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Experimental Investigation of the Generalization Performance of Neural Network in Defect Localization System for Steel Pipe Health Monitoring

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Abstract*—This study aimed to assess the generalization performance of a Metal Health Monitoring system, which is crucial for practical applications. Previous research has not thoroughly examined this aspect of performance. To enhance the system's performance, we conducted experiments using 90 metal pieces, anticipating improved results with increased sample size. The pieces were divided into nine classes, representing undamaged and damaged conditions at eight different positions. Vibration waveforms were obtained by attaching piezoelectric sensors to the pieces. The waveforms were then split into training and evaluation datasets, and a neural network (NN) was trained on the former to classify the latter. The findings revealed that the NN achieved a remarkable accuracy of up to 80.6% in classifying the damage positions, even for metal pieces not included in the training set. These results indicate a high level of generalization performance in the Metal Health Monitoring system.

***Keywords*—Neural Network, Generalization Performance, Steel Pipe Health Monitoring System, Machine Learning, Artificial Intelligence.**

I. Introduction

The number of vacant houses in Japan has continued to increase due to the aging of the population and the shift to nuclear families, and this has become a social problem. In addition, these buildings have become dilapidated and are in danger of collapsing due to natural disasters. A further problem is the management of vacant houses. Manually managing vacant houses individually requires an enormous amount of time, human effort, and costs. The system proposed in this research manages vacant houses by attaching sensors to them [1]. We focus on the braces, beams, and columns inside the walls of houses, which are very important for earthquake resistance, and aim to locate the damaged parts. Furthermore, a remote and real-time monitoring and management system is expected in the future by installing a module that combines a sensor and an artificial intelligence (AI) chip with a communication system [2]. In a previous study, the authors focused on braces in timber buildings [3]. Using a multi-layer neural network (NN) in machine learning, we were able to achieve a maximum damage identification rate of 83.8% for untrained wood samples by training it on the vibration waveforms of the wood. In this study, we focused on steel-frame buildings, which are expected to account for a growing proportion of buildings in the future, and researched health monitoring of metal building materials that emulates braces. Iron, which is a common material in construction, was chosen for the metal component. Wood and metal are different materials, each with their own unique characteristics. Extending the research conducted on wood to metal makes it possible to compare the properties and behaviors of the materials. This allows us to understand the specific characteristics, advantages, and limitations of metal. While iron is a strong material, it can deform or be damaged by significant force or external impacts. Common types of damage to iron structures include bending, fractures, and damage to joints. In the case of aging buildings, damage can also occur in iron structures, and due to iron having higher rigidity than wood, the entire building or partial structure may collapse during a collapse event. This is particularly relevant in earthquake-prone countries like Japan, where there is a high risk of building collapse. The aim of this investigation and study is to address these challenges through the improved generalization performance of an AI system, rather than relying solely on human intervention.

II. Experiment Summary

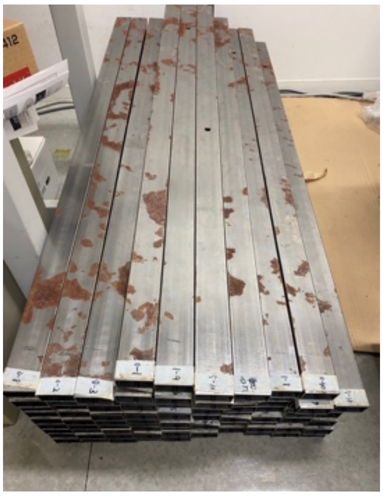
A. Data Acquisition

In pattern recognition, obtaining generalization performance is the ultimate goal for accurately identifying unknown data on the basis of training data. This is because the data that can be used for training is only a part of the whole when applied to the system. This is also true for steel pipe health monitoring systems. It is not practical to damage the metal installed in a house to obtain data. Therefore, sufficient generalization performance needs to be obtained with pre-prepared metals.

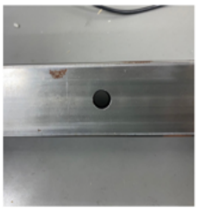
We prepared 90 pieces of steel commonly used in construction materials as shown in figure 1(a). Each rectangular pipe piece emulates a brace and is 1000 mm long, 40 mm wide, 30 mm high, and 1.5 mm thick. Each piece was marked and divided into ten equal sections of 100 mm each, and one of the eight central sections, excluding the two ends, was damaged (Figure 1(b)). The sections were classified into nine classes: undamaged (class 0) and damaged (classes 1~8) (10 pieces per class) (Figure 1(c)).

As shown figure 2(a), a piezoelectric sensor was mounted on the end to observe and record the vibration waveform of the metal using an oscilloscope. In addition, as shown figure 2(b), a vibration motor was fixed to the opposite end of the piezoelectric sensor with a rubber strap. Figure 2(c) shows the entire observation system.

The vibration motor is used to continuously vibrate the metal, and the sensor detects the vibration transmitted through the metal. The power output waveform of the sensor is observed and recorded by an oscilloscope, and machine learning is used to identify the class of damage. The waveform of the voltage for 2.5×10^2 ms was sampled and recorded at 2500 points, and 50 recordings were made for each metal piece, resulting in a total of 4500 vibration data.

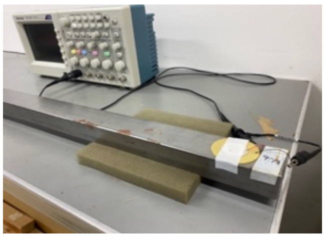


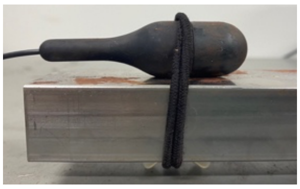
(a)



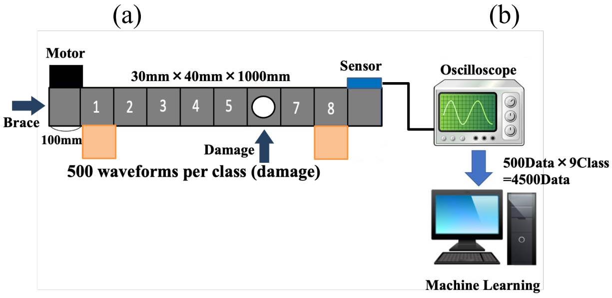
(b) (c)

Fig. 1 Prepared steel sample pieces. (a) Ninety pieces with the same shape were prepared and divided into nine classes (b) A hole in a piece of steel was drilled to represent damage. (c) Illustrated example of a Class4 piece of steel.





(a) (b)



(c)

Fig. 2 (a) A motor attached to the end of a steel pipe. (b) A piezoelectric sensor was attached to the oppsite end of a steel pipe to read the vibration waveform using an oscilloscope. (c) Metal vibration waveform observation system.

B. Machine Learning

Since the goal of this study is to classify waveforms with patterns like MNIST [4], NNs were used as the learning model for machine learning. A NN is a machine-learning algorithm that mimics the human nervous system. It can be used to find an output from an input. In object recognition, a convolutional NN (CNN) such as AlexNet is known to have high performance [5]. However, since a simple NN is best suited for our proposed system, we used a simple fully-connected NN without convolutional layers and trained the waveforms as a 1D array (Figure 3).

Each of the 4500 data acquired contains sampled waveform data as 2500 features. A feature value is a variable or attribute that represents an important feature to show the data. The input layer contained the voltage waveforms of the 2500 feature values obtained with an oscilloscope, and the number of intermediate layers and neurons was changed within a specified range depending on the experiment to run the program.

Figures 4 (a) and (b) represent vibration waveforms obtained from different metals in a Class 0 (undamaged) condition. Both waveforms have similar overall shapes, but it can be observed that (a) has a slightly larger difference between the maximum value of 13 and the minimum value of -14. (c) depicts a vibration waveform from Class 1. Upon examining the overall shape of the waveform, there is no significant difference in the main waveform frequency compared with (a) and (b) in Class 0. However, the Class 1 waveform evidently has higher frequency vibrations present in the finer waveform riding on top of the main waveform than Class 0 in (a) and (b). (d) represents a vibration waveform from Class 8, where it is notable that small and fine waveforms are uniformly present within the larger waveform.

As demonstrated, vibration waveforms are expected to exhibit different characteristics depending on the metal and the location of the damage. In this study, we chose to train the NN using the waveform itself as a feature, without extracting any specific features from it. The output layer was set to 9 because of the 9-class classification from 0 to 8, and the softmax function was applied. The optimization algorithm was the gradient descent method, the activation function was tanh, the loss function was a cross-entropy error, and the NN program was created in MATLAB. Information about the PCs used for the experiments in this study (CPU, GPU, and Matlab version) is given in the following table (Table 1).

In addition, the number of layers in the middle layer of this NN (1~7) and the number of neurons in the middle layer (10~4096) were changed along with the configuration. In this study, the evaluation was based on the high discrimination rate when the test data was classified into nine classes after training.

Table 1 Information about the PCs used for the experiments

CPU	1.6 GHz dual-core Intel Core i5
GPU	Intel UHD Graphics 617 1536 MB
Matlab ver.	2022b

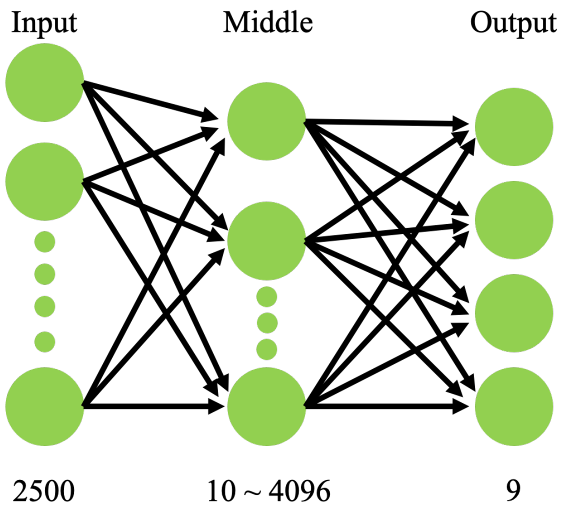
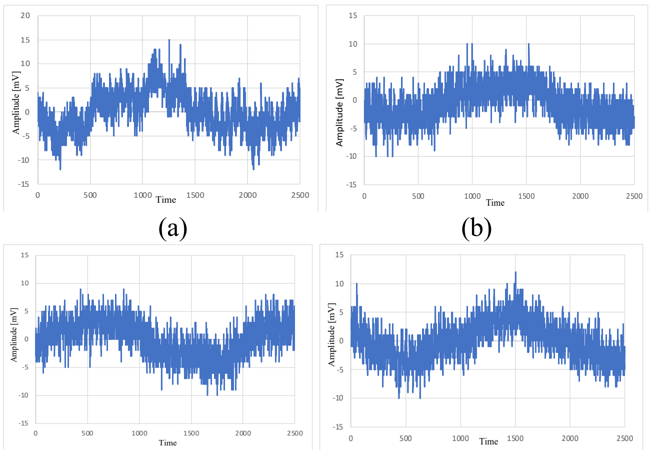


Fig. 3 Simplified diagram of a fully-connected NN.



(a) (b)

(c) (d)

Fig. 4 Acquired vibration waveforms. (a)(b) Class 0. (c) Class 1. (d) Class 8

C. Generalization Performance

Generalization performance is the ability of a machine-learning model to make correct predictions on data it has not seen before during training. Here, we describe a method for validating the generalization performance of a NN using measured metal vibration waveform data. All training and evaluation were performed using MATLAB.

In each validation, we completely separated the training and testing metals, and the improvement in the discrimination rate was considered an improvement in the generalization performance. The discrimination rate was calculated by taking the average of five runs of the program, and for cross-validation, there were five ways to select the test data, and the average was used as the discrimination rate for the results of this study.

D. Smoothing of Waveform Data and Generalization Performance

In figure 5, (a) and (b) show the vibration waveforms of wood and metal when vibrations of a similar magnitude were applied. Comparing the two, we can see that the amplitude of the metal waveform is smaller with more noise. This indicates that the noise will affect the discrimination rate even if the NN is trained as it is.

Therefore, to simplify learning, the waveforms were smoothed before input to the NN, and the discrimination rate was evaluated. The Savitzky-Golay filter and simple moving average were used for waveform smoothing, and the range of the moving average for the Savitzky-Golay filter was changed from 11 to 1001 and from 5 to 1500 for the simple moving average to evaluate the generalization performance.

III. Experimental Results and Examination

A. Smoothing of Waveform Data and Generalization Performance

In figure 6, (a) and (b) show the results of smoothing using the Savitzky-Golay filter and simple moving average, respectively.

Figure 6 (a) shows that the Savitzky-Golay filter has a maximum discrimination rate of 62.9% when the range is 41. This error of nearly 10% is due to the fact that when the range is too small, the noise is not fully removed, while when the range is too large, the waveform features are lost.

Also, figure 6 (b) shows that the simple moving average had a maximum discrimination rate of 67.8% when the range was set to 900. The discrimination rate decreased when the range was smaller or larger than 900. This may be due to the same reason as for the Savitzky-Golay filter.

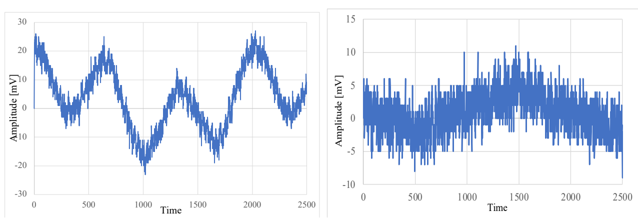
As previously shown, both the Savitzky-Golay filter and the simple moving average smoothing improved the discrimination rate significantly compared with the case without smoothing. This is because the metal vibration waveforms have small amplitude and are subject to large noise, so smoothing was effective in eliminating the noise.

Comparing the discrimination rates, the simple moving average improved by up to 11.9% before smoothing, while the Savitzky-Golay filter improved by up to 7.0%, suggesting that smoothing with the simple moving average is the best choice for the model in this study.

B. Investigation of the Relationship Between the Number of Neurons and the Discrimination Rate

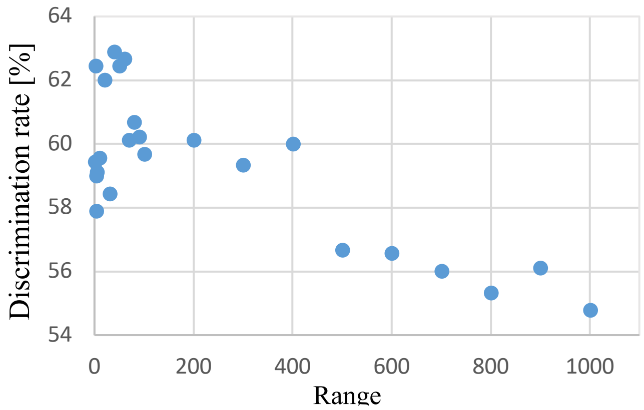
In a NN with one middle layer, the number of neurons was changed from 10 to 4096 for testing. The schematic and results are shown in Figures 7 and 8.

Figure 8 shows that the discrimination rate continues to improve as the number of neurons increases up to around 1024. On the other hand, when the number of neurons increases beyond 1024, the improvement in the discrimination rate stagnates, and the discrimination rate converges to about 80%. From this, the identification rate can be predicted to remain at

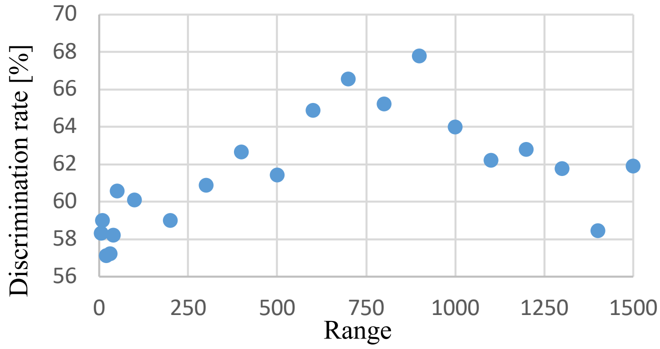


(a) (b)

Fig. 5 Vibration waveforms. (a) Wood. (b) Steel pipe.



(a)



(b)

Fig. 6 Relationship between smoothing and identification rate. (a) Savitzky-Golay filter. (b) Simple moving average.

around 80% even when the number of neurons is increased beyond 4096.

Therefore, when the middle layer is set to one layer, the discrimination rate improves up to a certain level as the number of neurons is increased. After that, however, the discrimination rate does not improve no matter by how much the number of neurons is increased, and it is expected to converge to a certain discrimination rate (80% in this experiment).

C. Investigation of the Relationship Between Intermediate Layers and Discrimination Rate

Next, in addition to the number of neurons in the middle layer, the number of layers was changed from 1 to 7. Since there are countless combinations of the number of neurons and that of layers, only specific cases are shown. If the number of neurons in the first intermediate layer was $'n'$, the number of neurons in the second and subsequent layers was set to $'n/2'$ when verifying more than two layers. In addition, five patterns of $'n'$ were prepared (32, 64, 128, 256, and 512), and the average discrimination rate was used. The schematic diagram and results are shown in Figures 9 and 10, respectively.

Figure 10 shows that as the number of middle layers is increased, the discrimination rate stabilizes at around 80%. When the number of neurons is small, the discrimination rate continues to improve as the number of middle layers increases, but when n=128, the discrimination rate stagnates after middle layer 3, and when n=256 and 512, the discrimination rate stagnates after middle layer 2.

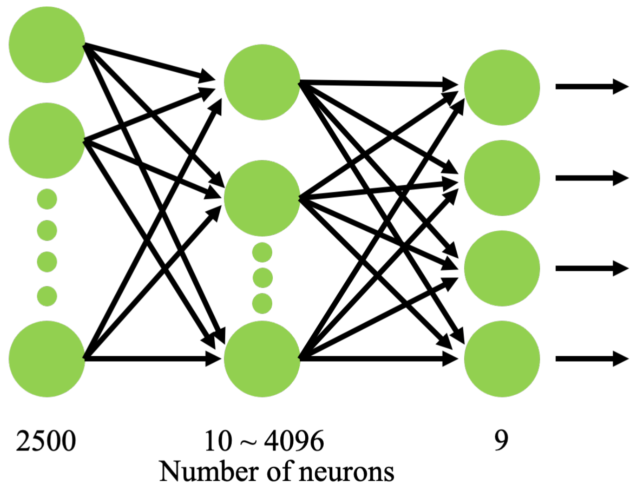


Fig. 7 Neural network with one middle layer.

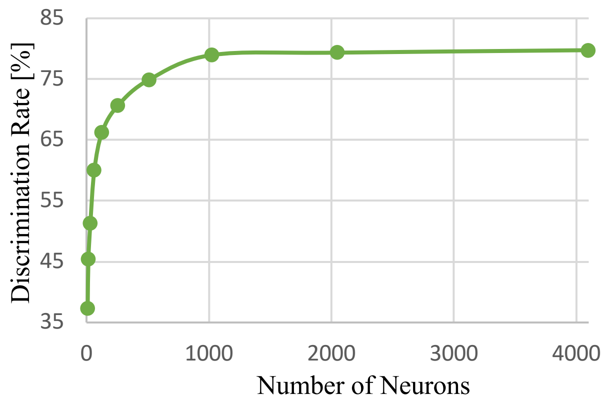


Fig. 8 Relationship between the number of neurons and discrimination rate.

As for n=512, the discrimination rate gradually decreased as the number of middle layers increased. This may be due to overlearning caused by the complexity of the model due to the increase in the number of layers and neurons. For this experiment, it is appropriate to terminate the experiment at middle layers 2 and 3, where the discrimination rate continues to improve and is near the maximum point of the graph's rough shape. By doing so, we consider that overlearning can be prevented.

For increasing the number of middle layers, the relationship between the number of middle layers and that of neurons could not be clarified to improve the discrimination rate while preventing overlearning.

D. Effectiveness of Smoothing for Experiments B and C

Tables 2 and 3 summarize the discrimination rates for B and C, respectively.

Table 2 shows that the best discrimination rate for B is 79.0% with one middle layer and 1024 neurons. When the program was run without smoothing and with all other conditions being the same, the discrimination rate was 74.7%, a decrease of 4.3%.

Table 3 also shows that the optimal maximum discrimination rate in C is 80.6% with middle layer 4 and n=128 neurons. At this time, when the program was run without smoothing and with the same other conditions, the discrimination rate was 71.8%, a decrease of 8.8%.

From the aforementioned results, the smoothing of vibration waveforms is clearly very effective in improving the discrimination rate when learning vibration waveforms in this model, since it decreased without smoothing in both experiments B and C.

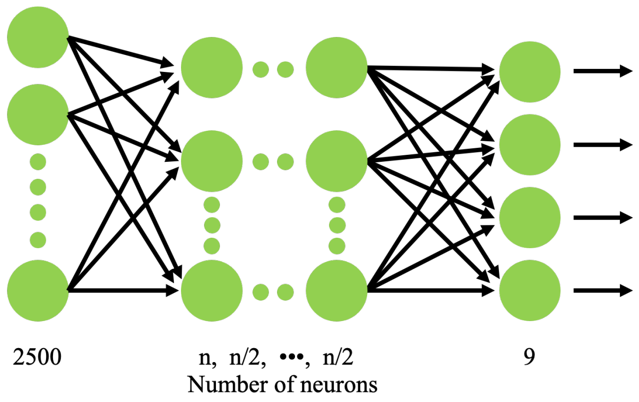


Fig. 9 NN with varied middle layers.

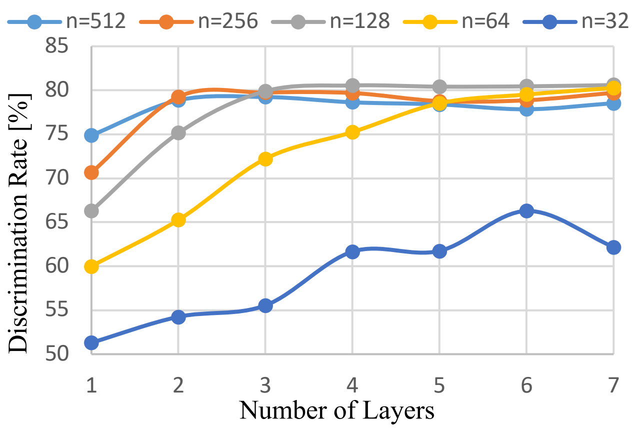


Fig. 10 Relationship between the middle layers and discrimination rate.

Table 2 Discrimination rates for one middle layer and varied number of neurons.

Neurons	256	512	1024	2048	4096
l=4	69.2	73.3	77.3	77.5	79.4
l=3	75.6	83.3	85.4	85.1	85.1
l=2	67.2	72.3	80.2	80.2	80.2
l=1	75.6	78.8	81.3	81.5	81.6
l=0	65.7	66.9	70.6	72.5	72.5
Average	70.6	74.9	79.0	79.4	79.8

E. Comparison of Metal and Wood

Although the wood used in the previous study and the steel pipe used in this study are different in shape and material, we consider that we were able to obtain a generalization performance that can produce a sufficient discrimination rate,

Table 3 Discrimination rates for varied middle layers and fixed number of neurons n=32, 64, 128, 256, 512.

Middle Layer	1	2	3	4	5	6	7
n=512	74.9	78.9	79.2	78.6	78.4	77.8	78.5
n=256	70.6	79.3	79.7	79.7	78.8	78.9	79.7
n=128	66.3	75.1	80.0	80.6	80.4	80.4	80.6
n=64	60.0	65.3	72.2	75.2	78.5	79.5	80.3
n=32	51.3	54.3	55.6	61.7	61.7	66.3	62.2

with a maximum discrimination rate of 80.6% for the steel pipe compared with 83.8% for the wood [3].

The reason for the 3.2% lower value for the metal is due to metal having a smaller amplitude of the vibration waveform than wood, which results in a larger effect of noise. This difference in amplitude is assumed to be due to the difference in the magnitude of intrinsic acoustic resistance. The intrinsic acoustic resistance is like the impedance in an electric circuit and is an indicator of the resistance to transmission of vibrations from the outside. In other words, the smaller this value is, the easier it is for vibration to be transmitted. The intrinsic acoustic resistance values of wood and metal are as follows.

- Wood: $0.25 \times 10^7 \sim 0.55 \times 10^7$
- Metal (steel): 4.8×10^7

Therefore, it can be seen that metal has a higher intrinsic acoustic resistance than wood. Therefore, it is difficult for external vibrations to be transmitted, and the amplitude of the vibration waveform becomes small. As a result, the noise becomes larger, and the different features of the waveforms are difficult to distinguish depending on the damaged area, making the damaged area difficult to identify using a NN.

IV. CONCLUSION

The study was conducted to acquire and improve generalization performance in steel pipe health monitoring. The aforementioned results show that (1) the discrimination rate can be improved by smoothing the vibration waveform before learning because the vibration waveform of metal has a small amplitude and is greatly affected by noise. (2) In the one middle layer, the larger the number of neurons, the higher the discrimination rate, but when the number of neurons exceeds a certain value (1024 neurons in this model), the discrimination rate converges (80% in this model). (3) When increasing the number of middle layers, the discrimination rate is improved by adjusting the combination of the middle layers and the number of neurons. (4) In both experiments B and C, smoothing improved the discrimination rate and thus strengthened the effectiveness of the smoothing shown in A. This is a good example of a system that can be used to improve the discrimination rate. (5) This model (proposed system) can obtain generalization performance for not only wood, which was verified in the previous study, but also metal.

It was also determined that the performance of the system could be improved by using a simple NN and acquiring data from a large number of samples. We believe that the proposed system could be applied to building materials other than wood and metal.

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