

**BED: A Real-Time Object Detection System for Edge Devices**

Guanchu Wang*  
guanchu.wang@rice.edu  
Rice University

Zaid Pervaiz Bhat*  
zaid.bhat1234@tamu.edu  
Texas A&M University

Zhimeng Jiang*  
zhimengj@tamu.edu  
Texas A&M University

Yi-Wei Chen*  
yiwei.chen@tamu.edu  
Texas A&M University

Daochen Zha*  
daochen.zha@rice.edu  
Rice University

Alfredo Costilla Reyes*  
acostillar@rice.edu  
Rice University

Afshin Niktash  
Afshin.Niktash@analog.com  
Analog Devices

Gorkem Ulkar  
Gorkem.Ulkar@analog.com  
Analog Devices

Erman Okman  
Erman.Okman@analog.com  
Analog Devices

Xuanting Cai  
caixuanting@fb.com  
Meta Platforms, Inc

Xia Hu  
xia.hu@rice.com  
Rice University

---

**ABSTRACT**

Deploying deep neural networks (DNNs) on edge devices provides efficient and effective solutions for the real-world tasks. Edge devices have been used for collecting a large volume of data efficiently in different domains. DNNs have been an effective tool for data processing and analysis. However, designing DNNs on edge devices is challenging due to the limited computational resources and memory. To tackle this challenge, we demonstrate object detection system for Edge Devices (BED) on the MAX78000 DNN accelerator. It integrates on-device DNN inference with a camera and an LCD display for image acquisition and detection exhibition, respectively. BED is a concise, effective and detailed solution, including model training, quantization, synthesis and deployment. The entire repository is open-sourced on GitHub1, including a Graphical User Interface (GUI) for on-chip debugging. Experiment results indicate that BED can produce accurate detection with a 300-KB tiny DNN model, which takes only 91.9 ms of inference time and 1.845 mJ of energy. The real-time detection is available at YouTube2.

---

**CCS CONCEPTS**

- Computing methodologies → Machine learning algorithms;
- Information systems → Mobile information processing systems.

**KEYWORDS**

Edge Device, Real-time System, Object Detection

---

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

ACM Reference Format:
Guanchu Wang*, Zaid Pervaiz Bhat*, Zhimeng Jiang*, Yi-Wei Chen*, Daochen Zha*, Alfredo Costilla Reyes*, Afshin Niktash, Gorkem Ulkar, Erman Okman, Xuanting Cai, and Xia Hu. 2022. BED: A Real-Time Object Detection System for Edge Devices. In Proceedings of the 31st ACM International Conference on Information and Knowledge Management (CIKM ’22), October 17–21, 2022, Atlanta, GA, USA. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3511808.3557168

---

1 INTRODUCTION

With the explosive growth of internet of thing technologies, billions of image data have been collected from the edge devices in different real-world scenarios [11]. For example, a single surveillance camera can collect nearly 60 GB traffic video per day [16]. This enables us to leverage powerful deep neural networks (DNNs) to process and analyze the data, which has various applications, such as action recognition, and object detection. However, DNN training/inference requires extensive computational resources, especially under the big data discipline. How can we efficiently deploy DNNs for image analysis on edge devices is an open challenge.

Traditional solutions embrace cloud-based services to transmit the collected data to the cloud for computation. Specifically, all the image data will be first uploaded to a cloud. Then a DNN will perform inference using powerful hardwares (e.g., GPUs) on the cloud. Finally, the inference results will be downloaded to the edge devices. However, such strategy suffers from high transmission delay [2]. To address this issue, edge computing has been proposed to transfer the major computations to devices [17]. It brings the computation closer to the source of the data for fast and efficient data processing. Moreover, it enjoys several benefits, such as low power consumption or risk of privacy invasion [15].

It is quite challenging to deploy DNNs to the edge devices due to the very limited hardware constraints, such as the memory capacity, computational resources or power consumption [18]. First,
the common convolution operations usually needs high precision, e.g., 32-bit floating points, which consumes massive computational resources [1, 3, 14]. Edge devices support 16-bit floating points, 8-bit integer operations or less to simplify the hardware complexity [7]. Second, DNNs require large memory to store the network weights and feature maps of intermediate layers during the feed-forward process [5]. The memory capacity of edge devices is not big enough for a large DNN model. Even though network pruning or distillation has been proposed to compress DNNs for the deployment [6], it is difficult to maintain the performance of DNNs. Therefore, deploying DNNs to edge devices requires non-trivial research and engineering efforts.

In this paper, we demonstrate the deployment of DNN models on edge devices for real-time object detection, which has broad real-world applications, such as surveillance, human computer interaction, and robotics [12]. In particular, we present object detection system for Edge Devices (BED), an end-to-end system which integrates a DNN practiced on MAX78000 with I/O devices. The system configuration is illustrated in Figure 1. Specifically, the DNN model for the detection is deployed on MAX78000, an efficient and low-power DNN accelerator; the I/O devices includes a camera and a screen for image acquisition and output exhibition, respectively. The DNN model is pre-trained and evaluated on the VOC2007 dataset [4]. Experiment results demonstrate BED can provide accurate object detection with a 300 KB tiny DNN model, and spend only 91.9 ms time and 1.845 mJ energy on the inference of each sample. We also develop a Graphical User Interface (GUI) in BED for users not familiar with the coding of MAX78000. In the live and interactive part of our demo, we will showcase BED for real-time object detection.

2 OBJECT DETECTION SYSTEM FOR EDGE DEVICES

Figure 2 shows the BED pipeline, which includes four stages: (i) model training stage that employs Quantization Aware Training to train a model, (ii) quantization stage that performs an 8-bit quantization, (iii) synthesis stage that converts the model to executable C code, and (iv) deployment stage that compiles the C code and loads the executable model to the edge device. We will first provide a background of MAX78000, and then elaborate on each of the stages.

Figure 1: BED implements a real-time and end-to-end object detection system from the camera to the screen.

Figure 2: BED pipeline.

2.1 MAX78000 DNN Accelerator

MAX78000 DNN Accelerator is a powerful AI microprocessor for efficient and low-power inference on edge devices. Figure 3 compares the inference time and the power consumption of MAX78000 with two non-AI microprocessors MAX32650 and STM32F7 on two representative DNN tasks KWS20 and FaceID [9]. MAX78000 enjoys significant advantages in both inference time and power consumption. Thus, we deploy object detection models on MAX78000.

Despite its clear advantages, MAX78000 has several hard constraints on the model, making it challenging to design DNNs. First, to speed up the inference, it only supports very few operators: 3×3 convolutional kernel, 1×1 convolutional kernel, average pooling, maximum pooling, Relu activation function, etc. Second, MAX78000 has only 432 KB flash for storing model parameters. It is challenging to achieve a good performance under such operator and memory constraints.

2.2 Model Training

This subsection introduces the neural architecture of BED and the training details. We focus on standard object detection tasks, which aim to learn a DNN to detect the coordinate and the class of the existing objects from an image.

To maximally utilize the limited memory for model parameters, BED adopts a fully convolutional networks [10] for the detection. Note that MAX78000 supports very limited operators. The DNN model is constructed fully based on 3×3 convolutional layer, Relu activation, Batch normalization, 2×2 max-pooling without other operators, as shown in Figure 4. In this way, BED spends only 300KB on the storage of model parameters. An input image is in the RGB format with a size of 224×224×3, and is divided into a 7×7 grid, where each cell has a 32×32 area. The model outputs a 7×7×15 tensor for each image, where each of the 7×7 cells corresponds to a 15 dimensional output vector consisting of class probabilities, two bounding boxes and their confidence scores. In such a manner, the model outputs the detection result which contains both the coordinates and the class.

The model is trained on a subset of VOC2007 dataset which contains the images of five classes with their annotations. To minimize the performance degradation after the post-quantization, we adopt Quantization Aware Training [8]. Specifically, in the training,
the model has the feed-forward process given by

\[ H_{l+1} = Q(f(W_l H_l + b_l)) \]  \hspace{1cm} (1)

where \(H_l, W_l\) and \(b_l\) denote the feature map, weights and bias of layer \(l\), respectively; \(Q(\bullet)\) denotes a simulative 8-bit quantization adopting FLOAT32 to simulate the INT8 inference. We follow the training strategy of Yolo-V1 [13] to update the model. Specifically, we adopt cross entropy and mean square error loss functions for the classification and the bounding box coordinates, respectively. Furthermore, we employ the SGD optimizer with \(3 \times 10^{-3}\) learning rate, and adopt the mini-batch updating with batch-size 16 to update the parameters of model for 400 epochs; we back up the snapshot of model at the end of each training epoch; and select the optimal model to maximize the mean average precision on the validating dataset. More training details are provided in our repository\(^9\).

2.3 Quantization and Synthesis

The trained model will be processed by quantization and synthesis such that it can be deployed on MAX78000.

The quantization stage reads a checkpoint file of the float pre-trained model and outputs the corresponding quantized model. During this process, the pre-trained model is processed by a 32-bit quantization for the last layer and an 8-bit quantization for the remaining layers, which involves the quantization of weight, bias and activation function for each layer of the model. The code of quantization is available in our repository\(^10\).

The synthesis stage converts the quantized pre-trained model into C program. Specifically, it reads the checkpoint of the pre-trained model after the quantization and automatically generate header files to store its weights, bias and hyper-parameters. It also wraps up other requirements including the configuration files for the deployment.

3 DEPLOYMENT

After the synthesis, the C program is compiled into executable code using the ARM embedding compiler\(^11\). The executable model is loaded to MAX78000 through serial protocol. The source code of the deployment is given here\(^12\).

As an integrated system, BED adopts a camera\(^13\) to capture the images and an LCD screen\(^14\) to display the detection results. The image captured by the camera is represented as a three-dimensional matrix with three channels of red, green and blue. The images are loaded to MAX78000 block by block, where the blocks are temporarily stored to a flash memory with 896KB capacity inside MAX78000 until all of the blocks have been loaded. After this, the model takes as input the image and outputs a \(7 \times 7 \times 15\) tensor via Non-maximum Suppression [13], where the non-maximum suppression will be stored to a flash memory. The result of classification and bounding box will be displayed on the LCD screen.

4 EVALUATION AND DEMONSTRATION

4.1 Offline Evaluation

The offline experiment focuses on evaluating the performance of the pre-trained model (after quantization) before loading it to the edge device. We visualize the detection results of some randomly selected images and an LCD screen to demonstrate the deployment.

---

\(^9\)https://github.com/datamllab/BED_main

\(^10\)https://github.com/MaximIntegratedAI/ai8x-synthesis/blob/develop/quantize.py

\(^11\)https://developer.arm.com/tools-and-software/open-source-software/developer-tools/gnu-toolchain/gnu-rm/downloads

\(^12\)https://github.com/datamllab/BED_GUI

\(^13\)https://github.com/datamllab/BED_camera

\(^14\)https://developer.arm.com/tools-and-software/open-source-software/developer-tools/gnu-toolchain/gnu-rm/downloads

\(^15\)https://www.crystalfontz.com/products/document/3032/CFAF320240F-035T-TS_Data_Sheet_2012-04-11.pdf
chosen images from the testing set of VOC2007 in Figure 6 (b). It is observed BED can accurately detect the objects in the input images.

4.2 Real-time Demonstration

We conduct two real-time experiments to demonstrate the on-device object detection. The first experiment focuses on on-device inference. Specifically, a computer will transmit images to MAX78000, which then sends the detection results back to the computer. In the computer-side, we implement a Graphical User Interface (GUI) to send the image, receive and show the detection results, as shown in Figure 5. For more results, please refer to our demo video\footnote{https://youtu.be/0tY31_cECCA}.

The second experiment demonstrates the whole pipeline of BED based on the testing bed in Figure 6 (b), where an image is shown on a source screen; BED captures the image by the camera and shows the detection results on the screen. We randomly select some images from the testing set of VOC2007, and give the real-time detection results in Figure 6 (c). BED can correctly detect the object in the image captured by the camera and show the results on the screen.

4.3 Latency of Real-time Detection

The latency of BED is measured by averaging 100 times of on-chip inference, which starts from an image loading to the output of detection results. The average inference time and energy of BED are given in Table 1, which are 91.9 ms and 1.845 mJ, respectively. Moreover, BED merely requires 299.52 KB memory to store the network weights of the deep object detection model. Generally, the latency of BED satisfies the demands of real-world scenarios in terms of the constraints of latency, energy and memory.

| Processing Step | Power (mW) | Inference Time (ms) | Energy (mJ) |
|----------------|------------|---------------------|-------------|
| Image loading and DNN inference | 20.08 | 91.9 | 1.845 |

5 LIVE AND INTERACTIVE PARTS

In the demo session, we will present a live demo of real-time object detection based on MAX7800 using our developed GUI. Moreover, we will give a tutorial of BED, including platform setup, model deployment and application of our developed GUI.

6 CONCLUSION AND FUTURE WORK

In this work, we build an integrated system, called BED, for real-time object detection on edge devices. We design a compact deep learning model under very limited memory, energy and computational resources. BED captures images with a camera, computes on-chip inference of the DNN, and displays the detection results on an LCD screen. In the future, we will explore neural architecture search to optimize network architectures under the constraints of memory, latency and power.
REFERENCES

[1] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018).

[2] Tharam Dillon, Chen Wu, and Elizabeth Chang. 2010. Cloud computing: issues and challenges. In 2010 24th IEEE international conference on advanced information networking and applications. Ieee, 27–33.

[3] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. 2020. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In International Conference on Learning Representations.

[4] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. [n.d.]. The PASCAL Visual Object Classes Challenge 2007 (VOC2007) Results. http://www.pascal-network.org/challenges/VOC/voc2007/workshop/index.html.

[5] Yanjie Gao, Yu Liu, Hongyu Zhang, Zhengxian Li, Yongzhao Zhu, Haoxiang Lin, and Mao Yang. 2020. Estimating gпу memory consumption of deep learning models. In Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. 1342–1352.

[6] Song Han, Huizi Mao, and William J Dally. 2015. Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. arXiv preprint arXiv:1510.00149 (2015).

[7] Najmul Hassan, Saira Gillani, Ejaz Ahmed, Ibrar Yaqoob, and Muhammad Imran. 2018. The role of edge computing in internet of things. IEEE communications magazine 56, 11 (2018), 110–115.

[8] Raghuraman Krishnamoorthi. 2018. Quantizing deep convolutional networks for efficient inference: A whitepaper. arXiv preprint arXiv:1806.08342 (2018).

[9] Ardis Kristopher and Muchsel Robert. 2020. Cutting the AI Power Cord: Technology to Enable True Edge Inference. https://cms.tinyml.org/wp-content/uploads/talks2020/tinyML_Talks_Kris_Ardis_and_Robert_Muchsel_-202007.pdf (2020).

[10] Jonathan Long, Evan Shelhamer, and Trevor Darrell. 2015. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition. 3431–3440.

[11] MG Sarwar Murshed, Christopher Murphy, Daping Hou, Nazar Khan, Ganesh Ananthanarayanan, and Faraz Hussain. 2021. Machine learning at the network edge: A survey. ACM Computing Surveys (CSUR) 54, 8 (2021), 1–37.

[12] Ajheet Ram Pathak, Manjusha Pandey, and Siddharth Rautaray. 2018. Application of deep learning for object detection. Procedia computer science 132 (2018), 1706–1717.

[13] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. 2016. You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition. 779–788.

[14] Joseph Redmon and Ali Farhadi. 2018. Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767 (2018).

[15] Weisong Shi, Jie Cao, Quan Zhang, Youhuizi Li, and Lanyu Xu. 2016. Edge computing: Vision and challenges. IEEE internet of things journal 3, 5 (2016), 637–646.

[16] Science U.S. Department of Homeland Security and Technology Directorate. [n.d.]. CCTV Technology Handbook. https://www.dhs.gov/sites/default/files/publications/CCTV-Tech-HBK_0713-508.pdf.

[17] Blesson Varghese, Nan Wang, Sakil Barabidiya, Peter Kilpatrick, and Dimitrios S Nikolopoulos. 2016. Challenges and opportunities in edge computing. In 2016 IEEE International Conference on Smart Cloud (SmartCloud). IEEE, 20–26.

[18] Wei Wei, Andrew T Yang, Weisong Shi, and Kewei Sha. 2016. Security in internet of things: Opportunities and challenges. In 2016 International Conference on Identification, Information and Knowledge in the Internet of Things (IIKI). IEEE, 512–518.