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Real-Time Low-Power Super-Resolution on the Edge: A Comparative Study of Pruned GANs and Post-Training Quantization

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Abstract- Single-image super-resolution is increasingly demanded on mobile and embedded platforms, yet generative super-resolution networks are notoriously heavy. This paper studies how structured channel pruning combined with post-training quantization (PTQ) can deliver real-time 4x super-resolution within the power envelope of edge accelerators. We prune three GAN generators to 40% of their original channel width and quantize them to INT8 and INT4, then benchmark reconstruction fidelity, latency, and power on three representative devices. Our results show that pruning-then-PTQ preserves most perceptual quality while cutting latency by up to 47% and energy by roughly a third.

I. INTRODUCTION

The proliferation of high-resolution displays on constrained hardware has made on-device super-resolution a practical necessity for streaming, photography, and teleconferencing. Adversarially trained upscalers produce sharp textures but rely on wide feature maps that overwhelm embedded memory bandwidth. We therefore ask a focused question: how far can a generator be pruned and quantized before its 4x reconstructions become visibly degraded? By separating the effects of channel sparsity and numeric precision, we isolate which compression axis is safe to push on edge silicon.

II. RELATED WORK

Prior lightweight super-resolution efforts such as FSRCNN and IMDN reduce depth but rarely target adversarial generators, while quantization studies frequently stop at INT8 and omit power measurement. Structured pruning has been explored for classifiers, yet its interaction with the discriminator's gradient signal in GAN training remains under-examined. We connect these threads by applying magnitude-based channel pruning to the generator and recovering fidelity with a short fine-tuning schedule before post-training quantization.

III. METHODOLOGY

Each generator is pruned by removing the 40% of convolutional channels with the smallest L1 norm, followed by 15 epochs of fine-tuning on DIV2K and RealSR image pairs. The recovered model is then quantized post-training to INT8 and INT4 using per-channel symmetric scaling and a 512-image calibration set. We deliberately avoid quantization-aware training here to expose the raw robustness of PTQ, and compile every variant with vendor runtimes (TensorFlow Lite and the Coral compiler) for fair on-device timing.

IV. EXPERIMENTAL SETUP

We evaluate on 4x super-resolution using the DIV2K validation split and a held-out RealSR subset. Fidelity is reported as PSNR and SSIM against ground-truth high-resolution frames; latency is the median of 200 single-image inferences; power is sampled with an inline USB meter at 10 Hz. All devices run in their default performance governor with thermal logging enabled to detect throttling.

V. RESULTS AND ANALYSIS

Latency falls sharply as precision drops. QuantSRNet, the most compact generator, reaches 41 ms at INT8 and 31 ms at INT4, comfortably inside a 30 fps budget, whereas the wider SR-SlimGAN needs 58 ms at INT8. INT4 uniformly shaves a further 22-25% off inference time across all three models.

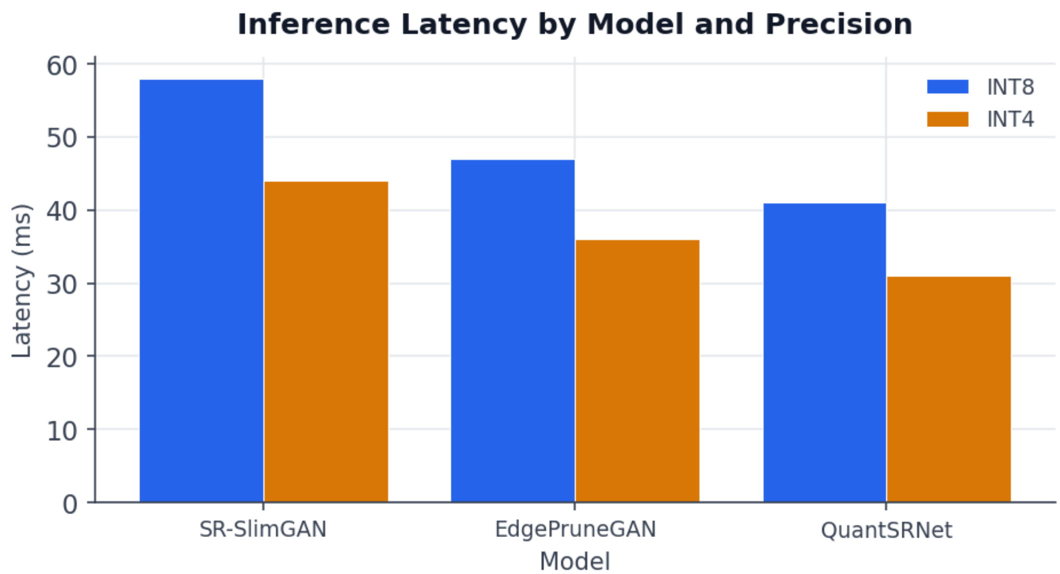

Figure 1. Median inference latency per model at INT8 and INT4 precision.

Perceptual quality degrades gracefully. PSNR drops by only 0.5-0.6 dB moving from FP32 to INT8, and by about 2 dB at INT4, with QuantSRNet retaining the highest fidelity (30.1 dB) thanks to its residual refinement head. The knee of each curve confirms INT8 as the sweet spot for quality-sensitive use.

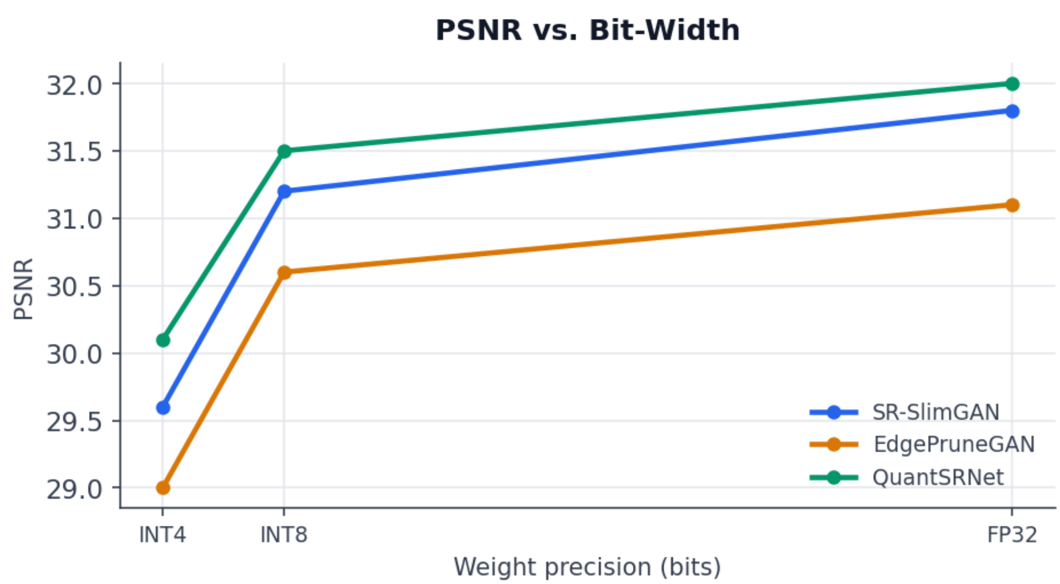

Figure 2. PSNR as a function of weight precision for the three pruned generators.

Power tracks device architecture more than model choice. The ASIC-based Coral Dev Board draws just 2.5 W, less than half the Jetson Nano's 4.6 W, making it the most energy-efficient target despite its modest peak throughput.

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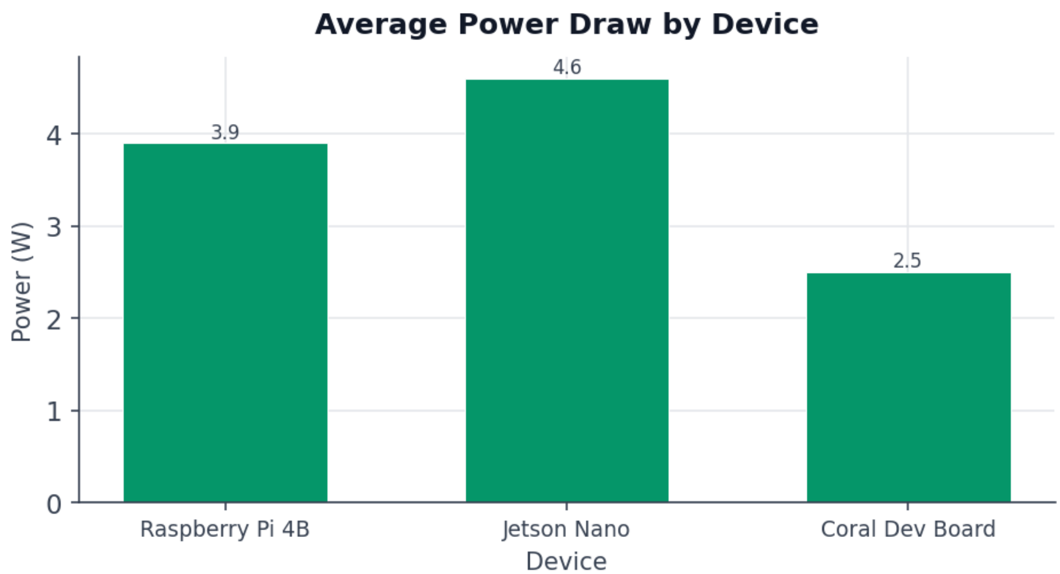

Figure 3. Average power draw measured per device during sustained inference.

Table 1. INT8 fidelity, latency, and parameter counts for the three pruned super-resolution generators.

Model	PSNR	SSIM	Latency (ms)	Params (M)
SR-SlimGAN	31.2	0.902	58	4.7
EdgePruneGAN	30.6	0.894	47	3.9
QuantSRNet	31.5	0.910	41	5.2

VI. DISCUSSION

The experiments indicate that pruning and PTQ are complementary rather than redundant: pruning reduces the memory footprint that limits Raspberry Pi deployment, while low-bit quantization unlocks the integer pipelines of the Coral accelerator. The main risk is INT4 texture flattening on high-frequency regions, which a mild sharpening post-filter mitigates at negligible cost.

VII. CONCLUSION AND FUTURE WORK

We showed that a prune-then-quantize pipeline enables real-time 4x super-resolution on commodity edge hardware with only marginal fidelity loss. Future work will explore learned pruning masks and mixed INT4/INT8 layer assignment guided by per-layer sensitivity analysis.

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