AttendSeg: A Tiny Attention Condenser Neural Network for Semantic Segmentation on the Edge

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Abstract

In this study, we introduce AttendSeg, a low-precision, highly compact deep neural network tailored for on-device semantic segmentation. AttendSeg possesses a self-attention network architecture comprising of light-weight attention condensers for improved spatial-channel selective attention at a very low complexity. The unique macro-architecture and micro-architecture design properties of AttendSeg strike a strong balance between representational power and efficiency, achieved via a machine-driven design exploration strategy tailored specifically for the task at hand. Experimental results demonstrated that the proposed AttendSeg can achieve segmentation accuracy comparable to much larger deep neural networks with greater complexity while possessing a significantly lower architecture and computational complexity (requiring as much as >27× fewer MACs, >72× fewer parameters, and >288× lower weight memory requirements), making it well-suited for TinyML applications on the edge.

1. Introduction

Semantic segmentation remains a challenging task in computer vision, with the underlying goal being to assign class labels on a per-pixel basis to an image. Much of the success in semantic segmentation has revolved around deep learning [23], where deep convolutional neural networks have been designed to model the relationship between input images and output label fields [30, 25, 37, 46, 4, 5, 6, 1, 24, 44]. Exemplary deep semantic segmentation network architectures include U-Net [30], RefineNet [25], TuSimple [37], PSPNet [46], and the DeepLab family of networks [4, 5, 6]. Despite such advancements, a major bottleneck to the widespread adoption of deep semantic segmentation networks in on-device, TinyML applications has been their high architectural and computational complexity.

Given the significant resource constraints imposed by low-cost, low-power edge devices, there has been great recent interest in strategies for producing highly compact networks tailored for low-power, on-device usage. These include efficient design principles [16, 31, 19, 32, 42, 45, 27, 14], precision reduction [20, 28, 7], model compression [12, 15, 29], network architecture search [17, 11, 34, 33], dynamic routing [24], and efficient self-attention [39, 40].

In this study, we introduce AttendSeg, a low-precision, highly compact deep semantic segmentation network tailored for TinyML applications. By leveraging both machine-driven design exploration and attention condensers, the proposed AttendSeg possesses a highly efficient self-attention architecture with unique macro-architecture and micro-architecture designs tailored specifically for low-power, on-device semantic segmentation.

This paper is organized as follows. Section 2 describes the underlying methodology behind the design of the proposed AttendSeg network architecture for semantic segmentation on the edge. Experimental results are presented and discussed in Section 3. Conclusions are drawn and future work are discussed in Section 4.

2. Methods

This work presents AttendSeg, a low-precision, highly compact deep neural network architecture tailored specifically for on-device semantic segmentation. Two key concepts are leveraged in the construction of the proposed AttendSeg: 1) attention condensers for enabling highly efficient selective attention, and 2) machine-driven design exploration to construct the macro-architecture and micro-architecture designs of the proposed deep neural network architecture. Both of these concepts, along with the final AttendSeg architectural design, are described in detail below.
2.1. Attention Condensers

The first concept we leverage to construct the proposed AttendSeg is the concept of attention condensers [39, 40]. One of the breakthroughs in deep learning in recent years has been the concept of self-attention [35, 18, 43, 10], which is inspired by human selective attention that filters out unimportant details to focus on what matters for the task at hand. Much of literature in self-attention has focused on accuracy, which has heavily influenced the design of such mechanisms. Recently, an efficient self-attention mechanism was introduced in the form of attention condensers [39, 40]. More specifically, attention condensers enable highly efficient selective attention by learning condensed embeddings of activation relationships, and in the case of AttendSeg they serve specifically for capturing joint spatial-channel activation relationships. An attention condenser consists of a condensation layer to reduce spatial-channel dimensionality, an embedding structure to characterize joint spatial-channel activation relationships, an expansion layer to increase dimensionality, and a selective attention mechanism for imposing selective attention.

2.2. Machine-driven design exploration

To construct the macro-architecture and micro-architecture designs of AttendSeg, we leverage a machine-driven design exploration strategy tailored around the operational requirements of on-device semantic segmentation. Here, we harness the concept of generative synthesis [41], where the design exploration problem is framed as a constrained optimization problem to identify a generator $G$ that, given a set of seeds $S$, can generate networks $\{N_s | s \in S\}$ maximizing a universal performance function $U$ (e.g., [38]) while satisfying requirements defined via an indicator function $1_r(\cdot)$,

$$G = \max_{G} U(G(s)) \text{ subject to } 1_r(G(s)) = 1, \forall s \in S.$$  \hspace{1cm} (1)

An approximate solution $\hat{G}$ to Eq. 1 can be obtained via iterative optimization, initialized based on a design prototype $\varphi$, $U$, and $1_r(\cdot)$. The resulting $\hat{G}$ can be thus used to generate the final AttendSeg architecture design. Here, the design prototype $\varphi$ is based on the multi-path refinement design
Table 1. Performance of tested networks on CamVid. Best results in **bold**. Results for AttendSeg based on 8-bit weights, while other tested networks based on 32-bit weights.

| Model             | Accuracy (%) | MACs (G) | Parameters (M) | Weight Memory (Mb) |
|-------------------|--------------|----------|----------------|--------------------|
| RefineNet [25]    | **90.0%**    | 202.47   | 85.69          | 343                |
| EdgeSegNet [26]   | 89.15%       | 77.89    | 7.09           | 28.3               |
| AttendSeg         | 89.89%       | **7.45** | **1.19**       | **1.19**           |

principles introduced in [25], which facilitate the refinement of high-level semantic representation in deeper layers based on fine-grained representation in earlier layers. The indicator function \(1_r(\cdot)\) is defined such that: 1) an accuracy of \(\geq 88\%\) is achieved on CamVid [3], to be within 2\% of EdgeSegNet [26], a state-of-the-art efficient deep semantic segmentation network, and 2) 8-bit weight precision.

2.3. Architectural Design

The network architecture of the AttendSeg is shown in Fig. 1, which possesses several interesting properties. First, AttendSeg is comprised of a heterogeneous mix of lightweight attention condensers, depthwise convolutions, and pointwise convolutions with unique micro-architecture designs, thus striking a strong balance between representational power and efficiency. Second, AttendSeg exhibits selective long-range connectivity where only select deeper layers are refined based on earlier layers, thus improving architectural efficiency by only refining at scales that benefit from it. Third, one can observe very aggressive dimensionality reduction via strided convolutions with large strides, thus greatly reducing complexity while preserving representational capacity. These properties illustrate the power of leveraging both machine-driven design exploration and attention condensers to produce highly compact network architectures tailored for edge scenarios.

3. Results and Discussion

We explore the efficacy of AttendSeg for on-device semantic segmentation on the edge using the Cambridge-driving Labeled Video Database (CamVid) [3], a dataset introduced for evaluating semantic segmentation performance with 32 different semantic classes. For comparison purposes, the results for ResNet-101 RefineNet [25] and EdgeSegNet [26], a state-of-the-art efficient deep semantic segmentation network, are also presented and all experiments are conducted at a 512×512 resolution in TensorFlow.

It can be seen in Table 1 that the proposed AttendSeg achieved similar accuracy as ResNet-101 RefineNet and higher than EdgeSegNet, but has \(>72\times\) and \(>5.9\times\) fewer parameters compared to RefineNet and EdgeSegNet, respectively. Due to the low-precision nature of AttendSeg, its weight memory requirements are \(>288\times\) and \(>23.6\times\) lower than RefineNet and EdgeSegNet, respectively. More interestingly, AttendSeg achieves \(>27\times\) and \(>10.4\times\) greater computational efficiency in terms of multiply-accumulate (MAC) operations compared to RefineNet and EdgeSegNet, respectively. An example semantic segmentation outputs produced using AttendSeg is shown in Fig. 2. Visually, it can be observed that AttendSeg achieves good segmentation performance. These experimental results demonstrate that AttendSeg can achieve strong semantic segmentation performance while possessing significantly lower architectural and computational complexity, making it well-suited for TinyML applications where resources are limited such as mobile, drone, vehicle, and robotic applications.

4. Conclusion

In this work, we introduced AttendSeg, a low-precision, highly efficient self-attention deep neural network architecture tailored for semantic segmentation on the edge. By leveraging a machine-driven design exploration strategy to discover unique macro-architecture and micro-architecture designs as well as leveraging the concept of attention condensers, the proposed AttendSeg architecture strikes a strong balance between representational power and efficiency. Experimental results show the efficacy of AttendSeg in achieving comparable segmentation accuracy with significantly more complex deep neural network architectures while achieving significantly lower architectural complexity.
complexity, lower computational complexity, and lower weight memory requirements, making it very well-suited for TinyML applications on edge and embedded devices. Future work involves exploring this approach for tackling other complex visual perception tasks such as object detection, instance segmentation, and depth estimation.

5. Broader Impact

TinyML (tiny machine learning) has been seen significant rise in attention in recent years as a disruptive technology that will accelerate the widespread adoption of machine learning across industries and society. In particular, the ability to perform real-time predictions automatically using machine learning on low-cost, low-power edge and embedded devices can enable a huge swath of applications ranging from autonomous vehicles and advanced driving assistance systems [2] to intelligent exoskeletons leveraging embedded sensing information for environmental-adaptive control [21, 22]. In addition, TinyML can enable greater privacy in machine learning applications by facilitating for tetherless intelligence without the need for continuous connectivity or at the very least reduce the amount of information that needs to be sent to the cloud. The hope is that knowledge and insights gained from TinyML research such as AttendSeg can contribute to the advancement of efforts in TinyML towards ubiquitous machine learning.

Despite all of these potential advantages and benefits of TinyML, it is also important to keep additional considerations in mind with regards to the design and development of such TinyML advancements in terms of not only potential sources of error and biases, but also take socioeconomical considerations into account to better understand how the availability of such technologies can impact society (e.g., privacy, inclusion, ethics, human-machine interaction, new risks, etc.) [13, 36, 8, 9].

References

[1] Nikita Araslanov and Stefan Roth. Single-stage semantic segmentation from image labels. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020. 1

[2] S.A. Bagloee, M. Tavana, M. Asadi, et al. Autonomous vehicles: challenges, opportunities, and future implications for transportation policies. J. Mod. Transport., 24:284–303, 2016. 4

[3] G. Brostow et al. Semantic object classes in video: A high-definition ground truth database. In PRL, 2008. 3

[4] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. IEEE transactions on pattern analysis and machine intelligence, 40(4):834–848, 2018. 1

[5] Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam. Rethinking atrous convolution for semantic image segmentation. In arXiv:1706.05587, 2017. 1

[6] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In ECCV, 2018. 1

[7] Matthieu Courbariaux, Yoshua Bengio, and Jean-Pierre David. Binaryconnect: Training deep neural networks with binary weights during propagations. In Advances in neural information processing systems, pages 3123–3131, 2015. 1

[8] Martin Cunneen, Martin Mullins, and Finbarr Murphy. Autonomous vehicles and embedded artificial intelligence: The challenges of framing machine driving decisions. Applied Artificial Intelligence, 33(8):706–731, 2019. 4

[9] Martin Cunneen, Martin Mullins, Finbarr Murphy, Darren Shannon, Irini Furxhi, and Cian Ryan. Autonomous vehicles and avoiding the trolley (dilemma): Vehicle perception, classification, and the challenges of framing decision ethics. Cybernetics and Systems, 51(1):59–80, 2020. 4

[10] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2018. 2

[11] Thomas Elsken, Jan Hendrik Metzen, and Frank Hutter. Multi-objective architecture search for cnns. arXiv preprint arXiv:1804.09081, 2018. 1

[12] Song Han, Huizi Mao, and William J Dally. Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. arXiv preprint arXiv:1510.00149, 2015. 1

[13] P. A. Hancock, Illah Nourbakhsh, and Jack Stewart. On the future of transportation in an era of automated and autonomous vehicles. Proceedings of the National Academy of Sciences, 116(16):7684–7691, 2019. 4

[14] K. He et al. Deep residual learning for image recognition. arXiv:1512.03385, 2015. 1

[15] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015. 1

[16] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861, 2017. 1

[17] Chi-Hung Hsu, Shu-Huan Chang, Da-Cheng Juan, Jia-Yu Pan, Yu-Ting Chen, Wei Wei, and Shih-Chieh Chang. Monas: Multi-objective neural architecture search using reinforcement learning. arXiv preprint arXiv:1806.10332, 2018. 1

[18] Jie Hu, Li Shen, Samuel Albanie, Gang Sun, and Enhua Wu. Squeeze-and-excitation networks, 2017. 1

[19] Forrest N Iandola, Song Han, Matthew W Moskewicz, Khalid Ashraf, William J Dally, and Kurt Keutzer. SqueezeNet: Alexnet-level accuracy with 50x fewer parameters and< 0.5 mb model size. arXiv preprint arXiv:1602.07360, 2016. 1
[20] B. Jacob et al. Quantization and training of neural networks for efficient integer-arithmetic-only inference. arXiv:1712.05877, 2017. 1

[21] Brock Laschowski, William McNally, Alexander Wong, and John McPhee. Exonet database: Wearable camera images of human locomotion environments. Frontiers in Robotics and AI, 7:188, 2020. 4

[22] Brokoslaw Laschowski, William McNally, Alexander Wong, and John McPhee. Computer vision and deep learning for environment-adaptive control of robotic lower-limb exoskeletons. bioRxiv, 2021. 4

[23] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. nature, 521(7553):436, 2015. 1

[24] Yanwei Li, Lin Song, Yukang Chen, Zeming Li, Xiangyu Zhang, Xingang Wang, and Jian Sun. Learning dynamic routing for semantic segmentation. In IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020. 1

[25] Guosheng Lin, Anton Milan, Chunhua Shen, and Ian Reid. Refinenet: Multi-path refinement networks for high-resolution semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1925–1934, 2017. 1, 3

[26] Zhong Qiu Lin, Brendan Chwyl, and Alexander Wong. Edgesegnet: A compact network for semantic segmentation, 2019. 3

[27] Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In Proceedings of the European Conference on Computer Vision (ECCV), pages 116–131, 2017. 1

[28] W. Meng et al. Two-bit networks for deep learning on resource-constrained embedded devices. arXiv:1701.00485, 2017. 1

[29] S. Ravi. ProjectionNet: Learning efficient on-device deep networks using neural projections. arXiv:1708.00630, 2017. 1

[30] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation, 2015. 1

[31] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4510–4520, 2018. 1

[32] Mohammad Javad Shafiee, Francis Li, Brendan Chwyl, and Alexander Wong. Squishednets: Squishing squeezenet further for edge device scenarios via deep evolutionary synthesis. NIPS Workshop on Machine Learning on the Phone and other Consumer Devices, 2017. 1

[33] Mohammad Javad Shafiee, Akshaya Mishra, and Alexander Wong. Deep learning with darwin: Evolutionary synthesis of deep neural networks, 2017. 1

[34] Mingxing Tan, Bo Chen, Ruoming Pang, Vijay Vasudevan, and Quoc V Le. Mnasnet: Platform-aware neural architecture search for mobile. arXiv preprint arXiv:1807.11626, 2018. 1

[35] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illlia Polosukhin. Attention is all you need, 2017. 2

[36] Linda Wang and Alexander Wong. Implications of computer vision driven assistive technologies towards individuals with visual impairment, 2019. 4

[37] Panqu Wang, Pengfei Chen, Ye Yuan, Ding Liu, Zehua Huang, Xiaodi Hou, and Garrison Cottrell. Understanding convolution for semantic segmentation. In Proceedings of WACV, 2017. 1

[38] Alexander Wong. Netscore: Towards universal metrics for large-scale performance analysis of deep neural networks for practical usage. arXiv preprint arXiv:1806.05512, 2018. 2

[39] Alexander Wong, Mahmoud Famouri, Maya Pavlova, and Siddharth Surana. TinySpeech: Attention condensers for deep speech recognition neural networks on edge devices, 2020. 1, 2

[40] Alexander Wong, Mahmoud Famouri, and Mohammad Javad Shafiee. Attendnets: Tiny deep image recognition neural networks for the edge via visual attention condensers, 2020. 1, 2

[41] Alexander Wong, Mohammad Javad Shafiee, Brendan Chwyl, and Francis Li. Ferminets: Learning generative machines to generate efficient neural networks via generative synthesis. Advances in neural information processing systems Workshops, 2018. 2

[42] Alexander Wong, Mohammad Javad Shafiee, Francis Li, and Brendan Chwyl. Tiny ssd: A tiny single-shot detection deep convolutional neural network for real-time embedded object detection. Proceedings of the Conference on Computer and Robot Vision, 2018. 1

[43] Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon. Cham: Convolutional block attention module, 2018. 2

[44] Yanchao Yang and Stefano Soatto. Fda: Fourier domain adaptation for semantic segmentation. In IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020. 1

[45] Xiangyu Zhang, Xinyu Zhou, Mengxiao Lin, and Jian Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1925–1934, 2017. 1

[46] Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network. In Proceedings of WACV, 2017. 1