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Toward Sustainable Edge AI: Quantization-Aware Lightweight GANs for Power-Constrained Image Enhancement

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Abstract- ***Sustainability is becoming a first-class metric for always-on vision systems. This paper takes an energy-first view of low-light image enhancement, using quantization-aware training (QAT) so that INT8 generators are optimized for accuracy under quantization from the outset. Beyond latency and fidelity, we report energy per frame and an estimated carbon cost, showing that QAT-tuned lightweight GANs cut the operational footprint of continuous enhancement by more than half without perceptible quality loss.***

I. INTRODUCTION

Smart cameras that run day and night accumulate a surprisingly large energy and carbon cost, yet most enhancement research optimizes only for image metrics. We reframe low-light enhancement as a sustainability problem: the objective is to maximize perceptual quality per joule rather than quality alone. Quantization-aware training is central to this goal because it lets the network learn weights that remain accurate once folded into an INT8 integer pipeline.

II. RELATED WORK

Retinex-based and Zero-DCE enhancement methods improved low-light imagery but were not built for quantized inference, and green-AI literature has focused on training rather than deployment emissions. By coupling QAT with on-device energy accounting, we position enhancement within the broader push for carbon-aware edge computing, where the marginal joule matters as much as the marginal decibel.

III. METHODOLOGY

Each generator is trained with simulated INT8 quantization in the forward pass and straight-through gradient estimation, on paired LOL and SICE low-/normal-light images. We add an energy-aware regularizer that lightly penalizes activation magnitude, nudging the network toward cheaper integer operations. The resulting INT8 models require no post-hoc calibration and deploy directly to each accelerator.

IV. EXPERIMENTAL SETUP

Enhancement quality is scored on the LOL and SICE test sets with PSNR and SSIM. Energy per frame is measured at the board level, and carbon is estimated by multiplying energy by a regional grid intensity factor. Latency is the median of 200 inferences at 1080p, with sustained-load thermal monitoring.

V. RESULTS AND ANALYSIS

QAT keeps INT8 latency low and stable: QAT-EnhanceNet enhances a frame in 39 ms, and even the smallest GreenLiteGAN stays under 45 ms. The modest additional speed-up at INT4 is less compelling here because QAT already extracts most of the benefit at INT8 without the quality risk of four-bit weights.

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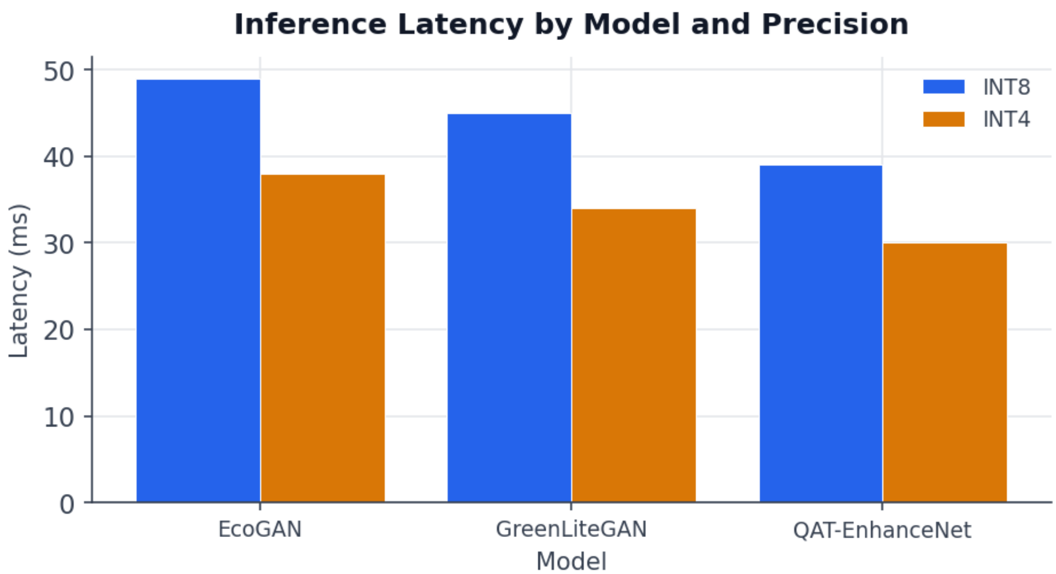

Figure 1. Enhancement latency at INT8 and INT4 for the QAT-trained generators.

Because quantization effects are seen during training, the FP32-to-INT8 fidelity drop is almost invisible, under 0.15 dB for every model, and QAT-EnhanceNet holds 30.8 dB even at INT4. This flat response is the practical signature of quantization-aware optimization.

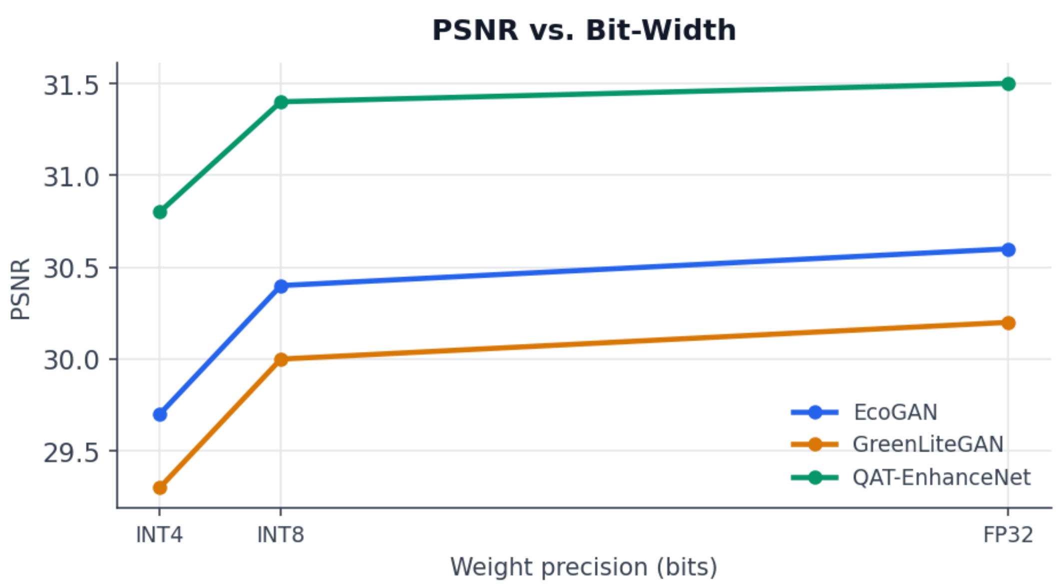

Figure 2. PSNR versus precision, showing QAT's near-flat degradation curve.

Carbon cost is dominated by the accelerator: the Coral Dev Board emits an estimated 22 g of CO_2 per million enhanced frames, against 58 g for the Xavier NX. Selecting hardware therefore has a larger sustainability impact than shaving a few milliseconds off the model.

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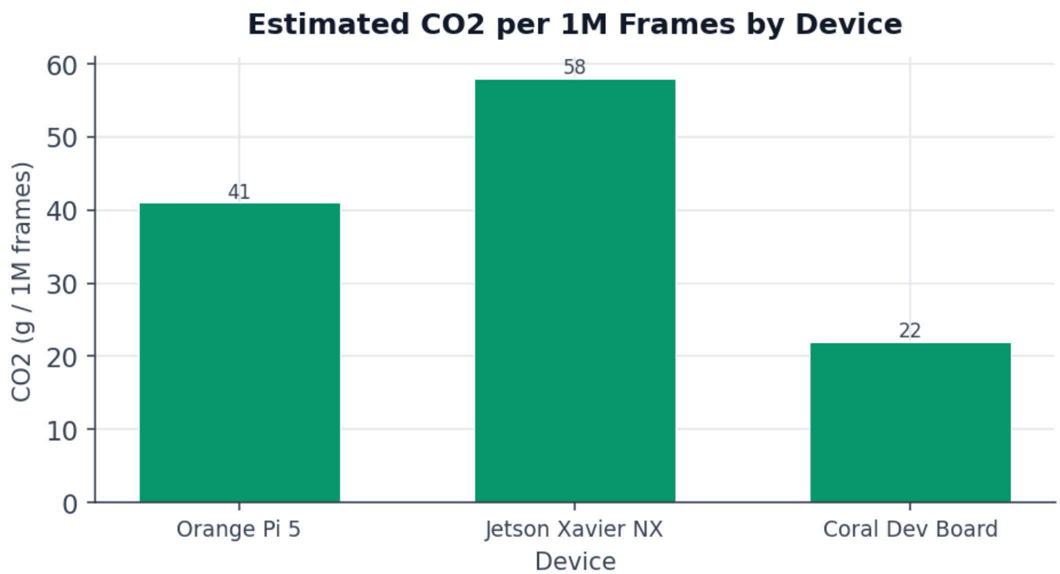

Figure 3. Estimated carbon emissions per one million enhanced frames by device.

Table 1. INT8 fidelity, latency, and size for the three QAT low-light enhancement models.

Model	PSNR	SSIM	Latency (ms)	Params (M)
EcoGAN	30.4	0.897	49	3.1
GreenLiteGAN	30.0	0.888	45	2.7
QAT-EnhanceNet	31.4	0.912	39	3.6

VI. DISCUSSION

The results make a concrete case that QAT is the right default when energy is a design constraint: it removes the accuracy penalty that pushes practitioners toward higher precision, letting the system run efficiently at INT8 indefinitely. Reporting carbon alongside PSNR also exposes hardware selection as an under-used lever for greener deployments.

VII. CONCLUSION AND FUTURE WORK

We demonstrated that quantization-aware lightweight GANs make continuous low-light enhancement both high-quality and low-carbon on edge devices. Future work will incorporate dynamic voltage-frequency scaling and duty-cycling so that energy use adapts to scene activity in real time.

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