# EdgeFaaSBench: Benchmarking Edge Devices Using Serverless Computing

Kaustubh Rajendra Rajput*§, Chinmay Dilip Kulkarni*§, Byungjin Cho†, Wei Wang‡, and In Kee Kim*
*University of Georgia, Computer Science, {kaustubh.rajput, chinmay.kulkarni, inkee.kim}@uga.edu
†Aalto University, Communications and Networking, byungjin.cho@aalto.fi
‡The University of Texas at San Antonio, Computer Science, wei.wang@utsa.edu

***Abstract*—Due to the development of small-size, energy-efficient, and powerful CPUs and GPUs for single board computers, various edge devices are widely adopted for hosting real-world applications, including real-time object detection, autonomous driving, and sensor stream processing. At the same time, serverless computing receives increasing attention as a new application deployment model because of its simplicity, scalability, event-driven processing, and short-lived computation. Therefore, there is a growing demand for applying serverless computing to edge computing environments. However, due to the lack of characterization of serverless edge computing (e.g., application performance and impact from resource heterogeneity), researchers and practitioners have to conduct tedious measurements to understand the performance of serverless applications on edge devices in non-systematic ways.**

**We create EdgeFaaSBench, a novel benchmark suite for serverless computing on edge devices, to bridge this gap. EdgeFaaSBench is developed on top of Apache OpenFaaS with Docker Swarm and can run various serverless benchmark workloads on edge devices with different hardware specifications (e.g., GPUs). EdgeFaaSBench contains 14 different benchmark workloads running on heterogeneous edge devices and captures various system-level, application-level, and serverless-specific metrics, including system utilization, response time, cold/warm start times, and impact of concurrent function executions. Experimental studies are conducted on two widely used edge devices, Raspberry Pi 4B and Jetson Nano, to show EdgeFaaSBench's capabilities to benchmark serverless computing on edge devices.**

***Index Terms*—Benchmarking and Performance Evaluation; Edge Computing; Serverless Computing;**

## I. Introduction

The proliferation of IoT devices has been generating an exponential amount of sensing data, often requiring real-time processing near data sources [1]–[3]. The edge computing paradigm is emerging because the edge cluster can be deployed near data sources, e.g., IoT sensors, and process the data without relying on traditional data-center computing [4]–[6]. In particular, the development of small, energy-efficient, and capable CPU and AI accelerators for edge devices facilitates the adoption of edge computing to servicing various real-world applications, e.g., autonomous driving, drone-based surveillance systems, and environmental sensing [7]–[10].

At the same time, serverless computing and Function-as-a-Service (FaaS) have gained increasing attention as the next-generation application deployment model because of its simplicity, event-based processing, scalability, and short-lived computation [11]–[17]. Various user-facing and data-intensive applications have been converted into serverless architecture [18]–[22]. Furthermore, there are increasing attempts to apply serverless computing to edge computing environments [23]–[26], and it is widely recognized as serverless computing models are well suited for edge computing's service offerings [27]–[32].

When serverless applications are designed and developed for edge computing environments, specifically if the serverless applications are intended to be hosted on resource-constrained edge devices, software developers wish to know the potential performances and behaviors of their serverless applications on edge devices. Given the heterogeneity and constrained capacity of resources on edge devices, understanding performance limitations and bottlenecks of serverless applications on edge devices are particularly challenging.

A standard approach to understanding an application's performance is to use benchmark suites that are designed for a target environment [33], [34]. There are several benchmark suites available for either serverless computing [35]–[38] or edge computing [39]–[44]. Unfortunately, none of the existing benchmark suites was tailored for comprehensively benchmarking characteristics of serverless computing on edge devices. The lack of benchmarks for serverless on edge devices makes it difficult to understand the performance of the target applications and their execution environments. For example, desired serverless applications on edge devices [24], [29], [30] can be significantly different from serverless applications for cloud computing [14]–[16], and serverless edge applications' workload arrival patterns [45], [46] may also be different from those of serverless computing in clouds [47], [48]. As a result, existing benchmark tools [35]–[44] may not correctly capture the necessary performance and characteristics for serverless deployment on edge devices, and developers and practitioners have to conduct tedious and time-consuming measurement processes to understand the performance of serverless applications on edge devices.

To address this problem, we create EdgeFaaSBench, a novel benchmark suite for serverless computing on edge devices. EdgeFaaSBench is developed on top of a widely used open-source FaaS framework and container orchestration tool, OpenFaaS [49] and Docker Swarm [50], and can perform various benchmark tests on edge devices with different hard-

§Equal contribution

ware specifications, i.e., arm64/aarch64 devices with GPUs. `EdgeFaaSBench` has 14 different serverless workloads performing micro- and application-level benchmarking on edge devices. Micro-benchmark workloads focus on measuring the performance of a specific resource type on the devices, e.g., CPU, memory, network bandwidth, and disk I/O. On the other hand, application-level benchmark workloads are developed based on real-world serverless computing use-cases to capture the performances and characteristics of serverless applications on edge devices. In particular, various machine learning and AI FaaS applications, e.g., image classification, object detection, are developed for `EdgeFaaSBench`. With 14 benchmark workloads, `EdgeFaaSBench` can measure various system-level, application-level, and serverless-level performances, including system utilization, application response time, cold/warm start times, and impact of concurrent function executions.

To show the effectiveness of `EdgeFaaSBench`, a thorough benchmark study is performed on two edge devices; Raspberry Pi 4B [51] and Jetson Nano [52]. Raspberry Pi 4B is a widely used device in edge computing settings, and Jetson Nano is an edge device equipped with small yet powerful GPU accelerators. The evaluation results report application response time, system utilization, cold and warm start times, the impact of concurrent function executions, and the performance comparison between GPU and GPU-based inferences.

The contributions of this work are as follows.

1. **Novel benchmark suite.** We present `EdgeFaaSBench`, the first comprehensive benchmark suite centered on evaluating the performance and characteristics of serverless applications on heterogeneous edge devices to the best of our knowledge. `EdgeFaaSBench` software is publicly available at https://github.com/kaustubhrajput46/EdgeFaaSBench.

2. **Comprehensive FaaS benchmark workloads.** 14 different workloads are employed for `EdgeFaaSBench` to collect various performance aspects of edge devices. `EdgeFaaSBench` can measure both system-level and application-level metrics, such as utilization and response times, as well as serverless-specific metrics, such as cold/warm startup time variations and the impact of concurrent function executions.

3. **A thorough evaluation with practical edge devices.** `EdgeFaaSBench` is tested on two widely used edge devices, Raspberry Pi 4B and Jetson Nano, to demonstrate the effectiveness and feasibility in performance benchmarking of serverless computing on edge devices.

We structure the rest of the paper as follows. Section II describes the design of `EdgeFaaSBench` by emphasizing our benchmark focus. Section III discusses 14 benchmark workloads in `EdgeFaaSBench`. Section IV reports the results from a benchmark study on two edge devices with `EdgeFaaSBench`. Section V describes related work regarding this work. Finally, Section VI concludes this paper.

## II. Design of EdgeFaaSBench

### A. Edge Computing Architecture and the Focus of Benchmark

**Edge Computing Architecture.** Fig. 1 illustrates the general architecture of edge computing. Edge computing architecture

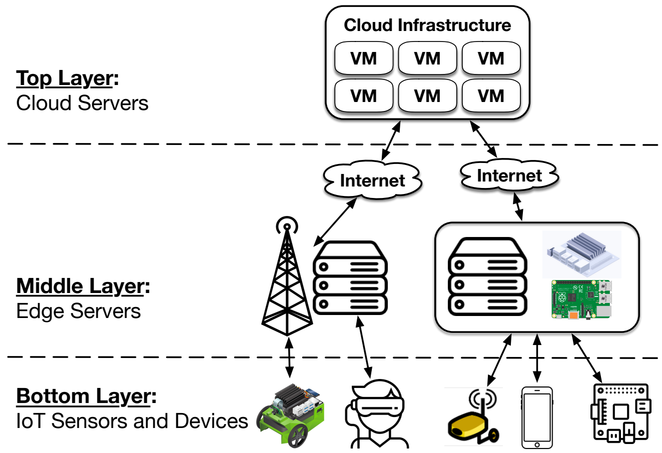



Fig. 1. Edge Computing Architecture

is commonly composed of three layers; 1) IoT sensor and device layer, 2) Edge server layer, and 3) Cloud layer.

*IoT sensor and device layer* ("bottom layer" in Fig. 1) has various IoT sensors and user devices, which perform diverse sensing operations, and user devices (including edge devices) are used to host lightweight applications to perform real-time on-board processing, including sensing data filtering and noise removal [53], lightweight AI inference tasks [10], [54], and stream processing [55].

*Edge server layer* ("middle layer" in Fig. 1) is the main computing component in the edge computing environment. Typically, the edge server layer is placed near data sources (IoT sensor and device layer) to provide low-latency computing services that process the data collected by IoT sensors. The edge servers host heavier-weight applications that cannot be executed on computing elements in the IoT sensor and device layer. The applications hosted on edge server layer perform deep learning (DL) inference [7] and big data analytics [56] operations, which tend to require high-performance processors, GPUs, and edge AI accelerators.

The last layer is *cloud server layer* ("top layer" in Fig. 1). Cloud server layer leverages the scalability and elasticity of cloud infrastructure to provide large-scale data storage and perform computation-intensive tasks with specialized HW accelerators, e.g., DL model training with TPU [57], that cannot be performed on the other two layers.

**Benchmark Focus of `EdgeFaaSBench`.** While edge computing has three different layers, `EdgeFaaSBench` focuses on benchmarking the performance of edge devices, explicitly adopting the idea of the FaaS paradigm [15], [16]. Moreover, existing edge benchmark suites, e.g., DeFog [41] and others [39], already offer the capability of end-to-end edge benchmarks. Please refer to Section V for more information.

Benchmarking the edge device performance has received significant attention from the research and development community because of the faster improvement of the small but powerful edge devices. In addition, HW developers and man-

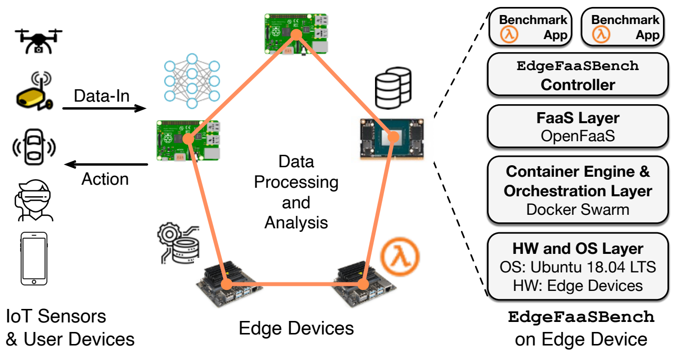



Fig. 2. The overview of EdgeFaaSBench on edge devices

ufacturers recently released high-performance edge devices, often equipped with GPUs [52], [58], [59], and Edge TPU accelerators [60]. Thanks to this development, understanding the performance and behaviors of edge applications running on such devices is particularly challenging due to the variety of resource models and their heterogeneity, and it has become a significant research task. Moreover, the development of edge devices opens up a new opportunity to leverage application deployment models recently developed by the cloud computing community; serverless computing and FaaS models [15], [16]. Therefore, benchmarking with the FaaS applications will provide essential indications to develop more flexible and lightweight applications models, which are more suitable for edge computing [27]–[32]. It is worth noting that edge devices can be deployed in both middle (edge server) and bottom (IoT sensor and device) layers. Generic and low-end edge devices like Raspberry Pi can be used in the IoT sensor and device layer, and high-end edge devices with GPU resources are typically deployed in the edge server layer.

### B. Overview of EdgeFaaSBench

Fig. 2 illustrates the overview of EdgeFaaSBench on edge devices. EdgeFaaSBench on edge devices is composed of four different hierarchical components.

**HW and OS Layer.** This layer refers to the edge devices and OS running on the devices. While there are some differences with devices, edge devices like Raspberry Pi 4B [51] and Nvidia's Jetson series [52], [58], [59] commonly have multi-core ARM CPU designed based on `arm64`/`aarch64` architecture, 4GB to 8GB of RAM, and storage with portable micro-SD card. Moreover, some edge devices, designed for facilitating AI inference tasks at the edge, are equipped with GPU accelerators. For example, Jetson Nano [52] has a 128-core Nvidia Maxwell GPU accelerator, and Jetson Xavier NX [59] is equipped with a Volta GPU with 384 CUDA cores and 48 Tensor cores. We also selected Ubuntu 18.04 LTS (64-bit) for the OS of the edge devices because this version of Ubuntu is commonly running on most edge devices.

**Container Engine and Orchestration Layer.** Docker [61] and Docker Swarm [50] are used for EdgeFaaSBench. Docker is the most widely used container engine, and Docker Swarm is the container orchestration framework for Docker. Both are used to support OpenFaaS (in the FaaS layer) and host serverless applications managed by OpenFaaS. Among the multiple capabilities Docker Swarm supports, the auto-scaling mechanism is particularly beneficial for benchmarking edge devices. For example, EdgeFaaSBench can leverage Docker Swarm's auto-scaling to characterize the performance with concurrent executions of serverless applications on the devices.

**FaaS Layer.** This layer uses OpenFaaS [49] as a primary serverless framework to manage various serverless benchmark workloads. OpenFaaS is selected for EdgeFaaSBench for the following reasons. First, OpenFaaS offers convenient and comprehensive capabilities of managing serverless applications with minimal HW requirements, various programming languages to write serverless applications, and packaging the applications in a containerized manner. Moreover, the programmable APIs and CLI of OpenFaaS allow convenient scaling-out and scaling-in operations for serverless functions on edge devices. EdgeFaaSBench uses `faas-cli`[1] with version 0.13.13 and OpenFaaS with version 0.20.5.

**EdgeFaaSBench Controller Layer and Benchmark Workloads.** These two layers comprise the core of EdgeFaaSBench. The controller layer is responsible for running the benchmark tasks and measuring system statistics (e.g., resource utilization) on edge devices. To start and stop a benchmark workload, EdgeFaaSBench collaborates with APIs and CLI functionality of OpenFaaS. Moreover, EdgeFaaSBench uses diverse system monitoring techniques, including `sysstat`[2] and `docker stats`[3], to monitor the changes in resource utilization and application performance. The detailed information on collected metrics and procedures from EdgeFaaSBench will be described in the following subsection (Section II-C).

EdgeFaaSBench offers both micro-benchmark and application-level benchmark capabilities to capture diverse aspects of edge devices. All the benchmark workloads used in EdgeFaaSBench will be discussed in Section III.

### C. Benchmark Metrics and Procedure of EdgeFaaSBench

As illustrated in Fig. 3, EdgeFaaSBench is composed of 1) *benchmark client* and 2) *device manager*. The *benchmark client* runs on a client machine that triggers the benchmark process, analyzes performance statistics collected by both devices and the client machine, and generates the final report for the benchmark. EdgeFaaSBench uses a workload generator (e.g., Apache bench[4] to send requests to serverless benchmark workloads on an edge device and measure the performance statistics (e.g., application's response time) from the client-side. The *device manager* controls the benchmark process on the device-side. The main component in the device manager is the system monitor that captures performance statistics

[1] https://github.com/openfaas/faas-cli
[2] http://sebastien.godard.pagesperso-orange.fr/
[3] https://docs.docker.com/engine/reference/commandline/stats/
[4] https://httpd.apache.org/docs/2.4/programs/ab.html

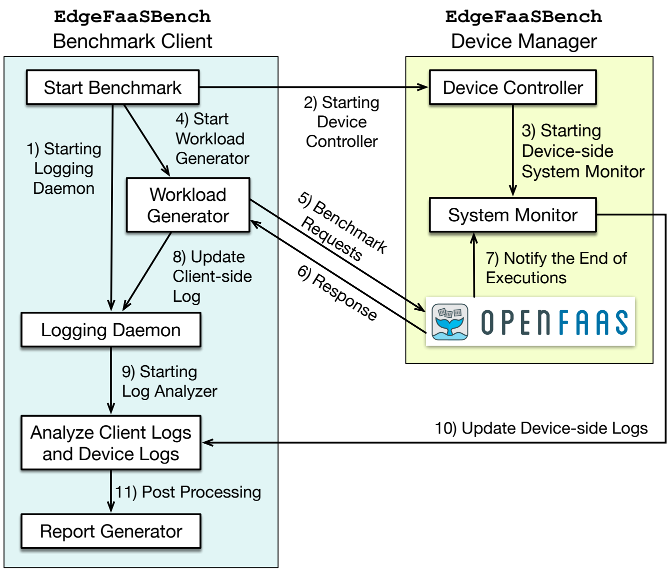



Fig. 3. Benchmark Procedure of EdgeFaaSBench

during the benchmark execution and reports the collected metrics/statistics to the benchmark client.

**Benchmark Metrics.** EdgeFaaSBench can measure three different categories of metrics for the performance benchmark.

*1) System Resource Utilization:* Four main resource utilization metrics, e.g., CPU, memory, disk I/O, and network bandwidth, can be measured by EdgeFaaSBench. To accurately collect CPU and memory usage on edge devices, a particular challenge for EdgeFaaSBench is to differentiate the resource consumption by FaaS containers (hosting serverless benchmark workloads) managed by OpenFaaS and that by other processes (e.g., EdgeFaaSBench system monitor on the device). Therefore, EdgeFaaSBench employs two different system monitoring techniques, `docker stats` and `sysstat`, to collectively measure separate resource consumption by FaaS containers and other processes. In particular, `docker stats` allows EdgeFaaSBench to measure resource utilization per each FaaS container. Other system metrics, e.g., disk I/O and network bandwidth, are measured using micro-benchmark serverless workloads developed based on *dd* and iPerf3[5].

*2) Serverless Application Performance:* The response times of the benchmark workloads are the main performance metric to understand the behavior of serverless applications. The response times are measured by both on benchmark client and device manager (edge devices) of EdgeFaaSBench. The benchmark client measures client-side response times. i.e., the actual execution time on the devices and the transmission latency. Furthermore, the device manager can collect the execution time of serverless applications inside the OpenFaaS docker container. EdgeFaaSBench can provide multiple types of statistics of the response time, including the average, tail (e.g., 99%ile), and distribution of the response time.

[5]https://iperf.fr/iperf-download.php

*3) Serverless-related Metrics:* To measure the performance and behavior of serverless applications on edge devices, EdgeFaaSBench can collect *cold* and *warm start times* of serverless applications. The cold start time represents the delay when the first function (serverless application) is invoked, and it includes both container creation and application deployment overhead. The cold start time is an initialization delay caused when the first function (serverless application) is invoked, and it includes both container creation and application deployment overhead. On the other hand, the warm start time is the function invocation delay when a request arrives in an existing serverless container. In particular, the cold start time is the primary performance bottleneck of serverless applications because the cold start time can be up to an order of magnitude slower than the warm start time [62], [63]. Therefore, it is critical to measure such overhead on edge devices. To measure the cold start time, EdgeFaaSBench leverages OpenFaaS CLI and customized `yml` files for benchmark workloads to intentionally create cold start cases (e.g., set `com.openfaas.scale.min`[6] to zero). Moreover, the cold start time can be further amplified with concurrent function executions. To measure such impact, EdgeFaaSBench dynamically changes the request rates in the workload generator and auto-scaling configuration in OpenFaaS to support more function executions.

**Benchmark Procedure.** Fig. 3 also shows the benchmark procedure of EdgeFaaSBench. EdgeFaaSBench begins by starting the logging daemon in the benchmark client (step #1). The logging daemon is responsible for collecting all the logs from both the benchmark client and system monitor on the target edge device. The benchmark client then notifies the device controller on the edge device about the start of the benchmark (step #2). The device controller initializes the system monitor (step #3), and the system monitor becomes ready to collect system statistics of the edge device (e.g., resource utilization).

The workload generator in the client is started (step #4), and then it sends benchmark requests to the serverless benchmark workloads in the OpenFaaS framework on the device (step #5). When the benchmark workload receives the requests from the workload generator, it starts conducting the performance benchmark on the device. At the same time, the system monitor starts data collection of the edge device's system statistics (e.g., the change of CPU usage). Once the benchmark workload processes the request from the workload generator, the application sends a response back to the workload generator (step #6). The workload generator measures the response time by calculating the difference between the time to send the request and the time to receive the response. When the benchmark workload finishes its execution, it notifies the end of the benchmark to the system monitor (step #7).

Then, the logging daemon in the benchmark client collects the client-side logs and measured statistics, including the application's response time (step #8), and starts the log analyzer

[6]https://docs.openfaas.com/architecture/autoscaling/

TABLE I
SUMMARY OF BENCHMARK WORKLOADS IN EdgeFaaSBench. (H: HIGH, M: MEDIUM, L: LOW)

| Category | Workload Name | Workload Type | | | | | Description |
|---|---|---|---|---|---|---|---|
| | | CPU | MEM | I/O | NET | GPU | |
| Micro-Benchmark | Matrix Multiplication (`MM`) | H | H | - | - | - | Performing matrix multiplication of different matrix sizes multiple times. |
| | Fast Fourier Transform (`FFT`) | H | H | - | - | - | Reading a random seed number and performing its Fast Fourier Transform operations multiple times. |
| | Floating Point Operation Sine (`FPO-SINE`) | H | M | - | - | - | Calculating the sine value of all 360 degrees multiple times. |
| | Floating Point Operation Square Root (`FPO-SQRT`) | H | M | - | - | - | Calculating the square root value of random numbers, ranging from 10,000 to 30,000 multiple times |
| | Sorter (`SORT`) | M | H | L | - | - | Reading a file containing random text data and sorting the text data using the Linux *sort* command. |
| | dd (`DD`) | L | L | H | - | - | Performing random read/write operations on storage (micro-SD) on edge devices using the Linux *dd* command. |
| | iPerf3 (`IPERF`) | L | L | - | H | - | Leveraging the iPerf3 tool to measure the achievable bandwidth of the IP network of edge devices. |
| Application-Level Benchmark | Image Processing (`IP`) | M | M | L | L | - | Resizing random images (from benchmark client) to a size of 400× 400 pixels. |
| | Sentiment Analysis (`SA`) | H | M | - | L | - | Downloading JSON files about different topics and calculating the ratio of positive and negative engagements about the topics. |
| | Speech to Text (`ST`) | M | M | L | M | - | Downloading a random audio file from external storage, generating translated text, and sending it back to the benchmark client. |
| | Image Classification on CPU (`IC-CPU`) | H | M-H | L | L | - | Receiving random images from the benchmark client, performing image classification tasks using pre-training CNN models on CPU, and transferring the classification results to the benchmark client. |
| | Image Classification on GPU (`IC-GPU`) | M | M-H | L | L | H | Performing a similar task with `IC-CPU`. But this benchmark enables GPU resources to perform the DNN inference task faster. It can be run on edge devices with GPU. i.e., Nvidia Jetson series |
| | Object Detection on CPU (`OD-CPU`) | H | H | L | L | - | Receiving random images from the benchmark client, and performing object detection tasks with YOLOv3 on CPU. |
| | Object Detection on GPU (`OD-GPU`) | M | H | L | L | H | Performing the similar task with `OD-CPU`, but enabling GPU for faster inference. This workload can run on GPU-equipped edge devices. |

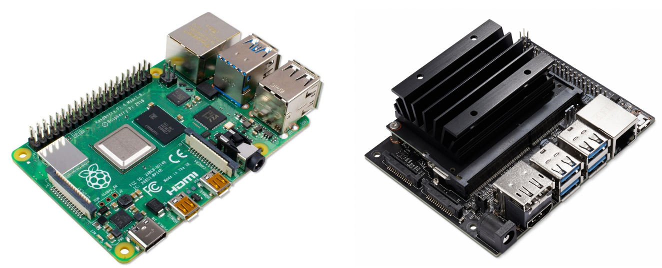
(step #9), which collects the device-side benchmark logs and statistics (step #10) and conducts further analysis of both client and device logs to understand the performance of the serverless benchmark workloads on the device. The results from the log analyzer will be given to the report generator to create the final performance benchmark reports for the user (step #10).

## III. BENCHMARK WORKLOADS IN EdgeFaaSBench

This section describes serverless benchmark workloads in `EdgeFaaSBench`. The benchmark workloads can be categorized into two types; 1) micro-benchmark and 2) application-level workloads. The summary of benchmark workloads in `EdgeFaaSBench` is shown in Table I.

**Micro-benchmark.** Micro-benchmark workloads are employed to benchmark the performance of specific resources on edge devices. i.e., CPU, memory. `MM` and `FFT` generate high workloads for both CPU and memory resources on edge devices by performing mathematical operations. `MM` uses three different matrix sizes ($300 \times 300$, $400 \times 400$, and $450 \times 450$) and performs the matrix multiplication operations 300 times. `FFT` calculates a Fast Fourier Transform of a random seed number. Both `FPO-SINE`, and `FPO-SQRT` are workloads to generate high CPU stress and moderate memory stress. `FPO-SINE` calculates the sine value of all 360 degrees, and `FPO-SQRT` calculates square root values of random numbers (ranging from $10,000$ to $30,000$) multiple times to generate stress to CPU.

Moreover, the micro-benchmark workloads incorporate off-the-shelf Linux commands and tools. `SORT` tests the memory performance on edge devices by generating high memory pressure from the sort operation of random text data with *sort* command. `DD` uses *dd* Linux command to benchmark Disk I/O performance of edge devices. `IPERF` uses the iPerf3 tool to measure the achievable network bandwidth of edge devices.



(a) Raspberry Pi 4B (b) Nvidia Jetson Nano

Fig. 4. Two edge devices, Jetson Nano and Raspberry PI 4B, used for evaluation with `EdgeFaaSBench`

For the micro-benchmark workloads, `python3-debian` template in OpenFaaS is commonly used to implement the workloads as a form of serverless applications on edge devices.

**Application-level Benchmark.** Application-level benchmark workloads employ realistic serverless application models to benchmark the performance of edge devices. `IP` is an image processing serverless application that receives random images from `EdgeFaaSBench` benchmark client and resizes them to $400 \times 400$ pixel size images. `IP` is implemented using the

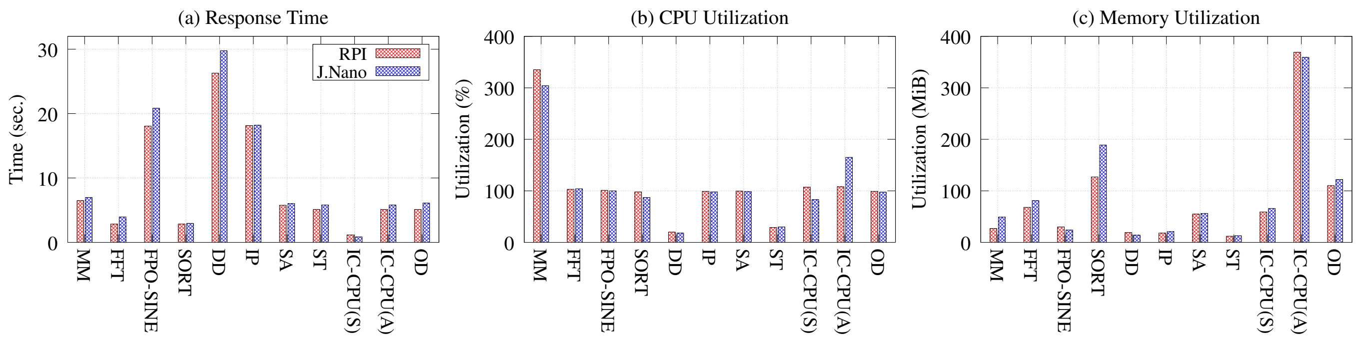



Fig. 5. Benchmark results of response time, CPU utilization, and memory utilization. Please note that `IC-CPU` (S) is the image classification workload with SqueezeNet, and `IC-CPU` (A) is the image classification workload with AlexNet.

`python-pillow`[7] library, which provides extensive image file format support, an efficient internal representation, and powerful image processing capabilities. `SA` is a sentiment analysis application that detects the ratio of positive and negative engagements about multiple random topics provided by benchmark client. To implement `SA`, `NLKT`[8] and `TextBlob`[9] libraries for Python3 are used. `ST` is an application that generates text data by transcribing the random audio files provided from `EdgeFaaSBench` benchmark client and sends it back to the client. Two Python3 libraries, `pyttsx3`[10] and `SpeechRecognition`[11], are used to implement `ST`.

Moreover, since the AI at the edge is increasingly adopted in edge computing, `EdgeFaaSBench` also employs four serverless benchmark workloads that perform DL inference tasks on edge devices. Both `IC-CPU` and `IC-GPU` perform image classification tasks on edge devices using two pre-trained DL models; AlexNet [64] and SqueezeNet [65]. The difference between `IC-CPU` and `IC-GPU` is as follows. `IC-CPU` uses the CPU of edge devices for performing image classification tasks to benchmark edge devices without GPU accelerator like Raspberry Pi. On the other hand, `IC-GPU` can perform the image classification tasks on GPU, which offers faster inference time. In particular, `IC-GPU` is designed to benchmark edge devices with GPU accelerators. i.e., Nvidia's Jetson series [52], [58], [59]. Also, both workloads generate slightly different memory pressure on edge devices with various models. For example, SqueezeNet is a lightweight DL model, and image classification with SqueezeNet shows moderate memory utilization. On the other hand, the image classification tasks with AlexNet, which is heavier than SqueezeNet, can generate high memory pressure. For both `IC-CPU` and `IC-GPU`, we use `PyTorch`[12] for the main DL framework. In addition, both `OD-CPU` and `OD-GPU` generate object detection workloads on edge devices. Similar to the previous workloads, `OD-GPU` is to benchmark GPU performance on edge devices. The object detection workloads use an open-source `darknet`[13] framework, which is written in C and CUDA, and it employs YOLOv3 [66] for performing the object detection tasks.

All seven application-level workloads are also implemented based on a `python3-debian` template to be run as serverless applications on OpenFaaS in edge devices.

## IV. Benchmark Results

This section describes our initial benchmark results measured by `EdgeFaaSBench` to show its effectiveness.

### A. Benchmark Edge Devices

This benchmark study uses two widely used edge devices shown in Fig. 4. Raspberry Pi 4B (RPI, shown in Fig. 4a) [51] is a small, low-cost, representative computing board for edge and IoT devices. RPI uses Broadcom BCM2711 SoC and has a quad-core ARM Cortex-A72 (1.5 GHz) and 4 GB LPDDR4 RAM. RPI can be deployed for various use cases, such as IoT sensor control, sending data collection and filtering, and lightweight data processing. RPI devices are typically deployed in the bottom (IoT sensor and device) layer in Fig. 1 in Section II.

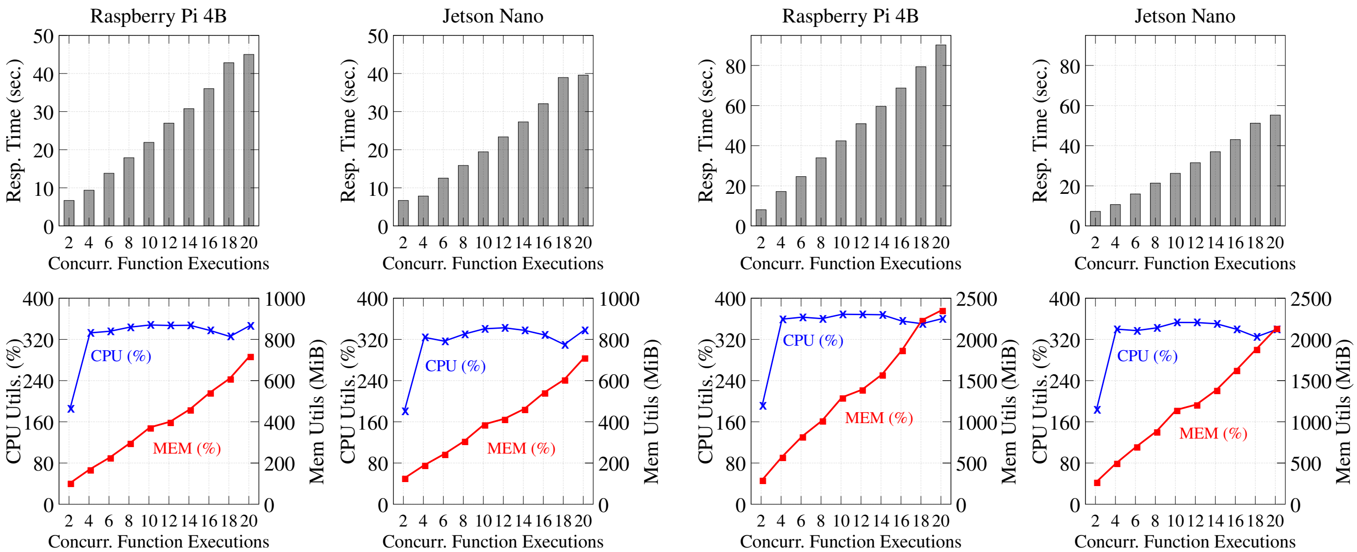
Jetson Nano (J.Nano, shown in Fig. 4b) has a slightly older version of ARM cores (a four-core Cortex-A57 at 1.5 GHz) and 4 GB LPDDR4 RAM. However, J.Nano is equipped with a 128-core Nvidia Maxwell GPU and can provide faster DL inference time with various DL frameworks like PyTorch and TensorFlow [10]. Because J.Nano is specialized in AI processing, the device can be deployed in both the middle (edge servers) and the bottom (IoT sensor and device) layers in Fig. 1 in Section II.

### B. Benchmark Results

We report four benchmark results with two edge devices, including response time and resource utilization, cold and warm start times, concurrent function executions, and the CPU and GPU performance comparison.

**Response Time and Resource Utilization.** Fig. 5 shows `EdgeFaaSBench`'s benchmark results on response time and

[7]https://pillow.readthedocs.io/en/stable/
[8]https://www.nltk.org/index.html
[9]https://textblob.readthedocs.io/en/dev/
[10]https://pypi.org/project/pyttsx3/
[11]https://pypi.org/project/SpeechRecognition/
[12]https://pytorch.org/
[13]https://pjreddie.com/darknet/




(a) Sentiment Analysis (SA) (b) Object Detection (OD-CPU)

Fig. 6. Benchmark results of concurrent function executions for two EdgeFaaSBench workloads. (a) SA workload with concurrent executions, (b) OD-CPU workload with concurrent executions

TABLE II
BENCHMARK RESULTS OF THE COLD AND WARM START TIME OF WORKLOADS ON TWO DEVICES. (SQN: SQUEEZENET, ALN: ALEXNET)

| | Raspberry Pi 4B | | Jetson Nano | |
|---|---|---|---|---|
| | **Cold Start** | **Warm Start** | **Cold Start** | **Warm Start** |
| MM | 7.8s | 1.4s | 7.3s | 1.3s |
| FFT | 9.2s | 1.8s | 8.0s | 1.4s |
| FPO-SINE | 7.6s | 0.2s | 5.6s | 0.2s |
| SORT | 7.9s | 0.3s | 5.7s | 0.3s |
| DD | 7.4s | 0.4s | 5.8s | 0.4s |
| IP | 8.5s | 0.8s | 8.0s | 0.9s |
| SA | 11.5s | 2.1s | 11.9s | 2.3s |
| ST | 7.6s | 0.3s | 6.4 | 0.3s |
| IC-CPU (SQN) | 10.3s | 1.9s | 10.6s | 2.3s |
| IC-CPU (ALN) | 30.0s | 5.3s | 42.1s | 7.7s |
| OD-CPU | 4.0s | 0.1s | 3.2s | 0.1s |

CPU/memory utilization. In this evaluation, we ran each benchmark workload 100 times to get reliable benchmark results. The results include all benchmark workloads except for GPU-enabled workloads (IC-GPU, OD-GPU), and IPERF.

As shown in the figure, while both devices showed similar response times for CPU-based workloads, RPI provided about 10% faster response time (except for IC-CPU with SqueezeNet) than J.Nano. This is mainly because RPI has a slightly faster CPU with a newer version of ARM cores. For the CPU and memory utilization, EdgeFaaSBench reported similar statistics for most of the workloads.

**Cold and Warm Start Time.** The next benchmark measures serverless functions' cold and warm start times on edge devices. The capability to measure the cold and warm start times is particularly important since the cold start overhead is recognized as the major performance overhead of serverless applications. To measure the cold start time, EdgeFaaSBench recorded the initial function invocation time collected by OpenFaaS when no serverless container was running. After this recording, EdgeFaaSBench compared the time with the first recorded time internally measured in the function in the benchmark workloads. For measuring the warm start time, EdgeFaaSBench also recorded the request invocation time in OpenFaaS and compared it with the first recorded time in a warm serverless container.

Table II shows the cold and warm start times on both devices measured by EdgeFaaSBench. While the cold and warm start times vary with different benchmark workloads, both devices showed an order of magnitude slower cold start times compared to the warm start times. For example, RPI and J.Nano had 16.9× and 13.6× slower cold start times, respectively. Such slower cold start times are consistent with existing measurement studies on serverless platforms on clouds [62]. As identified by prior work [63], the significantly slower cold start times are mostly because of container and package initialization used in the serverless functions. In particular, benchmark workloads like IC-CPU with AlexNet and SqueezeNet and SA require various packages in the serverless functions, so that they needed more time to initialize the serverless container and showed higher cold start times.

For comparing start times between two devices, J.Nano showed equivalent and slightly faster cold start times except for two IC-CPU workloads and SA, and both devices showed similar warm start times.

**Concurrent Function Executions.** Next, we measured the impact of concurrent invocation of serverless functions on edge devices. In this evaluation, EdgeFaaSBench generated the concurrent function invocations, gradually increasing from

TABLE III
DEEP LEARNING INFERENCE THROUGHPUT COMPARISON BETWEEN CPU (IC-CPU) AND GPU (IC-GPU) ON JETSON NANO (J.NANO).

| | DL Inference Throughput (# Infer/sec.) | |
|---|---|---|
| | with SqueezeNet | with AlexNet |
| Jetson Nano CPU (IC-CPU) | 3.06 | 2.78 |
| Jetson Nano GPU (IC-GPU) | 27.65 | 8.80 |

1 to 20, and measured response time and resource utilization.

Fig. 6 shows the benchmark results of two workloads, which are SA and OD-CPU. We omit the results of other benchmark workloads due to the page limitation, and the results from other workloads showed a similar pattern to the two workloads reported in the figure. As expected, the response times of concurrent functions increase with a higher level of concurrency. Also, resource utilization (CPU and memory) increases with more concurrent functions. An interesting observation is that CPU utilization was close to the maximum with a lower level of concurrency (e.g., 4 or 6 concurrent functions) on both devices. However, both devices were still able to process more functions while they showed such high CPU utilization. This is mainly because the memory usage did not reach the maximum. The devices were able to handle more concurrent functions unless the memory resources were not saturated. Based on this observation, we expect that the maximum degree of concurrent functions that can be processed by the edge devices will be determined by memory utilization, indicating that the upper bound of concurrent function executions can be determined when memory utilization becomes 100%.

Moreover, between the devices, J.Nano showed better performance to handle concurrent function executions. Interestingly, while the response time to handle a single function on J.Nano was slightly slower than RPI, J.Nano showed a 15% faster response time for SA and a 55% faster response time for OD-CPU with concurrent functions. For OD-CPU, we clearly observed that J.Nano showed 15% – 20% more efficient memory utilization with concurrency.

**Comparison of CPU and GPU Performance.** The last benchmark result is to show EdgeFaaSBench's capability to compare the DL inference performance on CPU and GPU. We performed this comparison on J.Nano executing IC-CPU and IC-GPU, by leveraging its CPU and GPU resources. In this evaluation, we report the end-to-end DL processing latency as well as DL throughput on CPU and GPU by performing multiple executions of 200 batches of images.

Fig. 7 shows the end-to-end DL processing latency of IC-CPU and IC-GPU on J.Nano. The end-to-end latency is the sum of DL loading inference (DL framework and model) and DL inference latency. IC-GPU (running on J.Nano's GPU) showed 3.2× and 1.2× faster processing latency with SqueezeNet and AlexNet compared to IC-CPU (only running on CPU), showing the benefit of leveraging GPU accelerator for DL inference tasks. Interestingly, the loading latency (blue

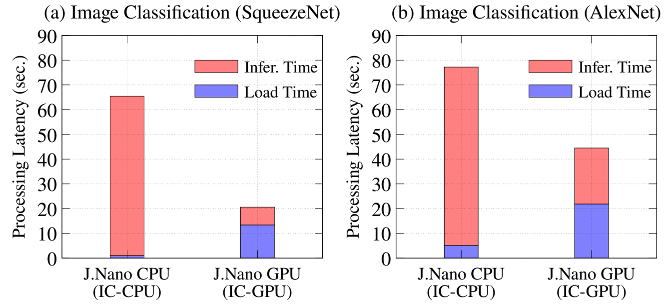



Fig. 7. End-to-end deep learning processing latency comparison between CPU and GPU on Jetson Nano (J. Nano). DL processing latency is composed of load and inference latency.

portion of Fig. 7) of IC-GPU was significantly slower than that of IC-CPU. For example, IC-GPU's loading latency was over 100× slower than the loading latency of IC-CPU when using SqueezeNet. This is because the GPU accelerator on J.Nano was much slower to initialize and load DL models. Therefore, Pytorch's initialization latency with GPU is much slower than that with CPU. However, once the DL model is loaded and the framework is initialized, the inference latency with IC-GPU is much faster than the inference latency of IC-CPU. The inference latency of IC-GPU was 7.1× (with SqueezeNet) and 1.8× (with AlexNet) shorter than those of IC-CPU. We also observed that the loading and inference latency could be varying with different DL models. In particular, the latency was significantly changed with DL model sizes.

We also confirm another benefit of enabling GPU on edge devices by reporting the throughput differences between IC-GPU and IC-CPU. As shown in Table III, IC-GPU processed 9× (with SqueezeNet) and 3.2× (with AlexNet) more images compared to IC-CPU, clearly indicating the benefit of GPU accelerator for the AI at the edge processing.

## V. RELATED WORK

The research community has proposed various benchmark suites for edge computing environments. This section summarizes the state-of-the-art benchmark suites [39]–[44] and discusses our novelty over the state-of-the-arts.

DeFog [41] is a comprehensive fog/edge computing benchmark suite containing six different edge applications. DeFog focuses on benchmarking the performance of edge computing with three different deployment modes; edge-cloud, cloud-only, and edge-only. DeFog performed an experimental study on three deployment modes using two edge devices (e.g., Raspberry Pi 3 Model B and Odroid XU 4) and an Amazon cloud server, and the experiment results showed the performance variations of benchmark applications with different deployment modes. While DeFog has broader benchmark coverage than EdgeFaaSBench in supporting different edge computing scenarios, EdgeFaaSBench has the following novelty over DeFog. First, we focus on benchmarking the performance of edge devices and their diverse resource types (e.g., CPU and GPU). And, differing from DeFog, all the benchmark

TABLE IV
COMPARISON OF EDGE COMPUTING BENCHMARK SUITES

| Benchmark | Edge Only | Edge + Cloud | Micro-Benchmarks (# of Apps.) | Application Benchmarks (# of Apps.) | Serverless Support on Edge Device | Serverless Metrics | GPU Support | Open Source |
|---|---|---|---|---|---|---|---|---|
| DeFog [41] | Yes | Yes | No | Yes (6) | No | No | - | Yes |
| Edge AIBench [43] | Yes | No | No | Yes (6) | No | No | Yes | No |
| pCAMP [54] | Yes | No | No | Yes (4) | No | No | Yes | No |
| Subedi et al. [10] | Yes | No | No | Yes (4) | No | No | Yes | No |
| EdgeBench'18 [40] | Yes | Yes | No | Yes (3) | No | No | No | Yes |
| EdgeBench'20 [42] | Yes | Yes | No | Yes (2) | Yes | No | No | No |
| Carpio et al. [44] | Yes | No | No | Yes (2) | Yes | No | - | No |
| **`EdgeFaaSBench`** | **Yes** | **No** | **Yes** (7) | **Yes** (7) | **Yes** | **Yes** | **Yes** | **Yes** |

workloads in `EdgeFaaSBench` are serverless applications, and `EdgeFaaSBench` can measure diverse serverless-oriented performance metrics. i.e., cold and warm startup times of serverless applications.

Due to the broader adoption of artificial intelligence (AI) at the edge paradigm [7], benchmark suites that are centered on measuring AI inference performance in edge computing have also been proposed [10], [43], [54]. Edge AIBench [43] is a benchmark suite with four realistic AI deployment scenarios for edge computing and offers capabilities to measure the end-to-end AI performance of various edge-computing scenarios. pCamp [43] conducted benchmarking the performance of machine learning (ML) packages and frameworks when running image classification tasks on edge devices and mobile devices. This work reported latency (including model loading time), memory usage, and energy consumption from different ML packages. Subedi et al. [10] also provided the benchmarking results of AI inference tasks on edge devices by using multiple deep neural networks (DNN) models on various combinations of four edge devices and two AI accelerators for edge devices (e.g., Coral EdgeTPU Accelerators [60]). Moreover, the work performed by Subedi et al. focused on characterizing the multi-tenancy aspects of DNN models' executions on the devices. While AI benchmark workloads are part of our benchmark suite, `EdgeFaaSBench` can perform benchmarks with broader FaaS applications models, offering AI-based, traditional applications, and micro-benchmarks. `EdgeFaaSBench` also focuses on measuring the feasibility and performance of FaaS offering on edge devices so that it can report various serverless-centric metrics, including cold/warm function startup times and performance variation with concurrent function executions.

EdgeBench'18 [40], EdgeBench'20 [42], and Carpio et al. [44] proposed earlier FaaS adoption to benchmark suites for edge computing. However, these works have limitations in correctly understanding the FaaS offering on edge devices because these benchmarks focused on collaborative cloud-edge environments. For example, EdgeBench'18 [40] relied on FaaS offerings from public cloud providers, such as AWS Greengrass with AWS Lambda. EdgeBench'20 [42] was designed to benchmark the efficacy of diverse cloud-edge workflows that can be used in edge computing deployment. Moreover, the benchmark suite by Carpio et al. [44] contains only two benchmark applications, hence not sufficient to capture various aspects of FaaS behaviors on edge devices.

We summarize the differences between `EdgeFaaSBench` and previous benchmark suites in Table IV. As shown in the table, `EdgeFaaSBench` employs more comprehensive benchmark workloads ranging from micro-benchmarks to application-level benchmarks (including AI workloads), which help edge users correctly identify the behavior of FaaS characteristics and performance on edge devices. Moreover, by supporting GPU capability on edge devices, `EdgeFaaSBench` can evaluate FaaS performance variations on heterogeneous edge devices if GPU resources are available.

## VI. CONCLUSION

Due to the fast development of serverless computing and edge devices (especially with AI accelerators), there is increasing demand for serverless edge computing. To evaluate the performance of serverless computing on edge devices, we present `EdgeFaaSBench`, a novel benchmark suite for edge devices with serverless computing. `EdgeFaaSBench` is prototyped on a modern container engine/orchestration and a widely used open-source serverless framework.

`EdgeFaaSBench` comprises 14 serverless workloads to correctly benchmark diverse aspects of edge devices' performance. Among the 14 workloads, 7 of them are micro-benchmark, and the others are application-level benchmark workloads. Micro-benchmark workloads evaluate the performance of a specific resource type (e.g., CPU) on edge devices, and application-level benchmark workloads evaluate the edge devices' performance with realistic application scenarios like DL inference and sentiment analysis. `EdgeFaaSBench` can collect diverse tradition and serverless-specific metrics reflecting the performance of edge devices. In particular, `EdgeFaaSBench` can collect cold and warm start times of serverless applications and performance degradation with concurrent function executions, which are the important performance bottleneck of serverless applications on edge devices. In addition, `EdgeFaaSBench` also enables GPU to benchmark the scenarios of AI at edge computing.

We performed a benchmark study on two widely used edge devices to show the effectiveness of `EdgeFaaSBench` and reported diverse performance metrics and serverless characteristics on the edge devices. Finally, `EdgeFaaSBench` is publicly available at https://github.com/kaustubhrajput46/EdgeFaaSBench.

## ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their insightful comments and constructive suggestions. This research was in part supported by the U.S. Department of Agriculture (USDA), under award number 2021-67019-34342, and the Academy of Finland (AoF), under grants 317432 and 318937. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of the USDA or AoF.


## REFERENCES


[1] Jayavardhana Gubbi, Rajkumar Buyya, Slaven Marusic, and Marimuthu Palaniswami. Internet of Things (IoT): A Vision, Architectural Elements, and Future Directions. *Future Generation Computer Systems*, 29(7):1645–1660, 2013.

[2] Rajiv Ranjan and et al. The Next Grand Challenges: Integrating the Internet of Things and Data Science. *IEEE Cloud Computing*, 5(3):12–26, 2018.

[3] Danny Yuxing Huang, Noah J. Apthorpe, Frank Li, Gunes Acar, and Nick Feamster. IoT Inspector: Crowdsourcing Labeled Network Traffic from Smart Home Devices at Scale. *ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)*, 4(2):46:1–46:21, 2020.

[4] Mahadev Satyanarayanan. The Emergence of Edge Computing. *IEEE Computer*, 50(1):30–39, 2017.

[5] Marcos Dias de Assunção, Alexandre Da Silva Veith, and Rajkumar Buyya. Distributed Data Stream Processing and Edge Computing: A Survey on Resource Elasticity and Future Directions. *Journal of Network and Computer Applications*, 103:1–17, 2018.

[6] Andy Rosales Elias, Nevena Golubovic, Chandra Krintz, and Rich Wolski. Where's The Bear?: Automating Wildlife Image Processing Using IoT and Edge Cloud Systems. In *ACM/IEEE International Conference on Internet-of-Things Design and Implementation (IoTDI)*, Pittsburgh, PA, USA, April, 2017. ACM.

[7] Zhi Zhou, Xu Chen, En Li, Liekang Zeng, Ke Luo, and Junshan Zhang. Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing. *Proceedings of IEEE*, 107(8):1738–1762, 2019.

[8] Shaoshan Liu, Liangkai Liu, Jie Tang, Bo Yu, Yifan Wang, and Weisong Shi. Edge Computing for Autonomous Driving: Opportunities and Challenges. *Proceedings of IEEE*, 107(8):1697–1716, 2019.

[9] Jianwei Hao, Piyush Subedi, In Kee Kim, and Lakshmish Ramaswamy. Characterizing Resource Heterogeneity in Edge Devices for Deep Learning Inferences. In *International Workshop on Systems and Network Telemetry and Analytics (SNTA@HPDC)*, Virtual Event, June, 2021.

[10] Piyush Subedi, Jianwei Hao, In Kee Kim, and Lakshmish Ramaswamy. AI Multi-Tenancy on Edge: Concurrent Deep Learning Model Executions and Dynamic Model Placements on Edge Device. In *IEEE International Conf. on Cloud Computing (CLOUD)*, September, 2021.

[11] AWS Lambda. https://aws.amazon.com/lambda/. Accessed: 2022-03-01.

[12] Azure Functions. https://azure.microsoft.com/en-us/services/functions. Accessed: 2022-03-01.

[13] Google Cloud Functions. https://cloud.google.com/functions. Accessed: 2022-03-01.

[14] Eric Jonas, Qifan Pu, Shivaram Venkataraman, Ion Stoica, and Benjamin Recht. Occupy the Cloud: Distributed Computing for the 99%. In *ACM Symposium on Cloud Computing (SoCC)*, Santa Clara, CA, USA, Septempber, 2017.

[15] Paul C. Castro, Vatche Ishakian, Vinod Muthusamy, and Aleksander Slominski. The rise of serverless computing. *Communications of ACM*, 62(12):44–54, 2019.

[16] Johann Schleier-Smith and et al. What serverless computing is and should become: the next phase of cloud computing. *Communications of ACM*, 64(5):76–84, 2021.

[17] Fei Xu, Yiling Qin, Li Chen, Zhi Zhou, and Fangming Liu. $\lambda$dnn: Achieving predictable distributed DNN training with serverless architectures. *IEEE Transactions on Computers*, 71(2):450–463, 2022.

[18] Lixiang Ao, Liz Izhikevich, Geoffrey M. Voelker, and George Porter. Sprocket: A Serverless Video Processing Framework. In *ACM Symposium on Cloud Computing (SoCC)*, Carlsbad, CA, USA, October, 2018.

[19] Ashraf Mahgoub, Karthick Shankar, Subrata Mitra, Ana Klimovic, Somali Chaterji, and Saurabh Bagchi. SONIC: Application-aware Data Passing for Chained Serverless Applications. In *USENIX Annual Technical Conference (ATC)*, Virtual Event, July, 2021.

[20] Anirban Bhattacharjee, Yogesh D. Barve, Shweta Khare, Shunxing Bao, Aniruddha Gokhale, and Thomas Damiano. Stratum: A Serverless Framework for the Lifecycle Management of Machine Learning-based Data Analytics Tasks. In *USENIX Conference on Operational Machine Learning (OpML)*, Santa Clara, CA, USA, May, 2019.

[21] Ingo Müller, Renato Marroquin, and Gustavo Alonso. Lambada: Interactive Data Analytics on Cold Data Using Serverless Cloud Infrastructure. In *International Conf. on Management of Data (SIGMOD)*, Portland, OR, USA, June, 2020.

[22] Djob Mvondo, Mathieu Bacou, Kevin Nguetchouang, Lucien Ngale, Stéphane Pouget, Josiane Kouam, Renaud Lachaize, Jinho Hwang, Tim Wood, Daniel Hagimont, Noël De Palma, Bernabé Batchakui, and Alain Tchana. OFC: an opportunistic caching system for FaaS platforms. In *Sixteenth European Conference on Computer Systems (EuroSys)*, Virtual Event, April, 2021.

[23] Stefan Nastic, Thomas Rausch, Ognjen Scekic, Schahram Dustdar, Marjan Gusev, Bojana Koteska, Magdalena Kostoska, Boro Jakimovski, Sasko Ristov, and Radu Prodan. A Serverless Real-Time Data Analytics Platform for Edge Computing. *IEEE Internet Computing*, 21(4):64–71, 2017.

[24] Luciano Baresi and Danilo Filgueira Mendonça. Towards a Serverless Platform for Edge Computing. In *IEEE International Conference on Fog Computing (ICFC)*, Czech Republic, June, 2019.

[25] Gareth George, Fatih Bakir, Rich Wolski, and Chandra Krintz. NanoLambda: Implementing Functions as a Service at All Resource Scales for the Internet of Things. In *IEEE/ACM Symposium on Edge Computing (SEC)*, San Jose, CA, USA, November, 2020.

[26] Bin Wang, Ahmed Ali-Eldin, and Prashant J. Shenoy. LaSS: Running Latency Sensitive Serverless Computations at the Edge. In *International Symposium on High-Performance Parallel and Distributed Computing (HPDC)*, Virtual Event, June, 2021.

[27] Nabil El Ioini, David Hästbacka, Claus Pahl, and Davide Taibi. Platforms for Serverless at the Edge: A Review. In *European Conference on Service-Oriented and Cloud Computing (ESOCC)*, Heraklion, Crete, Greece, September, 2021.

[28] Zhe Zhou, Bingzhe Wu, Zheng Liang, Guangyu Sun, Chenren Xu, and Guojie Luo. Is FaaS Suitable for Edge Computing? In *USENIX Workshop on Hot Topics in Edge Computing (HotEdge)*, Virtual Event, June, 2020.

[29] Mohammad Sadegh Aslanpour, Adel Nadjaran Toosi, Claudio Cicconetti, Bahman Javadi, Peter Sbarski, Davide Taibi, Marcos Dias de Assunção, Sukhpal Singh Gill, Raj Gaire, and Schahram Dustdar. Serverless Edge Computing: Vision and Challenges. In *2021 Australasian Computer Science Week Multiconference (ACSW)*, Dunedin, New Zealand, February, 2021.

[30] Phani Kishore Gadepalli, Gregor Peach, Ludmila Cherkasova, Rob Aitken, and Gabriel Parmer. Challenges and Opportunities for Efficient Serverless Computing at the Edge. In *38th International Symposium on Reliable Distributed Systems (SRDS)*, Lyon, France, October, 2019.

[31] Luciano Baresi and Danilo Filgueira Mendonça. Towards a Serverless Platform for Edge Computing. In *IEEE International Conference on Fog Computing (ICFC)*, Prague, Czech Republic, June, 2019.

[32] Thomas Rausch, Waldemar Hummer, Vinod Muthusamy, Alexander Rashed, and Schahram Dustdar. Towards a Serverless Platform for Edge AI. In *USENIX Workshop on Hot Topics in Edge Computing (HotEdge)*, Renton, WA, USA, November, 2019.

[33] Raj Jain. *The Art of Computer Systems Performance Analysis: Techniques for Experimental Design, Measurement, Simulation, and Modeling*. John Wiley & Sons, 1990.

[34] Lizy Kurian John and Lieven Eeckhout. *Performance Evaluation and Benchmarking*. Taylor & Francis, 2005.

[35] Jeongchul Kim and Kyungyong Lee. FunctionBench: A Suite of Workloads for Serverless Cloud Function Service. In *IEEE International Conference on Cloud Computing (CLOUD)*, Milan, Italy, July, 2019.

[36] Pascal Maissen, Pascal Felber, Peter G. Kropf, and Valerio Schiavoni. FaaSdom: A Benchmark Suite for Serverless Computing. In *ACM International Conference on Distributed and Event-based Systems (DEBS)*, Montreal, Quebec, Canada, July, 2020.

[37] Marcin Copik, Grzegorz Kwasniewski, Maciej Besta, Michal Podstawski, and Torsten Hoefler. SeBS: A Serverless Benchmark Suite for Function-as-a-Service Computing. *CoRR*, abs/2012.14132, 2020.

[38] Tianyi Yu and et al. Characterizing Serverless Platforms with Serverlessbench. In *ACM Symposium on Cloud Computing (SoCC)*, Virtual Event, October, 2020.

[39] Blesson Varghese, Nan Wang, David Bermbach, Cheol-Ho Hong, Eyal de Lara, Weisong Shi, and Christopher Stewart. A Survey on Edge Performance Benchmarking. *ACM Computing Surveys*, 54(3):66:1–66:33, 2021.

[40] Anirban Das, Stacy Patterson, and Mike Wittie. Edgebench: Benchmarking Edge Computing Platforms. In *IEEE/ACM International Conference on Utility and Cloud Computing Companion (UCC Companion)*, Zurich, Switzerland, December, 2018.

[41] Jonathan McChesney, Nan Wang, Ashish Tanwer, Eyal de Lara, and Blesson Varghese. DeFog: Fog computing benchmarks. In *ACM/IEEE Symposium on Edge Computing (SEC)*, Washington DC, USA, November, 2019.

[42] Qirui Yang, Runyu Jin, Nabil Gandhi, Xiongzi Ge, Hoda Aghaei Khouzani, and Ming Zhao. Edgebench: A Workflow-based Benchmark for Edge Computing. *arXiv preprint arXiv:2010.14027*, 2020.

[43] Tianshu Hao and et al. Edge AIBench: Towards Comprehensive End-to-End Edge Computing Benchmarking. In *International Symposium on Benchmarking, Measuring and Optimization (BENCH)*, Seattle, WA, USA, December, 2018.

[44] Francisco Carpio, Marc Michalke, and Admela Jukan. Engineering and Experimentally Benchmarking a Serverless Edge Computing System. *CoRR*, abs/2105.04995, 2021.

[45] Chanh Nguyen Le Tan, Cristian Klein, and Erik Elmroth. Multivariate LSTM-Based Location-Aware Workload Prediction for Edge Data Centers. In *IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGrid)*, Larnaca, Cyprus, May, 2019.

[46] Bin Cheng, Jonathan Fuerst, Gurkan Solmaz, and Takuya Sanada. Fog Function: Serverless Fog Computing for Data Intensive IoT Services. In *IEEE International Conference on Services Computing (SCC)*, Milan, Italy, July, 2019.

[47] Mohammad Shahrad, Rodrigo Fonseca, Iñigo Goiri, Gohar Chaudhry, Paul Batum, Jason Cooke, Eduardo Laureano, Colby Tresness, Mark Russinovich, and Ricardo Bianchini. Serverless in the Wild: Characterizing and Optimizing the Serverless Workload at a Large Cloud Provider. In *USENIX Annual Technical Conference (ATC)*, Virtual Event, July 2020.

[48] Shivani Arbat, Vinodh Kumaran Jayakumar, Jaewoo Lee, Wei Wang, and In Kee Kim. Wasserstein Adversarial Transformer for Cloud Workload Prediction. In *The Thirty-Fourth Annual Conference on Innovative Applications of Artificial Intelligence (IAAI-22)*, Vancouver, BC, Canada, February, 2022.

[49] OpenFaaS. https://www.openfaas.com/. Accessed: 2022-03-01.

[50] Swarm mode overview. https://docs.docker.com/engine/swarm/. Accessed: 2022-03-01.

[51] Raspberry Pi 4. https://www.raspberrypi.org/products/raspberry-pi-4-model-b/, 2022. Accessed: 2022-03-01.

[52] Jetson Nano — Nvidia Developer. https://developer.nvidia.com/embedded/jetson-nano, 2022. Accessed: 2022-03-01.

[53] Omid Setayeshfar, Karthika Subramani, Xingzi Yuan, Raunak Dey, Dezhi Hong, Kyu Hyung Lee, and In Kee Kim. ChatterHub: Privacy Invasion via Smart Home Hub. In *IEEE International Conference on Smart Computing (SMARTCOMP)*, Virtual Event, August, 2021.

[54] Xingzhou Zhang, Yifan Wang, and Weisong Shi. pCamp: Performance Comparison of Machine Learning Packages on the Edges. In *USENIX Workshop on Hot Topics in Edge Computing (HotEdge)*, Boston, MA, USA, July, 2018.

[55] Pinchao Liu, Dilma Da Silva, and Liting Hu. DART: A Scalable and Adaptive Edge Stream Processing Engine. In *USENIX Annual Technical Conference (ATC)*, Virtual Event, July, 2021.

[56] Gaurav Somani, Xinghui Zhao, Satish Narayana Srirama, and Rajkumar Buyya. Integration of Cloud, Internet of Things, and Big Data Analytics. *Software: Practice and Experience*, 49(4):561–564, 2019.

[57] Norman P. Jouppi and et al. In-Datacenter Performance Analysis of a Tensor Processing Unit. In *44th International Symposium on Computer Architecture (ISCA)*, Toronto, ON, Canada, June, 2017.

[58] Nvidia Jetson TX2. https://developer.nvidia.com/embedded/jetson-tx2, 2022. Accessed: 2022-03-01.

[59] NVIDIA Jetson Xavier NX. https://developer.nvidia.com/embedded/jetson-xavier-nx, 2022. Accessed: 2022-03-01.

[60] Coral USB Accelerator datasheet. https://coral.ai/docs/accelerator/datasheet/, 2022. Accessed: 2022-03-01.

[61] Docker. https://docs.docker.com/. Accessed: 2022-03-01.

[62] Anirban Das, Shigeru Imai, Stacy Patterson, and Mike P Wittie. Performance Optimization for Edge-Cloud Serverless Platforms via Dynamic Task Placement. In *IEEE/ACM International Symposium on Cluster, Cloud and Internet Computing (CCGRID)*, Melbourne, Australia, May, 2020.

[63] Liang Wang, Mengyuan Li, Yinqian Zhang, Thomas Ristenpart, and Michael M. Swift. Peeking Behind the Curtains of Serverless Platforms. In *USENIX Annual Technical Conference (ATC)*, Boston, MA, USA, July, 2018.

[64] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. ImageNet Classification with Deep Convolutional Neural Networks. In *Annual Conference on Neural Information Processing Systems (NIPS)*, Lake Tahoe, Nevada, USA, December, 2012.

[65] Forrest N. Iandola, Matthew W. Moskewicz, Khalid Ashraf, Song Han, William J. Dally, and Kurt Keutzer. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and $<$1MB model size. *CoRR*, abs/1602.07360, 2016.

[66] Joseph Redmon and Ali Farhadi. YOLOv3: An Incremental Improvement. *CoRR*, abs/1804.02767, 2018.