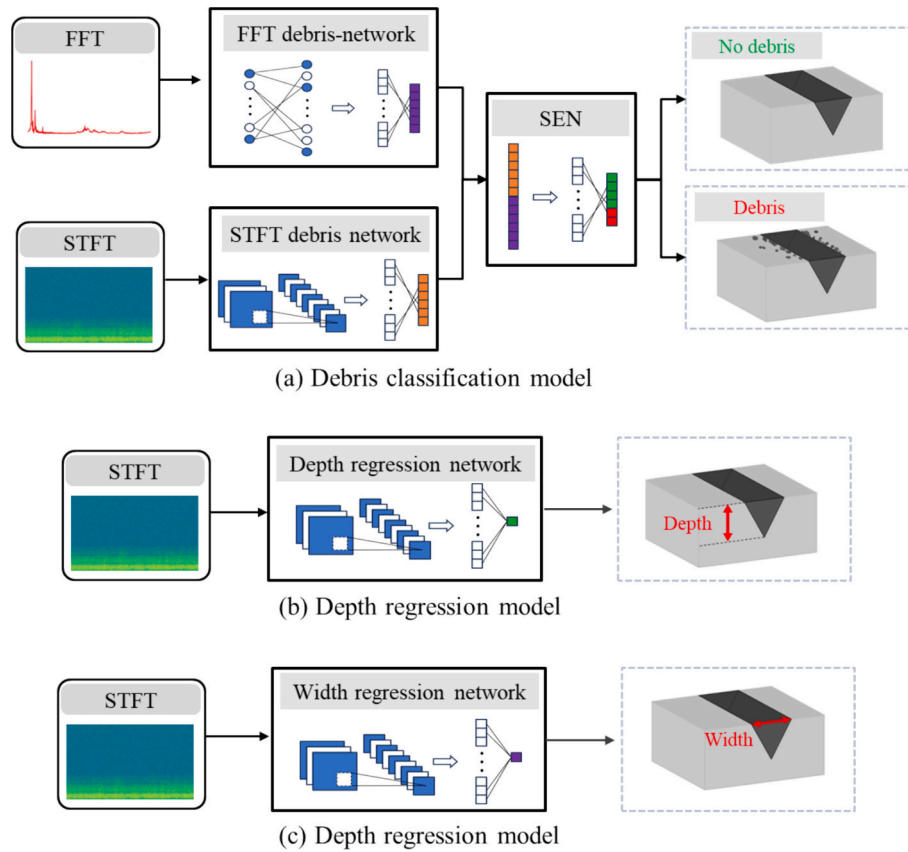


Fig. 7. Neural networks for (a) debris classification, (b) depth regression, and (c) width regression.

Consequently, the total number of samples in the dataset was 6000. These samples were divided into training and test datasets in a ratio of 7:3.

A Fourier transform was used to improve the performance of the deep learning models. First, FFT was applied to the segmented time-series samples. Among the amplitude values obtained from the FFT, only 400 amplitude values were selected using downsampling in order to reduce the input dimensions. Second, the STFT is applied to the time-series acoustic signal using 0.005 s length windows and 0.003 s overlap. A log scaling operation was applied to the STFT results. Frequency domain analysis methods (i.e., FFT and STFT) were used in this study because the frequency components showed distinct differences across the laser power levels, as shown in Fig. 6. A time-domain signal is typically a mixture of various frequency components, which makes it challenging to extract meaningful patterns directly from the raw signal. FFT and STFT effectively separate these components to identify distinct frequency signatures associated with different laser power levels. These methods also reduce the number of features compared to the time-series data. When the time-series data was used to train the classification model, the accuracy was not high. Moreover, both FFT and STFT have been widely used in previous studies to monitor machining processes [25].

3.2. Debris prediction model

The debris prediction model was developed by integrating the fully connected network (FCN), CNN, and stacking ensemble network (SEN), as shown in Fig. 7a. The FFT data were used as the input for the FFT-debris network, which consisted of two hidden layers with ReLU activation functions. This network was trained using the Adam optimizer, with a learning rate of 10^{-4} and a batch size of 4. The STFT data were used as input for the STFT-debris network consisting of three

Table 1
Architecture of FFT-debris network.

Layer	Input Shape	Output Shape	Activation	Number of parameters
FCN	400	256	ReLU	102,656
FCN	256	128	ReLU	32,896
FCN	128	32	ReLU	4128
FCN	32	6	SoftMax	198

convolutional layers, followed by one fully connected layer. This network was trained using the Adam optimizer with a learning rate of 10^{-5} and a batch size of 16. Subsequently, the outputs of the FFT-debris and STFT-debris networks were stacked and fed into the SEN. Note that the SEN was operated using the results of the FFT-/STFT-debris network. Thus, these two networks were trained first. The SEN is then trained using the trained FFT-/STFT-debris network. The SEN was trained using the Adam optimizer with a learning rate of 10^{-5} , and batch size of 16. The detailed model architectures are listed in Tables 1–3.

The debris model predicts the occurrence of debris using laser power prediction models. First, the networks were trained to classify laser power levels. In this experiment, debris was observed when the laser power exceeded 50 % of the 60 W laser power. Thus, if the predicted label of the laser power is less than 50 %, the model considers that there is no debris, and vice versa. Note that debris was selected as the value subject for prediction because it is an unfavorable byproduct of laser processing. The FFT-debris and STFT-debris networks were separately trained to classify laser power. Subsequently, the SEN was trained using the outputs of the FFT-debris and STFT debris networks.

3.3. Pattern depth and width regression

A regression model for predicting the depth and width of the laser

Table 2
Architecture of STFT-debris network.

Layer	Input Shape	Output Shape	Kernel Size	Stride /Padding	Activation	Number of parameters
Conv	(1,129,376)	(16,129,376)	3×3	1/1	ReLU	160
MaxPooling	(16,129,376)	(16,64,188)	2×2	2/0	–	0
Conv	(16,64,188)	(8,64,188)	3×3	1/1	ReLU	1160
MaxPooling	(8,64,188)	(8,32,94)	2×2	2/0	–	0
Conv	(8,32,94)	(4,32,94)	3×3	1/1	ReLU	292
MaxPooling	(4,32,94)	(4,16,47)	2×2	2/0	–	0
Flatten	(4,16,47)	3008	–	–	–	0
FC	3008	1024	–	–	ReLU	3,081,216
FC	1024	64	–	–	ReLU	65,600
FC (Output)	64	6	–	–	SoftMax	390

Table 3
Architecture of SEN.

Layer	Input Shape	Output Shape	Activation	Number of parameters
FCN	12	36	ReLU	468
FCN	36	6	SoftMax	222

pattern was created using two independent CNNs, as shown in Fig. 7b and c. Both CNNs used STFT data as inputs. They had three convolutional layers, followed by one FC layer. The regression model was trained using the Adam optimizer with a learning rate of 10^{-4} and batch size of 16. The detailed architectures are presented in Table 4.

4. Results

4.1. Debris prediction

The SEN significantly increased the accuracy of the laser power prediction by considering the outputs of the FFT-debris and STFT-debris networks. The STFT-debris network showed higher accuracy (90.11 %) than the FFT-debris network (82.78 %). The error of each class was different in the FFT-debris and STFT-debris networks, as shown in Fig. 8a and b. For example, while the FFT-debris network showed considerable errors in distinguishing between 5 % and 10 % laser power, the STFT-debris network accurately classified signals associated with 5 and 10 % power. Although the STFT-debris network frequently misclassified the signal at 30 % power as that at 10 % power, the FFT-debris network showed no errors in this case. Owing to this difference in error trends, desirable effects of the ensemble were expected. Consequently, the SEN increased the accuracy to 92.17 % by correcting the misclassification problem of the FFT-/STFT-debris networks.

No significant differences were observed in the accuracy of the three models (99.39 %, 99.67 %, and 99.50 % for the FFT-debris network, STFT-debris network, and SEN, respectively) for debris occurrence prediction, which is a binary classification problem that is only required to determine whether the laser power is above or below 50 %. However, as the laser power is accurately predicted from the acoustic signal, it can be extended to the debris-forecasting model by predicting the risk of

debris in greater detail.

4.2. Pattern depth and width regression

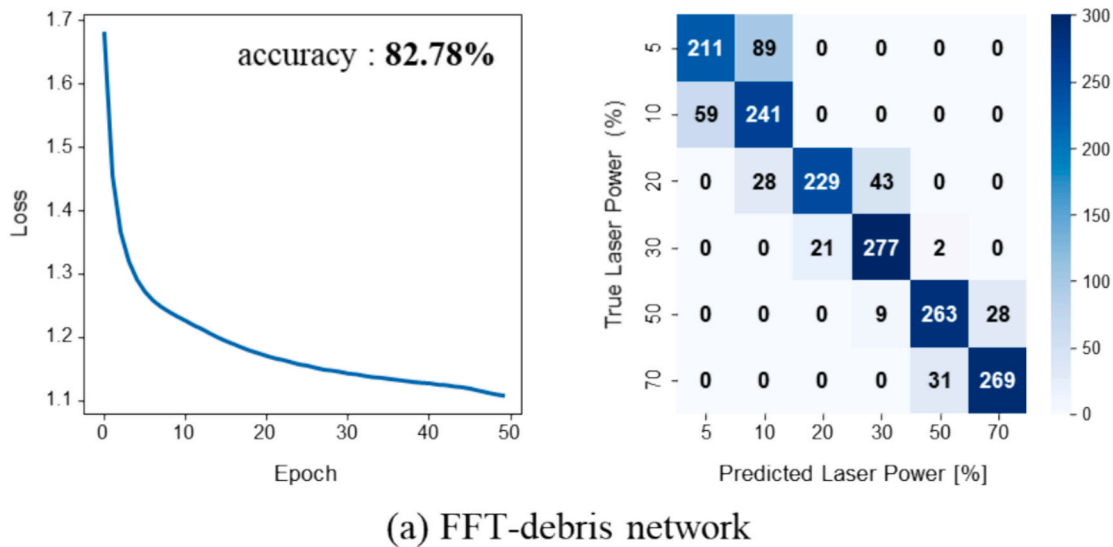
The performance of the depth/width regression model is represented by the root mean square error (RMSE), as listed in Table 5. Six dataset cases with different test sets were used for the cross-validation. In each case, laser powers at different levels, excluding the test data, were used as the training data. For instance, in Case 1, samples with 10 %, 20 %, 30 %, 50 %, and 70 % laser powers were used as the training data, and samples with 5 % power were regarded as the test data. For Case 2, samples of 5 %, 20 %, 30 %, 50 %, and 70 % were selected as the training data. The rest of the cases followed the same procedure for training and validation. As a result, the average values of RMSE for depth and width are 43.26 μm and 4.47 μm , respectively.

The error was small when the laser power of the test data was in the middle of the power range. However, significant errors were observed at the lowest laser power (Case 1) for depth and at both the lowest and highest laser power (Cases 1 and 6) for width. This error trend can be attributed to data deficiency at bounds and value intervals. First, regression can be particularly challenging when predicting values corresponds to the lower or upper bound conditions. For example, if the laser power of a test sample is 10 % (Case 2), the regression model can use the depth values of 5 %, 10 %, and 20 % laser power to predict depth. However, if the laser power is 5 % (Case 1), the model can only use the depth value of 5 % and 10 % to make predictions, which leads to a larger prediction error. This increase in error was observed in Case 1 and 6 for width and in Case 1 for depth. The depth error in Case 6, however, was not relatively large. This exceptional result can be caused by the small depth difference between neighboring laser powers. Specifically, the true depths of the 50 % and 70 % laser power are 500 and 525 μm , respectively, a small difference of only 25 μm . Thus, the error of Case 6 for depth is likely to be small. On the other hand, the true width difference between 5 % and 10 % laser power is much larger (i.e., 80 μm), resulting in a larger width error in Case 1 compared to Case 6.

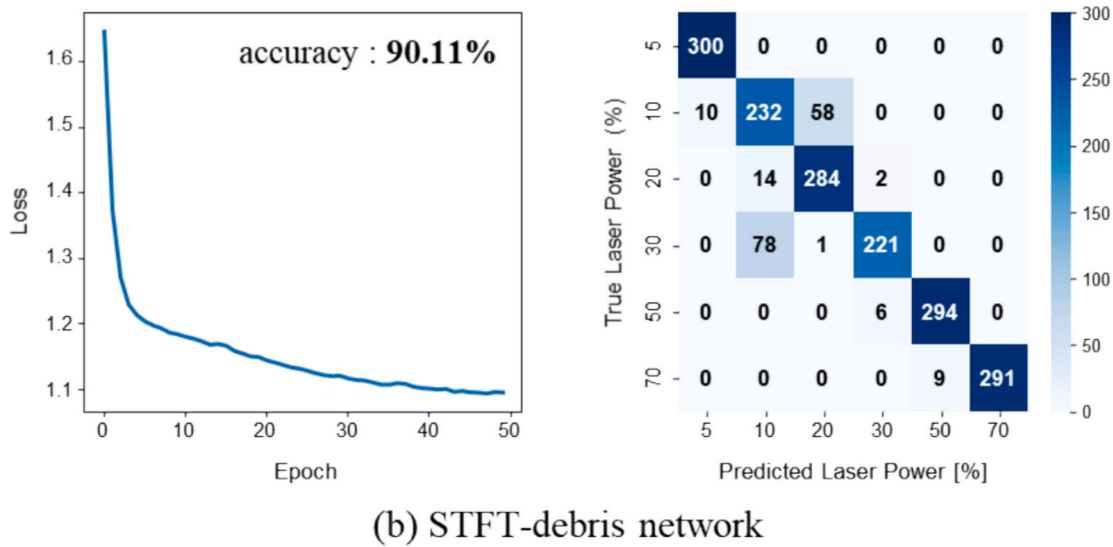
Considering the error trend, the RMSE values could be reduced if the depth and width were measured at finer laser power intervals. In addition, varying the intervals would be more effective in reducing errors. Specifically, the change in depth is more severe when the laser power $\leq$

Table 4
Architecture of depth/width regression network.

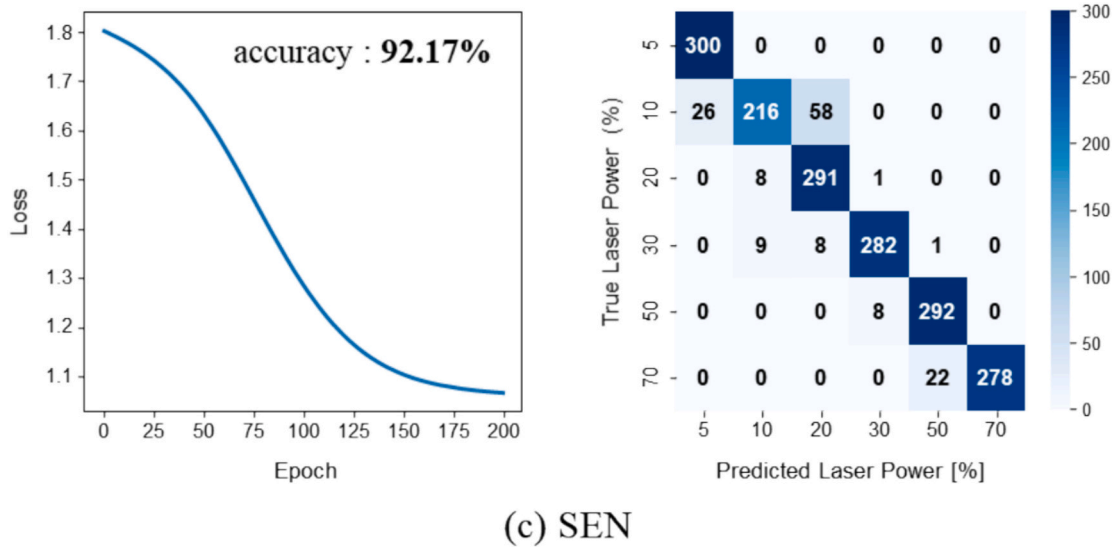
Layer	Input Shape	Output Shape	Kernel Size	Stride/Padding	Activation	Number of parameters
Conv	(1,129,376)	(16,129,376)	3×3	1/1	ReLU	160
MaxPooling	(16,129,376)	(16,64,188)	2×2	2/0	–	0
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MaxPooling	(4,32,94)	(4,16,47)	2×2	2/0	–	0
Flatten	(4,16,47)	3008	–	–	–	0
FCN	3008	1024	–	–	ReLU	3,081,216
FCN	1024	64	–	–	ReLU	65,600
FCN	64	1	–	–	–	65



(a) FFT-debris network



(b) STFT-debris network



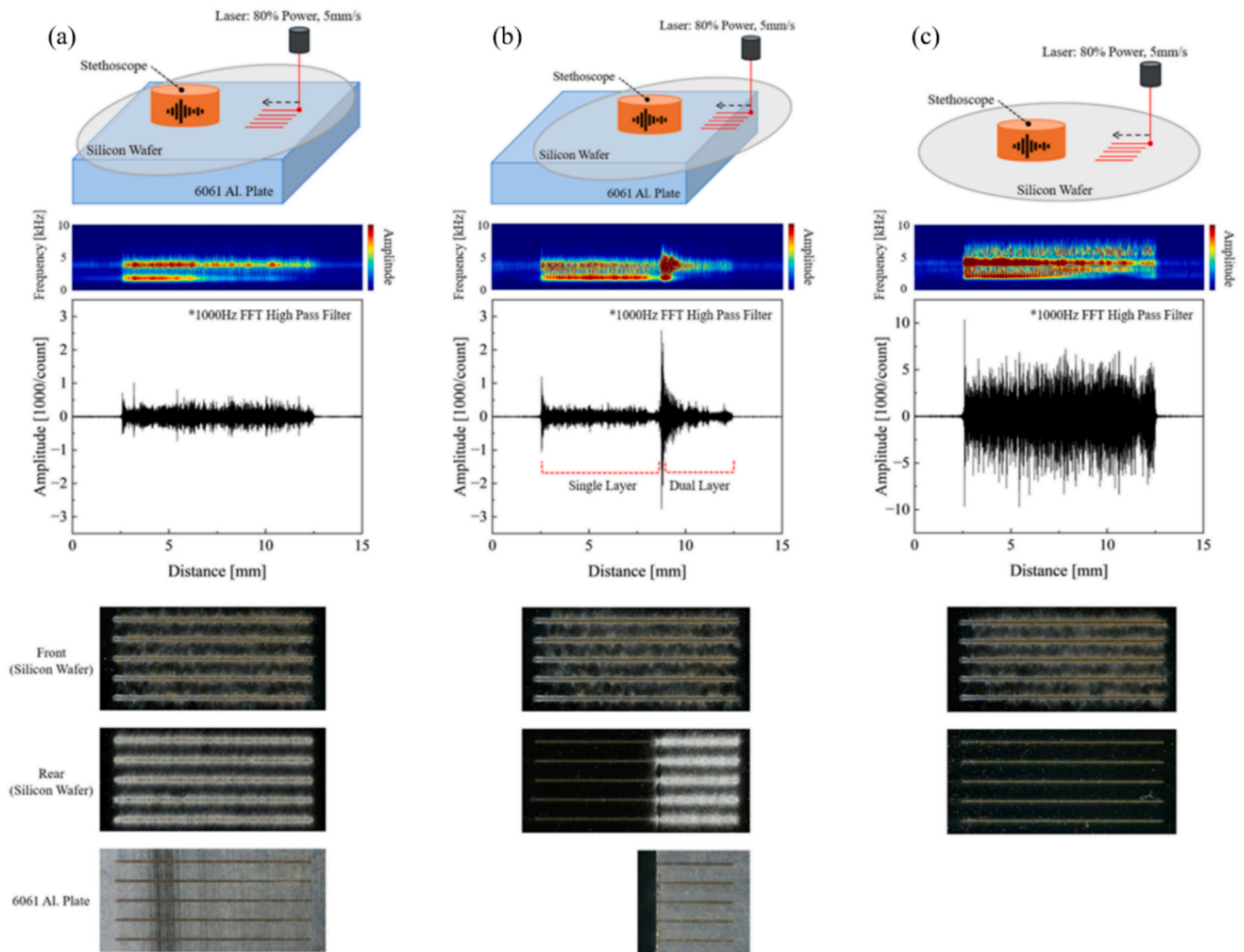
(c) SEN

Fig. 8. Confusion matrices of the debris prediction models: (a) FFT-debris network, (b) STFT-debris network, and (c) SEN.

Table 5

RMSE of depth and width prediction.

		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Average
Train data (Laser power)		10 %, 20 %, 30 %, 50 %, 70 %	5 %, 20 %, 30 %, 50 %, 70 %	5 %, 10 %, 30 %, 50 %, 70 %	5 %, 10 %, 20 %, 50 %, 70 %	5 %, 10 %, 20 %, 30 %, 70 %	5 %, 10 %, 20 %, 30 %, 50 %	
Test data (Laser power)		5 %	10 %	20 %	30 %	50 %	70 %	
Depth	True	20	100	260	380	500	525	–
	RMSE	58.51	40.79	48.98	34.33	39.13	37.84	43.26
Width	True	9	29	36	43	62	70	–
	RMSE	6.54	2.86	4.16	2.86	4.52	5.89	4.47

**Fig. 9.** Results of multi-layer laser process monitoring.

30 % than when the laser power ≥ 30 % (Fig. 4a). Thus, for depth prediction, very small laser power intervals are required for a power range between 0 % and 30 %. Similarly, the width changes considerably with laser power if the laser power is less than 10 %. Thus, small laser power intervals between 0 and 10 % of the laser power are required for width prediction.

5. Future work

The experimental and digital approaches showed that the stethoscope-based in-process monitoring technique has the potential to be adopted not only in laser machining applications but also in many

other machining applications, including traditional metal cutting and additive manufacturing. Acoustic waves were collected using a digital stethoscope when the laser machined the multilayered (silicon/aluminum) substrate, as shown in Fig. 9. The laser power and scanning speed were set as 80 % and 5 mm/s, respectively. The amplitudes of the acoustic waves for single-path laser scanning and front/backside substrate images after machining were collected. Additionally, the experimental results for the stacked and single-silicon substrate cases were compared. For the directly stacked substrate (Fig. 9a), there were no significant changes in the amplitude of the acoustic waves, and the surface quality of the machined areas of both substrates was similar for all the line patterns. To observe the dynamic behavior when the laser

machines were subjected to different substrate conditions, from a single substrate to a stacked substrate, the laser first machined the silicon substrate and then passed through the silicon/aluminum stacked substrate. A radical change in the acoustic waves was observed when the substrate conditions were changed, and surface debris was produced when the laser machined the bottom layer adhered to the top substrate. This result indicates that the acoustic waves induced by the ablation effect provide clues for monitoring and controlling depending on whether the laser is incident on the bottom layer and for machining the substrate. It is informative for operators to control, monitor, diagnose, and predict laser systems for various laser-based applications.

Although the developed neural networks successfully predicted the debris, depth, and width, they have some limitations. First, predicting the depth and width with high accuracy using the training dataset used in this study was challenging. Considering the nonlinear relationship between laser power and depth (or width), training with a new dataset that includes a broad laser power range and finer intervals is needed to obtain more accurate prediction. Second, additional data processing is required for a fully automatic monitoring system. Line patterning was conducted for 2 s, and the laser and stage were realigned for the subsequent patterning process, as shown in Fig. 5. The acoustic signals during the realignment were manually excluded from the dataset used in this study. Thus, an additional model is required to determine whether patterning is occurring. Third, the inference time of the prediction model should be considered for real-time monitoring and laser power control. If the inference time is too slow to perform real-time monitoring (or control), model reduction techniques (e.g., parameter precision reduction and layer fusion) are required.

6. Conclusions

In this study, the laser machining process was monitored using digital stethoscope combined with deep learning approach. The proposed neural network model successfully trained the digital stethoscope data collected during laser machining, extracted features according to the laser machining conditions, and created data-driven models of the laser machining performance indicators. These data-driven models predicted the laser machining performance by predicting the presence of surface debris with 99.50 % accuracy and by estimating the pattern width and depth with the RMSE of 43.26 μm and 4.47 μm , respectively. While previous machining process monitoring models require intensive signal preprocessing to obtain high-quality features, the developed model provides high accuracy, and the signal processing is not complicated. Thus, the model is suitable for real-time monitoring applications. Moreover, the debris prediction and depth/width prediction models shared the same input features. Thus, parallel computation for debris detection and width/depth estimation can reduce the computation time. Because of the difficulty in understanding physics-level laser-matter interactions in laser machining processes, data-driven models could be effective, easy, and cost-effective for the quality control of machined parts by updating the models with new data. The proposed study has the potential to enhance laser machining performance and can be easily adopted in high-end and high-volume manufacturing applications, such as microelectronics, semiconductors, and displays. In future work, the proposed sensing and deep learning approach will be implemented in an ultrafast (pico/femtosecond) laser machining process to feature the laser-matter interactions. Unlike continuous and long-pulsed laser machining processes, femtosecond lasers create patterns, ionize the material, and minimize the thermal effects on the substrate. Physics- and data-driven ultrafast laser machining models will be studied to monitor and understand the material removal processes.

CRediT authorship contribution statement

Heebum Chun: Validation, Visualization, Methodology. **Chulyong Lim:** Validation, Data curation, Formal analysis, Visualization,

Conceptualization. **William Park:** Formal analysis, Conceptualization, Data curation. **Jiyong Park:** Validation, Visualization, Data curation, Investigation, Methodology. **ChaBum Lee:** Methodology, Writing – original draft, Funding acquisition, Supervision, Investigation, Project administration. **Woochul Nam:** Visualization, Investigation, Funding acquisition, Methodology, Validation, Supervision, Writing – original draft.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability

The data underlying the results presented in this paper are not publicly available at this time but may be obtained from the authors upon reasonable request.

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