AI on the Edge: Characterizing AI-based IoT Applications Using Specialized Edge Architectures

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***Abstract*—Edge computing has emerged as a popular paradigm for supporting mobile and IoT applications with low latency or high bandwidth needs. The attractiveness of edge computing has been further enhanced due to the recent availability of special-purpose hardware to accelerate specific compute tasks, such as deep learning inference, on edge nodes. In this paper, we experimentally compare the benefits and limitations of using specialized edge systems, built using edge accelerators, to more traditional forms of edge and cloud computing. Our experimental study using edge-based AI workloads shows that today's edge accelerators can provide comparable, and in many cases better, performance, when normalized for power or cost, than traditional edge and cloud servers. They also provide latency and bandwidth benefits for split processing, across and within tiers, when using model compression or model splitting, but require dynamic methods to determine the optimal split across tiers. We find that edge accelerators can support varying degrees of concurrency for multi-tenant inference applications, but lack isolation mechanisms necessary for edge cloud multi-tenant hosting.**

I. Introduction

Edge computing has recently emerged as a complement to cloud computing for running online applications with low latency or high bandwidth needs [33]. Internet of Things (IoT) and mobile applications are particularly well-suited for the edge computing paradigm, since they often produce streaming data that requires real-time analysis and control, which can be optimally performed at the edge. Conventional edge computing comes in two different flavors. Cloudlets [34] represent one popular paradigm of edge computing that entails deploying server clusters at the end-points of the network; by deploying traditional servers at the edge, cloudlets enable "server-class" applications to be deployed at the edge rather than the cloud.

Edge gateways represent a different flavor of edge computing that involves deploying embedded nodes, individually or in groups, to serve as the hub for applications such as smart homes. Such edge gateways provide more limited compute capabilities at the edge, but nevertheless provide useful functionality, such as data aggregations and local on-node processing for certain low-latency tasks. These two flavors of edge computing provide very different tradeoffs. The latter paradigm utilizes small form-factor hardware (e.g., Raspberry Pi-class nodes), has low cost, low power consumption and also constrained compute capabilities, which increases reliance on the cloud. Cloudlet-style edge computing, on the other hand, provides much greater compute capabilities at the edge, but incurs higher hardware costs, larger form factor servers, and higher power consumption; there is also less reliance on the cloud for many applications.

Recently a third flavor of edge computing has emerged that combines the key advantages of both the cloudlet and edge gateway paradigms. This paradigm, which we refer to as specialized edge architectures, has become possible with the advent of special-purpose hardware designed to accelerate specific compute- or I/O-intensive operations. In particular, a number of edge hardware accelerators, such as Intel's Movidius Vision Processing Unit (VPU) [21], Google's Edge Tensor processing Unit (TPU) [17], Nvdia's Jetson Nano and TX2 edge GPUs [28], [29], and Apple's Neural Engine have emerged with the specific goal of supporting *edge-based AI* applications, including computer vision, visual and speech analytics, and deep learning inference.

By customizing silicon to a single, or a small, class of applications, these hardware accelerators claim to provide major performance improvements at much lower cost and energy points when compared to traditional general-purpose hardware. As a result, it is now possible to embed "wimpy" edge nodes with these accelerators and approach the compute capabilities of general-purpose servers (e.g., cloudlets) for specific applications.[1] Figure 1 depicts a 10 node cluster of low-end Pi-class nodes equipped with Jetson Nano GPUs; this entire embedded GPU cluster costs about $1,500 (or approximately the cost of a single traditional server), consumes only 90w at full GPU load, and measures 13x8x8 inches, an order of magnitude smaller footprint than a server rack. As a result, it opens up new possibilities for edge deployments in power-constrained or space-constrained settings that are not feasible with conventional flavors of edge computing.

In this paper, we address the question of how to rethink the design of edge-based AI applications in light of specialized edge architectures. Using an empirical approach, we seek to quantitatively understand the benefits and limitations of these architectures when compared to more traditional edge and cloud-based systems. In particular, we seek to answer three sets of research questions: (1) What are the price, performance, and energy tradeoffs offered by emerging edge

[1]Of course, cloudlets can also be equipped with hardware accelerators, further enhancing their capabilities.

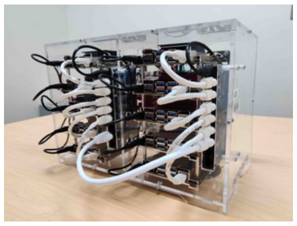


Fig. 1. A 10-node cluster of low-power Jetson nano GPUs.

hardware accelerators when compared to traditional edge and cloud computing? (2) How should modern IoT applications exploit the distributed processing capabilities of specialized edge nodes and the cloud by employing various types of split processing? (3) How suitable are edge accelerators for supporting concurrent edge applications from multiple tenants?

We seek to answer these questions through the lens of a particular class of applications—edge-based vision and speech processing—using an experimental testbed of several different edge accelerators and embedded nodes. Our results show that edge accelerators can yield up to 10-100× better normalized performance, on a performance-per-watt and performance-per-dollar basis, than general-purpose edge servers. They also show that split processing on machine learning inference, using model compression and model splitting, between device-edge, edge-edge, and edge-cloud tiers can yield significant bandwidth savings and latency benefits. Since the benefit can vary by the model and workload, we also find that such split processing must be done carefully on a per-application basis to maximize benefits. Finally, we find that systems optimizations such as model quantization and RAM model swapping can enhance the degree of concurrency supported by edge accelerators but that their lack of performance isolation and security can be a hurdle. Overall, our results show significant promise for specialized edge architectures, but also point to the need to address open research questions to fully realize their potential.

II. Background

In this section, we present background on cloud- and edge-based IoT applications as well as specialized edge architectures for edge-based AI applications.

Cloud- and Edge-based IoT Applications: Many IoT devices with networking (e.g., WiFi) capabilities employ a *two-tier* cloud architecture depicted in Figure 2(a), where the device transmits data to the cloud for processing. Examples of such IoT devices include the Nest thermostat [26], Wemo smart switch, and LiFX smart lights. It is also increasingly common for IoT devices to use a *three-tier* architecture, depicted in Figure 2(b), that leverages both the edge and the cloud [19]. Application processing is split between the edge and the cloud, with the edge performing some initial processing of the data and the cloud providing more substantive processing capabilities. Battery-powered IoT devices, such as smart door locks that use low-power wireless protocols (e.g., Bluetooth LE), employ a three tier architecture and rely on an intermediate edge node [20], [27], [38] to provide a gateway to the cloud. Edge computing has also shown promise for applications, such as augmented and virtual reality (AR-VR) [9] [43], computation offloading [6], [13] [14], and online gaming [37], which use Cloudlet-style edge clusters with more substantial compute capabilities to provide low latency processing.

Edge-based AI workloads: An emerging class of edge workloads, referred to as “AI on the Edge” or edge-based AI, involves running machine learning or deep learning inference on edge nodes. Some researchers have argued that such visual analytics and machine learning inference on edge nodes is poised to become the “killer app” for edge computing [5] [4]. This application use case has become promising due to the proliferation of smart cameras and smart voice assistants that generate significant amounts of video and audio data, which requires vision and speech processing in real time. Doing so involves deploying previously-trained deep learning models at the edge to perform near real-time inference or predictions on the video and audio data. Such inference may involve tasks, such as image classification or object detection in video feeds [18], [24], [40], [42] or speech recognition from voice assistants to understand spoken commands—all of which have low-latency and near real-time constraints.[2]

Special-purpose edge computing and edge accelerators: Specialized edge computing has emerged as a new paradigm in edge computing with the advent of edge accelerators that target acceleration of machine learning and deep learning inference tasks. Figures 2(c) and (d) depict edge computing with specialized architectures, where one or more tiers (device, edge, cloud) employ hardware accelerators. Each tier can leverage such specialized hardware, when available, to either boost the processing capabilities of that tier, which implies that each tier has less reliance on higher-level tiers. Figure 2(d) is a special case of Figure 2(c), where all application processing is performed on the device or on the edge using specialized hardware. In scenarios where the specialized edge is a cluster, as in Figure 1, more than one edge node may be leveraged for distributed edge processing.

Table I lists various edge accelerators and their characteristics. Intel’s Movidius Neural Compute Stick (NCS) employs a Vision Processing Unit (VPU) to accelerate deep learning models for computer vision tasks, such as object detection and recognition [21]. Google’s Edge Tensor Processing Unit (TPU) [17] can accelerate any Tensorflow ML model inference as long as it is compatible with the Tensorflow-lite framework. Nvidia’s edge GPUs include the Jetson Nano GPU [28], as well as the Jetson TX2 [29] GPU, which are both designed to provide full-fledged GPU capabilities on low-end edge nodes with a smaller power footprint than desktop- and server-class GPUs. From a power standpoint, Nvidia’s Jetson Nano uses a default power budget of only 5W, which is up to 40× lower than desktop-class GPUs, while Google’s TPU uses a power

[2]For example, a user who uses a voice assistant to turn on a smart light bulb using a spoken command expects the lights to turn on in near real time. Similarly, smart cameras send real-time push notifications when they detect something suspicious in their video feed, which requires low-latency real-time processing of video.

Device	Power (W)	Memory	Cost	Accelerated Workloads
Intel NCS2 VPU	1 - 2	512 MB	$99	vision, imaging
Google EdgeTPU	0.5 - 2	8MB	$75	8-bit quantized TensorFlow lite model
Nvidia Nano	5 - 10	4 GB	$99	any GPU workload; AI
Nvidia TX2	7.5 - 15	8 GB	$399	any GPU workload; AI

TABLE I
CHARACTERISTICS OF EDGE ACCELERATORS

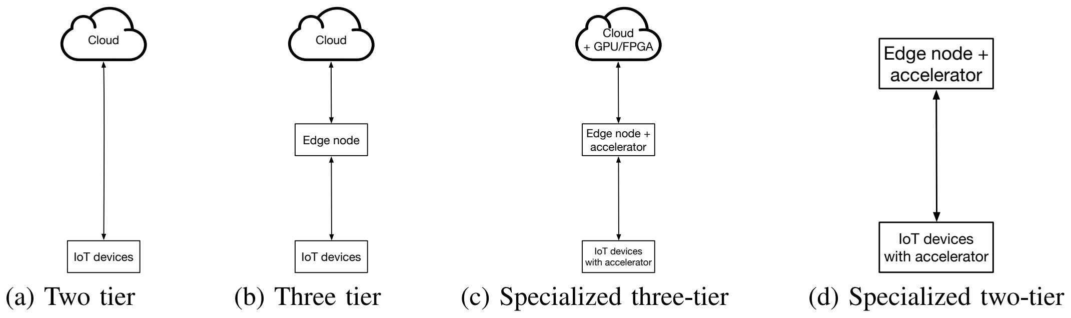


Fig. 2. Tiered architectures for IoT applications that use the device, edge, and cloud.

budget of only 2W. From a performance standpoint, all of these hardware accelerators promise large performance improvements for low-end edge nodes and, in some cases, server-like performance, even when running on low-end Raspberry PI-class nodes. Specialized hardware is also becoming available for end-devices, which allows the processing to be done on the device itself, when appropriate, rather than sending data to edge or cloud servers. Examples include the Sparkfun Tensorflow-lite hardware board for micro-controller-based IoT devices [15] and the GAP8 IoT processor [35]

In general, specialized architectures use various forms of distributed processing, with application processing split within and across tiers. Processing may be split across device, edge and cloud tiers by leveraging specialized hardware at each tier, yielding *vertical* splitting. Processing at each tier can be further split across nodes within that tier to leverage multiple hardware accelerators, yielding *horizontal* splitting. Model compression [36] and model splitting [23] are examples of distributed ML inference that use such split processing.

III. EXPERIMENTAL SETUP AND METHODOLOGY

Problem statement: The goal of our work is to empirically study the feasibility of using a hardware-accelerated specialized edge tier to achieve "server-class" performance of cloudlet-style edge servers at the cost, power, and form-factor of Pi-class edge nodes, with a specific emphasis on edge-based AI workloads. To do so, our study addresses the following questions: (1) What are the price, performance, and energy benefits, if any, offered by edge hardware accelerators when compared to general-purpose edge and cloud computing? How do specialized edge nodes compare to traditional edge nodes with respect to raw performance and normalized performance-per-watt and performance-per-dollar? How do these benefits vary with different workloads, such as image/video and audio processing, and different deep learning models? (2) How should IoT application exploit distributed and split processing capabilities offered at various tiers? How are the benefits and overheads of splitting application processing over centralized processing at a single tier? Are there scenarios where performing data processing at a single tier is better than splitting application processing across tiers? (3) How capable are these edge accelerators for supporting concurrent model execution to provide multi-tenancy in edge clusters?

Experimental setup: Our experimental setup comprises a small cluster of single-board computing ("Pi-class") nodes that are equipped with four edge accelerator platforms: Intel Movidius NCS2 VPU, Google Edge TPU, Nvdia Jetson Nano GPU, and Nvidia TX2 GPU. To compare with more traditional edge architectures, we also consider a Raspberry Pi3 node as an example of a resource-constrained edge device, and an x86 server with a 3.0GHz Xeon Skylake CPU as an example of a cloudlet-style edge server. We also consider a NVIDIA Tesla V100 GPU on Amazon EC2 `p3.2xlarge` cloud instance to mimic a specialized edge server or specialized cloud server.

Workloads: Our workload consists of three common vision-based image processing and speech-based audio-processing tasks that arise in many edge-based AI applications:

- *Image classification:* The goal of image classification is to assign a text label (i.e., "classify") to an image based on its contents. For example, a label such as "apple", "dog" or "car" may be assigned by the classifier based on the image. Typically model inference yields multiple labels with probabilities on the likely contents of the image.
- *Object detection:* Object detection is a harder task than classification since it involves determining all objects of interest that are present in the image, by computing a bounding box around each such object, and then assigning a probabilistic label to each object.
- *Keyword spotting:* Keyword spotting involves processing an audio stream to detect and recognize the occurrence of a set of keywords (e.g., "Hey Siri" function on iPhone).

All three workloads use deep learning models, and there has been a wealth of research on these problems over the

Workload	Model name	Input size	Model size (MB)	Params (M)	# Float operations per inference (M)	Depth multiplier
Image Classification	MobileNet V2	$224 \times 224 \times 3$	14	3.54	602.29	1.0
	Inception V4	$299 \times 299 \times 3$	163	42.74	24553.87	-
Object Detection	SSD MobileNet V1	$300 \times 300 \times 3$	28	6.86	2475.24	1.0
	SSD MobileNet V2	$300 \times 300 \times 3$	66	16.89	3751.52	1.0
Keyword Spotting	cnn-trad-fpool3	99×40	3.6	0.94	410.89	-

TABLE II
CHARACTERISTICS OF THE DEEP LEARNING MODELS USED IN OUR STUDY.

past decade [16]. Pre-trained deep learning models are now available for these tasks from multiple sources and these models are designed to run on a variety of hardware and software platforms. We use these pre-trained models for our micro-bechmarking study since it allows us to run the same standard model on all hardware devices, and also enables others to repeat our experiments. Our experiments use the following 5 models: MobileNet V2 and Inception V4 for image classification, SSD MobileNet V1 and SSD MobileNet V2 for object detection, and `cnn-trad-fpool3` in [32] for keyword spotting. Table II lists the key characteristics of the models along with the default model configurations used in our experiments.

IV. PERFORMANCE AND ENERGY MICROBENCHMARKS

Our first experiment involves comparing raw and normalized performance and power of specialized edge nodes to more traditional edge architectures comprising (i) resource-constrained edge nodes (Pi3), (ii) x86 server-based edge nodes ("cloudlet server"), and (iii) GPU-equipped x86 servers. We microbenchmark various edge nodes under our three workloads (classification, object detection and keyword spotting) and the corresponding models shown in Table II and measure throughput and power consumption under these workloads.

Methodology: To ensure a fair comparison across hardware platforms, we run the *same* model on all platforms and subject it to the *same* inference workload. For image classification and object detection, we use the CAVIAR test case Scenarios dataset [31] as our inference workload. For keyword spotting, we use the Speech Commands dataset [7] as our inference workload. Although the model and the inference workload used to drive the model are identical on all platforms, it should be noted that the deep learning (DL) software platform used to execute this model varies by device. This is because there is no single DL software platform that runs well on all hardware accelerators. While TensorFlow runs on many of our devices, we found that it almost always had worse performance than the native vendor-designed tool for running DL inference.

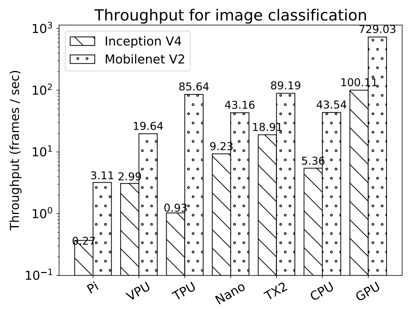
Thus, we choose the native vendor-recommended software DL platform for each device since it yields the maximum throughput and best results. Specifically, we use Intel Openvino [10] for the Intel VPU, the specialized *edgetpu* software module for Google's Edge TPU, and TensorRT [11] for Nvidia's Jetson Nano, TX2 and cloud GPUs. Finally, we use TensorFlow to execute our models on all CPUs, namely Raspberry Pi3 and Intel Xeon CPU. Our throughput microbenchmark, written in Python, iteratively involves making inferences using the above inference workloads and computes throughput in term of inferences per second. In addition to measuring sequential inference throughout, we also measure the impact of batching inference requests on the throughput—since batching is often used in production settings to enhance the throughput of deep learning model inference. Our power microbenchmarks measure the mean power consumption as well as the total energy consumed during an individual inference request.

We use a combination of hardware and software tools for our power microbenchmarks. For USB devices such as Intel VPU and Google EdgeTPU, we use a USB power meter with data logging capabilities to measure the energy used and instantaneous power consumption during inference. For NVidia GPUs, we use `nvidia-smi` software profiling tool that provides power statistics for NVidia GPUs [12]. For the cloud-based Intel Xeon CPU and Raspberry Pi CPU, we use the Turbostat Linux profiling tools [8] to measure the CPU power usage; Turbostat also works in virtualized environments such as cloud servers for power profiling.

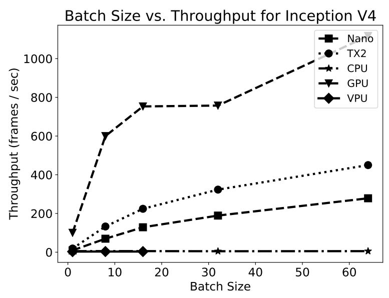
Performance results: We begin with microbenchmarking our hardware accelerators using the image classification workload. Figure 3 shows the throughput and power usage results for our two image classification models: Mobilenet V2 and Inception V4. As shown in Table II, Inception is a more complex model that is around $7\times$ larger in size and parameters than Mobilenet. Figure 3(a) depicts the mean inference throughput in terms of frames/s for various hardware accelerators running these models; note the log scale on the y-axis depicting throughput.

The figure yields the following observation: (1) All four edge accelerators provide a significant increase in performance when compared to a vanilla Pi3 edge node, yielding between $6\times$ to $28\times$ throughput increase for Mobilenet and $3.4\times$ to $70\times$ throughput increase for Inception. (2) Interestingly, some of the edge accelerators even outperform a modern x86 server processor, which satisfies their claims of "server-class" performance using low cost hardware. Both Nvidia GPUs outperform the x86 CPU by $1.7\times$ to $3.5\times$ for MobileNet and have comparable to $2\times$ higher throughput for Inception. The VPU is the slowest of the four and yields about half the CPU throughput, while the TPU is $5\times$ slower for Inception but $1.9\times$ faster for Mobilenet. (3) Not surprisingly, the cloud GPU still holds a significant performance advantage over all edge accelerators with $5\times$ to $8\times$ higher throughput than the fastest edge accelerator (TX2).

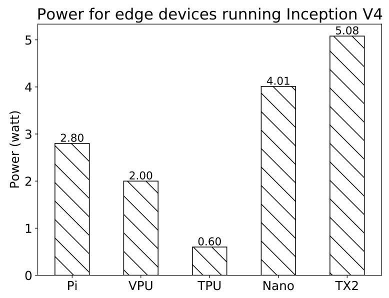
While the throughput microbenchmarks above assume sequential inference requests, we next measure throughput us-



(a) Throughput

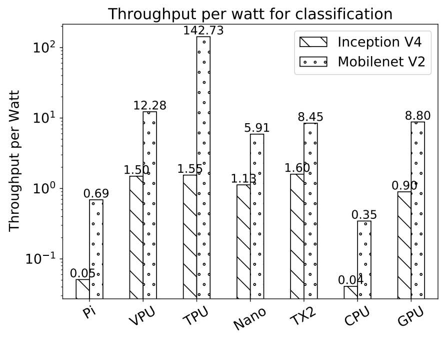


(b) Batch Throughput

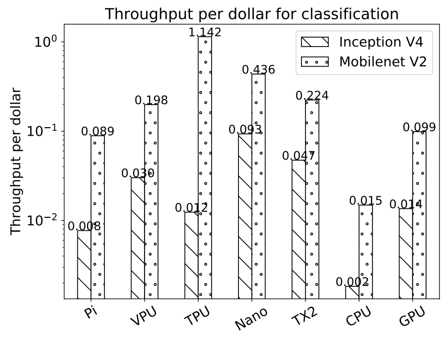


(c) Power consumption

Fig. 3. (a)Throughput of edge and cloud devices for image classification. (b) The impact of batch size for edge and cloud devices for the Inception V4 model. Pi and TPU are not shown here because Pi can only run with batch size of 1 for Inception V4 model and batching for TPU is not supported. (c) Power consumption of edge devices for the Inception V4 model. The server CPU and GPU consume 131.26W and 111.66W, respectively, for the same model.



(a) Throughput per watt



(b) Throughput per unit cost

Fig. 4. Normalized performance per watt and per unit cost for various devices. Price data used for normalization is shown in Table I

Workloads	Models	Pi	VPU	TPU	Nano	TX2	CPU	GPU
Image Classification	MobileNet V2	3.11	19.64	85.64	43.16	89.19	43.54	729.03
	Inception V4	0.27	2.99	0.93	9.23	18.91	5.36	100.11
Object Detection	SSD MobileNet V1	1.39	10.66	21.09	23.97	46.90	21.23	499.83
	SSD MobileNet V2	1.10	8.37	17.90	19.64	36.34	17.44	372.74
Keyword Spotting	cnn-trad-fpool3	15.85	26.65	33.31	299.98	449.15	201.33	2314.91

TABLE III
THROUGHPUT IN INFERENCES PER SECOND

ing input batching. Batching of multiple inputs enables the hardware accelerator to parallelize model inference, thereby increasing hardware utilization and the resulting throughput. We vary the input batch size from 1 to 64 and measure the inference throughout for different hardware accelerators. Figure 3(b) depicts the throughput results for the Inception model (results for Mobilenet are similar and omitted due to space constraints). The figure shows that batching is very effective for all GPUs; the throughout increases with batch size but shows diminishing improvements beyond a batch size of 16. A batch size of 16 yields 13.94× and 11.85× throughput increase for Jetson Nano and TX2 GPUs, while a batch size of 64 yields 30.17× and 23.79×. We also find that batching is not effective for the VPU. We attribute this behavior to the smaller memory capacity of these devices that reduces their effectiveness for batched input processing. Moreover, at the time of writing, batching is not supported for EdgeTPU.

Power results: Finally, Figure 3(c) plots the mean power consumption of various hardware devices when performing inference.[3] We also measured the total energy consumed per inference request but omit those results here since they directly correlate to the mean power usage. As shown in the figure, the TPU is the most power-efficienct device and consumes only 0.6 watts during inference, with the VPU being the next most power efficient with a power consumption of 2 watts. The Jetson Nano and TX2 GPUs consume 4.01 and 5.08 watts on average during inference. In contrast, the Tesla Cloud GPU and the Intel Xeon CPU consume 111.66 and 131.26 watts during inference, significantly higher than the edge accelerators.

Normalized performance: Figure 4(a) and (b) plot the normalized throughput of various hardware devices with respect to power and cost. The normalized metrics of performance per watt and performance per dollar, respectively, enable a different comparison of these devices in constrast to using

[3]The plot depicts power consumption of only the accelerator or the CPU and does not include power consumed by the rest of the node or its peripherals.

raw performance or power. Figure 4(a) plots the throughput per watt for various devices. When normalized for power consumption, all edge accelerators outperform the x86 CPU by 10-100$\times$ and become comparable or outperform the cloud GPU. Due to their low power consumption, the TPU and VPU offer the highest performance per watt across all devices. Overall, the performance per watt is 25.5 to 77% higher for the various edge accelerators when compared to the cloud GPU for the Inception workload. For Mobilenet, the TPU and VPU yield a 16$\times$ and 1.3$\times$ better performance per watt than the cloud GPU, respectively. Figure 4(b) plots the throughput per dollar cost for all devices. Once again, we see that all edge accelerators provide a higher throughput per dollar cost than the cloud GPU and x86 CPU due to their low cost. Even the TX2 GPU, which has a relatively high list price of $399, yields a 1.3$\times$ better performance per dollar cost than the cloud GPU.

Next, we repeat the above experiments for the object detection and keyword spotting workloads. Table III summarizes the inference throughput obtained for various hardware devices under various deep learning models and workloads. While there are some variations in throughput across audio and image workload and different models, the broad results from Figure 3 hold for these results. All edge accelerators provide very significant throughput improvements over low-end edge nodes, such as the Raspberry Pi, and many outperform even a x86 server processor. Broadly, the TX2 edge GPU provides the highest throughput across the four edge devices; performance can be roughly ordered as VPU, TPU, Jetson Nano, and TX2 for various workloads. The cloud GPU continues to provide the greater raw performance across all devices, but becomes comparable or slightly worse than the accelerators on a a normalized performance per watt and performance per dollar basis (not shown here to due to space constraints)—similar to the trends shown in Figure 4.

Key takeaways: On a raw performance basis, we see a rough performance order across edge accelerators for inference workloads, namely VPU $<$ TPU $<$ Nano $<$ TX2. Edge accelerators provide performance that is within one-half to 3.5$\times$ that of x86 server processors. When normalized for power and cost, edge accelerators easily outperform traditional server processors by 10-100$\times$ and become comparable to or better than even server GPUs. All edge accelerators exhibit very low power consumption, ranging from 0.6W to 8W, which is more than an order of magnitude lower than the server CPU and GPU. These results indicate that specialized edge architectures are very attractive for edge applications in power or space-constrained settings. Further, they have the potential to replace traditional ("cloudlet-like") x86 edge servers for deep learning inference workloads.

V. Split Processing across Application Tiers

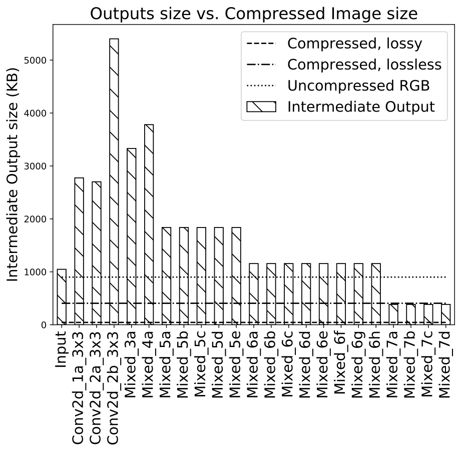
Next, we evaluate the benefits of hardware accelerators for distributed or split processing of edge-based AI workloads. We consider both model splitting and model compression, which are the two types of split processing that have been proposed.

A. Model Splitting

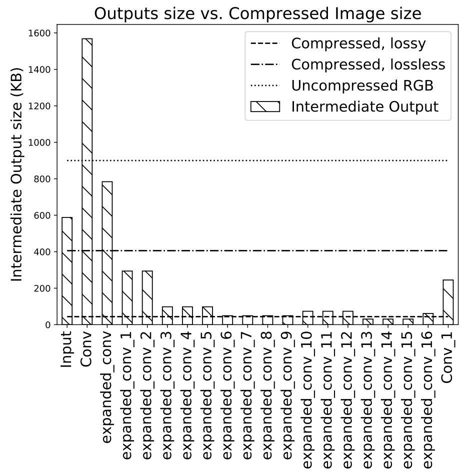
Our first method, *model splitting*, allows a deep learning model to be split across multiple nodes within or across tiers. In sequential splitting [23], the first k layers of the n layer model run on the first node accelerator and the remaining $n-k$ layers run on the next node or tier. In this case, the inference request is initially sent to the first node and the intermediate output of the k^{th} layer is then sent over the network to the $(k+1)^{st}$ layer running on the second node for subsequent processing. Model splitting can also be done in parallel, where a portion of each of the n layers is deployed on the first node, with the remaining portions of each layer deployed on the other node [46]. In this case, both nodes process the input data in parallel by feeding it through the layers of the model. Model splitting offers two possible benefits. First, in case of sequential splitting, if the output of an intermediate layer is smaller than the input, splitting the model at this layer consumes less network bandwidth than sending the original input to the higher tier for inference. Second, model splitting is also useful when the full model does not fit into the memory of a hardware accelerator; in such cases, the model can be split—sequentially or in parallel—across two or more edge nodes within a tier, enabling all processing to be performed at the edge tier even though no single accelerator can host and run the entire model.

Our first experiment evaluates the benefits of model splitting using sequential splitting for image classification (using our Inception V4 and MobileNet V2 models). Our experiments were performed by splitting the model between an Edge TPU and a cloud GPU. For each model, we systematically vary k, the layer after which the model is split between the two nodes, and measure the size of the intermediate output transmitted between layers k and $k+1$. Note that the inference result will always be the same regardless of the chosen k, and only the data transmitted between the split models varies with k. We compare this overhead to the non-split model inference where the entire model runs on a single node, and the input image data is sent over the network to that node using (i) uncompressed RGB format, (ii) lossless PNG compression and (iii) lossy JPEG compression.

Figure 5(a) shows the result obtained by splitting the Inception V4 model for image classification. As shown, the intermediate output produced by each layer varies from layer to layer. Interestingly, we find that *all* layers produce an intermediate output that *exceeds* the size of the input data when using using lossless or lossy compression to transmit the input. Only transmitting the input data in uncompressed RGB format incurs more network overhead. Thus, splitting at any layer will consume *more bandwidth* than sending JPEG or PNG compressed images to a non-split model. This result shows that, for Inception V4, there is no benefit from splitting the model between the edge and the cloud tiers, and it is better to either deploy the full model entirely on the edge tier and avoid all data transmissions to the cloud, or deploy the model entirely in the cloud by sending compressed inputs to the non-



(a) Inception V4



(b) MobileNet V2

Fig. 5. The intermediate output size of various layers of the models for image classification.

split model. Further, for Inception V4, the only benefit of split processing is for handling a large memory-footprint model that does not fit into the memory of a single edge accelerator. In this case, we can split the model across two (or more) edge node accelerators to accommodate it and perform distributed inference within the edge tier using horizontal splitting.

Figure 5(b) shows the result obtained by splitting the MobileNet V2 model for image classification. We find that the behavior of this model is different from the previous case. The figure shows that most layers, except for the first two, produce intermediate output that is far below the size of the input data when using lossless compression. We find that splitting the model at layer 10 (labelled "expanded_conv_6") yields nearly 8× network savings over using lossless compression for a non-split model. The maximum savings are obtained by splitting at layer 16 ("expanded_conv_13") with nearly an order of magnitude reduction in the used network bandwidth. Splitting even offers benefits when compared to using lossy JPEG compression, with layer 16 yielding 30.46% bandwidth savings. These network bandwidth savings come with a trade-off however—the total latency of performing split inference on two nodes is higher that performing a single non-split model inference, as shown in Table IV. The table shows that the latency of vertical splitting between the device-edge and edge-cloud tiers as well as horizontal splitting between edge-edge is always higher than the non-split inference latency (when using VPU, edge TPU and cloud GPU as the accelerators for the device, edge and cloud tiers). Thus, model splitting involves trading lower network overhead for higher inference latency.

Key takeaways: Taken together, the results above show that the benefits of model splitting are highly model dependent. In many cases, significant network savings can be obtained from splitting the model across tiers in an optimal manner, but at the cost of higher overall inference latency. In other cases, split processing is useful only *within* the edge tier when the model does not fit in the memory of a single accelerator,

Split between	Split Latency		Non-split Latency
	Node 1	Node 2	
device-edge	52.19ms	4.03ms	14.11ms
edge-edge	13.50ms	4.03ms	14.11ms
edge-cloud	13.05ms	0.50ms	1.45ms

TABLE IV
INFERENCE LATENCY FOR SPLIT VS. NON-SPLIT MODEL. THE MOBILENET V2 MODEL IS ASSUMED TO BE OPTIMALLY SPLIT AT LAYER 16. NETWORK LATENCY, WHICH IS THE SAME FOR BOTH, IS OMITTED.

while splitting across tiers is not beneficial from a network standpoint. Since the overheads and benefits will vary from model to model, adaptive run-time techniques are needed to analyze these overheads and determine whether to split and, if so, an optimal split for each particular model.

B. Model Compression

Model compression is an alternative form of split processing that takes a full deep learning model and constructs a smaller compressed version of that model with a lower memory footprint [36]. The smaller model is deployed for performing inference on a lower tier node with less resources, while the full model runs on a more capable higher-tier node. For example, the small model can be deployed on the device tier with a local accelerator, while the larger model runs on an edge node with accelerator capability. Alternatively, the compressed model can be deployed on an edge node with the full model running on a cloud server (the difference between these two scenarios is the relative sizes of the *device-edge* and *edge-cloud* models). In either case, inference is first run on the compressed model; since all models produce a probability (confidence) value along with each inference result, the method uses a threshold parameter to determine if the output of the compressed model is of adequate quality, in which case the output is assumed to be final. Otherwise the input data is sent over the network to the full model at the next tier for a second inference. Such an approach can provide bandwidth and latency savings—if a majority of the inference requests are handled by the compressed model, data need not be sent to the next tier, yielding bandwidth savings, and inference can be handled locally at lower latencies. The threshold parameter allows for a tradeoff between accuracy, bandwidth, and latency.

We now evaluate the efficacy of model compression-based split processing using hardware accelerators. We consider two scenarios, a *device-edge* case where a very small footprint model (6.4 MB) runs on the device tier accelerator (emulated using a VPU, which is the slowest of our accelerators) along with a larger (13MB) model running on the TX2 edge GPU. We also consider an *edge-cloud* case where we run a medium footprint (13MB) model on the TX2 edge GPU and a larger 23 MB model on the cloud GPU. We construct these models of varying size using MobileNet V2, yielding the `mobilenet_v2_0.35_96` device model, `mobilenet_v2_1.0_224` edge model and `mobilenet_v2_1.4_224` cloud model.

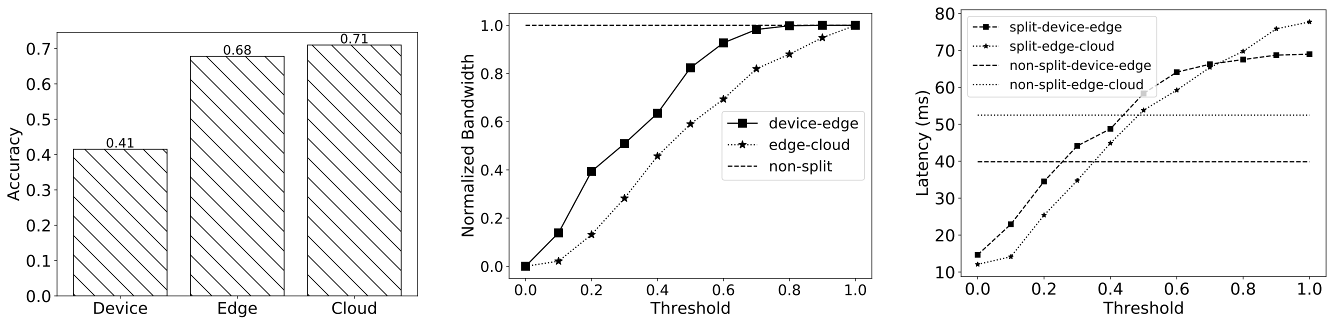
Figure 6(a) shows the accuracy of the three models on the ImageNet validation dataset (obtained by comparing the inference results with the ground truth in the dataset). As can be seen, the smaller the compressed model, the lower its accuracy. Figure 6(b) shows the network bandwidth usage for the device-edge and edge-cloud scenarios under varying thresholds; recall that the threshold determines the confidence level under which the input image is transmitted to the next tier for inference by the larger model. A lower threshold implies we are willing to accept predictions with lower confidence from the smaller model. As can be seen, as the threshold increases, a larger percentage of inference requests fail to meet the desired confidence using the compressed model and require a second inference from the larger model, which increases the network bandwidth usage. At a threshold of 0.5, the device-edge case yields a 18% network savings when compared to the non-split scenario; the savings for the edge-cloud are higher at 41% since the larger edge model is able to handle more inference requests locally than the smaller device model of the device-edge case. The savings fall to 0.1% and 11% for a higher threshold of 0.8 for the device-edge and edge-cloud, respectively, and diminish asymptotically to zero as the confidence threshold approaches 1.

Figure 6(c) shows the total latency of split processing for different thresholds. The total latency includes the inference latency of the compressed model, the network latency to send data to the larger model if necessary, and the latency of the second inference if the larger model is invoked. For the non-split case, all requests incur network latency to send data to larger model and also include the inference latency of the larger model. In our experiment, the mean edge-device network latency was around 4ms and the edge-cloud latency to the EC2 cloud server was 47.76ms. In contrast, the inference latency is highest at the device VPU and lowest at the cloud GPU. The figure shows that for lower thresholds, split processing offers lower overall latency since the compressed model is able to produce results of “adequate” quality (i.e., above the threshold), which avoids a network hop and a second inference by the larger model. As the threshold increases, more results need to be sent to the larger model since the compressed model is unable to produce results that meet this higher confidence. This causes the overall latency of split processing to rise due to more requests incurring a network hop and a second inference.

The figure also shows a cross-over point beyond which split processing incurs higher overall latency than non-split processing—since the overhead of two inferences is higher than performing a single inference. We find that the cross-over point occurs at a relatively low threshold of 0.26 for device-edge and 0.45 for edge-cloud scenarios. This implies that when subjected to a *random* set of inputs (from the Imagenet validation dataset), model compression in not able to outperform non-split inference when high confidence output is desired from the smaller model; model compression yields lower latencies only when we are willing to accept lower quality results from the compressed model.

We next consider a scenario where the inputs are not random but skewed towards the common case. In this scenario, we assume that the compressed model is well-trained for a small number of frequently occurring inputs. The larger model is invoked only for less common inputs for which the compressed model yields less confident and less accurate results. This is a likely deployment scenario for model compression where the compressed model is designed to perform well for common case inputs that are frequent, acting as a “filter” for such inputs; less common inputs are sent to the larger model, which is capable of handling a much greater range of inputs, for further processing. To evaluate such a scenario, we construct a skewed input dataset using the Imagenet validation dataset where common-case inputs (e.g., “car”) occur very frequently and all other inputs (e.g., all other vehicles) occur infrequently. Figure 7 depicts the latency of the device-edge and edge-cloud scenario for such inputs. As shown, model compression yields much lower latency ($3\times$ for device-edge and $4\times$ for edge-cloud) than non-split inference for a wide range of threshold values—since it performs inference well for the common case, and avoids a second inference for the majority of the inputs. The bandwidth savings (not shown here) are similarly higher than the non-split case for a broad range of threshold values.

Finally, we evaluate the impact of the network latency on these benefits. While the previous experiment used actual network latency to the EC2 cloud server, we evaluate the benefits of cloud latencies under different emulated cloud latencies. We vary the cloud latency from 20ms to 200ms and mesure the latency of using model compression relative to the non-split case. As can be seen in Figure 8, the higher the latency to the cloud server, the greater the benefits of using the compressed model to perform a single local inference. For a theshold of 0.8, 60ms cloud latency yields around 70.39% latency reduction and 100ms cloud latency yields a 79.83% lower latency. The figure also shows that higher thresholds yield lower benefits, since it causes more inputs to be sent to the larger model. Finally, for very high thresholds such as 0.99, split processing is always worse than non-split inference, since



(a) Accuracy (b) Bandwidth (c) Latency

Fig. 6. Accuracy of compressed models (a) and Bandwidth and latency savings for different cut-off confidence thresholds under model compression (b,c). For non-split case, all requests are sent to edge/cloud from device/edge and processed using the larger model

it causes the vast majority of the inputs to undergo inference at both the compressed and the larger model.

Key takeaway: Unlike model splitting which offers bandwidth savings by trading off higher latency, model compression can yield *both* bandwidth and latency reduction, but comes with an accuracy tradeoff. The smaller the compressed model, the lower its ability to perform local inference with good confidence and accuracy and the lower the bandwidth savings from split processing. Consequently, we find that edge-cloud split processing yield higher savings than the device-edge case due to the larger compressed model at the edge. The latency reductions depend significantly on the nature of the inputs. When optimized for frequent common case inputs, model compression can yield very good latency reduction by handling most of the frequently occurring inputs locally using the compressed model. The benefits of model compression also depend on the network latency—the higher the latency to the cloud, the more valuable is the ability to handle inference locally and avoid an expensive network hop. Conversely, the closer the cloud servers, the lower are the benefits of split processing using model compression.

VI. Concurrency and Multi-tenancy

Unlike clouds that are built using large data centers, edge clusters are more resource-constrained than traditional clouds. Thus, the ability to share servers across multiple users and applications is crucial for edge. Our final experiment focuses on concurrency and multi-tenancy considerations for specialized edge nodes. General-purpose nodes are capable of executing concurrent tenant application due to OS features, such as CPU time sharing and address space isolation. To understand such benefits for specialized edge nodes, we conduct an experiment to quantify the ability of hardware accelerators to run concurrent models. To do so, we load multiple SSD MobileNet V2 models, one for each tenant, onto each of our four edge accelerators. Each tenant application thread then invokes its loaded model for inference concurrently with others. We vary the number of concurrent models and measure the throughput of each device.

Figure 9 shows the inference throughput obtained for each hardware accelerator for different degrees of concurrency. The figure shows that all four edge accelerators are capable of supporting multiple concurrent models and provide inference throughput that is comparable to that under a single tenant scenario. However, the maximum degree of concurrency varies by device. Typically, the maximum concurrency will depend at least on the device memory size and the model size. For the SSD MobileNet V2 model used in this experiment, the Nvidia Nano and TX2 can support a a maximum of 2 and 4 concurrent tenants, respectively. Surprisingly, the Intel NCS2 VPU can support 8 concurrent models despite being more memory constrained than the GPUs. The Edge TPU has the best concurrency features—it can arbitrarily scale the number of concurrent models due to its ability to use the host RAM to store models that do not fit on the device memory and its use of context switches to swap models to and from RAM. When used in conjunction with a Raspberry Pi3 device, we are able to scale the number of concurrent models to 79 before exhausting memory. The figure shows a slow drop in throughput as we increase the degree of concurrency due to the increasing context switch overhead.

Further analysis revealed that the lower concurrency of the edge GPUs is due to software overheads. We find that each model, despite being 66MB in size, consumes 1244MB in memory when loaded. This is because GPUs are designed to be more general accelerators than the VPU and TPU, and its TensorRT software framework is designed for more general use and therefore more heavyweight (TensorRT libraries alone consume 600MB). In contrast, the VPU and TPU are specifically designed for deep learning inference and the software framework is heavily optimized for this use case, thereby imposing low overheads.

In addition to exploiting host RAM for model swapping, the edge TPU also employs model quantization to further reduce memory overheads. Post-training model quantization [25] is a technique to reduce the memory footprint of the trained model—for example, by quantizing 32bit floating point weights of the model to 8bit precision values. The *edgetpu* runtime framework has quantization turned on by default, enabling it to shrink the size of each model prior to loading. The tradeoff though is a possible drop in accuracy of the

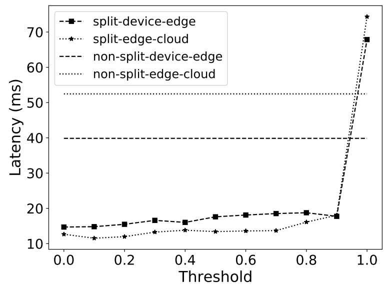


Fig. 7. Latency savings when compressed model produces high confidence results for common case inputs.

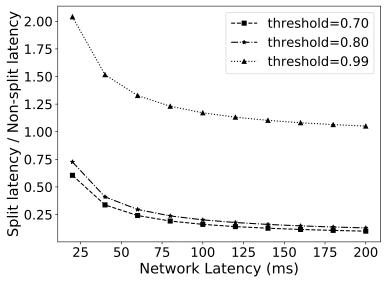


Fig. 8. Inference latency with varying network latency to cloud servers.

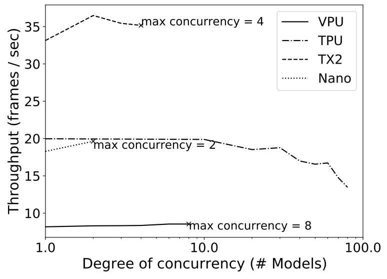


Fig. 9. Degree of concurrency supported by various device accelerators.

models due to quantization of the model weights.[4]

Finally, we note that none of the devices offer any isolation or security features for concurrent tenants. Currently a tenant thread can access models belonging to other tenants and even overwrite other models. The lack of isolation features implies that despite supporting concurrent model execution, the devices are not yet suitable for use in multi-tenant edge clusters or edge clouds.

VII. Summary and Implications of our Results

In this section, we summarize our results and discuss their broader implications. Our performance experiments revealed that edge accelerators provide comparable or better normalized performance than server CPUs and GPUs, outperform server CPUs on a raw performance basis, and consume an order of magnitude lower power for inference workloads. Our results imply that specialized edge clusters can potentially replace x86 edge clusters for such workloads. From a cost standpoint, deploying a large number of edge accelerators is no worse, but ofter better, than deploying a smaller number of more powerful GPUs at the edge. Specialized edge nodes are especially well suited for power and space constrained settings and open up new possibilities that are infeasible using current architectures.

Our split processing experiments provided several interesting insights. We found that model splitting across tiers can offer good bandwidth savings (up to $4\times$ in our experiments) but this comes at the cost of higher overall latency due to running split inference across a network. Even when there are no benefits to be had from splitting models across tiers, split processing *within* the edge tier is still beneficial for running large memory footprint models on constrained edge devices. Since the benefits are highly model dependent, our results point to the need for run-time methods to dynamically determine whether to split a model and how to do so optimally.

Unlike model splitting, model compression can offer *both* bandwidth savings and lower inference latency, but only when a majority of the inference requests can be handled by the compressed model with high confidence and accuracy. Highly compressed models or higher confidence thresholds diminish the benefits of model compression, since they cause a higher fraction of request to incur a network hop and a second inference. Our results also imply that the latency benefits of model compression will diminish as the latency to the cloud reduces gradually over time due to the ever increasing number of geographic cloud locations.

Finally, our concurrency experiments show that the degree of concurrency depends on the device memory, model size, framework software overheads, and system optimizations. Higher device memory does not always translate to a higher degree of concurrency, especially if the run-time framework is not memory-optimized. Conversely, devices with a small amount of memory can support a high degree of concurrency by heavily optimizing the run-time framework and employing optimizations, such as model swapping from the host memory and quantization of the model parameters. However, we find that the lack of isolation and security features between the concurrent models is a barrier for their use in multi-tenant edge cloud environments.

VIII. Related Work

Recent work on running deep learning applications on the edge falls into three categories: (i) cloud-only, (ii) edge-only, and (iii) collaborative edge-cloud. Cloud-only approaches [1]–[3] allow devices or the edge to offload compute-intensive inference to the cloud but at the expense of higher latency. In the context of edge-only approaches, pCAMP has compared various ML frameworks (TensorFlow, Caffe2, MxNet etc) on various edge devices (and found that not all frameworks support all devices) [44]. The efficacy of a 2-layer keyword spotting model and various CNNs on edge accelerators have also been studied [7], [30], [41]. None of these above efforts have considered split processing across tiers

Recent efforts have investigated collaborative edge-cloud split processing. Shadow Puppet [39] implements edge caching of results to reduce cloud processing. Several techniques to split DNN-based model and partition them between edge and cloud have also been studied [22], [23], [36], [45], [46]. However, edge-edge or device-edge splitting as well as accelerators-based splitting were not a focus of these efforts.

[4]Frameworks such as Tensorflow provide tools to verify that any such drop in accuracy is within tolerable limits.

IX. Conclusions

In this paper, we conducted an experimental study to evaluate the benefits and tradeoffs of using specialized edge architectures when compared to traditional edge architectures for running edge-based AI applications. Our experimental study showed that today's edge accelerators can provide comparable, and in many cases better, performance, when normalized for power or cost, than edge servers. We found that split processing workloads can yield good bandwidth or latency benefits, but these benefits were highly dependent on how the splitting was done from a model and tier perspective. We found that edge accelerators could support varying degrees of concurrency for deep learning inference, depending on hardware and software constraints, but lacked isolation mechanisms necessary for cloud-like multi-tenant hosting. Overall, our study found that many open issues still need to be addressed to fully realize the benefits of edge accelerators.

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