

Article

Hammering Test for Tile Wall Using Deep Learning

Atsushi Ito ^{1,*}, Masafumi Koike ^{2,†}, Masako Saito ^{2,†} and Katsuhiko Hibino ^{3,†}¹ Faculty of Economics, Chuo University, 742-1 Higashi Nakano, Hachioji, Tokyo 192-0351, Japan² Department of Engineering, Utsunomiya University, 7-1-2 Yoto, Utsunomiya, Tochigi 321-8585, Japan; koike@is.utsunomiya-u.ac.jp (M.K.); m_saito@cc.utsunomiya-u.ac.jp (M.S.)³ PORT DENSHI Corporation, 5-8-2 Miyanishi, Fuchu, Tokyo 183-0022, Japan; hibino@port-d.co.jp

* Correspondence: atc.00s@g.chuo-u.ac.jp

† These authors contributed equally to this work.

Abstract: Economic activities heavily rely on social infrastructure, such as bridges, tunnels, public structures, and buildings. In Japan, regular inspections are mandated by law to ensure these assets remain functional. This kind of requirement is rare worldwide. Similar regulations exist only in major cities in the United States and Canada. These inspections often focus on detecting issues that are not visible to the naked eye, such as cavities within concrete walls. The most widely used method for such inspections is the hammering test, in which inspectors analyze the sound variations produced when a hammer strikes a surface. By interpreting these auditory changes, they can assess the structural integrity and identify hidden defects within a structure. While effective, the accuracy of this method strongly depends on the inspector's sensory perception, which varies with individual experience and skill. Furthermore, because the test is conducted manually, it is time-consuming, especially for large-scale structures. The most critical problem is the shortage of skilled inspectors due to retirement. It is difficult to meet the demand for inspections. To solve this problem, this paper proposes an AI-based hammering test system that analyzes and evaluates structural health by detecting abnormal sounds during inspections. This system allows even less-experienced workers to accurately identify defective areas. The focus of this study is on the application of AI-driven sound analysis for inspecting adhesive-applied tile walls, a common feature in modern apartment buildings. By integrating AI technology, this approach promises to improve the consistency and quality of inspections, reduce reliance on human expertise, and significantly enhance the overall efficiency of the inspection process.

Keywords: hammering test; non-destructive testing; adhesive-applied tile wall; deep learning



Academic Editors: Chen Wang,
Mukhtar A. Kassem, Lincoln C. Wood
and Jeffrey Boon Hui Yap

Received: 31 December 2024

Revised: 26 January 2025

Accepted: 29 January 2025

Published: 1 February 2025

Citation: Ito, A.; Koike, M.; Saito, M.; Hibino, K. Hammering Test for Tile Wall Using Deep Learning. *Appl. Sci.* **2025**, *15*, 1500. <https://doi.org/10.3390/app15031500>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The aging of various social infrastructures and buildings has become a problem in recent years. So, the demand for infrastructure inspection services is increasing. This trend highlights the growing necessity for thorough assessments and maintenance of our infrastructure systems to ensure their safety and functionality for the future. As the condition of these structures will continue to deteriorate, the need for specialized inspection services will likely continue to escalate, emphasizing the importance of proactive measures in infrastructure management.

Infrastructure inspection encompasses a variety of maintenance and management tasks, with particular attention given to diagnosing structural integrity and assessing seismic resistance. For hard-to-reach areas, such as large bridges and the exterior walls of

high-rise buildings, inspection robots and drones are increasingly being used in place of traditional scaffolding [1].

While numerous methods exist for detecting hidden anomalies, such as those within concrete walls, including techniques like infrared inspection [2] and electromagnetic wave testing [3], the hammering test remains a widely employed method. This technique assesses the condition of the interior by analyzing the sound produced when the surface of the wall is struck with a hammer.

The hammering test is a highly accurate and cost-effective inspection method; however, it requires the expertise of experienced inspectors to correctly distinguish abnormal sounds. Figure 1 illustrates the fundamental principle behind the hammering test. When a structure is in good condition, with no cracks or cavities, the sound produced by the hammer strike closely resembles an impulse response, characterized by higher frequencies. Conversely, if the structure has issues such as cracks or cavities, the resulting sound is prolonged, reverberating with lower frequencies, indicating potential problems with the integrity of the structure.

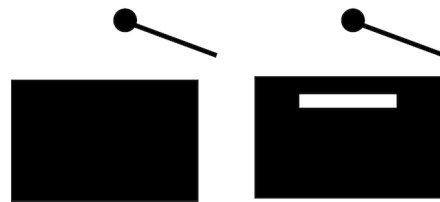


Figure 1. The idea of the hammering test of structures.

The decline in the number of skilled inspectors is becoming a significant concern due to the aging of the workforce. Hammering tests are essential for inspecting two main types of structures: concrete constructions such as bridges and high-rise buildings and decorative tiles commonly found in condominiums and low-rise buildings. The use of tiles as a form of decoration has a long history, dating back over 5000 years to the invention of pottery. Today, tiles continue to be a popular choice for exterior finishes, especially for apartment buildings, as they contribute to the aesthetic appeal of the structures.

There are two predominant methods for attaching tiles to surfaces: the mortar-applied method and the adhesive-applied method. The use of mortar to attach tiles dates back to ancient times, including the Egyptian dynasty. However, mortar-based tile adhesion is prone to large-scale peeling, meaning that when tiles start to peel, they tend to detach over a wide area. To address this issue, adhesives with stronger bonding capabilities have been recommended, as they localize the peeling to smaller areas. While adhesives are already widely used in more than half of newly constructed tiled buildings in urban areas, their adoption in rural areas has been slower due to the higher costs associated with their use.

Our research has focused on developing a method that enables even unskilled workers to perform hammering inspections efficiently by employing deep learning techniques to distinguish between different hammering sounds [4]. However, these efforts have so far been limited to inspecting tile walls adhered with mortar.

When it comes to adhesive-backed tile walls, peeling tends to be confined to individual tiles rather than large areas. This is because the adhesive material dampens the sound and vibration caused by the peeling, making it difficult to detect through traditional sound inspection methods. Even experienced inspectors face challenges in making accurate judgments under these conditions. As a result, ICT solutions have not yet been fully applied to sound-based inspections for adhesive-bonded tile walls. Instead, non-destructive testing methods, such as physically removing tile samples for closer inspection or using large, specialized equipment, are often employed to assess the condition of the tiles.

Building on our prior experience developing techniques for applying neural networks to sound inspections of concrete walls, we sought to extend this approach by creating an AI system capable of accurately evaluating the sound produced during inspections of adhesive-applied tile walls. Such inspections are challenging, even for skilled inspectors, because judging structural integrity based on sound alone is difficult.

The organization of this paper is structured into several key sections. In Section 2, a comprehensive review of the existing literature relevant to the study is presented, highlighting the contributions and findings of previous research in this field. Section 3 provides an overview of the hammering test and the research environment, detailing the specific conditions and setup for conducting the hammering test on tiles that have been applied using adhesive. Additionally, this section describes the methodology employed to ensure accurate and reliable results during the testing process. Moving on to Section 4, the performance of the artificial intelligence model developed specifically for analyzing the outcomes of the hammering tests is thoroughly evaluated, discussing its effectiveness and any notable findings. Finally, Section 5 concludes the paper with a summary of the study's findings, along with a discussion of the implications these results hold for future research and practical applications in the industry.

2. Related Works

2.1. Testing of Adhesive-Applied Tile Wall

We conducted tests on tiles applied to a wall using adhesive methods to evaluate their durability and adhesion strength. Numerous investigations have explored the issue of tile adhesion to exterior walls. For example, in the study referenced as [5], it was found that the stress experienced at the adhesive interface can sometimes surpass the adhesive's bond strength, ultimately resulting in the detachment of tiles. Furthermore, the research cited in [6] indicates that tile walls bonded with adhesive exhibit a significantly greater relative maximum amplitude within the sound zone when compared to those constructed using traditional mortar bonding techniques. These findings highlight the critical role of the adhesive properties in ensuring the durability and stability of tiled surfaces on exterior walls. Reference [7] highlights that when a cavity exists beneath a tile, two distinct frequency peaks can be detected, which produces a dull, muddy sound. Reference [8] reveals that detecting small floating areas can be challenging in sound inspections for tile walls. Despite these findings, research involving neural networks in this field has been lacking, prompting this study to assess the practical viability of such an approach.

2.2. Hammering Test

Several studies have explored hammering tests utilizing ICT-based methods. The research presented in [9,10] introduces advanced techniques for inspecting concrete that does not involve the use of hammers. However, it is essential to note that these methods necessitate the use of costly equipment, which may limit their accessibility for some users. As a result, while these innovative approaches offer a promising alternative to traditional inspection methods, the financial investment required for the necessary tools could be a significant consideration for potential adopters. Moreover, there still needs to be more research specifically focused on tile walls. In a study similar to ours, detailed in reference [11], the authors investigate sound-based hammering inspections, yet no research involving tiled walls was conducted. In our prior work, we examined hammering sound inspections for mortar-applied tile walls using neural networks [12], and the results from that research were applied to our current investigation.

3. Non-Destructive Test for Adhesive-Applied Tile Wall

3.1. Hammering Test

Huge structures, such as bridges, dams, and buildings, are made of concrete. In addition, low-rise buildings such as apartment buildings are often covered with tiles for decorative purposes. This paper focuses on a technique for testing the adhesive-applied tiles for exterior use. If the adhesion rate of a tile is low, the tiles may fall off and injure people walking near a building. Traditionally, mortar has been used as an adhesion method for exterior tiles. However, in recent years, adhesives have increasingly been used. In Japan, Article 12 of the Building Standard Act [13] mandates that a “visual survey and partial hammering test” be conducted every two or three years and a “full hammering survey” every 10 years.

- Visual survey: This test involves observation of the exterior using the naked eye, binoculars, telescope, etc., and a hammering test of the area within reach using a test hammer.
- Full hammering test: This test consists of a hammering test using a test hammer or an infrared survey.

In Japan, the number of apartment rooms is about 6.4 million and there were 0.12 million apartment buildings in 2022 [14], so that it is required 12,000 apartment buildings should be checked every year.

The infrared survey measures the surface temperature of tile surfaces using an infrared imaging device to determine sound and cavity under tiles. This method can be used when the area of the cavity is large, as in the case of mortar tile walls. However, it is difficult to detect small cavities, as in the case of adhesive-applied tile walls. Figure 2 displays the difference in the cavity behind a tile wall. In the case of the tile wall with mortar, the cavity behind the tiles is large; on the other hand, in the case of an adhesive-applied tile wall, the cavity is small. So, it is difficult to detect cavities behind the adhesive-applied wall. In inspections of mortar tile walls, not only a hammering test but also an infrared inspection is used. However, in the case of adhesive-applied tile walls, it is difficult to detect cavities using infrared inspection because the cavity is small. Therefore, a hammering test is necessary for adhesive-applied tile walls. However, the adhesive absorbs the sound caused by the hammer, making it difficult to distinguish the difference in sound.

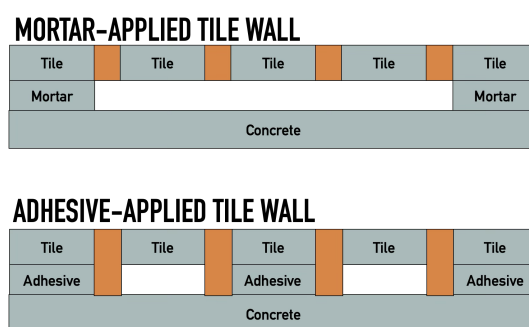


Figure 2. Tile wall applied using mortar and adhesive.

Recently, a technique to use microwaves has been developed [15]. The problem is measuring time. In [16], it is mentioned that it takes 30 s to test a tile using a microwave; on the other hand, it takes 0.3 s using the hammering test. So, the hammering test is the only method available.

So, we have started to develop an AI-based hammering test for adhesive-applied tile walls.

The Architectural Institute of Japan (AIJ) publishes *JASS (Japanese Architectural Standard Specification)*, which is a standard specification for building construction. In *JASS19* [17], page 163, it is mentioned that the rate of an adhesive-applied tile should be 60% or more. Therefore, it is important to distinguish whether it is over 60% or not, and it is not necessary to estimate the adhesion ratio exactly. This research aims to develop an AI model to determine whether the adhesion ratio of a tile is above or below 60%. It is not necessary to accurately determine adhesion rates such as 100%, 80%, 50%, 0%, etc.

A tile hammering test tool (hammering rod) for tile walls is shown in Figure 3. It consists of a steel or plastic rod with a 17–19 mm steel ball attached to the end of the rod. They weigh 70 to 200 g and are 130 to 2010 mm in length, and the price is between USD 15–USD 30 [18]. On the other hand, the price of a typical piece of infrared thermography equipment costs between USD 1500–USD 3000 [19]. So, the hammering test device is cheaper than other test devices.



Figure 3. Hammering rod.

Although there is no clear national standard for inspection tools used in the hammering test for tile walls, these tools are a de facto standard. On websites selling tools for construction, you will not find anything other than this kind of tool. On the other hand, for concrete, on page 9 of [20], “An inspection hammer (half-pound) should be used for hammering inspections”. Also, Nippon Expressway Company Limited (NEXCO, the highway construction and maintenance company in Japan) asks the civil engineering companies to use two types of hammer for inspection [21]. One is a half-pound hammer, and the other is a rolling hammer (see Figure 4).



Figure 4. Rolling hammer.

When using a testing rod for hammering test on a tile wall, an inspector usually swipes and rubs a tile wall with a small iron ball on the top of the testing rod. Hammers for concrete are too big for a tile wall. A ceramic tile is broken if we use this tool on a tile wall.

3.2. Hammering Test for Adhesive-Applied Tile Wall

For our hammering tests on tile walls, we have traditionally employed a rolling hammer [22]. However, the rolling hammer was originally designed for inspecting concrete

walls, where a stronger impact is necessary. Due to its forceful nature, using this tool on tile walls made of thin ceramic tiles carries the risk of damaging or breaking the tiles.

For tile wall inspections, a hammering rod is typically preferred. This tool generates a friction sound by rubbing a small metal ball attached to the end of an inspection rod against the tile surface, as illustrated in Figure 5. This method provides a gentler approach, minimizing the risk of damaging the tiles while still allowing for effective inspection.



Figure 5. Hammering test on a tile wall (rubbing the surface).

3.3. Test Specimen

The specimen depicted in Figure 6 consists of a total of 18 tiles, which are systematically arranged in a grid format featuring three horizontal rows and six vertical columns. This specific layout was chosen to facilitate detailed analysis and observation throughout the research process. Each tile plays a crucial role in the overall configuration, contributing to the integrity and purpose of the specimen in our investigations. A concrete board serves as the backing for the tiles.

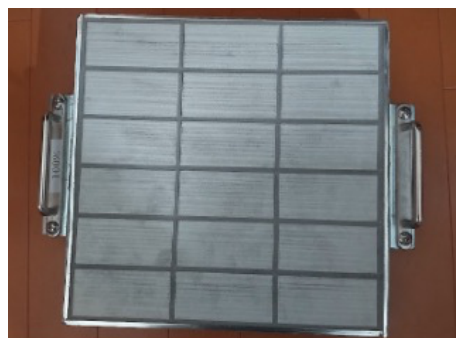


Figure 6. Test specimen for this experiment.

As shown in Figure 6, each tile has dimensions of a 6.75 cm length and a 14.25 cm width, and the total length of each row, including the joints, measures 44.25 cm.

According to the standards set by the Ministry of Land, Infrastructure, Transport, and Tourism [5], along with the guidelines provided by the tile industry [6], at least 60% of the tile's back surface should be adhered to the concrete wall. To reflect different bonding

conditions, we used four different specimens with adhesion rates of 100%, 80%, 60%, and 0%. Figures 7–10 show the respective adhesion conditions for 0%, 60%, 80%, and 100%.

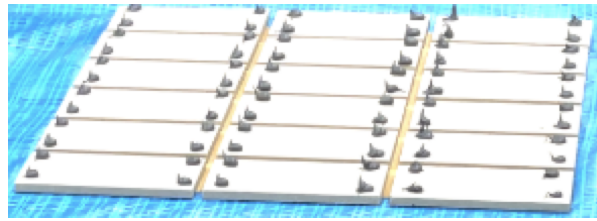


Figure 7. An example of 0% adhesion.



Figure 8. An example of 60% adhesion.



Figure 9. An example of 80% adhesion.



Figure 10. An example of 100% adhesion.

3.3.1. Procedure of Experiment

The experimental procedure for the hammering test conducted in this study is outlined in Figure 11. During the test, the sound produced by each strike was captured using the microphone of a smartphone that was set near the specimen by using a tripod. The sound generated from each tile was then isolated by separating the audio at the tile joints. Frequency components were extracted using the Fast Fourier Transform (FFT) and fed into a Deep Neural Network (DNN) model to evaluate the extent of peeling.

The process of preparing the data for this experiment followed several steps. First, the sound was recorded by rubbing the tile surface with a rod equipped with a 2 cm diameter sphere, as shown in Figure 3. The recording was performed using a smartphone positioned at a fixed distance, and 12 recordings of approximately 30 s each were made for every specimen. The audio data were extracted from the video files and converted to mono format. Silent sections were manually removed to ensure the data were clean for analysis.

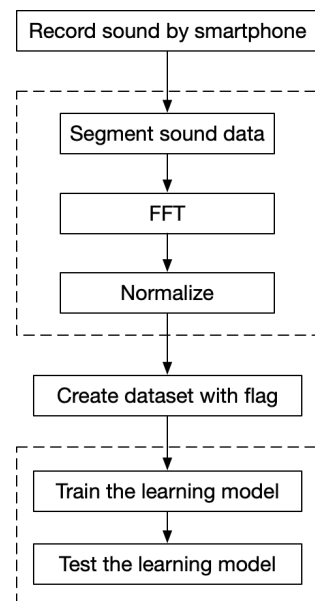


Figure 11. Procedure of experiment.

3.3.2. Recording Sound

Sounds were captured by rubbing the surface of the tile with a hitting rod equipped with a sphere that had a diameter of 2 cm, as illustrated in Figure 4. To ensure consistency, a smartphone was positioned at a fixed distance from the tile during the recording sessions. In total, 12 recordings were made for each specimen, with each recording lasting approximately 30 s. Following the recordings, the audio files were extracted from the corresponding videos and converted to a mono format for ease of analysis. Additionally, any silent sections within the recordings were meticulously removed to enhance the quality of the sound data.

The accurate assessment of the bonding condition for each individual tile is vital when inspecting adhesive-laminated tile walls. Therefore, it was necessary to isolate the sounds associated with each tile from the continuous friction noises that occurred during the inspection process. This isolation was achieved through effective segmentation techniques, which proved to be a fundamental aspect of the study. By segmenting the sounds, researchers were able to focus on the specific acoustic signatures of each tile, allowing for a more detailed and precise evaluation of their bonding conditions. The audio data were segmented using Python, adhering to the outlined steps detailed below. This process involved several methodical stages to ensure accurate division and analysis of the audio files. Each step was carefully executed to maintain the integrity of the original data while facilitating further examination and processing. Below are the steps we followed in detail.

1. Load the audio data using the librosa library [23]
2. Analyze the audio waveform to define the segment length L and the overlap rate O
3. Proceed with the segmentation. Each segment S_i , where i represents the i -th segment, is generated according to the formula below. Here, “audio” refers to the audio data, and “ n ” is the starting sample index for the segmentation.

$$S_i = \text{audio}[n : n + L], \quad n = i \times (L - L \times O)$$

4. Each sound sample is stored as a separate file to facilitate analysis by artificial intelligence systems. This approach allows for better organization and processing of the audio data, enabling AI to perform more effective evaluation and learning.

Table 1 presents the number of sampled sounds for each adhesion rate obtained using the segmentation method described above.

Table 1. The number of samples.

Adhesion Rate	The Number of Samples
100%	2313
80%	2375
60%	2435
0%	2389

3.3.3. Extracting Features of Sound

The Fast Fourier Transform (FFT) was employed to derive significant features from the speech data. This powerful technique is particularly effective for analyzing the frequency characteristics of speech signals, as it facilitates the conversion of these signals from their original representation in the time domain to a new form in the frequency domain. The transformation can be mathematically expressed through the following equation:

$$X_k = \int_{n=0}^{N-1} x_n e^{-j \frac{2\pi}{2048} kn}$$

In this study, we denote X_n as the signal in the time domain, while $x(k)$ represents the corresponding signal in the frequency domain. The total number of samples is indicated by N . For the transformation process, we utilized the `np.fft.fft` function from the widely used NumPy library in Python, as referenced in [24]. Specifically, a 2048-point Fast Fourier Transform (FFT) was computed, a standard procedure frequently employed in various speech-processing applications. This method was chosen as appropriate given the sampling rate of 44.1 kHz used for the recordings in this research. The calculation of the FFT was conducted according to the mathematical formula outlined below, which ensures a precise representation of the signal's frequency components. The choice of a 2048-point FFT is particularly beneficial, as it allows for a detailed analysis of the frequency spectrum while maintaining computational efficiency, making it a popular choice in the realm of audio signal processing.

$$X_k = \int_{n=0}^{2047} x_n e^{-j \frac{2\pi}{N} kn}$$

The inherent symmetry present in the results generated by the Fast Fourier Transform (FFT) allows for the utilization of only the first 1024 points of the computed frequency components. This selective approach effectively captures the essential aspects of the full spectrum of frequency information. By focusing on these initial points, we are able to extract significant frequency domain features from each segment of the speech data. These features play a crucial role in the subsequent data analysis and serve as foundational elements for training the machine learning models employed in this study. It is noteworthy that the FFT was systematically applied to all the data collected throughout this research. Prior studies have consistently shown that the frequency domain data derived from the FFT transformation provides enhanced accuracy compared to the original time-domain data. Adopting this methodology ensures a more robust and dependable analysis of the speech signals, facilitating better insights and interpretations from the data gathered.

3.3.4. Normalize

The features obtained from the FFT were then processed through a normalization procedure. This step was carried out using the `fit_transform` method, as outlined in [25], from the Standard Scaler library. Each set of data, corresponding to different adhesion rates,

was normalized separately. The normalization process was conducted according to the following formula, where x is the original feature, u is the mean of the feature, and s is the standard deviation of the feature. This process ensured that the features were standardized before being used for further analysis.

$$Z = (x - u) / s$$

The data were transformed by standardizing each feature so that it had a mean of 0 and a standard deviation of 1 for each adhesion rate. This scaling process was important for training and testing the deep learning model effectively. Standardization helps the model train more smoothly and improves its ability to work well with new, unseen data. The dataset was divided into three parts: 60% was used as the training set to help the model learn patterns, 20% was used as the validation set to fine-tune and evaluate the model during development, and the remaining 20% was used as the test set to check how well the model performs on new data. Using this prepared dataset, we developed a four-class classification model to identify data belonging to different adhesion rates.

At last, we show the difference in the sounds of each specimen in Figures 12–15.

From these graphs, it is clear that each graph has different characteristics. In particular, in the case of an adhesion rate of 100%, the tile did not vibrate. On the other hand, in the case of other adhesive rates, each specimen caused different spectrum patterns. So, we expected to obtain a learning model to distinguish the tile wall sounds caused by different adhesive rates.

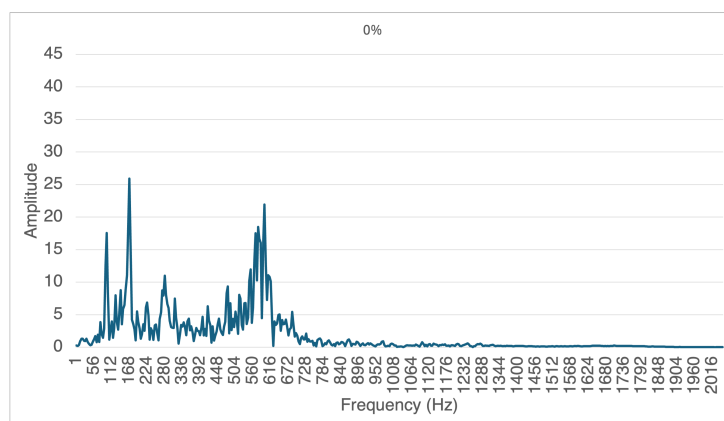


Figure 12. Power spectrum of the sound at 0% adhesion.

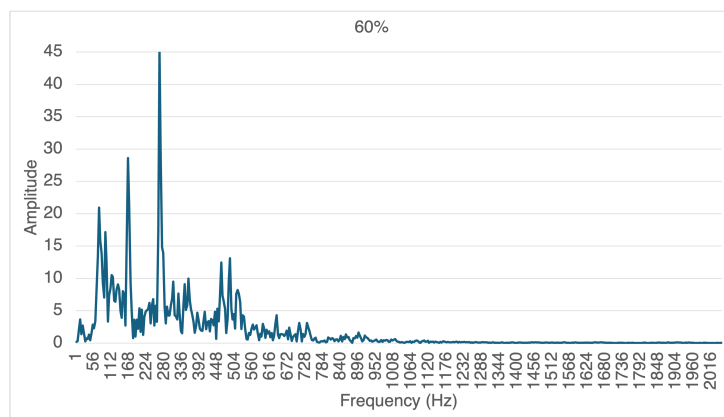


Figure 13. Power spectrum of the sound at 60% adhesion.

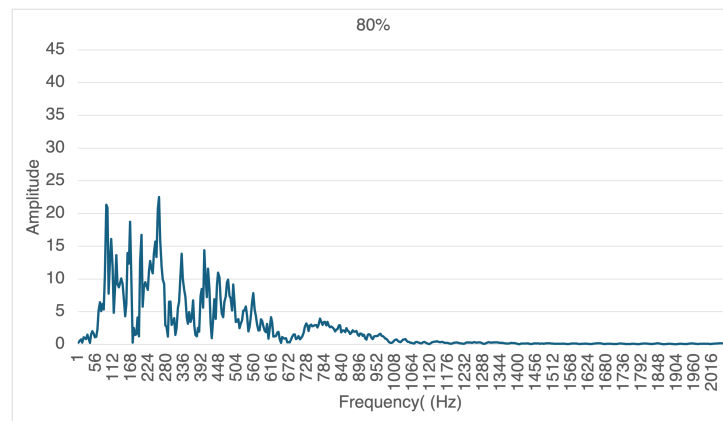


Figure 14. Power spectrum of the sound at 80% adhesion.

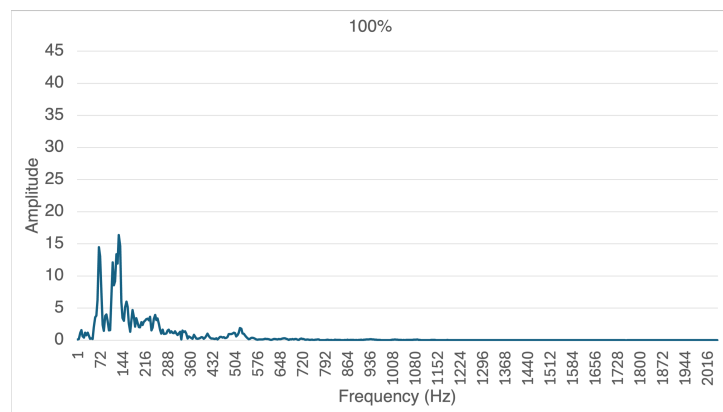


Figure 15. Power spectrum of the sound at 100% adhesion.

4. Learning Model and Evaluation

4.1. Our Learning Model

This study used TensorFlow 2 and Keras to build a deep learning model, named Model-1, which was designed to classify adhesion rate data into four categories. For each dataset of adhesion rates, Model-1 was trained and optimized to enhance the accuracy of classification, enabling precise differentiation among these four distinct classes, namely 100%, 80%, 60%, and 0%.

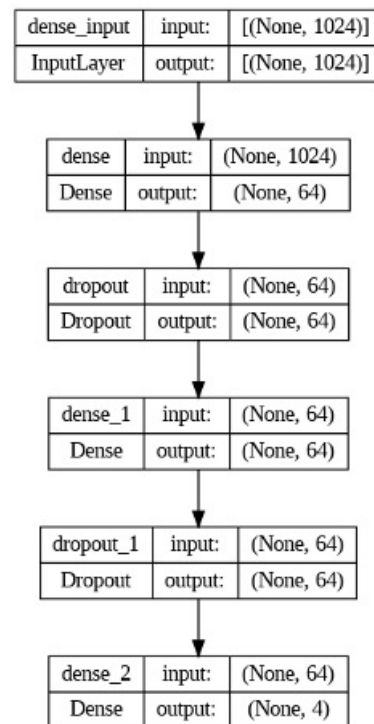
Figure 16 illustrates Model-1's detailed architecture. The model starts with an input layer, which is followed by a fully connected (dense) layer containing 64 units. After this, there is a dropout layer with a rate of 50%, helping to prevent overfitting. In the next step, another dense layer with 64 units is used, followed by a second dropout layer with the same 50% rate. The model concludes with an output layer of four units designed to produce the final predictions. This layered structure is intended to balance model capacity and generalization.

4.2. Hyperparameters

The hyperparameters used in this study are listed in Table 2. The model was trained using the Adam optimizer and the sparse categorical cross-entropy loss function. These settings were selected after careful analysis of learning curves from earlier experiments to ensure optimal performance. The training process used a batch size of 32 and ran for 75 epochs. This configuration was fine-tuned based on insights gained from multiple experimental trials, aiming to maximize the model's learning efficiency and accuracy.

Table 2. Hyperparameters of Model-1.

Adhesion Rate	Number of Samples
Activation (hidden)	Relu
Activation (output)	Softmax
Optimizer	Adam
Epoch	75

**Figure 16.** Structure of our learning model (Model-1).

4.3. Experiment

The accuracy achieved by Model-1 on the test dataset was around 82.40%. This result indicates a strong performance, reflecting the model's effectiveness in handling the test data and suggesting its reliability in similar tasks. The precision, recall, and F1 scores for each adhesion rate are presented in Table 3, while the corresponding confusion matrix is depicted in Figure 17. These metrics provide a detailed assessment of the model's performance in classifying each adhesion rate.

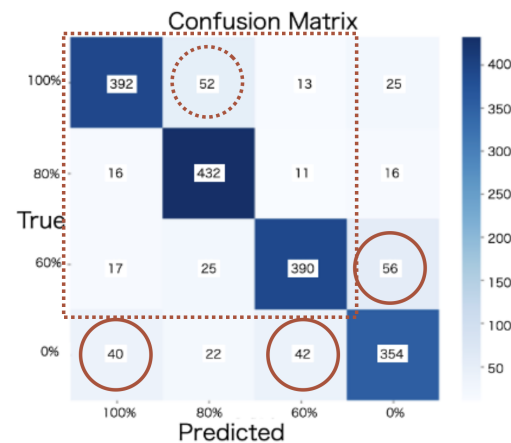
While there were instances of errors in identifying tiles with 0% adhesion, the model demonstrated consistent performance across all adhesion levels, achieving precision, recall, and F1 scores of over 77% in each case. This suggests that despite some misclassification at the lowest adhesion rate, the model maintains a strong ability to detect varying levels of adhesion with a high degree of accuracy. The outcome demonstrates the model's suitability for practical applications. In typical scenarios, the same area is tested multiple times. Assuming the accuracy of each individual test is 77%, testing the area three times would result in an overall accuracy of 88%.

A red dotted box in Figure 17 shows over 60%. So, the misjudgment in this area is not a problem. We need to consider the misjudgment of the outside of the box.

1. Of the data classified at 0%, 354 samples were correctly classified at 0%.
2. Of the data classified at 0%, 97 samples were misclassified as other.
3. Of the data classified at 60, 80, and 100%, 104 samples were misclassified as 0%.

Table 3. Result of the experiment (precision, recall, and F1 score).

Adhesion Rate	Precision	Recall	F1
100%	84.30%	81.33%	82.79%
80%	81.36%	90.95%	85.88%
60%	85.53%	79.91%	82.62%
0%	78.49%	77.29%	77.89%

**Figure 17.** Confusion matrix of the experiment.

Although there was only a limited amount of misclassified data, we aim to conduct a more in-depth investigation into the patterns and tendencies of this misclassification in future studies. The results from this experiment show the potential of utilizing neural networks to analyze hammering sounds by leveraging the friction sounds produced on tile walls where the adhesive has been applied. It was additionally verified that the friction sounds, corresponding to different levels of adhesion rates, demonstrate unique characteristics that a neural network can identify with high levels of accuracy and distinction.

4.4. Discussion

It is not necessary to make an accurate determination with a single test. Usually, the same area is inspected at least twice (swipe left to right and right to left) with a hammering rod and possibly several times. Table 4 shows the accuracy of detecting the cavity under a tile according to the number of swipes on a tile wall. Let us assume the good accuracy is over 95% and the cell color is gray in Table 4. If the learning model's accuracy is 80%, high accuracy can be determined if the test is performed twice or more. If it is 60%, fairly good accuracy can be obtained if the test is performed third or more.

Table 4. Estimation of accuracy in the real hammering test; N is the number of sweeps on the wall.

Accuracy	$1 - (1 - \text{Accuracy})^N$			
	Once	Twice	Three Times	Four Times
0.8	80.0%	96.0%	99.2%	99.8%
0.7	70.0%	91.0%	96.3%	99.2%
0.6	60.0%	84.0%	93.6%	97.4%

If the accuracy is 60%, it is possible to obtain fairly good accuracy if the test is performed three times or more.

From Figure 17, the total number of measurements was 1902. The problem is a False Positive (FP) case, such as misjudging 0% as 60, 80, or 100%. From the figure, the FP case is 5.1% (97 cases). The result shows that the accuracy is good. Of course, in the real case, the

accuracy will become lower; however, if the FP is over 80% and one swipes the tile surface twice, the possibility of misjudgment is about 4%.

5. Conclusions

This study presents the result of our research findings on using deep learning for hammering tests on tile walls that used adhesive to fix the tiles. This scenario is known to be particularly challenging even for experienced inspectors to identify problems. In prior research, we had already verified the effectiveness of applying deep learning to hammering tests for tile walls using mortar to fix the tiles. In this research, we conducted additional validation to confirm that deep learning techniques can effectively assess structural health by analyzing the friction sounds produced when an inspection stick with a spherical tip rubs against tile walls. This method, frequently employed in inspection settings, provides valuable auditory data for evaluating structural integrity, which our study has demonstrated can be interpreted accurately by deep learning models.

Moreover, the deep learning technique successfully classified the sound caused by friction using an inspection rod recorded in four classes, such as 100%, 80%, 60%, and 0% adhesion rates. In this study, we have successfully identified unique characteristics that enable the neural network to accurately distinguish between different adhesion rates. These distinctive features serve as key indicators, allowing the model to discern variations in adhesion levels across different samples effectively. These findings underscore the potential for creating a hammering test system capable of handling diverse adhesion rates. By training the model on data that span a broad array of adhesion conditions, such a system could be developed to adapt effectively across varying levels of adhesion.

Looking ahead, we plan to study adhesion rates in more detail by testing additional samples, such as those with adhesion rates of 20% and 40%. When we analyzed the confusion matrix, we noticed that the misclassified data often clustered around a specific adhesion rate. Interestingly, these mistakes did not always match the closest adhesion rate. This suggests that we need to introduce more precise and effective models to process the sound and also use more powerful machine learning techniques. In the future, we will take a closer look at these errors to better understand what is causing them and improve our methods.

In the real situation, we need to consider environmental noise such as road noise since we usually check the outsides of buildings. The sound caused by a tile piece is around 5 kHz. However, the road noise is 20 to 500 Hz [26]. A test in the real environment is for a future study. However, we think it is easy to filter road noise.

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

Funding: This research was supported by JSPS Kakenhi (24K14987, 23K28338, 23H03649, 22K12598, 20H05702) and Tokyo Metropolitan Small and Medium Enterprise Support Center.

Institutional Review Board Statement: This study did not involve humans or animals.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors thank Nishimura of Fujiyogyo Co., Ltd., for developing test specimens.

Conflicts of Interest: The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results. Author K.H. is working at PORT DENSHI Corporation, however there is no financial relationships that could be construed as a potential conflict of interest. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Terra Drone. Inspection Services. Available online: <https://terra-drone.net/service/inspection> (accessed on 24 January 2025).
2. Ministry of Land Infrastructure Transport and Tourism. Guidelines for Exterior Wall Surveys by Infrared Surveys (Including Infrared Surveys by Unmanned Aerial Vehicles) Under the Periodic Reporting System. Available online: <https://www.mlit.go.jp/jutakukentiku/build/content/001474154.pdf> (accessed on 24 January 2025).
3. Just-Corporation. Non-Destructive Testing by Electromagnetic Waves. Available online: <https://www.just-ltd.co.jp/service/existing/concreteexploration/electrowave/> (accessed on 24 January 2025).
4. General Construction Association of Fukuoka. Seminar on Construction Problems Seen in Tile Peeling and Problem-Solving from a Legal Point of View. Available online: <http://fukukenkyo.org/slide-koga.pdf> (accessed on 24 January 2025).
5. Soeda, T.; Mikami, T. Basic study into a diagnostic system for exterior tile debonding. *AIJ J. Technol. Des.* **2016**, *81*, 1779–1787. [CrossRef]
6. Yokoi, M. A study on diagnosis method using hammering test. *J. Osaka Sangyo Univ. Nat. Sci.* **2021**, *131*, 59–69.
7. Makatayama, M.; Tanano, H.; Nemoto, K. Research on the diagnostic accuracy of the tile finish external wall by various measuring methods. *AIJ J. Technol. Des.* **2015**, *21*, 919–924. [CrossRef]
8. Kasahara, L.; Fujii, H.; Yamashita, A.; Asama, H. Unsupervised learning approach to automation of hammering test using topological information. *Robomech. J.* **2017**, *4*, 13. [CrossRef]
9. Kurita, K.; Oyado, M.; Tanaka, H.; Tottori, S. Active infrared thermographic inspection technique for elevated concrete structures using remote heating system. *Infrared Phys. Technol.* **2009**, *52*, 208–213. [CrossRef]
10. Akamatsu, R.; Sugimoto, T.; Utagawa, N.; Katakura, K. Proposal of non contact inspection method for concrete structures using high-power directional sound source and scanning laser doppler vibrometer. *Jpn. J. Appl. Phys.* **2013**, *52*, 07HC12. [CrossRef]
11. Ministry of Land Infrastructure, Transport and Tourism. Periodic Report of the Result of Investigation of Tiles on Exterior Walls. Available online: https://www.mlit.go.jp/jutakukentiku/build/jutakukentiku_house_tk_000161.html (accessed on 24 January 2025).
12. Ministry of Land Infrastructure, Transport and Tourism. Study on Rationalization of Periodic Survey Methods for Wet Exterior Walls. Available online: <https://www.mlit.go.jp/common/001129988.pdf> (accessed on 24 January 2025).
13. Building Standard Act. Available online: <https://laws.e-gov.go.jp/law/325AC0000000201> (accessed on 24 January 2025).
14. Condominium Management Companies Association. Survey Report. 2024. Available online: https://www.kanrikyo.or.jp/report/doukou_r04.html (accessed on 24 January 2025). (In Japanese)
15. Osaki, S.; Mase, A.; Hirata, Y.; Iwakura, M. Imaging Diagnostics of Inside of a Building Wall Using Millimeter-Wave Reflectometer. *Appl. Sci.* **2022**, *12*, 2879. [CrossRef]
16. Daisue Construction Co., Ltd. Development of the Non-Destructive Electromagnetic Wave (Microwave) Inspection Apparatus for the Tiles Fixed by Organic Adhesives. Available online: <https://www.daisue.co.jp/uploads/2024/03/11e0a21723ddae503f7f23bf3316e0ec2fb4494e-1.pdf> (accessed on 24 January 2025). (In Japanese)
17. JASS19 Ceramic Tiling. 2022. ISBN 978-4-8189-1554-1. Available online: <https://www.maruzen-publishing.co.jp/item/b304786.html> (accessed on 24 January 2025).
18. Hammering Rod for Tile Wall. Available online: https://my.ebook5.net/dogyu/kensa_kougu/ (accessed on 24 January 2025).
19. Infrared Inspection Device. Available online: <https://ureruzo.com/ondo00/flir-ex-pro.html> (accessed on 24 January 2025).
20. Ministry of Land, Infrastructure, Transport and Tourism. Guideline for Preventive Measures Against Accident on Bridges (Draft). 2017. Available online: <https://www.pwri.go.jp/caesar/manual/pdf/201703.daisansya-youryou.pdf> (accessed on 24 January 2025).
21. Hammer for the Inspection of Concrete Wall. Available online: <https://www.e-nexco-engi.co.jp/product/special/corocoro-eye.html> (accessed on 24 January 2025).
22. Fukumura, T.; Aratame, H.; Ito, A.; Koike, M.; Hibino, K. Improvement of sound classification method on smartphone for hammering test using 5G network. *Int. J. Netw. Comput.* **2022**, *12*, 359–371. _359 [CrossRef] [PubMed]
23. McFee, B.; McVicar, M.; Faronbi, D.; Roman, I.; Gover, M.; Balke, S.; Seyfarth, S.; Malek, A.; Raffel, C.; Lostanlen, V.; et al. *librosa/librosa*: 0.10.0.post2. 2023. Available online: <https://zenodo.org/records/7746972> (accessed on 24 January 2025).
24. NumPy Developers. Numpy Reference. Available online: <https://numpy.org/doc/stable/reference/index.html> (accessed on 24 January 2025).

25. Yang, J.; Ito, Y.; Koike, M.; Hibino, K.; Ito, A. Live demonstration: Hammering test on a wall using AI. In Proceedings of the IEEE Sensors 2022, Dallas, TX, USA, 30 October–2 November 2022; p. 1. [\[CrossRef\]](#)
26. Takamatsu, Y. Active Structural Acoustic Control of Road Noise in a Structural/Acoustic Coupled Car Cabin. Doctoral Thesis, Graduate School of Integrated Frontier Sciences, Kyusyu University, Fukuoka, Japan, 2016; Volume 12. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.