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***Abstract*—**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

is a typical application of the combination of Internet of Things (**IoT**) technology and industrial fields [1], which plays a critical role in remote monitoring of construction site operation conditions. With increasing demands on system performance, economic development and environmental concerns, modern industrial processes are more complicated in both structure and degree of automation. Therefore, the reliability and safety issues of these complex processes become the most critical aspects in system design, and technologies that combine IoT with industrial monitoring are receiving more and more attention today [2].Compared with the traditional Internet of Things(IoT), the Industrial Internet of Things has its own characteristics [3], *e.g.*, the lifespan of equipment is usually measured in decades. In addition, most industrial machines are usually located in harsh environments, with a wide distribution range, physical environment and even unpredictable network environment. The design of IAEM needs to meet the following requirements: i. The installation and maintenance cost of monitoring equipment should be a few percent of machinery, so most use energy harvesting devices or battery power. ii. Surveillance system lifetime and maintenance intervals should be as long as possible, typically decades. iii. The IoT nodes in the monitoring system are widely distributed to reduce deployment costs and consume very little energy during operation.

Low-Power-Wireless-Area-Network(LPWAN) is a ...

II. Related Work

A. Acoustic scene classification

The prestigious detection and classification of acoustic scene and events (DCASE) [4] challenge covers state-of-the-art techniques for classifying acoustic environmental noise.

[5] [6] [7] both use data augmentation to expand the training set to bring larger samples for model training. [5] focuses on improving model performance on the data, demonstrating the importance of data preprocessing for embedded machine learning performance. From a data-centric perspective, [6] 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 [8], especially ResNet [9] and DenseNet [10]. 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. [11] 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. [12] proves the effect of receptive field on generalization ability in acoustic scene classification problem.

B. Model Compression

Model compression has abundant research achievement [13]. From the perspective of model structure, [14] [15] improves the convolution kernel structure of the commonly used convolutional neural network (CNN). [16]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. [17] [18] [19]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 [20] 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

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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 [21] [22] [23] 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, which is often used in acoustic scene classification problems [24].The development of knowledge distillation tends to two directions: In general, the ensemble network is considered to perform better, especially if the ensemble network is migrated to a student model, the latter will achieve better results [25]. Another trend is to transfer a deep complex network to a small and shallow network, also known as the teacher-student model. In this paper, we focus the latter, . Hinton [26] designed the teacher-student structure, that first training a huge teacher model, and then learning a relatively small model from the teacher model. [27] 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 [28]. [29]employs deep neural networks (DNNs) to intelligently explore data-driven test statistics to accurately characterize real-world environments. [30] 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.

[31] [32] [33] [34] [35]implement machine learning algorithms in embedded devices. [31] designed a serial-FFT-based Mel-frequency cepstrum coefficient circuit, and used binary depthwise separable convolution to reduce power consumption. [35] 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.

	Model	MCU	Task &Performance(Accuracy, energy)
[28]	DSCNN	28nm CMOS	One word KWS :98%, 510-nW Two word KWS:94.6%, 510-nW
[29]	SVM	nRF52840 Adafruit Feather,STM32f103c8 and so on	binary classification:92. 85%

Fig. 1.

REFERENCES

[1] P. Ray, "A survey on internet of things architectures," *Journal of King Saud University - Computer and Information Sciences*, vol. 30, no. 3, pp. 291–319, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1319157816300799

[2] S. Yin, S. X. Ding, X. Xie, and H. Luo, "A review on basic data-driven approaches for industrial process monitoring," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 11, pp. 6418–6428, 2014.

[3] P. Sommer, Y. Maret, and D. Dzung, "Low-power wide-area networks for industrial sensing applications," in *2018 IEEE International Conference on Industrial Internet (ICII)*, 2018, pp. 23–32.

[4] D. Stowell, D. Giannoulis, E. Benetos, M. Lagrange, and M. D. Plumbley, "Detection and classification of acoustic scenes and events," *IEEE Transactions on Multimedia*, vol. 17, no. 10, pp. 1733–1746, 2015.

[5] D. S. Park, W. Chan, Y. Zhang, C.-C. Chiu, B. Zoph, E. D. Cubuk, and Q. V. Le, "Specaugment: A simple data augmentation method for automatic speech recognition," *Interspeech 2019*, Sep 2019. [Online]. Available: http://dx.doi.org/10.21437/Interspeech.2019-2680

[6] W. Toussaint, A. Mathur, A. Y. Ding, and F. Kawsar, "Characterising the role of pre-processing parameters in audio-based embedded machine learning," in *Proceedings of the 19th ACM Conference on Embedded Networked Sensor Systems*, ser. SenSys '21. New York, NY, USA: Association for Computing Machinery, 2021, p. 439–445. [Online]. Available: https://doi.org/10.1145/3485730.3493448

[7] A. Y. Hannun, C. Case, J. Casper, B. Catanzaro, G. F. Diamos, E. Elsen, R. J. Prenger, S. Satheesh, S. Sengupta, A. Coates, and A. Ng, "Deep speech: Scaling up end-to-end speech recognition," *ArXiv*, vol. abs/1412.5567, 2014.

[8] Y. Lee, S. Lim, and I.-Y. Kwak, "Cnn-based acoustic scene classification system," *Electronics*, vol. 10, no. 4, 2021. [Online]. Available: https://www.mdpi.com/2079-9292/10/4/371

[9] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2015.

[10] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," 2018.

[11] B. Kim, S. Chang, J. Lee, and D. Sung, "Broadcasted residual learning for efficient keyword spotting," *ArXiv*, vol. abs/2106.04140, 2021.

[12] K. Koutini, H. Eghbal-zadeh, M. Dorfer, and G. Widmer, "The receptive field as a regularizer in deep convolutional neural networks for acoustic scene classification," 2019.

[13] L. Deng, G. Li, S. Han, L. Shi, and Y. Xie, "Model compression and hardware acceleration for neural networks: A comprehensive survey," *Proceedings of the IEEE*, vol. 108, no. 4, pp. 485–532, 2020.

[14] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," 2015.

[15] B. Wu, A. Wan, X. Yue, P. Jin, S. Zhao, N. Golmant, A. Gholaminejad, J. Gonzalez, and K. Keutzer, "Shift: A zero flop, zero parameter alternative to spatial convolutions," 2017.

[16] V. Klema and A. Laub, "The singular value decomposition: Its computation and some applications," *IEEE Transactions on Automatic Control*, vol. 25, no. 2, pp. 164–176, 1980.

[17] M. Courbariaux, Y. Bengio, and J.-P. David, "Binaryconnect: Training deep neural networks with binary weights during propagations," in *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 2*, ser. NIPS'15. Cambridge, MA, USA: MIT Press, 2015, p. 3123–3131.

[18] K. Hwang and W. Sung, "Fixed-point feedforward deep neural network design using weights +1, 0, and –1," in *2014 IEEE Workshop on Signal Processing Systems (SiPS)*, 2014, pp. 1–6.

[19] L. Deng, P. Jiao, J. Pei, Z. Wu, and G. Li, "Gxnor-net: Training deep neural networks with ternary weights and activations without full-precision memory under a unified discretization framework," 2018.

[20] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "Squeezenet: Alexnet-level accuracy with 50x fewer parameters and ¡0.5mb model size," 2016.

[21] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," 2017.

[22] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "Mobilenetv2: Inverted residuals and linear bottlenecks," 2019.

[23] A. Howard, M. Sandler, G. Chu, L.-C. Chen, B. Chen, M. Tan, W. Wang, Y. Zhu, R. Pang, V. Vasudevan, Q. V. Le, and H. Adam, "Searching for mobilenetv3," 2019.

[24] J.-W. Jung, H.-S. Heo, H.-J. Shim, and H.-J. Yu, "Knowledge distillation in acoustic scene classification," *IEEE Access*, vol. 8, pp. 166 870–166 879, 2020.

[25] Z. Allen-Zhu and Y. Li, "Towards understanding ensemble, knowledge distillation and self-distillation in deep learning," *CoRR*, vol. abs/2012.09816, 2020. [Online]. Available: https://arxiv.org/abs/2012.09816

[26] G. Hinton, O. Vinyals, and J. Dean, "Distilling the knowledge in a neural network," 2015.

[27] M. Gao, Y. Wang, and L. Wan, "Residual error based knowledge distillation," *Neurocomputing*, vol. 433, pp. 154–161, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925231220318117

[28] A. J. Onumanyi, A. M. Abu-Mahfouz, and G. P. Hancke, "Towards cognitive radio in low power wide area network for industrial iot applications," in *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)*, vol. 1, 2019, pp. 947–950.

[29] C. Liu, J. Wang, X. Liu, and Y.-C. Liang, "Deep cm-cnn for spectrum sensing in cognitive radio," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 10, pp. 2306–2321, 2019.

[30] M. Chen, Y. Miao, X. Jian, X. Wang, and I. Humar, "Cognitive-lpwan: Towards intelligent wireless services in hybrid low power wide area networks," *IEEE Transactions on Green Communications and Networking*, vol. 3, no. 2, pp. 409–417, 2019.

[31] W. Shan, M. Yang, T. Wang, Y. Lu, H. Cai, L. Zhu, J. Xu, C. Wu, L. Shi, and J. Yang, "A 510-nw wake-up keyword-spotting chip using serial-fft-based mfcc and binarized depthwise separable cnn in 28-nm cmos," *IEEE Journal of Solid-State Circuits*, vol. 56, no. 1, pp. 151–164, 2021.

[32] A. Andreadis, G. Giambene, and R. Zambon, "Convolutional neural networks for audio classification on ultra low power iot devices," in *2021 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)*, 2021, pp. 1–6.

[33] S. Jung, C. Liao, Y. Wu, S.-M. Yuan, and C.-T. Sun, "Efficiently classifying lung sounds through depthwise separable cnn models with fused stft and mfcc features," *Diagnostics*, vol. 11, no. 4, Apr. 2021, publisher Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland.

[34] G. Cerutti, R. Prasad, and E. Farella, "Convolutional neural network on embedded platform for people presence detection in low resolution thermal images," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Conference Proceedings, pp. 7610–7614.

[35] J. Lin, W.-M. Chen, Y. Lin, J. Cohn, C. Gan, and S. Han, "Mcunet: Tiny deep learning on iot devices," 2020.