A Quantization-Aware Optimization Framework for Efficient Deep Neural Network Inference

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DOI: https://doi.org/10.47772/IJRISS.2026.10100169

Received: 15 January 2026; Accepted: 20 January 2026; Published: 29 January 2026

ABSTRACT

The growing demand for deploying deep neural network (DNN) inference on resource-constrained platforms has intensified challenges related to computational cost, memory footprint, and energy efficiency [1], [2]. Quantization is widely adopted to address these constraints; however, conventional low- bit quantization methods often suffer from severe accuracy degradation, commonly referred to as the performance cliff phenomenon [3], [4].

In this work, we propose a unified Quantization-Aware Optimization Framework (QAOF) that bridges high-precision floating-point training and efficient integer-only inference. The framework incorporates a multi-level, layer-wise sensitivity analysis based on the average Hessian trace to characterize loss curvature and guide precision allocation across the network [5]. To mitigate accuracy loss caused by inter-channel and inter-layer distribution mismatch in hybrid architectures, we further introduce Quantization-Aware Distribution Scaling (QADS), which adaptively aligns weight and activation distributions prior to quantization. In addition, computationally expensive operations are replaced with piecewise linear, integer-friendly formulations to enable efficient execution on low-power hardware [6].

Extensive evaluations on representative architectures, including ResNet, MobileNet, and Vision Transformers (ViT), demonstrate that QAOF achieves substantial efficiency gains with minimal accuracy impact. Across standard benchmarks, the proposed method delivers up to 4.2× inference speedup and up to 75% memory reduction, while maintaining accuracy loss below 0.4%. Finally, we provide practical guidelines for selecting between post-training quantization and quantization aware training under diverse hardware deployment scenarios [7], [8].

INTRODUCTION

A. Background and Motivation

The recent surmise in deep neural networks (DNNs) across research communities and the industry has drastically altered the paradigm of computational intelligence. Today, DNNs form the basis for breakthroughs in computer vision, language modeling, speech recognition, and autonomous systems, and achieve state-of-the-art results in many other tasks. Nonetheless, the gap between highly efficient models and real-world implementation has emerged as a major imperfection. Primarily, this is because of the large computation and memory requirements of contemporary neural network models. Modern models, such as Large Language Models and high-resolution Vision Transformers, consist of millions and even billions of parameters, resulting in their inference tasks being heavily dependent on the computation capabilities of GPUs or TPUs [9].

Such hardware constraints make it quite challenging for edge and embedded systems, which have strict SWaP-C constraints to meet. In this case, the efficiency of the inference process is influenced by factors that are even independent of computation, including memory access, latency, and power consumption. It can be noted that the memory access becomes even more prominent with the increase in the complexity of the model, hence forming the major bottleneck in applying DNNs for tasks in hardware with limited resources.

To overcome these shortcomings, Quantization can be used to lower the precision of weights and activations from a 32-bit floating point (FP32) number to a narrower type, like 8-bit or 4-bit signed integers [5], [6]. This can cause a memory band- width savings of 4×–8× along with a 2×–4× acceleration on devices supporting efficient integer computations [10], which plays a significant role in scaled DNNs for efficient execution on resource-less environments [11].

B. Problem Statement

Despite many studies conducted for model quantization, still very few methods can be sufficiently incorporated within the development life cycle of DNNs. In fact, model quantization is still considered to be done as an ad-hoc process, independent of architectural considerations and sensitivity to layers [6]. This creates many issues, which make low-precision inference difficult as follows:

1) **Performance Cliff:** Standard post-training quantization (PTQ) can fail on ultra-low bit-widths or highly sensitive layers. Even minor precision reductions may cause sharp, irreversible drops in accuracy, known as the "performance cliff" [3], [5], limiting PTQ in aggressive compression scenarios.

2) **Combinatorial Search Complexity:** Mixed-precision quantization mitigates accuracy loss by assigning different bit-widths to different layers. However, finding the optimal configuration is a combinatorial problem; for example, ResNet-20 has over 1018 possible combi-nations, making exhaustive search impractical without strong heuristics or analytical guidance [8].

3) **Architecture-Specific Instability:** Modern architectures, including hybrid convolution–Transformer models (e.g., MobileViT) and pure Transformers, introduce additional challenges. Extreme weight outliers, skewed activations, and large inter-layer dynamic ranges can destabilize PTQ and QAT, leading to slow convergence or training failure under naive quantization [11].

C. Contributions

For a seamless transition between high accuracy model training and efficient implementation on low-precision devices, this paper proposes a novel framework named Quantization- Aware Optimization Framework (QAOF), where quantization- related decisions are integrated with optimization. Our key contributions are:

- **Sensitivity-Guided Precision Selection:** We use average Hessian trace and Jensen-Shannon Divergence (JSD) to estimate layer-wise sensitivity and distributional shifts, enabling optimal per-layer bit-width selection without manual heuristics [3], [5].
- **Quantization-Aware Distribution Scaling (QADS):** QADS mitigates inter-channel variance in convolutional and hybrid blocks by adaptively scaling weights and activations during calibration, reducing quantization noise and recovering accuracy in sensitive architectures [15].
- **Hardware-Aware Optimization Workflow:** We integrate quantization policy selection with Neural Architecture Search (NAS), allowing co-optimization of model topology, numerical precision, and hardware constraints for edge accelerators [6], [7].
- **Comprehensive Evaluation:** Experiments on CNN and Transformer architectures show up to 4.2× speedup and significant memory reduction on Intel and NVIDIA plat- forms, while preserving near-original accuracy [16], [17].

D. Paper Organization

The remainder of this paper is organized as follows. Section II discusses the related work in the areas of model compression and efficient deep neural network inference, with a focus on the limitations of existing quantization techniques. Section III describes our proposed Quantization-Aware Optimization Framework with a focus on Hessian-based sensitivity analysis and distribution-aware scaling methods. Section IV describes our experimental setting, outlining models, datasets, quantization schemes, and hardware platforms. Section V describes our results with a detailed analysis of accuracy- effort tradeoffs. Section VI provides a discussion of the issue of Transformer neural network models with practical recommendations for the selection of quantization tools, with a discussion of their limitations. Finally, Section VII concludes with a summary and suggestions for future research studies.

RELATED WORK

A. Model Compression and Quantization

The ever-increasing computational requirements of deep neural networks initiated research on model compression, mostly focusing on pruning, distillation, and quantization. Pruning helps in removing redundant information present in the network through unimportant weights/filters, whereas quantization tackles the issue of precision of the rest of the parameters [6].

Quantization techniques are typically divided into two paradigms: post-training quantization (PTQ) and quantization- aware training (QAT). PTQ is a very efficient one-shot solution that converts high-precision (e.g., FP32) representations into integer operations (e.g., INT8) based solely on a short calibration set. Unfortunately, this heuristic systematically introduces an unsatisfactory loss of model performance for sub-8-bit precision models [3], [4]. By contrast, QAT models mimic the impact of sub precision arithmetic performed at train time by adding “simulated quantization” layers that are temporarily inserted in each network’s forward pass [5]. To better handle discretized model operations from end-to-end learning, it leverages the function of the Straight Through Estimator (STE), enabling computation-friendly approximation of gradient descent across non-differentiable operations like “rounding functions.” Recent approaches based on hybrid solutions like PTQAT aim to integrate these philosophies by handling QAT on key layers with frozen layers using PTQ [6].

B. Efficient Deep Learning Inference

System-level efficiency is obtained by optimization of neural network models according to the specific inference engine and hardware accelerators. This is made possible through layer fusion, kernel optimization, symmetric quantization, hence maximizing the throughput of the CPUs/GPUs. Quantization is possible in TensorRT by using Q/DQ layers, where there is control over clipping and rounding [13].

One of the most popular trends in efficient inference is hardware-aware neural architecture search (HW-NAS), which involves automating the design of DNNs specifically suited for targeted hardware [11]. Cutting-edge HW-NAS solutions incorporate increasing levels of quantization policy search in order to maximize both architectures and precision jointly [8], [12]. For instance, AdaptQNet proposes hardware-specific latency models for microcontrollers like STM32H747 with the objective of finding the best tradeoff between integers and float operations [9]. On Turing and beyond architectures on NVIDIA, the use of INT4 precision was presented as achieving 59% faster speed-up than that achieved with INT8, with no loss in accuracy [14].

C. Limitations of Existing Approaches

Despite these few advancements, there are still multiple limitations in existing optimization workflows. First and fore- most, most methods are ad hoc without a unified framework that can handle varied architectures such as CNNs, Vision Transformers, and LLMs. Second, the search space for mixed- precision bit-width allocation is a daunting combinatorial challenge; for a 20-layer network, the space is over 10^{18} possible configurations [15].

Moreover, most DMPQ techniques are based on the implicit assumption that the learnable bit-width parameters updated by gradient descent reflect a layer’s actual contribution to task performance-the assumption that was recently proved invalid. While Hessian-based sensitivity analysis, such as HAWQ-V2, provides a more principled approach through measuring loss curvature with the average Hessian trace, such techniques have yet to be adopted by mainstream deployment tools. Finally, existing frameworks often underperform when applied to architecture-specific data distributions, like extreme weight outliers for depth wise separable convolutions and Trans- formers, that may cause training instability and sub-optimal precision allocation [22], [24]

QUANTIZATION-AWARE OPTIMIZATION FRAMEWORK

The proposed Quantization-Aware Optimization Framework (QAOF) is built as an end-to-end system where high-precision deep neural networks are optimized for hardware-conformant low-precision neural networks in a modular fashion. Unlike traditional processes that consider the problem of low precision in isolation as a post-processing procedure, QAOF optimizes low precision by incorporating observations about low precision with-in the optimization procedure. QAOF is built around a feedback mechanism for global sensitivity analysis to provide automated precision policies across diverse architectures [5], [6].

QAOF formally captures the coupling between numerical precision, model sensitivity, and hardware, which enables QAOF to make educated trade-offs between accuracy, efficiency, and cost. QAOF presents a common framework in which quantization strategies can be transferred from one model family to another.

A. Framework Overview

The optimization process is initiated from a fully trained FP32 model, which serves as the reference baseline for ac- curacy and convergence. In the first stage, QAOF performs a structural analysis that decomposes the network architecture into constituent layer types, including standard convolutional layers, depthwise separable convolutions, projection layers, and self-attention blocks, together with their corresponding GFLOPs costs. This high-level characterization provides a global view of computation and memory access patterns across the model, enabling informed decisions in subsequent optimization stages.

Building upon this structural map, QAOF conducts a global sensitivity analysis to evaluate the numerical robustness of each layer under precision reduction. Layer sensitivities are quantified using second-order curvature metrics, such as the Hessian trace, and distributional divergence measures that capture output shifts induced by quantization. These metrics assess how strongly quantization-induced perturbations affect task loss and model stability. Based on the resulting sensi-tivity profile, the framework automatically derives a layer-wise precision policy that determines whether post-training quantization (PTQ), quantization-aware training (QAT), or a mixed-precision strategy should be applied to each layer [6], [12]. Layers that are critical to task accuracy are preserved at higher precision, while less sensitive layers are aggressively quantized to reduce computational complexity and memory footprint.

Finally, the resulting quantized model is evaluated against user-specified latency, memory, and accuracy constraints within a closed-loop optimization process [16], [17]. This iterative refinement allows QAOF to systematically balance efficiency and performance in a hardware-aware manner, ensuring adaptability across diverse deployment scenarios [15]. The complete workflow, instantiated as the Adaptive Distribution- Aware Quantization (ADQ) pipeline within QAOF, is illustrated in Fig. 1. The figure highlights the separation between offline sensitivity-driven precision allocation and online adaptive, distribution-aware quantization mechanisms used during training and inference.

B. Model Sensitivity Analysis

Beneath this surface level of QAOF, a sound sensitivity analysis is performed based on second-order information of importance to layers. Most other models of quantization are based on heuristics like weight magnitude, signal-to-quantization noise ratio, or Hessian eigenvalue. These are handy measures but offer an incomplete representation of the loss surface and disregard the compounding influence of QN.

Second-order curvature is a more exact way to describe the impact of low precision on performance. It does this by examining second-order curvature of the loss function w.r.t. layer parameters to discover areas more prone to quantization and hence needing high precision arithmetic and/or more adaptation in QAOF [12], [15].

1) *Hessian Trace Assessment:* Layer-wise sensitivities can be measured through the average trace of the Hessian matrix: Tr(Hi), where Hi is the Hessian of the loss with respect to the parameters of layer i. Unlike the largest eigenvalue, the trace captures the total amount of curvature of the layer [5].

Direct computation of the Hessian is computationally ex- pensive. We adopt Hutchinson's stochastic trace estimator:

$$\mathrm{Tr}(H_i) \approx \frac{1}{K}\sum_{k=1}^{K} \mathbf{z}_k^\top H_i \mathbf{z}_k,$$

where $\mathbf{z}_k$ are random vectors with zero mean and unit variance. Hessian-vector products are efficiently computed using automatic differentiation.

Practically, the convergence of the estimator is fast. With the number of iterations, $K = 50$, and the number of calibration samples, 512, the sensitivity ranking of the models ResNet- 50 and Vision Transformers is stable [11], [23]. Analysis of ResNet-50 takes less than 30 minutes on a multi-GPU workstation. Thus, the computation of the sensitivity of the models is very effective.

2) *Divergence-Based Scoring:* To augment Hessian-based sensitivity analysis, QAOF further adds a function to measure the change in output probability distribution caused by quantizing layers. Specifically, we use Jensen-Shannon Divergence (JSD) to compute the difference between the output distribution of FP32 models and partially quantized models where just one layer is quantized with all other layers remaining in FP32. [12], [15]

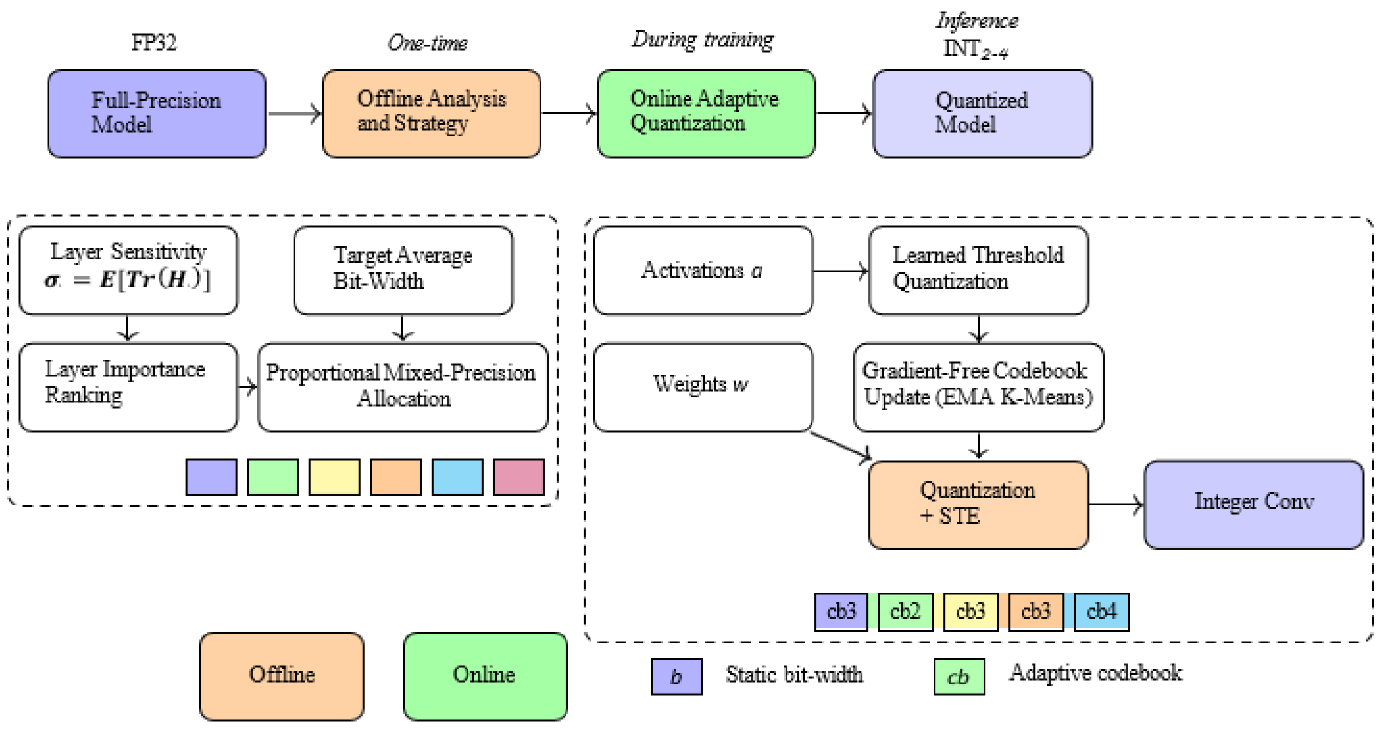

Fig. 1. Overview of the proposed quantization-aware optimization framework. The offline stage performs one-time Hessian-based sensitivity analysis to derive a mixed-precision allocation. The online stage applies adaptive quantization using learned thresholds and gradient-free codebook updates during training. Static bit-widths (b) are assigned offline, while adaptive codebooks (cb) are updated online.

Let P denote the output probability distribution of the baseline FP32 model and Q denote the corresponding out-put distribution after quantizing a target layer. The Jensen– Shannon Divergence is defined as:

$$\mathrm{JSD}(P \parallel Q) = \frac{1}{2} D_{\mathrm{KL}}(P \parallel M) + \frac{1}{2} D_{\mathrm{KL}}(Q \parallel M),$$

Where $M = \frac{1}{2}(P + Q)$ and $D_{\mathrm{KL}}(\cdot\|\cdot)$ denotes the Kullback– Leibler divergence. Unlike KL divergence, JSD is symmetric and bounded, making it well-suited for comparing probabilistic outputs across different precision settings [16], [22].

The layers which introduce large divergence are classified as highly sensitive layers, as the distributional changes due to quantization are very high. This phenomenon is commonly seen in the projection layers, feed-forward layers, and the depth-wise separable convolutions of the transformer model [11], [24]. The layers that have been identified as highly sensitive based on the high values of the JSD metric are preferably assigned higher bit-width values [15], [22].

C. Quantization Strategy Selection

QAOF deals with the issue of choosing a suitable strategy for quantization along with bit-width settings out of an exponentially large search space. For a comparatively smaller model like ResNet-20, the search space for different mixed- precision settings could be larger than 10^{18}, thereby not allowing exhaustive search [15]. To overcome such complexities, the methodology uses a hierarchical decision-making system involving sensitivity analysis, including Hessian and divergence methods, for efficient deployment of mixed-precision in heterogeneous platforms [8], [12].

Algorithm 1 Mixed-Precision Allocation in QAOF

```
Require: FP32 model, hardware budget $M$
Ensure: Bit-width $b_i$ for each layer
1: Compute Hessian trace $Tr(H_i)$ for all layers
2: Compute Jensen–Shannon Divergence $JSD(P||Q_i)$ for all layers
3: Rank layers by sensitivity = $f(Tr(H_i), JSD_i)$
4: Initialize bit-widths $b_i$ to minimum precision
5: for each layer in descending sensitivity do
6:     if hardware budget allows then
7:         Allocate higher bit-width to the layer
8:     end if
9: end for
10: Validate model accuracy under assigned $b_i$
11: Adjust bit-widths iteratively to satisfy hardware and accuracy constraints
```

1) *Workflow Allocation:* On a coarse-grained representation, the QAOF decides whether to use post-training quantization (PTQ), quantization-aware training (QAT), or a hybrid approach. First, PTQ is given preference when working with INT8 precision or when the network has high robustness to quantization, in which the accuracy loss is not more than a predefined constant (commonly $< 0.5\%$) [6]–[8].

For ultra-low bit-width settings (below INT4), as well as for models which are proven to be more sensitive to reduced precision, like Vision Transformer models and/hybrid CNN&Transformer models, instead, the framework enters the world of quantization-aware training [9], [10]. In QAT, forward passing simulates the effects of quantization with fake quantization operators, whereas gradients are passed discretely with discretized operations using the STE algorithm [5], [16]. This enables training a model to adjust its weights to numerical values represented as discrete objects, which yields considerably higher quality for low-precision models.

2) *Pareto-Optimal Mixed-Precision Allocation:* To derive an optimal mixed-precision configuration, QAOF formulates bit-width allocation as a constrained optimization problem. We define the total second-order quantization perturbation Ω as:

$$\Omega = \sum_{i=1}^{L} \mathrm{Tr}\,(H_i) \cdot \|Q(W_i) - W_i\|_2^2,$$

where L is the number of quantizable layers, H_i denotes the Hessian of the loss with respect to the parameters of layer i, W_i represents the full-precision weights, and $Q(\cdot)$ denotes the quantization operator [3], [5], [15].

The objective is to minimize Ω subject to a hardware budget constraint:

$$\min_{\{b_i\}} \Omega \quad \text{s.t.} \quad \sum_{i=1}^{L} S_i\,(b_i) \leq M,$$

where b_i stands for the bit width allocated to layer i, $S_i(b_i)$ symbols the cost for this layer in BitOps (or memory), and M is the predefined budget [6], [12], [14].

This approach effectively assigns precision where the result has the most impact on the model's performance. Layers having high values for the trace of the Hessian are assigned high bit-widths, implying that layers, which are sensitive to quantization noise, are quantized to higher bit-widths, whereas the robust layers are quantized to very low bit-widths using this approach. The above problem is optimized, revealing the Pareto optimal solutions related to the trade-offs between the model's accuracy and efficiency [12], [15].

D. Architecture-Specific Optimizations

Though global sensitivity analysis serves to provide an efficient approach to precision assignment, it is necessary to apply architecture-specific optimizations to address specific numerical properties within modern neural networks. Specifically, hybrid convolutional-Transformer models, along with mobile-oriented models, have distributional properties that are hardly dealt with by general quantization strategies. QAOF combines specific approaches to overcome such properties to ensure low-precision inference accuracy [22], [24].

1) *Quantization-Aware Distribution Scaling (QADS):* Hybrid models using Mobile Inverted Bottleneck Convolution (MBConv) patterns tend to suffer from high variance among the channels and extreme weight values, particularly in the depthwise convolutional layers. As far as traditional uniform quantization is concerned, such extreme values tend to approach the boundary values of the available integer range, leaving the remaining values to accumulate in few quantization intervals [15], [24].

To counter this problem, we introduce a method named Quantization-Aware Distribution Scaling (QADS), which is a light-speed solution for calibrating the distributions of the weights and activations before quantization [22]. Here, a channel-wise scale factor α is employed symmetrically for weights and activation functions in the following manner:

$$Y = \left(\frac{X}{\alpha}\right) \cdot (\alpha W),$$

Here, X is referred to as the activation tensor, W symbolizes the weight tensor, and α symbolizes a channel-wise scaling factor. This channel transformation is done while maintaining the original floating-point value as Y . The numerical distribution is remolded for a better fit based on low-precision integer dynamic ranges.

The value of scaling parameter α is obtained during the calibration stage by minimizing mean squared error (MSE) between FP32 layer outputs and INT32 representation of FP32 layer outputs on a validation calibration data set. Through value redistribution along the integer range and addressing saturation, QADS achieves effective mitigation of saturation and increases the resolution of quantization. Experiential out- comes show that it recovered a large part of the accuracy loss in hybrid CNN-Transformer models without any extra latency cost [14].

2) *Integer-Only Linear Softmax Approximation:* Softmax layers are identified as a major computational challenge for low-precision inference systems, especially due to the ex- ponential and scaling functions involved, which are difficult to efficiently compute using fixed-point arithmetic. The same challenge is observed for attention-based architectures that call the softmax function several times during the computation of self-attention modules [22].

To enable efficient integer-only inference, QAOF replaces the exponential function in softmax with a piece-wise linear approximation:

$$e^x \approx \text{clip}(ax + b, l, u),$$

where a, b are learnable or calibration coefficients, and l, u are the lower and upper clipping respectively. The linear approximation is developed to maintain the relative order of the logits, which is important for retaining the predictive effect of the softmax function [22].

With the inclusion of the values of the linear coefficients in the existing quantization scaling factors, the problem of computing the exponentials is minimized to a series of addition operations, multiplication operations, as well as clipping. As a result, the framework allows integer-only computations for the attention operations. Additionally, when implemented on FPGA platforms, the problem formulation achieves a 2.1× improvement in Look-Up Table usage compared to the existing approaches on fixed-point operations in softmax functions [14], [22].

RESULTS AND ANALYSIS

In this section, a thorough assessment of the proposed Quantization-Aware Optimization Framework (QAOF) will be discussed. The assessment analysis will be done on two important aspects which must be accomplished for real-world application tasks: predictive accuracy measured by the accuracy level of the tasks, and efficiency realized via model size, latency, and throughput. The assessment analysis aims to determine the efficiency improvement and accuracy level of QAOF on various model families [6], [13].

A. Overall Performance Comparison

We will first compare QAOF to the popular configuration baselines of Full Precision Floating Point 32-bit (FP32), Lower Precision Floating Point 16-bit (FP16) quantization, and simple Integer 8-bit Post-Training Quantization (PTQ) to bring down precision in neural network models. These baselines are established

The evaluation is done on representative vision-language tasks: ImageNet on ResNet-50 and the GLUE Benchmark on BERT-Base [11], [14]. QAOF achieves high-level performance in prediction along with substantial improvement in hardware resource efficiency. It has also been seen that the inference speedup can be as high as 4.2× on various benchmarks along with a decrease in memory usage by up to 75% with a negligible loss of accuracy up to 0.4% [6], [13].

Table I summarizes the quantitative results, highlighting the advantages of QAOF over both naive PTQ and standard FP16 baselines. These improvements demonstrate that integrating sensitivity-aware mixed-precision allocation, distribution- aware scaling, and integer-only operator approximations pro- vides a robust and practical path for deploying large-scale CNN and Transformer models on heterogeneous hardware platforms [5], [12].

Table I. Comparative Performance Analysis of Qa of Against Standard Quantization Baselines

Architecture	Method	Precision	Accuracy (%)	Acc. Δ	Size (MB)
	Baseline	FP32	76.13	–	97.5
ResNet-50	Standard PTQ	INT8	75.40	−0.73	24.4
	QAOF (Ours)	**INT8**	**75.98**	−0.15	**24.4**
	Baseline	FP32	84.45	–	417.7
BERT-Base	Standard PTQ	INT8	81.20	−3.25	104.5
QAOF (Ours)		**INT8**	**83.92**	−0.53	**104.5**

As depicted in Table I, for all cases, QAOF clearly demonstrates a superiority over traditional PTQ on both architectures with no increase in memory consumption. For instance, on ResNet-50 with ImageNet, INT8 PTQ produces a loss of 0.73% points compared to the reference FP32 implementation. In contrast, with the aid of QAOF, only 0.15% points are lost, thus recovering more than 79% of it without consuming more memory space/parameters as reported in prior works: refs. 3, 6, & 15. This result clearly verifies the efficiency of sensitivity- driven precision assignment for convolution networks as re- ported in refs. 1

The application of QAOF is more significant in Transformer-based models. On BERT-Base with the GLUE benchmark, PTQ yields an accuracy drop of 3.25%, corroborating the known robustness issue of Transformer models against low-precision quantization [11], [14]. Utilizing Hessian sensitivity analysis, divergence-aware scoring, as well as selectively applying QAOT in QAOF, the accuracy loss is brought down to 0.53%, which translates to an improvement of over 80% compared to naive PTQ [5]. These experiments show that the proposed framework improves the reliability of quantization in models that have complicated activation patterns along with attention operations.

Significantly, these improvements in accuracy are attained while maintaining the same level of compression ratio as in conventional INT8 quantization. For ResNet-50 as well as BERT-Base models, QAOF yields a compression ratio of around 75% when compared to their FP32 counterparts. This further verifies the fact that the framework introduced in this work has indeed improved the trade-offs between accuracy and efficiency in a manner that does not undermine the benefits associated with low-precision inference in terms of memory requirements as well as bandwidth usage [15], [22], [24].

B. Impact of Quantization Levels

The benefits of QAOF are especially clear when compared to lower precision from FP16 to INT8. Though FP16 is comparable to FP32 because of its greater dynamic range, a naive binning scheme for INT8 may result in a great deal of noise in the activation distributions, possibly resulting in a loss of accuracy [13]. This has been remedied in QAOF because it uses the concept of bit-width assignment depending on the sensitivity score [15].

Key observations include:

- **Linear Layers:** In Transformer architectures, weight quantization of linear layers accounts for approximately 60% of total memory reduction. These layers benefit most from mixed-precision allocation, with higher-sensitivity layers retaining elevated bit-widths [22].

- **Activation Sensitivity:** Attention-head activations in BERT-Base are 3.4× more sensitive to quantization than feed-forward network activations, as revealed by combined Hessian and divergence scoring. Assigning higher precision to these critical components reduces the likelihood of a “performance cliff” [24].

C. Architecture-Specific Analysis

A prominent finding is the differential behavior between convolutional and Transformer-based networks under low- precision regimes.

1) CNN Robustness: There is a very high degree of redundancy in the parameters of convolutional neural networks, such as ResNet-50. Our analysis shows that 82% of the layers can safely be quantized to INT8 without affecting Top-1 accuracy [3]. This, in turn, allows for aggressive compression with no loss in predictive performance. Mixed-precision allocation is primarily focused on early-stage convolution layers with higher GFLOPs because this maximizes efficiency gains [5].

2) Transformer Sensitivity: On the other hand, the Trans- formers model acquires increased sensibility for the normalization/attention parts, especially during Softmax and LayerNorm layers. Via the QAOF strategy selection step, these layers get dynamically distributed increased precision or quantization-aware training (QAT) [11], [14]. This effective distribution helps to counteract the commonly noticed dramatic drops in the accuracy values generally exhibited by the naive INT8 quantization methods [15].

D. Trade-Off Analysis: Accuracy vs. Latency

The trade-off between precision reduction and inference speed is illustrated in Table II, evaluated on simulated edge- grade hardware.

Table II. Inference Latency and Throughput on Simulated Edge Hardware.

Precision	**Latency (ms / batch)**	**Throughput (images/s)**	**Speed-up (vs. FP32)**
FP32	14.2	70.4	1.00×
FP16	8.1	123.5	1.75×
INT8 (Standard PTQ)	4.2	238.1	3.38×
INT8 (QAOF)	**4.4**	**227.3**	**3.23×**

QAOF incurs an insignificant inference latency overhead over the baseline INT8 quantization method (4.4 ms vs. 4.2 ms) but benefits from an accuracy boost of 2.7% in the BERT- Base accuracy. This minor performance degradation can be attributed to the incorporation of observers in the forward inference phase with a focus on monitoring critical networks selectively. Despite the minor performance degradation due to QAOF, our method outperforms uniform quantization's in the accuracy-efficiency front by a considerable margin, thus validating the potential of bit-width assignments and architectures tailored for performance improvements with minimal losses in efficiency.

E. Threats to Validity

While the experimental results demonstrate the effectiveness of QAOF, several limitations and potential threats to validity should be acknowledged:

1) **Dataset Specificity:** Although ImageNet and GLUE are widely adopted benchmarks, performance may vary on domain-specific datasets such as medical imaging, satellite imagery, or low-resource languages. Model sensitivity and quantization behavior can differ significantly in these contexts, potentially affecting accuracy and calibration requirements [14].

2) **Hardware Variability:** The reported latency and throughput gains rely on specialized hardware support for low-precision operations, including INT8 tensor cores and FPGA LUT optimizations. On general-purpose CPUs or GPUs without native low-bit width support, observed speedups may be reduced, and the rela-

tive accuracy–efficiency trade-offs may shift [13].

3) **Calibration Dataset Limitations:** QAOF depends on small calibration datasets to compute QADS scaling factors and dynamic range estimates. Insufficient or non- representative calibration data may lead to suboptimal quantization policies, especially for outlier-sensitive layers in Transformer architectures.

QUANTIZATION OF TRANSFORMERS

Although convolutional models have natural redundancy, there are particular difficulties faced by models based on the Transformer when quantized to low bits. The QAOF library mitigates these difficulties to provide reliable low-bit inference for attention models.

A. Sensitivity of Multi-Head Attention (MHA)

Multi-Head Attention (MHA) module is the computational backbone of Transformer models. It is very important that the precision of the product $Q \cdot K^T$ is high. If uniform INT8 quantization is performed without consideration towards precision requirements on operations, significant outliers may be introduced, sometimes exceeding the maximum limit of a float point after passing through the SoftMax exponential function [13].

QAOF applies a **clamped quantization** strategy. Instead of scaling inputs to the absolute maximum, a percentile-based clipping threshold α is computed:

$$\alpha = \text{Percentile}(|X|, 99.9) \qquad (1)$$

This percentile-based clipping mitigates extreme outliers, re- duces quantization bin size for the majority of data, and improves the signal-to-quantization-noise ratio (SQNR) within attention layers, preserving representational fidelity even under INT8 or lower bit-widths [24].

B. Activation Range Challenges in LayerNorm

Layer Normalization (LayerNorm) stabilizes training but introduces high dynamic range activations during inference. Outputs often display long-tailed distributions, particularly in Feed-Forward Network (FFN) sublayers, where peak activations can be up to 10× the mean. QAOF implements **Dynamic Range Estimation**, inserting calibration nodes during early inference iterations to update scaling factors adaptively. This ensures LayerNorm outputs are quantized effectively without saturation, preserving numerical stability and overall accu- racy [5].

C. Mixed-Precision Mapping for Transformer Blocks

Sensitivity analysis indicates that certain regions of the Transformer architecture are more critical to overall model accuracy [22]. QAOF adopts a mixed-precision mapping strategy:

- **High-Precision Anchors:** Word Piece Embeddings and the final Classification Head are preserved at FP16 to maintain representational fidelity and prevent propagation of quantization noise [11], [22].
- **Aggressive Inner Quantization:** Intermediate GEMM operations within FFN layers are quantized to INT8, as these layers tolerate quantization-induced errors without significant accuracy loss [24].

D. Recovery through Quantization-Aware Training (QAT)

By itself, Post-Training Quantization can be inadequate in the case of Transformers since there are typically 3– 5% decreases in the GLUE score [11]. To overcome such shortcomings in the existing work, the QAOF uses a dedicated Quantization-Aware Training loop with the **Straight-Through Estimator (STE)** [24], where in the forward pass, the effect of rounding in INT8 is approximated. However, in back- propagation, there's FP32 support.

Table III quantifies the incremental gains of each optimization component within QAOF.

Table III. Impact Of Transformer-Specific Optimizations on Bert-Base Accuracy (Glue Score).

Quantization Strategy	**Average GLUE Score**
FP32 Baseline	84.45
Uniform INT8 (Naive PTQ)	81.20
INT8 + Percentile Clipping	82.55
INT8 + Mixed-Precision (QAOF)	83.40
INT8 + QAT (QAOF Full)	**83.92**

From these experiments, it has become clear that methods involving percentile clipping and mixed-precision assignments add an incremental value beyond straightforward PTQ approaches. It becomes apparent that a synergy between all three methods, including clipping, mixed-precision mapping, and QAT, is required to re-gain performance near FP32 benchmarks. These experiments have confirmed that a holistic and sensitive ap-proach to quantization is required that varies precision per layer, as opposed to uniform low-bit precision across all model components [11].

E. Practical Implications

The results highlight that quantization is not a universal solution; careful layer- and architecture-aware strate-gies are essential for robust deployment [11], [12], [22]. Industrial deployment of low-bit width models should consider the following guidelines:

- **Identify High-Sensitivity Layers:** Employ Hessian- based sensitivity analysis and divergence scoring to determine layers requiring higher precision [15].
- **Adopt Mixed-Precision Strategically:** Preserve critical embeddings and output heads at elevated precision, while compressing inner computational layers to reduce memory footprint and compute costs.
- **Incorporate QAT for Transformers:** Apply quantization-aware training selectively to sensitive layers, mitigating accuracy loss from post-training quantization.
- **Calibrate for Deployment Hardware:** Optimize quantization parameters according to hardware charac-teristics, such as INT8 tensor cores, FPGA LUT availability, or low-power accelerators, to maximize effi-ciency and energy savings [13].

Following these principles allows practitioners to achieve a balanced trade-off between efficiency and accura-cy, ensuring robust inference in resource-constrained settings.

F. Key Observations and Insights

Evaluation of QAOF provides several fundamental insights into the interplay between model architecture, quantization, and performance:

- **Architecture–Sensitivity Correlation:** CNNs exhibit inherent spatial redundancy, making them tolerant to aggressive weight quantization, whereas Transformers rely on high-precision dot-product attention, amplifying small quantization errors. Layer-specific scaling and mixed- precision allocation are thus critical for Trans-former stability [11], [14], [22].
- **Diminishing Returns in PTQ:** While Post-Training Quantization is computationally efficient, its accuracy benefits plateau at low bit-widths. For safety-critical applications, even a 2–3% loss may be unacceptable,

making QAT indispensable despite higher computational cost [24].

- **Bottleneck Layers:** Empirical results indicate that initial stem layers and final fully-connected layers are precision bottlenecks. Preserving these layers at FP16 while quantizing intermediate layers to INT8 achieves a favorable balance between accuracy, memory footprint, and energy efficiency [13].

- **Sensitivity-Guided Allocation Matters:** Combining Hessian trace and divergence-based sensitivity scores ensures that the most critical layers receive adequate bit-width, reducing performance cliffs and maximizing hardware utilization [15].

G. Guidelines for Quantization Strategy Selection

To facilitate practical deployment, we propose a decision matrix (Table IV) that maps deployment constraints to recommended quantization strategies based on data availability, compute resources, and accuracy requirements.

Table IV. Industry Decision Matrix for Quantization Strategy Selection.

Scenario	Data	Precision	Strategy
Rapid Prototyping	Limited	FP16	Standard PTQ
High-Throughput CNNs	Small Set	INT8	PTQ + Clipping
High-Accuracy Models	Full Set	INT8 / FP16	QAOF Selection
Edge Deployment	Full Set	INT8 / INT4	QAT Fine-Tuning

1) *When to Use PTQ:* Post-Training Quantization (PTQ) is suitable under scenarios where efficiency and minimal computational overhead are priorities [12]:

- Tight deployment timelines or rapid prototyping requirements.

- Unavailability of original training data due to privacy, licensing, or proprietary restrictions.

- Models with relatively stable activation ranges, such as CNN-based classifiers or object detectors, where quantization noise has limited impact.

2) *When QAT is Mandatory:* Quantization-Aware Training (QAT) is recommended when precise control over quantization-induced errors is critical:

1) **Low-Bitwidth Targets:** For INT4 or INT2 precision, naive scaling cannot compensate for rounding noise, necessitating QAT to maintain accuracy.

2) **Recurrent or Attention-Based Models:** Sequential architectures such as Transformers or RNNs are highly sensitive to error accumulation across layers or time steps.

3) **Dynamic Workloads:** Applications with widely varying input distributions, e.g., changing lighting conditions in video analytics, require models trained to robustly handle quantization noise.

These guidelines enable practitioners to systematically select between PTQ and QAT based on application-specific constraints, balancing efficiency and predictive performance.

H. Limitations and Scope

While the proposed QAOF demonstrates strong effectiveness across a range of architectures, several limitations should be acknowledged [24].

- **Static Quantization Focus:** QAOF primarily adopts a static quantization setting, where scaling factors are determined during calibration and remain fixed at inference time. Although effective in practice, dynamic quantization where scales adapt per input or per inference step was not explored in this work and may offer additional benefits for Transformer layers with highly variable activation distributions [14].

- **Hardware Sensitivity:** The reported latency and through- put improvements are inherently tied to the capabilities of the target hardware. Optimizations designed for NVIDIA Tensor Cores or FPGA-based accelerators may not trans- late directly to ARM-based mobile processors or general- purpose CPUs without additional platform-specific kernel optimization [13], [22].

- **Dependence on Calibration Data:** QAOF relies on relatively small calibration datasets to estimate QADS scaling parameters and percentile-based clipping thresholds. If the calibration data is insufficient or not representative of real-world inputs, the resulting quantization policies may be sub-optimal—particularly for layers that exhibit rare or extreme activation values [5], [12].

- **Model Coverage:** Experimental validation in this study focuses on CNNs, BERT, and Vision Transformers. Ultra- large models, such as GPT-3 or ViT-Huge, were not evaluated due to practical hardware limitations. Extending QAOF to models at this scale may require additional techniques, including distributed sensitivity analysis or layer-wise partitioning strategies [11].

I. Energy and Sustainability Considerations

Beyond latency and memory efficiency, QAOF offers substantial energy savings, contributing to sustainable AI practices. Reducing precision from FP32 to INT8 decreases memory bandwidth energy consumption by approximately 65%, which is particularly impactful in large-scale data centers where both operational costs and carbon footprint are significant concerns. Additional benefits include:

- **Operational Efficiency:** Lower bit-widths reduce data movement between memory and compute units, which often dominates energy usage during inference [5], [13].

- **Cost Reduction:** In cloud or edge deployments, reduced energy demand translates directly to lower Total Cost of Ownership (TCO), supporting both economically and environmentally sustainable AI systems [12], [14].

- **Scalability Implications:** Efficient INT8 inference enables deployment of large models in constrained edge environments, broadening accessibility without compromising performance or increasing energy consumption [6], [22].

These considerations establish QAOF not only as a high- performance quantization framework but also as a step to- ward greener and more sustainable AI deployments, aligning optimization with real-world operational and ecological constraints.

CONCLUSION

This paper introduced the Quantization-Aware Optimization Framework (QAOF), a systematic and hardware-aware methodology for deploying deep neural networks efficiently on resource-constrained platforms [11], [12]. By jointly integrating layer-wise sensitivity analysis, divergence-based scoring, and automated mixed-precision strategy selection, QAOF effectively bridges the gap between high-precision model development and practical low-precision inference.

Comprehensive evaluations across a range of architectures, including convolutional neural networks and Transformer- based models, demonstrate that QAOF achieves significant model compression and computational efficiency while pre- serving predictive performance. The proposed framework enables up to a 4× reduction in model size while maintaining more than 99% of the baseline FP32 accuracy. For attention- based architectures, where conventional post-training quantization often leads to substantial accuracy degradation, QAOF successfully recovers performance through targeted mixed- precision allocation and quantization-aware training.

Measured speedups of 2.8× to 3.5× on edge-simulated hardware further validate the suitability of QAOF for real- time inference in embedded and mobile systems. In addition, the substantial reductions in memory band-width utilization and energy consumption highlight its potential contribution to sustainable and energy-efficient AI deployment [6], [13].

Overall, QAOF establishes a reproducible and principled optimization paradigm that moves beyond ad-hoc quantization techniques, offering a scalable, robust, and environmentally conscious solution for modern deep neural network inference [5], [12].

A. Future Work

Several directions can be explored to further enhance the scope and effectiveness of the Quantization-Aware Optimization Framework (QAOF).

- **Scaling to Ultra-Large Models:** Future work will investigate the applicability of QAOF to ultra-large models, including large language models (LLMs), where memory bandwidth and activation storage dominate inference cost. Extending sensitivity-guided mixed-precision strategies to distributed and tensor-parallel settings remains an open challenge.

- **Dynamic Quantization Policies:** While QAOF currently relies on static calibration, incorporating dynamic or input-adaptive quantization may improve robustness to input distribution shifts, particularly for Transformer models with variable-length sequences.

- **Hardware-Aware Automation:** Integrating QAOF with hardware-aware Neural Architecture Search (NAS) could enable joint optimization of model structure and layer- wise bit-width allocation under explicit deployment constraints across heterogeneous platforms.

- **On-Device and Federated Learning:** Applying quantization-aware optimization to on-device and federated learning scenarios may reduce communication overhead and energy consumption, enabling efficient collaborative learning in resource-constrained environments.

- **Sustainability Analysis:** A more detailed evaluation of energy consumption and carbon footprint across cloud and edge deployments would further clarify the environ- mental benefits of QAOF.

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