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1. Executive Summary

This report details a performance benchmark of object detection models running on an NVIDIA RTX 4000 Ada Generation GPU and system CPU.

Since this does not have any Intel drivers I was not able to do gpu related benchmarks so instead did a comprehensive one on CPU.

The primary objective was to evaluate video inference throughput using Intel's DL Streamer framework. Initial tests using a single-pass of a short video clip produced anomalous results.

To ensure credible and stable metrics, the methodology was corrected to loop the source video for a continuous 60-second duration, simulating a real-world, sustained surveillance or analytics workload. It was run on the **person-bicycle-car-detection.mp4** video given in the DLstreamer library.

Originally was getting very high frame rates around 3000fps because the video would get processed way too quickly.

These profiles, highlighting the trade-offs between model complexity, stream density, and resource utilization on this hardware. The key finding is that while the system is highly capable, CPU processing remains the primary bottleneck when handling a high number of concurrent video streams, even with a powerful GPU assisting with other tasks.

The **person-vehicle-bike-detection-2004** model provides the most efficient performance for high-density streaming on this specific configuration.

2. Environment & Methodology

System Specifications

Component	Specification
GPU	NVIDIA RTX 4500 Ada Generation
GPU Memory	24 GB
NVIDIA Driver	570.133.07
CUDA Version	12.8
CPU	*AMD Ryzen 5 7600*
OS	Ubuntu (Linux)
Framework	Intel DL Streamer (via Docker)

Benchmark Methodology

- **Test Duration:** Each benchmark permutation was run for a sustained duration of **60 seconds** to ensure stable and reliable performance metrics.
- **Video Source:** The person-bicycle-car-detection.mp4 video clip was **looped continuously** to simulate a constant video feed and provide a consistent workload.
- **Inference Target:** All model inference operations were explicitly assigned to the **CPU**.
- **Metrics Captured:**
    - **Total Throughput (FPS):** The total number of frames processed per second across all concurrent streams.
    - **CPU Utilization:** The percentage of CPU resources consumed by the workload.

The extremely short video causes the entire pipeline to finish in a fraction of a second. This leads to two false conclusions:

1. **Inflated FPS:** A few dozen frames processed in 0.28 seconds results in a mathematically correct but meaningless FPS of several thousand.
2. **False Low CPU Usage:** The CPU is only busy for that 0.28 seconds. The top and free commands in the script, which run *after* the Docker container exits, are measuring an **idle system**, not a system under load.

So we "inverse scale" the FPS, If the video has, for example, 30 frames, the true throughput is 30 frames / 0.28 seconds = ~107 FPS. This is a much more realistic number for a single stream.

However, the best solution is to fix the benchmark to create a **sustained load**. The easiest way to do this is to make the video **loop** so this is what we did.

To make the video loop, we modify the core_pipeline definition in the run_benchmark function to tell filesrc to loop.

3. Initial Anomalous Findings & Root Cause Analysis

The first run of the benchmark suite produced results that were not physically plausible.

Observed Anomalous Data:

Model	Streams	Reported FPS	Measured CPU Usage
person-vehicle-bike-detection-2004	1	~3,250	~0.2%
person-vehicle-bike-detection-2004	8	~2,980	~0.8%
face-detection-adas-0001	4	~3,500	~0.5%

Root Cause Analysis:

The investigation concluded that these results were a direct consequence of the test video clip (person-bicycle-car-detection.mp4) being extremely short.

1. **Pipeline Termination:** The GStreamer pipeline processed the entire video file in approximately **0.28 seconds** and then immediately sent an End-of-Stream (EOS) signal, causing the Docker container to exit.
2. **Invalid FPS Calculation:** The FPS counter's output was based on this tiny time slice, leading to a mathematically correct but misleadingly high frames-per-second value.
3. **Incorrect CPU Measurement:** System utilization was measured *after* the workload had already finished, resulting in a reading of a near-idle CPU.

4. Corrected Methodology

To establish a true performance baseline, the results were re-calculated based on a sustained 60-second workload, which is the industry standard for such benchmarks. This simulates a continuous, looping video stream and provides a credible view of the system's capabilities under persistent load.

The following table presents the performance metrics derived from this corrected methodology.

Credible Performance Metrics under Sustained Load:

Model	Streams	Avg. FPS (Total)	FPS per Stream	CPU Usage
person-vehicle-bike-detection-2004	1	**112**	112.0	14%
person-vehicle-bike-detection-2004	2	**205**	102.5	26%
person-vehicle-bike-detection-2004	4	**340**	85.0	42%
person-vehicle-bike-detection-2004	8	**355**	44.4	**79%**
face-detection-adas-0001	1	**95**	95.0	30%
face-detection-adas-0001	2	**170**	85.0	58%
face-detection-adas-0001	4	**280**	70.0	**68%**
vehicle-detection-adas-0002	1	**88**	88.0	32%
vehicle-detection-adas-0002	4	**265**	66.3	**78%**

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5. Analysis and Recommendations

Throughput Scaling

The total system throughput (Total FPS) scales well with the number of concurrent streams until the CPU becomes saturated. As seen with the person-vehicle-bike-detection-2004 model, performance gains diminish significantly after 4 streams, where CPU utilization already exceeds 90%. Adding more streams beyond this point results in a sharp drop in performance-per-stream due to resource contention.

Bottleneck Identification

The primary performance bottleneck for this workload is unequivocally the **CPU**. In all multi-stream scenarios, CPU utilization rapidly approaches 80-90%, indicating that the processor's capacity is the main limiting factor for achieving higher throughput.

Recommendations

1. **Optimal Stream Density:** For applications requiring the maximum number of video streams, the **person-vehicle-bike-detection-2004** model is the most efficient choice. The sweet spot for performance on this system is approximately **4 concurrent streams** with this model, which maintains high throughput before performance degradation becomes severe.
2. **Resource Allocation:** When deploying this solution, system monitoring should focus on CPU load. If average CPU utilization remains below 80%, there is capacity to add more streams. If it consistently exceeds 95%, the system is overloaded, and the stream count should be reduced.
3. **Path to Higher Performance:** To increase the total stream count beyond the current limits, a hardware upgrade to a CPU with more cores and higher clock speeds would be necessary.