Robust and Efficient Multi-Crop Disease Diagnosis via Quantization Aware Training for Edge Deployment

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***Abstract*—High computing costs and poor network access make it difficult to implement deep learning models for crop disease diagnostics in agricultural settings with low resources, like rural India. This calls for the creation of effective, lightweight models that can infer on-device. A reliable process for building such models with Quantization Aware Training (QAT) is presented in this research.To provide a high-performance baseline, we train a full-precision MobileNetV3-Large model using a composite dataset of photos taken in both lab and field conditions. We next refine this model using QAT, adjusting its weights to fit 8-bit integer (INT8) requirements. With a 74% size reduction (from 16.55 MB to 4.24 MB) and a 2x speedup in CPU inference time (from 57.28 ms to 27.72 ms), the resulting INT8 model is not only noticeably more efficient, but it is also clearly more accurate, with a 1.59% absolute improvement in classification accuracy over its 32-bit floating-point counterpart. Our results confirm that QAT is an excellent method for improving performance and compressing models. We show that QAT can function as a potent regularizer, enhancing model generalization and making it an essential tool for creating workable, field-deployable AI solutions in agriculture, in contrast to the widely held belief that there will be an accuracy trade-off.**

***Index Terms*—Deep Learning, Computer Vision, Agriculture, Model Quantization, Edge AI, MobileNetV3, QAT**

I. Introduction

The foundation of the Indian economy is the agricultural sector, but it is constantly threatened by pests and illnesses, which cause significant losses in crop output each year—up to 35%, according to some estimates [1]. The demand for resilient and productive farming systems is increased by the growing global population and the increasing impacts of climate change. In this regard, Convolutional Neural Networks (CNNs), a type of deep learning in artificial intelligence (AI), have become a game-changing technology that could improve crop management by providing quick and precise disease identification. [2].

Nevertheless, there is a sizable ”deployment gap” between these sophisticated models' potential and actual use in rural agricultural environments. There are two main limitations that determine this gap. First, cloud-dependent solutions are impracticable for field decision-making in real time due to the unpredictability of internet connectivity in many agricultural settings. Second, most small and marginal farmers cannot afford or logistically manage the high computational and memory requirements of state-of-the-art CNNs, which require costly, high-performance gear like GPUs. This fact necessitates that research concentrate on energy-efficient, lightweight solutions that can execute inference directly on inexpensive, widely used edge devices, such as smartphones.

This deployment issue is accompanied by a significant ”generalization gap” in terms of model resilience. Using datasets like PlantVillage, which include photos taken in a controlled laboratory setting with consistent lighting and plain backgrounds, a significant amount of research has shown good diagnosis accuracy. [3]. However, the performance of these same models frequently declines significantly when tested on ”in-the-wild” datasets like PlantDoc, which contain photos captured in actual field settings with cluttered backdrops, fluctuating illumination, and a variety of camera angles. [4]. This emphasizes how important it is to create models that are both effective and resilient enough to generalize from clean training data to the intricate visual environments that are encountered in real-world scenarios.

By creating and validating a thorough model optimization methodology, this study directly solves these two issues. As a crucial enabling technology for on-device deployment, we present model quantization. This paper's main contribution is the empirical proof that Quantization Aware Training (QAT) can generate a concurrent multi-crop disease diagnostic model:

1) **Lightweight:** Reducing the model's size by about four times to make it easier to distribute and store on mobile devices.
2) **Fast:**Enabling real-time analysis by providing a CPU inference time speedup of more than two times.
3) **More Accurate:** demonstrating a notable increase in classification accuracy compared to its full-precision baseline, defying the belief that quantization requires a performance compromise.

The effectiveness of this strategy demonstrates a potent synergy: by serving as an efficient regularizer, the method selected to address the deployment problem (QAT) simultaneously makes a substantial contribution to the resolution of the generalization problem. Because of these two advantages, QAT is a very effective technique for developing agricultural AI that is ready for the field.

II. Related Work

A. Lightweight Architectures for Plant Pathology

With the introduction of deep learning, the use of computer vision in plant pathology has changed dramatically. Early studies effectively used deep, potent CNN architectures like ResNet [5] and VGG [6], which showed an amazing capacity to learn discriminative features from leaf pictures and attain high classification accuracies. These "heavyweight" models, however, are inappropriate for edge devices with limited resources due to their huge computational loads and tens of millions of parameters.

This limitation spurred the development of novel, "lightweight" architectures explicitly designed for efficiency. The MobileNet family of models has been particularly influential, introducing depthwise separable convolutions to dramatically reduce the number of parameters and computations with minimal impact on accuracy [7]. The MobileNetV3-Large architecture, selected for this study, builds upon this legacy by using inverted residuals, lightweight attention mechanisms, and other optimizations found through neural architecture search to maximize performance on mobile CPUs [8]. This focus on architectural efficiency is crucial for addressing the deployment gap.

However, architecture alone does not solve the generalization problem. The performance disparity between models trained on the controlled PlantVillage dataset and those tested on the challenging, in-the-wild PlantDoc dataset remains a critical research frontier. This highlights that a successful deployment strategy requires not only an efficient model architecture but also a robust training and optimization methodology that can produce a model resilient to real-world visual variability.

B. Neural Network Quantization

Neural network quantization is a powerful model compression technique that reduces the numerical precision of a model's weights and activations, typically from 32-bit floating-point (FP32) to low-bit integer formats like 8-bit integers (INT8) [9]. This conversion leads to a substantial reduction in model size and can dramatically accelerate inference, especially on hardware with specialized support for integer arithmetic. This conversion relies on a standard affine mapping between the floating-point reals (r) and the quantized integers (q), governed by the equation $r \approx S \cdot (q - Z)$. Here, S represents a per-tensor or per-channel scale factor, and Z is an integer zero-point that ensures the real value of zero is represented without error [9].

Two primary paradigms for quantization exist: Post-Training Quantization (PTQ) and Quantization-Aware Training (QAT).

Post-Training Quantization (PTQ) is applied to an already-trained model. It is a simpler and faster method that typically uses a small, unlabeled calibration dataset to determine the optimal quantization parameters (S and Z) for each layer. Recent advancements in PTQ have sought to minimize the accuracy degradation associated with this process. For instance, Padeiro et al. proposed Similarity-Preserving Quantization (SPQ), a state-of-the-art PTQ method that introduces a novel reconstruction loss [10]. Instead of merely matching the output values of the full-precision and quantized models, SPQ aims to preserve the pairwise activation similarities between them. This forces the quantized model to maintain the relational structure of the original model's feature space, leading to better performance preservation.

Quantization-Aware Training (QAT), in contrast, simulates the effects of quantization during a model fine-tuning phase [9]. By inserting "fake quantization" operations into the model graph, QAT allows the model's weights to adapt to the precision loss and quantization noise during training. This process is more computationally intensive than PTQ but often yields a quantized model with significantly higher accuracy.

The methodology presented in this paper is a practical and robust application of QAT. While advanced PTQ methods like SPQ show great promise, their implementation can be complex and may face compatibility issues with certain model operations or deep learning library backends. The initial stages of this project encountered such challenges, where attempts to apply Post-Training Static Quantization (PTSQ) to an EfficientNetV2 model failed due to unsupported operations and library incompatibilities [11]. This experience underscores a crucial engineering reality: the maturity and stability of the supporting toolchain can be as critical to success as the theoretical elegance of the algorithm itself. The pivot to MobileNetV3-Large and QAT was a pragmatic decision driven by the robust and well-integrated support for this combination within the PyTorch framework, providing a reliable pathway to achieving a high-performance quantized model.

III. Methodology for Efficient Model Development

The development of the final optimized model followed an iterative, multi-stage process, beginning with careful data curation and culminating in the application of Quantization Aware Training.

A. Dataset Curation and Augmentation

To build a model capable of generalizing, we combined a foundational lab-style dataset (PlantVillage), which includes over 54,000 images taken in controlled settings [3], with a more challenging field-captured dataset (PlantDoc) [4]. The latter introduces the visual complexity of "in-the-wild" photos, featuring cluttered backgrounds and variable lighting, which is crucial for improving robustness.

The combination of these datasets resulted in a rich and diverse collection covering 66 unique crop/disease classes. A subset of 72,000 images was utilized for the final training run to provide a comprehensive learning environment for the model [11]. To further enhance robustness and mitigate the risk of overfitting, a strong data augmentation pipeline was applied to the training set. All images were first resized to 224x224 pixels. Subsequently, a series of random transformations were applied, including random cropping, horizontal and vertical flips, rotations, and color jittering. This process artificially expanded the diversity of the training data, forcing the model

to learn features that are invariant to changes in orientation, scale, and lighting.

B. Baseline FP32 "Teacher" Model Training

A critical prerequisite for successful quantization is the creation of a high-quality, full-precision (FP32) "teacher" model to serve as a performance baseline. The MobileNetV3-Large architecture was selected for this purpose, owing to its high efficiency and excellent support for quantization within the PyTorch ecosystem [8].

Initial training attempts with this model yielded a low validation accuracy of approximately 28%, which was diagnosed as severe overfitting [11]. This outcome highlighted that the success of the final quantized model was contingent upon first establishing a well-generalized teacher model. Consequently, a deliberate, three-part strategy was implemented to improve the baseline:

1) **Increased Data:** The training subset was expanded to 72,000 images, providing the model with a much larger and more diverse set of examples to learn from.
2) **L2 Regularization:** To discourage the model from memorizing the training data, L2 regularization was introduced by adding a 'weight$_d ecay$'of1e-4$to the Adam optimizer. This penalizes large weight values, promoting a simpler and more generalizable model.$ **Advanced Learni**
$style approach$1001[12]$. This method smoothly decays the learni$ *ngrate from its initial maximum to a set minimum according to a* c
at any given epoch t is determined by the function:

$$\eta_t = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min})(1 + \cos(\frac{T_{cur}}{T_{max}}\pi)) \quad (1)$$

where η_{max} is the initial learning rate, η_{min} is the minimum learning rate, T_{max} is the total number of epochs, and T_{cur} is the current epoch number.

This refined training regimen was highly effective, boosting the final validation accuracy of the FP32 baseline model to a robust 42.46% [11]. This meticulous process of creating a strong teacher model was a foundational and necessary step for the success of the subsequent quantization phase.

C. Quantization Aware Fine-Tuning

The core of our optimization was applying QAT, following the standard workflow available in modern deep learning frameworks [9]. The process involved three conceptual stages: First, the trained FP32 model was prepared by inserting nodes into the computational graph that simulate the noise and precision loss of INT8 arithmetic. Second, the model underwent a brief fine-tuning period, allowing its weights to adapt to these simulated quantization effects. Finally, the model was converted into a true INT8 format, where the learned scale and zero-point parameters are finalized and the model is ready for efficient integer-only inference.

IV. Experiments and Results

A. Experimental Setup

To ensure reproducibility and provide a clear context for the results, the experimental setup is detailed below.

3) **Hardware:** All model training and fine-tuning were conducted within a Kaggle notebook environment, leveraging an NVIDIA T4 GPU with 16GB of VRAM for accelerated computation. Crucially, all final evaluations of model performance, including inference latency and accuracy measurements, were performed exclusively on the CPU. This was a deliberate choice to simulate the target deployment environment of a standard smartphone or low-cost edge device, which typically lacks a dedicated GPU [11].

- **Software:** The implementation was built using PyTorch version 2.6.0. The quantization backend was explicitly configured to use 'qnnpack' [13]. This backend is highly optimized for ARM CPUs, which are prevalent in mobile devices. This choice was essential for ensuring broad compatibility and for overcoming library bugs and unsupported operations that were encountered with the default 'fbgemm' backend during initial experimentation [11].
- **Evaluation Metrics:** The performance of the baseline FP32 model and the final INT8 QAT model were rigorously compared on an unseen test set using three key metrics:
  1) **Top-1 Classification Accuracy:** The percentage of test images correctly classified by the model.
  2) **Model Size:** The on-disk file size of the model checkpoint, measured in megabytes (MB).
  3) **CPU Inference Latency:** The average time required to perform a forward pass on a single image, measured in milliseconds (ms) on the CPU.

B. Quantitative Analysis

The comparative evaluation of the full-precision baseline model against the final optimized INT8 model yielded exceptional results. The key performance metrics are summarized in Table I, providing a direct and clear comparison of the impact of the Quantization Aware Training workflow.

TABLE I
Performance Comparison of FP32 and INT8 Models

Model	Accuracy (%)	Size (MB)	Latency (ms)
FP32 Baseline	42.46	16.55	57.28
INT8 QAT	**44.05**	**4.24**	**27.72**

Note: All results are from the project's final evaluation [11].

C. Discussion of Findings

The results presented in Table I are highly compelling and provide strong validation for the proposed methodology. The analysis reveals three significant outcomes:

1) **Successful Compression:** The model's on-disk size was reduced from 16.55 MB to 4.24 MB, a substantial 74.4% reduction. This nearly 4x decrease in the storage footprint is a critical achievement, making the model significantly easier to distribute, deploy, and store on mobile devices, where storage capacity is often limited [11].

2) **Drastic Inference Speed-Up:** The average CPU inference latency was more than halved, dropping from 57.28 ms per image to just 27.72 ms. This represents a 2.07x speed-up, enabling genuine real-time diagnostic capabilities. A farmer can capture an image and receive a diagnosis almost instantaneously, a crucial feature for practical in-field use [11].
3) **Counter-Intuitive Accuracy Improvement:** Most significantly, the final INT8 QAT model achieved a Top-1 accuracy of 44.05%, an absolute improvement of 1.59% over the 42.46% accuracy of its FP32 baseline. This result is particularly noteworthy as it defies the common expectation that quantization involves an accuracy-efficiency trade-off. Instead of a performance penalty, the optimization process yielded a demonstrably more accurate model.

This unexpected accuracy improvement suggests a deeper mechanism at play. It is hypothesized that the QAT process itself acts as a powerful form of regularization. The introduction of simulated quantization noise during the fine-tuning phase constrains the model's weight space, making it more difficult for the model to overfit to the training data by memorizing noise or non-essential features. This constraint forces the model to learn more robust and generalizable representations of the underlying data patterns. The result is a model that not only performs better on the held-out test set but is also likely to be more resilient to the subtle variations encountered in real-world field data [11].

This regularization effect may be particularly synergistic with an already compact architecture like MobileNetV3. Parameter-efficient models, by their nature, can be more susceptible to overfitting than larger, over-parameterized networks. The additional, strong regularization imposed by QAT appears to be exceptionally effective in this context, pushing the limited set of parameters to form an even more robust and efficient feature space. This synergy could explain the pronounced boost in accuracy, a phenomenon that might be less significant in a much larger model with greater redundancy.

V. Comparative Analysis with State-of-the-Art

To contextualize our findings, we compare our results with those from the recent paper by Padeiro et al., "Lightweight Maize Disease Detection through Post-Training Quantization with Similarity Preservation," which introduces a state-of-the-art Post-Training Quantization (PTQ) method called Similarity-Preserving Quantization (SPQ) [10].

A. Methodological Distinctions

Several key differences exist between our approach and the one presented by Padeiro et al.:

- **Quantization Strategy:** Our work employs Quantization Aware Training (QAT), which integrates simulated quantization into a model fine-tuning phase, allowing the model's weights to adapt to the constraints of lower precision [9]. In contrast, SPQ is a PTQ method that calibrates the INT8 model by preserving the activation similarity structure of the original model, rather than only matching output values [10].
- **Dataset Scope and Complexity:** Our model was trained and evaluated on a challenging, composite dataset combining lab-condition (PlantVillage) and "in-the-wild" (PlantDoc) images across 66 diverse crop and disease classes [11]. The SPQ method was evaluated on a more focused dataset of a single crop (maize) with three disease classes [10]. This difference in dataset complexity is crucial for interpreting the absolute accuracy scores.

B. Performance Comparison

A direct comparison of the reported outcomes reveals the strength of our QAT-based workflow.

TABLE II
Comparison of QAT vs. SPQ PTQ

Metric	Our QAT	SPQ PTQ (W8A8)
Accuracy Change	**+1.59%**	+0.01%
Model Size Reduction	**∼4x**	∼3.1x
CPU Inference Speed-up	**∼2.07x**	∼1.33x

Note: Our results are on MobileNetV3-Large. SPQ results are for MobileNetV2 as reported in [10].

As shown in Table II, our methodology demonstrates superior results across all three key metrics:

- **Accuracy:** The most significant finding is that our QAT process yielded a **1.59% absolute improvement** in accuracy. The SPQ method, by contrast, achieved near-perfect accuracy preservation (+0.01% on mAP@50) on MobileNetV2 but resulted in a notable accuracy drop of -1.57% on ResNet-50 [10]. This highlights the powerful regularization effect of QAT, which not only mitigates accuracy loss but can actively enhance model generalization.
- **Efficiency Gains:** Our approach achieved a greater model compression ratio (∼4x vs. ∼3.1x) and a substantially higher inference speed-up (∼2.07x vs. ∼1.33x) compared to the results reported for SPQ on a similar MobileNet architecture [10], [11].

This comparative analysis validates that our QAT-based workflow is not only highly effective but also outperforms a state-of-the-art PTQ technique in achieving a superior balance of model accuracy, size, and speed, reinforcing its suitability for developing robust, field-deployable diagnostic tools.

VI. Conclusion

This paper has successfully developed and validated a robust workflow for creating lightweight, efficient, and accurate deep learning models for multi-crop disease diagnosis, tailored for deployment in resource-constrained environments. By applying Quantization Aware Training to a well-trained MobileNetV3-Large baseline, this work produced an 8-bit integer model that is approximately 4x smaller, 2x faster on CPU, and, most importantly, 1.59% more accurate than its full-precision counterpart.

The primary takeaway from this research, further strengthened by comparison with state-of-the-art post-training methods, is that QAT should be viewed not merely as a post-hoc compression tool but as an integral part of the model development pipeline that can serve as a powerful regularization technique to improve generalization. This dual benefit—simultaneously enhancing both efficiency and accuracy—makes it an exceptionally valuable method for developing AI solutions that are practical, scalable, and impactful for real-world agricultural applications.

While this work provides a definitive proof-of-concept, it is acknowledged that the final accuracy of $\sim$44% leaves room for improvement, which could be achieved through more extensive training on an even larger and more diverse dataset. Building on this foundation, future research should focus on integrating these optimized models into resilient, tiered Fog-Edge computing architectures. Such systems could enable fully offline functionality at the edge (on a farmer's device) while using a local fog node for data aggregation and periodic model recalibration, further enhancing utility in disconnected environments [14]. Furthermore, to build farmer trust and drive adoption, future iterations should incorporate Explainable AI (XAI) techniques, such as Grad-CAM [15]. Providing visual explanations for a model's diagnosis can demystify the technology and transform it from a "black box" into a trusted and transparent decision-support tool.

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