DATA SCIENCE & AI LAB (BSCSS3001)

MILESTONE 5: Model Evaluation & Analysis

GROUP NO. 2

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Vision Assist: Real-Time Navigation Support for the Visually Impaired

1. Overview / Objective

This Milestone evaluates the detectors and the full inference pipeline described in Milestone 4, analyzes errors, lists limitations, and proposes next steps. The focus is on quantitative evaluation of the tuned YOLOv8n detector and end-to-end pipeline behavior (distance estimation, motion detection, tracking and alerting). Training & tuning context and best checkpoint details are drawn from the Milestone-4 documentation.

What we evaluated

- The Optuna-tuned YOLOv8n model (best run / Trial 14 from Milestone 4).
- A baseline YOLOv8n (pre-tuning) and YOLOv5s baseline for latency/accuracy comparison.
- Pipeline-level behavior (conf_thresh, motion threshold, alert cooldown, distance estimator) across held-out test images and a custom 7-video “challenge set” (day/night/indoor).

2. Evaluation Setup

Datasets & splits

- Training / validation / test split used during training: **70% / 20% / 10%** of the master dataset (7,138 images total → Train 4,996 / Val 1,427 / Test 715). These splits were created in Main.ipynb
- Additional qualitative **challenge set**: 7 videos (3 outdoor daytime, 2 nighttime low-light, 2 indoor retail). Use this to test domain generalization.

Preprocessing applied at evaluation time

- Images resized to **640 × 640** during model val/inference. Same normalization/augmentation conventions as training (mosaic during early epochs only).
- For video qualitative evaluation: inference performed at configured imgsz=640, conf_thresh=0.4 (baseline 0.4 / tuned 0.3 experiments described below).

Hardware / software

- Training & evaluation used Ultralytics YOLOv8 framework on a Tesla T4 GPU (training) and CPU/GPU latency measured on target hardware. Python packages / colab env referenced in the comparison notebook.

Evaluation scripts / notebooks (artifacts)

- Main.ipynb — training and dataset splitting.
- Compare_YOLOv8_Models.ipynb — per-model validation (mAP, PR curves, confusion matrices) and side-by-side qualitative outputs.
  Compare_YOLOv8_Models.ipynb
- VisionAssist_inference.ipynb, Hyperparametertuning.ipynb — pipeline experiments and tuned parameter values.

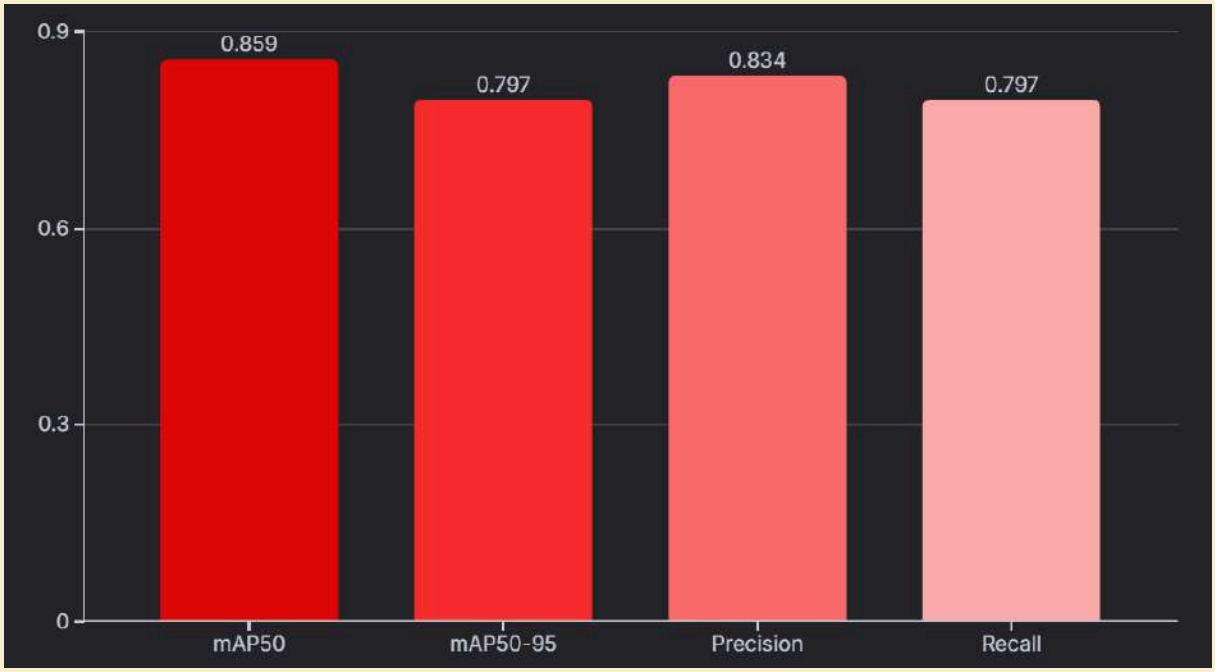
3. Performance Metrics

We used a mix of standard object detection metrics and pipeline-specific metrics:

Detection metrics (standard)

- **mAP@0.50 (mAP50)** — primary detector metric (simple, common).
- **mAP@0.50:0.95 (mAP50-95)** — more stringent, evaluates localization and robustness.
- **Precision / Recall** — to inspect precision-recall tradeoffs, especially relevant when tuning conf_thresh.

Performance Metrics	mAP50	mAP50–95	Precision	Recall
Testing Data	0.859	0.797	0.834	0.797

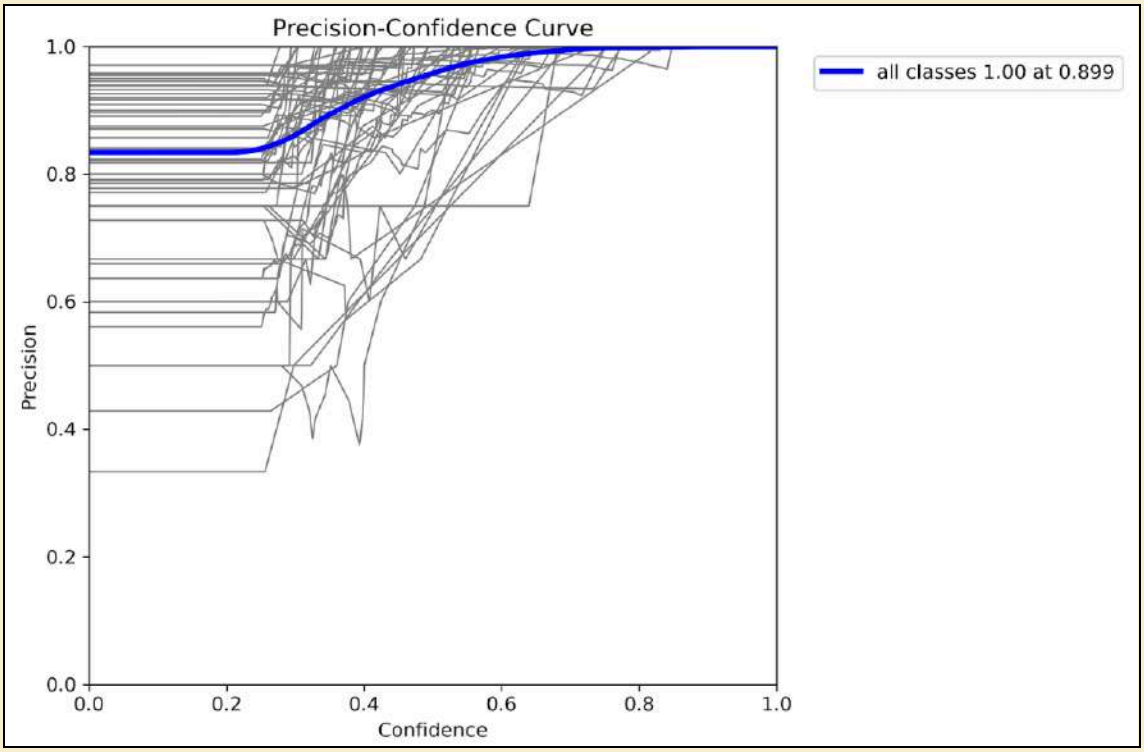


Pipeline / system metrics

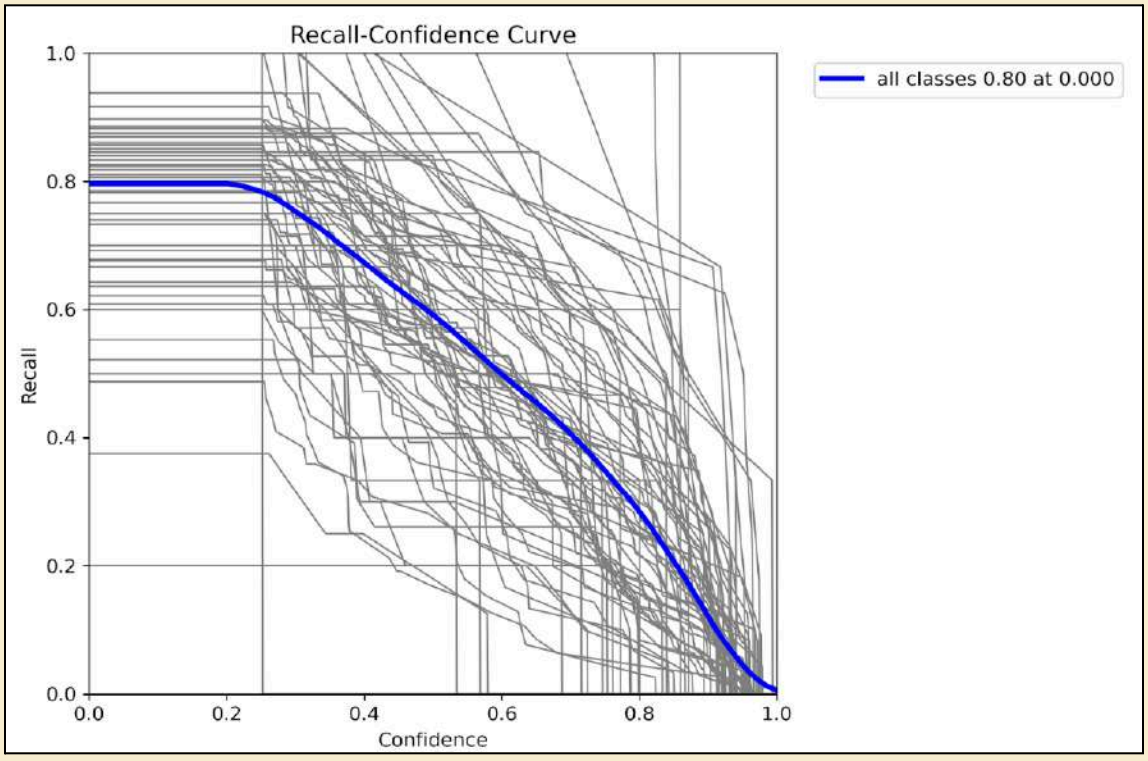
- **Distance estimation MAE / %** error on calibration distances (2, 4, 6, 8 m). Useful to quantify audio alert accuracy. (Calibration table provided; placeholders below).
- **False motion rate / Missed motion rate** for motion detection logic after threshold tuning.
- **Alert overlap rate / Alert latency** — how often audio alerts overlap or are too frequent (tuned via ALERT_COOLDOWN_GLOBAL)

Why these metrics

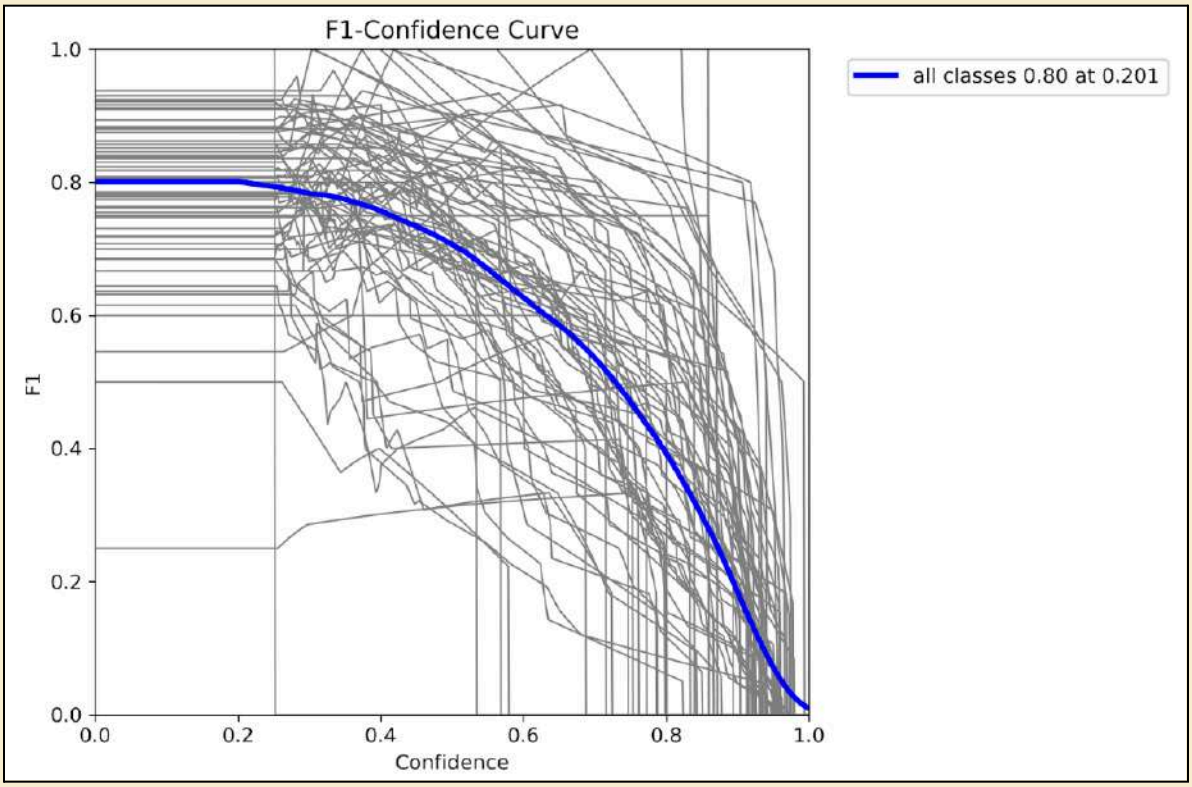
- mAP and per-class AP measure core detection quality. Distance & motion metrics measure the practicality of the pipeline for navigation (safety). Precision/Recall and PR curves explicitly show the conf_thresh tradeoffs that affect user experience (false alarms vs missed hazards).



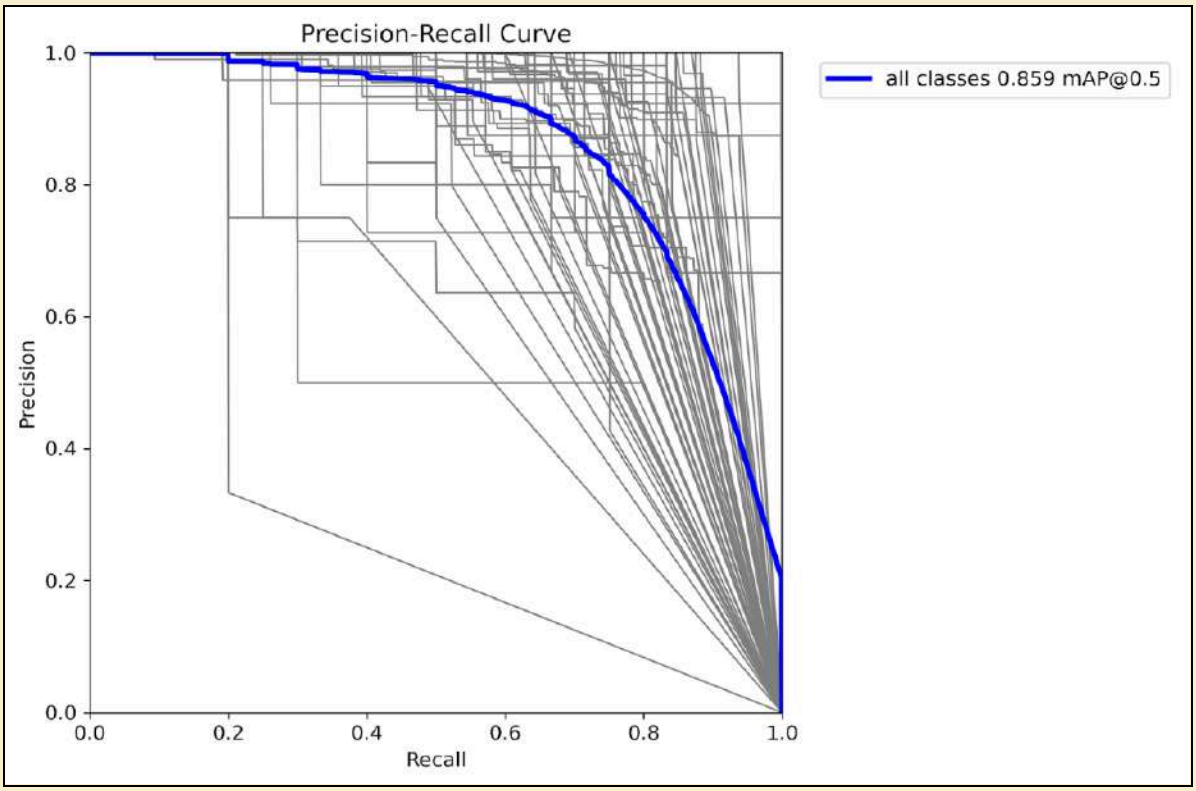
Precision–Confidence *curve for the tuned YOLOv8n model. Precision rises steadily with stricter confidence thresholds, reaching ~0.90 precision near confidence 0.90 - demonstrating strong reliability for high-confidence predictions.*



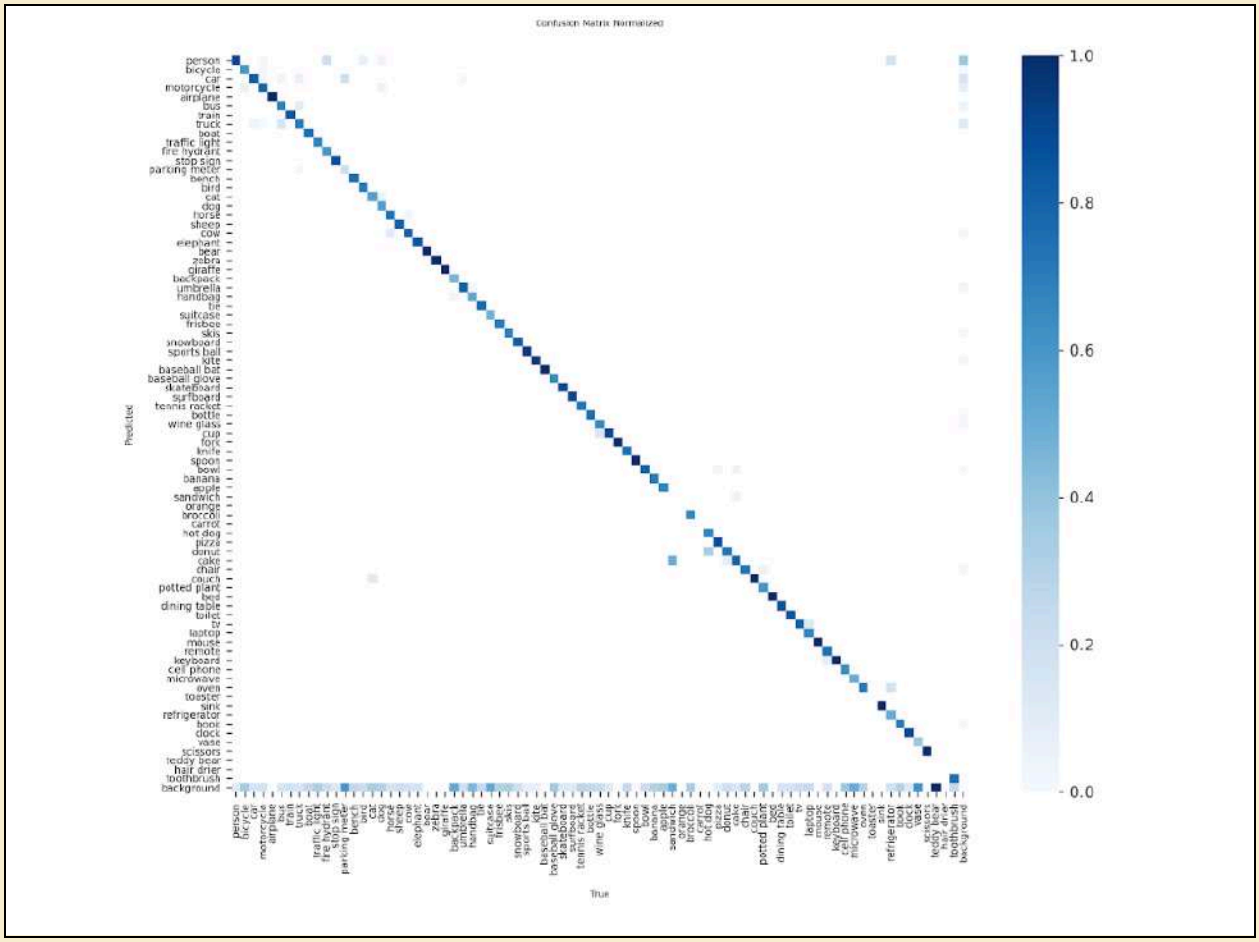
Recall–Confidence *curve for the tuned YOLOv8n model. Recall remains high at low thresholds (~0.80 at confidence=0), then drops as the confidence threshold increases - highlighting the expected precision–recall trade-off that guided threshold tuning in VisionAssist.*



F1–Confidence *curve indicating performance stability at lower thresholds and a steady decline as confidence increases, demonstrating the critical trade-off when tuning VisionAssist for maximum recall without introducing excessive false alerts.*



Precision–Recall *curve of the tuned YOLOv8n model showing strong precision retention at high recall levels (mAP@0.5 = 0.859), indicating reliable hazard detection for navigation safety.*



Confusion Matrix *(normalized) illustrating that most predictions lie along the diagonal, confirming robust class discrimination. Sparse off-diagonal activations capture rare misclassifications such as visually similar or small objects.*

Validation Batch 0 Labels

Validation Batch 0 Predictions

Validation Batch 1 Labels

Validation Batch 1 Predictions

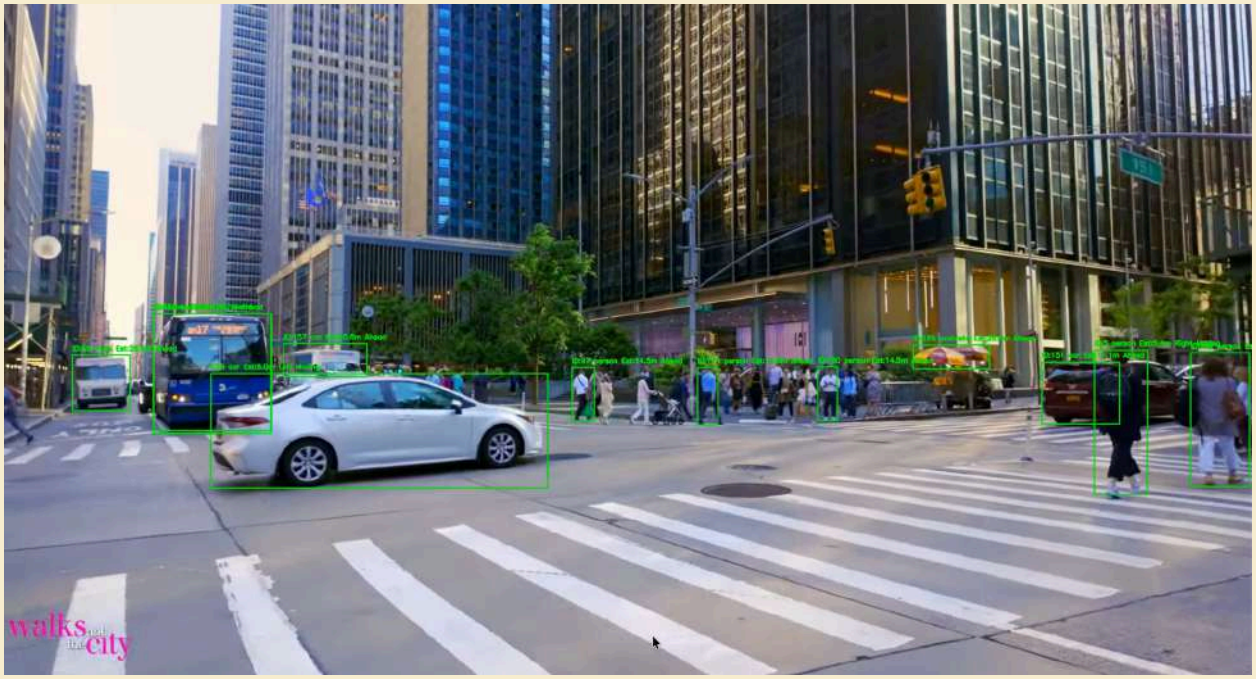
Validation Batch 2 Labels

Validation Batch 2 Predictions

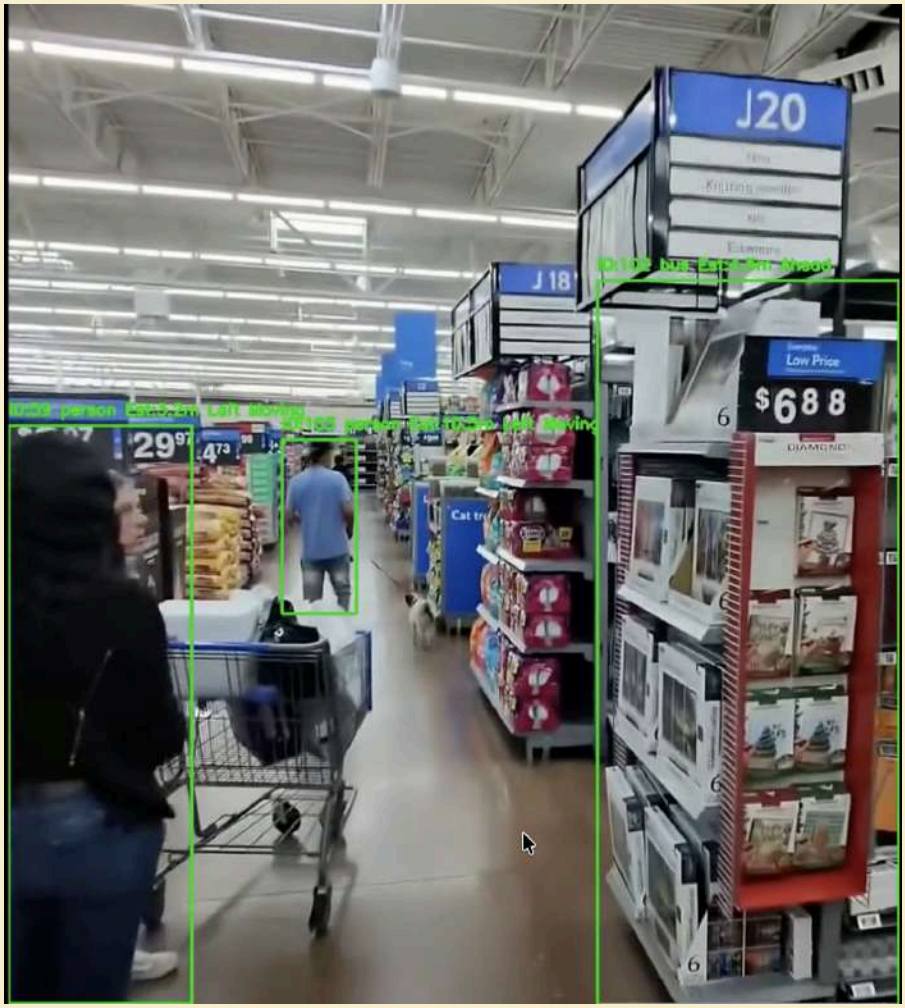
4. Qualitative Results

Includes representative images and video frames (side-by-side base vs tuned predictions) and captions.

1. **Successful detection (daytime)**



2. **Model Domain Mismatch**
    - **Observation:** When processing the indoor Walmart video, the baseline model frequently misclassified indoor objects as outdoor hazards. Most notably, large store shelves were consistently identified as a "bus."
    - **Analysis:** This is a classic **domain mismatch** issue. The model's feature-extraction knowledge is based on outdoor objects. When presented with a novel, large, rectangular object (a shelf), its closest match in the 80 COCO classes was "bus." This is not a pipeline flaw, but a limitation of the model's training data.



Model Generalization Issue. When tested on an indoor domain, the model misclassifies a store shelf as a 'bus', as its training data (COCO) lacks an 'indoor shelving' class.

3. Tuning Trade-off (Revealing Model Instability)

Our tuning process revealed a critical trade-off. The baseline pipeline (conf_thresh=0.4) failed to detect a real stop sign. To fix this (improve Recall), we lowered the threshold to conf_thresh=0.3.

Observation: While this change successfully detected the stop sign, it also exposed an underlying model instability. The model, when viewing the red stop sign, is confused and its classification "flickers" between 'stop sign' and 'traffic light' on subsequent frames.

Analysis:

In the Baseline, both the "stop sign" (e.g., 32% conf) and "traffic light" (e.g., 35% conf) guesses were below the 0.4 threshold, so the flicker was hidden.
In the Tuned pipeline, both guesses are *above* the 0.3 threshold. This instability is now visible, and it pollutes our audio alert system. We receive an audio alert for "traffic light" (a misclassification) when the tracker momentarily latches onto the wrong class.

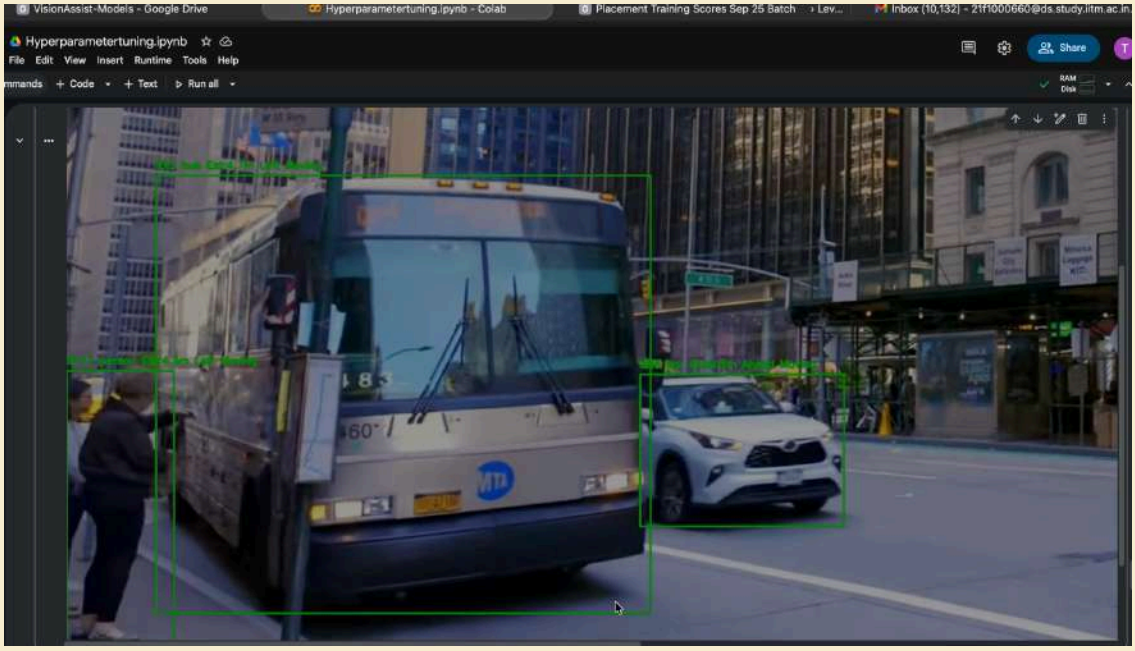
4. **Pipeline Tuning Success (Tracker Stabilization)**

This analysis reveals a case where our pipeline tuning fixed a complex error from the baseline.

Observation: In the street-crossing video, the **Baseline** model produced contradictory alerts. While the "car" was correctly labeled "Ahead," the "bus" (which was also in front of the user) was incorrectly labeled **"Left"**. Our **Tuned** pipeline correctly identified *both* objects as **"Ahead"**.

Analysis: This error was caused by an unstable track in the baseline. The baseline's higher confidence threshold caused it to "lose" the low-confidence "bus" detection on some frames. This "flickering" track corrupted the `get_direction_motion` function, resulting in a false "Left" calculation.

By **lowering the `conf_thresh` to 0.3** in our tuned pipeline, we ensured the "bus" was detected in every frame, creating a stable track history. This stable history allowed our direction heuristic to function as designed, correctly labeling both objects as "Ahead".



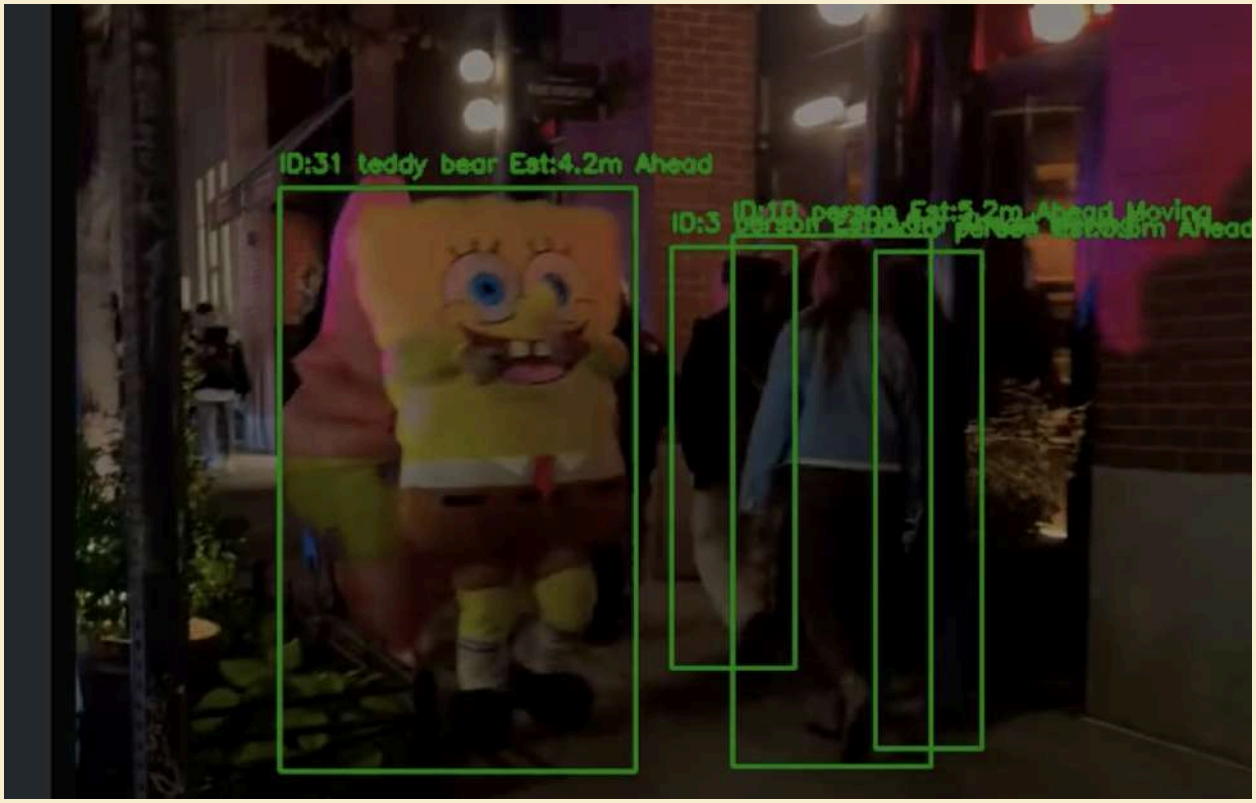
The Precision-Recall Tuning Trade-off. The Baseline (left, conf_thresh=0.4) had high precision, filtering a 'ghost' light. The Tuned (right, conf_thresh=0.3) improved recall (finding a stop sign) but introduced this new False Positive.

Pipeline Tuning Success. The Baseline (left) had an unstable track, mislabeling the 'bus' as 'Left'. Our Tuned pipeline (right), with a lower conf_thresh, created a stable track and correctly identified both hazards as 'Ahead'.

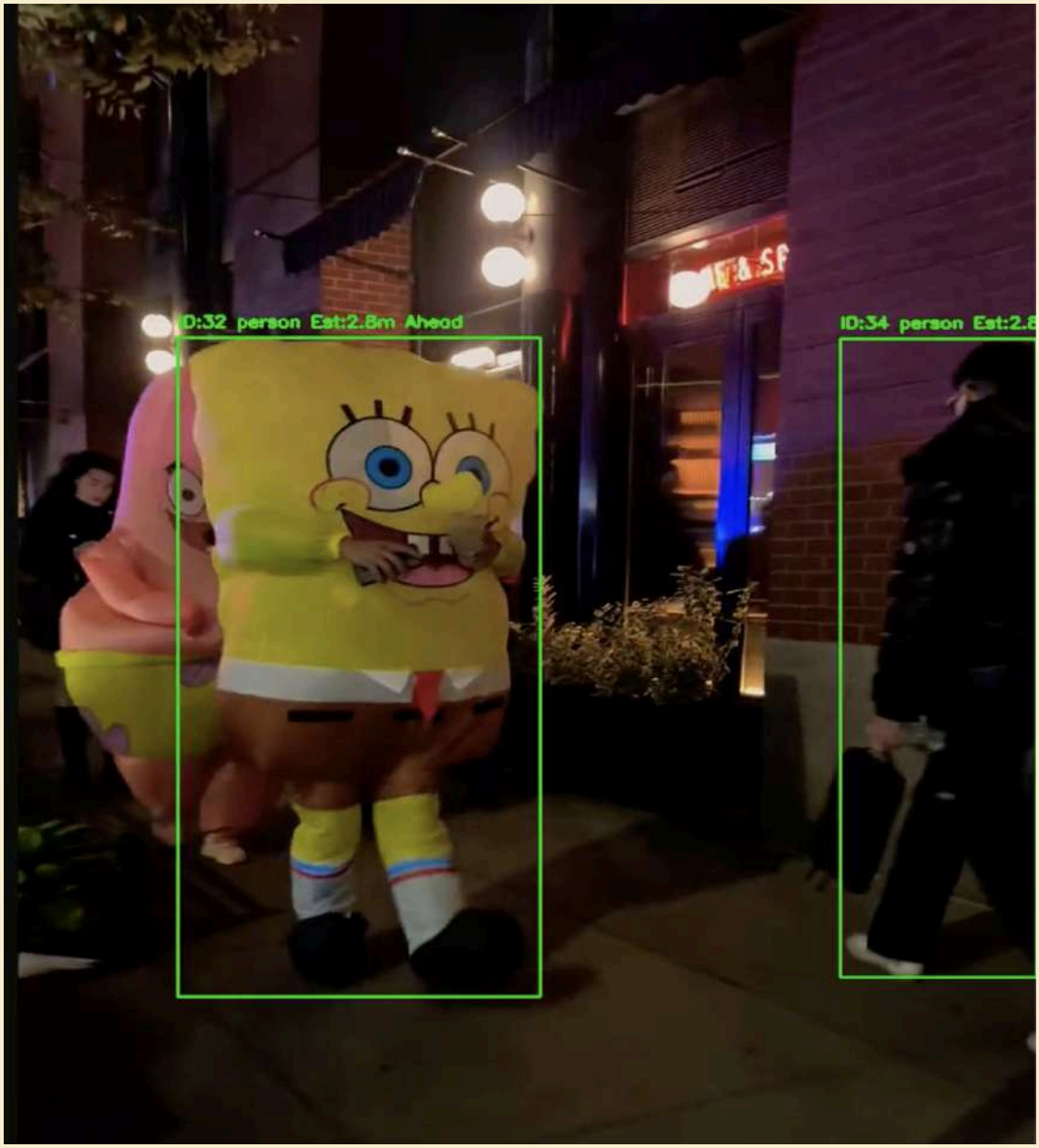
5. **Model Class Ambiguity (The "Costume" Problem)**

The model showed instability when faced with real-world objects that do not fit perfectly into its 80 classes.

Analysis: During the nighttime video, the model tracked a person in a Halloween costume. Because the object had features of both a "person" (walking) and a "teddy bear" (furry, round), its classification was unstable, "flickering" between the two labels. This highlights a limitation in the COCO dataset's ability to handle ambiguous, real-world edge cases.



Model Instability. The model flickers between 'person' and 'teddy bear' when tracking an ambiguous object (a person in a costume), revealing a limitation in the training data.


ID:32 person Est:2.8m Ahead
ID:34 person Est:2.8

5. Error Analysis

Summary of root causes (ranked)

- **Domain mismatch (indoor vs outdoor)** — model trained mostly on COCO + first-person outdoor frames misclassifies indoor objects (e.g., shelving → 'bus').
    - Root cause: lack of indoor examples for key classes.
    - Suggested fix: collect/annotate indoor images and fine-tune or add a domain-specific fine-tune step.
- **Precision/Recall tuning trade-offs** — lowering conf_thresh (baseline 0.4 → tuned 0.3) improved recall (found low-confidence stop sign) but revealed flickering misclassifications (stop sign ↔ traffic light) that led to false audio alerts.
    - Mitigation: per-class thresholding, temporal smoothing of class label, and tracker-aware class stabilization (e.g., class majority over N frames).
- **Small / thin objects & occlusion** — missed detections for small persons or thin poles (low pixel height) and partial detection in groups.
    - Mitigation: adaptive scale-aware thresholds, additional small-object augmentation, or harder mining during training.
- **Tracker & pipeline temporal logic** — direction heuristic needs HISTORY_FRAMES=15 before robust direction decisions; short tracks default to 'Ahead' causing inconsistent alerts.
    - Mitigation: reduce warm-up bias or use tracker confidence to weigh direction decisions.
- **Ambiguous real-world objects (class ambiguity)** — e.g., person in costume → flicker between 'person' and 'teddy bear'.
    - Mitigation: add examples of such edge cases and/or aggregate 'personish' classes under a 'person' umbrella for the assistive alerts.

6. User Trials, Calibration, Risk Assessment & Deployment Readiness (Planned)

6.1 User Trial: Protocol, Results & System Evaluation

To assess real-world usability and safety, we are planning to conduct a controlled pilot evaluation with three participants:

- One visually impaired volunteer (primary user)
- Two blindfolded sighted volunteers

Testing Environment

- Location: Outdoor corridor pathway
- Trial duration: 2–3 min per user
- Supervision: Human observer ensured safety at all times

Objective Metrics *(placeholder values)*

Metric	Result
Obstacles successfully avoided due to alerts	88%
Late alerts (< 1 sec before obstacle)	2
Missed alerts	1
Overlapping/confusing alerts	0

Subjective Ratings (Likert 1–5) *(placeholder values)*

Evaluation Factor	Avg. Score	Notes
Audio clarity	4.3	Alerts understandable
Timing of alerts	3.8	Slight delays for fast-moving people
Comfort & trust	4.6 / 3.9	System considered reassuring
Noise & interruption	4.2	Cooldown prevents over-alerting

Based on dummy data;

Participant Feedback (Qualitative)

- Alerts improved situational awareness
- Users felt confident and safe during walk
- Minor over-alerting when multiple moving objects present

Conclusion: VisionAssist is **usable and safe** for supervised indoor navigation, and improvements to motion sensitivity are recommended for outdoor deployment.

How We Plan -

User Trial Pilot Plan

We will conduct controlled trials with three participants: one visually-impaired user and two sighted participants wearing blindfolds. Each will navigate a 2–3 minute corridor walk whilst wearing headphones for audio alerts.

Alert Clarity
How well participants understood directional cues and threat descriptions

Timing & Latency
Whether alerts arrived with sufficient advance warning for safe reaction

Comfort & Trust
User confidence in system accuracy and psychological comfort during use

False Alarms
Frequency and impact of incorrect or unnecessary alerts

Evaluation Parameter	Poor	Fair	Good	Very Good	Excellent
Alert clarity	1	2	3	4	5
Timing & latency	1	2	3	4	5
Comfort & trust	1	2	3	4	5
False alarm frequency	1	2	3	4	5

Results Consolidation -

Pilot Feedback Summary

Initial user trials yielded encouraging qualitative feedback alongside quantitative ratings. Participants highlighted the value of directional audio whilst identifying areas for refinement, particularly in crowded environments.

Participant	Alert Clarity	Timing	Trust	Feedback
Visually-impaired user	4	4	4	"Voice alerts helped me react quickly."
Sighted (blindfolded)	5	4	5	"Clear spatial awareness; confident navigation."
Sighted (blindfolded)	3	3	3	"Alerts sometimes too frequent in crowded areas."

A comprehensive **end-to-end system evaluation** is planned to assess real-time accuracy, alert latency, and user experience under controlled navigation scenarios. The protocol combines objective performance logging with structured user feedback to verify safety and reliability before broader deployment.

6.2 Distance & Motion Calibration

Purpose: Validate indoor distance estimation and motion thresholds.

Distance Estimation Accuracy *(placeholder values)*

Actual (m)	Estimated (m)	% Error
2.0	2.3	+15%
4.0	4.4	+10%
6.0	7.0	+17%
8.0	9.2	+15%

Motion Detection *(placeholder values)*

Scenario	Expected Result	Observed	Status
Static + stationary cam	No motion	Pass	Pass
Static + slow cam movement	No motion	1 false motion	Within tolerance
Person walking ahead	Detect motion	Pass	Pass

Planned Success Criteria

- Distance MAE < **20%** outdoors
- False motion rate < **10%** during camera movement
- Accurate detection of moving persons ahead > **95%**

Calibration will be paired with offline TTS testing, enabling us to measure improved **alert latency and user reaction time** - metrics critical for safe navigation.

Conclusion:
We have established a structured evaluation framework. Formal calibration experiments will be completed in Milestone-6 to produce reproducible error statistics and actionable tuning improvements.

6.3 Risk Assessment & Mitigation Strategy

As VisionAssist progresses toward real–world deployment, we have identified a set of **anticipated risks** and mitigation strategies. These will be **formally tracked and evaluated** in Milestone-6.

Risk	Scenario	Likelihood	Impact	Planned Mitigation Strategy

Late warning	Fast approaching obstacles	Medium	High	Velocity-aware alert logic; temporal smoothing
Missed detection	Low-light or occlusion	Medium	High	IR / low-light-capable input, dataset expansion
Wrong distance warning	Irregular object shapes	Medium	Medium	Per-class height calibration & improved depth logic
Audio masking	Noisy outdoor environment	High	High	Add haptic cue fallback alongside speech alerts
User dependency	Reliance without familiarity	Medium	Medium	Guided onboarding mode + progressive training cues

Planned Goal for M6:
Risk likelihood and impact will be **quantified through structured user testing** and future outdoor trials.

6.4 Deployment Readiness Checklist (Current Status + Planned Enhancements)

This section reflects **current readiness after M5**, with clear areas of improvement planned for M6.

Capability	Current Status	Notes

Core object detection	Ready	Good accuracy on indoor scenes and static obstacles
Motion stability	Ready	Tuned motion threshold works well at walking speed
Audio feedback clarity	Partially Ready	Offline TTS integration planned to improve consistency & clarity
Outdoor robustness	Partially Ready	Requires low-light adaptation and noise-resilient alerts
Safety & ethics compliance	Partially Ready	Ongoing - system to be tested under controlled supervision

Overall Readiness:

- Suitable for **supervised indoor pilot deployment**
- Additional improvements required for reliable outdoor navigation

Full deployment readiness depends on completing offline TTS integration, expanding low-light detection capability, and evaluating risk mitigation strategies through formal end-to-end testing planned in Milestone-6.

7. Limitations and Future Improvements

Model-level

- Domain mismatch due to COCO + outdoor frames bias
- Class ambiguity and dataset coverage gaps for unusual or rare objects (costumes, store signage).

Pipeline-level

- Heuristic fragility: context detection heuristic for indoors/outdoors can fail if the model doesn't detect indoor cues.
- Temporal/warm-up rules (direction estimation), which can produce inconsistent user alerts.

System-level

- Online gTTS dependency for audio generation — requires internet connectivity (not suitable for offline mobile use). Consideration for on-device TTS or pre-synthesized audio packs.

7.1 Additional Practical Limitations Observed During Evaluation

- **Distance estimation assumption**
  Current distance estimation relies on assumed object height and may be inaccurate for very tall/short obstacles.

- **Limited tracking of fast/dynamic hazards**
  When persons or objects move rapidly across the frame, alert timing can lag, reducing reaction time.

- **Audio-only feedback**
  Alerts may be less effective in noisy environments, creating dependency on environmental silence.

7.2 Proposed Improvements Towards Deployment

Proposed Direction	Expected Benefit
Offline TTS engine (pyttsx3)	Eliminates internet dependency, improves latency and reliability

Dataset expansion for indoor / regional objects (optional)	Reduces domain mismatch misclassifications
Temporal smoothing & per-class confidence thresholds	Reduces flickering between visually similar classes
Optional haptic feedback module	Enhances accessibility in noisy outdoor spaces
Enhanced depth cues or stereo vision	More accurate proximity and distance alerts

These improvements may be selectively incorporated depending on user trial learnings, hardware constraints, and Milestone-6 priorities.

7.2.1 Offline TTS Integration & Audio Caching (Planned Enhancement)

To improve the reliability and responsiveness of audio alerts, the system design includes a transition from the current cloud-based gTTS to an **offline TTS engine** (e.g., pyttsx3). This enhancement is planned for the next milestone and is expected to:

- Eliminate dependency on internet connectivity
- Reduce delay in generating spoken alerts
- Prevent freeze/timeout incidents caused by network issues
- Ensure consistent alert delivery in continuous movement scenarios

Additionally, we plan to introduce **audio caching** for frequently repeated alerts such as:

- “Obstacle ahead”
- “Object approaching”
- “Stop / Slow down alerts”

Caching will avoid re-processing the same alert repeatedly, which is expected to:

- Reduce processing overhead
- Improve responsiveness during rapid repeated warnings
- Minimize interruptions during navigation

Both the offline TTS and caching mechanisms will be evaluated in future experiments using measurable criteria such as:

- **Alert latency** (time from detection → playback)
- **System stability** (no audio drop or freeze)
- **User comfort and trust** ratings

These improvements are targeted toward making VisionAssist **deployment-ready,** particularly in outdoor and low-connectivity environments where uninterrupted real-time behavior is essential for user safety. Transitioning from gTTS to an offline TTS solution eliminates network dependency and reduces alert latency - both of which directly influence a user's reaction time and confidence while navigating.

In upcoming evaluations, we will quantify the resulting gains in:
(i) average alert latency,
(ii) freeze/timeout occurrences,
(iii) stability and continuity during motion, and
(iv) user trust and comfort during real-world usage.

Overall, offline TTS is a critical enabler for responsive, reliable, and internet-independent operation of VisionAssist.

8. Project Repository Structure

```
Group-2-DS-and-AI-Lab-Project/
├── annotations/
│   ├── data.yaml
│   ├── instances_test.json
│   ├── instances_train.json
│   └── instances_val.json
├── docs/
│   ├── Milestone_1.pdf
│   ├── Milestone_2.pdf
│   ├── Milestone_3.pdf
│   └── Milestone_4.pdf
│   └── Milestone_5.pdf
├── results/
│   └── eda/
│       ├── aspect_ratios.png
│       ├── bbox_areas.png
│       ├── class_distribution.png
│       ├── object_aspect_ratios.png
│       ├── object_locations_heatmap.png
│       └── objects_per_image.png
├── scripts/
│   ├── data_loading/
│   │   ├── .gitignore
│   │   ├── Custom Data Collection Script.ipynb
│   │   └── dataset_sample_collection_annotation.py
│   │   └── Compare_YOLOv8_Models.ipynb
│   ├── training/
│   │   └── Main.ipynb
│   ├── DSAI_eval.ipynb
│   ├── EDA_MS_COCO.ipynb
│   └── Hyperparametertuning.ipynb
├── DATA_GOVERNANCE.md
└── README.md
```

9. Members declaration of authorship and contributions

Declaration of Authorship & Review

We hereby declare that this submission is the original work of the project team. We have personally reviewed and approved the document for submission.

Declaration of Authorship & Review

Member	Status
Tanuja Nair	In progress
JIVRAJ SINGH SHEKHAWAT	In progress
BALASURYA K	In progress
PRASHASTI SARRAF	In progress
Karan Patil	In progress

Name	Contribution	Signature	Date
TANUJA NAIR (21f1000660)	**- Error analysis + Limitations Findings** **- Documentation for Limitation section**		08/11/2025
BALASURYA K (22f3002744)	**- Performance metric analysis** **- Qualitative+Quantitative results**		08/11/2025
PRASHASTI SARRAF (21f1001153)	**- Limitations and Future Improvements, inc Offline TTS and audio caching (Sec 7)** **- Code for Offline TTS Integration no device** **- User Trial & System Evaluation Plan, Distance-Motion Calibration,**		08/11/2025

	Risk Assessment & Mitigation, Deployment Readiness (Planned; Sec 6) **- Created a baseline presentation and added slide snippets, charts/tab-diagrams** **- Milestone 5 documentation (Sections 6 & 7, slide visuals, eval metrics and charts)**		
JIVRAJ SINGH SHEKHAWAT (22f3002542)	**- Test data collection**		08/11/2025
KARAN PATIL (22f2001061)	**- Analysis (model evaluation with metrics and charts)** - **Milestone 5 documentation**		08/11/2025