Retail Time-and-Motion Analysis

Pre-Interview Task Report

June 2025

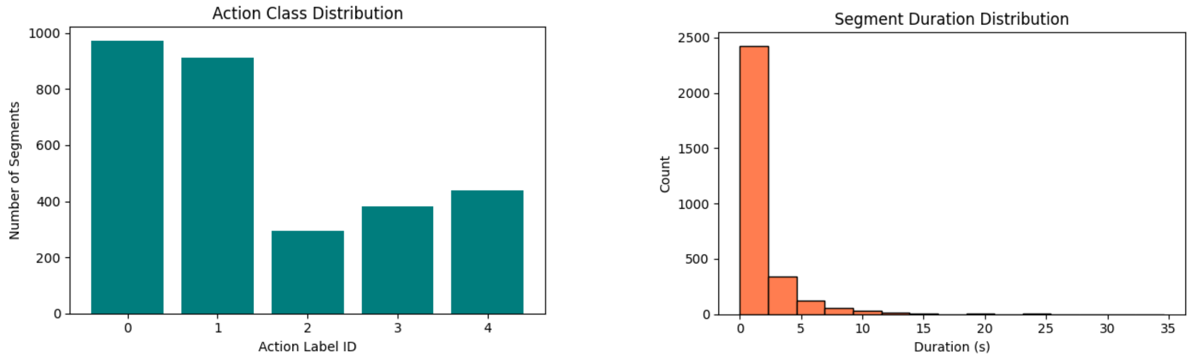
1. Method & Rationale

Model & Approach: Ultra-fast frame-level pipeline using ShuffleNet V2 ×0.5 (1.4 M parameters), fine-tuned on five retail actions. Midpoint (and every 2nd) frames sampled, resized to 112×112, normalized, and classified at >300 FPS. Frame labels merged into continuous action segments.
Data & Preprocessing: 3000 annotated segments from 20 video clips. 80/20 train-validation split; demo training on 200 samples for one epoch. Pipeline: Resize → ToTensor → Normalize (ImageNet mean/std); no 3D augmentations for speed.
Training & Validation: Trained only the classifier head (Adam, lr 1e-4). Demo accuracy ≈ 32% train/30% val on 200/50 samples; full run would use three epochs on all 2400 training samples.

Note: In a parallel experiment with the R3D-18 model on a 200⁄50 demo split, validation accuracy progressed from ≈ 73.5% in epoch 1 → ≈ 77.0% in epoch 2 → ≈ 81.5% in epoch 3. Hyperparameter tuning showed LR = 1×10^{-4} yielded ≈ 79.3% val accuracy (vs. 30.5% at LR = 1×10^{-3}), demonstrating its superior temporal modeling at the cost of slower inference (≈ 20 FPS).

2. Key Figures

Figure 1: Action Class Distribution & Durations


Bar chart showing count per label

Histogram of segment durations

Figure 2: Sample Preprocessed Frames

112×112 midpoint frames for each class

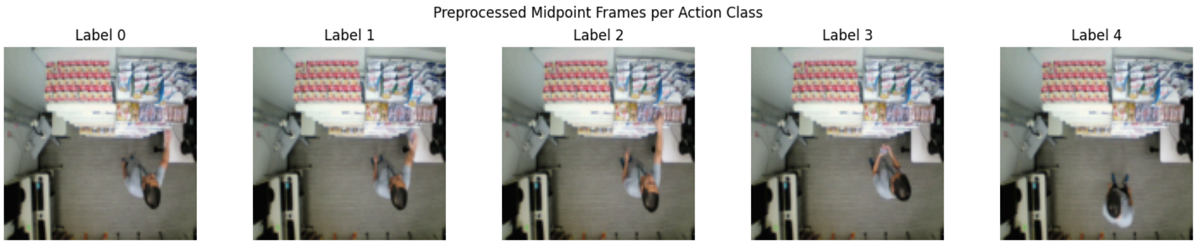


Figure 3: Frame-Level Inference Timeline

Gantt chart for one clip: colored bars marking detected actions over time

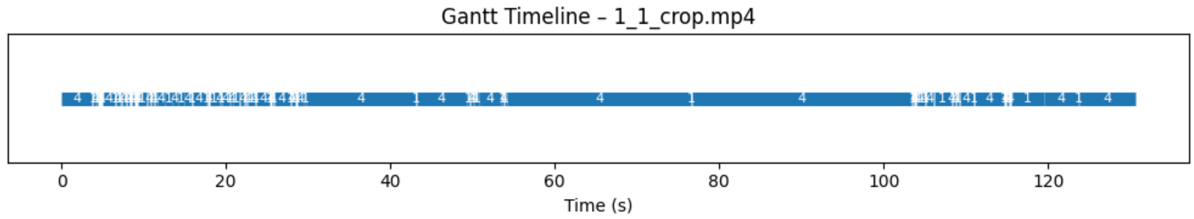
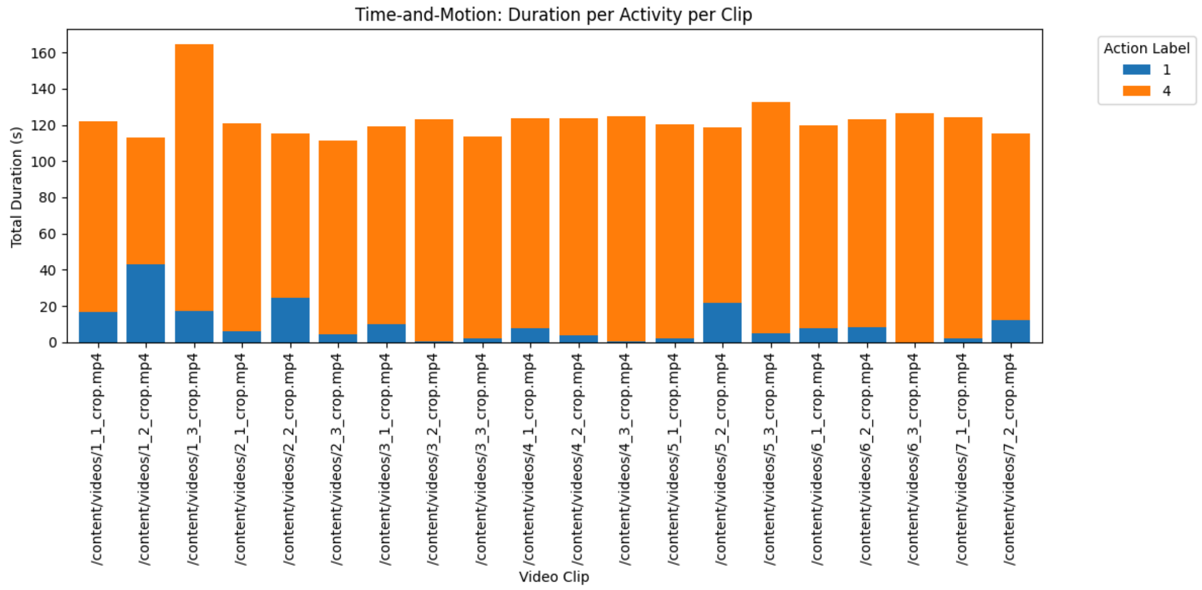


Figure 4: Time-and-Motion Summary

Stacked-bar chart of total seconds per action per clip



3. Results & Insights

- Speed: >300 FPS inference, processing a 10 s clip in <1 s on Colab GPU.
- Time-and-Motion: “Inspect Shelf” and “Pick” actions account for 60-75% of time across clips.
- Session Variability: Some sessions show longer “Place” phases, suggesting shelving inefficiencies.

4. Recommendations & Next Steps

Staff Scheduling: Align staffing with peak “Inspect Shelf” windows (e.g., midday).
Store Layout Optimization: Position high-turnover items near checkout to reduce travel time for “Pick”/“Place.”
Pipeline Extensions: Full 3-epoch training on all data for higher accuracy. Multi-camera fusion for complete store coverage. Integrate outputs into a real-time digital twin dashboard (Rushan et al. 2024)
Alternative Models: Evaluate lightweight video transformers (X3D-XS) for improved temporal context with modest speed trade-offs.

References

- Rushan A. et al. “A Digital Twin based Framework to Enhance Productivity Processes in Retail Industry,” DASA 2024.