

# QiandaoEar22: A high quality noise dataset for identifying specific ship from multiple underwater acoustic targets using ship-radiated noise

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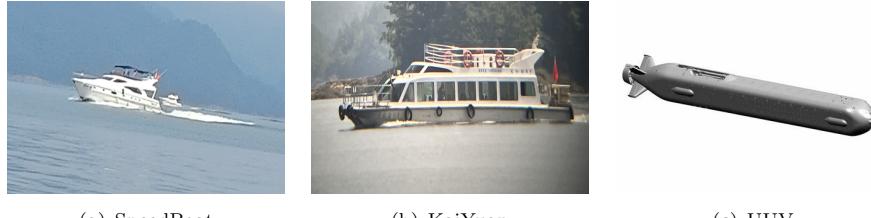
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## Abstract

Target identification of ship-radiated noise is a crucial area in underwater target recognition. However, there is currently a lack of multi-target ship datasets that accurately represent real-world underwater acoustic conditions. To tackle this issue, we conducted experimental data acquisition, resulting in the release of QiandaoEar22 —a comprehensive underwater acoustic multi-target dataset. This dataset encompasses 9 hours and 28 minutes of real-world ship-radiated noise data and 21 hours and 58 minutes of background noise data. To demonstrate the availability of QiandaoEar22, we executed two experimental tasks. The first task focuses on assessing the presence of ship-radiated noise, while the second task involves identifying specific ships within the recognized targets in the multi-ship mixed data. In the latter task, we extracted eight features from the data and employed six deep learning networks for classification, aiming to evaluate and compare the performance of various features and networks. The experimental results reveal that ship-radiated noise can be successfully identified from background noise in over 99% of cases. Additionally, for the specific identification of individual ships, the optimal recognition accuracy achieves 99.56%. Finally, based on our findings, we provide advice on selecting appropriate features and deep learning networks, which may offer valuable insights for related research. Our work not only establishes a benchmark for algorithm evaluation but also inspires the development of innovative methods to enhance UATD and UATR systems.

**Keywords:** Underwater acoustic dataset, Underwater target recognition, Underwater acoustics, Deep learning



**Fig. 1.** Target ships

## 1 Introduction

The significance of underwater target sound as a vital source of information has been underscored since the invention of sonar by American Fessenden in 1913 [1]. Consequently, underwater acoustic technology has been progressively applied, facilitating the differentiation of various sounding target types and enabling analysis of environmental signals. Notably, the focus has shifted towards the ship-radiated noise due to its enhanced concealment, and security.

However, publicly available datasets for underwater acoustic target research are scarce for two primary reasons. Firstly, military secrecy restricts access to numerous recordings made in military facilities [2]. Secondly, the high cost associated with conducting underwater experiments, compounded by signal loss during propagation and limited data quality due to underwater communication equipment constraints, presents challenges in dataset creation [3, 4]. Data, labeling further contribute to the time and energy consumption.

Some small scale datasets have been created, including those from cargo ships, navy vessels, and personal watercraft [2, 5–9]. While some recent datasets like ShipsEar [10] and Deepship [11] are available, they primarily consist of single-target ship data in simple environments, lacking the complexity of multi-target scenarios often encountered in real-world conditions.

To address this issue, we present the QiandaoEar22 dataset, containing 21 hours and 58 minutes of background noise data and 9 hours and 28 minutes of multi-target ship noise signal data. Collected using digitalHyd SR-1 self-capacitance hydrophones in a real underwater acoustic environment at Qiandao Lake, China, during June 2022, this dataset serves as a high-quality ship-radiated noise recording.

Underwater acoustic target identification focuses on discerning the class of ship-radiated noise from background noise. Additionally, underwater acoustic target detection aims to determine the presence or absence of ship targets through binary classification, classifying received signals as either ship-radiated or background signals. This preliminary classification streamlines subsequent tasks. To accomplish this, we first identify ship-radiated noise and background noise signals from acquired underwater acoustic data. Extracting three 1D features (spectrum, power spectral density, DEMON spectra [12]) and five 2D features (LOFAR spectrum [13], Log Mel spectrum, MFCC [14], PNCC [15], GFCC [16]) for the multi-target ship sound signal. Then we employ diverse deep neural networks, including CNN [17], CRNN [18], BiLSTM

[19], DenseNet [20], ResNet [21], and ECAPA-TDNN [22] to classify these features. Finally three specific types of ship signals: speedboat, KaiYuan and UUV are identified from the multi-target ship signals, respectively, as shown in Fig.1. Furthermore, we explore the labeling and formatting aspects of the dataset. Our objective is that the dataset, along with the experimental results, assists researchers in benchmarking algorithms and promotes the development of innovative methods to improve Underwater Acoustic Target Detection (UATD) and Underwater Acoustic Target Recognition (UATR) systems.

The main contribution of this paper is as follows.

Firstly, we have experimentally collected and constructed a high-quality underwater acoustic dataset named QiandaoEar22. This dataset comprises 21 hours and 58 minutes of background noise data and 9 hours and 28 minutes of multi-target vessel noise signal data. QiandaoEar22 dataset closely simulates real recognition environments, providing researchers with a valuable resource to comprehensively evaluate and enhance their underwater acoustic target recognition algorithms.

Secondly, using QiandaoEar22 dataset, this article first distinguishes ship signals and background noise signals from the underwater acoustic data. Then we successfully recognize three specific types of ship signals—speedboats, KaiYuan, and UUV—from the multi-target ship signals, showcasing the practicality of our dataset.

Lastly, we simplifies the identification of specific ship signals from multi-target ship signals by extracting three spectral features and five t-f features. These features are tested using six popular deep learning classifiers, offering researchers a benchmark for algorithm evaluation and some advice on selecting appropriate features and deep learning networks, which may offer valuable insights for related research.

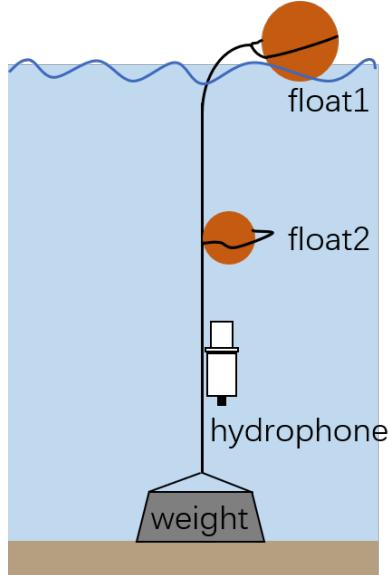
Section 2 details the experiments on acquisition and labeling of the QiandaoEar22 dataset. Section 3 introduces the evaluation of experimental tasks, encompassing the experimental setup, presentation of the two tasks, and analysis and discussion of the results. Conclusions are presented in Section 4.

## 2 The QiandaoEar22 dataset

### 2.1 Recording system and methodology

The data collection took place from June 24 to 28, 2022, at the Xin' anjiang Experimental Site of the Institute of Acoustics, Chinese Academy of Sciences (CAS), situated in the town of Qiandao Lake, Zhejiang, China. Two primary deployment sites were utilized, with coordinates at 118.974532°E, 29.557795°N, and 118.947097°E, 29.548708°N, respectively. Throughout the deployment, a hydrophone was anchored to the center of the deployment area using a counterweight and buoy system, as depicted in Fig.2. The water depth ranged from approximately 30 to 50 meters, and the hydrophone was positioned at a depth of 10 to 15 meters. A dedicated hydrophone was employed for the data collection, using a stand-alone setup positioned near the channel to capture a broader range of radiated noise from the ships.

The hydrophone model used is DigitalHyd SR-1, illustrated in Fig. 3, with key specifications provided in Table 1. The DigitalHyd SR-1 features a sample frequency of 52,734 Hz, a sample resolution of 16 bits, a usable acoustic band of 1–25.8 kHz, a



**Fig. 2.** Schematic diagram of the experimental hydrophone to be deployed in Qiandao Lake in June 2022



**Fig. 3.** DigitalHyd SR-1 hydrophone

receive sensitivity of -162.2~126.1 dB re 1V/ $\mu$ Pa, and an input sound pressure level range of 46.3 dB re 1 $\mu$  Pa~172.5 dB re 1 $\mu$  Pa. The operating depth can reach up to 100 meters, constructed with plastic steel, weighing approximately 0.77 kg. It operates within a temperature range of 0~40°C and employs a USB interface. The device is powered by a rechargeable lithium-ion battery, enabling continuous data collection for up to 12 hours. Acoustic data is stored in WAV format on a removable memory card, which also retains all configuration parameters for subsequent data analysis.

## 2.2 Dataset structure

Following the hydrophone deployment, we observed ships navigating through the channel. We recorded the time when a ship approached and moved away from the hydrophone, approximately 1 kilometer away, along with the ship number and name at those moments. Subsequent data alignment involves identifying the moment at the waveform peak and associating it with the corresponding ship number, thereby correlating the labeling and data for that specific segment. The experimental period

**Table 1.** DigitalHyd SR-1 Hydrophone specifications

Index	Parameter
Sample frequency	52,734 Hz
Sample resolution	16 bits
Usable Acoustic Band	1~25.8kHz
Receive sensitivity	-162.2~ -126.1dB re 1V/ $\mu$ Pa
Input sound pressure level range	46.3dB re 1 $\mu$ Pa~172.5dB re 1 $\mu$ Pa
Operation depth	100m
Surface material	plastic steel
Weight	0.77kg
Operation temperature	0~40 °C
Device interface	USB interface
Power supply	rechargeable lithium-ion battery



**Fig. 4.** Duration of sound data for all vessels

coincided with the tourist season, resulting in recorded ship-radiated noise primarily originating from sightseeing boats and speedboats. Due to the hydrophone's proximity to the navigation channel, passing vessels, including sightseeing boats, speedboats, and other watercraft, contribute to a composite radiated noise. Additional targets include large tour boats, cargo ships, sanitation vessels, small boats, research ships, and ambient noise.

Based on experimentally recorded document information and signal amplitude and spectral characteristics, we determine the start and end time nodes for each audio segment. We label each data piece based on auditory sensation, distance, and labeling data, recording the information in a text document. During this process, the data is segmented into 3-second intervals for ease of subsequent processing. The final database consists of 10,611 records in WAV format, totaling 9 hours, 28 minutes, and 13 seconds of ship-radiated noise data. Each audio file, along with its corresponding data, forms a record in the QiandaoEar22 dataset. The example information fields for each record is as following:

20220624102345 \_ DATA0008 \_ M \_ GreenCity \_ N \_ S & SpeedBoat \_ M \_ W

**Table 2.** Background-Target ship Dataset

Dataset	Train		Test		Valid		Total	
	target	back	target	back	target	back	target	back
Kind								
Num	3500	3550	750	700	750	750	5000	5000
Time(s)	10500	10650	2250	2100	2250	2250	15000	15000
Total time(s)	21150		2350		4500		30000	

(start/stop time - single/multiple targets(S/M) - ship name - distance(N/M/F) - audibility(S/M/W) & name - distance - audibility)

- "filename": filename.
- "time": The start and end time of the audio recording.
- "single/multiple target": The audio capture object is a single ship target or multiple ship targets, which is denoted by S for single target and M for multiple targets.
- "name": name of the vessel.
- "distance": Indicates the distance of the vessel from the hydrophone, N for near, M for medium and F for far.
- "audibility": indicates the audibility of the voice, S for strong, M for Middle, W for weak.
- If multi-target, link with & in order, for each ship including "name", "distance", "audibility".

Based on the consistency of labels, we identified a total of 143 recordings containing both single and multiple ship targets. These data primarily include 20 categories of ship targets, and the overall time distribution of data containing individual targets is illustrated in Fig. 4.

Simultaneously, we selected time slices without targets and other interference to constitute the background noise data, labeled as files DATA0XXX. Ultimately, we obtained a total of 21 hours and 58 minutes, comprising 25,900 records of background noise data, each with a duration of 3 seconds. The dataset can be download following the instructions on <https://github.com/xiaoyangdu22/QiandaoEar22>.

### 3 Ship noise detection experimental tasks and analysis of results

Underwater acoustic target detection focuses on discerning the presence or absence of a target and classifying the received signal as either underwater target radiated noise or non-target noise, involving binary classification. Hence, using this dataset, we undertook two tasks. Task 1 involves identifying ship signals from the acquired underwater acoustic signal data, which includes background noise signals. In Task 2, our objective is to identify three specific types of ship signals—speedboats, KaiYuan, and UUVs—respectively, from the mixed multi-target ship-radiated noise signals.

**Table 3.** The structure of deep learning network

Network	Structure
CNN	Conv <sup>1</sup> (cin=1, cout=4, k=5, s=2, p=1)+ BN(4) + Dropout(0.1)+ ReLU+ MaxPool(k=2, s=2) Conv(cin=4, cout=16, k=5, s=2, p=1)+ BN(16) + Dropout(0.1)+ ReLU+ MaxPool(k=2, s=2) Conv(cin=16, cout=32, k=3, s=2, p=1)+ BN(32) + Dropout(0.1)+ ReLU+ MaxPool(k=1, s=1) Conv(cin=32, cout=64, k=3, s=2, p=1)+ BN(64) + Dropout(0.1)+ ReLU+ MaxPool(k=1, s=1) Linear(64*128, 4*128)+ Linear(4*128, 32)+ Linear(32, 2)
CRNN	Conv(cin =1, cout =4, k=5, s=2,p=1)+ BN(4) + Dropout(0.1)+ ReLU+ MaxPool(k=2, s=2) Conv(cin =4, cout =16, k=5, s=2,p=1)+ BN(16) + Dropout(0.1)+ ReLU+ MaxPool(k=2, s=2) Conv(cin =16, cout =32, k=3, s=2,p=1)+ BN(32) + Dropout(0.1)+ ReLU+ MaxPool(k=1, s=1) Conv(cin =32, cout =64, k=3, s=2,p=1)+ BN(64) +Dropout(0.1)+ ReLU+ MaxPool(k=1, s=1) LSTM( 256,512, 2) Linear(512, 32) + Linear(32, 2)
BiLSTM	LSTM( input, 256, 2)
ResNet	ResNet18 [21]( num classes=2)
DenseNet	DenseNet121 [20]
ECAPA-TDNN	ECAPA-TDNN [22]

<sup>1</sup> Note: Conv1d is used for 1D features and Conv2d for 2D features

### 3.1 Task 1: determine whether the audio contains ship-radiated noise

The objective of Task 1 is to determine whether the audio contains ship-radiated noise. We ultimately selected the first 5000 ship noise recordings, along with the initial 30 recordings from DATA0001 and 20 recordings from DATA0002, to compose the final dataset. Data segmentation details has been introduced in Part 2. We use 70% of the dataset for training, 15% for validation, and 15% for test. The characteristics of the final dataset are presented in Table 2. Log Mel spectra features were extracted for the data. Deep learning networks were employed for feature classification, and the network structures used are shown in Table 3. Each experiment was conducted ten times to calculate the mean and variance.

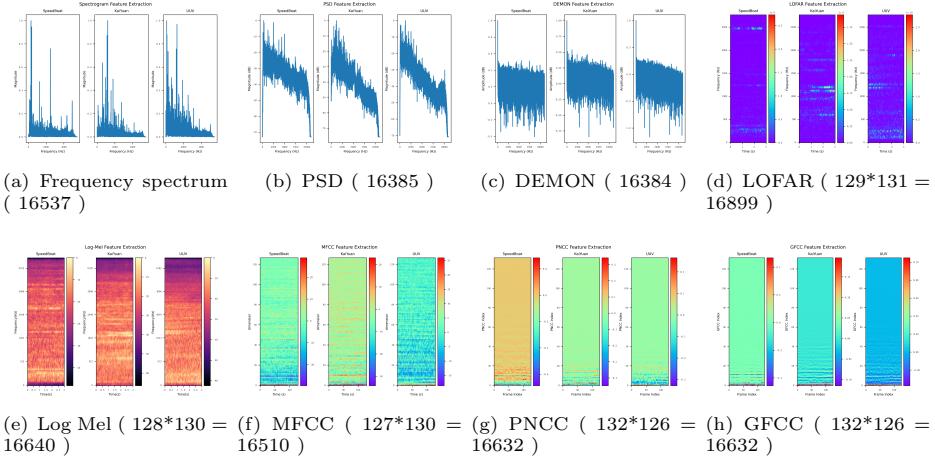
Table 4 presents the accuracy results for all deep learning methods. Excep BiLSTM, the classification accuracy for other methods exceeded 99%. Notably, the CRNN exhibited the most robust classification performance, achieving an accuracy of 99.79%. Additionally, its recall, precision, F1 score, FNR, and FPR values also reached 99.79%, 99.80%, 99.79%, 0.00%, and 0.43%, respectively. The experimental results indicate a high level of distinguishability between ship-radiated noise data and background noise data within the dataset, showcasing the significant application value of our dataset.

**Table 4.** Accuracy Comparison (%) for task 1

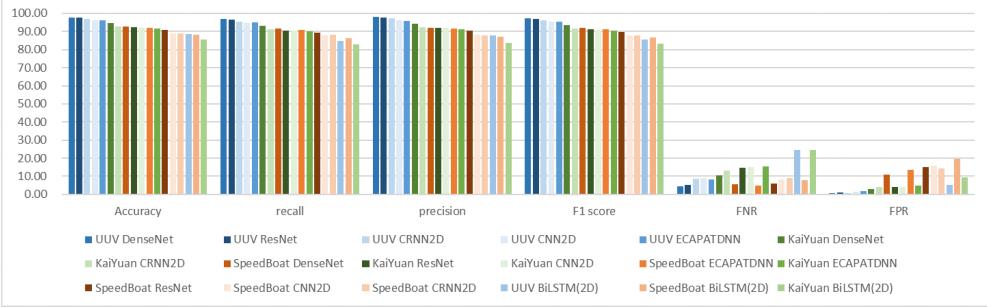
net	accuracy	recall	precision	f1	FNR	FPR
CNN2d	99.66±0.00	99.65±0.00	99.66±0.00	99.65±0.00	0.27±0.00	0.43±0.00
CRNN2d	99.79±0.05	99.79±0.09	99.80±0.18	99.79±0.05	0.00±0.13	0.43±0.00
DenseNet	99.72±0.04	99.72±0.06	99.73±0.06	99.72±0.05	0.13±0.21	0.43±0.06
ECAPA-TDNN	99.31±0.00	99.42±0.00	99.29±0.01	99.42±0.00	0.67±0.02	0.71±0.01
BiLSTM	91.17±0.01	91.37±0.00	91.61±0.01	91.17±0.01	14.27±0.03	0.30±0.00
ResNet	99.52±0.01	99.50±0.01	99.53±0.01	99.52±0.01	0.13±0.03	0.86±0.01

**Table 5.** The SpeedBoat, KaiYuan and UUV datasets

data		Train		Test		Valid	
		Kind	SpeedBoat	Other	SpeedBoat	Other	SpeedBoat
SpeedBoat	Num	4848	2578	1041	554	1038	552
	Time(s)	14544	7734	3123	1662	3114	1656
	Total time(s)	22278		4785		4770	
	Kind	Kaiyuan	Other	Kaiyuan	Other	Kaiyuan	Other
KaiYuan	Num	1363	2801	293	599	291	600
	Time(s)	4089	8403	879	1797	873	1800
	Total time(s)	12492		2676		2673	
	Kind	UUV	Other	UUV	Other	UUV	Other
UUV	Num	631	1401	136	299	135	300
	Time(s)	1893	4203	408	897	405	900
	Total time(s)	6096		1305		1305	



**Fig. 5.** The examples of feature extraction



**Fig. 6.** Average experimental results of deep learning methods for 2D feature classification

### 3.2 Task 2: determine if there are any targets of interest in the multi-ship mixed data

In Task 2, our primary goal is to determine the presence of any targets of interest in the multi-ship mixed data. The selected research objects include speedboats, passenger ship KaiYuan, and underwater unmanned Vehicle UUV. Corresponding datasets were constructed for each research object, as illustrated in Table 5. Subsequently, examples of the extracted features and their corresponding dimensions are depicted in Fig. 5.

To facilitate performance comparison among different features, we constrained the feature dimensions within the range of 16,384 (128128) to 16,900 (130130). Finally, deep learning networks were employed for feature classification, with the network structures consistent with Task 1. For 1D features, CNN, CRNN, and BiLSTM were exclusively used for comparative experiments. Model performance was evaluated using recall, precision, accuracy, F1 score, FNR, and FPR.

For the three target datasets established, we conducted various comparative experiments with different features and networks. To better analyze the experimental results, we summarize the results from different perspectives, forming the following three sections: Comparison of Network 3.2.1, Comparison of Feature 3.2.2, and Summarize 3.2.3.

#### 3.2.1 Comparison of Network

In this section, to compare the performance of different networks, we calculated the average indicators for 1D and 2D features separately in experiments with different datasets using the same network. The results in the figures represent all UUV experiment outcomes with varying shades of blue bars, all KaiYuan experiment results with varying shades of green bars, and similarly, all SpeedBoat experiment outcomes with varying shades of orange bars.

##### Comparison of network for 2D Feature Classification

The experimental results of different networks for 2D feature classification are shown in the Table 6 and Fig. 6. We can observe that in the UUV experiment, the network performance from best to worst is DenseNet, ResNet, CRNN, CNN, ECAPA-TDNN, BiLSTM. In the KaiYuan experiment, the network performance from best to worst is DenseNet, CRNN,

**Table 6.** Average results of deep learning methods for 2D feature classification(%)

experiment	net	accuracy	recall	precision	F1 score	FNR	FPR
UUV	DenseNet	97.78	96.96	97.93	97.36	4.34	0.84
UUV	ResNet	97.56	96.75	97.59	97.08	5.43	1.07
UUV	CRNN2D	96.93	95.45	97.45	96.30	8.45	0.59
UUV	CNN2D	96.21	94.81	96.35	95.48	8.93	1.46
UUV	ECAPA-TDNN	96.15	94.99	95.97	95.41	8.10	1.65
KaiYuan	DenseNet	94.52	93.24	94.39	93.69	10.51	3.02
KaiYuan	CRNN2D	92.73	91.17	92.32	91.60	13.36	4.29
SpeedBoat	DenseNet	92.61	91.82	91.92	91.83	5.60	10.76
KaiYuan	ResNet	92.49	90.63	92.17	91.30	14.77	3.96
KaiYuan	CNN2D	92.19	90.33	91.93	90.98	15.10	4.24
SpeedBoat	ECAPA-TDNN	92.08	90.78	91.65	91.14	4.97	13.48
KaiYuan	ECAPA-TDNN	91.82	90.00	91.31	90.45	15.30	4.70
SpeedBoat	ResNet	90.85	89.43	90.33	89.78	5.90	15.25
SpeedBoat	CNN2D	89.14	87.98	88.21	88.00	8.23	15.81
SpeedBoat	CRNN2D	89.05	88.22	88.00	87.94	9.11	14.22
UUV	BiLSTM	88.48	84.68	87.68	85.39	24.47	5.20
SpeedBoat	BiLSTM	88.06	86.22	87.18	86.57	7.74	19.80
KaiYuan	BiLSTM	85.50	82.91	83.79	83.27	24.64	9.54

ResNet, CNN, ECAPA-TDNN, BiLSTM. In the SpeedBoat experiment, the network performance from best to worst is DenseNet, ECAPA-TDNN, ResNet, CNN, CRNN, BiLSTM. In the UUV experiment using the DenseNet network, the average recognition accuracy can reach 97.78%, 96.96% of the data containing UUV targets are accurately recognized, and 97.93% of the data predicted by the network containing UUV targets are correct targets. The average F1 score also reaches 97.36%, with only 4.34% of the data containing UUV targets being falsely recognized, and the mispredicted UUV accounts for only 0.84% of the non-target ship samples.

Combining the results from the three experiments, it's evident that the networks demonstrating the best overall performance for 2D feature classification are DenseNet and CRNN, followed by ResNet, which exhibits certain advantages for small-scale datasets (UUV). ECAPA-TDNN, on the other hand, presents a more pronounced advantage in classifying large-scale and complex datasets (SpeedBoat). CNN performs at an average level, while the network with the poorest classification performance is BiLSTM.

To better assess network performance, we computed the scale and computational complexity of deep learning models, primarily using two indicators: model parameters and FLOPs (Floating Point Operations Per Second). Model parameters refer to the total number of trainable parameters in a deep learning model, including weights and biases in neural networks. A higher number of parameters indicate a larger model capacity, but it also implies higher computational costs for training and inference. FLOPs represent the number of floating-point operations per second, commonly used to measure the performance of computers or computing devices. In deep learning, FLOPs are often used to describe the computational complexity of a model, indicating the total number of floating-point operations. A higher FLOPs value suggests that the model requires more computational resources. These two metrics provide comprehensive insights into the scale and computational requirements of a model.

The computational experimental results, as presented in the Table 7, have been visually represented in Fig. 6 by incorporating computational complexity into the classification outcomes. In the figure, darker colors in the bars indicate higher computational complexity. From these two perspectives, it is evident that DenseNet and ResNet exhibit higher computational

**Table 7.** Computational complexity and scale of deep learning models

Method	FLOPS	parameters
CNN2D	0.96M	0.33M
CRNN2D	4.76M	0.07M
DenseNet	933.09M	7.97M
ECAPA-TDNN	169.44M	1.53M
BiLSTM	102.24M	0.80M
ResNet	829.26M	13.96M

**Table 8.** Average results of deep learning methods for 1D feature classification(%)

experiment	net	accuracy	recall	precision	F1 score	FNR	FPR
UUV	CNN1D	97.22	96.17	97.36	96.70	6.62	1.04
UUV	CRNN1D	96.80	95.72	96.77	96.18	7.16	1.39
UUV	BiLSTM	96.50	94.84	97.08	95.69	9.59	0.33
SpeedBoat	CNN1D	94.82	89.14	89.87	89.46	6.41	15.32
KaiYuan	CRNN1D	93.82	92.52	93.34	92.87	11.25	3.70
KaiYuan	CNN1D	92.74	91.94	91.84	91.82	10.37	5.74
SpeedBoat	CRNN1D	91.53	90.67	90.72	90.64	6.51	12.16
KaiYuan	BiLSTM	90.24	87.79	89.71	88.58	19.34	5.08
SpeedBoat	BiLSTM	86.54	84.08	85.71	84.59	7.84	24.00

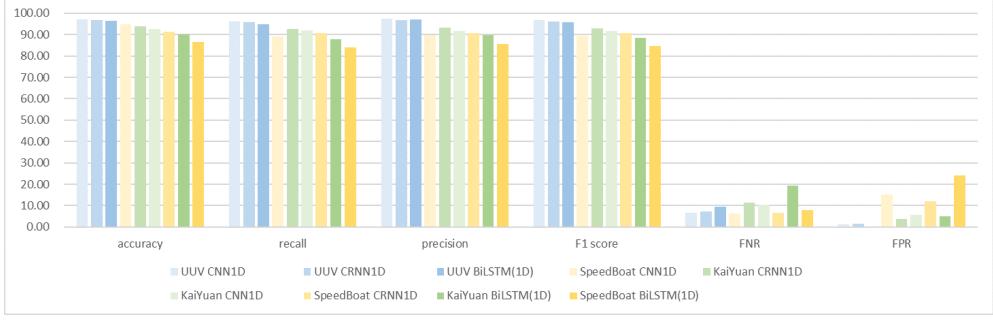
complexity and, correspondingly, superior classification performance. Models with moderate computational efficiency, such as ECAPA-TDNN and BiLSTM, demonstrate relatively poorer classification results. On the other hand, CNN and CRNN, being light-weight models, achieve above-average classification performance. This further underscores the principle that there is no free lunch, and pursuing exceptional accuracy inevitably requires sacrificing computational efficiency at a certain cost.

In conclusion, for underwater acoustic target recognition tasks using 2D features, we propose the following network selection strategy:

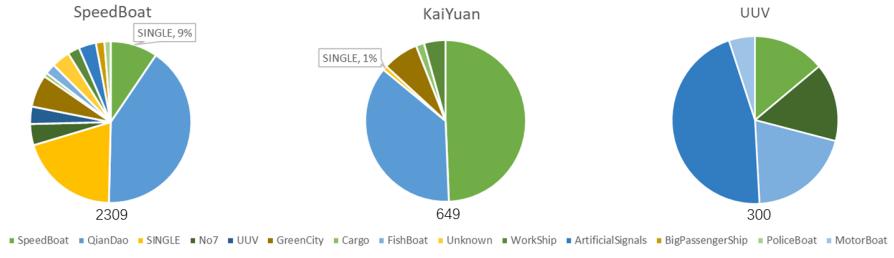
1. For small to medium-scale datasets, the CRNN (Convolutional Recurrent Neural Network) is recommended due to its lower computational complexity and relatively good classification performance.
2. For large-scale datasets, the ECAPA-TDNN (Emphasized Channel Attention, Propagation and Aggregation in Time Delay Neural Network) network is suggested. It exhibits moderate computational complexity but demonstrates a certain advantage in handling large-scale datasets.
3. If the primary focus is on achieving extremely high classification accuracy without considering computational efficiency, the DenseNet (Densely Connected Convolutional Network) can be directly chosen. It consistently presents the best classification results across datasets of different scales.

#### Comparison of network for 1D Feature Classification

The network classification results for 1D data are illustrated in Table 8 and Fig. 6. In the UUV experiment, the CNN network outperformed CRNN and BiLSTM. In the KaiYuan experiment, CRNN demonstrated superior performance to CNN based on FPR and FNR indicators; however, CNN outperformed CRNN based on the other four metrics. In the SpeedBoat experiment, CNN exhibited better accuracy compared to CRNN, whereas CRNN outperformed CNN in terms of FPR, F1 score, and recall metrics. The performance of both



**Fig. 7.** Average experimental results of deep learning methods for 1D feature classification



**Fig. 8.** The data distribution for the three experiments. In the SpeedBoat experiment, the total number of vessels is 2309, while in the KaiYuan experiment, the total number of vessels is 649, and in the UUV experiment, the total number of vessels is 300.

**Table 9.** Average results of the same feature (%)

feature	accuracy	recall	precision	F1 score	FNR	FPR
Spectrum	96.73	96.43	96.30	96.35	3.49	3.65
MFCC	95.47	94.92	95.06	94.95	5.36	4.54
Log Mel	94.24	93.24	93.89	93.48	7.43	6.09
PSD	93.73	92.40	93.55	92.87	7.84	7.35
GFCC	92.77	91.43	92.25	91.75	10.23	6.66
PNCC	92.56	91.25	91.96	91.54	10.16	7.25
DEMON	89.61	85.46	87.62	86.29	17.02	11.92
LOFAR	87.22	83.72	86.89	84.83	20.99	11.58

networks was relatively comparable in terms of FNR and precision. It's worth noting that BiLSTM consistently showed poorer performance across all experiments. With the exception of the SpeedBoat experiment based on BiLSTM, the classification results for all other networks consistently achieved above 90%. Notably, the UUV experiment using CNN1D demonstrated an impressive average classification result of 97.22%.

Combining the above experimental results, we can infer that 1D features contain relatively simple information, and satisfactory results can be achieved by employing straightforward

**Table 10.** Spectrum feature classification results (%)

data	net	accuracy	recall	precision	f1	FNR	FPR
SpeedBoat	<b>CNN1d</b>	<b>95.40</b>	<b>94.57</b>	<b>95.27</b>	<b>94.89</b>	<b>2.69</b>	<b>8.18</b>
	CRNN1D	94.09	93.71	93.34	93.52	5.03	7.55
	BiLSTM	93.66	93.50	92.69	93.07	5.99	7.00
KaiYuan	CNN1d	97.11	96.71	96.74	96.72	4.44	2.14
	<b>CRNN1D</b>	<b>97.15</b>	<b>97.15</b>	<b>96.47</b>	<b>96.80</b>	<b>2.87</b>	<b>2.84</b>
	BiLSTM	95.45	94.82	94.86	94.84	7.03	3.34
UUV	CNN1d	98.64	98.49	98.38	98.43	1.91	1.11
	CRNN1D	99.49	99.23	99.60	99.41	1.47	0.07
	<b>BiLSTM</b>	<b>99.56</b>	<b>99.68</b>	<b>99.32</b>	<b>99.49</b>	<b>0.00</b>	<b>0.63</b>

network classification. Therefore, for underwater acoustic target recognition tasks based on 1D features, we propose the following strategy: For small-scale datasets (UUV), CNN networks can be used for classification, while for medium and large-scale datasets (KaiYuan, SpeedBoat), CRNN networks can be employed for classification.

#### Comparison of network for three datasets experiments

Based on Fig. 6 and Fig. 7, it can be observed that in the majority of metrics, the UUV experiment outperforms the KaiYuan experiment, while the results of the KaiYuan experiment are also superior to those of the SpeedBoat experiment. Particularly notable is the FPR metric, where the indicator FPR is significantly higher in the SpeedBoat experiment compared to the UUV and KaiYuan experiments. This is primarily due to the diverse range of vessels included in the SpeedBoat experiment, resulting in more complex combinations of different ships. We have depicted pie charts corresponding to the vessels in each of the three experimental datasets, as shown in Fig. 8. The SpeedBoat experiment comprises a total of 2309 data points, involving 13 types of ships such as QianDao and GreenCity; the KaiYuan experiment includes 649 data points with ships like WorkShip and PoliceBoat; the UUV experiment, with only 300 data points, features vessels like PoliceBoat and FishBoat. Under the same feature and network conditions, the model exhibits better classification performance on smaller and less complex datasets, leading to the result where the UUV experiment performs better than the KaiYuan experiment, which, in turn, outperforms the SpeedBoat experiment.

Furthermore, in the evaluation of the FNR metric, we observed that the KaiYuan experiment had a higher FNR than the UUV experiment, and both were higher than the SpeedBoat experiment, contrary to the conclusions drawn earlier. We speculate that the reason of this experimental result is related to the composition of the data. Firstly, the SpeedBoat dataset contains 9% single-target data, which is advantageous for the model to learn the characteristics of SpeedBoat targets, resulting in a low false-negative rate. For the KaiYuan dataset, although it includes 1% single-target data, the proportion is too small. Additionally, compared to the UUV data, there is a serious imbalance in the types of samples, which may be the reason for the slightly higher false-negative rate in the KaiYuan dataset. As for the UUV dataset, although it does not contain single-target data, its sample combinations are relatively simple and evenly distributed, resulting in a moderate false-negative rate.

#### 3.2.2 Comparison of Feature

In the feature comparison analysis, we consider that an excellent feature must be applicable in different environments and networks. Therefore, we directly average the results obtained for each feature, as shown in Table 9. Among all features, the spectrum performs the best

**Table 11.** The strategies of feature and deep learning network selection for underwater acoustic target recognition tasks

	1D feature:spectrum	2D feature: MFCC	
small scale dataset	CNN	CRNN	
medium scale dataset	CRNN	CRNN	
massive scale dataset	CRNN	ECAPA-TDNN	Excluding costs: DenseNet

while MFCC features perform the best among the 2D features, with both achieving accuracies of over 95%. Our experimental results indicate that the spectrum and MFCC features of ship-radiated noise play crucial roles in classification. The spectrum of ship-radiated noise consists of continuous, line, and modulation spectra, providing essential information about ship operations, engine status, and underwater environments. Meanwhile, MFCC features, designed based on human auditory perception, process signals through Mel filters and employ methods like logarithmic scaling and Discrete Cosine Transform (DCT) to reduce redundant features. This approach better captures features at different frequencies in ship-radiated noise.

Regarding other features, PNCC utilizes power-law nonlinearity instead of the traditional logarithmic nonlinearity in MFCC coefficients. It introduces a noise suppression algorithm based on asymmetric filtering to mask background excitation and a module for implementing temporal masking. However, these adjustments are disadvantageous for recognizing ship noise signals. GFCC features, employing Gammatone filters, enhance recognition of impulse signals. Still, as ship noise contains very few impulse signals, their recognition effect is not as robust as that of MFCC features. DEMON spectral features respond to information such as the number of propeller blades on a ship, but since the signals identified in this paper are multi-target signals, this feature poorly distinguishes between different signals. LOFAR features are more suitable for finding narrow-band features in signals and low signal-to-noise ratio situations.

### 3.2.3 Summarize

Based on the raw experimental results, we observe that in the KaiYuan experiment, the best-performing recognition network is the combination of CRNN network with spectrum features. In the SpeedBoat experiment, the best-performing recognition network is the combination of CNN network with spectrum features. In the UUV experiment, the best-performing recognition network is the combination of BiLSTM network with spectrum features. Spectrum features perform excellently in all three experiments, and the complete experimental results for this feature are shown in the Table 10. The highest accuracy for features containing targets in the three experiments can reach 97.15%, 95.40%, and 99.56%, respectively. Moreover, they exhibit extreme stability across ten tests, with the vast majority of variances nearly approaching zero. Even with networks like BiLSTM that demonstrate comparatively poor overall performance, using Spectrum features can still yield high accuracy. This also indirectly indicates that in the field of underwater target recognition, the importance of feature decision-making may surpass that of network decision-making.

Based on our experimental results, we propose the following strategy of feature and deep learning network selection for underwater acoustic target recognition tasks, which has been shown in Table 11. Firstly, feature selection is more crucial than network selection. Spectrum is preferred as the choice for 1D features, while MFCC features are preferred for 2D features. Secondly, for 1D feature classification, CNN can be chosen for small-scale datasets, while CRNN is suitable for medium to large-scale datasets. For 2D feature classification, CRNN is recommended for small to medium-scale datasets, while ECAPA-TDNN is suitable for

massive-scale datasets. If high recognition accuracy is desired, DenseNet network can be selected. We hope that our experimental results can provide some reference for future related research.

## 4 Conclusion

This paper introduces QiandaoEar22, an underwater acoustic multi-target mixing dataset constructed through the field experiment collection in Qiandao Lake. The data set contains 9 hours and 28 minutes of ship-radiated acoustic noise and 21 hours and 58 minutes of background noise. To demonstrate the availability of QiandaoEar22, we executed two experimental tasks. The first task focuses on assessing the presence of ship-radiated noise, while the second task involves identifying specific ships within the recognized targets in the multi-ship mixed data. For latter task, we extracted eight features from the data and employed six deep learning networks for classification, aiming to evaluate and compare their performance. We set speedboat, passenger ship KaiYuan, and underwater unmanned vehicle UUV as the research object. The best recognition accuracy achieved is 99.56%. Additionally, based on our findings, we provide advice on selecting appropriate features and deep learning networks, which may offer valuable insights for related research. In the future, we hope to establish some form of collaborative network to better learn the semantic information contained in different features, and to develop more efficient deep learning networks with higher robustness to better accomplish underwater acoustic target recognition tasks.

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**Availability of data and materials** The authors confirm that the data supporting the findings of this study are available within the article.

## Declarations

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** All authors consent to the publication of this manuscript.

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