ToyADMOS2025: The Evaluation Dataset for the DCASE2025T2 First-Shot Unsupervised Anomalous Sound Detection for Machine Condition Monitoring

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Abstract—Recently, various applications have been explored that utilize machine learning to detect anomalies in machinery solely by listening to operational sounds. This paper introduces the newly recorded ToyADMOS dataset, "ToyADMOS2025", for the DCASE 2025 Challenge Task 2: First-shot anomalous sound detection for machine condition monitoring (DCASE2025T2). New machine types, such as AutoTrash, HomeCamera, ToyPet, and ToyRCCar, were recorded as part of the Additional training and Evaluation datasets. This paper also shows benchmark results of the First-shot baseline implementation (with a simple autoencoder and selective Mahalanobis modes) on the ToyADMOS2025. The dataset, ground truth labels, and source code for the baseline were made available.

Index Terms—DCASE 2025 Challenge Task 2, First-Shot Anomalous sound detection, ToyADMOS dataset

1. INTRODUCTION

Recently, various applications have been explored that utilize machine learning to detect anomalies in machinery solely by listening to operational sounds. Since 2020, this line of research has been formalized as an annual challenge task under the Detection and Classification of Acoustic Scenes and Events (DCASE) Challenge, specifically focusing on anomalous sound detection (ASD).

In the DCASE 2020 Challenge, Task 2 – titled Unsupervised Detection of Anomalous Sounds for Machine Condition Monitoring (DCASE2020T2) [1] – was introduced. This task required systems to learn only from normal operating sounds and determine whether a given machine sound was normal or anomalous.

Since it is generally difficult to collect real recordings of malfunctioning machines, the task employed datasets such as ToyADMOS and MIMII [2], [3], which consist of recordings of intentionally damaged components like toy cars and electric motors.

In the following year, the challenge evolved into DCASE 2021 Challenge Task 2: Unsupervised Anomalous Sound Detection for Machine Condition Monitoring under Domain-Shifted Conditions (DCASE2021T2) [4]. In 2022, the task continued as DCASE 2022 Challenge Task 2: Unsupervised Anomalous Sound Detection for Machine Condition Monitoring Applying Domain Generalization Techniques (DCASE2022T2) [5]. These editions utilized newly recorded datasets including ToyADMOS2, MIMII DUE, and MIMII DG [6]–[8]. Results from these challenge tasks have shown that a system design treating different configurations of the same machine type as pseudo-anomalous classes in a classification-based approach is particularly effective.

However, from a practical deployment perspective, there are many scenarios in which training data encompassing various machine configurations may not be available in advance. To address this, First-shot Anomalous Sound Detection for Machine Condition Monitoring has been introduced in 2023 (DCASE2023T2) [9]. This task investigated whether anomalous sounds could be detected after training solely on normal operating sounds of a previously unseen target machine. This First-shot task introduced a new set of constraints aimed at improving real-world applicability [6], [8]–[11]. Though ToyADMOS2



Fig. 1: Images of toy-model configurations A, B, and C for (a) AutoTrash, (b) HomeCamera, (c) ToyPet, and (d) ToyRCCar.

and MIMII DG were used as development datasets, newly recorded data were required for evaluation.

In DCASE2023T2, ToyADMOS2+ [12] was used as a part of the Additional Training and Evaluation dataset. This includes machine types such as Vacuum, ToyTank, ToyNscase, and ToyDrone.

The First-shot task paradigm continued in DCASE 2024 and 2025 Challenge Task 2: First-shot Unsupervised Anomalous Sound Detection for Machine Condition Monitoring (DCASE2024T2 and DCASE2025T2) [10], [13].

The dedicated dataset called ToyADMOS2#(sharp) [14] was collected for DCASE2024T2, and provided as a part of the Additional Training and Evaluation Datasets. These include recordings from devices such as HairDryer, HoveringDrone, ToothBrush, and ToyCircuit.

For DCASE2025T2, yet another dataset, ToyADMOS2025, was introduced to provide the First-shot ASD. This paper provides the recording details of the ToyADMOS2025 dataset, which has been newly collected as the Additional Training and Evaluation Dataset. This dataset is designed to further support research and development on First-shot anomalous sound detection systems. Other papers utilizing this dataset can simply make reference to this paper. The ground truth of those has been made available at GitHub. The benchmark performance of the DCASE 2023 Task 2 baseline [11] on this dataset is also shown.

Note that the series of datasets is named ToyADMOS; however, the recordings emulate real-world use cases of condition monitoring for complex systems, making it useful for evaluating ASD systems.

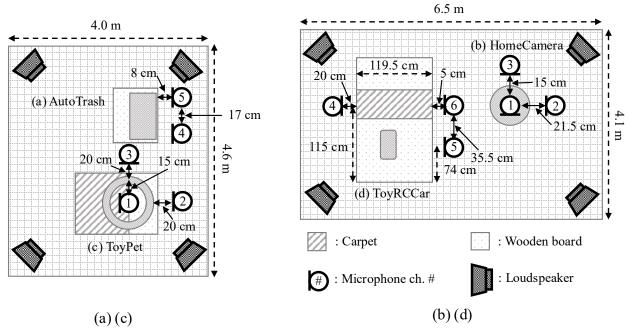


Fig. 2: Recording-room layouts and microphone arrangements, (a) AutoTrash, (b) HomeCamera, (c) ToyPet, and (d) ToyRCCar.

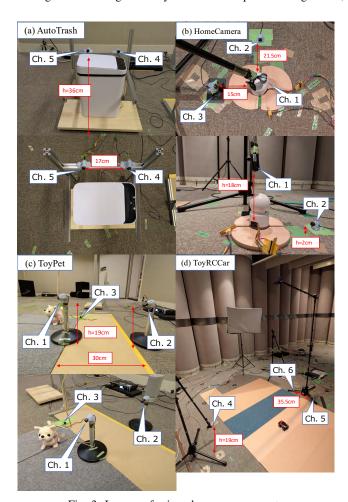


Fig. 3: Images of microphone arrangements (a) AutoTrash, (b) HomeCamera, (c) ToyPet, and (d) ToyRCCar.

Table 1: Anomaly conditions for each machine type.

(a	a) AutoTrash	(b) HomeCamera			
Part	Condition	Part	Condition		
Lid Hinge	Weighted LidMisalignmentForeign objectForeign object	Camera head Joint	- Weighted head - Foreign scuff - Foreign wire - Foreign wires		
		(d) ToyRCCar			
	(c) ToyPet	(d)	ToyRCCar		
Part	(c) ToyPet Condition	(d)	ToyRCCar Condition		

2. TOYADMOS2025: ADDITIONAL DATA FOR THE DCASE2025 CHALLENGE TASK 2

To provide the First-shot training data for DCASE2025T2, the following four machine types, (a) AutoTrash, (b) HomeCamera, (c) ToyPet, and (d) ToyRCCar, were newly recorded. Each machine type has three model configurations (A, B, C) shown in Fig. 1. The machine operating sounds were recorded with the room layout and the microphone settings shown in Figs. 2 and 3.

AutoTrash: The AutoTrash is an automatic trash box shown in Figs. 2(a) and 3(a). It automatically opens and closes its lid.

HomeCamera: The HomeCamera swings its camera head. Sound data were recorded using two microphones as shown in Figs. 2(b) and 3(b).

ToyPet: The ToyPet is on a leash and walks around a pole and barks as shown in Figs. 2(c) and 3(c).

ToyRCCar: The ToyRCCar runs on a wooden board partially covered with carpet as shown in Figs. 2(d) and 3(d).



Fig. 4: Images of anomaly conditions for (a) AutoTrash.

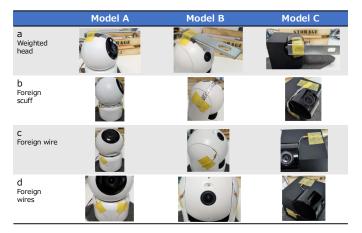


Fig. 5: Images of anomaly conditions for (b) HomeCamera.

Table 2: Recording conditions for DCASE2025T2 Eval. dataset.

	AutoTrash	HomeCamera	ToyPet	ToyRCCar
Model variations	A, B, C	A, B, C	A, B, C	A, B, C
Speed levels Mic. config Noise type* ³ Sample duration	2.7-3.2 V*1 (a) Ch. 4 - 5 N3 6 sec	Four (b) Ch. 1 - 3 N2 6 sec	2.7-3.2 V*1 (c) Ch. 1 - 3 N1 10 sec	200-450 ms* ² (d) Ch. 4 - 6 N4 7 sec

- *1Randomly variable power voltage range.
- *2Randomly variable operation duration.

Table 3: Domain shift settings for DCASE2025T2 Eval. dataset.

Source domain	AutoTrash	HomeCamera	ToyPet	ToyRCCar	
Machine ID Speed	A, B 2.8-3.1 V*1	A, B 2, 3	A, B 2.8-3.1 V*1	A, B A: 350-450 ms* ² B: 200-300ms	
Mic. Noise* ³	(a) Ch. 5 N3	(b) Ch. 3 N2	(c) Ch. 2 N1	(d) Ch. 5 N4	
Target domain	AutoTrash	HomeCamera	ToyPet	ToyRCCar	
Machine ID Speed Mic. Noise* ³	C 2.7-3.2 V*1 (a) Ch. 5 N3	C 1, 4 (b) Ch. 3 N2	C 2.7-3.2 V*1 (c) Ch. 2 N1	C 300-400 ms* ² (d) Ch. 5 N4	

^{*1}Randomly variable power voltage range.

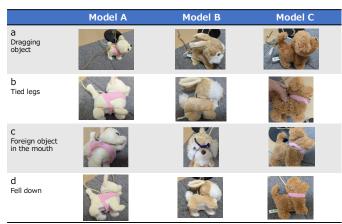


Fig. 6: Images of anomaly conditions for (c) ToyPet.



Fig. 7: Images of anomaly conditions for (d) ToyRCCar.

To generate anomaly samples, some of the parts were intentionally damaged. Anomaly conditions for each machine type are shown in Table 1. The images representing those anomaly conditions are shown in Figs 4, 5, 6 and 7.

Table 2 shows the recording setting. All the operating sound and noise samples were recorded with 48 kHz sampling, 24-bit for each channel, and then downsampled to 16 kHz, 24-bit, monaural. Sample duration varies from 6 sec to 10 sec, depending on the machine type, as shown in Table 2. Domain shift conditions were controlled by changing machine instances (ID), operating speed, mic position, and mixed background noise samples. Table 3 shows the domain shift conditions of source and target domains.

For training data (Additional training dataset), there are 1000 normal samples given for training, where 990 samples are from the source domain, and 10 samples are from the target domain. For evaluation data (Evaluation dataset), 50 normal and 50 anomaly samples are from each source and target domain. In total, there are 200 samples for each machine type. In total, 960 min of data was prepared.

The data is available at the Zenodo links ^{1 2}, under the Creative Commons Attribution 4.0 International Public License³.

^{*3}N1: large air conditioner's outlet noise, N2: city noise near a river under a bridge, N3: server fan noise, and N4: running water sound in a drainage ditch in a park.

^{*2}Randomly variable operation duration.

^{*3}N1: large air conditioner's outlet noise, N2: city noise near a river under a bridge, N3: server fan noise, and N4: running water sound in a drainage ditch in a park.

¹DCASE 2025 challenge task 2 additional training dataset, available at https://zenodo.org/record/15392814

 $^{^{\}hat{2}}DCASE~2025$ challenge task 2 evaluation dataset, available at https://zenodo.org/record/15519362

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Table 4: AUC results of the DCASE 2025 Challenge Task 2 Evaluation dataset.

System	metric	hmean*1	amean*1	AutoTrash	HomeCamera	ToyPet	ToyRCCar	BandSealer	CoffeeGrinder	Polisher	ScrewFeeder
First-shot compliant	AUC (source)	0.6880	0.6996	0.8102	0.8140	0.6770	0.5284	0.7198	0.7304	0.6686	0.6486
simple Autoencoder	AUC (target)	0.4495	0.4721	0.3436	0.4976	0.3670	0.6272	0.3956	0.4436	0.4430	0.6592
mode (FS-AE) [15]	pAUC (src & tgt)	0.5453	0.5468	0.5421	0.5284	0.5500	0.5553	0.5205	0.5342	0.5232	0.6211
	TOTAL score	0.5443	0.5729								
Selective	AUC (source)	0.7199	0.7297	0.7726	0.8616	0.6982	0.5586	0.7638	0.7498	0.7042	0.7290
Mahalanobis	AUC (target)	0.4788	0.5082	0.5260	0.4264	0.5090	0.5548	0.3268	0.4042	0.5278	0.7904
AE mode [15]	pAUC (src & tgt)	0.5459	0.5515	0.5416	0.5184	0.5684	0.5400	0.4911	0.5142	0.5379	0.7005
	TOTAL score	0.5651	0.5965								
DCASE2025T2 Top 1	AUC (source)	0.6198	0.6489	0.7142	0.6536	0.6394	0.3956	0.6356	0.6070	0.6416	0.9042
Wang_MYPS_task2_3 [16]	AUC (target)	0.6574	0.6858	0.9252	0.5978	0.6140	0.5046	0.6490	0.5542	0.7408	0.9006
(Efficient Audio Transformer based pretrained model)	pAUC (src & tgt) TOTAL score	0.5769 0.6163	0.5934 0.6427	0.7705	0.5379	0.5405	0.5284	0.5163	0.5216	0.5405	0.7916

^{*1}hmean denotes harmonic mean, and amean denotes arithmetic mean.

3. BENCHMARK RESULTS WITH THE DCASE2023T2 FIRST-SHOT BASELINE

3.1. The DCASE2023T2 First-shot baseline

The DCASE2023 Challenge Task 2 baseline has the following two operating modes. For the details, see Sec. 3.2 and [11].

First-shot-compliant simple Autoencoder mode (FS-AE): This is a simple autoencoder. For training, the model parameter θ of the AE is trained to minimize the mean square error (MSE) between a normal input sample x^- and its reconstruction \hat{x}^- using

$$Loss = MSE(x^-, \hat{x}^-), \tag{1}$$

where
$$\hat{x}^- = \mathrm{Dec}_{\theta}(\mathrm{Enc}_{\theta}(x^-)).$$
 (2)

For the testing phase, the anomaly score A_{θ} is calculated with the reconstruction error of the given query sample x using

Anomaly Score
$$A_{\theta} = MSE(x, \hat{x}),$$
 (3)

where
$$\hat{x} = \text{Dec}_{\theta}(\text{Enc}_{\theta}(x)).$$
 (4)

When the anomaly score exceeds the pre-set threshold, the sample is detected as an anomaly sample.

Selective Mahalanobis Autoencoder mode: The anomaly score A_{θ} is calculated using the covariance matrixes Σ_s^{-1} and Σ_t^{-1} of distance between normal samples x^- and its reconstruction \hat{x}^- for the source and target domains with:

Anomaly Score
$$A_{\theta} = \min\{D_s(x,\hat{x}), D_t(x,\hat{x})\},$$
 (5)

where
$$D_s(\cdot) = \text{Mahalanobis}(x, \hat{x}, \Sigma_s^{-1}),$$
 (6)

$$D_t(\cdot) = \text{Mahalanobis}(x, \hat{x}, \Sigma_t^{-1}).$$
 (7)

3.2. Experimental setup and evaluation criterion

For the First-shot compliant baseline, the model hyperparameters were set to the values described in [11].

The frame size for STFT was 64 ms with 50 % hop size translated into 128 frequency bands Log-mel energies. Five consecutive frames were concatenated to formulate 640 dimensions (128 \times 5) as input to the system. In the autoencoder model, there were three layers of 128 dimensions linear, Batch normalization, and Activation with ReLU each, in encoder and decoder. The bottleneck layer had eight dimensions. The number of epochs for training was 100. The batch size was 256, and the Adam optimizer used a 0.001 learning ratio.

The performances of the two operating modes of the DCASE2023T2 baseline [11] with the ToyADMOS2025 dataset were evaluated. For those baseline systems, hyperparameters were set to the ones used in the corresponding previous DCASE Challenges [17], [18]. The total scores Ω for evaluating the systems are calculated based on Area Under the Receiver Operating Characteristic (ROC) curve (AUC) and partial AUC (pAUC) with a harmonic mean (hmean) and an arithmetic mean (amean) of AUC and pAUC. All the results were the averaged score of systems trained with three different random seeds, except for the top winning system Wang_MYPS_task2_3 [16], that were copied from the official score.

3.3. Experimental results

Experimental results of the DCASE2023T2 First-shot baseline and the DCASE2025T2 first place winner, Wang_MYPS_task2_3 [16], on the DCASE2025T2 Evaluation datasets are shown in Table 4.

Those results can be categorized into three machine type groups, (A) AutoTrash, ToyPet, Polisher, ScrewFeeder, (B) HomeCamera, BandSealer, CoffeeGrinder, and (C) ToyRCCar.

For group (A) machine types, the DCASE2023T2 baseline with the selective Mahalanobis AE mode performed better than that of the simple Autoencoder (FS-AE) mode. Especially, AUC score of the FS-AE for the target domain data was less than 0.5 which is worth than chance rate. In contrast, Mahalanobis AE provided better than 0.5 accuracy on both source and target domain input. For group (A) machine types, Wang_MYPS_task2_3 further improves detection accuracy compared to the baseline systems. For group (B) machine types, both Mahalanobis AE and FS-AE showed worth than chance rate 0.5 in target domain and Mahalanobis AE performs worse. Wang_MYPS_task2_3 showed the best AUC scores that is better than the chance rate. Group (C) is interesting because the winning system Wang_MYPS_task2_3 performed AUC 0.3956 for ToyRCCar which both baseline systems, FS-AE and Mahalanobis AE, provided better than 0.5 for both source and target domain.

4. CONCLUSION

This paper introduces the newly recorded ToyADMOS dataset for the DCASE 2025 Challenge Task 2, First-shot anomalous sound detection for machine condition monitoring. New machine types, such as AutoTrash, HomeCamera, ToyPet, and ToyRCCar are newly recorded as a part of the Additional training and Evaluation datasets. The ToyADMOS2025 dataset (DCASE 2025 Challenge Task 2 Additional Training Dataset and Evaluation Dataset) is available at Zenodo ¹ ², under the Creative Commons Attribution 4.0 International Public License³. The source code of the baseline and the ground truth of those have been made available at GitHub ^{4 5}.

Note that the dataset is named ToyADMOS; however, the recordings emulate real-world use cases of condition monitoring for complex systems, making it useful for evaluating ASD systems.

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¹DCASE 2025 challenge task 2 additional training dataset, available at https://zenodo.org/record/15392814

 $^2 DCASE\ 2025$ challenge task 2 evaluation dataset, available at https://zenodo.org/record/15519362

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⁴https://github.com/nttcslab/dcase2023_task2_baseline_ae

⁵https://github.com/nttcslab/dcase2025_task2_evaluator

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