A Semi-Automated Earthquake Evacuation System Using Early Warning Detection

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Abstract: - This paper presents the development and validation of a semi-automated evacuation route system designed for rapid response during seismic events. Given Japan's frequent earthquakes, ensuring timely evacuation is a critical issue. The proposed system utilizes the Earthquake Early Warning (EEW) system to detect seismic activity and offers residents the option to automatically open doors or windows, securing evacuation routes before structural deformation occurs. A prototype of the system was developed using a Raspberry Pi and tested with pre-recorded EEW signals. Results show that while the system reliably detected EEW and transmitted notifications to residents, the time required for window opening reached 14 seconds, indicating room for improvement in response time. Future work will focus on reducing this delay through local server implementation and bypassing cloud-based systems. This system not only aids in disaster response but also has potential for everyday applications, such as baby cry detection, ensuring its continued relevance in daily life.

Key-Words: - Earthquake, Evacuation system, Semi-automated, Earthquake Early Warning, Raspberry Pi.

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1 Introduction

Earthquakes are among the most devastating natural disasters in Japan, and due to their frequency and magnitude, earthquake countermeasures are an urgent issue that concerns society as a whole. Geographically, Japan is located at the convergence of four tectonic plates, making it a country with a very high frequency of seismic activity. Approximately 18% of the world's earthquakes with a magnitude of 6 or higher occur in Japan [1], a notably high proportion compared to other countries, [2]. For instance, in 2023 alone, over 2,000 earthquakes were observed in Japan, with 19 of them reaching a magnitude of 6 or higher, [3].

Despite decades of global research, earthquake prediction technology has yet to achieve full accuracy. Current earthquake forecasts rely on factors such as seismic activity history [4], crustal deformation [5], and the behavior of underground faults [6]. Statistical methods and physical models are employed to predict the timing, location, and magnitude of earthquakes, but due to the complex nature of seismic phenomena, perfect prediction remains technically challenging, [7]. For example, research based on plate tectonics theory suggests that earthquakes occur when stress accumulated along plate boundaries is released, but the timing and magnitude of such releases are inherently uncertain, [8].

Additionally, some studies have reported anomalous geomagnetic variations as potential precursors to earthquakes, which has led to further investigation into their predictive capabilities, [9], [10]. Other phenomena, such as unusual animal behavior [11], and changes in hot spring activity [12], have long been regarded as possible earthquake precursors, and some researchers are exploring the scientific validity of these observations as predictive tools.

In terms of post-earthquake response, Japan has implemented an "Earthquake Early Warning" system, provided by the Japan Meteorological Agency, to rapidly disseminate information after an earthquake has been detected. This system detects the initial seismic wave (P-wave) and issues an alert before the more destructive secondary wave (S-wave) arrives, giving people critical time to take shelter. Unlike traditional prediction methods, this system focuses on mitigating damage after the earthquake has occurred, playing a crucial role in saving lives. However, both current prediction technologies and the Earthquake Early Warning system have limitations. Improving prediction accuracy remains an important goal, and the development of better preemptive measures for large-scale earthquakes is necessary.

In earthquake-prone Japan, ensuring rapid evacuation during seismic events is a critical issue, and the implementation of systems to aid evacuation efforts is essential for reducing casualties caused by earthquake-related disasters.

In light of this, the goal of this study is to develop an automatic evacuation door-opening system for use during earthquakes. Currently, securing evacuation routes during seismic events relies on manual actions, such as opening doors or windows. However, when an Earthquake Early Warning is received, individuals should prioritize their safety, and many cases have been reported where building deformation or damage after the earthquake made it difficult to operate doors and windows, [13].

To address this issue, this paper proposes a semi-automated evacuation door-opening system. Specifically, the system is designed to automatically open evacuation routes in response to an Earthquake Early Warning, allowing residents to evacuate quickly and safely. Based on the results of the preliminary survey described in Chapter 3, concerns were raised regarding the reliability of a fully automated system and its functionality during power outages, resulting in a preference by most users for a semi-automated approach. In response to these needs, the proposed system supports residents in securing evacuation routes promptly in the event of an earthquake while also allowing for manual intervention. A prototype of this system, utilizing a Raspberry Pi, has also been developed and will be introduced in this paper.

If implemented, the proposed system is expected to contribute to faster evacuation and improved safety, while also playing a role in preventing secondary disasters following earthquakes. Furthermore, even in situations where voluntary evacuation is not possible, the semi-automated system can facilitate rescue efforts by allowing emergency responders swift access to the building interior, thus enhancing the efficiency of rescue operations.

2 Preliminary

2.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs), a type of neural network, are widely used for pattern recognition tasks, particularly in the domains of image and audio data. CNNs are highly effective in feature extraction through convolutional operations. Having demonstrated superior performance in image processing applications [14], CNNs have been widely adopted in numerous studies and have significantly contributed to advancements in processing not only images but other data types as well.

The basic structure of CNNs consists of convolutional layers, pooling layers, and fully connected layers. The convolutional layer applies filters (kernels) to the input data, performing convolution operations to extract local features from image or audio data. The convolution operation can be expressed by the following equation:

$$y_{ij}^{k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x_{(i+m)(j+n)} w_{mn}^{k} + b^{k} \tag{1}$$

Here, y_{ij}^{k} represents the output from filter k, x_{ij} is the input data, w_{mn}^{k} are the filter weights, and b^k is the bias. This operation allows CNNs to capture local features from images or audio signals.

The pooling layer serves to reduce the size of the feature map extracted by the convolutional layer. Typically, max pooling is used, which selects the maximum value within a specific region to downsample the data, reducing its dimensions and preventing overfitting. The output of the pooling layer is defined as:

$$y_{ij}^{'} = \max_{(m,n)\in P} y_{(i+m)(j+n)} \tag{2}$$

Here, $y_{ij}^{'}$ is the output after pooling, and P represents the pooling region.

In the fully connected layer, the output from the pooling layer is flattened and connected to every node in the next layer. This layer is responsible for producing the final classification results. For example, in tasks such as image or speech recognition, a Softmax function is often applied at the output layer to compute the probabilities for each class.

One of the major advantages of CNNs is their ability to share parameters and utilize a local receptive field, which significantly improves computational efficiency. By applying filters to large-scale data like images, CNNs can efficiently learn local features, resulting in a substantial reduction in the number of parameters compared to fully connected networks. This leads to faster learning and helps prevent overfitting.

Another key feature of CNNs is their hierarchical approach to learning. In the early layers, the network captures low-level features such as edges and corners, while deeper layers progressively learn more abstract features, such as object shapes and patterns. This hierarchical feature extraction is particularly effective in tasks such as speech recognition and image classification, [15].

2.2 Speech Recognition using CNN and Spectrograms

In speech recognition technology, CNNs have found broad application not only in image recognition but also in processing audio data. A particularly effective approach involves converting audio signals into spectrograms and then inputting these spectrograms into a CNN to efficiently learn the frequency characteristics of the audio, [16].

However, since audio signals exist in the time domain, they are not directly suitable for processing by CNNs. To address this, Short-Time Fourier Transform (STFT) is employed to convert time-domain signals into the frequency domain, producing a spectrogram. The formula for STFT is expressed as follows:

$$X(t,f)=\int_{-\infty}^{\infty} x(\tau)w(\tau-t)e^{-j2\pi f\tau}d\tau \quad (3)$$

Here, $x(\tau)$ represents the audio signal, $w(\tau-t)$ denotes the window function, t represents time, and f indicates frequency. Through this transformation, the frequency components of the audio signal are visualized over time as a spectrogram. The spectrogram is represented as a three-dimensional dataset, where the horizontal axis shows time, the vertical axis represents frequency, and the color intensity reflects the energy strength. For instance, a spectrogram created from a recording of an Earthquake Early Warning is shown in Figure 1. By feeding the generated spectrogram into a CNN, the model can learn and infer from the data.

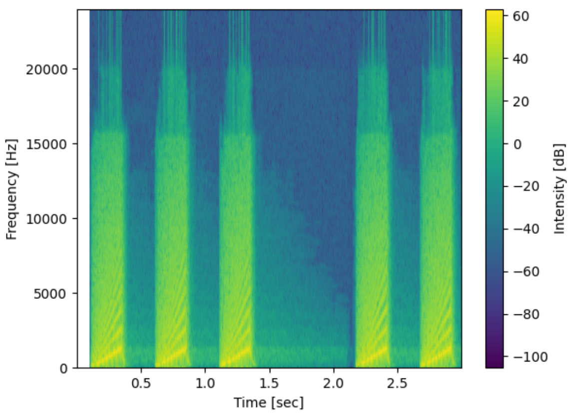

Figure 1: Spectrogram created from a recording of an Earthquake Early Warning. The horizontal axis represents time, the vertical axis represents frequency, and the color intensity reflects energy strength.

CNNs extract features from spectrograms to use in classification tasks. The convolutional layers of CNNs typically respond to various frequency components and temporal variations in the spectrogram, allowing the model to learn distinctive audio patterns. For example, the filter w in the convolutional layer, which reacts to different frequency components, is expressed as follows:

$$y_{ij}^{k}=\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} X_{(i+m)(j+n)}w_{mn}^{k}+b^{k} \quad (4)$$

Here, X denotes the spectrogram, w is the convolutional filter, b represents the bias term, and y_{ij}^{k} represents the output feature map.

Additionally, in speech recognition, Mel-Frequency Cepstral Coefficients (MFCC) are widely used alongside spectrograms. MFCCs capture the characteristics of audio signals based on a nonlinear frequency scale, mimicking the human auditory system. The process for generating MFCCs follows these steps:

1. Segment the audio signal into frames
2. Apply Short-Time Fourier Transform (STFT) to each frame
3. Convert the frequency axis to the mel scale
4. Extract the log-amplitude spectrum
5. Apply the Discrete Cosine Transform (DCT) to compute MFCCs

MFCCs, which take the logarithm of frequency components, consider the nonlinearity of human hearing, contributing to improved accuracy in speech recognition, [17].

Recently, hybrid models combining CNNs with Recurrent Neural Networks (RNNs) have also been applied to speech recognition tasks. While CNNs extract localized temporal features from spectrograms, RNNs capture long-term dependencies in the audio data. This hybrid architecture has been shown to significantly enhance speech recognition accuracy compared to traditional models, [18].

In this study, since complex speech recognition is not required, a simple CNN is used to recognize Earthquake Early Warnings from spectrograms.

3 Proposed System

This section describes the system proposed in this study.

3.1 Preliminary Survey via Questionnaire

A preliminary survey was conducted to gather information relevant to the development of the system. The survey was conducted online from February 4, 2020, to February 11, 2020, with a total of 874 respondents, consisting of men and women across Japan aged between their teens and seventies.

The survey included the following questions:

- What is the maximum seismic intensity you have experienced, and have you ever encountered difficulty opening doors or windows during an earthquake?
- If an automatic evacuation door-opening system were available, would you want to use it?
- Would you prefer a fully automatic or semi-automatic system for opening evacuation doors?

The results of the survey are summarized in Table 1, Figure 2, and Figure 3.

Table 1: Percentage of respondents who experienced difficulty opening doors or windows, based on the maximum seismic intensity they have experienced. The higher the seismic intensity, the more likely respondents were to report difficulty.

Maximum seismic intensity experienced	Percentage reporting difficulty [%]
3 or lower	4.7
4	4.0
5 lower	5.0
5 upper	10.8
6 lower	14.4
6 upper	29.6
7	30.3

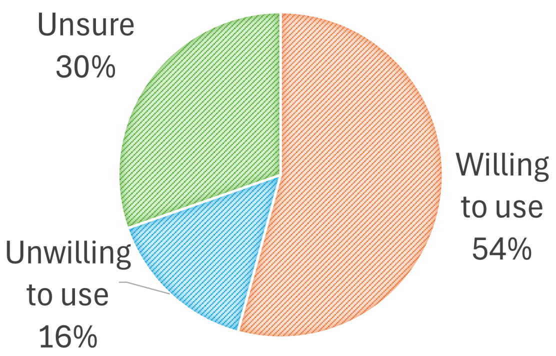

Figure 2: Survey results regarding the willingness to use an automatic evacuation door-opening system.

As shown in Table 1, the percentage of respondents who experienced difficulty opening doors or windows increases with the seismic intensity they experienced. Therefore, the greater the seismic intensity, the more essential it becomes to secure evacuation routes by opening doors or windows in advance. However, in practice, the stronger the earthquake, the more difficult it becomes to move to

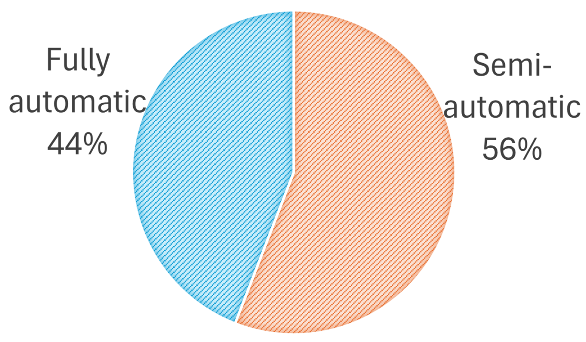

Figure 3: Survey results on preferences for fully automatic or semi-automatic evacuation door-opening systems.

a safe location while simultaneously opening doors or windows, as it becomes challenging to walk freely once the shaking starts.

In Figure 2, approximately 54.2% of respondents expressed a willingness to use an automatic evacuation door-opening system, indicating that securing evacuation routes is a significant concern for many. Conversely, some respondents provided reasons for not wanting to use the system, such as:

- Concern that doors or windows might open automatically when no one is at home.
- The system would be ineffective during power outages, rendering its installation pointless.
- A desire to maintain manual control over the opening and closing of doors or windows.

The concern that the system might open doors or windows when no one is home highlights the need for the system to confirm whether residents are nearby. As for concerns regarding power outages, the system would simply revert to its non-installed state in the event of a power failure, so this does not present a significant problem. However, it is important to avoid mechanisms that lock doors or windows during a power outage, preventing manual operation. The possibility of adopting backup power solutions should also be considered.

For those who wish to control the opening and closing of doors or windows manually, this issue can be addressed by opting for a semi-automatic rather than fully automatic system.

A fully automatic system automatically opens designated doors or windows without human intervention when an earthquake occurs. In contrast, a semi-automatic system prompts human decision-making during an earthquake, and doors or windows are mechanically opened only if the resident chooses to do so. According to Figure 3, 55.9% of respondents preferred a semi-automatic system, which slightly outnumbered those who favored a fully automatic system. This suggests that a semi-automatic system better aligns with users' needs.

Based on these results, it was determined that a semi-automatic system is the preferred option for the system being developed.

3.2 System Overview

The flow of the proposed system is illustrated in Figure 4.

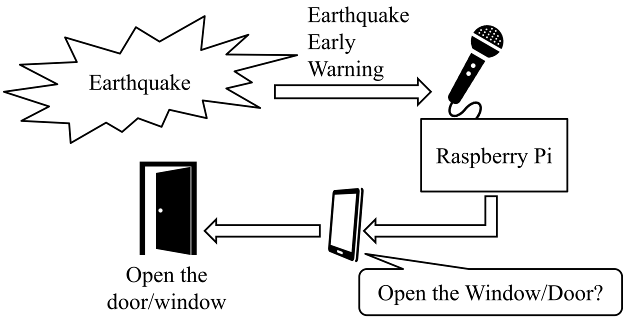

Figure 4: Overview of the proposed system. When an earthquake occurs and the reception of an Earthquake Early Warning is detected, a confirmation message is sent to the resident's smartphone, prompting whether to open windows or doors. The system will then execute the opening process based on the resident's input.

When an earthquake occurs, an Earthquake Early Warning is broadcasted via smartphones or television. This system constantly monitors environmental sounds using a microphone. Upon detecting the Earthquake Early Warning sound, the system sends a confirmation message to the resident's smartphone, asking whether they wish to open doors or windows. If the resident opts to open them, the system initiates the process to open the specified doors or windows.

3.3 System Configuration

A prototype of the system has been created, as shown in Figure 5. The system is built around a Raspberry Pi 3 Model B+, with the operating system running Ubuntu Server. A USB microphone is connected to monitor environmental sounds.

3.4 Speech Recognition

The environmental sound input from the microphone is divided into 3-second intervals and converted into frequency spectrogram images within the Raspberry Pi. These images are then fed into a machine learning

Figure 5: The developed prototype. The system is based on a Raspberry Pi running Ubuntu Server with an external USB microphone connected.

model built using Microsoft's Azure AI Custom Vision service. The model was pre-trained using the following audio sources:

- Earthquake Early Warning sound from smartphones
- Earthquake Early Warning sound from television broadcasts
- Baby crying sounds

The Earthquake Early Warning sounds from smartphones and television were treated as separate audio sources due to their differences. The reason for including baby crying sounds in the training will be explained later. When the Azure AI Custom Vision model predicts the Earthquake Early Warning with more than 70% confidence, the system determines that an Earthquake Early Warning has been detected and sends a confirmation message to the resident about whether to open the doors or windows. Figure 6 shows a screenshot of the program in operation.

The reason for including baby crying sounds is as follows: While this system is designed for use during Earthquake Early Warnings, in reality, such warnings occur infrequently, and thus, the system may not often be put to use. There is a concern that users might forget about the system's existence, which could reduce its effectiveness in emergencies. To mitigate this risk, it is preferable that the system can be used regularly for other purposes, thereby maintaining its presence in users' minds.

For example, in households with infants, the system could be set to notify residents when a baby is crying. This would make the system useful in

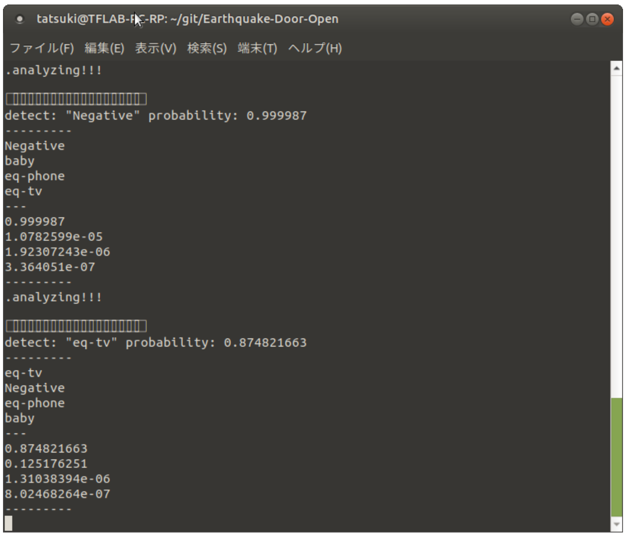

Figure 6: Screenshot of the program in operation. The audio input from the microphone is classified into four categories: Earthquake Early Warning from smartphone (eq-phone), Earthquake Early Warning from television (eq-tv), baby crying (baby), and other sounds (Negative).

daily life and keep users aware of it. Even in households without infants, the system could serve as a general notification service, alerting residents to various events and making the system more practical for everyday use.

3.5 Notifications to Residents

In Japan, the SNS application LINE is widely used, so to lower the barriers to system adoption, a LINE Bot was implemented. When the system determines that an Earthquake Early Warning has been detected via audio recognition, the LINE beacon function is activated. If residents who have registered their devices in advance are within the range of the beacon, the system responds to the beacon signal. A cloud server, pre-configured with an HTTPS server, receives the beacon response via Webhook, and sends a confirmation message to the resident's LINE application asking whether to open the doors or windows (Figure 7). The resident can choose to tap either "Open" or "Don't open" on the displayed options to issue a command.

For the cloud server, Microsoft Azure was utilized. After receiving the resident's response, the Webhook transmits the result to the cloud server. If the resident chooses to open the doors or windows, the signal is sent to the local Raspberry Pi to initiate the opening process.

3.6 Opening Doors and Windows

If the resident opts to open the doors or windows, the system proceeds with the opening process before the

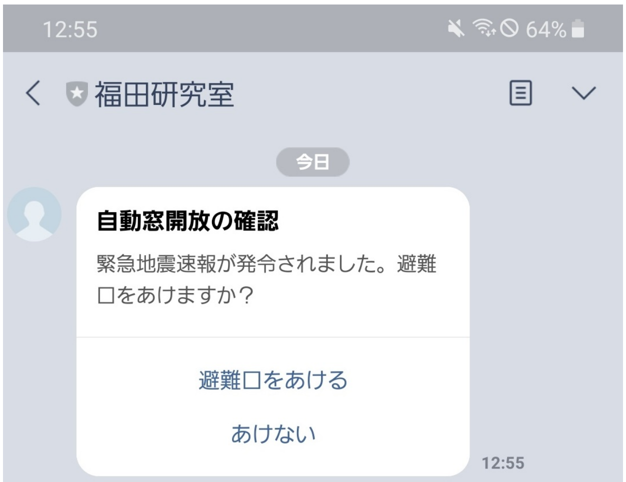

Figure 7: Screen showing the LINE-based confirmation message asking the resident whether to open the doors or windows. The message reads "An Earthquake Early Warning has been issued. Would you like to open the evacuation routes?" with options to "Open" or "Don't open."

earthquake causes deformation to the door or window frames. For the prototype, the SAWOACSS product from Sanko Co., Ltd. was used. SAWOACSS is a device that allows windows to be opened and closed via smartphone, and its operation can be controlled using the Javascript-based TuyAPI. When the system receives the signal via LINE, TuyAPI is used to control SAWOACSS to open the windows. Figure 8 shows the installed setup, with the arrow pointing to the SAWOACSS device mounted at the top of the window.

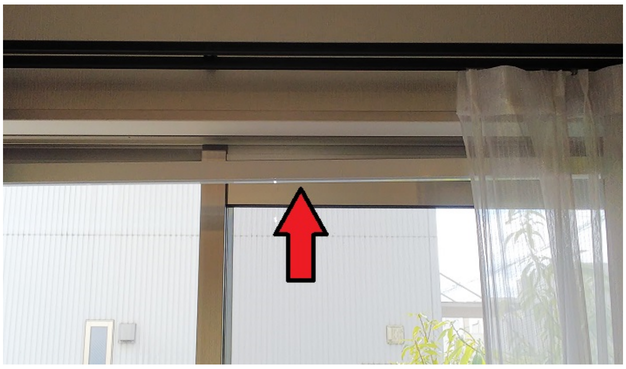

Figure 8: The SAWOACSS device from Sanko Co., Ltd., installed to automatically open and close windows. The arrow points to the SAWOACSS, mounted at the top of the window.

A key point to consider is that TuyAPI is an API for controlling devices within a local network. Therefore, both the Raspberry Pi running TuyAPI and the SAWOACSS must be on the same network. When the cloud server sends the open signal to the local Raspberry Pi, TuyAPI communicates the command to the SAWOACSS, triggering the window opening process.

4 System Verification and Discussion

System verification was conducted using the developed prototype system.

4.1 System Verification

In this test, pre-recorded Earthquake Early Warning sounds were played. Two types of recordings were prepared: one from a television broadcast and the other from a smartphone. Each recording was played fifteen times, for a total of thirty trials. The time required for each process was measured.

When the pre-recorded Earthquake Early Warning sound was played, the Raspberry Pi, running the sound recognition program, successfully responded. Subsequently, a message was delivered to the resident's smartphone, allowing them to select whether to open the door or window. Upon selecting the option to open, the window was successfully opened.

On average, it took 4.9 seconds from the Earthquake Early Warning sound to the arrival of the confirmation message. Additionally, it took an average of 2.7 seconds from receiving the message to issuing the command to open the window. From the time the command was issued, it took 3.4 seconds for the window opening process to begin. Depending on the size of the window, it takes approximately 5 to 7 seconds to fully open a large window that connects to a garden, allowing human passage. However, for opening to a minimum width sufficient for entry, i.e., about 600 mm [19], it took around 3 seconds.

4.2 Discussion

First, all thirty trials successfully detected the Earthquake Early Warning. Additionally, the system ran for several hours during the experiment without any false detections.

Although it took 4.9 seconds for the message to be delivered via LINE after the Earthquake Early Warning was triggered, residents would likely need more than 4.9 seconds to hear the warning and move to a safe location. Therefore, considering that this system operates semi-automatically, the response speed is considered sufficient.

Furthermore, it took a total of 14.0 seconds from the Earthquake Early Warning sound to the point where the window was opened to a width of approximately 600 mm.

Earthquakes generate primary waves (P-waves), which cause initial minor shaking, followed by secondary waves (S-waves), which cause the main shaking and often lead to structural deformations. The time between receiving an Earthquake Early Warning and the arrival of the S-waves, known as the lead time, typically ranges from a few seconds to several tens of seconds, [20]. Thus, it is crucial to complete the window-opening process in under 10 seconds.

To achieve this, it would be beneficial to establish the TuyAPI connection as soon as the Earthquake Early Warning is detected, allowing the system to initiate the opening process immediately after receiving the command. Moreover, implementing a local server instead of relying on a cloud server or adopting a system independent of LINE could further reduce latency, improving the system's overall response time.

5 Conclusion

In this study, we proposed and developed a semi-automated evacuation door-opening system designed to automatically open evacuation routes during earthquakes and evaluated its prototype. The system is designed to detect Earthquake Early Warnings (EEW) and prompt residents with a confirmation to open evacuation routes, thereby supporting rapid and safe evacuation. The results of system verification demonstrated that the system reliably detected EEW, and the processes leading to the resident's decision to open evacuation doors or windows functioned as expected. However, it was found that the time required to open doors or windows reached 14 seconds, indicating that further improvements are necessary to ensure that evacuation routes are opened before the arrival of the primary seismic waves. Future efforts will focus on optimizing the TuyAPI connection, implementing local servers, and adopting independent systems other than LINE to reduce latency and improve response times.

In addition, this system includes features useful in daily life. For instance, it can detect a baby's cry, offering potential support for child-rearing. With further development, the system might even assess why a baby is crying, adding a deeper level of assistance for caregivers. Furthermore, by detecting sounds from pets, such as a dog barking, the system could alert users to possible issues at home when they are away. Regular use of the system in daily life would increase familiarity, contributing to smoother utilization in the event of an earthquake.

In terms of real-world impact, implementing this system is expected to enable rapid evacuation during earthquakes, especially in a country like Japan, where seismic activity is frequent. The system could potentially become a standard safety feature in many homes. Moreover, by providing everyday functionalities, the system extends its utility beyond disaster scenarios, offering continuous value in daily life.

Considering potential user feedback, improvements based on user concerns are crucial. Survey results revealed concerns about the reliability of fully automated systems and functionality during power outages. Therefore, future system enhancements should focus on increasing reliability and safety by incorporating user feedback. Solutions such as backup power supplies and manual override features during emergencies are considerations for future development.

By advancing this system, not only will it accelerate evacuation during disasters, but it will also enhance residents' sense of security, contributing to both emergency preparedness and everyday convenience. The system is expected to have broad societal benefits, potentially becoming a standard safety feature in many homes.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly for language editing. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Conflicts of Interest

The author is affiliated with Shimonoseki City University, a public university corporation located in Shimonoseki City, which is the subject of this research.