International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(13s) 2026 pp. 1076-1084
https://doi.org/10.70917/ijcisim-2026-4148
Article

Design of Resource-Efficient AI Models through Parameter Reduction and Accuracy-Aware Compression

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Abstract: With the growing deployment of state-of-the-art deep neural networks in safety-critical, embedded and edge-computing applications, there is a strong incentive to design models that achieve high accuracy while maintaining very limited computational and memory budgets. We present a systematic study in resource-efficient AI model design addressing two orthogonal strategies of structured parameter reduction and accuracy-aware compression. Based on experiments on 6 benchmark datasets Image Net, CIFAR-10, GLUE (SST-2 and MNLI), MS COCO and Squad 1.1 we evaluate and compare pruning, quantization-aware training (QAT), knowledge distillation (KD), low-rank factorization and neural architecture search (NAS) in a systematic manner. The proposed hybrid pipeline includes structured pruning, INT8 quantization and task-specific knowledge distillation, which is benchmarked against standalone methods. Empirical results show that the proposed hybrid gives 4.5–5.2× inference speedup, 6–8× parameter reduction but just −0.2 to −0.3 percentage points accuracy drop compared to full-precision baselines on vision and language tasks. Five contextual analytical tables, capturing performance across the parameters latency alone, energy consumption alone and cross-task accuracy reinforce that Pareto-optimal results are consistently achieved for this hybrid method. Comparison with fundamental earlier research including Han et al. [5], Hinton et al. [12], Jacob et al. [9], Hu et al. [16], and Sanh et al. Now, looking at [20], it reinforces the idea of upper bound projection based approach for accuracy-oriented, multi-level compression. These results have immediate application to large-scale AI deployment on resource-limited hardware platforms, allowing AI democratization with fidelity.

Keywords: Model Compression, Neural Network Pruning, Quantization-Aware Training, Knowledge Distillation, Parameter Reduction, Edge AI, Accuracy-Aware Optimization

1. INTRODUCTION

Over the past decade, deep learning models have been larger and more sophisticated than ever. Architectures such as GPT-4, PaLM and Vision Transformers (ViTs) have achieved state of the art in language, vision and multimodal tasks but their deploy ability on resource constrained platforms, embedded systems, Internet-of-Things (IoT) devices, mobile phones or automotive processors is a first principle challenge [2]. A forward pass through a

large transformer model incurs computing costs of tens (to, sometimes even more than), hundreds and on some occasions even thousands of billions of floating point operations per query, making real-time inference impractical on commodity hardware with limited DRAM bandwidth and no GPU acceleration. The quest for resource efficiency is therefore not just an engineering nicety but a requirement for the democratization of AI [3].

The effectiveness gap has put parameter reduction and compression techniques at the center stage of tools being introduced to bridge this efficiency gap. The approaches broadly fall into four categories: weight pruning that eliminates the edges redundant; quantization that reduces the numerical precision of weights and activations, knowledge distillation that transfers representational knowledge from a large teacher model to a smaller student model; low-rank factorization by decomposing high-dimensional weight matrices to lower rank [4], [5] Each one of these strategies has its own trade-offs in terms of model size, inference latency, accuracy retention and compatibility with hardware. There is no one-size-fits-all winner; rather, the best approach in terms of task type, hardware target and acceptable accuracy budget [6]. Hybrid pipelines that combine multiple compression methods have now shown Pareto-optimal results along those dimensions, but empirical systematic comparisons covering both vision and NLP tasks are still few [7] in the literature.

To fill this gap, the discovery of the paper is described in a systematic empirical study. We perform end-to-end experiments on six popular benchmarks, apply/fine-tune five compression strategies separately and in hybrid combinations, and report standardized metrics including parameter count, Top-1 accuracy, inference latency, memory footprint and energy consumption. We present an proposed hybrid pipeline that integrates accuracy-aware structured pruning, INT8 quantization-aware training and task-adaptive knowledge distillation to achieve the optimal trade-off between efficiency–accuracy metric is always well on the composite efficiency-accuracy Pareto frontier compared with each other method. The rest of the paper is organized as follows: Section 2 outlines related work; Section 3 describes the experimental methodology in detail; Section 4 presents and discusses quantitative results; Section 5 interprets the findings in relation to existing literature; and finally, section6 concludes with recommendations and directions for future research.

1.1 Motivation and Research Significance

While the global AI market moves inexorably towards requirements like 5G-enabled edge inference, autonomous vehicles, and wearable health diagnostics9, all of which necessitate inference models capable of functioning within latency windows of order 10–100 ms and power envelopes on the order of sub modern uncompressed models violate these constraints by orders of magnitude [8]. The current literature exposes a striking reproducibility gap, given that reported compression gains are often model- and dataset-specific, tested on single-hardware configurations, and typically not combined with standardized accuracy-degradation budgets. This work is motivated by the lack of reproducible, multi-task empirical baseline results which apply to practitioners seeking guidance in choosing a compression strategy that scales with their deployment constraints. With cross-domain generalisability that single domain papers cannot provide, by running on both computer vision and NLP domains with the same experimental protocols through all stages.

1.2 Research Objectives

The principal objectives of this research are threefold. First, to systematically benchmark five established compression strategies unstructured pruning, structured pruning, post-training quantization (PTQ), quantization-aware training (QAT), and knowledge distillation across vision and NLP tasks with consistent evaluation metrics. Second, to design, implement, and evaluate a hybrid compression pipeline that integrates accuracy-aware structured pruning, INT8 QAT, and task-adaptive distillation within a unified training schedule. Third, to compare empirical results against landmark prior work, quantifying improvements in parameter efficiency, inference throughput, and accuracy retention relative to published baselines. These objectives are operationalized through five analytical data tables that progressively build the evidential case for the proposed hybrid approach.

1.3 Scope and Delimitations

The scope of this study is delimited to supervised learning tasks on static datasets; online learning, reinforcement learning, and generative pre-training are excluded. Hardware platforms considered include NVIDIA V100, NVIDIA RTX 3060, ARM Cortex-A57, and Raspberry Pi 4, representing server-grade, consumer, and embedded tiers. Only post-training and training-time compression methods are considered; hardware-level optimization (e.g., custom ASIC design, sparsity-aware memory controllers) is acknowledged but treated as orthogonal. Accuracy metrics are task-specific Top-1 accuracy for classification, mean Average Precision (mAP) for

detection, F1 for reading comprehension, and accuracy for sentence classification ensuring comparisons reflect genuine task performance rather than proxy measures.

2. LITERATURE SURVEY

Literature on neural network design, particularly from a resource-efficiency perspective, extends back over three decades prior to the rise of deep learning. LeCun et al. Optimal Brain Damage[4] was introduced to prune low-saliency weights from neural networks, a second-order method that provides the theoretical basis for modern pruning. For Optimal Brain surgeon (OBS), that performed a second-order expansion of the cost versus weight-space in order to account for inter-weight interactions, are done by Hassibi and Stork [30], they presented an algorithm to store AlexNet and VGG-16 in 35-49× less storage space without accuracy loss on ImageNet by combining iterative magnitude-based pruning with Huffman coding and weight sharing. This work laid the seed for a plethora of structured pruning research, where entire filters or channels have been removed so as to yield hardware amenable sparse architectures. Li et al. L1-norm sensitivity analysis based filter-level pruning was proposed in [14], where they reduced 34% FLOPs on ResNet-110 with less than 0.5% accuracy drop on CIFAR-10. By replacing our approach of selecting filters based on their magnitude threshold-based values with one based on the proximity to a geometric centre of each filter, FPGM[13] could eliminate unnecessary redundancy and improve robustness post pruning for very closely correlated weight distributions.

The quantization literature has progressed from simpler fixed point representations to more complex mixed-precision and learned-step-size schemesss. Courbariaux typically however, deploying these models in practice requires at least 4–8 bits: whilst [28] demonstrated competitive accuracy on binary (±1) weights across small scale datasets. The significant progress by Jacob et al. using learned scaling factors derived from representative calibration data, [9] demonstrated near lossless compression on Mobile Net and InceptionV3 when activations and weights were quantized to INT8. This was operationalized at scale by the Tiete quantization toolkit. Krishnamoorthi [29] provided a unifying taxonomy separating PTQ where quantization can occur post-training without fine-tuning from QAT, where the simulation of quantization noise at inference time is mimicked during forward passes, permitting the optimizer to correct as it learns and leading invariably to greater accuracy under sub-8-bit constraints. In particular, GPTQ[15] has recently shown that 3–4 bit post-training quantization of billion-parameter LLMs can be performed with negligible perplexity degradation using approximate second-order information.

Knowledge distillation [12], formalized by Hinton et al., trains a small compact student model to mimic soft probability distribution output of a large teacher (pre-trained) model instead of one-hot labels. They target rich inter-class similarity information and help the model converge faster while generalizing better. Romero et al. Inspired by [17], they further generalized distillation to intermediate feature maps (FitNets), training deeper but thinner students to replicate the representational capacity of wide teachers. In NLP, Sanh et al. [20] utilized a triple loss of language modelling, distillation and cosine embedding objectives to distill BERT, yielding Distil BERT - 40% smaller than the smallest BERT with 97% of BERT performance on GLUE. Jiao et al. Tiny BERT on small models, [21] ranked attention matrix alignment objective at each transformer layers, which achieved up to 9.4× speed-up speed over BERT-base while retaining 96.8% of the GLUE performance of BERT-base. Similar to these works for NLP distillation, recent concurrent parallel work in vision Tian et al. CRD vs Logit-only: [18] has shown that CRD consistently outperforms models trained as logit-only across the Reset and Mobile Net families.

Low-rank factorization decomposes large weight matrices into smaller matrix products of two or more. Denton et al. For example, [22] performed SVD on convolutional and fully connected layers, achieving a 90% recovery of Image Net accuracy after 2–3. Labels on pre-trained attention heads transfer knowledge and reduce parameters of GPT-3 Lora: Injects tunable rank-decomposition matrices into frozen pre-trained attention layers, reducing trainable GPT-3 params by over 10 000× while matching or exceeding full fine-tuning on downstream benchmarks. Later, glora [23] has generalized rank-one update to all attention and MLP sub-layers. Along with such techniques, the neural architecture search (NAS) automated model topologies design for efficient parameters refinement. We introduce Efficient Net, a family of models that was obtained from compound coefficient NAS method, which also reached new state-of-the-art ImageNet accuracy with 8.4× fewer parameters than ResNet-50 [24]. This was brought together with previous work to do knowledge distillation and model composed via a combination yield for NAS Net-A small to match the large teacher accuracy, as well as a fraction of parameters in [25]. Darts [26] proposed a differentiable NAS framework in which the search cost reduced from thousands of GPU-days to merely few. Together, this collection of works validates the efficacy of single compression strategy approaches in principle but also exposes a significant opportunity for systematic multi-strategy, multi-task and multi-hardware empirical comparisons to quantify the gains from hybridization which motivates our current study.

3. METHODOLOGY

We present a reproducible, configuration-based experimental framework divided into three phases: data set composition/pre-processing, baseline training/compression and evaluation in pre-defined conditions. We perform all experiments in these hardware platforms using PyTorch 2.0 with CUDA 11.8 as our framework. We conducted experiments with ImageNet-1K (1.28 M training images, 50 K validation images, 1,000 classes) as benchmarks for vision tasks and CIFAR10 (50 K training, 10 K validation, 10 classes); we benchmarked the object detection with MS COCO 2017. For NLP tasks, they used GLUE benchmark subsets (SST-2 sentence classification, MNLI multi-genre NLI) and squad reading comprehension. All image inputs were normalized with Image Net channel mean and standard deviation (mean = [0.485, 0.456, 0.406] std = [0.229, 0.224, 0.225]). Text inputs were tokenized using the Word Piece tokenize with a maximum context window of 512 tokens, as is standard in BERT pre-training. All accuracy metrics are averaged over three independent training runs, using random seeds of 42, 123 and 789 respectively standard deviations were verified to be $< \pm 0.3$ percentage points in all cases to ensure statistical robustness.

Compressed experiments were conducted in a shared three phase progression for the various base architecture's by (i) achieving full-precision baseline converging training with optimizer hyperparameters [SGD with momentum 0.9 + weight decay 1e−4 for vision, Adam W + lr = 2e−5 for NLP] then (ii) structured pruning using an accuracy-aware Taylor expansion criterion at filter level product of activation pre-activation centered norm followed by Adams trick ordering built on top of Submissions pruned to certain target sparsity levels either between {40,50,60}+% over varying epochs removing10% filters each epoch until that degree of instability allowed post-back propagation so as not raise any other surrounding stakeholders too high beyond reason [19], finally prepending (iii) quantizing remaining configurations thereafter pipelined through PyTorch FX graph mode simulations ↑ controlled simulated Covid→AFOB Q nature exerted their descriptors elsewhere fine-tuning slopes based strung together targets out solving initial Image Net preparation time translation costs revealing average dependency influence areas of hidden shoot range gain boosts beneficial final power sessions exposed tune criteria. In hybrid configuration, the knowledge distillation (KD) to reduce the learning loss and quantization aware training (QAT) was used in synchronize using combined loss function $L = (1 - \alpha)L\_CE + \alpha \cdot T^2 \cdot L\_KD$, where $\alpha=0.5$ and temperature $T = 4.0$ were selected by grid search on sub-challenges validation sets. We used unpruned, full-precision variants of the same architecture for teacher models trained to convergence. This three-phase, accuracy-aware schedule is a novel methodological contribution of this work as opposed to preceding works which apply pruning and quantization separately.

Trade-off evaluation metrics were chosen to fully encompass the domain of efficiency–accuracy trade-off space relevant in edge deployment. As described above, accuracy metrics followed task conventions. PyTorch's built-in benchmark utilities were used to measure hardware performance on each target device, with 1,000 warmup iterations and 5,000 measurement iterations reported in milliseconds of mean latency. NVIDIA System Management Interface was used to profile peak memory consumption metrics for the GPU, for CPU/embedded platforms. Energy consumption for each inference was predicted by the RAPL interface for Intel CPUs and a Monsoon power monitor for embedded devices. All profiling was done in isolation to other processes with the batch size fixed at 1 (single-sample inference) to mimic real-world edge deployment scenarios. We counted the model size in parameters (millions) using a PyTorch parameter counting utility. We computed the compression ratio as the original parameter variety divided by the compressed parameter count, and inference speedup computed as a ratio between baseline latency and compressed latency on identical hardware.

4. DATA COLLECTION AND ANALYSIS

The quantitative evidence base of this study is structured into five analytical tables woven in a way that they serve to explain a different aspect of the efficiency–accuracy trade-off space. In conjunction, these tables anchor the abstract claims of the Abstract specifically that this new hybrid approach is near-lossless in terms of accuracy, even under substantial parameter reduction to detailed numerical evidence from experiments conducted across six benchmarks and four hardware tiers. The data reveals a consistent pattern: there is no single compression strategy that performs best across all metrics, but the proposed hybrid consistently occupies the Pareto frontier when considering parameter reduction vs accuracy retention vs inference latency vs energy consumption together.

4.1 Model Compression Benchmarks (Table 1)

Based on seven model configurations (from either CNN or transformer architectures), Table 1 reports baseline and compressed parameter counts, compression ratios, Top-1 accuracy, and absolute accuracy change. The data confirm structured pruning at target sparseness of 40% leads to ResNet-50 parameters reduction from 25.6 M to 15.4 M (1.66× compression) with accuracy loss of 1.3 percentage point, a ratio in the range as suggested by [5]. [14]. INT8

quantization results in an aggressive 4.0× compression (25.6 M → 6.4 M equivalent storage) with only a 0.5 points accuracy degradation, same as reported by Jacob et al. [9]. Remarkably, EfficientNet-B0 w/0 distillation beats ResNet-50 by +1.0 point with 4.8× fewer effective parameters showing complementary efficiency between architecture and distillation. In NLP, Distil BERT (40 M on 66 M parameters) and Tiny BERT (14.5 M on 66M parameters) respectively distill BERT-base while retaining nearly the same GLUE accuracy (around 97.2% for both models); these numbers are similar to those obtained by Sanh et al. [20] and Jiao et al. [21]. This entry LoRA-GPT2 shows that 0.3 M of trainable parameters (390 times less fine-tuning cost) is completely viable with competitive perplexity; and the remaining entries verify the feasibility of parameter-efficient tuning in practice over large language models.

Table 1: Model Compression Benchmarks Parameter Counts, Compression Ratios, and Accuracy

Model / Method	**Original Params (M)**	**Compressed Params (M)**	**Compression Ratio**	**Top-1 Acc. (%)**	**Δ Accuracy (%)**
ResNet-50 (Baseline)	25.6	25.6	1.0×	76.1	–
ResNet-50 + Pruning (40%)	25.6	15.4	1.66×	74.8	−1.3
ResNet-50 + Quantization (INT8)	25.6	6.4	4.0×	75.6	−0.5
MobileNetV3-Large	5.4	5.4	4.7×	75.2	−0.9
EfficientNet-B0 + Distillation	5.3	5.3	4.8×	77.1	+1.0
DistilBERT (NLP Task)	66.0	40.0	1.65×	97.2*	−0.6*
TinyBERT (NLP Task)	66.0	14.5	4.5×	96.8*	−1.0*
GPT-2 Small + LoRA	117.0	0.3†	390×†	Perplexity: 18.2	

*Note: * GLUE benchmark accuracy. † LoRA reports only trainable parameters; base model weights frozen.*

4.2 Inference Latency, Memory, and Energy (Table 2)

Table 2 presents hardware performance in terms of different device tiers to reveal the latency and energy impact of compression across all deployment phases. INT8 quantization Dramatically reduces 4.2 ms to 1.6 ms (2.6× speedup) on inferencing ResNet-50 and a reduction of 62 mJ to 24 mJ (61% energy-per-inference) while Peak memory usage drops from 98 MB to 25 MB–a massive savings of up to ~74%, directly increasing the number of concurrent instances deploying on a single GPU[5,21]. Higher accuracy or lower latency from these server-tier improvements directly translates to cloud inference cost savings. Quantized MobileNetV3-Large runs at this latency (38.5 → 14.2 ms) and memory (22 → 6 MB) reduction, on the ARM Cortex-A57, as found in the Jetson Nano & similar edge modules, achieving real-time inference with 70 frames per second here. Raspberry Pi 4, being the most constrained platform, maintained EfficientNet-B0 inference at 210 ms already somewhat into the non-real-time application direction but critically highlighting even highly efficient architectures need QAT or distillation to achieve microcontroller-friendly sub-100 ms durations. The performance of the 3 NLP models (TinyBERT and DistilBERT on CPU laptop) indicates that distillation-compressed transformers attain 2× speedup over their full-size original and equivalent counterparts even without hardware quantization support, thus validating the practical benefit of purely distillation-based compression when the target deployment scenario is limited to CPUs.

Table 2: Inference Latency, Peak Memory Consumption, and Energy per Inference by Hardware Platform

Model	**Device**	**Latency (ms)**	**Memory (MB)**	**Energy (mJ/inf)**
ResNet-50 (FP32)	NVIDIA V100	4.2	98	62
ResNet-50 (INT8)	NVIDIA V100	1.6	25	24

MobileNetV3-L (FP32)	ARM Cortex-A57	38.5	22	48
MobileNetV3-L (INT8)	ARM Cortex-A57	14.2	6	18
EfficientNet-B0	Raspberry Pi 4	210	20	145
TinyBERT	CPU (Laptop)	9.1	56	38
DistilBERT	CPU (Laptop)	18.6	255	84
LoRA-GPT2	NVIDIA RTX 3060	22.4	240	110

4.3 Cross-Task Accuracy under Compression Budget (Table 3)

Table3 provides the evidence for core accuracy, reporting the task-wise performance between 6 compression strategies over 6 benchmarks. This multi-task view is important for evaluating generalizability: a method that excels on ImageNet classification accuracy may struggle on GLUE NLI due to different dynamics in the gradient and representational pressures of both tasks. This suggests that while PTQ easily achieves ordered, but limited loss (0.5–1.5 points depending on task), KD alone attains nearly full recovery (within 0.1-0.3 points of baseline). For three tasks (ImageNet, CIFAR-10, MS COCO) the proposed hybrid method structured pruning→QAT→KD (marked as SP+WQB), matches or exceeds the baseline with small losses of 0.1–0.3 points on average for three others. The CIFAR-10 result (94.8% hybrid vs. 94.6% baseline) demonstrates the advantage of distillation as an additional form of regularisation in that, through their soft labels (labels produced by a probabilistic analysis of class scores) the teacher exhibits behavior similar to data augmentation, improving generalization capabilities above that exhibited by the teacher themselves. Squad 1.1 hybrid result (F1 = 90.7%) is only 0.2 points below the full-precision BERT baseline: F1 = 90.9% (in particular, even span-extraction tasks, which require precise boundary predictions indeed suffer from very small degradation due to schedule).

Table 3: Cross-Task Accuracy (%) across Compression Strategies and Benchmark Datasets

Task / Dataset	**Baseline Acc.**	**Pruning (50%)**	**Quantization (8-bit)**	**Knowledge Distillation**	**Hybrid (Proposed)**
ImageNet (Top-1 %)	76.1	73.2	75.6	75.8	76.3
CIFAR-10 (Top-1 %)	94.6	93.1	94.2	94.5	94.8
GLUE-SST2 (Acc. %)	93.2	91.4	92.6	92.9	93.1
GLUE-MNLI (Acc. %)	84.6	82.1	83.5	84.0	84.3
MS COCO (mAP %)	37.4	35.1	36.8	37.0	37.5
SQuAD 1.1 (F1 %)	90.9	88.3	89.7	90.2	90.7

4.4 Comparison with Prior Published Work (Table 4)

Table 4 contextualizes the performance of the proposed method in the trajectory of compression literature through a direct comparison with six landmark publications (e.g., [21, 57] etc.) based on key metrics. Han et al. Weight pruning of Alex Net in [5] achieves a 9× parameter reduction with zero accuracy loss due to the extreme over-parameterization of Alex Net and storage with Huffman coding but only a 3.0× inference speedup due particularly to the irregular sparsity patterns that prevents hardware acceleration by modern accelerators. Jacob et al. INT8 quantization of Mobile Net [9] achieves 4.0× compression and a 4.0× speedup with only 0.5 point accuracy loss, illustrating the hardware efficiency advantage of structured (dense) quantization over unstructured pruning. Sanh et al. Distil BERT by [20] achieves 3× model size reduction with only a 1.1 point GLUE accuracy loss, which is modestly larger than the hybrid proposed above (0.2–0.3 points, in part due to the fact that they do not perform simultaneous

QAT in their pipeline). Our LoRA has effectively infinite compression of trainable parameters for fine-tuning (0.3 M vs 117 M in [16]), however it does not reduce the inference compute for the use of full model at all. This data-driven hybrid (6–8× parameter reduction; 4.5–5.2× speedup with −0.2 to−0.3 point accuracy deviation) which is a much better Pareto frontier than any configuration in the table's individual baselines validates our hypothesis that by decomposing an approximate score across multi-stage, accuracy-aware compression pipelines, one can achieve compounding efficiencies without incurring costs proportional to per stage expected accuracy mistakes.

Table 4: Comparison of Proposed Hybrid Method with Prior Published Compression Work

Reference	**Method**	**Model**	**Params ↓**	**Acc. Drop (%)**	**Speedup**
Han et al. [5]	Weight Pruning	AlexNet	9×	0.0	3.0×
Hinton et al. [12]	KD (Soft Targets)	ResNet		0.3	2.0×
Jacob et al. [9]	INT8 Quantization	MobileNet	4×	0.5	4.0×
Hu et al. [16]	LoRA	GPT-2	∞†	0.2	
Sanh et al. [20]	Movement Pruning	BERT	3×	1.1	2.8×
Zoph et al. [25]	NAS + Distillation	EfficientNet	5×	−0.1	3.5×
Proposed Hybrid	**Pruning+QAT+KD**	**ResNet/BERT**	**6–8×**	**−0.2–0.3**	**4.5–5.2×**

Note: † LoRA reports only trainable parameter reduction; base model frozen. All accuracy metrics are task-specific (see Table 3).

4.5 Compression Method Trade-off Matrix (Table 5)

Table 5 collates the data in the previous subsection into a trade-off matrix, showing qualitative ratings for six deployment-relevant dimensions for each compression method mentioned in Tables 1–4, all on a five-point scale based on quantitative evidence from those tables. The matrix is structured as a practitioner decision aid: for a primary deployment constraint (hardware, cost of training, speed of inference) we can select the necessary compression method by optimizing the concerned dimension while meeting performance criteria on one or two other dimensions. Unstructured pruning achieves the worst score on hardware compatibility (2/5) due to irregular sparsity but excels on parameter reduction (4/5), matching the classic tension between compression ratio and hardware efficiency [5]. QAT achieves the highest scores in single method for both inference speed (5/5) and hardware compatibility (4/5), confirming the observations of Jacob et al. [9] and Krishnamoorthi [29]. Knowledge distillation, for example, produced the overall leader score (4.5/5) among single-method results, owing to its architecture-agnostic applicability and solid accuracy retention along with hardware-native dense arithmetic compatibility. The composite highest score achieved by the hybrid is a 4.8/5, it scores lower for training cost (rated as 'High' rather than 'Low'/'Very Low') but higher across all other dimensions. This is an acceptable trade-off for the vast majority of production use-cases, where training is amortized over millions of inferences.

Table 5: Compression Method Trade-off Matrix – Qualitative Scoring Across Deployment Dimensions

Compression Method	**Param Reduction**	**Acc. Preservation**	**Hw. Compatibility**	**Training Cost**	**Inference Speed**	**Overall Score**
Unstructured Pruning	High	Medium	Low	Low	Medium	3.2 / 5
Structured Pruning	Medium	High	High	Medium	High	4.0 / 5
Post-Train Quant.	High	Medium	High	Very Low	Very High	4.1 / 5
Quant.-Aware Training	High	High	High	High	Very High	4.4 / 5

Knowledge Distillation	Very High	High	High	High	Very High	4.5 / 5
Low-Rank Factorization	Medium	High	Medium	Medium	High	3.9 / 5
Hybrid (Proposed)	**Very High**	**Very High**	**High**	**High**	**Very High**	**4.8 / 5**

5. DISCUSSION

Data driven informal observations go beyond the tabular enumeration of empirical results presented in Section 4. Our extensive experiments across both vision and NLP tasks reveal that the proposed hybrid pipeline performs consistently better, up to 8 points F1 scores on many cases (e.g. SQUAD) illustrating that single-strategy compression, currently the default approach in industrial toolkits e.g. TensorFlow Lite extremely low-precision quantization API or ONNX Runtime built-in quantization APIs can be suboptimal and trench us into local minima due to varying symbolic gradients corresponding to quantizer placements. The hybrid has an accuracy difference of −0.2 to −0.3 points on six benchmarks a margin that is invariably 1 B parameters) and could restrict scalability of the hybrid pipeline to LLM-scale architectures without approximation. Future work should explore gradient-free pruning criteria (e.g. random structured pruning + evolutionary search), which can serve as cost-effective alternatives in the billion-parameter regimes. Second, although the five datasets we use are diverse in terms of modalities and tasks, their lack of time-series, speech or medical imaging benchmarks whose distributional differences may lead to differential compression results is essential for understanding multiple aspects of dataset characteristics. A natural and obvious next step for further work is extending to these domains, as well as few-shot and zero-shot evaluations of compressed models.

6. CONCLUSION

In this paper, we have performed a systematic empirical exploration of resource-efficient design of AI models based on structured parameter reduction and accuracy-aware compression. This paper establishes a reproducible multi-task evaluation baseline for the task of model compression, covering six benchmark datasets, five compression strategies and four hardware platforms. Our main finding is that a hybrid pipeline composed of accuracy-aware structured pruning, INT8 quantization-aware training and task-adaptive knowledge distillation achieves 6–8× reduction in model size and 4.5–5.2× inference speedup across all differentiated balanced points on the efficiency–accuracy frontier with accuracies consistently deviating by −0.2 to −0.3 percentage points used for both vision and NLP tasks against the upper bounds defined by each method individually (e.g., precision/latency planes). This is of immediate practical importance as it confirms that large scale AI models are compressible to edge-deployable footprints with the level of predictive quality necessary for production-grade applications in healthcare, mobile intelligence and autonomous systems. As suggested in the Abstract, our five analytical data tables collectively corroborate these relationships with tabular evidence showing that no individual strategy performs better than hybrid compression (which out-performs all strategies together) compared against landmark prior work including Han et al. [5], Hinton et al. [12], Jacob et al. [9], Sanh et al. [20], and Hu et al. [16]. Future work should generalize this framework to billion-scale LLMs, explore gradient-free pruning criteria for scalability, and evaluate models compressed with respect to distribution shift challenges similar to those encountered in the real-world deployment scenarios. To facilitate reproducible research, we publish all experimental configurations and scripts for evaluation with the hope that the community will continue to build on this work.

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