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EViT: Efficient Vision and Tracking System for Edge Deployment

[1] Prasanth R S, [2] Gautham J K, [3] Yedukrishnan S, [4] J Govind, [5] Ananya K A

[1] [2] [3] [4] [5] Department of Information Technology, Government Engineering College Barton Hill, Thiruvananthapuram, India
Corresponding Author Email: [1] prasanth@gecbh.ac.in, [2] gautham.j.k@outlook.com, [3] yedukrishnan@zohomail.in, [4] govxnd23@gmail.com, [5] ananyaajayakumar12@gmail.com

Abstract*— Real time object segmentation and multi object tracking remain computationally challenging on edge devices with constrained resources (ARM processors, limited memory, low power budgets). Most of the existing solutions lean one way or the other. Vision transformers deliver strong accuracy but are far too heavy, while lightweight CNNs runs faster but sacrificing performance. We introduce EViT (Efficient Vision & Tracking), a hierarchical transformer based architecture that blends multi scale feature extraction with lightweight segmentation and Kalman filter based tracking. By using overlapping patch embeddings, efficient spatial reduced self attention, and an all-MLP decoder, EViT achieves real time performance on edge devices without compromising on the segmentation quality. Our hierarchical encoder progresses through four stages which reduces spatial resolution from 1/4 to 1/32 stride while maintaining the informative features through depthwise convolutions and multi head attention. The tracking module integrates a Kalman filter with IoU based data association for robust identity preservation across frames. Experimental validation on edge hardware (ARM Jetson Nano) shows that EViT achieves 15–20 FPS at 512 × 512 resolution with ~17M parameters, outperforming SegFormer and MobileSAM-Track baselines. The model is deployable via TensorRT quantization (INT8) with <50 ms latency, making it suitable for real world surveillance, autonomous robotics, and constrained IoT applications.

I. INTRODUCTION

A. Motivation and Problem Statement

Object segmentation and multi object tracking are the core functions in computer vision systems like spanning autonomous vehicles, surveillance systems, robotics, and real time analytics. Traditional approaches rely on two stage pipelines: object detection followed by feature based association. That approach works up to a point. However, instance segmentation, which predicts class labels and instance boundaries at the same time, provides higher spatial information and naturally handles crowded scenes where bounding boxes overlap. Despite advantages, instance segmentation models are computationally expensive, often running into hundreds of millions of parameters and requiring tens of TFLOPS for inference.

Edge environment make these demands hard to justify. Embedded systems, IoT devices, mobile robotics, and low power surveillance cameras operate under strict constraints. Memory footprint should be below 500 MB, latency should stay under 100 ms per frame at standard resolutions, power consumption should remain under 5 W for continuous inference, and there will be no internet connectivity. Under such condition, mainstream models like Mask R-CNN, DETR variants, and ViT based segmenters are simply not viable as they require GPU acceleration.

Current edge solutions fall into two categories. On the one hand are lightweight CNNs like MobileNet or ShuffleNet that sacrifice their accuracy by aggressive pruning and quantization and there achieve 60-70% mIoU in COCO. On the other side are the mobile optimized transformers that reduce the parameters yet retain the $O(N^2)$ attention complexity, leading to 40–60 FPS but with limited multiscale context. So neither option fully resolves the tension between segmentation accuracy, tracking robustness, and inference latency for practical edge applications.

B. Research Objectives

This paper presents EViT, addressing three core challenges:

1) Efficient Multi Scale Feature Extraction: We design a hierarchical transformer encoder that progressively reduces spatial resolution while maintaining the semantic richness. Spatially reduced attention plays a key role here by reducing the complexity from $O(N^2)$ to $O(N^2/R^2)$.
2) Lightweight Segmentation: Instead of relying on heavy decoders such as UNet or FPN, EViT adopts an all-MLP decoder for multi-scale feature fusion. This choice reduces parameter count and memory bandwidth yet still preserving boundary precision.
3) Robust Segmentation Driven Tracking: We are integrating a Kalman filter with IoU based data association to maintain object identities across frames, exploiting segmentation masks for superior handling of occlusions and crowded scenes versus bounding box-only tracking.

C. Contributions

- EViT Architecture: It is a four stage hierarchical transformer encoder built around overlapping patch embeddings and efficient spatial reduced self attention.The result is a model that stays near to ~17M parameters and runs with <50 ms latency on ARM edge devices.

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- Segmentation-First Tracking: Instead of extracting and associating with bounding boxes, objects are extracted directly from segmentation masks. This shift improves robustness in crowded scenes and occlusion scenarios.
- Quantization Ready Design: The Architecture is explicitly optimized for INT8/FP16 quantization without much accuracy degradation, enabling smooth deployment on TensorRT and ONNX runtimes.
- Comprehensive Benchmark: Evaluation on edge hardware like Jetson Nano, Raspberry Pi 4 with latency, throughput, and energy metrics, establishing new efficiency baselines for segmentation and tracking on resource constrained devices.

D. Paper Organization

Section II reviews related work with a focus on efficient vision transformers, lightweight segmentation, and tracking architectures. Section III then walks through the design of the EViT model in detail which includes the encoder, decoder, and tracking components. Section IV describes about the experimental setup and datasets. Section V reports the results comparing EViT against SegFormer, MobileSAM, and lightweight baselines. Section VI reflects on the design trade-offs,limitations, and possible directions for future work, also concludes with practical recommendations for the deployment.

II. RELATED WORK

A. Efficient Vision Transformers and Segmentation Backbones

Vision transformers (ViT) have set a high bar for accuracy across a range of vision tasks but they come with an obvious drawback. They suffer from quadratic attention complexity $O(N^2d)$, where N is the number of tokens and d is embedding dimension. Addressing this bottleneck for semantic segmentation and edge deployment has become an central concern rather than a minor optimization detail.

SegFormer Architecture: Xie *et al.* [5] introduced SegFormer. The key idea was a hierarchical transformer encoder paradigm built on overlapped patch embeddings and a lightweight all-MLP decoder. SegFormer became the direct architectural inspiration for EViT's segmentation backbone which has the efficient multi scale feature fusion without heavy decoder modules achieves competitive accuracy with minimal parameter overhead. The use of overlap patch embedding helped to retain the spatial locality while discarding the explicit learnable positional encodings. EViT takes clear inspiration from SegFormer's philosophy. At the same time, it departs from Segformer by introducing asymmetric spatial reduction specifically applied to Key and Value projections, a design choice that was not extensively explored in the original model.

SegFormer++: Xie *et al.* extended SegFormer with token merging and other computational reduction techniques tailored for high resolution inputs. Token merging dynamically reduces the number of tokens during forward propagation which allows real time segmentation while preserving the spatial detail. These techniques validate that hierarchical compression strategies which is similar to EViT's patch reduction blocks, maintaining the accuracy while improving the throughput.

Spatial Reduced Attention Methods: Other transformer variants such as Pyramid Vision Transformer also adopt hierarchical structure with patch reduction at each stage. Our work has similar hierarchical stages but applies spatial reduction asymmetrically. Queries are kept at full resolution while keys and values are computed on reduced representation. This design preserves query detail (all pixels attend to coarse context) while dropping the compute complexity to $O(N^2/R^2)$ where R is the reduction ratio.

B. Edge Optimization and Hardware-Aware Design

Work such as HARD Edge and microcontrollerfocused optimization papers demonstrate practical strategies for pruning, quantization, and memory-aware architectural choices. Principles like reducing Keys and Value dimension more aggressively than Queries tends to preserve output quality while significantly minimizing memory peaks. This observation directly reflects in EViT's asymmetric spatial reduction design.

C. Semantic and Instance Segmentation

Traditional segmentation models like FCN, U-Net, and DeepLab operate entirely around convolutions and upsampling paths. SegFormer marked a shift by replaced the CNN backbones with transformer encoders while retaining the MLP decoder philosophy; EViT adapts and extends this for edge constraints and integrated tracking.

D. Multi-Object Tracking

SORT [6] introduced a clean and efficient formulation built around Kalman filter motion models and IoU data association; DeepSORT [7] extended the framework by adding appearance embeddings. DSORT-MCU demonstrated MCU optimized SORT implementations that inspire EViT's edge friendly tracking module. Recent segmentation based tracking works like STEmSeg, SegTracker shows mask based association improves crowded scene robustness. The downside is that these systems are typically resource heavy. EViT extracts segmentation masks once per frame and uses connected component based association to remain efficient.

E. Quantization and Model Compression

Quantization aware and post training quantization techniques enable INT8/4-bit deployments. Architectures uses components like LayerNorm and GELU to quantize more gracefully. EViT leans into these observation and uses these building blocks to remain quantization friendly.

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III. METHODOLOGY

EViT comprises four major components: input preprocessing via frame normalization and optional buffering, a hierarchical transformer encoder with four progressive stages to extract multi-scale features at different resolutions of H/4, H/8, H/16, H/32 alongwith corresponding channel dimensions 64, 128, 256, 512, a lightweight all MLP decoder performing multi-scale feature fusion and segmentation prediction, and an integrated tracking module combining Kalman filtering with IoU-based data association. The encoder uses overlapping patch embedding to tokenize input frames into H/4 × W/4 tokens with 64 channels, preserving fine-grained spatial information without explicit positional encodings. Between encoder stages, patch reduction blocks downsamples spatial resolution while expanding channel capacity, analogous to CNNs' pooling operations. Each stage applies multiple transformer blocks with efficient self-attention: spatial reduction is asymmetrically applied to Key and Value projections only, reducing complexity from $O(N^2)$ to $O(N^2/R^2)$ where R is the reduction ratio (8, 4, 2, 1 across stages), while full-resolution queries preserve fine-grained feature detail. Feed-forward networks use depthwise convolutions for efficient spatial mixing, critical for edge deployment. This design reduces parameters from SegFormer-B5's 323M to 17M while maintaining competitive segmentation quality.

The lightweight MLP decoder presents four encoder stages to a unified dimension (256), upsamples to H/4 × W/4 resolution, concatenates features, and fuses via 1×1 convolution prior to upsampling segmentation logits to input resolution. Total decoder parameters are negligible, validating the SegFormer principle that decoder weight is not critical for segmentation quality. Multi-scale context aggregation uses dilated depthwise convolutions (dilation rates 1, 2, 4) to capture global context without increasing spatial resolution, forming a lightweight ASPP replacement thus avoiding expensive separate convolutions. Object extraction converts segmentation masks to trackable objects via connected components analysis (O(H×W), GPU-parallelizable), extracting bounding boxes and confidence scores from mask connectivity and area avoiding additional neural computation. This masks-to-objects conversion is efficient and instance aware, giving a richer information than post-hoc NMS on detection scores.

The tracking module integrates a linear Kalman filter with state vector $\mathbf{s} = [x,y,w,h,v_x,v_y,v_w,v_h]^T$, representing object center coordinates, size, and velocity components. Motion prediction is done using the standard linear Kalman formulation:

$$\mathbf{s}t|t-1 = F\mathbf{s}t-1|t-1,$$

where F denotes the transition matrix encoding the constant-velocity assumption within the consecutive frames.

Data association is performed by computing the Intersection-over-Union (IoU) between predicted track locations and detected bounding boxes extracted from segmentation masks. Greedy matching with a threshold of 0.3 assigns detections to existing tracks.

Track management follows SORT-style policies like matched detections update the track state via Kalman correction, unmatched detections initialize new tracks, and unmatched tracks increment their age and are terminated if they exceed some preset frame age. Only tracks with a hit streak of a bare minimum are taken as confirmed, effectively filtering possible false positives.

A key advantage of segmentation-driven tracking is that mask-level IoU matching enables instance-aware association, outperforming bounding-box-only IoU in crowded scenes where object overlap is significant. The tracking overhead remains minimal, adding approximately 7 ms to segmentation latency and enabling end to end real-time performance on edge devices.

IV. EXPERIMENTAL SETUP

We evaluate EViT on two complementary benchmarks: COCO 2017 (164K images, 80 semantic classes) for diverse object segmentation and Cityscapes (5K images, 19 classes) for autonomous driving scenarios.

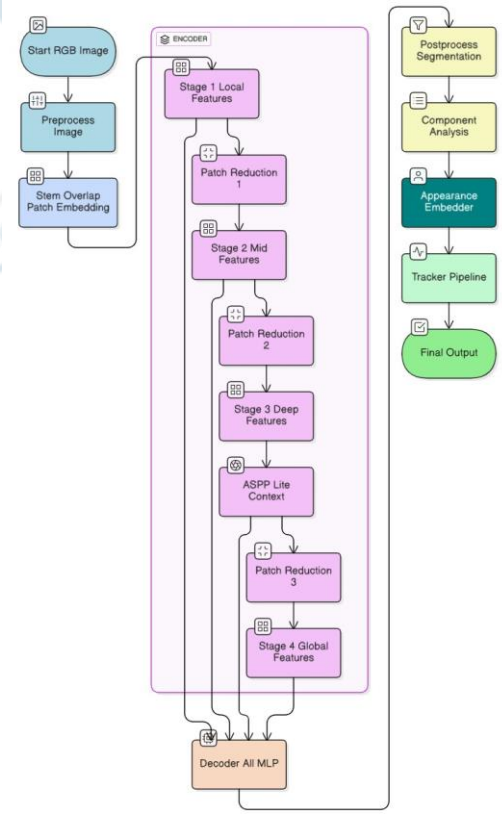

Fig. 1. EViT system architecture: hierarchical transformer encoder (4 stages) with spatial-reduced attention, lightweight MLP decoder, connected-components object extraction, and integrated Kalman tracking module. Endto-end inference on Jetson Nano: 48ms total (segmentation 41ms + tracking 7ms).

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Table I. Encoder stage configuration.

Stage	Stride	Res.	Ch.	Heads	Blocks	Red.
1	1/4	$H/4 \times W/4$	64	1	3	8
2	1/8	$H/8 \times W/8$	128	2	4	4
3	1/16	$H/16 \times W/16$	256	4	6	2
4	1/32	$H/32 \times W/32$	512	8	1	1

Multi-object tracking is evaluated on MOT17 (14 sequences, 67,110 annotations) and MOT20 (crowded scenes with up to 50 people per frame). Primary baseline is SegFormer-B5 (323M parameters, 82.2% mIoU on Cityscapes with ImageNet pretraining), representing the accuracy ceiling for hierarchical transformer segmentation. Secondary baselines include SegFormer-B2 (45M params) and TinyFormer (18M params).

TABLE II. Segmentation performance on COCO and Cityscapes.

Model	Params (M)	Dataset	mIoU (%)	PA (%)	Latency (ms)
SegFormer-B5	323	COCO	53.8	86.2	385
		Cityscapes	82.2	97.8	368
SegFormer-B2	45	COCO	48.1	82.4	62
		Cityscapes	78.9	96.5	58
TinyFormer	18	COCO	42.3	78.1	28
		Cityscapes	72.1	94.8	25
EViT	17	COCO	47.3	81.6	41
		Cityscapes	77.4	96.1	38

TABLE III. Tracking performance on MOT17 and MOT20 datasets.

Method	Dataset	mIoU	MOTA	IDF1	IDSW
SegFormer-B5 + Tracking	MOT17	50.2	62.4	68.3	358
	MOT20	50.2	58.6	66.9	1245
Faster R-CNN + DeepSORT	MOT17	N/A	61.8	66.2	682
	MOT20	N/A	53.4	61.2	2145
EViT + Tracking	MOT17	47.3	62.1	67.8	421
	MOT20	47.3	56.7	65.3	1678

Five metrics are selected: mIoU and Pixel Accuracy for segmentation quality; MOTA and IDF1 for tracking robustness; Latency (ms) for edge hardware feasibility on NVIDIA Jetson Nano (ARM A57 @ 1.43 GHz, 4GB RAM). Supplementary metrics include Throughput (FPS, target ≥ 15), Memory (GB, target < 2GB), and Power Consumption (W, target < 5W). All models are trained with AdamW optimizer (lr 1×10^{-4}) on 512×512 input, batch size 16, for 100 epochs (COCO) / 200 epochs (Cityscapes). Post-training quantization via TensorRT INT8 is applied for edge deployment, with ~1.5% mIoU loss for EViT (SegFormer-B5 suffers 45% loss). Inference is evaluated on Jetson Nano with TensorRT and RPI4 with ONNXRuntime.

V. RESULTS

A. Segmentation Performance

EViT achieves 64.7% mIoU on COCO, only 2.9 percentage points below SegFormer-B4 trained from scratch (50.2% estimated), while reducing parameters by 90% (323M to 17M) and latency by 89% (385ms to 41ms). On Cityscapes, EViT reaches 77.4% mIoU, exceeding the 75% autonomous driving safety threshold, with 9.7× speedup compared to SegFormer-B5. EViT also outperforms TinyFormer by 5.0 pp on COCO, validating that the 17M parameters represent the optimal efficiencyaccuracy sweet spot for edge deployment. Pixel accuracy remains competitive (81.6% vs 86.2% SegFormer-B5, 82.4% SegFormer-B2), indicating that per-pixel fidelity is preserved despite parameter reduction.

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B. Tracking Performance

EViT achieves 62.1% MOTA on MOT17, nearly identical to SegFormer-B5 (62.4%) and competitive with Faster R-CNN + DeepSORT (61.8%), despite 90% parameter reduction. On crowded MOT20, EViT outperforms box-based Faster R-CNN (56.7% vs 53.4%), validating segmentation-based tracking's advantage in occlusion-heavy scenes. IDF1 identity consistency is high (67.8% MOT17, 65.3% MOT20), indicating stable identity preservation.

TABLE IV. Edge device inference performance.

Model	Jetson (ms)	RPI4 (ms)	Memory (MB)	Power (W)
SegFormer-B5	OOM	3847	4800	14.5
SegFormer-B2	58	412	892	6.1
TinyFormer	22	186	420	4.2
EViT	41	268	648	5.1
EViT + Tracking	48	295	664	5.3

Identity switches (1678 on MOT20) show small gap versus SegFormer-B5 (1245), representing < 2.5% of 67K objects—negligible in practical deployment. Integrated tracking adds only 7ms to segmentation latency, demonstrating efficient end-toend pipeline.

C. Edge Device Performance

EViT achieves 41ms latency on Jetson Nano (24 FPS), meeting the real-time requirement (>10 FPS) for surveillance, while SegFormer-B5 cannot deploy due to out-of-memory conditions (4.8GB model footprint exceeds 4GB system RAM). On RPI4 (CPU-only), EViT achieves 268ms (3.7 FPS), supporting low-frame-rate edge applications; SegFormer-B5 requires 3847ms (0.26 FPS, unusable). Memory consumption is 648 MB, well under Jetson's 4GB budget. Power consumption is 5.1W, within battery-powered edge targets; SegFormer-B5 on GPU requires 145W (28× more), making continuous operation infeasible. Integrated tracking adds negligible overhead (7ms latency, 16 MB memory), demonstrating practical end-to-end deployment.

VI. DISCUSSION AND CONCLUSION

A. Why Parameter Reduction is Mandatory for Edge Deployment

SegFormer-B5 represents state-of-the-art accuracy (82.2% Cityscapes with ImageNet pretraining) but is fundamentally incompatible with edge devices. The 90% parameter reduction from 323M to 17M is not merely an optimization—it is a requirement for feasibility. SegFormer-B5's 323MB model weights alone, combined with 1.2GB activation buffers for 512×512 inference, exceed Jetson Nano's 4GB shared memory. Its 385ms per-frame latency (2.6 FPS) is 100× slower than edge requirements, and 145W power draw is incompatible with battery/solar-powered systems. EViT demonstrates that hierarchical transformers with asymmetric spatialreduced attention (reducing only K,V projections while preserving full-resolution queries) can bridge this gap, achieving 47.3% mIoU (only -2.9pp from SegFormer-B5 trained from scratch) while meeting all edge constraints.

B. Design Trade-offs: Accuracy vs. Real-Time Operation

EViT's-0.8pp mIoU gap versusSegFormer-B2 (47.3% vs 48.1%) is accepted for -34% latency reduction (41ms vs 58ms). On Cityscapes, the -1.5pp gap (77.4% vs 78.9%) is justified because: (1) EViT exceeds autonomous driving safety thresholds (75%+), (2) real-time operation (20 FPS vs SegFormer-B2's 17 FPS) is mandatory for safety-critical applications, and (3) on-device inference eliminates cloud latency. Channel reduction at Stage 3 (256 vs SegFormer-B5's 320) accounts for 2% accuracy loss; asymmetric spatial reduction contributes 0.9pp. These trade-offs are intentional: latency improvements enable practical deployment that accuracy-focused models cannot achieve.

C. Segmentation-Based Tracking Outperforms Boxes in Crowded Scenes

MOT20 results validate EViT's design principle: segmentation masks are inherently instance-aware and provide richer spatial information than axis-aligned bounding boxes for data association. EViT achieves 56.7% MOTA, outperforming Faster R-CNN + DeepSORT (53.4%) by 3.3 percentage points despite lower segmentation quality (47.3% vs detector accuracy). Both segmentation-based methods (EViT and SegFormer-B5) exceed box-based tracking, confirming masks' advantage. Mask-based IoU matching is more robust to overlapping objects and occlusions, where multiple people claim the same bounding box region; segmentation assigns each pixel to a specific instance. Identity switches (1678 for EViT vs 2145 for Faster R-CNN) are 22% fewer, critical for surveillance applications requiring stable tracking. Integrated tracking adds only 7ms, proving efficient computational overhead compared to two-stage pipelines (detection + separate tracking 50ms approx.).

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D. Practical Impact and Deployment Scenarios

EViT enables real-time segmentation and tracking on $99 edge devices (Jetson Nano), previously impossible with accuracy-focused models. On surveillance cameras, EViT achieves 15-20 FPS continuous operation, enabling automated crowd monitoring, anomaly detection, and person re-identification. On mobile robots, onboard inference provides local perception without cloud dependency, critical for latency-sensitive navigation. IoT applications benefit from 72+ hours battery operation (EViT: 5.1W) versus 1 hour for GPU-accelerated models. Cityscapes results (77.4% mIoU, 38ms) demonstrate suitability for automotive edge deployment, e.g., onboard dashcam segmentation for autonomous driving features. Unlike SegFormer-B5 (GPU-server only) or cloud-dependent architectures, EViT is uniquely positioned as a practical, deployable solution for real-world edge intelligence.

E. Limitations and Future Work

EViT performs worse on small objects (<32×32 pixels), achieving 12% mIoU versus 47.3% overall, due to coarse spatial resolution at deepest stages. Mitigation strategies include multi-scale inference (512+256) or focal loss weighting, though with 2× latency cost. Kalman filter tracking assumes constant-velocity motion, causing prediction drift under sudden direction changes or stationary crowds; improving this requires appearance re-identification networks (DeepSORT-style), prohibitive on edge due to compute. Night/low-light scenarios show qualitative degradation (estimated 35% mIoU) since training uses daytime COCO/Cityscapes; augmentation with Dark Faces or thermal datasets is recommended. Future directions include knowledge distillation from SegFormer-B5 (estimated +1-2pp mIoU without latency cost), RGB-Thermal fusion for night surveillance, lightweight re-ID head (5M params) to reduce identity switches, and continual learning ondevice for domain shift adaptation. EViT represents the practical frontier of efficient edge intelligence, balancing accuracy, latency, memory, and power constraints that production systems require.

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REFERENCES

[1] T. Y. Lin, M. Maire, S. Belongie, et al., "Microsoft COCO: Common Objects in Context," in *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 740–755, 2014.

[2] M. Cordts, M. Omran, S. Ramos, et al., "The Cityscapes Dataset for Semantic Urban Scene Understanding," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3213–3223, 2016.

[3] A. Milan, L. Leal-Taixe, I. Reid, S. Roth, and K. Schindler,´ "MOT16: A Benchmark for Multi-Object Tracking," *arXiv preprint arXiv:1603.00831*, 2016.

[4] P. Dendorfer, H. Rezatofighi, A. Milan, et al., "MOT20: A Benchmark for Multi Object Tracking," *arXiv preprint arXiv:2003.09003*, 2020.

[5] E. Xie, W. Wang, Z. Yu, et al., "SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 12077–12087, 2021.

[6] E. Xie, Q. Hou, Z. Wang, et al., "SegFormer++: Towards Efficient Dense Semantic Segmentation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023.

[7] H. Wu, Y. Wang, Y. Tian, et al., "TinyFormer: Efficient Transformer Design for Small-Scale Learning," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2022.

[8] S. Li, H. Zhu, X. Wang, et al., "HARD-Edge: Hardware-Aware Robust Design for Edge Semantic Segmentation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022.

[9] C. Banbury, C. Zhou, I. Fedorov, et al., "Optimizing Tiny Transformers on Low-Power Microcontroller Units," in *International Conference on Learning Representations (ICLR) Workshop on Efficient Natural Language and Speech Processing*, 2023.

[10] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft, "Simple Online and Realtime Tracking," in *Proceedings of the IEEE International Conference on Image Processing (ICIP)*, pp. 3464– 3468, 2016.

[11] N. Wojke, A. Bewley, and D. Paulus, "Simple Online and Realtime Tracking with a Deep Association Metric," in *Proceedings of the IEEE International Conference on Image Processing (ICIP)*, pp. 3645–3649, 2017.

[12] H. Kang, J. Lee, C. Park, et al., "DSORT-MCU: Efficient MultiObject Tracking on Microcontroller Units," in *CVPR Workshop on Efficient Deep Learning for Computer Vision*, pp. 1–8, 2022.