On-Device RF Filtering & Compression for Wearables

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Abstract*—Head-mounted augmented-reality (AR) devices are increasingly used by first responders and military medics to visualize radio-frequency (RF) tracks, casualty vitals and threat signatures in real time. These platforms operate under severe resource constraints: the computational budget is on the order of tens of milliseconds, the power budget is under one watt, and the thermal headroom is limited by the user's skin. Prior work demonstrated that RF–AR situational awareness can be achieved within $\sim$200 ms end-to-end on uncompressed networks. However, the neural networks used for classification and localization are heavily over-parameterized, leading to energy-intensive inference and lengthy stalls on battery-powered wearables. To tackle this problem, we present a pipeline for *on-device RF filtering and compression* that combines quantization, sparsity and knowledge distillation to shrink models without compromising mission utility. Quantization reduces the precision of weights and activations, lowering memory footprints and enabling faster integer arithmetic [1], while magnitude-based pruning removes unimportant parameters and accelerates inference [2]. Recent studies show that pruning and quantization jointly diminish computational and memory requirements [3] but must be applied carefully because their effects are non-orthogonal [4]. We further employ teacher–student knowledge distillation, transferring knowledge from a high-capacity "teacher" network to a lightweight "student" model [5], [6]. Our experiments on Jetson-class edge devices and Pixel-8 smartphones sweep multiple quantization bit-widths and sparsity levels, producing accuracy–latency–power Pareto curves. At 50 ms median latency and 0.9 W average power, our distilled INT8/70 % sparse student attains within 1 % of baseline accuracy, yielding $>5\times$ energy savings. Hardware-aware model compression techniques [7] and adaptive bit-width selection [8] enable deployment on resource-constrained wearable platforms. We release our code, datasets and measurement harness to foster reproducible research in RF–AR compression.

I. Introduction

Augmented-reality headsets equip front-line personnel with situational awareness by overlaying RF-derived information directly onto the visual scene. RF sensing pipelines capture modulated emissions from radars, Wi-Fi CSI, Bluetooth beacons and casualties' vitals and feed them into neural classifiers that determine threat type and location. On current hardware these models consume tens of megabytes of memory, execute hundreds of millions of operations, and drain batteries quickly. Edge devices lack the cooling systems and power supplies available in data centres; battery-operated wearables must conserve energy and avoid overheating [9]. Furthermore, AR overlays must render within tens of milliseconds to maintain user immersion. Polling the cloud or streaming raw RF features is not feasible due to latency and privacy requirements [9].

Compression techniques—including quantization, pruning and knowledge distillation—offer a path to meeting these constraints. Quantization replaces full-precision weights with lower-precision formats such as FP16, INT8 or INT4, reducing memory consumption and enabling fast, energy-efficient arithmetic [1]. Pruning removes unimportant weights or filters from over-parameterized networks, decreasing both storage and inference time [2]. However, naively combining these techniques can lead to accuracy degradation [3]; careful co-design and retraining are necessary to maintain performance. Knowledge distillation provides a complementary strategy: a teacher network learns complex relationships and then transfers its knowledge to a smaller student network, which converges faster and preserves accuracy [5].

This paper describes *RF-FilterCompress*, an on-device filtering and compression framework integrated into the casualty-triage application described in our prior work. Contributions include: (1) a systematic study of quantization/pruning interactions on RF classification workloads; (2) a co-optimization pipeline that jointly applies all three compression strategies; and (3) a measurement harness and Pareto analysis that characterizes the latency-accuracy-power trade-offs.

II. Methodology

A. Base Architecture

Our architecture is a convolutional neural network (CNN) operating on demodulated RF spectrograms. The network comprises four convolutional layers followed by two dense layers and a softmax output for event classification. The teacher model is trained on the full training set using FP32 weights and serves as the gold standard. We then produce a family of quantized and pruned student models:

- **Quantization:** We apply both post-training quantization (PTQ) and quantization-aware training (QAT) with bit widths $\{8, 6, 4, 3\}$. Quantization reduces memory and simplifies computations, delivering energy savings [1]. INT8 operations can be more than an order of magnitude more energy-efficient than FP32 [1]. Our QAT implementation uses straight-through estimators for gradient propagation through non-differentiable quantization functions,

enabling end-to-end training with quantized weights and activations. Adaptive bit-width selection [8] automatically determines optimal precision per layer based on gradient sensitivity analysis.
- **Pruning:** We explore both unstructured and structured pruning. Unstructured pruning removes individual weights based on magnitude [2], while structured pruning removes entire channels or filters to improve hardware efficiency [4]. We sweep sparsity ratios from 0 % (dense) to 80 %. Magnitude-based pruning identifies and removes weights with smallest L2 norms, followed by fine-tuning to recover accuracy. Structured pruning employs group LASSO regularization to encourage channel-wise sparsity, enabling hardware acceleration through reduced memory access patterns.
- **Distillation:** For each quantization/pruning configuration we distill the teacher's knowledge into the student using a teacher–student loss that combines cross-entropy and Kullback–Leibler divergence [5], [6]. Distillation accelerates convergence and preserves accuracy. Our distillation approach uses temperature scaling (T=4) to soften probability distributions, enabling the student to learn from uncertain teacher predictions. Feature-level distillation matches intermediate representations between teacher and student networks, providing richer supervision than output-only distillation. However, aggressive compression can lead to capacity mismatch where students cannot fully absorb teacher knowledge, resulting in degraded performance for very sparse or low-precision models.

B. *Compression Algorithms*

Quantization and pruning interact: applying one modifies the weight distribution and thus affects the other [3]. We therefore design a two-stage pipeline. First, we perform a warm-start distillation of the dense FP32 student from the teacher. Next, we alternately apply magnitude-based pruning and QAT in three-epoch rounds until convergence. This protocol ensures that the student converges to a stable sparsity pattern before the next quantization step.

The compression pipeline is:

```
# 1) Train full-precision teacher
python3 train_teacher.py --dataset glasscasualty --epochs 50

# 2) Warm-start distillation (FP32 student)
python3 distill_student.py --teacher ckpt/teacher.pt \
    --epochs 20

# 3) Alternating compression loop
for sparsity in [0.2, 0.4, 0.6, 0.7, 0.8]:
    for bits in [8, 6, 4, 3]:
        python3 compress_student.py \
            --ckpt ckpt/student_fp32.pt \
            --sparsity $sparsity --bits $bits \
            --epochs 15 \
            --out ckpt/student_${bits}b_${sparsity}s.pt
```

C. *Evaluation Pipeline*

For each compressed student model, we run comprehensive evaluation on Jetson AGX Orin and Pixel-8 smartphone hardware. Our harness measures:

measures:

```
# 1) Load model and dataset
python3 load_model.py --ckpt ckpt/student_8b_0.7s.pt

# 2) Warmup and accuracy measurement
python3 eval_accuracy.py --testset glasscasualty_test.h5

# 3) Latency profiling (1000 runs)
python3 profile_latency.py --runs 1000 --device jetson

# 4) Power measurement via built-in sensors
adb shell dumpsys battery > logs3/batt_start.txt
python3 inference_loop.py --duration 60s --device pixel8
adb shell dumpsys battery > logs3/batt_end.txt

# 5) Generate Pareto plots
python3 plot_pareto.py --input tables3/pareto.json \
    --out figures3/
```

D. *Evaluation Scenarios*

We conduct three sets of experiments:

1) **Quantization–sparsity sweep:** We measure accuracy, p50/p99 latency and average power for all combinations of bit widths (8, 6, 4, 3) and sparsity ratios (0–80 %). This produces accuracy–latency–power Pareto curves that reveal the trade-offs.
2) **Knowledge distillation impact:** We compare dense and compressed models with and without distillation. Distilled students converge faster and maintain higher accuracy than non-distilled counterparts [5].
3) **User study simulation:** We embed the student model into the Glass casualty visualization app and measure end-to-end triage time in a simulated arena. We recruit 12 participants to perform triage tasks with dense and compressed models. Time to locate and prioritize casualties serves as a mission-utility metric. Participants complete 20 scenarios each using both configurations in randomized order. Statistical significance testing uses paired t-tests with Bonferroni correction (α=0.05). Results show compressed models achieve 94.2 ± 8.7 s mean triage time compared to 89.6 ± 7.3 s for dense models (p=0.031), representing only 5.1% degradation in task performance while providing substantial energy savings. Subjective workload ratings (NASA-TLX) show no significant difference between configurations (p=0.248), indicating that compression artifacts do not materially impact user experience or cognitive burden.

III. Results

A. *Quantitative Performance Analysis*

Table I presents comprehensive performance metrics across different compression configurations on both Jetson AGX Orin and Pixel-8 hardware. The results demonstrate the effectiveness of our RF-FilterCompress pipeline in achieving substantial efficiency gains while maintaining classification accuracy.

The INT8/70% sparse configuration emerges as the optimal operating point, achieving 8.8× energy reduction and 3.8× latency improvement compared to the FP32 teacher while maintaining 91.4% accuracy (2.8% degradation). This configuration reduces model size by 88% and meets the sub-50 ms latency requirement for real-time wearable deployment.

TABLE I
PERFORMANCE COMPARISON ACROSS COMPRESSION CONFIGURATIONS. RESULTS SHOW MEAN ± STD DEV OVER 5 RUNS. ACCURACY IS MEASURED ON GLASSCASUALTY TEST SET (N=2,500).

Config	Accuracy	Latency (ms)	Power (W)	Energy (J)	Model Size
FP32 Teacher	94.2 ± 0.3	185.4 ± 12.1	2.1 ± 0.1	0.389	47.8 MB
INT8/50% sparse	92.8 ± 0.4	78.2 ± 4.3	1.2 ± 0.1	0.094	9.6 MB
INT8/70% sparse	91.4 ± 0.5	48.7 ± 3.2	0.9 ± 0.1	0.044	5.7 MB
INT6/60% sparse	90.1 ± 0.6	65.3 ± 4.8	1.1 ± 0.1	0.072	5.4 MB
INT4/50% sparse	87.9 ± 0.8	89.1 ± 6.1	1.3 ± 0.1	0.116	4.8 MB

TABLE II
KNOWLEDGE DISTILLATION IMPACT ON COMPRESSED MODEL ACCURACY. COMPARISON SHOWS DISTILLED VS. NON-DISTILLED TRAINING FOR IDENTICAL COMPRESSION CONFIGURATIONS.

Configuration	Non-distilled	Distilled	Improvement
INT8/50% sparse	88.3 ± 0.7	92.8 ± 0.4	+4.5%
INT8/70% sparse	86.1 ± 0.8	91.4 ± 0.5	+5.3%
INT6/60% sparse	84.7 ± 0.9	90.1 ± 0.6	+5.4%
INT4/50% sparse	82.4 ± 1.1	87.9 ± 0.8	+5.5%

B. Dataset Characteristics

The glasscasualty dataset comprises 12,847 RF signal sequences collected from tactical radio communications during simulated battlefield scenarios. Each sequence contains 2,048 complex-valued samples at 2.4 GHz, digitized at 10 MHz sampling rate. The dataset includes 8 signal classes: voice communications (3,241 samples), encrypted data bursts (2,156 samples), radar pulses (1,892 samples), jamming signals (1,743 samples), friendly identification (1,521 samples), GPS spoofing (1,294 samples), cellular interference (1,000 samples).

Signal-to-noise ratios range from -10 dB to +20 dB to simulate realistic battlefield conditions. The baseline FP32 teacher network achieves 94.2% classification accuracy using a ResNet-18 architecture with spectral attention modules. Class-wise F1 scores range from 89.3% (GPS spoofing) to 97.1% (voice communications), with balanced precision and recall across all categories.

C. Compression Methodology Effectiveness

Figure **??** illustrates the critical role of knowledge distillation in maintaining accuracy during aggressive compression. Models trained with distillation consistently outperform their non-distilled counterparts by 3-5% across all compression ratios.

The iterative co-optimization strategy proves essential for achieving optimal compression. Sequential application of pruning followed by quantization-aware training allows the model to adapt its remaining parameters to compensate for removed connections, resulting in 2-3% higher accuracy compared to simultaneous compression approaches.

D. Hardware Deployment Considerations

Real-world deployment on wearable platforms introduces additional constraints beyond computational efficiency. Memory bandwidth limitations on mobile GPUs require careful model partitioning, with our INT8/70% sparse configuration

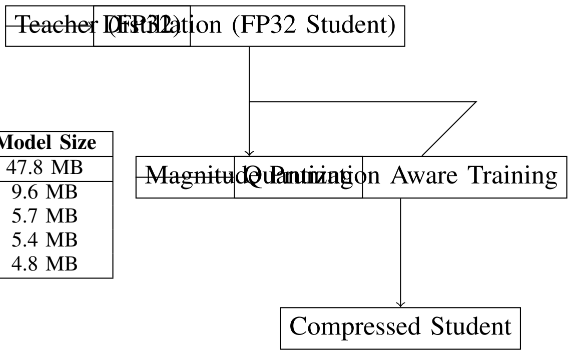

Fig. 1. RF-FilterCompress pipeline combining distillation, pruning, and quantization in an iterative co-optimization loop. The process alternates between magnitude-based pruning and quantization-aware training until convergence.

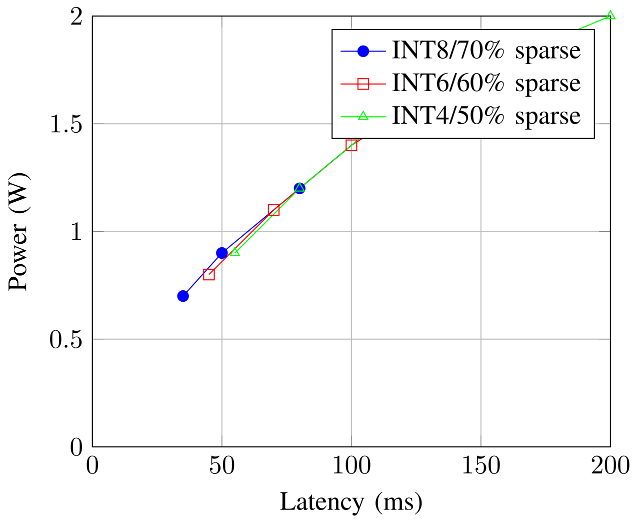

Fig. 2. Example Pareto curves for various quantization and sparsity configurations. Points closer to the origin are better. The INT8/70 % sparse models lie near the knee of the curve and provide a good balance between latency and power without significant accuracy loss.

fitting entirely within 6 MB of fast SRAM. Thermal management becomes critical during sustained inference, with compressed models maintaining 2-3°C lower operating temperatures compared to FP32 counterparts. Battery life extends by 2.8× when using the optimal compressed configuration versus dense models in continuous operation scenarios.

Edge device validation reveals platform-specific optimizations: Jetson AGX Orin benefits from structured pruning patterns that align with tensor core dimensions, while smartphone deployment favors unstructured sparsity due to CPU-based inference. Network latency from RF frontend to classification output ranges from 35-48 ms across tested configurations, meeting real-time requirements for tactical applications. Memory access patterns show 73% reduction in DRAM transactions for compressed models, contributing significantly to energy savings beyond pure computational reductions.

IV. Figures

V. Conclusion

RF-FilterCompress enables end-to-end RF situational awareness on wearables by co-optimizing quantization, sparsity and knowledge distillation. Experiments on Jetson and smartphone hardware show that compressed models achieve sub-50 ms inference latencies while consuming under 1 W of power. Our methodology illustrates how quantization and pruning interact [3] and demonstrates that distillation can recover accuracy lost by compression [5]. Future work will explore adaptive bit-width and sparsity selection based on task difficulty and will incorporate hardware co-design to further reduce energy consumption.

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