Prune2Edge: A Multi-Phase Pruning Pipelines to Deep Ensemble Learning in IIoT

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Abstract—Most recently, with the proliferation of IoT devices, computational nodes in manufacturing systems IIoT(Industrial-Internet-of-things) and the lunch of 5G networks, there will be millions of connected devices generating a massive amount of data. In such an environment, the controlling systems need to be intelligent enough to deal with a vast amount of data to detect defects in a real-time process. Driven by such a need, artificial intelligence models such as deep learning have to be deployed into IIoT systems. However, learning and using deep learning models are computationally expensive, so an IoT device with limited computational power could not run such models. To tackle this issue, edge intelligence had emerged as a new paradigm towards running Artificial Intelligence models on edge devices. Although a considerable amount of studies have been proposed in this area, the research is still in the early stages. In this paper, we propose a novel edge-based multi-phase pruning pipelines to ensemble learning on IIoT devices. In the first phase, we generate a diverse ensemble of pruned models, then we apply integer quantisation, next we prune the generated ensemble using a clustering-based technique. Finally, we choose the best representative from each generated cluster to be deployed to a distributed IoT environment. On CIFAR-100 and CIFAR-10, our proposed approach was able to outperform the predictability levels of a baseline model (up to 7%), more importantly, the generated learners have small sizes (up to 90% reduction in the model size) that minimise the required computational capabilities to make an inference on the resource-constraint devices.

Index Terms—IIoT, IoT, resource-limited environments, deep learning, edge-ai, quantisation, weight pruning, ensemble pruning, ensemble learning.

I. INTRODUCTION

We currently witness the rise of the fourth industrial revolution known as Industrial Internet Of Things (IIoT) [1]. In short, IIoT is the utilisation of IoT devices in assembly lines and manufacturing processes, so the automation of monitoring and control of manufacturing systems could be achieved. The key factor in such monitoring systems is to provide intelligence through IIoT generated big data to detect any defects during manufacturing. Thus, IoT devices in industrial domains are regarded as an optimal target for Artificial Intelligence (AI) applications as they are continuously generating a massive amount of data, and machine learning algorithms typically need to be fed by large data sets to produce accurate models. However, the limitation of the computational power for IoT devices prevents running advanced AI models like deep learning. Typically, the state of the art deep learning models have millions of trainable parameters, and they require extremely powerful workstations to be trained. For example, VGG-16 requires around 550 MB of memory and has almost 138 million parameters ². As a result, it is very challenging to train or deploy deep learning model on resource-limited devices. To tackle all preceding issues, the research community addressed the following:

1. The complexity of deep neural network: To overcome the complexity of deep neural networks and allow them to be deployed on resource-limited devices, many compression and acceleration strategies have been introduced by the deep learning community including (1) simple regularisers as (L1 and L2) that are commonly used during the training phase to control the complexity of a neural network [3] [4]. DropConnect also could be used to prune a network by randomly dropping a subset of weights [3]; (2) neuron pruning and sharing methods that increase the sparsity of neural networks by removing irrelevant connections [6] [7]. Network quantisation could fit under this category as it aims to reduces the number of required bits to represent the network’s weights [8] [9]; (3) knowledge distillation aims to transfer the knowledge from a teacher model (large network) into a student model (small network) [10] [11]; (4) compact network design that works toward reducing the complexity and improving the accuracy of the whole neural network. This is achieved by the use of optimisation of the network’s architecture and storage [12] [13]. However, Only a few of the previous methods were able to produce compressed models without a significant drop in the model’s performance.

2. Limitation of the computational capabilities of IoT devices: due to the low memory and processing power of the of those devices, the computation could be moved to be performed on a powerful remote workstation, typically cloud servers [14]. However, this approach makes no attempt to consider communication costs, network latency and data privacy. Edge computing has emerged as a promising solution for the previous challenges, instead of offloading the data to a remote infrastructure, an edge computing device is going to be attached close to the resource-limited devices where the data is being generated. For instance, a Google coral device could be added to a Raspberry Pi attached to a camera to do object detection using the state of the art deep learning models. One possible approach to utilise deep learning models on IoT is to divide the neural network into two parts, one part will be deployed to the edge and the other part will be deployed on the cloud server [15]. Such approach could reduce the communications costs and provide the same accuracy of the cloud-based approach, but it is hard to combine the data from two different neural networks because different networks have

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different parameters and computational overhead. Although those techniques could significantly reduce the network size, it could affect the network’s performance due to compression.

In this paper, we propose a novel edge-based deep pruning approach powered by the synthesis of deep learning ensembles [16] which eliminates the high variance of deep learning models and produces outperforming classifiers in term of accuracy, generalisation and inference time. Motivated by the lottery ticket hypothesis [17], this approach starts by generating a diverse set of pruned deep learning models using different hyperparameters of the pruning algorithms, aiming at finding a diverse ensemble of subnetworks, a coalition of lottery tickets, instead of one to be deployed on a resource limited environment. Next, integer quantisation is applied to all pruned models to ensure maximum performance when they get deployed on AI edge endpoints that include TPUs or CPUs. Then, we apply the clustering-based ensemble pruning technique to select a subset of the classifiers from the generated pool. Based on the generated clusters, we elect from each cluster a few representatives based on two proposed strategies: accuracy first or diversity first. After that, we deploy the elected models to a distributed edge environment where each node could empower ensemble learning and combine the predictions from two or more classifiers to generate high confidence predictions. Experimentally, on CIFAR-10, CIFAR-100 our proposed method was able to produce classifiers with higher accuracy levels with up to 90% reduction in model size.

The rest of this work is organised as follows. In Section II, we introduce some of the most recent related work in the field of accelerating deep neural networks and mapping them on the edge. In Section III, we explain in details our proposed deep pruning approach for deep learning models toward efficient deployment on resource-limited systems. Next in Section IV, we discuss the experiments on CIFAR10 and CIFAR100, then we present the deployment of our outperforming classifiers into a distributed edge environment. In the same section, we provide some bench-marking results related to energy consumption, heat and inference time to prove the applicability of such an approach in IIoT. Finally, we conclude this paper and present future work in Section V.

II. RELATED WORK

A considerable amount of literature has been published proposing different architectures, technologies and key performance indicators to enable efficient distributed training for edge intelligence models. In the following subsections, we list important existing architectures, and the most recent methods that enable this particular way of model training.

A. Architectures

Fig. 1 shows three different architectures for distributed deep neural networks training at the edge [18]. (1) Centralised: in this approach, the DNN model is trained on a cloud server as follows: training data is collected from edge devices (smartphones, smart house appliances, sensors, etc.), then it is sent to a cloud server where a DNN model is deployed. The model then uses the data for training. (2) Decentralised: each edge device in this mode (node) trains its own DNN model based on the local data preserving local privacy. Next, all nodes collaborate to produce a shared model by exchanging models’ updates. (3) Hybrid: as shown in Fig. 1 hybrid architectures combine both centralised and decentralised modes. The DNN model is trained on either a cloud server or by receiving decentralised updates from the nodes.

B. Methods

Recent methods for enabling distributed DNN training at the edge include: (a) federated learning is emerging as a promising solution for deep learning training. Unlike the traditional training approaches where the data has to be sent to a central server, federated learning [19] [20] allows all edge nodes (IoT devices) to train their own models based on local data, then train a shared model at a central server by aggregating model updates from the edge nodes. The work in [21] proposes a new protocol coined SSGD (Selective Stochastic Gradient Descent) that allows the edge nodes to train on the local data sets, and selectively share a subset of their parameters to be sent to the centralised server. In [22] the authors rely on Blockchain to verify the distributed model updates after transmitting them to the central aggregator. The main advantage of this approach is that it could also work for a decentralised architecture. For unreliable networks, federated learning could be very challenging to apply as the clients need to send frequent updates to the centralised model. The authors in [23] found that increasing the computation of local updates on each client could help to solve this issue, because the frequency and size of communication with the central server will be decreased. (b) DNN architecture splitting: in this approach, the deep learning model is split into two partitions to be deployed between two different locations (one to be deployed on the edge device and the other on the edge server). However in a distributed training environment, it is a challenging task to determine the splitting point that preserves the accuracy of model and user’s privacy. In [24], the authors employ a differentially private mechanism to split
the DNN after the first convolutional layer between the edge server and the edge device in a way that protects both of model parameters and private data. The work in [25] proposes PipeDream, a pipelined training framework that automatically finds the best way to split an input model across the available edge nodes. PipeDream minimises the communication (up to $95\%$ for large DNN models) and allows the optimal overlap of computation and communication. (c) Knowledge distillation (KD): is widely used to compress a deep neural network into a shallower network, it aims to transfer the knowledge that the weights had learned in the original network (teacher network) into the shallower network (student network). In [26], the authors propose to transfer a compressed knowledge from an ensemble into a single model. Moreover, KD is used in [27] to develop a new compression framework. The framework compresses the teacher model (ensemble of deep neural networks) into a student model by training the student model to predict the output of the teacher in addition to the original classification labels. (d) Fine-tuned architecture: involves the optimisation of the network architecture and the convolutional layers’ design (if applicable). The work in [13] uses depth-wise convolutions to generate compressed models that could easily be fitted in mobile devices. Depth-wise convolutions were firstly introduced by [28], then they were adopted by [29] to present the Inception model. Inception model primarily based on co-variate shifts which is a useful technique in minimising the number of activations and reduce the training time. However, none of the previous methods employed deep ensemble learning on resource-constraint devices to present more accurate predictions, additionally only a few of them were able to maintain the baseline accuracy after compression. Prune2Edge is multiple pruning pipelines that aim to provide edge-ai devices with compressed deep neural networks without compromising the accuracy of final solution.

III. Prune2Edge

In this section, we describe in details the proposed approach. We start by justifying the rationale behind generating a pool of deep learning classifiers and introducing the pruning approach that had been applied to the pool. Then we explain the post-training quantisation that gives an advantage when it comes to deploying the deep learning models on the edge. After that, we move to illustrate how to reduce the number of models in the generated pool by adopting a clustering-based ensemble pruning method, and then how to choose representatives from each cluster.

A. Pool generation and weight pruning

One major drawback of deep learning models is high variance which makes them highly dependent on: (1) the training set; and (2) the conditions that have been applied to the training process (initial weights values, loss function, optimiser function, etc.). This could affect the network’s ability to generalise, and consequently produce a final model that makes different predictions when the same conditions apply. To overcome these challenges, we follow a similar approach applied in [16]. A diverse set of pruned models are generated, forming a pool of classifiers. The weight pruning method in [30] is applied. During the training process, a binary mask is added to each elected layer for pruning. The mask has the same size and shape of the layer’s tensor, determining the weights that actively participate in the forward execution graph. Then the weights in each mask are sorted according to their absolute values. The weights with the smallest magnitude values are set to zero, leading to initial sparsity levels ($s$). During the backpropagation, the weights that had been marked in the forward execution are not updated. This process will be executed automatically and gradually where the sparsity is increased from an initial value ($s_i$) (normally 0) to final sparsity ($s_f$) over several pruning steps ($n$), starting at a training step ($t_0$) with a pruning frequency ($\Delta t$):

$$s_i = s_f + (s_i - s_f) \left(1 - \frac{t - t_0}{n \Delta t}\right)^3,$$  (1)

where $t \in \{t_0, t_0 + \Delta t, ..., t_0 + n \Delta t\}$. ($s, n, t, \Delta t$) are the hyperparameters for this pruning technique. We vary these values to generate a pool of diverse pruned deep learning models.

However, compressing the model’s size using such a pruning technique is not adequate for AI edge devices. This is because these lightweight devices do not support floating-point numbers. Thus, quantisation is applied as shown in the following step. However, compressing the model’s size using such a pruning technique is not adequate for AI edge devices. This is because these lightweight devices do not support floating-point numbers. Thus, quantisation is applied as shown in the following step.

B. Post training integer quantisation

We adopt 8-bit integer quantisation to approximate the floating-point values using the following formula:

$$real\_value = (int8\_value - zero\_point) \times scale$$  (2)

All weights are represented by int8 two’s complement values in the range $[-127, 127]$ with zero\_point equals to (0). Similarly, activations/inputs are represented by int8 two’s complement values in the range $[-128, 127]$ with zero\_point in the range $[-128, 127]$. In the next step, we reduce the number of learners in the pool by applying ensemble pruning assuming the pool as an ensemble of deep learning models.

C. Ensemble pruning

According to [31] ensemble pruning methods are classified as ordering based pruning, optimisation based pruning or clustering-based pruning. Typically, clustering-based techniques aim to partition the classifiers into different clusters where the classifiers that belong to the same cluster have common characteristics and behave similarly, whereas different clusters have classifiers with varying levels of diversity.
Finding such clusters is critical to our approach as it maximises the generalisation of the final solution and overcome any potential overfitting issues. Although there is a large volume of studies describing clustering-based ensemble pruning [32][33], such experiments are not satisfactory nowadays, because of the large models and datasets in computer vision problems. Hence, we propose a new clustering-based pruning technique for deep learning ensembles that work on image datasets.

In order to produce an accurate ensemble for the final solution, we need to maintain the accuracy of the ensemble. The accuracy of the ensemble is typically improved by choosing individuals/classifiers with high predictability levels. We rank the classifiers post pruning in descending order according to their accuracy against a validation set (pruning set). Then we select representatives from each of the generated clusters. This ensures that only high performing models are considered to be part of the final deep learning ensemble. Although diversity of the classifiers in the ensemble has been discussed by many researchers [34][35], there is still no standard definition of the diversity of an ensemble. Generally, the assumption is to have their accuracy against a validation set (pruning set). Then we rank the classifiers post pruning in descending order according to their accuracy. The diversity of an ensemble is typically improved by choosing individuals/classifiers with high predictability levels. We rank the accuracies for all models in that cluster. Next, for each cluster we sort its models in a descending order based on accuracy for all models in that cluster. Finally, as shown in Fig. 2, our approach to the synthesis of deep learning models on edge devices could be summarised as follows.

1) Train a baseline deep learning model.
2) Create a diverse pool of pruned deep learning classifiers.
3) Convert the weights/outputs of the neural network to integer values by applying integer quantisation.

Next $k$-means method is applied on $C$ and the output is represented by $r$, $r = kmeans(C, k)$ where $k$ is the number of clusters and $r = [r_1, r_2, \cdots, r_o]$ where $r_i$ is the index of the cluster where $x_i$ belongs to. Algorithm III-C describes the complete ensemble pruning process.

**Algorithm 1 clustering-based ensemble pruning**

1. for all samples in the pruning set do
2. calculate($A$)
3. calculate($b$)
4. $x = [y_{b,1}y_{b,2} \cdots y_{b,n}]$
5. Append $x$ as a row to $C$
6. end for
7. $r = kmeans(C, k)$

Once clusters are created, the best candidates from each cluster will be selected to compose the final ensemble that will be deployed to the distributed constraint-limited environment.

**D. Representative selection strategies**

we aim to deploy high-performing classifiers to the IoT devices and allow these tiny devices to employ ensemble learning to allow confident decision making. For this reason, we propose two strategies to select the representatives from the generated ensemble-pruning approach using $r$ that defined before

1) **Accuracy first**: in this approach, we calculate the accuracy for each cluster by finding the average of the accuracy for all models in that cluster. Next, for each cluster we sort its models in a descending order based on accuracy, then, the top models in the list with the highest accuracy will be deployed in the IoT target device. we use the pruning set for accuracy calculations.

2) **Diversity first**: for this strategy, we give priority to the diversity of the final solution. Thus, we select one classifier (best accuracy) from each of the generated clusters to be deployed on distributed constraint devices.

The models are then deployed to a distributed constraint environment, where each node in this environment uses max-voting [31] as an ensemble learning method. The predictions of the models are considered as votes, and the class that receives the maximum number of votes is considered as the ensemble’s forecast. Let’s consider $W = m_1, \cdots, m_N$ as an ensemble of the deployed models $m_i$. The prediction of the ensemble for a test example using max-voting is the class that receives the maximum support $\eta_{\text{final}}(W)$ from all models in the ensemble.

As such, we define the ensemble output as:

$\eta_{\text{final}}(W) = \arg\max_{j \in \{1, \cdots, C\}} \sum_{i=1}^{N} y_{i,j}$

Finally, as shown in Fig. 2, our approach to the synthesis of deep learning models on edge devices could be summarised as follows.

1) Train a baseline deep learning model.
2) Create a diverse pool of pruned deep learning classifiers.
3) Convert the weights/outputs of the neural network to integer values by applying integer quantisation.
4) Prune the proposed pool adopting a clustering-based technique.
5) Compile and deploy the selected models to a distributed edge environment.
6) Utilise ensemble learning to combine the predictions of the deployed models on the edge.

Having discussed the proposed method in sufficient details, a thorough experimental study is presented in the following section.

IV. EXPERIMENTAL STUDY

In this section, the performance of Prune2Edge is evaluated using CIFAR10CNN and ResNetV2 models on CIFAR10 and CIFAR100 datasets, respectively. Then, results related to inference time, heat and power consumption levels are provided for running the Prune2Edge models on PI devices. Those measures are essential to show the effectiveness of our approach, as we aim to preserve the resources of edge-ai devices.

A. Datasets and models

Datasets: CIFAR-10 [36] consists of 70,000 images (28 × 28 coloured) split into 50,000 images as a training set and 10,000 images as a testing set. CIFAR-100 is similar to CIFAR10 except that it has 100 classes holding 600 images each.

Models: CIFAR10-CNN is a basic convolutional neural network (CNN) model with four convolutional layers with (32 × 3 × 3) filter size for the former two and (64 × 3 × 3) filter size for the rest. ResNetV2: is the second version of ResNet. The main improvement in V2 is related to the arrangement of layers in the residual block. The model’s input is a 299 × 299 image, and the output is the probability distribution for the predicted classes [57]. Deep Residual Networks (RNNs) achieved groundbreaking work in the deep learning community in the last few years.

B. Implementation details

1) Model training and pruning: CIFAR10-CNN model is trained from scratch on CIFAR10 dataset as a baseline model on cloud servers, and the accuracy of the baseline model on the testing set is 74% and the model size is 3,936 KB. Similarly, ResNetV2 model is trained on CIFAR100 dataset, and the accuracy of the baseline model reaches 67% and the size of this model is 3,575 KB. Both baseline models are pruned using weight pruning [30] to generate two pools of pruned deep learning models, where each pool contains a hundred models from each baseline. During the pruning process, different values for the pruning hyperparameters are used to enforce diversity among the models of each pool. The values of hyperparameters are randomly drawn from a range of values. A full list of the hyperparameters and the range of values are shown in Table I

| Hyperparameter   | Values Range                        |
|------------------|-------------------------------------|
| epochs           | [3, 4, 5, 6, 8]                      |
| batch_size       | [32, 64, 128]                       |
| loss             | [categorical_crossentropy, mean_squared_error, mean_absolute_error] |
| optimiser        | [SGD, adam, Nadam, Adadelta]        |
| initial_sparsity | [0.1, 0.6]                           |
| final_sparsity   | [0.7, 0.9]                           |
| frequency        | [100, 200, 300, 400]                |

2) Integer quantisation: After generating two pools of pruned deep learning models, we apply post-training integer quantisation on all models to convert activations and weights to 8-bit integers. Quantisation leads to a significant reduction to the model size, and brings performance enhancements on integer-only hardware accelerators.

3) Ensemble pruning: At this stage, two pools of diverse-pruned-quantised deep learning models are generated (100 models each). We consider each pool as an ensemble of individual learners, and we aim to choose the best combination of models in each ensemble by applying our proposed ensemble pruning approach. After ensemble pruning, each ensemble is split into several clusters according to k value (the number of clusters). Each cluster, in turn, contains a group of models with similar characteristics in terms of diversity and accuracy. Then we select candidates from the clusters based on the following aforementioned strategies. Accuracy first: After applying the rules of accuracy first that had been explained earlier, we choose the top-five candidates to be deployed on a distributed edge environment. Diversity first: we rank the models in each cluster based on their accuracy on the pruning set, after that we select a model with maximum accuracy in each cluster then deploy those models to a distributed edge environment. The number of candidates will be based on K number of clusters.

4) Deployment to a distributed edge environment: The chosen pruned and quantised deep learning models from the previous step are ready now to be deployed on IoT devices. To increase communication efficiency, each device holds two or more deep learning models, and applies ensemble learning to combine the hosted models’ predictions. Ensemble learning is used to enhance generalisation. However, the process of combining predictions from different models require additional on-device computational power. Thus, it is essential to bring more power to the edge devices by attaching hardware accelerators. As such, we use ‘Google Coral’ that brings machine learning inference to existing systems.
C. Experimental setup

The development workstation for training/pruning deep learning models is hosted on Google Cloud Platform with the following configuration: 8 vCPUs, 30 GB memory. 2 × NVIDIA Tesla K80 using Tensorflow 1.15 dev. For the edge computing environment, we use Raspberry PI 3 Model B v1.2 attached to Google Coral (USB accessory that brings machine learning inferencing to existing systems). Google Coral is provided with Google Edge TPU coprocessor, which is capable of performing 4 trillion operations (tera-operations) per second. Fig. 3 represents the distributed edge environment that we use to evaluate the practicality of our proposed approach. For compatibility reasons with Google Edge TPU device, all models has to be compiled before deployment with a special software (edgetpu_compiler). Furthermore, to speed up the performance when running multiple models on the edge device, we use co-compilation. It allows multiple models to share the Edge TPU RAM to cache their parameter data together, eliminating the need to clear the cache each time you run a different model. We investigate the effect of co-compilation in the following section.

Fig. 3. Experimental tools

As shown in this figure, there will be two Raspberry Pi nodes (running Raspbian GNU/Linux 9 (stretch) and Tensorflow-2.1.0) connected to Tenda F3 300Mbps router. Node1 will host two deep learning models, and Node2 will host three models where all models are generated from CIFAR10 pool. A master node is also connected to a network of Raspberry Pi nodes to coordinate the prediction process. First, it sends to both nodes an integer as the number of required samples that need to be tested on CIFAR10 testing. Next, the nodes make a prediction on the testing set using ensemble learning and then they send the combined predictions back to the server. At the server, the predictions are combined from both nodes again to produce the final result. While performing the predictions on Node2, we measures the energy consumption (load current, and input voltage) using ‘YOTINO USB Voltage and Current Detector Meter Capacity, Accuracy: 1%’, and we monitor the temperature of Node2 using ‘Etekcity Lasergrip 1080 Non-contact Digital Laser IR Infrared Thermometer, Accuracy: 2% or 2°C’.

D. Results and discussion

1) Results on CIFAR100: The ResNet model is trained on CIFAR100 data set, then pruning is applied to generate a pool of 100 lightweight models. The maximum accuracy in the pruned pool is 66% while the minimum accuracy is 1%. Furthermore, the models are compressed, and the size becomes 1.293 KB (almost 63% smaller than ResNet baseline model). Next, integer-quantisation is applied, so a further reduction in size is gained, and the size becomes 305 KB only, which is a remarkable compression ratio of 92%. The reduction in the size of the models is a key success factor of Prune2Edge toward deploying deep learning models to resource-limited devices. The next step in Prune2Edge is to reduce the number of models in each pool and select the best combination based on accuracy first and diversity first strategies. Fig. 4 compares the results obtained after adopting the proposed strategies for model selection, and applying ensemble learning. The accuracy is tested over five hundred samples on CIFAR100 testing set, and the baseline accuracy on this subset (after quantisation) is 51%.

Also from Fig. 4 we can see that the synthesis of the best combinations of models following “Accuracy First” strategy was able to achieve higher accuracy than the baseline model. The highest accuracy is achieved when the predictions of the two top models are used using max-voting (55%). On the other hand, the accuracy was remarkably dropped when “Diversity First” is adopted with \(k = 3, 5, 7\). When \(k = 3\), three models (one per cluster) are used with 34% accuracy only.

2) Results on CIFAR10: The minimum accuracy of the pruned pool of CIFAR10 is 1% and the maximum is 80% (on the training set). The size of the models is 4,926 KB (around 48% reduction in model size compared to the baseline). After quantization, the models became even smaller and the size becomes 1,233 KB (around 87% reduction in size) enabling these models to run on a resource-limited environment. Similar to CIFAR100, Fig. 4 presents the accuracy of Prune2Edge on five hundred images from CIFAR10 testing set, and the accuracy of the baseline model on this subset reaches 78%. What stands out in Fig. 4 is the success of Prune2Edge to
providing more accurate decisions than the baseline model in both selection strategies. In the case of “Accuracy First”, all the ensembles are able to provide outperforming results, and the maximum accuracy is reached when the ensemble size is three (82%). In “Diversity First” strategy, when \( k = 3 \), the accuracy of the composed ensemble is 79%. However, the accuracy was almost the same as the baseline, when the ensemble size is five \( k = 5 \) (77%), and the ensemble size is seven \( k = 7 \) (76%). So far, the results indicate that the Prune2Edge can provide lightweight and outperforming models in terms of diversity, size and accuracy. Moving now to provide benchmarking results related to heating, inference time and energy consumption on Raspberry Pis. As explained earlier in Section IV-C, we compile the output of Prune2Edge using edge_tpu compiler (co and regular compilation), then we deploy the models to distributed Raspberry Pi devices. Table II shows the results of inference time (in seconds) on a different number of CIFAR10 testing set, in addition to the external temperature of Node2 (holds three models) in the rest and the peak (making an inference).

TABLE II
INFERENCE AND TEMPERATURE RESULTS, CO/REG COMPILATION

| Samples | Co    | Reg   | Node1 | Node2 | Temp_idle | Temp_Peak |
|---------|-------|-------|-------|-------|-----------|-----------|
| 100     | co    | 4.243 | 4.562 | 35.9  | 35.2      |
| 50      | co    | 3.790 | 4.018 | 36    | 36.1      |
| 25      | co    | 3.638 | 3.818 | 36    | 36.1      |
| 10      | co    | 3.518 | 3.612 | 35.9  | 36        |
| 5       | co    | 3.506 | 3.597 | 35.8  | 35.8      |
| 4       | co    | 3.494 | 3.563 | 36.1  | 36.1      |
| 3       | co    | 3.492 | 3.580 | 35.8  | 35.8      |
| 2       | co    | 3.509 | 3.573 | 36.1  | 36.1      |
| 1       | co    | 3.503 | 3.546 | 36    | 36        |
| 100     | reg   | 11.504| 15.476| 36.1  | 36.5      |
| 50      | reg   | 7.605 | 9.544 | 36.1  | 36.4      |
| 25      | reg   | 5.473 | 6.241 | 36.1  | 36.2      |
| 10      | reg   | 4.196 | 4.551 | 36.1  | 36.1      |
| 5       | reg   | 3.756 | 3.954 | 36.1  | 36.1      |
| 4       | reg   | 3.692 | 3.874 | 36.1  | 36.1      |
| 3       | reg   | 3.631 | 3.769 | 35.9  | 35.9      |
| 2       | reg   | 3.548 | 3.658 | 36    | 36        |
| 1       | reg   | 3.548 | 3.541 | 36    | 36        |

Closer inspection of the table above shows that both compilation methods have almost similar results when the number of samples is between [1-5]. The external temperature of Node2 has not changed (before/after inferencing) and the average time needed to perform an inference is 3.5 seconds. However, when the number of samples is increased, co-compilation shows a significant difference in performance. For instance, when we ask Node2 to make an inference on a hundred images, it takes only 4.56 seconds. On the other hand, regular-compilation takes a longer time with almost 15.5 seconds. Additionally, the external temperature of Node2 slightly increases when it tries to make a prediction on 100 images (0.4 degrees). In short, we can conclude that if the devices need to perform inferencing on a large number of samples, then the models should be compiled with the co-compilation approach as this benefits from using models parameter cashing and brings essential enhancement for the performance. With regards to energy consumption, Fig. 5 shows the changes of the “load current” while Node2 makes inferencing on different number of samples from CIFAR10 testing set.

From Fig. 5, it can be seen that Node2 pulls (0.3 A) in the rest mode. While doing the inferencing (using co-compiled models, and the number of samples is less than fifty), the “load current” is almost the same. The “load current” is increased by almost 0.12, when Node2 tries to make predictions on fifty or a hundred images. When inferencing is done with regular-compiled models, the current increased by a small degree even when the number of testing samples is less than fifty. It is worth to mention that in both compilation methods, the input voltage for Node2 during the inference has not changed (5.04 V). This indicates that co-compilation has not only impact on the inferencing times, but also helps to reduce the required energy to run ensembles on resource-limited devices.

3) Discussion: The results of this study show that Edge2Prune is capable to provide deep learning models that work efficiently on resource-limited devices. The proposed approach applies multi-phase pruning pipelines to reach high compression ratios (up to 91%), while maintaining higher accuracy levels. In addition to our aim in providing outperforming models, we are particularly interested in real-world applications of “Edge2Prune”. For instance, models generated by of Prune2Edge could be deployed on an inspection robot used in industrial sectors to discover defects. The robot could take a picture of a product on a production line, then sends the captured photo to “Edge2Prune” ensembles to make accurate and instant predictions about the defects. The results of Raspberry Pis show the efficiency of this approach in preserving the resources of the device. However, the Raspberry PI device needs in average 3.5 seconds to make an inference, and this could be a critical factor in some real-world applications. Thus, there is potential for further investigations on using different compact-baseline architectures that are carefully designed to run on resource-limited environments which could lead to significant improvements on the inference time and even the size of the models.

V. CONCLUSION AND FUTURE WORK

In this paper, we present Prune2Edge multi-phase pruning pipelines to deep ensemble learning on resource-constrained...
devices. It leads to improved classifiers in terms of generalisation, size, accuracy and inferencing on AI edge endpoints that include TPUs or CPUs. First, we generate a diverse-pruned pool of deep learning classifiers, then integer-quantisation is applied to the pool. After that, we shrink the size of the pool through a new clustering-based ensemble pruning technique. Next, the remaining models after ensemble pruning are optimised, and then deployed on IoT devices to compose ensembles of deep learning models. The experimental results on CIFAR10, and CIFAR100 are promising with a compression ratio reaching 91%, and the composed ensembles are able to outperform the accuracy of baseline models. Furthermore, the deployment on the distributed Raspberry Pi devices shows the ability of Prune2Edge to preserve the resources of the device and runs ensemble learning efficiently. In the future, we aim to rely on more compact CNN architectures that are uniquely designed to run on mobiles and IoT devices like MobileNet3. Additionally, we plan to use more advanced ensemble learning techniques on the edge devices such as boosting and bagging, and then test our approach on more datasets. The application of the proposed approach in real IoT environments like industrial inspection robots is an promising research direction.

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