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I. Introduction

Learning in acoustic environmental noise is challenging due to its own characteristics. On the one hand, the noise waveforms of different acoustic scenes are relatively stable, and it is difficult to extract useful features. On the other hand, there are similarities in the acoustic characteristics of different environments, for example, there may be human voices in the speech data collected for several seconds from both the parks and public squares scenarios, which brings greater challenges to feature extraction.

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II. Related Work

A. Acoustic scene classification

The prestigious detection and classification of acoustic scene and events (DCASE) [1] challenge covers state-of-the-art techniques for classifying acoustic environmental noise.

[2] [3] [4] both use data augmentation to expand the training set to bring larger samples for model training. [2] focuses on improving model performance on the data, demonstrating the importance of data preprocessing for embedded machine learning performance. From a data-centric perspective, [3] proves that the parameter setting of data preprocessing has a certain impact on model fairness.

In recent years, research in acoustic scene classification has focused on CNN network [5], especially ResNet [6] and DenseNet [7]. They have excellent performance in the field of image processing, but due to the characteristics of the acoustic scene, if the resnet is directly applied to them, the network performance will be greatly reduced. [8] proves this, and proposes to use 1D and 2D convolution in speech data at the same time, extending the time output to the frequency time dimension. [9] proves the effect of receptive field on generalization ability in acoustic scene classification problem.

B. Model Compression

Model compression has abundant research achievement [10]. From the perspective of model structure, [11] [12] improves the convolution kernel structure of the commonly used convolutional neural network (CNN). [13]Tensor (or matrix) operations are the basic operations of neural networks, so tensor decomposition is an effective way to shrink and speed up neural network models. [14] [15] [16]Data quantization is designed to solve the problem that most embedded devices do not support floating-point operations, and is widely used in model compression of mobile devices.

In addition, in the image domain, many lightweight networks for compressing models emerge, which greatly

reduces the amount of parameters and memory overhead. The fire module of Squeezenet [17] is composed of squeeze and expand parts. The commonly used 3×3 convolution kernel is replaced with a 1×1 convolution kernel, which effectively reduces the number of parameters. In order to improve the model accuracy, a small number of 3×3 convolution kernels are spliced in the expand layer. The great thing about MobileNets [18] [19] [20] are the design of the depthwise separable convolutional structure, which reduces the complexity exponentially. These studies have achieved certain performance on images, but the compressed models are still difficult to use in low-power embedded devices.

Another perspective is the knowledge distillation method. Hinton [21] designed the teacher-student structure, that first training a huge teacher model, and then learning a relatively small model from the teacher model. Knowledge distillation is often used in acoustic scene classification problems [22]. [23] verifies that although the knowledge distillation method can reduce the loss of the student model, there is still a big gap compared with the teacher model. So an assistant model called RKD was introduced to further distill the knowledge.

C. Machine learning in LPWAN

In recent years, the compressed models are mostly deployed on mobile devices, which are all implemented relying on the backbone network. The implementation of AI technology in LPWAN is mainly concentrated in the field of cognitive radio [24]. [25]employs deep neural networks (DNNs) to intelligently explore data-driven test statistics to accurately characterize real-world environments. [26] proposed a cognitive C-LPWAN architecture based on an artificial intelligence cognitive engine to reduce network latency and minimum energy consumption rate, incorporating sensor selection for a battery-powered IoT-assisted cognitive radio (CR-IoT) network The strategy is applied in LPWAN to extend the life of LoRa network.

[27] [28] [29] [30] [31]implement machine learning algorithms in embedded devices. [27] designed a serial-FFT-based Mel-frequency cepstrum coefficient circuit, and used binary depthwise separable convolution to reduce power consumption. [31] jointly designed a framework for an efficient neural architecture (TinyNAS) and a lightweight inference engine (TinyEngine), and its inference speed is 1.7-3.3× faster than TF-Lite Micro and CMSIS-NN

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