ADDRESSING GAP BETWEEN TRAINING DATA AND DEPLOYED ENVIRONMENT BY ON-DEVICE LEARNING

A PREPRINT

Kazuki Sunaga
Keio University
3-14-1 Hiyoshi, Kohoku-ku, Yokohama, Japan
sunaga@arc.ics.keio.ac.jp

Masaaki Kondo
Keio University
3-14-1 Hiyoshi, Kohoku-ku, Yokohama, Japan
kondo@acsl.ics.keio.ac.jp

Hiroki Matsutani
Keio University
3-14-1 Hiyoshi, Kohoku-ku, Yokohama, Japan
matutani@arc.ics.keio.ac.jp

December 27, 2023

ABSTRACT

The accuracy of tinyML applications is often affected by various environmental factors, such as noises, location/calibration of sensors, and time-related changes. This article introduces a neural network based on-device learning (ODL) approach to address this issue by retraining in deployed environments. Our approach relies on semi-supervised sequential training of multiple neural networks tailored for low-end edge devices. This article introduces its algorithm and implementation on wireless sensor nodes consisting of a Raspberry Pi Pico and low-power wireless module. Experiments using vibration patterns of rotating machines demonstrate that retraining by ODL improves anomaly detection accuracy compared with a prediction-only deep neural network in a noisy environment. The results also show that the ODL approach can save communication cost and energy consumption for battery-powered Internet of Things devices.

Keywords Machine learning · Neural network · Edge AI · On-device learning · OS-ELM · Wireless sensor node

1 Challenges on Edge AI

Edge intelligence has gained significant attention due to the proliferation of emerging Internet of Things (IoT) and artificial intelligence (AI) technologies [1]. Most edge AI applications are generally viewed as an edge-cloud cooperative system, as shown in Figure[1]. Classical edge applications are usually responsible for sensing environmental data and sending them to the cloud. Due to the wide spread of edge AI technologies, AI inference is becoming a major task of edge devices.

These “prediction-only edge AI” systems work properly if the target environment around the edge devices is fairly static. However, an environment incessantly changes over time in the real world. For example, a vibration pattern of some equipment captured by an IoT sensor would be affected by the setting of a room ventilation fan, as demonstrated later in this article. This problem is known as the concept drift [2]. An on-device learning (ODL) approach [3], in which edge devices learn the target phenomenon by themselves, is practical to address this problem without demanding an excessive generalization performance.

Prediction-only edge AI needs a high generalization performance to achieve good accuracy wherever it is deployed. However, this is not necessarily important in the ODL scenario since it is trained in a deployed environment and operated in the same environment unless concept drifts occur. This enables us to use low-cost neural networks as machine learning models if they can be trained in deployed environments. In this article, we extend our previous work...
Figure 1: Edge-cloud AI system where sensing, preprocessing, prediction, and training are done by edge devices (left) while their monitoring and controlling interfaces are provided by the cloud (right). Edge devices transmit prediction results to a gateway wirelessly.

In [4] to implement multiple neural networks for complex patterns. We then demonstrate that they can be trained in relatively low-end IoT devices, such as a Raspberry Pi Pico (Figure 3), using an online sequential learning algorithm tailored for such devices.

In the ODL approach, we do not upload raw sensing data to a cloud server except for prediction results. This is one of the most important characteristics, especially for wireless sensor nodes since they are mostly restricted by energy budgets and wireless communication dominates their energy consumption. Reducing the energy consumed in wireless communication is one of the perpetual demands for IoT devices. In this article, we demonstrate that the ODL approach is beneficial for reducing the energy consumption (and thereby increasing the battery life) of wireless sensor nodes that use long range (LoRa) as a low-power wide-area (LPWA) network technology.

2 ON-DEVICE LEARNING

In [1], edge AI systems are classified into six levels from “cloud-edge coinference and cloud training” (Level 1) to “all on-device” (Level 6). A typical prediction-only edge AI system corresponds to Level 3 while our ODL approach is Level 6. As the level increases, the data transmission latency and network bandwidth decrease, while the data privacy and computation cost at edge increase. Thus, reducing the computation cost is a primary concern in the ODL scenario, and it is addressed by redesigning the machine learning algorithm as introduced in this section.

A de facto approach to train artificial neural networks is using a backpropagation algorithm combined with a stochastic gradient descent (SGD) or its variant. A batch of training samples is processed at a time assuming that an entire training dataset is available. This assumption is infeasible in low-end IoT devices with limited memory capacity (e.g., 264 KiB in a Raspberry Pi Pico). In fact, it is reasonable that sensor data is generated continuously as a stream.

OS-ELM [4] takes a different approach to sequentially train artificial neural networks. It is an online sequential learning algorithm for feedforward neural networks consisting of an input layer, hidden layer, and output layer, as shown in Figure 2. Weight parameters between the input and hidden layers are denoted as $\alpha$, and those between the hidden and output layers are $\beta$. Prediction is done by $G(x_i \alpha + b) \beta$, where $G$ is an activation function, $x_i$ is an n-dimensional input data at time $i$, and $b$ is a bias vector. As for the training phase, $\alpha$ is initialized with random numbers once, while $\beta$ is sequentially updated for every incoming data using preceding values. That is, at time $i$, $\beta$ is updated with preceding parameters $\beta_{i-1}$, temporary vector $P_i$, and hidden layer output $H_i$ calculated by input data $x_i$, as shown in Figure 2. Such sequential processing is suited to IoT devices with limited memory capacity since only a single data item is retained at a time.

For semi-supervised anomaly detection, OS-ELM is combined with an autoencoder [5], where the numbers of input nodes $n$ and output nodes $m$ are the same. At the training phase, $\beta$ is updated to minimize the loss defined by $L(y, t)$, where $L$ is a loss function, $y$ is a neural network output, $t$ is a normal data, and $t = x$. It is then used for anomaly detection. Since it has been trained with normal data, the reconstruction error $L(y, x)$ is interpreted as an anomaly score of an input data $x$. Only normal data is needed at the training phase, enabling the ODL approach to be adapted
Addressing Gap between Training Data and Deployed Environment by On-Device Learning

Figure 2: Prediction and sequential training algorithms of ODL with multiple instances, where $x$ is input data, $l$ is anomaly score, $k$ is output class, $\alpha$ and $\beta$ are weight parameters, $b$ is bias vector, $P$ is temporary vector, $G$ is activation function, $H$ is hidden layer output, $L$ is loss function, $n$ is number of input nodes, $N$ is number of hidden layer nodes, $m$ is number of output nodes, and $K$ is number of ODL instances. Predict and train modes are switched manually or automatically.

$y_0 = G(x_i \alpha + b) \beta_0$

$l_o = L(y_0, t)$

$l = \min_{j=K} l_j$

$k = \arg \min_{j=K} l_j$

$P_{k,i} = P_{k,i-1} - P_{k,i-1}H_i^T (I + H_iP_{k,i-1}H_i^T)^{-1}H_iP_{k,i-1}$

$\beta_{k,i} = \beta_{k,i-1} + P_{k,i}H_i^T (t - H_i\beta_{k,i-1})$

An instance with the smallest loss value is interpreted as the closest instance to a given pattern. By repeating this sequential training process, the instances are specialized to a number of specific patterns. Note that an initial clustering is done by a sequential k-means algorithm during an initial training phase.

ODL has two modes: predict and train (Figure 2b). In the predict mode, weight parameters are not updated. These modes are switched either manually or automatically. The manual mode change is triggered by a train button; users or field-engineers push the train button when retraining is needed, indicating the current input data is the new normal. The initial training and clustering rely on the manual training. The modes can also be switched automatically when pre-specified concept drifts, such as sudden, gradual, incremental, and reoccurring ones [2], are detected by algorithms. For example, a fully-sequential concept drift detection algorithm [7] can also be used in conjunction with the ODL algorithm toward the autonomous retraining.

1. Prediction is done by $K$ instances to produce loss values using their own parameters. The smallest loss value among them is used as an anomaly score, as shown in Figure 2b.

2. Sequential training is performed by a single instance that outputs the smallest loss value, as shown in Figure 2b.

An instance with the smallest loss value is interpreted as the closest instance to a given pattern. By repeating this sequential training process, the instances are specialized to a number of specific patterns. Note that an initial clustering is done by a sequential k-means algorithm during an initial training phase.

ODL has two modes: predict and train (Figure 2b). In the predict mode, weight parameters are not updated. These modes are switched either manually or automatically. The manual mode change is triggered by a train button; users or field-engineers push the train button when retraining is needed, indicating the current input data is the new normal. The initial training and clustering rely on the manual training. The modes can also be switched automatically when pre-specified concept drifts, such as sudden, gradual, incremental, and reoccurring ones [2], are detected by algorithms. For example, a fully-sequential concept drift detection algorithm [7] can also be used in conjunction with the ODL algorithm toward the autonomous retraining.
3 IMPLEMENTATION

We built an edge-cloud anomaly detection system as shown in Figure 1. Figure 3 illustrates implementations of our edge devices, where four ODL instances are implemented on a Raspberry Pi Pico (consisting of an ARM Cortex-M0+ CPU at 133 MHz and 264 KiB SRAM). We use the GCC cross compiler for ARM Cortex-R/M processors v6.3.1, and the optimization level is -O3. The edge devices are equipped with an accelerometer or a thermal camera, and those with the accelerometer are used in this article. They are attached to target objects using a magnet to observe vibration patterns on the targets. Anomaly detection results on the vibration patterns are sent to a wireless gateway with LoRa as an LPWA technology. They are then transferred to the cloud so that users can monitor the results via a web interface as shown in Figure 1. Grafana and MySQL are used for the visualization and database, respectively, at the cloud side. In the edge devices, STMicroelectronics STM32WLE5JC SoC (consisting of an ARM Cortex-M4 CPU at 48 MHz) that supports LoRa modulation is used for the wireless communication. These edge devices are battery-powered in our system, so their power consumption determines their lifetime.

Figure 4a shows the execution time breakdown at the edge side when anomaly detection is executed every second. The breakdown consists of the following six parts:

1. A 1024-point acceleration data is received from an accelerometer via Serial Peripheral Interface (SPI) at 2 MHz. It is referred to as sensing.
2. Fast Fourier transformation (FFT) and downsampling are executed to produce a 256-point frequency spectrum ranging from 1 to 512 Hz at a 2 Hz resolution. They are referred to as preprocessing.
3. Prediction with four instances is performed to calculate their loss values.
4. Sequential training is performed by a single instance that outputs the smallest loss value.
5. A 20 B anomaly detection result containing an anomaly score $l$, output class $k$, and headers is transmitted to a gateway via LoRa (see Figure 1). It is referred to as communication.
6. Deep sleep mode of Raspberry Pi Pico.

The four ODL instances each with $n = 256$, $N = 32$, and $m = 256$ are implemented on the Raspberry Pi Pico. Sigmoid and mean squared error are used as an activation function $G$ and loss function $L$, respectively. $\alpha$ is shared by all four instances, while $P$ and $\beta$ are individual for each instance. The parameter size is thus $nN + 4NN + 4Nm$ in total. Assuming float32 is used as a number format, the memory usage is 176 KiB, which can be implemented in the 264 KiB SRAM of the Raspberry Pi Pico. Execution times of the prediction and sequential training of possible configurations are shown in Figure 4b. The execution time of a single prediction is shorter than that of sequential training while it is executed four times when the number of ODL instances is four. A larger $N$ enriches the expressive power while it consumes more memory and thus limiting the input size $n$. In any cases, their execution times do not overwhelm the others, as shown in Figure 4a.
4 EXPERIMENTAL RESULTS

4.1 Energy and Execution Time

The following four cases are examined to see energy and execution time benefits of ODL.

- Case 1: ODL that performs sensing, FFT, prediction, and sequential training at edge. Prediction result (20 B) is transmitted to a gateway with LoRa.
- Case 2: Prediction-only edge AI that performs sensing, FFT, and prediction at edge. In addition to the prediction result, preprocessed data after FFT (1024 B) is also transmitted to the gateway if needed for a retraining purpose at the cloud.
- Case 3: Vibration sensor that performs sensing and FFT at edge. Preprocessed data after FFT (1024 B) is transmitted to the gateway.
- Case 4: Acceleration sensor that performs only sensing at edge. Raw acceleration data (2048 B) is transmitted to the gateway.

ODL (case 1) can reduce the communication size compared with the other cases.

Figure 4 shows the evaluation results of the four cases. The X-axis indicates the number of operations per hour as workload. The left and right Y-axes are the active execution time (not including the sleep time) in seconds and energy consumption in milliwatts per hour (mWh), respectively. They are log-scaled. We assume that case 2 transfers preprocessed data for future retraining at the cloud to align with case 1, which can retrain. The necessity of the retraining in a deployed environment will be demonstrated later in this section. In all cases, their time and energy differences are not significant at low workloads (e.g., once per hour). As the workload is increased to once per minute or more, the time and energy for wireless communication become dominant in cases other than ODL. Only ODL
Figure 5: Cooling fan dataset containing vibration patterns of different speeds in silent and noisy environments (right). They were measured with and without noises (left).

Table 1: DNN and ODL models used in accuracy evaluation. DNN models consume more memory for mini-batch training compared with on-device sequential training. Hyperparameters of DNN models are selected to maximize prediction accuracy.

| Train method                  | DNN (anomaly detection) | DNN (classification) | ODL                  |
|-------------------------------|-------------------------|-----------------------|----------------------|
| Train method                  | Backprop & SGD (mini-batch) | Backprop & SGD (mini-batch) | OS-ELM (sequential) |
| Layers & nodes                | {512, 128, 64, 128, 512} | {512, 256, 96, 16, 4} | {512, 64, 512} × inst_num |
| Hyperparameters               | batch: 5, epoch: 5, learn_rate: 0.002 | batch: 24, epoch: 5, learn_rate: 0.001 | inst_num: 4 |
| Input data memory             | 600 KiB                 | 2400 KiB              | 2 KiB               |
| Weights & features            | 1748 KiB                | 1854 KiB              | 733 KiB             |

(Blue bars and line) can implement the per-second operation while providing a retraining capability to adapt to a new environment, which will be evaluated next.

4.2 Accuracy

We evaluate the benefits of ODL when target environments around the edge devices are changed. The ODL model that can be retrained in a given environment is compared with prediction-only models of DNN and OS-ELM in terms of prediction accuracy. The DNN models here have three hidden layers and are trained by a backpropagation algorithm. They are implemented in C/C++.

4.2.1 Experimental Setup

In this experiment, we use the vibration patterns of a cooling fan dataset captured by a PCB M607A11 accelerometer, as shown in Figure 5a. Normal and damaged 12 cm fans supporting three speed levels (i.e., 2500, 2000, and 1500 rpm) are running in an office room (referred to as a silent environment) and near a ventilation fan as a noise source (referred to as a noisy environment), as shown in Figure 5a. Examples of their vibration patterns after FFT are shown in Figures 5b and 5c. Each contains a frequency spectrum ranging from 1 to 512 Hz. The leftmost waveforms are those at 2500 rpm, and the rightmost ones are at 0 rpm. Anomaly detection is conducted in the noisy environment. We assume the prediction-only models were trained in the silent environment, while the ODL model can be retrained in the deployed environment. To align with the cooling fan dataset, the input size of the ODL and prediction-only models is set to 512. Their model parameters are listed in Table 1. The hyperparameters of the DNN models, such as batch size and number of epochs, were selected so as to maximize the prediction accuracy.

The cooling fan dataset containing more than 11,000 waveforms is publicly available on GitHub [1]. The following seven tasks are used for the accuracy evaluation.

- 2500 rpm: Fan speeds are changed among 2500, 2000, 1500, and 0 rpm in the noisy environment. The task is to detect different fan speeds other than 2500 rpm as anomalous.
- 2000 rpm: Same conditions as those for 2500 rpm, but the task is to detect fan speeds other than 2000 rpm as anomalous.

[1] https://github.com/matutani/cooling-fan
Addressing Gap between Training Data and Deployed Environment by On-Device Learning

Figure 6: Accuracy of ODL and prediction-only models (DNN and OS-ELM) in noisy environment (left). The ODL model recognizes normal patterns accurately while prediction-only model does not (right).

- 1500 rpm: Same conditions as those for 2500 rpm, but the task is to detect fan speeds other than 1500 rpm as anomalous.
- 0 rpm: Same conditions as those for 2500 rpm, but the task is to detect fan speeds other than 0 rpm as anomalous.
- Damage1: Normal fan operates first, and then an unbalanced fan with holes (Damage1 in Figure 5a) operates instead. The task is to detect the damaged one as anomalous.
- Damage2: Same as Damage1 but an unbalanced fan with a chipped blade (Damage2 in Figure 5a) is used to be detected as anomalous.
- 4 speeds: Same conditions as those for 2500 rpm, but the task is to classify four speeds to see classification accuracy.

For the 2500 rpm task, 300 samples and 235 samples were used for training and prediction, respectively, for each test scenario. Multiple tests were executed both for the ODL and the prediction-only cases using different samples. The same test procedure was applied to the 2000, 1500, and 0 rpm tasks. For the Damage1 task, 1200 samples and 470 samples were used for training and prediction, respectively for each test scenario. The same procedure was applied to the Damage2 and 4 speeds tasks.

The 4 speeds task is evaluated with classification accuracy while the other tasks are with an area under the receiver operating characteristic curve (AUC), which is calculated with anomaly scores $l$. The classification accuracy is calculated with classes $k$ predicted by the ODL instances.

4.2.2 Results and Discussion

Figure 6 shows the evaluation results of the ODL (blue bars) and prediction-only models (DNN in white bars and OS-ELM in green bars) with the seven tasks. The Y-axis is the classification accuracy for the 4 speeds task, and the AUC for the other tasks. Detecting 0 rpm as normal is an easy task for all the approaches even in the noisy environment, while in the 2500 rpm task, the prediction-only models fail to detect 2500 rpm as normal in the noisy environment. Figure 6b illustrates a part of the result in the 2500 rpm task, in which samples 0-60 are normal (i.e., 2500 rpm) and the others are anomalous (i.e., 2000, 1500, or 0 rpm). The ODL model (blue line) recognizes this difference accurately while the prediction-only model (OS-ELM in green line) does not in the noisy environment. For the Damage1, Damage2, and 4 speeds tasks, the ODL model is also better than the prediction-only models in the noisy environment. Figure 6c illustrates a part of the result in the Damage1 task, in which samples 0-234 are normal and the others are anomalous (i.e., Damage1). As shown, the loss value of the ODL model is stably high after the damaged
fan is used, while mispredictions are observed in the prediction-only model. These results demonstrate the advantages of the ODL model when there is a gap between the trained and deployed environments.

5 SUMMARY

In real-world anomaly detection, normal and anomalous patterns may vary depending on a given environment. This article introduces a neural network based ODL approach to address this issue. Our approach is the semi-supervised sequential training of multiple neural networks tailored for low-end IoT devices, such as wireless sensor nodes. The experimental results demonstrate that retraining by the ODL model improves the accuracy compared with a prediction-only DNN model when there is a gap between the trained and deployed environments. It also saves the communication cost and energy consumption for battery-powered IoT devices. A demonstration video of the proposed ODL approach on wireless sensor nodes is available on YouTube[1]. Our future plan includes an ODL chip design and its application development.

Acknowledgements This work was supported in part by JST AIP Acceleration Research JPMJCR23U3, Japan. The authors would like to thank Dr. Mineto Tsukada for discussions.

References

[1] Zhi Zhou et al. Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing. *Proc. of IEEE*, 107(8):1738–1762, 2019.
[2] Jie Lu et al. Learning under Concept Drift: A Review. *IEEE Trans. on Knowledge and Data Engineering*, 31(12):2346–2363, 2019.
[3] Mineto Tsukada et al. A Neural Network-Based On-device Learning Anomaly Detector for Edge Devices. *IEEE Trans. on Computers*, 69(7):1027–1044, 2020.
[4] Nan-ying Liang et al. A Fast and Accurate Online Sequential Learning Algorithm for Feedforward Networks. *IEEE Trans. on Neural Networks*, 17(6):1411–1423, 2006.
[5] G. Hinton et al. Reducing the Dimensionality of Data with Neural Networks. *Science*, 313(5786):504–507, 2006.
[6] Michal Woźniak et al. A Survey of Multiple Classifier Systems as Hybrid Systems. *Information Fusion*, 16:3–17, 2014.
[7] Takeya Yamada et al. A Lightweight Concept Drift Detection Method for On-Device Learning on Resource-Limited Edge Devices. In *Proc. of IPDPS Workshops*, pages 761–768, May 2023.

[1]https://youtu.be/xCQNZ7AuB-M