Energy Optimization for Deep Learning in Edge Computing: An Overview

# INTRODUCTION

Edge computing

Deep learning

Energy concerns, optimization and challenges

# BACKGROUND

## Background on Edge computing

## Background on Deep Learning

# Industrial Applications (Energy-efficient DEEP LEARNING in Edge)

There are many existing studies on applying energy-efficient deep learning techniques in edge computing. They mainly focus on the following industrial applications.

## Internet of vehicles (6)

Vehicular edge computing (VEC) is the application of mobile edge computing (MEC) in vehicular scenarios, and it has received great attention.

Wang *et al.* [1] consider an increasingly prominent challenge of meeting communication and computational needs of vehicles with the emergence of vehicular applications. Fog computing improves the performance of vehicular services by using computational offloading at the network edge. They design a fog-cloud computational offloading method in Internet of Vehicles (IoVs) for minimizing both the power consumption of vehicles and that of computational facilities. An offloading problem is formulated as an NP-hard one, and solved by a heuristic algorithm gradually. Specifically, a predictive combination transmission mode is designed for vehicles, and a deep learning model is establishes for computational facilities for determining the optimal allocation of workload.

Ning *et al*. [75] consider the challenge of how to meet quality of experiences of users in intelligent networks with limited computing abilities of vehicular fog nodes. Fog computing infrastructure is deployed closely to terminals, and provides updated communication and computing platforms to emerging vehicular services. They develop a three-layer offloading framework for Internet of Vehicles (IoV) to minimize their total energy consumption while meeting delay constraints of users. Considering the high computational complexity, an optimization problem is formulated and decomposed into two parts including flow redirection and offloading decision. Then, a deep reinforcement learning-based mechanism is proposed to solve it. Real-world data-based evaluations show that the average energy consumption is reduced by 60% compared with the baseline algorithm.

Jiang *et al*. [19] consider a hybrid mobile edge computing (HMEC) platform including ground vehicles (GVs), ground stations (GSs) and unmanned aerial vehicle (UAVs). They are connected with mobile edge cloud that enables Internet of thing (IoT) devices or user equipments (UEs) to offload intensive computing tasks. It aims to develop an online offloading algorithm to achieve the energy consumption minimization for all UEs by optimizing positions of UAVs and GVs, user association and resource allocation in a dynamic environment. Then, a hybrid deep learning-based online offloading framework is designed and it applies a large-scale path-loss fuzzy c-means algorithm to predict the optimal positions of GVs and UAVs. A fuzzy membership matrix U-based particle swarm optimization algorithm is adopted to produce sample datasets for a deep neural network (DNN). Then, a DNN with a scheduling layer is developed to obtain computing resource allocation and user association while meeting practical latency needs of tasks with limited computing resources and energy of HMEC.

Lammie et al. [76] consider the challenging problem of the robust and efficient detection of weed species in robotic weed control technologies. Deep neural networks (DNNs) have demonstrated remarkable performance for plant classification. Training DNNs on graphics processing units (GPUs) provides higher levels of performance; however, GPUs consume large power. The field programmable gate array (FPGA)-based DNNs have many advantages in energy efficiency compared with traditional GPU- and CPU-accelerated networks. DNNs networks that are properly designed and customized on GPUs and FPGAs, are ideal candidates for inference and learning in resource-constrained and power-limited portable devices, e.g., robots and edge devices in Internet of Things (IoT). They adopt GPU- and FPGA-accelerated DNNs that are deterministically binarized for weed species classification in robotic weed control. Their results show that the FPGA-accelerated binarized networks dramatically outperform the GPU-accelerated ones in terms of power consumption reduction and weed image inference time. It provides a significant step for deep learning and inference on IoT edge devices, and portable machines like agricultural robots.

The fast increase of data processing needs from users in MEC, the traditional mobile edge servers (MESs) fail to provide effective and timely services. To solve it, Li *et al.* [37] tries to adopt unmanned aerial vehicle (UAV) as an MES that provides offloading of computational tasks for users. They aim to maximize the migration throughput for users’ tasks with UAV that only has limited energy. A maximization problem is formulated as a semi-Markov decision process without transition probability. Then, a deep reinforcement learning (DRL)-based scheme is proposed to maximize the migration throughput of user tasks. It achieves a maximum autonomic migration throughput for users’ tasks with limited UAV energy and improves quality of service of MEC.

Zhan *et al.* [81] consider a computation offloading scheduling problem in a VEC scenario, where a vehicular terminal (VT) travels along an expressway, and makes the scheduling decision for tasks waiting in their task queue. These tasks are independently produced by different applications, and therefore they have heterogeneous characteristics in terms of data size and computation-to-volume ratio. They lead to dynamical changes of data transmission time, energy consumption and transmission failures. Servers in MEC are equipped in roadside units (RSUs) are executed to perform computation for the VT. The resource-demanding tasks can be offloaded to MEC servers in RSUs for significantly reducing the energy consumption and execution latency of in-vehicle applications. They consider a key challenge of how to achieve a trade-off between energy consumption and task execution latency. To tackle it, a DRL-based offloading approach is designed to minimize the long-term cost in terms of a trade-off between task latency and energy consumption. Their DRL implementation is proposed according to a proximal policy optimization algorithm. It combines a parameter-shared network architecture with a convolutional neural network to approximate both value and policy functions for effective representative feature extraction.

## Microgrid (5)

Munir *et al.* [3] consider a problem of risk-sensitive microgrid energy profiling for a MEC network. It considers conditional value-at-risk and determines the predicted energy shortfall risk by using the coordination with uncertainties of both supply and demand. A multi-agent system is designed to specify an optimal scheduling strategy for the agents. Then, a multi-agent deep reinforcement learning based on asynchronous advantage actor-critic is adopted to mitigate the dimensionality curse and design the optimal energy profile among agents. Their results show that the proposed model realizes high-accuracy energy profiling than a single agent solution. Munir *et al.* [39] propose an energy supply plan for MEC networks supported by microgrid. An energy consumption minimization problem is formulated for microgrid-enabled MEC networks. It is a mixed integer nonlinear optimization one with tasks’ latency and computational constraints, and it also considers the uncertainty of both energy generation and consumption. It is decomposed into two subproblems including energy-efficient tasks allocation and energy supply plan. In addition, a density-based spatial application clustering is applied to solve the first one for each base station, and a model-based deep reinforcement learning is adopted to the second one. Naderializadeh and Hashemi [66] consider a computation offloading problem in a MEC architecture, and many energy-constrained users simultaneously offload their tasks to servers with a shared wireless medium. A multi-agent deep reinforcement learning method is proposed where an agent is designed for each server and it observes its associated users’ status and chooses the optimal offloaded user in each step. The task completion time and system lifetime are selected as two key performance factors, and their results prove that the proposed method achieves better performance than baseline algorithms. Khan *et al.* [95] introduce the factors that affect the selection of microgrids as major electrical grids, and gives benefits of microgrids. In addition, they consider the problems that hinder benefits brought by distributed energy production in microgrids, and then design an architecture based on artificial intelligence (AI) to address these challenges. Furthermore, a simulation framework is designed and useful data is adopted to build AI capabilities within energy utilities. In addition, a scalable framework that applies deep learning techniques is also implemented. Based on it, the AI inference at nodes and sensors in edge is realized to optimize the benefits brought by microgrids at different scenarios including community, enterprise and campus levels in smart cities.

## Computer Vision

Luo *et al.* [10] jointly optimize quality of experience (QoE) and energy consumption for video streaming in software-defined mobile networks. Specifically, a mechanism is proposed to jointly consider video quality adaption, buffer dynamics, video transcoding, edge caching and transmission. The time-varying channel is assumed as a discrete-time Markov chain, based on which two optimization problems are formulated as a Markov decision process (MDP) and a constrained MDP. A Lyapunov technique is adopted to transform a constrained MDP into regular one, which is further solved by an asynchronous advantage actor-critic algorithm. Then, the energy saving is achieved while QoE is also enhanced. Xu *et al*. [55] present an efficient CNN to reconstruct speckle image in cloud-edge computing for better image resolution with fewer inputs. A self-back stacked efficient residual factorized network is designed to reconstruct image through scattering medium. It includes two training stages, and the model is used for analyzing speckle image from low resolution to high one. Results show that a high resolution is achieved even if there are a small input samples. Lim *et al*. [38] propose an energy-efficient communication method in edge computing with deep learning, and it decreases power consumed by image transmission using edge computing. An energy-efficient IoT camera called CamThings is implemented by using the proposed communication and periodic on-off scheduling. CamThings performs better than the method that only adopts periodic on-off scheduling with respect to lifetime and power consumption. Zhang *et al*. [54] propose an offloading prediction algorithm to minimize real-time transmission of images. It predicts the future need for deep learning of each unmanned aerial vehicle (UAV), and transmits images only when necessary. Holistic allocation of resources is determined at edge according to the likelihood analysis of offloading for multiple UAVs. Monburinon *et al*. [68] present a hierarchical image recognition system based on edge computing, and its major processing is implemented at Raspberry Pi. A dynamic learning method is implemented and a convolutional neural network is trained to achieve recognition of animals in a specific environment. The recognition module is deployed in edge servers on gateway devices for performing offline image classification.

## Mobile Edge Computing (7)

Jin *et al*. [17] investigate a multi-user MEC system and propose computation offloading and resource allocation policies with the objective of minimization of energy consumption and service delay in a dynamic environment. An optimization framework is proposed based on deep reinforcement learning to maximize long-term cumulative rewards. Zhu *et al*. [44] propose a computation offloading mechanism to decrease completion time of applications and energy consumed by user devices. The formulated computation offloading problem is transformed into a time and energy optimization one. The optimal cost strategy is obtained with deep Q-learning. It outperforms local execution and random offloading with respect to energy consumption and completion time of service workflows.

Wang *et al*. [18] propose a DRL-based offloading framework to solve problems of task adaption and dependency in dynamic scenarios. It well learns an offloading policy represented by a sequence-to-sequence neural network. The offloading policy is inferred by automatically finding common patterns in different applications in various scenarios. Li *et al*. [23] investigate a multi-user MEC system in which many user equipments (UEs) realize computation offloading through wireless channels connected to an MEC server. The weighted cost of energy consumption and delay for UEs is formulated as an optimization objective. The offloading and allocation of computational resources are jointly optimized in an MEC system. A reinforcement Learning-based optimization framework is proposed by adopting Q-learning schemes. Zhang *et al*. [72] design an offloading framework for a network architecture including an MEC server and a mobile user based on deep reinforcement learning. The task flow offloading process is modeled as a Markov decision process. It aims to minimize the weighted sum of power consumption and offloading latency, which is transformed into the reward in each time slot. Yang *et al*. [30] consider a problem of joint minimization of energy and latency for hierarchical machine learning task distribution in mobile edge computing. The shallow neural network models are embedded in mobile devices in the framework. The computing-intensive and latency-sensitive tasks are offloaded to a nearby MEC server, which supports a deep neural network model. A piecewise convex optimization problem is formulated to minimize the weighted-sum of energy and latency. Then, a closed-form solution for an optimal strategy of partial offloading is obtained analytically. Dong *et al*. [21] investigate a mobile edge computing system supporting both low-latency and ultra-reliable communication services and delay tolerant ones. The normalized energy consumption is minimized by optimizing resource allocation, user association and offloading probabilities while meeting quality-of-service needs. A deep learning (DL) architecture is proposed and it is trained in a central server. An optimization algorithm is proposed to obtain the optimal offloading and resource allocation.

## Smart Grid (5)

Cheung *et al*. [16] design an unsupervised disaggregation model for the disaggregation of solar production from measurements of advanced metering infrastructures (AMI) without training data. The model only needs the inputs of AMI measurements from users in a regional area and solar irradiance. Then, users’ consumption is modeled by neighboring households and it does not need rooftop photovoltaics for achieving the disaggregation. Li *et al*. [69] develop a home energy management system in a demand side management (DSM) program and it is equipped with an edge computing server. It maximizes the expected total reward of a home owner, which is obtained by calculating the difference between reward of edge computing tasks and the sum of electricity cost, the computation offloading cost and the violating penalty of DSM needs. Then, the deep deterministic policy gradient is adopted to solve long-term temporal interdependency and high-dimensional state space in their formulated MDPs. Sirojan *et al*. [77] present a deep learning-based sustainable method for an edge device and it can be used on top of a power pole for detecting high impedance faults in a real-time manner. In the embedded edge node, larger throughput, less latency and network traffic offloading are achieved by using feature extraction, data acquisition and deep learning based fault identification. In addition, hardware pipelining and parallelism are used to realize the real-time fault identification on edge nodes, and guarantee efficient usage of resources. Zhang *et al*. [85] adopt a deep learning method named deep stacked autoencoder (SAE) to discover anomalies in physical system measurements. The proposed unsupervised method is evaluated to discover anomalies and investigate root cause analysis with an end-to-end transactive energy system testbed. It provides a transactive control mechanism for energy production of a large number of devices in edge computing and Internet of Things (IoT).

Wang *et al*. [2] .

Therefore, this paper proposes a novel MobileNets convolutional neural network (MCNN) model to identify the GIS PD patterns. We first construct the PD pattern recognition classification datasets by means of experiments and FDTD simulation, and also preprocess images via binarization processing. After constructing the MCNN model, depthwise separable convolutions and an inverse residual structure are adopted to deal with the vanishing gradient of the deep convolutional neural network (DCNN) in the GIS PD pattern recognition process. Then, through the graphics standardization process, the MCNN model is trained and tested.

The whole training process is visualized by Tensorboard. Compared with other deep learning models and traditional machine learning methods, MCNN particularly stands out in recognition accuracy and time consumption with a 96.5% overall recognition rate and merely 7.3 seconds in training time. This research explores how to optimize the model by improving the recognition accuracy, and by reducing its computing load, storage space and energy consumption for better incorporation into intelligent terminals in the UPIoT context.

With the construction and promotion of the Ubiquitous Power Internet of Things (UPIoT), it is an increasingly urgent challenge to comprehensively improve the recognition accuracy of the gas-insulated switchgear (GIS) partial discharge (PD), and to incorporate the model into UPIoT intelligent terminals supported by edge computing in embedded systems.

## Healthcare system (5)

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## Smart Cities (5)

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# DNN-based mechanisms for energy optimization

## DNN compression (5)

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[20] pCAMP compares the packages’ performances (with respect to the latency, memory footprint, and **energy**) [4]. resulting from five edge devices and observes that no framework could win over all the others at all aspects. It indicates that there is much room to improve the frameworks at the edge. Currently, developing a lightweight, efficient, and high-scalability framework to support diverse deep learning modes at the edge cannot be more important and urgent. Based on the application, certain optimizations can also be employed at run-time to reduce the number of samples to be processed. For example, in case of object detection application [58], a high-resolution image can be divided into multiple smaller images (known as tiling) and a selection criterion can be applied to select images with high activity regions. This process enables us to design DNNs which accept smaller inputs and thus are more computationally and latency-wise efficient.

DNN compression is an attractive solution to reduce the complexity of a given network. The work of [14] proposed a 3-step method (pruning, quantization and encoding) to significantly reduce the memory footprint of a given DNN. Network pruning was first used in [10] to reduce the number of connections. Several different pruning methodologies have been explored in the literature Different magnitudebased pruning methods are shown in Figure 2. Structured pruning [75] employs constraints on some DNN parameters (e.g., kernel, filter, channel) to maintain a certain structure. Another approach is to prune the redundant and least significant weights, regardless of the structure of the DNN itself [15] [45], and share the weights to reduce the dimensionality [14]. Other compression methods, based on variational dropout [44], knowledge transfer [24] and low-rank approximations [70] are promising as well. On the other hand, techniques which are focusing on reducing the precision, like quantization [79] [71], binarization [54] and approximate computing [4] [44] have to leverage the trade-off between accuracy and efficiency.

Hardware Accelerators: The optimizations at the software level should be supported by specialized hardware accelerators in a codesign fashion [47] [19]. Recent advances in the datacenter computing deep learning [27] have inspired accelerators for edge devices. Specialized accelerators like [5] [28] exploit the concurrency and the parallelism available in the processing of the DNNs, especially for convolutional leyers, while [20] takes care also of the fully-connected layers. These architectures, however, accelerate dense DNNs, and cannot exploit the sparsity introduced by pruning. Therefore, specialized accelerators for sparse DNNs are required [13] [52]. Challenging aspects of these accelerators are flexibility, reconfigurability and data reuse [35] [39] [65]. Moreover, particular types of DNNs, like CapsuleNets [60] and GANs [91]present several differences in the computation patterns, as compared to traditional DNNs. These challenges are addressed by their specialized accelerators. For example, CapsAcc [46] adopts a data reuse policy to efficiently process the routing-by-agreement algorithm on a systolyc array-based accelerator for CapsuleNets, and GANAX [76] propose a unified MIMD-SIMD design for concurrent execution of GANs. The software-level optimizations mainly include network pruning (Step-1 in Fig. 3) and quantization (Step-2 in Fig. 3) of the parameters.

## DNN partitioning (5)

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## Power/Battery Management (7)

[22]. Recently, distributed sustainable data centers based on **renewable** power generators have been deployed in order to efficiently reduce both the energy cost and carbon emission. The proposed method adopts long short-term memory approach to improve the prediction accuracy of renewable power capacity for a long period, and unsupervised deep learning (DL) solver to resolve the coordinated DRS/FS optimization.

[24] we study the dynamic MEC-access control problem for maximizing the long-term average uplink transmission rate whilst minimizing the transmission energy consumption for green IoT networks, in which the IoT device is powered by a rechargeable battery that can harvest energy from the surrounding environments.

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## Resource Allocation (9)

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## Computational offloading (8)

In order to achieve lower average task’s latency and energy consumption, we minimize the weighted summation of the average task’s delay and energy consumption by optimizing the task’s offloading decision [91].

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## DNN hardware architecture (9)

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## DNN packages and tools (11)

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Neurosurgeon [5] is a lightweight scheduler that can automatically partition DNN computation between mobile devices and datacenters at the granularity of neural network layers. By effectively leveraging the resources in the cloud and at the edge, neurosurgeon achieves low computing latency, **low energy consumption**, and high traffic throughput.

FPGA-based accelerators can achieve high-performance computing with low energy, high parallelism, high flexibility, and high security [6].

An efficient speech recognition engine (ESE) is designed to speed up the predictions and save energy when applying the deep learning model of LSTM. ESE is implemented in a Xilinx XCKU060 FPGA operating at 200 MHz. For the sparse LSTM network, it can achieve 282 GOPS, corresponding to 2.52 tera operations per second (TOPS) on the dense LSTM network. In addition, energy efficiency improvements of 40× and 11.5× are achieved, respectively, compared with the CPU- and GPU-based solution [7].

NVIDIA Jetson TX2 is an embedded AI computing device, which is designed to achieve low latency and high power efficiency. It is built upon an NVIDIA Pascal GPU with 256 CUDA cores, an HMP Dual Denver CPU, and a Qualcomm ARM CPU. It is loaded with 8 GB of memory and 59.7 GB/s of memory bandwidth and the power is about 7.5 W. The GPU is used to execute the deep learning task, and CPUs are used to maintain general tasks. It also supports the NVIDIA Jetpack SDK that includes libraries for deep learning, computer vision, GPU computing, and multimedia processing [8].

Edge TPU is Google’s purpose-built ASIC for edge computing. It augments Google’s Cloud TPU and Cloud IoT to provide an end-to-end infrastructure and facilitates the deployment of customers’ AI-based solutions. In addition, Edge TPU can combine the custom hardware, open software, and state-of-the-art AI algorithms to achieve high performance with a small physical area and low power consumption [9].

Prevalence of internet of things (IoT) enabled applications provide a new opportunity to low-cost FPGA devices to act as edge computing neural network nodes. Although FPGA vendors provide neural network development environments, they often target high-end devices. At the same time these development platforms are not as user friendly as their software counterparts. In this work we introduce ZyNet, a Python package, which enables faster implementation of deep neural networks (DNNs) targeting low-cost hybrid FPGA platforms such as the Xilinx Zynq. Based on hardware-software co-design approach, this platform supports pre-trained or on-board trained networks with development environment very similar to the popular TensorFlow. Implementation results show that the DNNs generated by the platform achieve accuracy very close to software implementations at the same time gives throughput by an order of magnitude compared to other edge computing devices at lower energy footprint. The platform is integrated with Xilinx development tools and is distributed as open source.

# NEW TRENDS AND OPEN CHALLENGES (Duplicated papers)

OPEN RESEARCH CHALLENGES

**Hardware Software Co-Design**: A common trend is to optimize the DNN for achieving high accuracy, without caring much about the underlying hardware complexity and energy consumption of a computing device. On the other hand, hardware designers have to implement a-posteriori architectures to exploit the software-level optimizations. However, hardware-aware software-level optimizations, e.g., for DNN architecture exploration [69] or compression [43] are promising and need further efforts to succeed. [20].

**In-Memory Computing**: It seems to be a promising paradigm for developing accelerators that can offer orders of magnitude of energy-efficiency gains compared to the conventional CPU and GPU based systems. However, the high variation characteristics associated with ReRAM and other non-volatile memories limit the accelerators which are based on them to offer precise functionality. Towards this, the multi-level cell (MLC) ReRAM technology has to be mature enough to offer reasonable precision while offering high data density. Also, a significant amount of work is required to develop methods which can be used to train networks such that they can offer high accuracy even when operated on NVM-based in-memory computing devices. [20].

**Hardware-Aware Hyperparameter Tuning and DNN Architectural Exploration**: Several software-level optimization techniques have been proposed which highlight that sparse DNNs, i.e., having lesser number of parameters, can also offer nearly the same level of output accuracy as dense DNNs. Systematic methodologies are required which, while being aware of the underlying hardware architecture and the system, can tune the network such that it offers near-optimal energy and performance efficiency while maintaining the baseline accuracy. [20].

Event-based Spiking Neural Networks: They have the potential to be much more energy-efficient, as compared to digital-based DNNs, because the power is only consumed when a spike is firing. Such event-driven processing are promising. Therefore, companies like IBM and Intel are investing into their respective neuromorphic architecture chips and its accelerators [48] [9]. [20].

## Distributed and Collaborative DNN

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## Relationship to SDN and NFV Technologies

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## Management and Scheduling of Edge Compute Resources

## Emerging Technologies

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## Deep Learning Benchmarks on Edge Devices

# CONCLUSION

References

1. X. Wang, X. Wei and L. Wang, "A deep learning based energy-efficient computational offloading method in Internet of vehicles," in China Communications, vol. 16, no. 3, pp. 81-91, March 2019.
2. A MobileNets Convolutional Neural Network for GIS Partial Discharge Pattern Recognition in the Ubiquitous Power Internet of Things Context Optimization- Comparison- and Application
3. A Multi-Agent System toward the Green Edge Computing with Microgrid-- M. S. Munir, S. F. Abedin, D. H. Kim, N. H. Tran, Z. Han and C. S. Hong, "A Multi-Agent System toward the Green Edge Computing with Microgrid," 2019 IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 2019, pp. 1-7.
4. X. Zhang, Y. Wang, and W. Shi, “pCAMP: Performance comparison of machine learning packages on the edges,” in Proc. USENIX Workshop Hot Topics Edge Comput. (HotEdge), Boston, MA, USA, 2018. [Online]. Available: https://www. usenix.org/conference/hotedge18/presentation/zhang
5. Y. Kang et al., “Neurosurgeon: Collaborative intelligence between the cloud and mobile edge,” ACM SIGPLAN Notices, vol. 52, no. 4, pp. 615–629, 2017.
6. T.Wang, C. Wang, X. Zhou, and H. Chen, “A survey of FPGA based deep learning accelerators: Challenges and opportunities,” 2018, arXiv:1901.04988. [Online]. Available: <https://arxiv.org/abs/1901.04988>
7. J. Qiu et al., “Going deeper with embedded FPGA platform for convolutional neural network,” in Proc. ACM/SIGDA Int. Symp. Field-Program. Gate Arrays, 2016, pp. 26–35.
8. (2019). NVIDIA Jetson TX2 Module. [Online]. Available: <https://developer>. nvidia.com/embedded/buy/jetson-tx2
9. Z. Du et al., “Shidiannao: Shifting vision processing closer to the sensor,” ACM Sigarch Comput. Archit. News, vol. 43, no. 3, pp. 92–104, 2015.
10. Adaptive Video Streaming With Edge Caching and Video Transcoding Over Software-Defined Mobile Networks A Deep Reinforcement Learning Approach
11. An Associativity-Agnostic in-Cache Computing Architecture Optimized for Multiplication
12. An overview of next-generation architectures for machine learning Roadmap- opportunities and challenges in the IoT era
13. M. M. Sabry Aly et al., "Energy-Efficient Abundant-Data Computing: The N3XT 1,000x," in Computer, vol. 48, no. 12, pp. 24-33, Dec. 2015.
14. Architecture-aware design and implementation of CNN algorithms for embedded inference the ALOHA project
15. Area and Energy Optimization for Bit-Serial Log-Quantized DNN Accelerator with Shared Accumulators
16. Behind-the-Meter Solar Generation Disaggregation using Consumer Mixture Models
17. Computation Offloading and Resource Allocation for MEC in C-RAN A Deep Reinforcement Learning Approach
18. Computation Offloading in Multi-Access Edge Computing Using a Deep Sequential Model Based on Reinforcement Learning
19. F. Jiang, K. Wang, L. Dong, C. Pan, W. Xu and K. Yang, "Deep Learning Based Joint Resource Scheduling Algorithms for Hybrid MEC Networks," in IEEE Internet of Things Journal.
20. Deep Learning for Edge Computing Current Trends- Cross-Layer Optimizations- and Open Research Challenges
21. Deep Learning for Hybrid 5G Services in Mobile Edge Computing Systems Learn From a Digital Twin
22. Deep Learning-Based Sustainable Data Center Energy Cost Minimization With Temporal MACRO-MICRO Scale Management
23. Deep reinforcement learning based computation offloading and resource allocation for MEC
24. Deep Reinforcement Learning for Dynamic Access Control with Battery Prediction for Mobile-Edge Computing in Green IoT Networks
25. Deep Reinforcement Learning-Based Computation Offloading in Vehicular Edge Computing
26. Distributed Deep Deterministic Policy Gradient for Power Allocation Control in D2D-Based V2V Communications
27. Energy-Efficient Processing and Robust Wireless Cooperative Transmission for Edge Inference
28. Federated Learning-Based Computation Offloading Optimization in Edge Computing-Supported Internet of Things
29. GeneSys Enabling Continuous Learning through Neural Network Evolution in Hardware
30. Joint Communication and Computing Optimization for Hierarchical Machine Learning Tasks Distribution
31. Joint DNN Partition Deployment and Resource Allocation for Delay-Sensitive Deep Learning Inference in IoT
32. Joint Optimization of Networking and Computing Resources for Green M2M Communications Based on DRL
33. Performance Optimization in Mobile-Edge Computing via Deep Reinforcement Learning
34. Power- and Endurance-Aware Neural Network Training in NVM-Based Platforms
35. Privacy-Aware Edge Computing Based on Adaptive DNN Partitioning
36. S. Teerapittayanon, B. McDanel, and H. Kung, “Distributed deep neural networks over the cloud, the edge and end devices,” in Distributed Computing Systems, 2017 IEEE 37th Int’l Conf. on, pp. 328–339.
37. J. Li, Q. Liu, P. Wu, F. Shu and S. Jin, "Task Offloading for UAV-based Mobile Edge Computing via Deep Reinforcement Learning," 2018 IEEE/CIC International Conference on Communications in China (ICCC), Beijing, China, 2018, pp. 798-802.
38. J. Lim, J. Seo and Y. Baek, "CamThings: IoT Camera with Energy-Efficient Communication by Edge Computing based on Deep Learning," 2018 28th International Telecommunication Networks and Applications Conference (ITNAC), Sydney, NSW, 2018, pp. 1-6.
39. M. S. Munir, S. F. Abedin, N. H. Tran and C. S. Hong, "When Edge Computing Meets Microgrid: A Deep Reinforcement Learning Approach," in IEEE Internet of Things Journal, vol. 6, no. 5, pp. 7360-7374, Oct. 2019.
40. Z. Ali, L. Jiao, T. Baker, G. Abbas, Z. H. Abbas and S. Khaf, "A Deep Learning Approach for Energy Efficient Computational Offloading in Mobile Edge Computing," in IEEE Access, vol. 7, pp. 149623-149633, 2019.
41. S. H. Lee, T. Lee, S. Kim and S. Park, "Energy Consumption Prediction System Based on Deep Learning with Edge Computing," 2019 IEEE 2nd International Conference on Electronics Technology (ICET), Chengdu, China, 2019, pp. 473-477.
42. Q. Zhang, M. Lin, L. T. Yang, Z. Chen, S. U. Khan and P. Li, "A Double Deep Q-Learning Model for Energy-Efficient Edge Scheduling," in IEEE Transactions on Services Computing, vol. 12, no. 5, pp. 739-749, 1 Sept.-Oct. 2019.
43. H. Ke, J. Wang, H. Wang and Y. Ge, "Joint Optimization of Data Offloading and Resource Allocation With Renewable Energy Aware for IoT Devices: A Deep Reinforcement Learning Approach," in IEEE Access, vol. 7, pp. 179349-179363, 2019.
44. A. Zhu et al., "Computation Offloading for Workflow in Mobile Edge Computing Based on Deep Q-Learning," 2019 28th Wireless and Optical Communications Conference (WOCC), Beijing, China, 2019, pp. 1-5.
45. M. Min, L. Xiao, Y. Chen, P. Cheng, D. Wu and W. Zhuang, "Learning-Based Computation Offloading for IoT Devices With Energy Harvesting," in IEEE Transactions on Vehicular Technology, vol. 68, no. 2, pp. 1930-1941, Feb. 2019.
46. Y. Liu, C. Yang, L. Jiang, S. Xie and Y. Zhang, "Intelligent Edge Computing for IoT-Based Energy Management in Smart Cities," in IEEE Network, vol. 33, no. 2, pp. 111-117, March/April 2019.
47. P. Zhang, Q. Zhao, J. Gao, W. Li and J. Lu, "Urban Street Cleanliness Assessment Using Mobile Edge Computing and Deep Learning," in IEEE Access, vol. 7, pp. 63550-63563, 2019.
48. L. Lei, Y. Yuan, T. X. Vu, S. Chatzinotas and B. Ottersten, "Learning-Based Resource Allocation: Efficient Content Delivery Enabled by Convolutional Neural Network," 2019 IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Cannes, France, 2019, pp. 1-5.
49. G. Cui, X. Li, L. Xu and W. Wang, "Latency and Energy Optimization for MEC Enhanced SAT-IoT Networks," in IEEE Access, vol. 8, pp. 55915-55926, 2020.
50. M. Ahn et al., "AIX: A high performance and energy efficient inference accelerator on FPGA for a DNN-based commercial speech recognition," 2019 Design, Automation & Test in Europe Conference & Exhibition (DATE), Florence, Italy, 2019, pp. 1495-1500.
51. J. Heydari, V. Ganapathy and M. Shah, "Dynamic Task Offloading in Multi-Agent Mobile Edge Computing Networks," 2019 IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 2019, pp. 1-6.
52. J. Granados, H. Chu, Z. Zou and L. Zheng, "Towards Workload-Balanced, Live Deep Learning Analytics for Confidentiality-Aware IoT Medical Platforms," 2019 IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS), Hsinchu, Taiwan, 2019, pp. 62-66.
53. M. Asadikouhanjani and S. Ko, "A Novel Architecture for Early Detection of Negative Output Features in Deep Neural Network Accelerators," in IEEE Transactions on Circuits and Systems II: Express Briefs.
54. Z. Zhang, L. L. Njilla, S. Yu and J. Yuan, "Edge-Assisted Learning for Real-Time UAV Imagery via Predictive Offloading," 2019 IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 2019, pp. 1-6.
55. L. Xu, J. Han, T. Wang and L. Bai, "An Efficient CNN to Realize Speckle Correlation Imaging Based on Cloud-Edge for Cyber-Physical-Social-System," in IEEE Access, vol. 8, pp. 54154-54163, 2020.
56. Y. Yan and Q. Pei, "A Robust Deep-Neural-Network-Based Compressed Model for Mobile Device Assisted by Edge Server," in IEEE Access, vol. 7, pp. 179104-179117, 2019.
57. S. Dey, J. Mondal and A. Mukherjee, "Offloaded Execution of Deep Learning Inference at Edge: Challenges and Insights," 2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Kyoto, Japan, 2019, pp. 855-861.
58. M. Hartmann, H. Farooq and A. Imran, "Distilled Deep Learning based Classification of Abnormal Heartbeat Using ECG Data through a Low Cost Edge Device," 2019 IEEE Symposium on Computers and Communications (ISCC), Barcelona, Spain, 2019, pp. 1068-1071.
59. C. R. T, G. Sirisha and A. M. Reddy, "Smart Healthcare Analysis and Therapy for Voice Disorder using Cloud and Edge Computing," 2018 4th International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Mangalore, India, 2018, pp. 103-106.
60. C. Gong, Z. Jiang, D. Wang, Y. Lin, Q. Liu and D. Z. Pan, "Mixed Precision Neural Architecture Search for Energy Efficient Deep Learning," 2019 IEEE/ACM International Conference on Computer-Aided Design (ICCAD), Westminster, CO, USA, 2019, pp. 1-7.
61. R. Dong, C. She, W. Hardjawana, Y. Li and B. Vucetic, "Deep Learning for Hybrid 5G Services in Mobile Edge Computing Systems: Learn From a Digital Twin," in IEEE Transactions on Wireless Communications, vol. 18, no. 10, pp. 4692-4707, Oct. 2019.
62. B. Lu, J. Yang, L. Y. Chen and S. Ren, "Automating Deep Neural Network Model Selection for Edge Inference," 2019 IEEE First International Conference on Cognitive Machine Intelligence (CogMI), Los Angeles, CA, USA, 2019, pp. 184-193.
63. J. Lee, J. Lee, D. Han, J. Lee, G. Park and H. Yoo, "An Energy-Efficient Sparse Deep-Neural-Network Learning Accelerator With Fine-Grained Mixed Precision of FP8–FP16," in IEEE Solid-State Circuits Letters, vol. 2, no. 11, pp. 232-235, Nov. 2019.
64. J. Edstrom, H. Das, Y. Xu and N. Gong, "Memory Optimization for Energy-Efficient Differentially Private Deep Learning," in IEEE Transactions on Very Large Scale Integration (VLSI) Systems, vol. 28, no. 2, pp. 307-316, Feb. 2020.
65. H. Lu, X. He, M. Du, X. Ruan, Y. Sun and K. Wang, "Edge QoE: Computation Offloading with Deep Reinforcement Learning for Internet of Things," in IEEE Internet of Things Journal.
66. G. Stamatescu, R. Entezari, K. Römer and O. Saukh, "Deep and Efficient Impact Models for Edge Characterization and Control of Energy Events," 2019 IEEE 25th International Conference on Parallel and Distributed Systems (ICPADS), Tianjin, China, 2019, pp. 639-646.
67. N. Naderializadeh and M. Hashemi, "Energy-Aware Multi-Server Mobile Edge Computing: A Deep Reinforcement Learning Approach," 2019 53rd Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, 2019, pp. 383-387.
68. N. Monburinon, S. M. S. Zabir, N. Vechprasit, S. Utsumi and N. Shiratori, "A Novel Hierarchical Edge Computing Solution Based on Deep Learning for Distributed Image Recognition in IoT Systems," 2019 4th International Conference on Information Technology (InCIT), Bangkok, Thailand, 2019, pp. 294-299.
69. T. Li, Y. Xiao and L. Song, "Deep Reinforcement Learning Based Residential Demand Side Management With Edge Computing," 2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Beijing, China, 2019, pp. 1-6.
70. G. Ascia, V. Catania, S. Monteleone, M. Palesi, D. Patti and J. Jose, "Networks-on-Chip based Deep Neural Networks Accelerators for IoT Edge Devices," 2019 Sixth International Conference on Internet of Things: Systems, Management and Security (IOTSMS), Granada, Spain, 2019, pp. 227-234.
71. Y. Dai, D. Xu, K. Zhang, Y. Lu, S. Maharjan and Y. Zhang, "Deep Reinforcement Learning for Edge Computing and Resource Allocation in 5G Beyond," 2019 IEEE 19th International Conference on Communication Technology (ICCT), Xi'an, China, 2019, pp. 866-870.
72. H. Zhang, W. Wu, C. Wang, M. Li and R. Yang, "Deep Reinforcement Learning-Based Offloading Decision Optimization in Mobile Edge Computing," 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakesh, Morocco, 2019, pp. 1-7.
73. K. Vipin, "ZyNet: Automating Deep Neural Network Implementation on Low-Cost Reconfigurable Edge Computing Platforms," 2019 International Conference on Field-Programmable Technology (ICFPT), Tianjin, China, 2019, pp. 323-326.
74. B. Gu, J. Kong, A. Munir and Y. G. Kim, "A Framework for Distributed Deep Neural Network Training with Heterogeneous Computing Platforms," 2019 IEEE 25th International Conference on Parallel and Distributed Systems (ICPADS), Tianjin, China, 2019, pp. 430-437.
75. Z. Ning et al., "Deep Reinforcement Learning for Intelligent Internet of Vehicles: An Energy-Efficient Computational Offloading Scheme," in IEEE Transactions on Cognitive Communications and Networking, vol. 5, no. 4, pp. 1060-1072, Dec. 2019.
76. C. Lammie, A. Olsen, T. Carrick and M. Rahimi Azghadi, "Low-Power and High-Speed Deep FPGA Inference Engines for Weed Classification at the Edge," in IEEE Access, vol. 7, pp. 51171-51184, 2019.
77. T. Sirojan, S. Lu, B. T. Phung, D. Zhang and E. Ambikairajah, "Sustainable Deep Learning at Grid Edge for Real-time High Impedance Fault Detection," in IEEE Transactions on Sustainable Computing.
78. A. Gaballo, M. Flocco, F. Esposito and G. Marchetto, "ADELE: An Architecture for Steering Traffic and Computations via Deep Learning in Challenged Edge Networks," 2019 4th International Conference on Computing, Communications and Security (ICCCS), Rome, Italy, 2019, pp. 1-8.
79. A. Ganguly, R. Muralidhar and V. Singh, "Towards Energy Efficient non-von Neumann Architectures for Deep Learning," 20th International Symposium on Quality Electronic Design (ISQED), Santa Clara, CA, USA, 2019, pp. 335-342.
80. I. Wu, P. Huang, C. Lo and W. Hwang, "An Energy-Efficient Accelerator with Relative- Indexing Memory for Sparse Compressed Convolutional Neural Network," 2019 IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS), Hsinchu, Taiwan, 2019, pp. 42-45.
81. W. Zhan et al., "Deep Reinforcement Learning-Based Offloading Scheduling for Vehicular Edge Computing," in IEEE Internet of Things Journal.
82. N. C. Luong, Z. Xiong, P. Wang and D. Niyato, "Optimal Auction for Edge Computing Resource Management in Mobile Blockchain Networks: A Deep Learning Approach," 2018 IEEE International Conference on Communications (ICC), Kansas City, MO, 2018, pp. 1-6.
83. M. Verhelst and B. Moons, "Embedded Deep Neural Network Processing: Algorithmic and Processor Techniques Bring Deep Learning to IoT and Edge Devices," in IEEE Solid-State Circuits Magazine, vol. 9, no. 4, pp. 55-65, Fall 2017.
84. S. R. Young et al., "Evolving Energy Efficient Convolutional Neural Networks," 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA, 2019, pp. 4479-4485.
85. Y. Zhang et al., "Cyber Physical Security Analytics for Transactive Energy Systems," in IEEE Transactions on Smart Grid, vol. 11, no. 2, pp. 931-941, March 2020.
86. Y. C. Xiang et al., "Analog Deep Neural Network Based on NOR Flash Computing Array for High Speed/Energy Efficiency Computation," 2019 IEEE International Symposium on Circuits and Systems (ISCAS), Sapporo, Japan, 2019, pp. 1-4.
87. W. Chen et al., "A 65nm 1Mb nonvolatile computing-in-memory ReRAM macro with sub-16ns multiply-and-accumulate for binary DNN AI edge processors," 2018 IEEE International Solid - State Circuits Conference - (ISSCC), San Francisco, CA, 2018, pp. 494-496.
88. S. Wan, J. Lu, P. Fan and K. B. Letaief, "Towards Big data processing in IoT: Path Planning and Resource Management of UAV Base Stations in Mobile-Edge Computing System," in IEEE Internet of Things Journal.
89. X. Chen, H. Zhang, C. Wu, S. Mao, Y. Ji and M. Bennis, "Optimized Computation Offloading Performance in Virtual Edge Computing Systems Via Deep Reinforcement Learning," in IEEE Internet of Things Journal, vol. 6, no. 3, pp. 4005-4018, June 2019.
90. Y. Liu, Q. Cui, J. Zhang, Y. Chen and Y. Hou, "An Actor-Critic Deep Reinforcement Learning Based Computation Offloading for Three-Tier Mobile Computing Networks," 2019 11th International Conference on Wireless Communications and Signal Processing (WCSP), Xi'an, China, 2019, pp. 1-6.
91. S. Jiang et al., "Accelerating Mobile Applications at the Network Edge with Software-Programmable FPGAs," IEEE INFOCOM 2018 - IEEE Conference on Computer Communications, Honolulu, HI, 2018, pp. 55-62.
92. J. H. Ko, T. Na, M. F. Amir and S. Mukhopadhyay, "Edge-Host Partitioning of Deep Neural Networks with Feature Space Encoding for Resource-Constrained Internet-of-Things Platforms," 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), Auckland, New Zealand, 2018, pp. 1-6.
93. B. Yang, X. Cao, X. Li, T. Kroecker and L. Qian, "Joint Communication and Computing Optimization for Hierarchical Machine Learning Tasks Distribution," 2019 IEEE Symposium on Computers and Communications (ISCC), Barcelona, Spain, 2019, pp. 1-6.
94. P. A. Zientara, J. Sampson and V. Narayanan, "Noise Aware Power Adaptive Partitioned Deep Networks for Mobile Visual Assist Platforms," 2018 31st IEEE International System-on-Chip Conference (SOCC), Arlington, VA, 2018, pp. 186-191.
95. S. Khan, D. Paul, P. Momtahan and M. Aloqaily, "Artificial intelligence framework for smart city microgrids: State of the art, challenges, and opportunities," 2018 Third International Conference on Fog and Mobile Edge Computing (FMEC), Barcelona, 2018, pp. 283-288.
96. E. Kasaeyan Naeini, S. Shahhosseini, A. Subramanian, T. Yin, A. M. Rahmani and N. Dutt, "An Edge-Assisted and Smart System for Real-Time Pain Monitoring," 2019 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), Arlington, VA, USA, 2019, pp. 47-52.
97. Tuli S, Basumatary N, Gill SS, Kahani M, Arya RC, Wander GS, Buyya R. HealthFog: An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments. Future Generation Computer Systems. 2020 Mar 1;104:187-200.
98. S. H. Lee, T. Lee, S. Kim and S. Park, "Energy Consumption Prediction System Based on Deep Learning with Edge Computing," 2019 IEEE 2nd International Conference on Electronics Technology (ICET), Chengdu, China, 2019, pp. 473-477.