Tongaraas: Tongs for Recognizing Littering Garbage with Active Acoustic Sensing

Koki Tachibana
tachibana.koki.ti0@is.naist.jp
Nara Institute of Science and Technology
Ikoma, Nara, Japan

Yuki Matsuda
yukimat@is.naist.jp
Nara Institute of Science and Technology
Ikoma, Nara, Japan

Kaito Isobe
kaito.isobe@iis.ise.ritsumei.ac.jp
Ritsumeikan University
Kusatsu, Shiga, Japan

Daiki Mayumi
mayumi.daiki.mb9@is.naist.jp
Nara Institute of Science and Technology
Ikoma, Nara, Japan

Takamasa Kikuchi
rb22308r@osaka-pct.ac.jp
Osaka Metropolitan University College of Technology
Neyagawa, Osaka, Japan

Hirohiko Suwa
h-suwa@is.naist.jp
Nara Institute of Science and Technology
Ikoma, Nara, Japan

Keiichi Yasumoto
yasumoto@is.naist.jp
Nara Institute of Science and Technology
Ikoma, Nara, Japan

Kazuya Murao
murao@cs.ritsumei.ac.jp
Ritsumeikan University
Kusatsu, Shiga, Japan

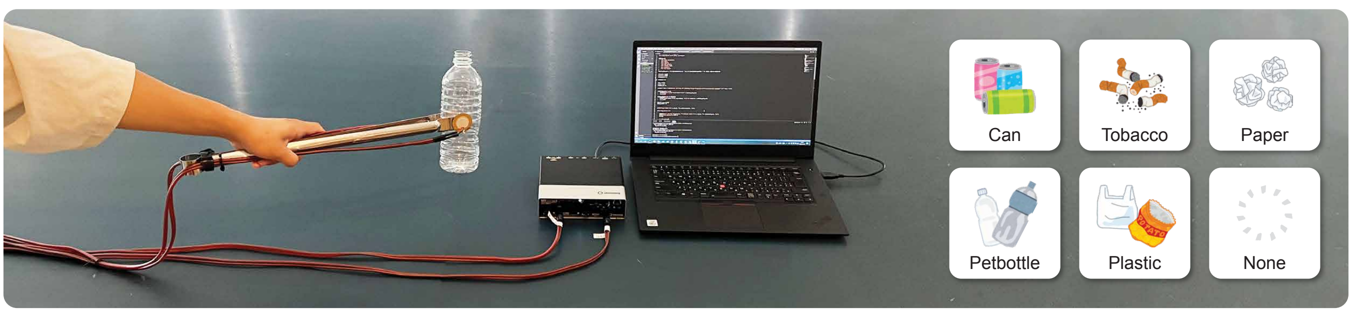

Figure 1: Tongaraas: IoT Tongs for Littering Garbage Recognition with Active Acoustic Sensing

ABSTRACT

Littering has developed into a serious environmental problem. However, the actual situation of litter and the results of litter pickup activities are not organized as information. Therefore, the objective of this research is to grasp the distribution of the type and location of litter comprehensively. To achieve the objective of this research, we have proposed a method for recognizing litter using an acoustic sensor on a smartwatch worn on the wrist and a method for recognizing litter using a small camera mounted on tongs. However, in these studies, there were limitations in the range of litter type estimation, lack of recognition accuracy, and privacy issues. To solve the above problem, we propose a litter type recognition system, named Tongaraas, that combines active acoustic sensing with tongs. In the evaluation experiment, we built the litter type recognition model for six categories of litter. The evaluation results showed the models, which were trained with dataset collected by single person and three people, perform at F-value of 0.978 (SVM) and 0.849 (LightGBM), respectively. It suggests it is possible to estimate with common litter type recognition model, although there is a certain level of negative effects due to the individual difference.

IoT '22, November 7–10, 2022, Delft, Netherlands

ACM ISBN 978-1-4503-9665-3/22/11…$15.00
https://doi.org/10.1145/3567445.3571112

CCS CONCEPTS

• **Human-centered computing → Ubiquitous computing**; • **Information systems → Location based services**.

KEYWORDS
Smart city, Littering, Active acoustic sensing.

ACM Reference Format:
Koki Tachibana, Yuki Matsuda, Kaito Isobe, Daiki Mayumi, Takamasa Kikuchi, Hirohiko Suwa, Keiichi Yasumoto, and Kazuya Murao. 2022. Tongaraas: Tongs for Recognizing Littering Garbage with Active Acoustic Sensing . In *Proceedings of the 12th International Conference on the Internet of Things (IoT '22), November 7–10, 2022, Delft, Netherlands.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3567445.3571112

1 INTRODUCTION

Littering is a global problem, adversely affecting the health of wildlife and causing death. Solving this problem is an urgent task. Yamane *et al.* [17] point out that there are three approaches to solving the littering problem: (1) continuous litter cleanup, (2) installation of trash cans and signs encouraging people not to litter, and (3) government intervention. However, the actual situation of litter and the results of litter pickup activities are not organized as information. Therefore, anti-littering measures currently rely on experimental rules. In addition, litter pick-up activities are conducted individually in each region and community and are not coordinated. In response to this situation, there are services [14] that survey the distribution of litter for a fee, and several municipalities are actually operating such services. However, these surveys require investigator to travel around the region, which makes them difficult to cover and sustain spatiotemporally. This research aims to realize a sensing technology that enables the collection of information on litter types and locations with high spatiotemporal coverage. Previous studies have explored approaches to apply the participatory sensing framework [2] to people who routinely pick up litter. Specifically, we have proposed a method for recognizing litter using an acoustic sensor on a smartwatch worn on the wrist [15] and a method for recognizing litter using a small camera mounted on tongs [16]. However, the former method requires the user to rap litter by hand to generate a sound, and the later method also has the problem that image recognition accuracy is degraded in the early morning when the surroundings are dark.

Therefore, we focused on active acoustic sensing as an approach to realize new litter recognition. Active acoustic sensing is a method of estimating the state of an object by attaching a microphone and a loudspeaker to the surface of the object, emitting a specific acoustic signal through the loudspeaker and propagating it inside the object, and analyzing the frequency of the response signal obtained by the microphone. An example of the application of this method to cutlery shows that this method can recognize foodstuffs that come into contact with the cutlery [11]. we propose a system, named *Tongaraas*, that recognizes litter types by employing active acoustic sensing to tongs (Figure 1).

In the evaluation experiment, we constructed two types of datasets collected by single person and three people targeting five types of litter (cans, tobacco, paper, plastic, plastic bottles, and nothing) and built the litter type recognition models for each dataset. For single person dataset, the results showed the model with SVM performs at F-value of 0.978 through leave-one-group-out cross-validation (LOGO-CV). It suggests active acoustic sensing will be an effective clue for distinguishing types of litter. Because acoustic signal might be affected by hands holding the tongs, individual differences can lead to give negative effects for recognition models. To investigate this concern, we evaluated performance of the model trained with three person dataset. The results showed the model with LightGBM performs at F-value of 0.849 with LOGO-CV. It suggests it is possible to estimate with common recognition model, although there is a certain level of negative effects due to the individual difference.

2 RELATED WORK

2.1 Research of litter recognition

There are many studies on recognizing litter. Several research projects [1, 3, 6] use machine learning to identify litter using video data collected from a fixed camera. However, a fixed camera can only collect information on the type and location of litter, so this method can't collect information on a wide range of litter. Although it is possible to place fixed cameras in the entire area where we want to collect litter information, it is not realistic considering the number of fixed cameras to be installed.

Inoue *et al.* [7] studied the relationship between the distribution of litter and the shape of the banks by manually identifying litter along the riverbanks. Pirika Inc. is developing Pirika [13], a social networking application for volunteer litter pickers. Volunteer litter pickers take pictures of litter with their smartphones and upload them. However, the method of manually recording types and locations of litter [7] requires time-consuming input of litter information and does not efficiently collect types and locations of litter. Similarly, using Pirika [13] to upload photos of individual pieces of litter is time-consuming for volunteer litter pickers.

Pirika Inc. has also developed Takanome that analyzes the type, quantity, and location of litter captured on video and plots it on a map when a person takes pictures of litter on the road with a smartphone [14]. Hong, Fulton, Kraft *et al.* [4, 5, 9] use robots to recognize types and locations of litter. These researches not only collect information on types and locations of litter, but also assume that the litter is actually picked up by robots. However, Takanome [14] has higher operating costs because of the labor required to survey distributions of litter. In addition, the method using robots [4, 5, 9] incurs the cost of operating the robots.

To solve the above problems, we have proposed a litter type recognition system using an acoustic sensor in a smartwatch worn on the wrist [15]. However, this system has the problem that it needs to generate sound by rapping litter by hand and that it cannot recognize objects that do not generate sound even if they are rapped. For example, no sound is generated by rapping a littered cigarette. In addition, we have proposed a method for recognizing litter type using a small camera mounted on tongs [16]. Although this system can recognize litter such as tobacco, image recognition accuracy is degraded during dark hours such as early morning, when litter pickups are often conducted. In addition, there are concerns about privacy issues arising from acoustic data collected from the smartwatch's microphone and image data collected by the tong-mounted camera.

2.2 Research on object recognition by active acoustic sensing

There are many studies on object recognition using active acoustic sensing. Ono *et al.* [12] have proposed a touch recognition technique using this active acoustic sensing. This is a method to recognize the grasping state of an existing object by attaching a contact microphone and a contact speaker to the object and acquiring differences in the way the object is touched. Adiyan *et al.* [10] proposed a method to infer the position of contact and gestures on the body by resonating the skin surface with low-frequency ultrasound and receiving it at different points on the body. Nishii *et al.* [11] have developed fork-shaped and spoon-shaped device capable of active acoustic sensing and proposed a method for recognizing foodstuffs that come into contact with it. Thus, it has been shown that active acoustic sensing can be used to recognize objects in contact, and the technology has been used for various applications.

2.3 Position of this research

This study aims to expand the range of recognizable objects and reduce environmental dependence, which are the remaining challenges in our previous research [15, 16], by incorporating active acoustic sensing as a new approach to litter recognition.

3 TONGARAAS

In this section, we propose a new litter type recognition system, Tongaraas (IoT Tongs for Littering Garbage Recognition with Active Acoustic Sensing), which incorporates active acoustic sensing into tongs.

3.1 Overview

In this paper we focus on that litter and tongs come in contact with each other when picking up litter. In addition, litter is composed of materials with different acoustic properties (metal, paper, plastic, etc). For example, cans and pet-bottles are cylindrical, whereas plastic are bag-shaped. These differences in shape are thought to appear in the frequency response. The materials of each type of litter also differ in the same way. Cans are mainly made from aluminum or steel, while pet-bottles are made from polyethylene terephthalate. We think that this difference in material properties is similarly shows up in the frequency response. Based on the above, we believe that active acoustic sensing can be adapted to the task of estimating the type of litter.

Tongaraas can classify types of litter such as tobacco, which could not be classified by the method of classifying the type of litter by rapping litter [15]. Also, because Tongaraas don't use an image recognition method to determine types of litter [16], there is no change in accuracy even when the surrounding area is dark. In addition, the use of sensing based on acoustic signals in the ultrasonic domain has the advantage of protecting privacy. In summary, if Tongaraas can sense types of litter, it is expected to expand the range of litter types, improve recognition accuracy, and protect privacy.

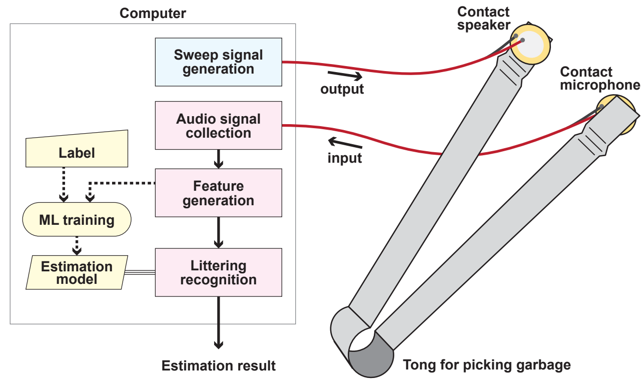

Figure 2: System architecture of Tongaraas

3.2 System architecture

An overview of Tongaraas is shown in Figure 2. The system consists of litter picker tongs fitted with a contact loudspeaker that emits acoustic signals and a contact microphone that collects the acoustic signals, the computer with sweep signal generator section, acoustic signal collector section, feature extractor section and litter type recognition section.

The procedure for litter type recognition is as follows.

(1) A sweep signal whose frequency varies with time is generated by the sweep signal generator in the computer and emitted from the contact speaker.
(2) The acoustic signal is collected by a contact microphone (the acoustic signal varies depending on the type and shape of the litter in contact with the tongs).
(3) From the collected acoustic data, the frequency band of the Sweep signal is extracted for feature extraction.
(4) Recognize the type of unknown litter in contact with the tongs using the litter type recognition model.

In the following sections, sweep signal generator section, acoustic signal collector section, feature extractor section, and litter type recognition section are described in detail.

3.3 Sweep signal generation and acoustic signal collection

The sweep signal generator section generates a sweep signal (also called a chirp signal) whose frequency varies linearly from 20 kHz to 40 kHz. This frequency band was determined with reference to previous research papers [12]. When the sweep signal is played back repeatedly, recognition may be affected by the impulse noise generated by the large change in frequency at the repetition break (the moment when the frequency changes to 40 kHz and then returns to 20 kHz). In this system, this problem is solved by increasing the frequency to 40 kHz and then decreasing the frequency, as shown in Figure 3. The sampling frequency is 96 kHz in order to convert the analog sweep signal transmitted through the tongs into a digital signal for acoustic signal collection.

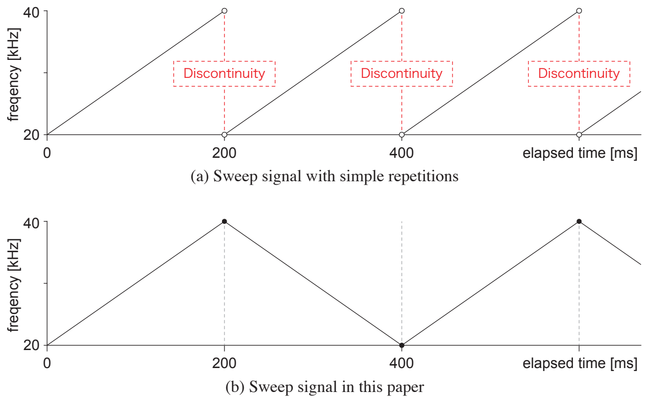

Figure 3: Sweep signal generation method

Table 1: List of feature values

Feature	Number of dimensions
MFCC	104
Chroma	12
Melspectrogram	128
Spectral contrast	7
Total	251

3.4 Feature extraction and litter type recognition

As a pre-processing step, a frequency band between 20 kHz and 40 kHz is extracted from the collected acoustic data using a band-pass filter to eliminate acoustic signals in a frequency band different from the Sweep signal.

Next, features are extracted from the acoustic data. The list of features to be extracted is shown in Table 1, with a dimension number of 251. These features are commonly used in acoustic recognition; therefore, they are used in our system. In this system, each feature is extracted using the librosa[1] library in Python.

Mel-frequency cepstral coefficient (MFCC) is a feature that is obtained by performing a fast Fourier transform (FFT) on sound data and then an inverse discrete cosine is applied to transform the output through a mel filter bank. Chroma is a feature that is a superposition of all the components of the same scale in different octaves, reduced to the 12 components of the chromatic scale within an octave. Melspectrogram is a spectrogram created after the FFT and the frequency is converted to the mel scale. Spectral contrast is a feature that is obtained by applying a FFT, passing the result through an octave filter bank, processing to detect and extract the peak, and finally transforming using the Karhunen-Levé method [8].

4 EXPERIMENT

To evaluate the effectiveness of Tongaraas, acoustic data of multiple litter objects are collected, and litter type recognition models are constructed. We also investigate the difference in performance between the models built with single person's dataset and multiple people dataset.

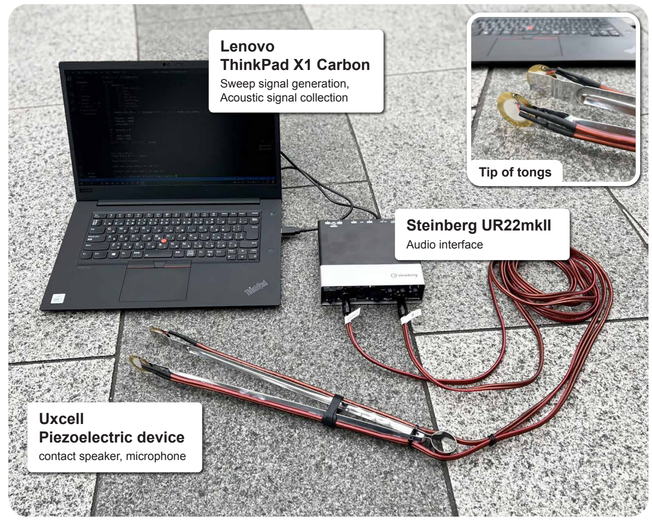

Figure 4: Tongaraas data collection experiment setup

4.1 System setup

The setup of the data collection system used in the evaluation experiment is shown in Figure 4. A Lenovo ThinkPad X1 Extreme Gen3 (CPU: Intel Core i7-10750H, RAM: 64GB, OS: Windows 10) is used as the computer for sweep signal generation and acoustic signal collection, and sound input/output is performed via a USB-connected audio interface Steinberg UR22mk. The contact speaker microphone used was an uxcell piezoelectric device (35 mm diameter, 0.3 mm thick), attached to the tip of the tongs as shown in the upper right.

4.2 Target litter categories

In this paper, a total of six categories were targeted: five representative types of litters (cans, tobacco, paper, plastic, and pet-bottles) and a state in which the litter is not pinched. Figure 5 shows appearance of each litter. The 20 litter objects are prepared for each litter type. Even if they are the same type of litter, their materials and shapes are greatly different. For instance, cans differ in the capacity (185mℓ, 300mℓ, 355mℓ), the shape (pull-tab or cap type, and degree of concavity), and the material (steel, alminium).

4.3 Data collection and evaluation procedures

Using the system described in Section 4.1, the participants collect acoustic dataset for each litter object as explained in in Section 4.2. The acoustic signal is recorded while the tongs are pinching the target litter. The data will be collected for 12 seconds per a time, and extract 10 seconds data by removing first and last 1 second for excluding acoustic noise at the start and the end of recording. From the cut-out acoustic data, split the data into 1 second segments and generate 10 samples of acoustic data in total.

In this paper, we made two types of datasets for evaluating the following two points. First, we aim to confirm the feasibility of litter type recognition based on an active acoustic sensing approach, with a dataset collected by a single person. Second, because acoustic signals might be affected by hands holding the tongs, individual

[1]https://github.com/librosa/librosa

Figure 5: Photographs of litter used in the evaluation experiment (5 types, 20 objects each)

differences can lead to give negative effects for recognition models. Hence, we aim to investigate the effects of individual differences on recognition models, with a dataset collected by multiple people. Data collection and evaluation procedures for both datasets are following.

Evaluation of a model built with acoustic data from single person. We collected the acoustic dataset of 20 litter objects for each target litter category by single person. Regarding each litter object, the acoustic data will be collected five times with changing the pinching way. Consequently, we acquired the dataset with 6,000 samples of acoustic data (6 litter categories × 20 litter objects × 5 pinching ways × 10 samples). As a evaluation method, we adopted Leave-one-group-out cross-validation (LOGO-CV). The method of splitting dataset into training and testing data for LOGO-CV is shown in Figure 6. Specifically, the one object from 20 litter objects for each litter category will be taken and used as testing data, and remaining will be used as training data. For each trial, the dataset will be split into the 5,700 samples of training data (6 litter categories × 19 litter objects × 5 pinching ways × 10 samples) and the 300 samples of testing data (6 litter categories × 1 litter object × 5 pinching ways × 10 samples). By changing testing data, the recognition model will be built and evaluated 20 times in total, with a setting where the training data does not include data from the same litter object.

Evaluation of a model built with acoustic data from multiple people. We collected the acoustic dataset of five litter objects for each target litter category by three people. Regarding each litter object, the acoustic data will be collected three times with changing the pinching way. Consequently, we acquired the dataset with 2,700 samples of acoustic data (3 people × 6 litter categories × 5 litter objects × 3 pinching ways × 10 samples). As a evaluation method, we adopted LOGO-CV same with case of single person.

To build litter type recognition model with 251 dimensional features (Table 1) as input and six litter categories as output, by using LightGBM which has been shown higher classification performance

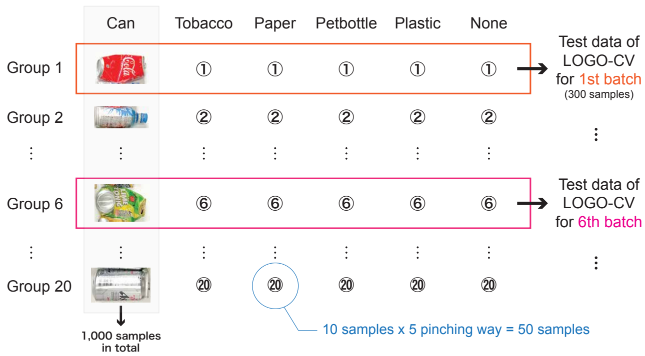

Figure 6: How to split training and test data for LOGO cross-validation. The data from same garbage is belonging to only one group.

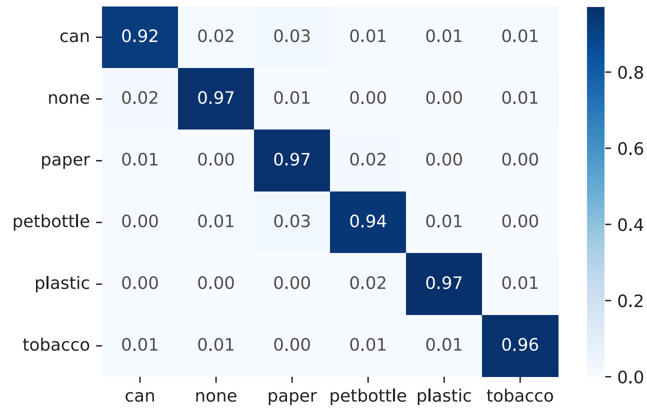

Figure 7: Average confusion matrix of the model built with dataset of single person (LightGBM).

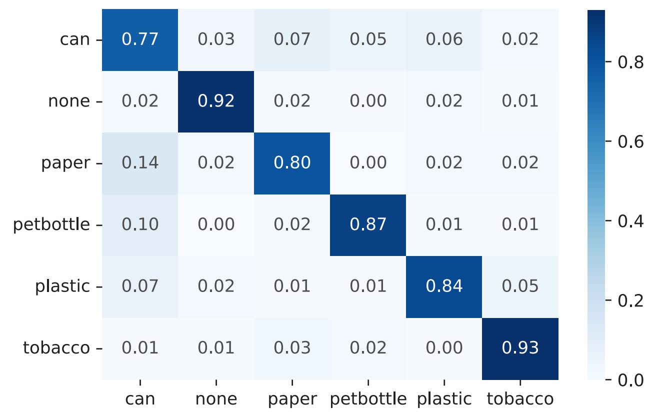

Figure 8: Average confusion matrix of the model built with dataset of three people (LightGBM).

than other machine learning methods in our previous study [15]. To compare performance with common machine learning methods, we additionally selected SVM and Random Forest. Also, we applied Hyperopt[2] for hyperparameter tuning.

4.4 Result and discussion

The evaluation results are shown in Table 2. When the model was built using dataset of single person, the best performance is showed with SVM: the average accuracy was 0.978, the average precision was 0.979, the average recall was 0.978, and the average F-value was 0.978. Compared with the baseline method [16], our proposed method shows better performance though it uses lighter-weight machine-learning algorithms. Then, when the model was built using dataset of three people, the best performance is showed with LightGBM: the average accuracy was 0.855, the average precision was 0.871, the average recall was 0.855, and the average F-value was 0.849. Here in after, we will describe detailed results and discussions in the case of LightGBM which shows the best performance for multiple people dataset.

Figure 7 and Figure 8 show the average confusion matrix of a model built with dataset of single person and three people, respectively.

For the model built with the dataset of a single person, Table 2 and Figure 7 showed it performs with quite high F-value of 0.955. It suggests that if the user used a model built with their own acoustic data, it is possible to recognize types of litter with high performance. From this result, we have confirmed the approach in this paper employing active acoustic sensing is feasible for recognizing litter.

Then, for the model built with the dataset of a three people, Table 2 and Figure 8 showed its performance dropped to the F-value of 0.849, but it is confirmed relatively high performance is kept. It suggests This result suggests we need to take into account the effects of individual differences for building robust recognition models. One possible reason for the lower performance is that different users hold different parts of the tongs. To solve this problem, it might be necessary to design affordance to unify the position of grasping the tongs, and filter the specific frequency band for removing effects by the user's hand.

To investigate the reason for low performance in the case of three people, we focused on the worst case among trials of LOGO-CV whose average F-value was 0.634 as shown in Figure 9. From Figure 9, we found out that the performance of "none" and tobacco are relatively high but the others are low. This trend was observed in many other trials. In the case of "none," it is reasonable the reason for the high performance because the tongs are not grabbing litter. In the case of tobacco, we considered that because the shape of tobacco is smaller than others and has uniformed shape, the F-value of tobacco became higher (Figure 5). Compared with them, other litter types have various shapes and sizes. It might cause confusion for the recognition models. Especially, the shapes of cans are varied as shown in Figure 5. As can be seen from Figure 5, most of cans are crushed. Therefore, we believe that the cans are not making good contact with the surface of the tong tips due to the degree of concavity of the cans, which is affecting the F-value. We consider that the problem can be solved by modifying shape of tong's tip

[2]https://github.com/hyperopt/hyperopt

Table 2: Result of evaluation

Dataset	Method	Accuracy	Precision	Recall	F-value
Single person	LightGBM	0.956	0.959	0.956	0.955
	SVM	0.978	0.979	0.978	0.978
	Random Forest	0.945	0.951	0.945	0.945
	Baseline [16][*a]	-	0.905	0.902	0.903
Multiple people	LightGBM	0.855	0.871	0.855	0.849
	SVM	0.850	0.869	0.850	0.844
	Random Forest	0.843	0.852	0.843	0.839

[*a] The model has been built using MobileNet.

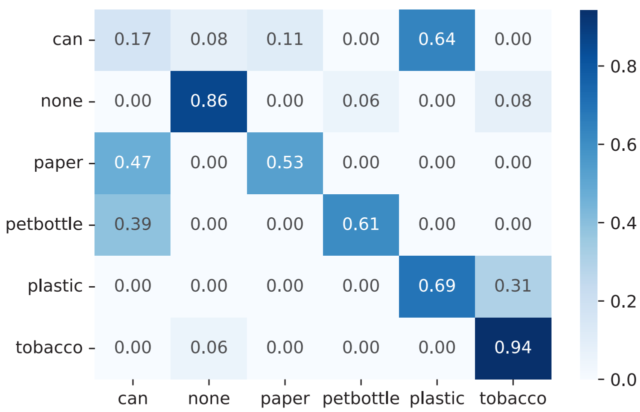

Figure 9: Confusion matrix of a model built with dataset of three people at the worst trial (LightGBM).

for capturing audio signals effectively. For example, we attach a deformable gel to the surface of the tongs tips so that the tongs can make contact with concavity of the cans.

5 CONCLUSION

This paper proposes, a litter type recognition system, named Tongaraas, which employs active acoustic sensing to tongs. In the result, when the model was built using acoustic data from single person, the average F-value was 0.978 (SVM). From the result, it was suggested that if the user used a model built with acoustic data collected by himself, it might be possible to recognize types of litter precisely. Also, when the model was built using acoustic data from three people, the average F-value was 0.849 (LightGBM). From the result, when acoustic data was collected by more than one person, we found that individual difference give negative effects to the performance of recognition. As future work toward improving performance, we will explore to recognition model which is robust to individual differences by filtering frequency band affected due to human body (hand) and litter shape differences by modifying shape of tong's tip for capturing audio signals effectively.

ACKNOWLEDGMENTS

This study was supported in part by JST PRESTO under Grant No. JPMJPR2039 and JPMJPR1937.

REFERENCES

[1] Kashif Ahmad, Khalil Khan, and Ala Al-Fuqaha. 2020. Intelligent Fusion of Deep Features for Improved Waste Classification. *IEEE Access* 8 (2020), 96495–96504.

[2] J. A Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M. B Srivastava. 2006. Participatory sensing. *Center for Embedded Network Sensing* (2006).

[3] João Borges de Sousa, Ana Rebelo, and Jaime S. Cardoso. 2019. Automation of Waste Sorting with Deep Learning. *2019 XV Workshop de Visão Computacional (WVC)* (2019), 43–48.

[4] Michael Fulton, Jungseok Hong, Md. Jahidul Islam, and Junaed Sattar. 2019. Robotic Detection of Marine Litter Using Deep Visual Detection Models. In *2019 International Conference on Robotics and Automation (ICRA'19)*. 5752–5758.

[5] Jungseok Hong, Michael Fulton, and Junaed Sattar. 2020. TrashCan: A Semantically-Segmented Dataset towards Visual Detection of Marine Debris. *ArXiv* abs/2007.08097 (2020).

[6] Minh-Hieu Huynh, Phu-Thinh Pham-Hoai, Anh-Kiet Tran, and Thanh-Dat Nguyen. 2020. Automated Waste Sorting Using Convolutional Neural Network. (2020), 102–107. https://doi.org/10.1109/NICS51282.2020.9335897

[7] Yoshiki Inoue and Hideshige Toda. 2003. Drifted Litters of Lake Suwa and Upper Reaches of the Tenryu River. *ENVIRONMENTAL SCIENCE* 16, 3 (2003), 167–178. https://doi.org/10.11353/sesj1988.16.167

[8] Dan-Ning Jiang, Lie Lu, Hong-Jiang Zhang, Jian-Hua Tao, and Lian-Hong Cai. 2002. Music type classification by spectral contrast feature. In *Proceedings. IEEE International Conference on Multimedia and Expo*, Vol. 1. 113–116. https://doi.org/10.1109/ICME.2002.1035731

[9] Marek Kraft, Mateusz Piechocki, Bartosz Ptak, and Krzysztof Walas. 2021. Autonomous, Onboard Vision-Based Trash and Litter Detection in Low Altitude Aerial Images Collected by an Unmanned Aerial Vehicle. *Remote Sensing* 13, 5 (2021), 965. https://doi.org/10.3390/rs13050965

[10] Adiyan Mujibiya, Xiang Cao, Desney S. Tan, Dan Morris, Shwetak N. Patel, and Jun Rekimoto. 2013. The Sound of Touch: On-Body Touch and Gesture Sensing Based on Transdermal Ultrasound Propagation. In *Proceedings of the 2013 ACM International Conference on Interactive Tabletops and Surfaces (ITS'13)*. 189–198. https://doi.org/10.1145/2512349.2512821

[11] Haruna Nishii, Kyosuke Futami, and Kazuya Murao. 2021. Design and Evaluation of Food Recognition Cutlery Using Active Acoustic Sensing. In *IPSJ Interaction 2021*. 164–167. (in Japanese).

[12] Makoto Ono, Buntarou Shizuki, and Jiro Tanaka. 2013. Touch & Activate: Adding Interactivity to Existing Objects Using Active Acoustic Sensing. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology (UIST '13)*. 31–40. https://doi.org/10.1145/2501988.2501989

[13] Pirika Inc. 2011. Pirika | Anti-litter social media. https://en.sns.pirika.org/. Accessed: 2021-07-09.

[14] Pirika Inc. 2016. Pirika Research | Towards Litter-Free Cities. https://en.research.pirika.org/. Accessed: 2022-09-04.

[15] Koki Tachibana, Yugo Nakamura, Yuki Matsuda, Hirohiko Suwa, and Keiichi Yasumoto. 2021. Evaluation of Classification and Location Recognition System for Litter by Using Smartwatch. In *Proceedings of the Symposium on Multimedia, Distributed, Cooperative and Mobile (DICOMO 2021)*. 325–332. (in Japanese).

[16] Koki Tachibana, Rei Nakaoka, Atsushi Miyaji, Shusaku Tomita, Yuki Matsuda, Yugo Nakamura, and Hirohiko Suwa. 2022. Proposal and Evaluation of a Method for Recognizing Type of Litter Using Sensor-Mounted Tongs. In *The 28th Symposium on Social Information Systems (ISS28)*. 1–6. (in Japanese).

[17] Daizi Yamane and Naohiro Matsumura. 2019. An experiment to deter littering by a shikake reminding the existence of an invisible person. In *The 6th shikake Work-in-Progress Study Group*. 1–9.