[1] N. D. Lane et al., "DeepX: A Software Accelerator for Low-Power Deep Learning Inference on Mobile Devices," 2016 15th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN), Vienna, Austria, 2016, pp. 1-12, doi: 10.1109/IPSN.2016.7460664. Available: <https://ieeexplore-ieee-org.libweb.lib.utsa.edu/stamp/stamp.jsp?tp=&arnumber=7460664>

Comment: Pair of resource control algorithms to effectively scale down deep learning models to run on edge devices. Runtime Layer Compression (RLC) compresses individual layers during inference using singular value decomposition (SVD) without requiring model retraining. Deep architecture decomposition (DAD) partitions models into unit-blocks that are assigned to available local and remote processors to enhance energy efficiency and reduce latency.

[2] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, “SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size,” \*arXiv preprint arXiv:1602.07360\*, 2016. Available: <https://openreview.net/pdf?id=S1xh5sYgx>

Comment: Key strategies for compression: Replace 3x3 filters with 1x1 filters because they have 9x fewer parameters. Decrease number of input channels to the number of 3x3 filters. Delay downsampling to improve classification accuracy on a limited budget of parameters. The Fire module is the basic building block of SqueezeNet. It consists of a squeeze layer (only 1x1 filters) and an expand layer (a mixture of 1x1 and 3x3 filters), The three filter counts are tunable dimensions.

[3] S. Han, H. Mao, and W. Dally, “DEEP COMPRESSION: COMPRESSING DEEP NEURAL NETWORKS WITH PRUNING, TRAINED QUANTIZATION AND HUFFMAN CODING,” ICLR, 2016. Available: <https://arxiv.org/pdf/1510.00149>

Comment: A three-prong approach to compressing a model. Pruning weight connections below a certain threshold and retrain on the sparse weights. Trained quantization and weight sharing forces multiple connections to share the same weight and fine tune those weights to be represented in fewer bits. Use Huffman coding on quantized weights to further reduce memory overhead.

[4] A. Howard *et al.*, “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,” Apr. 2017. Available: <https://arxiv.org/pdf/1704.04861>

Comment: A class of efficient models for mobile and embedded **computer vision applications**. Core layers of MobileNet architecture: Depthwise separable convolutions that split a conventional convolution into two simpler operations. Width multiplier is a parameter to reduce the number of channels per layer. Resolution multiplier is a parameter to reduce input image resolution.

[5] Y.-H. Chen, T. Krishna, J. S. Emer, and V. Sze, “Eyeriss: An Energy-Efficient Reconfigurable Accelerator for Deep Convolutional Neural Networks,” *IEEE Journal of Solid-State Circuits*, vol. 52, no. 1, pp. 127–138, Jan. 2017, Available: <https://ieeexplore-ieee-org.libweb.lib.utsa.edu/stamp/stamp.jsp?tp=&arnumber=7738524>

Comment: A hardware accelerator designed for energy efficiency on the entire system running a DNN model. Main features include: A spatial architecture of 168 processing elements with a four-level memory hierarchy to minimize data access at high-cost levels. Row stationary – reconfigurable mapping to CNN shape. A reconfigurable communication architecture. Compression and data gating to reduce memory footprint

[6] M. Triki, A. C. Ammari, Y. Wang and M. Pedram, "Reinforcement Learning-Based Dynamic Power Management of a Battery-Powered System Supplying Multiple Active Modes," 2013 European Modelling Symposium, Manchester, UK, 2013, pp. 437-442, doi: 10.1109/EMS.2013.74. Available: <https://ieeexplore-ieee-org.libweb.lib.utsa.edu/stamp/stamp.jsp?tp=&arnumber=6779885>

Comment: Remove from bibliography. Not a machine learning model.

[7] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-Efficient Learning of Deep Networks from Decentralized Data,” *proceedings.mlr.press*, Apr. 10, 2017. Available: <https://proceedings.mlr.press/v54/mcmahan17a/mcmahan17a.pdf>

Comment: An introduction to federated learning. A model is trained on local data and weight updates are communicated to a central server that averages weight updates from multiple devices. Local data is never shared between devices. Introduces the FederatedAveraging Algorithm – local stochastic gradient descent and model averaging on a central server, eliminating communication overhead between devices.

[8] Yiping Kang, Johann Hauswald, Cao Gao, Austin Rovinski, Trevor Mudge, Jason Mars, and Lingjia Tang. 2017. Neurosurgeon: Collaborative Intelligence Between the Cloud and Mobile Edge. In Proceedings of the Twenty-Second International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS '17). Association for Computing Machinery, New York, NY, USA, 615–629. Available: <https://dl.acm.org/doi/pdf/10.1145/3093337.3037698>

Comment: Introduces a system to intelligently partition a DNN between the cloud and an edge device. Experiments were run on the AlexNet model. A performance analysis is done to determine data and computation characteristics of each layer and is combined with the communication latency between the cloud and the device. These metrics determine the ideal partitions for the model.

[9] M. Kumar, X. Zhang, L. Liu, Y. Wang and W. Shi, "Energy-Efficient Machine Learning on the Edges," 2020 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW), New Orleans, LA, USA, 2020, pp. 912-921, doi: 10.1109/IPDPSW50202.2020.00153. Available: <https://ieeexplore-ieee-org.libweb.lib.utsa.edu/stamp/stamp.jsp?tp=&arnumber=9150337>

Comment: Emphasizes the importance of a holistic approach to deploying ML on edge devices by discussing the need to integrate optimizations in both hardware and software. The paper explores various advances in hardware, software and algorithm design, and introduces a Java plugin aimed at optimizing the energy efficiency of Java code.

[10] Kim, K.; Jang, S.-J.; Park, J.; Lee, E.; Lee, S.-S. Lightweight and Energy-Efficient Deep Learning Accelerator for Real-Time Object Detection on Edge Devices. *Sensors* **2023**, *23*, 1185. Available: <https://doi.org/10.3390/s23031185>

Comment: Introduces an optimized machine learning model based on SqueezeNet and a lightweight hardware accelerator for use in real-time object detection. Their methodology further compresses SqueezeNet for this application and the hardware architecture is optimized for latency and energy consumption. There are ample data on hardware implementation details and experimental results.

[11] Fanariotis, A.; Orphanoudakis, T.; Kotrotsios, K.; Fotopoulos, V.; Keramidas, G.; Karkazis, P. Power Efficient Machine Learning Models Deployment on Edge IoT Devices. *Sensors* **2023**, *23*, 1595. Available: <https://doi.org/10.3390/s23031595>

Comment: A study constrained to investigating energy performance of well known ML models on embedded systems, such as those found in IoT devices. The devices used in the study are an ESP32 board and a STM32H743 board. The development framework used is TensorFlow Micro (TinyML), a framework specifically designed for microcontrollers. They found that the SRAM usage of a particular hardware architecture is a better power efficiency indicator, and thus power efficiency is closely tied to hardware architecture.

[12] J. Azar, A. Makhoul, M. Barhamgi, and R. Couturier, “An energy efficient IoT data compression approach for edge machine learning,” *Future Generation Computer Systems*, vol. 96, pp. 168–175, Jul. 2019, Available: <https://doi.org/10.1016/j.future.2019.02.005>

Comment: An introduction of a technique to reduce communication overhead of IoT devices in a ML context. The paradigm consists of fast data compression technique at the IoT device before transmission to an intermediate edge device, where the data is decompressed and analyzed before transmission to the cloud. The results show a 103x reduction in data transmission for the IoT device, significantly lowering power consumption.

[13] Walid A. Hanafy, Tergel Molom-Ochir, and Rohan Shenoy. 2021. Design Considerations for Energy-efficient Inference on Edge Devices. In Proceedings of the Twelfth ACM International Conference on Future Energy Systems (e-Energy '21). Association for Computing Machinery, New York, NY, USA, 302–308. Available: <https://doi.org/10.1145/3447555.3465326>

Comment: A study that focuses on the perspective of the developer who wishes to deploy a DNN model in an edge, embedded or IoT device. A three-part tradeoff is considered between accuracy, energy consumption, and latency. They introduce a metric of accuracy-per-joule to compare accuracy and energy efficiency, as well as a recommendation algorithm to assist in the best compromise of choosing a specific DNN model for specific hardware settings and constraints.

[14] 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, doi: 10.1109/ACCESS.2019.2947053. Available: <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8866714>

Comment: Introduces a machine learning algorithm (EEDOS) for optimal computational offloading between a mobile edge device and the cloud. The algorithm considers a variety of conditions, including remaining battery life (possibly the first algorithm to do so), in picking the best set of partitions. The training dataset is exhaustive, which allows EEDOS to be 100% accurate. Thus, EEDOS outperforms previous approaches.

[15] Xiaolong Tu, Anik Mallik, Dawei Chen, Kyungtae Han, Onur Altintas, Haoxin Wang, and Jiang Xie. 2024. Unveiling Energy Efficiency in Deep Learning: Measurement, Prediction, and Scoring across Edge Devices. In Proceedings of the Eighth ACM/IEEE Symposium on Edge Computing (SEC '23). Association for Computing Machinery, New York, NY, USA, 80–93. Available: <https://doi.org/10.1145/3583740.3628442>

Comment: A comprehensive study focused on gathering accurate energy consumption data for deep learning applications on edge devices. They develop an expedient method of measuring real-time power consumption with sufficient time granularity across mobile devices. Additionally, they perform kernel-level energy measurements to predict energy consumption on untested DNN models. And finally, they present scoring metrics to make the data more understandable for end-users.

[16] W. Liu, B. Li, W. Xie, Y. Dai and Z. Fei, "Energy Efficient Computation Offloading in Aerial Edge Networks With Multi-Agent Cooperation," in IEEE Transactions on Wireless Communications, vol. 22, no. 9, pp. 5725-5739, Sept. 2023, doi: 10.1109/TWC.2023.3235997. Available: <https://ieeexplore-ieee-org.libweb.lib.utsa.edu/document/10021296>

Comment: This paper explores the problem of optimal computation offloading between mobile devices and a base station server with the support of UAVs that can aid in computation tasks or act as a communication relay. They leverage the concept of a digital twin edge network (DITEN) hosted on the base station to model the optimization process before deploying a solution to the devices on the network.

[17] Z. Safavifar, E. Gyamfi, E. Mangina and F. Golpayegani, "Multi-Objective Deep Reinforcement Learning for Efficient Workload Orchestration in Extreme Edge Computing," in IEEE Access, vol. 12, pp. 74558-74571, 2024, doi: 10.1109/ACCESS.2024.3405411. Available: <https://ieeexplore-ieee-org.libweb.lib.utsa.edu/document/10538273>

Comment: This paper proposes a deep reinforcement learning algorithm that orchestrates computational tasks in edge devices with a priority of sharing tasks between devices over offloading them to an edge server. The multi-objective problem solved is assigning minimum computational capacity per task and maximizing total success rate per task. What is lacking is a discussion of data security.

[19] Q. Wei, Z. Zhou and X. Chen, "DRL-Based Energy-Efficient Trajectory Planning, Computation Offloading, and Charging Scheduling in UAV-MEC Network," 2022 IEEE/CIC International Conference on Communications in China (ICCC), Sanshui, Foshan, China, 2022, pp. 1056-1061, doi: 10.1109/ICCC55456.2022.9880711. Available: <https://ieeexplore-ieee-org.libweb.lib.utsa.edu/document/9880711>

Comment: An introduction of a deep reinforcement learning framework for optimizing multiple objectives in UAV operations for mobile edge computing networks. A priority mechanism is built into the learning framework to handle complex decision making. The objectives are energy efficiency, trajectory planning, communication scheduling, charge scheduling and task offloading.

[21] S. Chouikhi, M. Esseghir and L. Merghem-Boulahia, "Energy-Efficient Computation Offloading Based on Multiagent Deep Reinforcement Learning for Industrial Internet of Things Systems," in IEEE Internet of Things Journal, vol. 11, no. 7, pp. 12228-12239, 1 April1, 2024, doi: 10.1109/JIOT.2023.3333044. Available: https://ieeexplore-ieee-org.libweb.lib.utsa.edu/document/10318207

[22] A. Cleary, K. Yoo, P. Samuel, S. George, F. Sun and S. A. Israel, "Machine Learning on Small UAVs," 2020 IEEE Applied Imagery Pattern Recognition Workshop (AIPR), Washington DC, DC, USA, 2020, pp. 1-5, doi: 10.1109/AIPR50011.2020.9425090. Available: https://ieeexplore-ieee-org.libweb.lib.utsa.edu/document/9425090

[23] A. O. Hashesh, A. S. Tag Eldien, M. M. Fouda and R. M. Zaki, "AI-Aided Height Optimization for NOMA-UAV Networks," 2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE), Jakarta, Indonesia, 2023, pp. 843-846, doi: 10.1109/ICCoSITE57641.2023.10127675. Available: https://ieeexplore-ieee-org.libweb.lib.utsa.edu/document/10127675

[24] P. K. Barik, S. Shah, K. Shah, A. Modi and H. Devisha, "UAV-Assisted Surveillance Using Machine Learning," 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), Solan, Himachal Pradesh, India, 2022, pp. 384-389, doi: 10.1109/PDGC56933.2022.10053282. Available: https://ieeexplore-ieee-org.libweb.lib.utsa.edu/document/10053282

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