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Improvement of Sound Classification Method on Smartphone for Hammering Test Using 5G Network

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Abstract

The demand for inspections has increased due to the aging of concrete structures and tile wall surfaces. The hammering test is a simple inspection method, but the inspector needs much experience distinguishing the hammering sounds. Therefore, we developed a device that automatically classifies the hammering sounds using deep learning. However, the hardware with GPU for deep learning is the one-board microcomputer, which has no display, a battery, or an input device, so the inspector cannot change the settings or check the status during the hammering test. Therefore, we used a smartphone instead of a one-board microcomputer. We also used a cloud GPU since a smartphone does not have GPU. The results showed that communication time was the bottleneck. So we considered using a 5G network and compared the classification time, training time, and battery life of the smartphone. As a result, although the training time remained the same, we found that the classification speed was 1.46 times faster than the conventional method, and the smartphone's battery life was sufficient.

Keywords: 5G network, Neural Network, Hammering test, Non-destructive testing

1 Introduction

Recently, many accidents have happened worldwide due to cracks in concrete structures or flaking of tiles. In September 2006, De la Concorde overpass in Canada collapsed [23]. The overpass was made of concrete, and lack of inspection was one of the causes of this accident. In December 2012, the Sasago Tunnel, a 130-m high Japanese twin-bored motorway tunnel, collapsed, and many people died [3]. This structure was made of concrete. In July 2016, tiles of a nine-story building in Osaka fell, and the tiles hit the head of a woman standing under the building, and she was injured [19]. Therefore, inspecting the concrete structure or tile walls is essential to prevent such accidents worldwide.

We need an effective inspection method. The hammering test is a simple inspection method in which the inspector hits walls with a metal rod and listens to the sound. This method needs the experience to distinguish between the hammering sounds. We developed a device that classifies the hammering sounds automatically using deep learning to solve this problem. However, the device had a problem that the hardware was a one-board microcontroller called Jetson Nano (Figure 1). Jetson Nano has the following problems.

- It does not have a display. It is difficult to show the inspector's detailed results of continuous sound classification.
- It requires an external battery so that the equipment sometimes becomes larger.
- It does not have an input device; thus, the inspector cannot adjust the parameters of the sound classification in the field.

In this study, we examined the possibility of using a smartphone to classify the hammering sounds instead of Jetson Nano. The smartphone can overcome the problems mentioned above because it has a display, a battery, and an input device. However, the smartphone's graphics processing unit (GPU) performs poorly. Thus, we experimented with the effectiveness of hammering tests using the local GPU and GPU in the cloud (cloud GPU). The cloud GPU provides higher calculation performance than local GPUs, such as Jetson Nano. As a result of our experiments, we found to classify the hammering sounds using smartphones. However, when the inspector moved the hammer too fast, the smartphone could not process the data.

Additionally, in the cloud GPU, we needed to send 23.45 KB of data in about 0.02 s. It is required a 10Mbps uploading speed. In our experiment in our laboratory at Utsunomiya University, the 4G upload speed we used was 4.2 Mbps (details are described in section 4.1), so it was too slow. We considered the hammering test using 5G because we found that the communication speed between a smartphone and a cloud GPU was a bottleneck, and we measured the communication time. We have developed a system that can classify the hammering sounds of tiles on a smartphone. However, the environment of the hammering test is always different, such as noise from cars and wind. So, we need to train the NN model in the field. Therefore, we measured the training time on Jetson Nano, the smartphone, and the cloud GPU (4G and 5G). Currently, 5G is being researched and developed in various ways. For example, real-time video distribution through drone aerial photography [20], remote control of construction equipment [20], cooperative control schemes suitable for local 5G [14], 5G for the hammering test have the following two advantages.

- The inspector can improve the inspection speed because 5G and cloud GPU can reduce the processing time.
- 5G will improve the efficiency of inspections because the inspector can save the test result in the cloud faster.

In the first advantage, 5G and cloud GPUs can reduce processing time so that the inspector can move the hammer faster. Therefore, the speed of the inspection is improved. The inspector can save the test result in the cloud faster in the second advantage. There will be much data on the

[0] This research was performed as the research collaboration between PORT DENSI Inc. and Utsunomiya University.

Figure 1: Jetson Nano

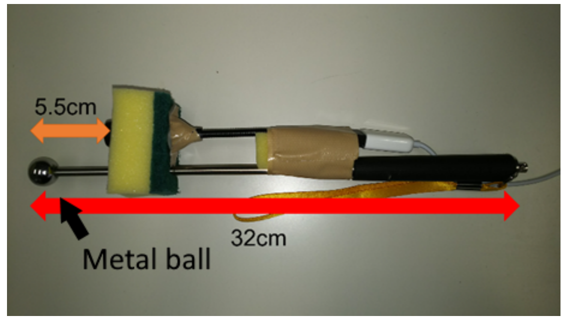


Figure 2: Hammer used in the previous study

hammering test since many buildings will be inspected. Therefore, it will take a long time to save the data with traditional communication methods, but the inspector can save it quickly with 5G. Also, by saving the data in the cloud, the inspectors can quickly share the data and not worry about losing it.

In addition, using the smartphone eliminates the need for an external battery of the Jetson Nano. However, the smartphone will consume a lot of power because of communication. Therefore, we compared their battery lives.

In Section 2, we introduce our previous study and related studies. We explain a new device for the efficient hammering test, and the flow of the hammering sounds classification on a smartphone in Section 3. Then we discussed the result of the comparison of processing times and the effect of the 5G network in Section 4. Finally, we conclude the study in Section 5.

2 Our Previous Study and Related Works

2.1 Our previous study

Our previous study developed a device that allows the hammering test easily. The device captures the hammering sounds using a microphone and classifies the sounds via deep learning. Figure 2 shows the hammer and the microphone. It has a metal ball on the top, and the inspector uses it to tap on the wall to make a sound. The hardware was Jetson Nano. As a result, using 2321 training data and 702 test data, the accuracy of the hammering test experiment reached 90.2% [11]. However, this device had some problems.

- Since the inspector taps directly on the wall, the impact is high, and noise is generated. Noise may reduce the accuracy of the system.
- The inspector taps on the wall one by one, so the inspection takes a long time.

We developed a new device to solve these problems. We will discuss the new device in Section 3.

2.2 Related works

Table 1 shows the list of related work in this study. At the top of the table study, the authors evaluate the hammer sounds based on the amplitude. However, the accuracy is 74%, and it is too low. The second study from the top of the table is similar to ours. However, this paper does not describe the specific accuracy. In the third study, the authors developed a hammering robot. However, humans evaluated the hammer sounds, so our raised problems cannot be solved. In the fourth study, the authors developed a testing apparatus for Unmanned Aerial Vehicle for labor-saving inspection. This apparatus is helpful, but the hovering sound is large. Therefore, the accuracy of inspection drops. In the fifth and sixth studies, the authors inspect concrete with the methods without a hammer. Their methods will inspect concrete efficiently. However, it is not easy to prepare their devices for

Table 1: List of related works

An inspector hit the concrete specimen with a hammer and recorded the sounds. As a result of evaluating the sounds based on the amplitude, the accuracy was 74%. [21]
An unsupervised online method is presented to automate hammering tests using clustering techniques to find defects in concrete structures. Tests on two commonly found defects were conducted on experimental test blocks and yielded satisfying results. [16]
In Japan, engineers that manage them are insufficient due to aging. Therefore, the authors developed a hammering robot that can imitate the hammering sounds of inspection workers. [22]
Infrastructure such as bridges and dams requires periodic inspection. However, it would need to cost and effort. Therefore, the authors developed a testing apparatus for Unmanned Aerial Vehicle (UAV) for labor-saving inspection. It is a hammering test equipment to be mounted to a medium-size UAV. [18]
A problem with a hammering test is that it is difficult to inspect places people cannot reach. Therefore, the authors propose a high-power directional sound source system and a scanning laser doppler vibrometer (SLDV). In this method, an air-borne sound wave is used for the excitation of a concrete wall, and then the vibration velocities on the concrete wall are measured two-dimensionally by the SLDV. [8]
Conventionally, the inspection of elevated concrete structures requires scaffolding or an aerial truck. Therefore, elevated railway structures constructed of reinforced concrete were inspected using active infrared thermography. [15]

inspection. Also, they did not inspect tiles in their study. We devised a new method to inspect concrete and tiles for the above reasons.

3 Tile Hammering Test Using Neural Network

3.1 Efficient device for generating hammering sounds

We created a neural network (NN) model on a computer and compared the classification speed of the hammering sounds on a smartphone and Jetson Nano using the NN model. Our NN model is simple. It has two layers of "dense" since the sound pattern of the hammering test is simple and short. Hyperparameters of the NN model are described in section 3.3. If tiles are flacking, the hammering sound is different from the sound caused by a tile firmly adhered to a wall. This difference is not affected by the difference in tiles. For the efficient hammering test, we used the device shown in Figure 3 to collect the training and test data. Figure 3 shows an image of the hammer and microphone connected to the smartphone. The upper part of Figure 3 shows the device that can effectively generate the hammering sounds. Figure 4 shows the top view of the new device. The device has a hexagonal metal tip. When the inspector moves the device along the wall, the tip rotates, and the inspector can generate the hammering sounds. In our experiment, the hitting interval was about 0.3 seconds when we hit the wall with an ordinary hammer. However, using the new device continuously generated the hammering, and the interval of sounds was about 0.04 seconds (Figure 5) so that the efficiency of the inspection process could be increased. However, this device has the problem that it is difficult to show the results of the hammering test without a display because the interval between the hammering sounds is very short. The conventional device (Figure 2) had a long interval between the hammering sounds, so there were several ways to show the results to the inspector without a display. When using the Jetson Nano with the new device, the inspector must carry the display around, which is not convenient. However, the inspector can easily use the new device for the hammering test with the smartphone instead of the Jetson Nano. Therefore, we needed to consider using smartphones as hardware.

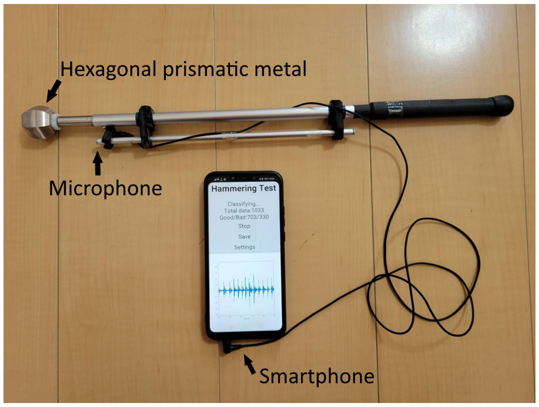


Figure 3: Image of the hammer and microphone connected to the smartphone

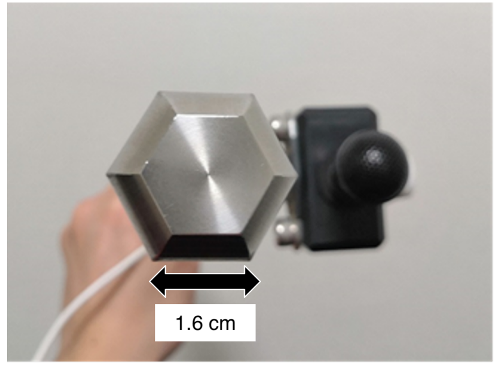
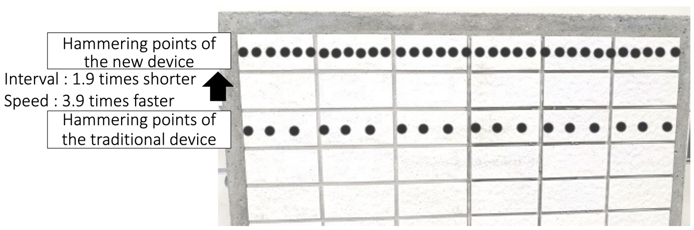


Figure 4: Top view of the new device



	New device	Traditional device
Number of hammering sounds in one row	35	18
Inspecting time for one row	1.4 sec	5.4 sec
Interval between consecutive hitting points	0.04 sec	0.3 sec

Figure 5: Comparison of hammering test speed and interval

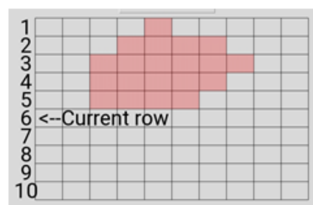


Figure 6: Image of the hammering test results displayed on a smartphone

3.2 How to show the results of the new device on display

The inspector needs a display to know the results of the hammering test with the new device because the intervals between the hammering sounds are short, and it is challenging to convey results with simple sounds or lights. This section explains how to display the results. Figure 6 shows the image of the hammering test results displayed on a smartphone. The black grid represents the shape of the tiles. First, the inspector records the hammering sounds of the tile wall one row at a time with a new device. Second, the smartphone indicates the flaking part of the inspected column with a red square. By repeating the above, the smartphone can clearly show the inspector the flaking part of the tiles.

3.3 NN model creation

Figure 7 shows the flow of NN model creation on the computer. First, we hit the tile test sample using the device in Figure 3, recorded the hammering sounds with a microphone, and sampled at 44.1 kHz [7]. Figure 8 shows a tile test specimen. The tiles with green dots represent the good parts (not flaking), and the tiles with red dots represent the bad parts (flaking). We captured the sounds on the computer and detected each hammering sound. We focused on the fact that the graph of the hammering sounds resembles an electrocardiogram (ECG) and used the peak detection algorithm of ECG to detect the hammering sounds. There are several different algorithms for peak detection, but we used Hamilton's algorithm [12]. Third, we used Fast Fourier Transform (FFT [10]) to convert the detected hammering sounds into frequencies. By converting sounds into frequencies, the machine can learn the features of the sounds. Fourth, we labeled the frequency data as Good or Bad. Finally,

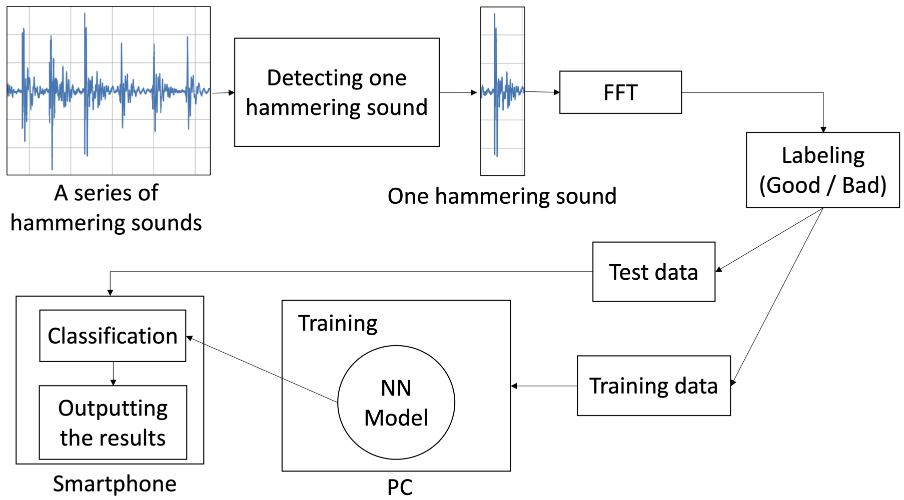


Figure 7: Flow of NN model creation on computer and the hammering sounds classification on smartphone

Table 2: Hyper parameters of NN

Structure of neural network	Input node : 2048 Hidden layer node : 32 Output node : 2
Activation Function	Relu
Optimizer	Adam

we created a NN model with these 8641 training data. Table 2 shows the hyperparameters of the NN model. We used TensorFlow as a machine learning library [6]. We transferred the NN model from the computer to the smartphone.

3.4 The flow of the hammering sounds classification using the NN model on a smartphone

Figure 7 also shows the flow of classifying the hammering sounds on a smartphone, and Figure 9 shows the pseudocode of processing. The sound recording, detection, and FFT method are the same as in the previous section. However, the difference is that we use smartphones instead of computers. After converting the hammering sounds into frequency data, we classified the data on the smartphone using the NN model. We used TensorFlow as a machine learning library on Pydroid3 [1]. We then output Good or Bad on the smartphone. Figure 10 shows a typical audio waveform caused by a tile hit by an inspection rod. The higher amplitude indicates the hammering sound at impact, and the vibration appears following the impact. Figure 11 is an audio waveform recorded by the device. The hammering sounds are recorded continuously. The interval between the hammering sounds is about 0.04 s. In other words, to continuously classify the hammering sounds, the hardware must process one hammering sound within 0.04 s.

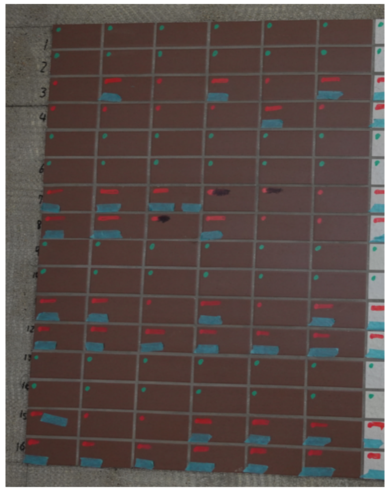


Figure 8: Tile test specimen

```
Record sounds and save the wave file.
wave_data = Read the wave file.

if wave_data == a hammering sound.
     window_function = Create a window function.
     fft_data = FFT(wave_data, window_function).
     nn_model = Read a neural network model.
     evaluated_data = nn_model.evaluate(fft_data)

     if evaluated_data == a good part.
          Save this label as a good part.
     else
          Save this label as a bad part.
else
     print(error).
```

Figure 9: Pseudocode of processing

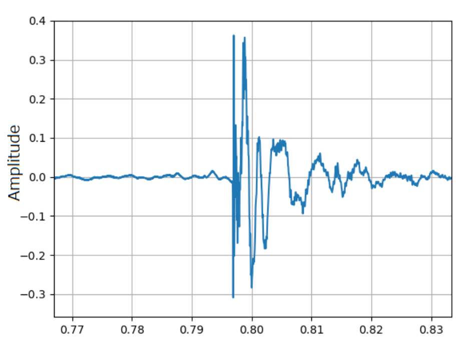


Figure 10: Audio segment

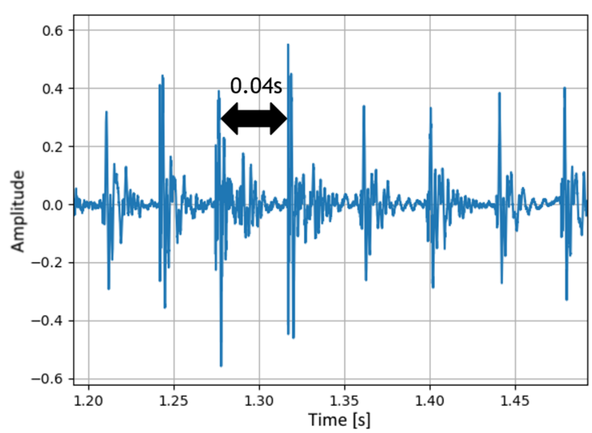


Figure 11: Waveform recorded by the new device

Table 3: List of experiments

	Hardware	GPU
EX1	Jetson Nano	Local
EX2	Smartphone	Local
EX3	Smartphone	Cloud (4G)

Table 4: List of experiments

	CPU	GPU	RAM	Weight
Jetson Nano [4]	ARM A57 Quad-core	Maxwell 128-core (921MHz)	4GB	140g
Huawei Nova3 [2] (Smartphone)	Kirin970 Octa-core (2.36GHz)	-	4GB	166g
Google Colaboratory [5]	-	Tesla K80 2496-core (875MHz)	8GB	-

4 Experiments to Compare Processing Time

4.1 Measurement of processing times

We performed three experiments to measure the time of the classification process, and we checked to see if the total time was within 0.04 s. In Experiment-1 (EX1), the hardware was Jetson Nano, and the GPU was local. In Experiment-2 (EX2), the smartphone (Huawei Nova3) was the hardware, and the GPU was local. In Experiment-3 (EX3), the smartphone's hardware and the GPU come from the cloud. We used Google Colaboratory as a cloud GPU. Table 3 shows these experiments, and Table 4 shows the hardware and GPU performance used. This smartphone is powered by android. Figure 12 represents the data flow between the smartphone and the GPU, where ST is the time taken to upload the data to the cloud GPU, RT is the time taken to download the result from the cloud GPU, and PT is the data processing time. We measured them in each of the above three experiments. Because ST and RT are the time to send and receive data to the cloud, they are 0 s in EX1 and EX2. Incidentally, the sound data and NN model used in the three experiments were the same.

Table 5 shows the accuracy of classifying 1120 sound data samples. In all experiments, the accuracy was consistent. We collected data for the research in the test environment so that evaluation in the actual situation is the further study. Table 6 shows the confusion matrix of EX1, EX2, and EX3. We combined them into one table since the results of EX1, EX2, and EX3 were the same. Table 7 shows the performance index calculated from the results in Table 6. Table 8 shows the accumulation of processing time of each segment, such as ST, RT, and PT. These results are the average of the 1120 sound sample data. When we measured them, the download speed was 33.2 Mbps, and the upload speed was 4.2 Mbps. From Table 8, only EX2 took less than 0.04 s for the whole classification process. "ST + RT" represents the communication time. We can see that EX3 has the fastest PT. As shown in Table 7, F-measure was 99.6% in the three cases (EX1, EX2, EX3), so the performance of the classification job on a smartphone is accurate enough.

Table 5: Accuracy of NN model by experiment

	Ephoc	Training data	Test data	Accuracy
EX1	30	8641	1120	99.6%
EX2	30	8641	1120	99.6%
EX3	30	8641	1120	99.6%

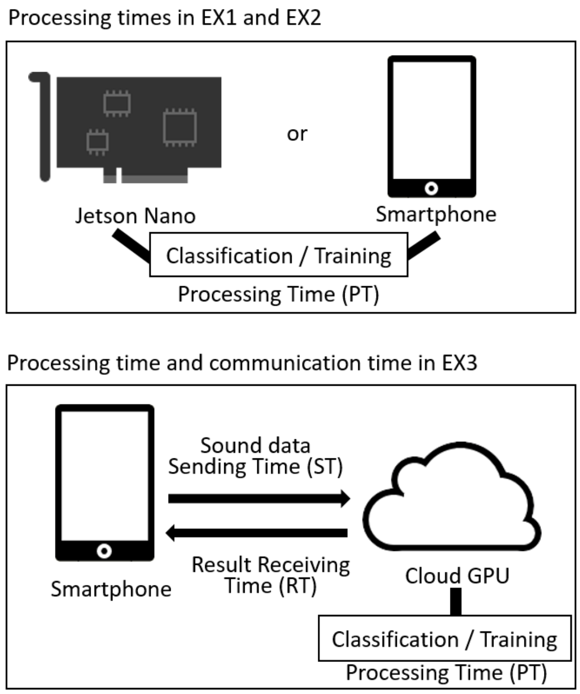


Figure 12: Relationship of each processing time

Table 6: Confusion matrix of EX1, EX2 and EX3

	Positive	Negative
Positive	TP 643	FP 0
Negative	FN 5	TN 472

Table 7: Performance index

Accuracy	99.6%
Precision	100%
Recall	99.2%
Specificity	100%
F-measure	99.6%

Table 8: Comparison of classification times (s)

	ST	RT	PT	Total	ST+RT
EX1	0	0	0.0500	0.0500	0
EX2	0	0	0.0382	0.0382	0
EX3	0.1148	0.0023	0.0128	0.1300	0.1172

Table 9: Comparison of the training times for the NN model (s)

	ST	RT	PT	Total	ST+RT
EX1-training	0	0	134.106	134.106	0
EX2-training	0	0	122.750	122.750	0
EX3-training	588.140	2.494	25.791	616.425	590.634

4.2 Comparison of training time for the NN model

We have developed a system that can classify the hammering sounds of tiles on a smartphone. However, the environment of the hammering test is always different, such as noise from cars and wind. In the future, we would like to train the NN model again by using Transfer Learning [13]. The training time can be reduced if we use GPU in the cloud. On the contrary, the communication time to upload training data could be a bottleneck. So, we performed the comparison of training time for the NN model. Recent high-performance smartphones can train NN models in a short time. In addition, in our previous study, we have shown that Transfer Learning is effective for training models in the field with little training data [11]. However, the environment to run Transfer Learning on the smartphone is not ready, so we compared the time to train the NN model on Jetson Nano (EX1-training), the smartphone (EX2-training), and the cloud GPU (EX3-training). We used the hyperparameters shown in Table 2. The number of training data is 8641, and the number of epochs is 30. Table 9 shows the result of the measurements of time for training. ST shows the time to send 8641 training data from the smartphone to the cloud GPU in the table. Then the NN model was created in the cloud. PT shows the time to create the NN model. RT shows the time to send the created NN model from the cloud GPU to the smartphone. Jetson Nano and the smartphone took more than two minutes to train a model each time, and this is not a reasonable time because we have to train the models for each type of tile. PT of the cloud GPU was about a fifth of the Jetson Nano and the smartphone, but the ST was too long.

4.3 Consideration of 5G use

The total time taken in EX2 was slightly less than 0.04 s; thus, if the inspector moved the hammer a little faster, the smartphone would not be able to classify the next hammering sound precisely. Thus, we need a method to classify the hammering sound with a shorter PT. The communication time is the bottleneck in EX3. If we can reduce the communication time, we can classify the hammering sounds much faster on smartphones. PT using the cloud GPU was the shortest training time, but ST was too long. If we can shorten the communication time, the training time will also be shorter. Thus, we considered using 5G for communication. We used 4G in EX3 and EX3-training, but 5G is 100 times faster than 4G [17]. However, we assume that the spot area with millimeter-wave expands worldwide. If we were to use 5G, ST + RT in EX3 would be 1/100th of the time (0.00117 s), and ST +RT in EX3-training would be 1/100th of the time (5.906 s). We conducted an experiment using 5G to test this assumption. We measured the communication times of EX3 and EX3-training using 5G instead of 4G. When we measured the communication speeds of 5G at Utsunomiya Station by using Galaxy S21, the download speed was 448.5 Mbps, and the upload speed was 100.8 Mbps when using Sub-6 GHz. The experimental environment other than the communication was the same as EX3 and EX3-training. Table 10 shows the results of the measurements of the communication times. The communication times (ST+RT) of EX3 and EX3-training using 5G were not as short as theoretical values. However, the total time in EX3 using 5G was well below 0.04 s. Figure 13 shows the classification times for EX1, EX2, EX3 and EX3 (5G) respectively. The classification speed of the smartphone using 5G is 1.46 times faster than the smartphone with the local GPU. Thus, the inspector can move the hammer 1.46 times faster than EX2. Figure 14 shows the training times for EX1-training, EX2-training, EX3-training, and EX3-training (5G), respectively. The training time through a smartphone using 5G was almost the same as that with a local GPU. If we use Transfer Learning, the communication time will be even shorter because we can reduce the training data.

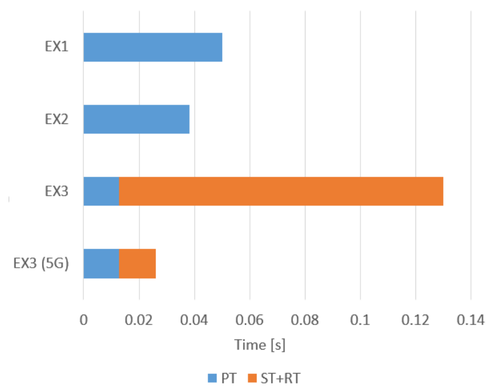


Figure 13: Graph of the accumulation of the classification times

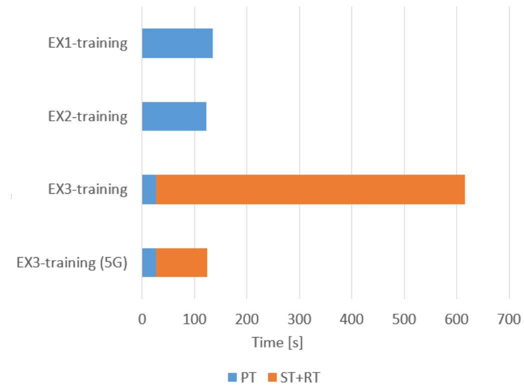


Figure 14: Graph of the accumulation of the training times

Table 10: Communication times using 5G (s)

	ST	RT	PT	Total	ST+RT
EX3 (5G)	0.0133	0.0001	0.0128	0.0262	0.0134
EX3-training (5G)	97.650	0.443	25.791	123.844	98.093

4.4 Comparison of battery life

We estimated the battery life for EX1, EX2, and EX3. We measured the battery life for EX2 and EX3; however, we did not use the battery for EX1. So, we estimated the battery life for EX1 from power consumption, assuming the battery capacity was 3750 mAh. Table 11 shows the result. The Jetson Nano consumed the least power, and the smartphone with the cloud GPU consumed the most power. However, the smartphone's battery life is sufficient for a day of the hammering test.

5 Conclusion

In this study, we studied the classification of the hammering sounds using the NN model on a smartphone. Because of the high performance of smartphones recently, the PT was shorter than that of Jetson Nano. Thus, this result shows that smartphones can classify the hammering sounds without a network connection. Additionally, the communication time was a bottleneck while using the cloud GPU. However, a 5G network can significantly reduce the communication time, and we can quickly classify the hammering sounds using a cloud GPU. Our experiments show that the overall classification time of the hammering test with a 5G network is 1.46 times faster than that of the traditional hammering test without a 5G network. We also need to select the most appropriate trained and trained model on-site since there are many types of tiles and different types of sound characteristics. Therefore, we measured the training times. As a result of the measurements, the training time using 5G was almost the same as the traditional training time. Transfer Learning can reduce the training time using 5G since Transfer Learning requires less training data. Therefore,

Table 11: Comparison of battery life

	Milliampere-hours	Voltage	Battery life
EX1	3750mAh	9V	14.29h
EX2	3750mAh	9V	9.4h
EX3	3750mAh	9V	8.4h

in the future, we will develop an easy way to train models on smartphones with 5G and the cloud GPU using Transfer Learning, and we will be able to choose the learning model depending on the type of tile. In addition, we expect that the use of beyond 5G can further improve the efficiency of the hammering test. Beyond 5G is a further advancement of 5G's features such as high speed, low latency, and many simultaneous connections, and has the features of low power consumption, reliability, scalability [9]. The processing speed will be even faster, and the smartphone's battery life will be extended in the hammering test. The inspector will also use a robot to inspect remotely by using beyond 5G because of low latency. It is easier to make a repair plan in parallel if we could share the inspection result simultaneously. In addition, we can create hazard maps of the flaking buildings to prepare for a large disaster such as a large earthquake by sharing the hammering data collected on a cloud through 5G.

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