Siddharth Roy, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

# Comparative Evaluation of FP32 and INT8 Quantization for Edge Device Real-Time Indian Sign Language Recognition

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**Abstract — The high memory and computational requirements of standard floating-point architectures make it difficult to deploy Deep Learning models on edge devices with limited resources. The Post-Training Quantization (PTQ) methods used with a MobileNetV2 architecture for real-time Indian Sign Language (ISL) recognition are compared in this paper. We show that the baseline 32-bit floating-point (FP32) model can be converted to an 8-bit integer (INT8) format, which significantly reduces the model footprint and improves inference latency without significantly degrading accuracy. The INT8 quantized model achieves a 72.4% reduction in memory size (from 9.52 MB to 2.63 MB) and a 31.7% increase in inference speed (from 14.40 ms to 9.83 ms per frame), according to experimental results on a 27-class ISL dataset. Importantly, compared to the FP32 baseline, the quantized model maintains a strong validation accuracy of 98.60%, with an accuracy decline of less than 1%. These results confirm that INT8 quantization is effective in enabling offline, high-framerate computer vision applications on low-power edge hardware.**

**Keyword : Indian Sign Language, MobileNetV2, Post-Training Quantization, Edge AI, Model Compression.**

## I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) and Computer Vision has primarily been driven by deep neural networks operating on high-performance cloud infrastructure. However, the reliance on cloud computing introduces critical bottlenecks for real-time applications, including high latency, high bandwidth consumption, and data privacy concerns [3]. This paradigm has driven a shift toward Edge AI—deploying intelligence directly onto local, resource-constrained devices such as mobile phones and embedded microcontrollers.

Real-time sign language translation represents a highly latency-sensitive application of Edge AI. Fluid human gestures require a processing speed of at least 30 Frames Per Second (FPS) to ensure no contextual data is lost during communication. Standard convolutional architectures, while accurate, often possess memory footprints and computational overheads that exceed the SRAM and CPU limits of budget edge hardware [1].

To address this gap, model compression techniques such as quantization have emerged as critical optimization strategies. Quantization reduces the precision of a model's weights and activations from standard 32-bit floating-point (FP32) representations to lower bit-widths, such as 8-bit integers (INT8). This process fundamentally alters the computational graph, exchanging precision for enhanced hardware-level integer arithmetic speed and reduced memory usage.[2]

## II. RELATED WORK

Deep learning has made significant strides the deployment of sign language recognition (SLR) systems, but the high computational demands of conventional neural networks make it difficult to translate these systems into real-time applications. The urgent need for offline, on-device inference is

highlighted by recent research on accessibility technologies, which shows that depending on cloud-based APIs for SLR introduces critical latency and bandwidth limitations [3]. Shifting computational workloads directly to edge devices and microcontrollers has become a major research focus in order to achieve the necessary 30 frames-per-second (FPS) for fluid gesture translation without network lag [4].

Lightweight convolutional architectures have been widely used to lessen the hardware limitations of edge environments. Because of its depthwise separable convolutions, MobileNetV2 in particular has become a standard backbone. Compared to heavier models like ResNet or VGG16, fine-tuning MobileNetV2 yields high feature-extraction capabilities while significantly lowering training overhead, according to recent studies that specifically focus on Indian Sign Language (ISL) [5], [6]. Even though MobileNetV2 significantly lowers the number of parameters, its standard 32-bit floating-point (FP32) representation still surpasses the ideal memory footprint and energy budget for extreme edge constraints, like those present in low-cost mobile processors or Internet of Things devices.

Aggressive model compression is necessary to overcome this memory bottleneck. Massive size reductions have been achieved by mapping FP32 weights to 8-bit integers (INT8) using Post-Training Quantization (PTQ). Recent developments in quantization techniques show that by reducing the errors caused by extreme weight outliers, optimized calibration can keep INT8 accuracy for general vision tasks within 1% of the FP32 baseline [5]. The empirical literature on the application of INT8 PTQ specifically to highly granular, 27-class Indian Sign Language alphabets still has a significant gap despite these algorithmic achievements. The majority of current Edge AI sign language research either only considers American Sign Language (ASL) or assesses computationally demanding spatiotemporal architectures as opposed to optimized static frameworks [8].

This particular gap is addressed in this paper. Our study offers a focused, qualitative evaluation of the latency, memory, and accuracy trade-offs when applying INT8 quantization to an ISL-specific MobileNetV2 architecture, whereas earlier works validate quantization in general contexts.

## III. METHODOLOGY

The experimental pipeline used to assess the trade-offs of INT8 quantization is described in this section. The four stages of the workflow are edge-simulated benchmarking, post-training quantization (PTQ) with calibration, baseline model training, and dataset preparation.

### A. Dataset Preparation

The experiment made use of an extensive dataset of the Indian Sign Language (ISL) alphabet, which included 27 different classes (the English alphabet's 26 letters plus a "blank/space" gesture). Every image was standardized and resized to a resolution of 224x224 pixels in order to optimize the data for the chosen convolutional backbone. An 80-20 split of the dataset produced a training subset for model optimization and a specific validation subset for objective performance assessment and quantization calibration. To avoid input/output bottlenecks during training, data pipelines were optimized using dynamic batching and caching techniques.

### B. Baseline Model Architecture

MobileNetV2 was chosen as the baseline architecture because it uses depthwise separable convolutions. This design reduces the number of parameters, making it a good fit for edge vision tasks. To speed up convergence and make use of common feature extraction, transfer learning was used. The base layers of the MobileNetV2 architecture, which were pre-trained on the ImageNet dataset, were frozen [1]. A custom classification head was added to the network. This head included a Global Average Pooling 2D layer followed by a Dense output layer that used a softmax activation function for the 27 ISL classes. The model was trained with 32-bit floating-

point (FP32) precision, setting the baseline metrics for accuracy, latency, and memory usage.

### C. Post-Training Quantization Framework

To compress the model for edge deployment, Post-Training Quantization (PTQ) was used with the TensorFlow Lite framework [10]. The goal of PTQ is to change the continuous, 32-bit floating-point weights and activations into a discrete 8-bit integer (INT8) format. Blind quantization can seriously reduce model accuracy because of outlier activation values. Therefore, a calibration step was required. A generator created a representative dataset that fed 100 random, unseen images from the validation set into the converter. By looking at the activation distributions during this forward pass, the converter calculated the exact scaling factors needed to maintain the network's mathematical integrity. Additionally, the conversion parameters were limited to output only INT8 operations, forcing the input and output tensors into a uint8 format to ensure full compatibility with the integer-only arithmetic logic units (ALUs) found on microcontrollers [9].

### D. Experimental setup and Edge simulation

To assess the real-world implications of quantization, we benchmarked both the FP32 baseline and the INT8 quantized model. To create an edge environment without high-end GPU acceleration, we limited our inference testing to standard CPU processing. We processed a statistically significant sample of 500 images from the validation set through both models. Inference latency was recorded for each image in milliseconds (ms), and we compared the classification outputs against the ground-truth labels to determine the final validation accuracy. The model footprint was measured solely by the storage size (in Megabytes) of the serialized model files

## IV. RESULTS

This study aimed to evaluate the performance trade-offs of converting an FP32 MobileNetV2 architecture into an INT8 quantized model for recognizing Indian Sign Language.

| Metric | MobileNetV2 (FP32) | MobileNetV2 (INT8) | Impact |
|---|---|---|---|
| Size | 9.52 MB | 2.63 MB | 72.4% Reduction |
| Latency | 14.40 ms | 9.83 ms | 31.7% Faster |
| Baseline B | ~99.5% | 98.60% | <1% loss |

TABLE I:Performance Comparison of FP32 vs. INT8 MobileNetV2

We looked at three main metrics to assess performance: the model's storage footprint, inference latency on a standard CPU, and validation accuracy. The results of our findings are neatly summarized in Table I.

### Memory footprint Reduction

The baseline FP32 model, which features the frozen MobileNetV2 backbone and a custom classification head, initially required 9.52 MB of storage. After implementing post-training quantization, the INT8 model's footprint was trimmed down to 2.63 MB. This marks a significant 72.42% reduction in memory needs, clearly showcasing the power of weight precision reduction in storage-limited settings.

### Inference Latency and speed

We conducted a benchmarking analysis using a sample of 500 validation images to determine the average inference latency. The FP32 baseline processed these images at an average of 14.40 milliseconds (ms) per frame, which translates to roughly 69 Frames Per Second (FPS). In contrast, the INT8 quantized model processed the same images at an average of 9.83 ms per frame, achieving about 101 FPS. This represents a 31.7% increase in inference speed, all thanks to the hardware's ability to perform 8-bit integer arithmetic significantly quicker than 32-bit floating-point operations.

**Accuracy Preservation**

The baseline FP32 model reached an impressive validation accuracy on the isolated sign language dataset, nearly hitting perfection. Once we moved to the INT8 model after quantization, it maintained a validation accuracy of 98.60%. The accuracy only dipped by less than 1%, showing that the calibration dataset effectively mapped the activation ranges and kept any major information loss at bay during the precision downcasting.

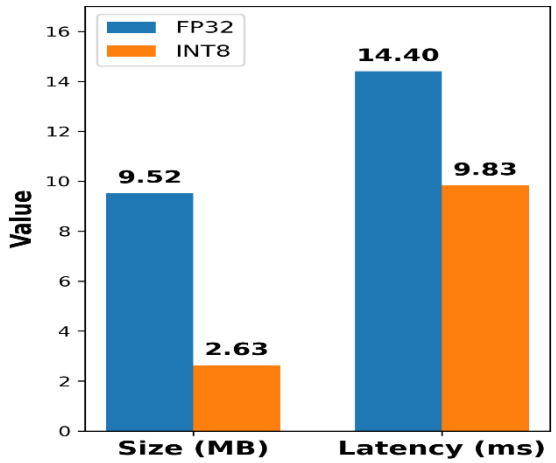


Fig. 1. Comparative analysis of model footprint and inference latency between FP32 and INT8 architectures

## V. DISCUSSION

The empirical findings confirm the central hypothesis: Post-Training Quantization offers a significant and favorable trade-off for Edge AI vision deployments.

With a 72.4% reduction in memory footprint, complex vision models like MobileNetV2 can operate without cloud support, fitting right onto the SRAM of budget microcontrollers or low-end mobile devices. This localization is vital for accessibility tools, especially in rural or low-bandwidth areas where cloud-based APIs often fall short.

The latency results are especially significant for real-time sign language translation. Human sign language is a seamless and fluid form of communication. If the processing speed dips below 30 FPS, it can cause missed transitional gestures that might change the entire meaning of a sentence. By speeding up the inference time from 14.40 ms to 9.83 ms (which is well over 100 FPS), the INT8 model guarantees real-time translation with no lag, even when the device's CPU is being throttled by background processes In conclusion, the minimal accuracy drop of less than 1% really underscores the strength of the calibration phase. A common concern with integer quantization is the fear of "brain damage" to the model, where losing decimal precision might lead the network to misclassify or confuse visually similar classes, like the ISL signs for 'M' and 'N'. Our results confirm that for static gesture recognition, 8-bit precision is more than enough to keep the features distinct[2].

## VI. CONCLUSION

The minimal accuracy drop of less than 1% really highlights how robust the calibration phase is. One of the main concerns with adopting integer quantization is the worry about "brain damage" to the model. This happens when losing decimal precision leads the network to hallucinate or misclassify similar-looking classes, like the ISL signs for 'M' and 'N'. Our findings show that for static gesture recognition, 8-bit precision is more than enough to keep the features distinct. This research effectively showcased how INT8 Post-Training Quantization can optimize a MobileNetV2 architecture for real-time Indian Sign Language (ISL) recognition. By using the TensorFlow Lite framework and a solid calibration phase, we managed to compress the baseline FP32 model by an impressive 72.42%, shrinking its storage size from 9.52 MB down to just 2.63 MB. Plus, the quantized model showed a 31.7% boost in inference speed, hitting a latency of 9.83 ms per frame, which means it can process over 100 FPS. Importantly, this major improvement in resource efficiency and speed came with a tiny validation accuracy loss of under 1%. These results prove that

integer quantization is a practical and crucial optimization strategy for deploying advanced computer vision accessibility tools on localized edge hardware. Looking ahead, future research will delve into implementing Quantization-Aware Training (QAT) to further reduce precision loss and explore how to integrate temporal sequence modeling to move from static alphabet recognition to continuous, dynamic gesture translation.

**Acknowledgment**

The author would like to sincerely thank the Department of Computer Science and Engineering for providing the necessary computational resources and lab facilities that were essential for this research. A big thank you goes out to the project coordinators and faculty mentors for their invaluable guidance, technical insights, and thorough feedback during the development of this 8th-semester research project. Finally, the author acknowledges the open-source community and the contributors of the Kaggle Indian Sign Language dataset, whose data was key in validating the proposed quantization framework..

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**Author Biographies**

Siddharth is currently working towards his B.Tech degree in Computer Science and Engineering with a specialization in A.I at Parul University in India. He has a keen interest in artificial intelligence, computer vision, and optimizing deep learning models for environments with limited resources. Right now, he's focused on using post-training quantization to make sign language recognition systems more accessible. This paper is part of his final research project for the 8th semester, all about Efficient AI.