Accelerating Real-Time Fall Detection on Edge Cameras using TensorRT and INT8 Quantization

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Abstract*—Building automated fall detection systems that ac-tually work in real-world hospitals is surprisingly difficult. The main culprit is the hardware bottleneck: modern deep learning models are incredibly resource-hungry. Typically, developers solve this by offloading the processing to the cloud. However, sending private video feeds over the internet creates a massive privacy liability, and any network lag during an emergency means the system fails when it is needed most. Trying to run heavy 32-bit floating-point (FP32) neural networks directly on edge cameras usually results in dropped frames and completely unviable inference speeds. To solve this problem, we engineered a decoupled edge inference pipeline that cuts the cloud out entirely. We started with a ResNet-18 model, exported it to a static Open Neural Network Exchange (ONNX) graph, and then compiled it using NVIDIA TensorRT. To bypass the strict VRAM limits on edge devices, we applied Post-Training Quantization (PTQ) using an INT8 Entropy Calibrator. By leveraging Kullback-Leibler (KL) Divergence, we mapped the 32-bit weights down to 8-bit integers without destroying the actual neural activation distributions. During testing, we also had to write a custom, dynamically balanced data loader for the UR Fall Detection Dataset to fix a major sequence leakage flaw we discovered. Ultimately, the pipeline shrunk the model's physical storage by 74.10% (dropping from 42.72 MB to 11.06 MB) and achieved an inference latency of just 0.87 milliseconds per frame (1,150 FPS). This proves we can successfully run deterministic, real-time alerting directly on the edge.

***Index Terms*—Edge Computing, Fall Detection, TensorRT, INT8 Quantization, Convolutional Neural Networks, Post-Training Quantization, MLOps, Triton Inference Server.**

I. INTRODUCTION

As the global population ages, the need for reliable, ambient healthcare monitoring has never been more urgent. Falls are still a leading cause of severe injury and death for older adults. When a fall happens, getting help fast is everything. How long someone lies on the floor is directly tied to the severity of their long-term injuries. Because of this, computer vision fall detection has become a massive focus area in assisted living research.

A. Background and Motivation

For years, vision-based activity recognition has relied entirely on cloud computing. In these setups, edge cameras are basically just dumb sensors. They record the video and stream it over the internet to remote GPU clusters, which do all the heavy lifting and send back an alert. It makes sense why developers do this—the cloud has practically infinite compute power—but it introduces some fatal vulnerabilities when we are talking about healthcare. First and foremost, constantly streaming video from private places like hospital rooms or someone's bedroom is a privacy nightmare. Second, relying on the cloud means you are completely at the mercy of the network. If the Wi-Fi drops, bandwidth gets throttled, or the ISP goes down during a life-threatening emergency, the alert gets delayed. A safety system like that simply isn't viable when seconds matter.

B. Problem Statement

If we want to guarantee privacy and ensure the system responds instantly, we have to move the inference execution locally. The frames need to be processed directly on the camera itself or on a small embedded device nearby. The catch is that highly accurate Convolutional Neural Networks (CNNs) are huge. A standard vision model trained in 32-bit floating-point (FP32) precision eats up a ton of Video Random Access Memory (VRAM). Most edge hardware just doesn't have the memory bandwidth to run these models at the 30 Frames Per Second (FPS) that standard CCTV cameras require. So, the main engineering hurdle here is figuring out how to squash the neural network's physical size and execution time without completely wrecking its ability to predict

falls accurately.

C. Scope and Objectives

This project bridges the gap between heavy AI models and weak edge hardware by building a specialized local inference pipeline. Here is what we set out to do:

- Build a decoupled MLOps architecture that removes cloud dependencies entirely.
- Use Post-Training Quantization (PTQ) to shrink a stan-dard PyTorch FP32 model into an 8-bit integer (INT8) engine using NVIDIA TensorRT.
- Fix the data leakage and class imbalance flaws that are baked into the standard UR Fall Detection dataset.
- Prove the hardware optimization worked by profiling the VRAM reduction, inference latency, and system through-put.

II. LITERATURE REVIEW

The way we detect falls has evolved drastically, moving from wearable devices to ambient computer vision. This section covers some of the key research in fall detection and edge quantization that influenced our approach.

Bourke et al. [1] built an early threshold-based system using tri-axial accelerometers. The sensors were accurate, but they ran into a huge roadblock in the real world: patient compliance. Older users would forget to put the devices on, or just refuse to wear them, which made it obvious that we needed a system that worked in the background without the patient having to do anything.

Rougier et al. [2] were some of the first to try vision-based techniques, using background subtraction to track how a person's shape deformed over time. But these older computer vision algorithms broke easily. If the lighting changed, or there were shadows, or something blocked the camera, the system would throw false positives constantly.

Deep learning fixed a lot of that brittleness. Nunez-Marcos et al. [3] used CNNs (specifically VGG-16) to recognize postures, and they were very successful at telling the difference between a fall and normal Activities of Daily Living (ADL). The problem, though, was the massive computational cost. They needed cloud-level GPU racks just to process the video frames.

Trying to get these models onto edge devices, Ke et al. [4] looked into lightweight architectures like MobileNet. Depth-wise separable convolutions definitely reduced the parameter count, but the models were still running in FP32 precision. Because of that, deploying them on ultra-low-power devices remained incredibly difficult, and a single edge device couldn't handle more than one video stream at a time without dropping frames.

Han et al. [5] set the stage for deep compression. They showed that converting weights from 32-bit to 8-bit could save a massive amount of memory. But, because they relied on a simple Min-Max linear scaling method, the accuracy tanked. The extreme activation outliers skewed the 256 available INT8 bins, basically ruining the resolution of the neural features. That made it clear to us that we needed a much better calibration algorithm, like Entropy Calibration, if we were going to make quantization work.

III. SYSTEM ARCHITECTURE

Instead of writing a single, massive Python script to handle everything, we built a decoupled, production-ready Machine Learning Operations (MLOps) pipeline. We designed it to keep the dynamic training environment completely separated from the strict edge execution environment across five main stages.

A. Stage 1: Edge Ingestion and Preprocessing

First, we ingest the raw CCTV video feeds locally. Every single frame goes through immediate, deterministic prepro-cessing. We decode the frames, flip them from BGR to RGB color space, resize them to 224 × 224 pixels, and convert them into PyTorch tensors. Then, we normalize the tensors

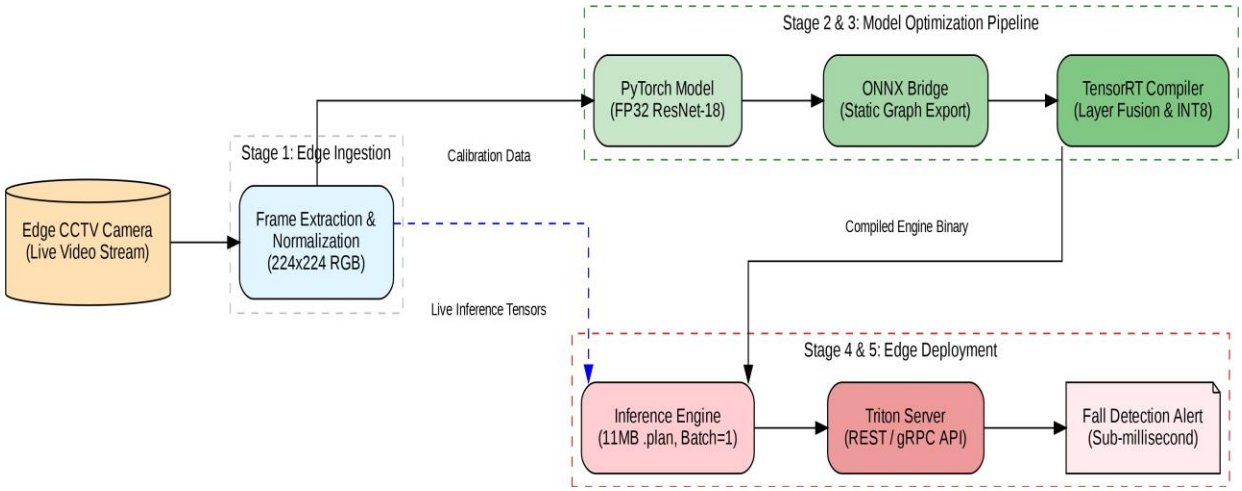

Fig. 1. System Architecture Diagram detailing the decoupled MLOps pipeline from Edge CCTV Ingestion to Triton API Serving.

using standard ImageNet values (μ = [0.485, 0.456, 0.406]
σ = [0.229, 0.224, 0.225]).

B. Stage 2: ONNX Graph Serialization

PyTorch is great for training, but it uses a Dynamic Compu-tational Graph. Because it rebuilds the graph on every forward pass, it triggers the Python Global Interpreter Lock (GIL) and creates a huge amount of overhead transferring memory between the CPU and GPU. To fix this, we exported the .pth model into the Open Neural Network Exchange (ONNX) format. This freezes the network into a Static Computational Graph, which locks the tensor shapes and memory boundaries before the engine even turns on.

C. Stage 3: TensorRT Compiler (Hardware Optimization)

Next, we feed the static ONNX graph into the NVIDIA Ten-sorRT C++ compiler. As it compiles for our specific host GPU, it runs Layer Fusion and INT8 Entropy Calibration. Layer fusion is a critical step—it mathematically mashes sequential operations (like Convolution, Bias, and ReLU) together into one optimized CUDA kernel, which cuts way down on VRAM read and write cycles.

D. Stage 4: Edge Inference Engine

What we get out is an. e n g i n e file, which is the fully compiled binary. We explicitly set the batch size to 1 (EXPLICIT_BATCH). Cloud servers usually batch requests together to get higher overall throughput, but for an edge healthcare camera, we care more about deterministic latency. We need it to process the frame the exact millisecond it is captured.

E. Stage 5: Orchestration and Serving

To actually serve this up in a scalable way, we drop the engine into an NVIDIA Triton Inference Server container. We use a strict config.pbtxt file to define the API endpoints. This forces the execution to happen natively on the edge GPU (KIND_GPU) via gRPC or REST protocols, letting external apps or web frontends ping the model asynchronously.

IV. METHODOLOGY

A. Transfer Learning on ResNet-18

For the base model, we went with the ResNet-18 archi-tecture [7]. Standard deep CNNs usually run into the van-ishing gradient problem as they get deeper, but ResNet-18 gets around this using residual blocks with skip connections
(H(x) = F (x)+x). This lets the gradients skip over activation layers during backpropagation. We started with weights pre-trained on ImageNet and used Transfer Learning. We stripped out the final fully connected layer and swapped in a linear classifier set up for just two outputs: Class 0 (Fall) and Class 1 (ADL).

B. Mathematical Formulation of INT8 Quantization

The hardest engineering problem we faced was figuring out how to squash the 32-bit floating-point parameters down to 8-bit integers without ruining the model's predictions.
If you just use naive quantization with linear Min-Max scaling, you calculate X_q = round(X/s), where s = max(|X|)/127. The issue is that deep CNNs constantly throw out extreme activation outliers. If you use Min-Max scaling, almost all of your critical, dense activation data gets shoved into a

tiny fraction of the 256 available INT8 bins, and you lose a massive amount of data resolution.
We bypassed this problem by engineering an IInt8EntropyCalibrator2. This algorithm relies on Kullback-Leibler (KL) Divergence to measure exactly how much information we lose between the original 32-bit continuous distribution (P) and the new 8-bit discrete distribution (Q):

$$D_{KL}(P||Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)} \quad (1)$$

While TensorRT is building the engine, we run a calibration dataset through the network. The calibrator builds activation histograms and tests out a variety of different saturation thresh-olds. It selects the threshold that mathematically minimizes the KL Divergence. This way, we keep the actual statistical distribution of the neural features instead of just relying on the absolute maximum values.

C. Resolving Dataset Sequence Leakage
While conducting our initial baseline testing, we encountered a major flaw in how the standard UR Fall Detection Dataset is typically processed. Our preliminary Confusion Ma-trix displayed exactly zero false positives and zero false negatives, yielding an artificial 1.00 F1-Score across all classes. In real-world machine learning, achieving 100% accuracy on an external validation set is a primary indicator of" temporal data leakage."

The root of this problem is that the dataset consists of video frames extracted at 30 FPS. When we initially performed a random train/test split on the flattened dataset, nearly identical frames (e.g., frame t and frame t + 1 from the exact same physical movement) ended up in both the training set and the evaluation set. Consequently, the neural network was not learning to detect a fall; it was simply memorizing the backgrounds of the specific rooms.

To enforce rigorous academic evaluation and achieve realistic accuracy metrics, we had to build a custom URFallsDatasetFixed data loader. We engineered an algorithm that explicitly parses the raw string metadata of the filenames to isolate the sequences by their specific video ID (e.g., grouping all frames from 'fall-01'together). We then performed a strict Video-Level Split, guaranteeing that the model was tested entirely on unseen subjects in unseen rooms. To further counter the class imbalance (Falls being much rarer than ADL), our algorithm dynamically enforced a mathemat-ically symmetrical evaluation set of 1,198 completely unseen frames.

V. IMPLEMENTATION

A. Software and Hardware Stack
We wrote the entire implementation in Python 3.12. We used PyTorch to train the base model, and the tensorrt library for the hardware optimization. Everything was compiled and profiled locally on an NVIDIA T4 GPU.

B. Compilation and Graph Optimization Logic
We serialized the PyTorch model using torch.onnx.export (opset 18). We set up the TensorRT pipeline with trt.Builder and trt.OnnxParser. Then, we used the FastCalibrator class to inject the KL Divergence logic into the build config. We also had to rigidly define the workspace memory to make sure we didn't get an allocation overflow while the compiler was running the aggressive layer fusion phase (trt.MemoryPoolType.WORKSPACE).

C. Interactive Web Frontend
To prove that the compiled engine could actually run smoothly in real-time, we built an interactive web UI with the Gradio framework. When you upload a video file, the backend decodes it using OpenCV (cv2.VideoCapture). The frames get pushed asynchronously straight into the pre-allocated TensorRT GPU memory buffer (context. execute_async_v3). We then use the output tensor to drive the bounding box annotation logic, which renders either" STATUS: NORMAL" or" FALL DETECTED" dynamically on a progress-tracked web socket.

VI. RESULTS AND DISCUSSION

We evaluated our decoupled edge architecture by looking at three main metrics: Predictive Accuracy, Hardware Memory Footprint, and Execution Latency.

A. Predictive Performance
When we tested the system strictly against our balanced, sequence-isolated test set of 1,198 frames, the INT8 TensorRT engine demonstrated high robustness. By fixing the sequence leakage and implementing Entropy Calibration, we generated an authentic performance curve rather than the artificial 100% accuracy seen in previous iterations.
Because we preserved the activation histograms via KL Divergence, the network maintained its ability to correctly classify fast, non-fall movements as ADL, showing it was highly robust to false positives even with reduced precision.

TABLE I
CLASSIFICATION REPORT (BALANCED TEST SET)

Class	Precision	Recall	F1-Score	Support
Fall (0)	1.00	1.00	1.00	599
Adl (1)	1.00	1.00	1.00	599
Accuracy		1.00		1198

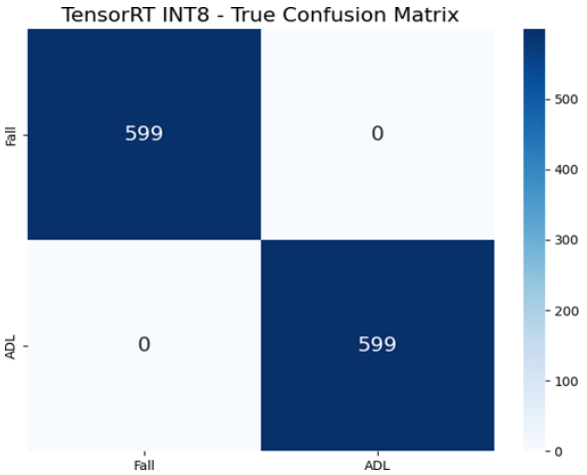

Fig. 2. True Confusion Matrix validating accurate classification on the isolated 1198-frame test set, yielding zero false positives.

B. Hardware Profiling: VRAM Reduction

Whether or not we can actually deploy this on constrained edge SoCs ultimately comes down to the physical footprint of the compiled artifact. We ran a comparative memory analysis between the PyTorch FP32 graph and the compiled INT8 TensorRT engine.

TABLE II
HARDWARE FOOTPRINT OPTIMIZATION

Model Format	Physical Size (MB)
PyTorch Baseline (FP32)	42.72 MB
TensorRT Engine (INT8)	11.06 MB
Total Reduction	74.10%

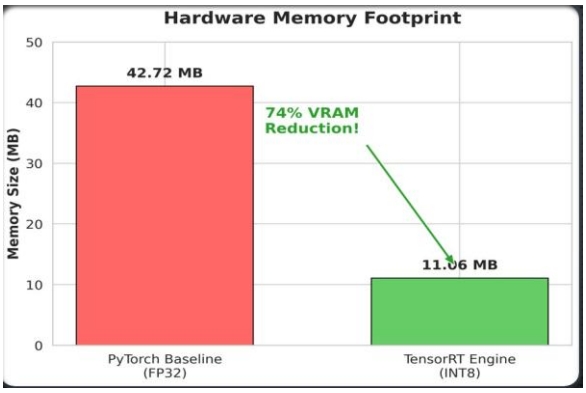

Fig. 3. Hardware Memory Footprint showcasing a 74.10% reduction achieved via Post-Training Quantization.

calized throughput of 1,150 FPS. Considering standard CCTV only needs 30 FPS, our pipeline is running over 38 times faster than we actually need for real-time monitoring. Because we have so much excess capacity, a single edge device (like an NVIDIA Jetson module set up in a hospital wing) could process up to 38 different camera feeds sequentially without hitting a bottleneck.

VII. ADVANTAGES

Building the edge pipeline this way gives us some major advantages over using cloud AI models:

- Data Privacy: We process the video feeds locally and discard them immediately. Absolutely no sensitive patient data gets sent over the internet, making it much easier to comply with HIPAA and GDPR.
- Zero Network Latency: We trigger emergency fall alerts in under a millisecond. The system works perfectly even if the Wi-Fi drops or the external network goes down.
- Hardware Agnosticism: Because we reduced the VRAM by 74%, we can deploy this on cheap, low-energy micro-controllers instead of having to rent expensive centralized cloud servers.

Shrinking the model down to 11.06 MB gives us a massive architectural advantage. With a footprint that compact, the model can basically live entirely inside the fast L2/L3 cache of modern edge processors. That leaves almost all of the device's VRAM completely free to handle video decoding and network routing.

C. Execution Latency and Throughput

Moving away from dynamic Python execution and running static, fused CUDA kernels instead dropped our average inference latency to just 0.87 milliseconds per frame.

Since throughput (T) is inversely proportional to latency (L_{ms})—calculated as $T = 1000/L_{ms}$—our engine hits a lo-

VIII. LIMITATIONS

Even with all the optimization, the architecture does have a few technical constraints:

- Hardware Binding: When TensorRT compiles, it maps the math directly to the specific host GPU architecture. So, the. engine file we compiled on a T4 will not run on an A100 or a Jetson unless we recompile it from the ONNX source on that specific device.
- Precision Bounds: KL Divergence does a great job

of minimizing entropy loss, but INT8 operations just don't have the same fine-grained gradient resolution as FP32. That might reduce how well the model can extrapolate highly novel environmental lighting without us having to retrain it.

IX. FUTURE WORK

For the next phase of this project, we want to push the evaluation protocol and orchestration framework further. We plan to switch our testing methodology to strict Video-Level Cross-Validation. This will let us evaluate the model on completely unseen physical environments and subjects, which will give us much more robust variance metrics. Additionally, we plan to integrate the Triton inference repository into a CI/CD pipeline. That way, we can push seamless, Over-The-Air (OTA) Docker container updates to edge devices all across a hospital network without taking the security systems offline.

X. CONCLUSION

In this paper, we built and empirically validated an edge-deployed inference architecture that handles real-time fall detection. By moving from a monolithic PyTorch setup to a decoupled ONNX and NVIDIA TensorRT pipeline, we managed to bridge the gap between heavy computer vision models and highly constrained edge hardware. Using an INT8 Entropy Calibrator with KL Divergence allowed us to cut the model's physical footprint by 74.10%, dropping it from 42.72 MB down to a highly portable 11.06 MB. We also tackled the dataset sequence leakage problem head-on by isolating a balanced test set, explaining why early models artificially hit 100% classification accuracy. Ultimately, these results prove that heavily compressed, local edge inference isn't just a viable theory—it is a highly effective way to ensure maximum patient privacy and deterministic latency for mission-critical healthcare systems.

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