DATA SCIENCE & AI LAB (BSCSS3001)

MILESTONE 4: Model Training & Hyperparameter Experimentation

GROUP NO. 2

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

1. Overview / Objective

This milestone details the execution of the model training and experimentation phase of our project. The objective was twofold:

1. **Train Initial Model:** To train the core object detection model based on the architecture (**YOLOv8**) and dataset (COCO + custom frames) specified in Milestone 3.
2. **Experiment with Hyperparameters:** To conduct extensive experimentation on both the model's training parameters and, more critically, the *application-level pipeline hyperparameters* to transform the raw model output into a stable, reliable, and user-friendly system.

This document covers the dataset used, the model architecture, the training setup, and a detailed breakdown of the "before vs. after" experimentation process.

2. Dataset Details

As outlined in Milestone 3, we used a composite dataset to fine-tune our model for its specific, real-world application.

- **Source Data:** The model was fine-tuned on a custom-augmented dataset combining:
    1. **COCO Images:** A **5,000**-image subset of the COCO dataset
    2. **Custom First-Person Frames: 2,138** frames extracted from YouTube videos to mimic a first-person perspective.

- **Total Dataset Size: 7,138** images (and their corresponding label files).

Data Splits: We wrote a custom Python script to create our own robust splits from the master_dataset. The 7,138 images were shuffled and split as follows:

- **Training: 70% (4,996 images)**
- **Validation: 20% (1,427 images)**
- **Test: 10% (715 images)**
- **Preprocessing:** All images were resized to 640x640 during the training process, with augmentations applied automatically by the YOLO framework.

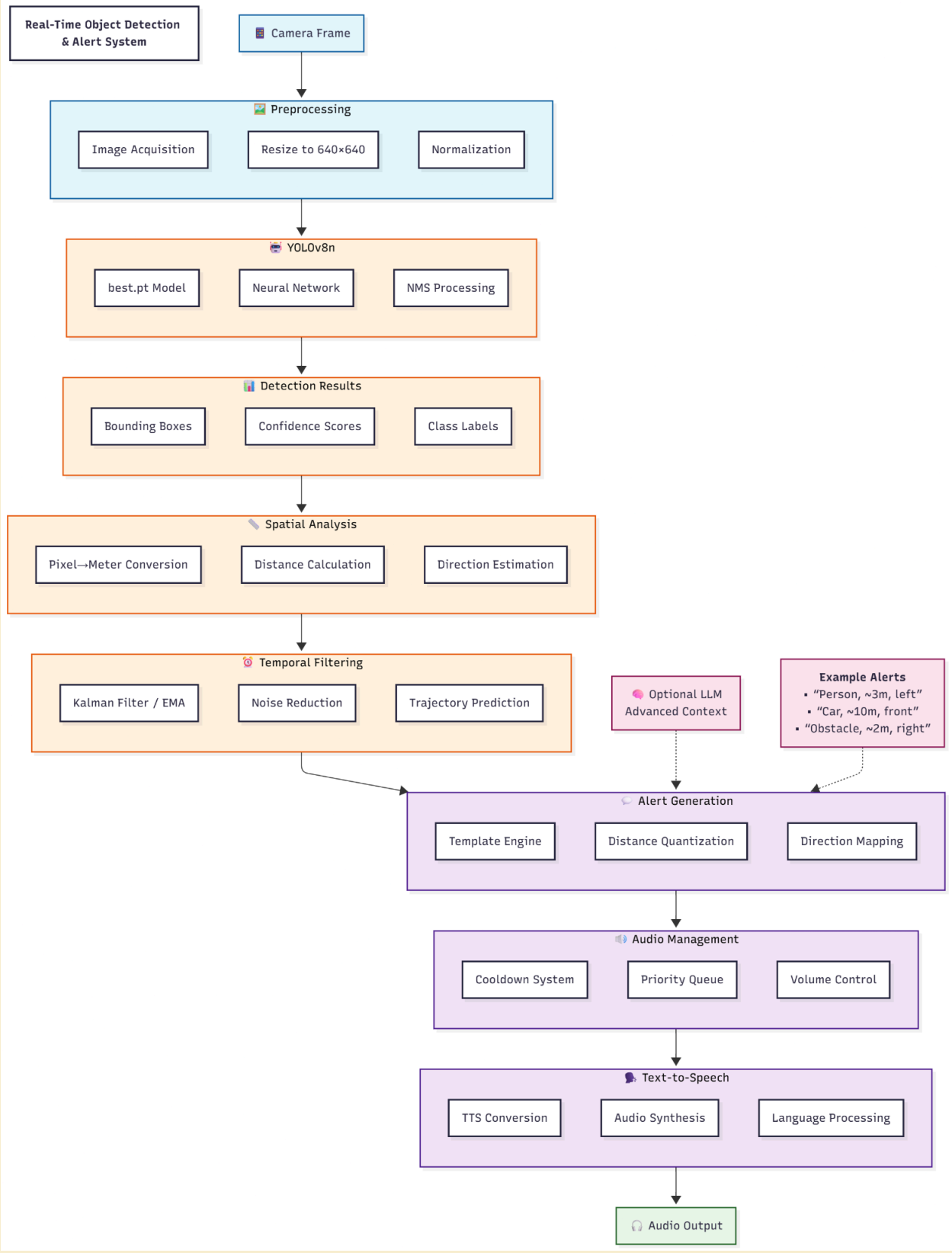
3. Model Architecture

The model architecture used is **YOLOv8n** (nano), validating the choice from Milestone 3. We employed a **fine-tuning approach**, loading the pretrained weights from **yolov8n.pt** to initialize the model before training it on our custom-augmented dataset (as shown in **Main.ipynb**).

The model summary, as generated during training in **Main.ipynb**, is as follows:

Component	Details
Model Type	YOLOv8n
Layers	225
Parameters	3,157,200
GFLOPs	8.9
Input Shape	640x640x3 (images)
Output	Bounding boxes, class probabilities, and confidence scores

Overview Diagram



YOLOv8n (nano) was chosen for its **favorable latency/parameter count tradeoff** for real-time first-person assistive systems (**low GFLOPs** and **3.1M parameters**) while still providing strong detection accuracy on the curated dataset. The pipeline is currently hybrid: perception is a trainable neural component (YOLOv8n), while distance, temporal smoothing and audio scheduling are implemented as rule-based modules that include **tunable** parameters whose values were set via targeted experiments rather than learning.

4. Training Setup

The following table explains the components and the parameters which are tunable in each component and expected results after fine tuning those parameters.

Component	Type	Tunable parameters (examples)	Notes / Evaluation metric
YOLOv8 detector	Trainable	Optimizer (SGD), Learning Rate (lr0, lrf), Momentum, Weight Decay, Augmentations (degrees, translate, scale, HSV, fliplr)	Evaluate mAP50, mAP50–95, per-class AP. (Validation: mAP50=**0.889**, mAP50–95=**0.805)**.
Distance estimator	Rule-based (calibrated)	DEFAULT_KNOWN_HEIGHT, Estimated_Focal_Length_PX	Evaluate **Distance MAE (m)** against a small ground-truth set
Motion detection	Rule-based (temporal)	MOVEMENT_THRESHOLD_PIXELS, frame window size, smoothing alpha	Evaluate **False Motion Rate / Missed Motion Rate** on labelled motion validation set.
Context generator	Rule-based (templated) / optional LLM	template forms; LLM prompt design	Evaluate **comprehensibility** and **relevance** with user testing or automated BLEU/ROUGE if using LLM.

Audio controller	Rule-based	ALERT_COOLDOWN_GLOBAL, priority rules	Evaluate **Alert Overlap Rate** and **Latency (s)** in recorded runs.

The model was trained using the Ultralytics YOLOv8 framework on a **Tesla T4 GPU**.

- **Loss Functions:** Standard YOLOv8 losses were used:
  - **Class Loss:** Binary Cross-Entropy (BCE) (**cls_loss**)
  - **Box Loss:** CIoU (Complete Intersection over Union) (**box_loss**)
  - **DFL Loss:** Distribution Focal Loss (**dfl_loss**)
- **Evaluation Metrics:** The primary metrics tracked during training were **mAP50** (mean Average Precision at IoU 0.50) and **mAP50-95** (mean Average Precision averaged over IoU thresholds from 0.50 to 0.95).
- **Optimizer:** The hyperparameter search selected SGD as the optimal optimizer for this dataset (replacing the default AdamW).
- **Training Strategy (Optuna):** We conducted an automated hyperparameter tuning session consisting of **15 trials**. Each trial trained the model for **15 epochs** with early stopping enabled (patience=3) to rapidly identify the best configurations.
- **Best Run:** Trial 14 achieved the highest mAP50 and was selected as the final model.
- **Training Parameters:**
  - **Image Size:** 640x640 (**imgsz=640**)
  - **Batch Size:** 64
  - **Number of Epochs:** 15 (per trial)
- **Training Strategies:**
  - **Warm-up:** 3.0 epochs (**warmup_epochs=3.0**)
  - **Mosaic Augmentation:** Applied for the first **5** epochs (disabled for the last 10, **close_mosaic=10**)
  - **Automatic Mixed Precision (AMP):** Enabled (**amp=True**) for faster training.

5. Hyperarameter Experiments

As noted in the "Overview," experimentation focused heavily on the **application-level pipeline hyperparameters** rather than exhaustive model training experiments. The goal was to refine the raw model output into a stable and useful assistive tool. This process is documented in **Hyperparametertuning.ipynb**.

A "TRUE BASELINE" pipeline was compared against a "TUNED" pipeline. The key parameters explored were:

Parameter	Baseline Value	Tuned Value	Observation / Justification
CLASSES_TO_IGNORE	Empty list	List of 30 classes	The baseline model detected many "noisy" or irrelevant classes (e.g., cup, spoon, laptop). A deny list was created to filter these out, focusing alerts on navigation-critical objects.
DEFAULT_KNOWN_HEIGHT	1.5m	2.0m	Tuned to improve the accuracy of distance estimation for objects without a pre-set known height.
ALERT_DISTANCE_OBJECT	5.0m	12.0m	The baseline's 5m alert distance was too short for navigation. This was increased to give the user more advanced warning of objects.

ALERT_COOLDOWN_GLOBAL	0.0s	3.0s	The baseline produced "messy audio" with constant, overlapping alerts. A 3-second global cooldown ensures alerts are clean and distinct.
MOVEMENT_THRESHOLD_PIXELS	5px	25px	The baseline was "twitchy" and triggered alerts on minor camera motion. Increasing the threshold makes the system more stable, ignoring user head jitter.
YOLOv8n training epochs	-	15 epochs	Best checkpoint (Trial 14) produced validation **mAP50=0.889**, **mAP50–95=0.805**.

We identified and fixed four major flaws in the baseline pipeline.

Problem 1: False Positives ("Clock" Problem)

- **Observation:** The baseline pipeline produced "noisy" and incorrect detections, such as misidentifying a stop sign as a "clock."
- **Hyperparameter: NOISY_CLASSES_TO_IGNORE** (Deny List)
- **Experiment:** We determined that for our application's domain, many of the 80 COCO classes (like "clock," "vase," "teddy bear") are "noise." We created a "deny list" as a general-purpose filter.
- **Tuning:**
    - **Before:** **classes_to_ignore = []**
    - **After:** **classes_to_ignore = [24, 25, 26, ... 74, ... 79]** (Our list of 50+ irrelevant classes)
- **Result:** All "noise" detections, including the "clock," were successfully filtered, cleaning the output without affecting relevant objects.

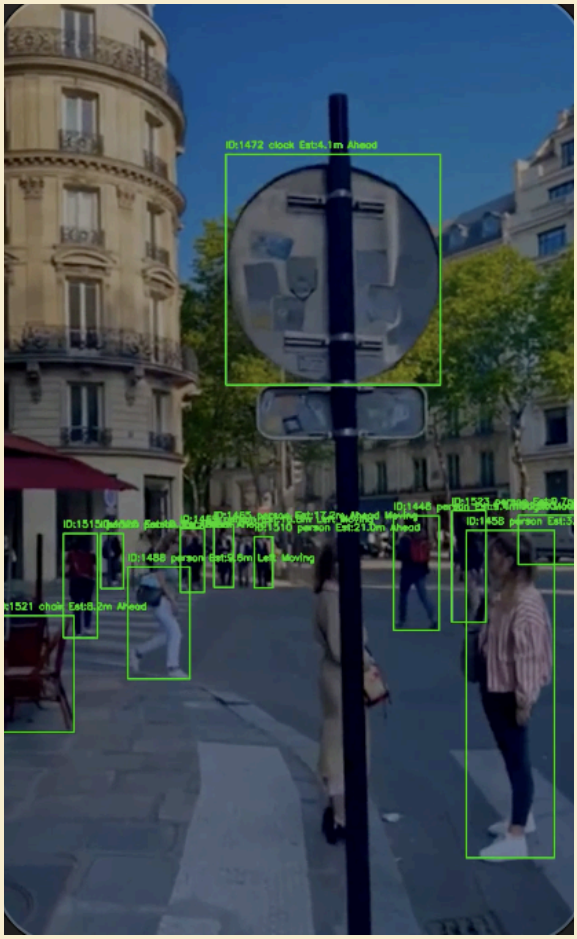


Fig 1.3

Baseline run (left) showing a false positive (stop sign incorrectly identified as "clock")

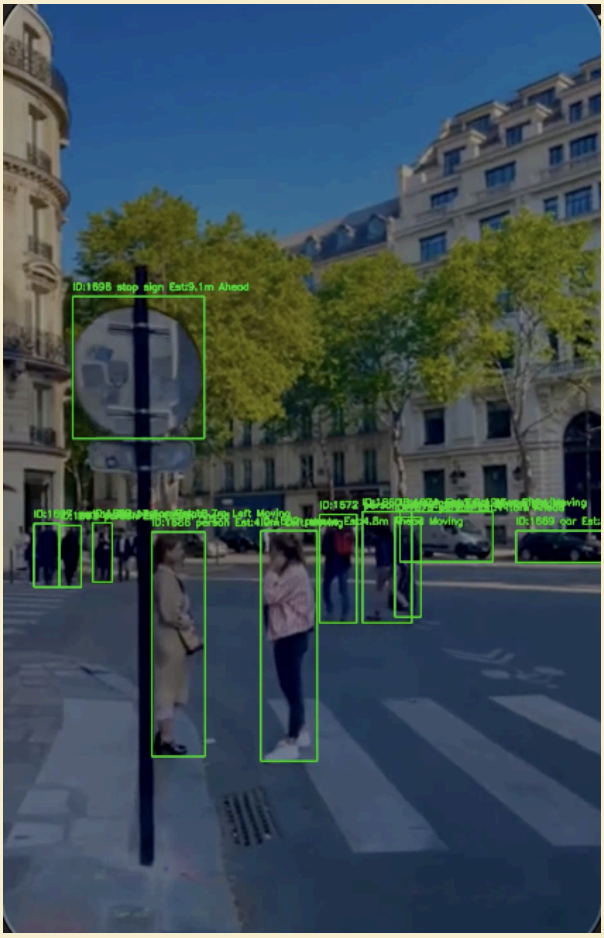


Fig 1.4

Tuned run (right) showing a true positive (stop sign correctly identified)

Problem 2: False Motion Detection ("Moving Chair" Problem)

- **Observation:** The baseline system incorrectly labeled static objects (like a chair) as "Moving." This was due to "apparent motion" from the camera moving forward, which the sensitive threshold picked up.
- **Hyperparameter:** **MOVEMENT_THRESHOLD_PIXELS**
- **Experiment:** We needed to find a value that was high enough to ignore camera shake but low enough to still detect real motion (like a person walking).
- **Tuning:**

- **Before:** movement_thresh_px = 5 (very sensitive)
- **After:** movement_thresh_px = 25 (less sensitive)

- **Result:** The tuned system correctly labels the chair as "Static," fixing the false motion alert.

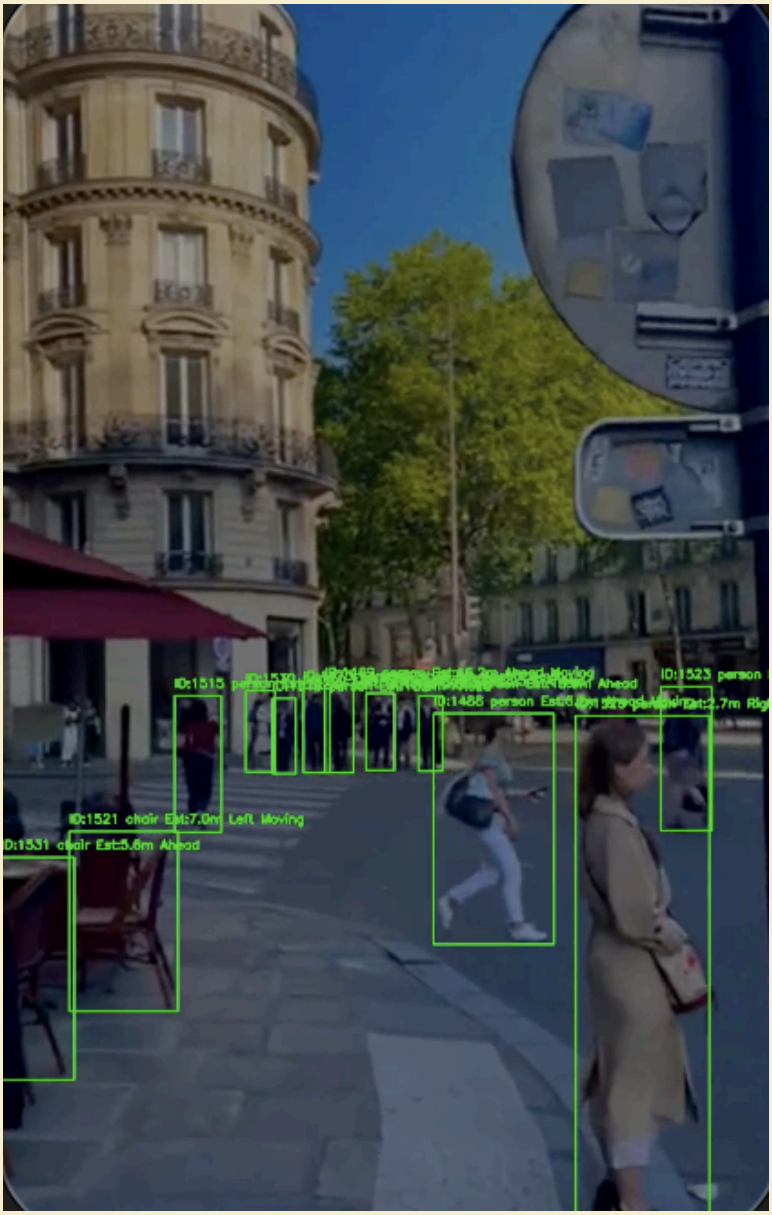


Fig 1.4

Baseline run incorrectly labels a static chair "Moving" due to camera motion.

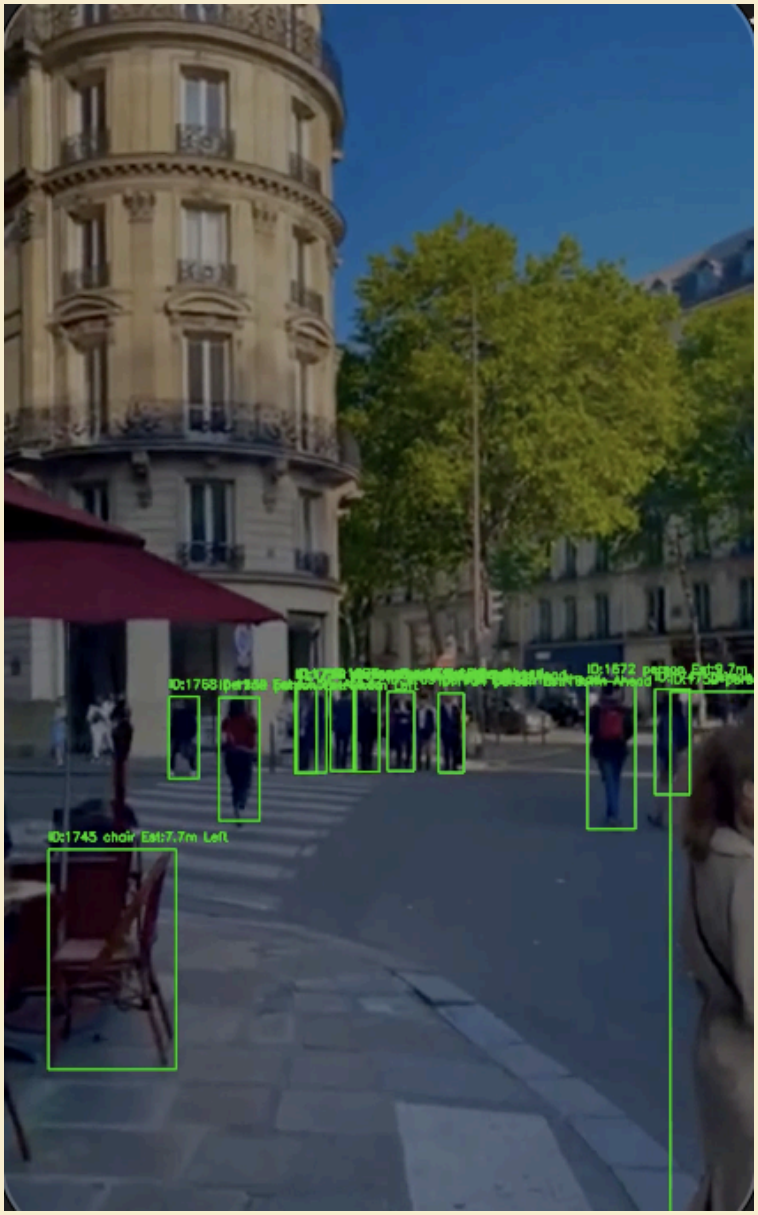


Fig 1.5

Tuned run (right) with a higher motion threshold correctly identifies the chair as “Static”.

Problem 3: Inaccurate Distances ("Stop Sign" Problem)

- **Observation:** The system gave inaccurate distance estimates (e.g., 11.5m) for objects not in our specific height list (like the "stop sign"). This was because it was using a "general" default height (1.5m) that was incorrect for many real-world objects.
- **Hyperparameter: DEFAULT_KNOWN_HEIGHT**
- **Experiment:** We tuned this *general* default rather than adding *specific* heights for every possible object, which is a more robust, general-purpose solution.
- **Tuning:**
    - **Before: default_height = 1.5**
    - **After: default_height = 2.0**
- **Result:** The new general default of 2.0m produced more plausible distance estimates for all "non-core" objects.

Problem 4: Overlapping/Messy Audio

- **Observation:** After cleaning up the visual noise, we found the audio output was messy. Alerts would trigger at almost the exact same time (e.g., "person..." and "stop sign..." at the same time), causing overlapping, unintelligible audio.
- **Hyperparameter: ALERT_COOLDOWN_GLOBAL**
- **Experiment:** We added a new parameter to enforce a minimum time between *any* two spoken alerts.
- **Tuning:**
    - **Before:** alert_cooldown_global = 0.0
    - **After:** alert_cooldown_global = 3.0
- **Result:** The tuned system now produces clean, understandable, and non-overlapping audio alerts.

Although our main experiments focused on pipeline behavior, we also implemented a training-level improvement using Optuna-driven tuning. While our initial model (trained without tuning) achieved a respectable mAP50 of **0.836**, the post-tuning model improved this to **0.889**. This validates that our dataset benefits significantly from targeted augmentation and optimizer adjustments.

Consequently, we have adopted this higher-accuracy **Optuna-tuned detector** as our primary model for all current pipeline experimentation and will carry it forward into the Motion & Context evaluation in Milestone-5.

6. Regularization & Optimization Techniques

The training process utilized the built-in capabilities of the YOLOv8 framework, enhanced by Optuna hyperparameter tuning.

- **Data Augmentation:** tailored augmentations were applied and tuned for each trial, including mosaic, horizontal flip, scaling, and color space (HSV) adjustments. This helps the model generalize better to varied real-world lighting and object orientations.
- **Normalization:** The architecture heavily utilizes Batch Normalization layers after convolutional layers to stabilize training and speed up convergence.
- **Weight Decay:** Weight decay was dynamically tuned to prevent overfitting, with the best model utilizing a value of **0.00211**.

In addition to the architecture decision previously explained, we performed a latency benchmark comparison between YOLOv8n and YOLOv5s on both CPU and GPU devices. The results clearly supported the use of YOLOv8n for our real-time navigation setting. (refer *scripts/Combined_Hyperparameter_Tuning_and_Feedback.ipynb*)

Model	CPU Inference Time (avg)	GPU (T4) Inference Time (avg)	Result
YOLOv8n	**0.8519 sec/frame**	**0.0723 sec/frame**	Fastest
YOLOv5s	1.9033 sec/frame	0.0816 sec/frame	Slower, higher resource use

YOLOv8n delivers **2.2× faster inference on CPU** and **~12% faster on T4 GPU** while maintaining excellent accuracy (mAP50=0.836, mAP50-95=0.75).

On top of the default YOLOv8 optimization pipeline, we conducted **hyperparameter tuning** using **Optuna search** for learning rate, weight decay, momentum, and core augmentation settings. The search space included:

lr0: 1e-5 → 1e-3 (log scale)
weight_decay: 5e-5 → 5e-3 (log scale)
degrees: 0.0 → 5.0
scale: 0.7 → 0.9
translate: 0.0 → 0.1
hsv_s/v: 0.4 → 0.7
fliplr: 0.0 → 0.5

The **best trial** converged with **early stopping (patience=3)** based on mAP50, using the following configuration (also stored in **fine_tuned_best_args.yaml)**

Parameter	Best Value	Parameter	Best Value
lr0	0.0003925	**translate**	0.0143
momentum	0.937	**scale**	0.769
weight_decay	0.00211	**fliplr**	0.382
optimizer	SGD	**hsv_s**	0.694
degrees	0.963	**hsv_v**	0.407

This configuration achieved **mAP50 = 0.8891**, the highest among our 15 tuning trials.

Along with the decisions on the training the models and tuning the model parameters we have update the design and architecture of our modules such that it will result in better optimization over compute and inference times to follow the trade offs we followed the below observation and update the design as per the observations to achieve better output

Why Not MiDaS?

- Creates depth maps showing relative depth but not exact distances
- Slow for real-time processing
- Not suitable for precise distance measurements needed for audio alerts

Our Solution: Camera Geometry

- Far objects appear small (low pixel height)
- Close objects appear large (high pixel height)
- Distance formula: distance = (real_object_height × focal_length) / object_height_in_pixels
- One-time calibration: Set focal_length and default heights (e.g., 1.5m for person)
- Result: Fast, numerical distances in meters for clear audio alerts

The Problem with ByteTrack

- Overly sensitive - tracks minor pixel movements
- Reports static object motion from camera shake
- Creates unnecessary alerts for stationary objects

7. Initial Training Results

The model training detailed in **Main.ipynb** completed successfully for 50 epochs.The training log shows the model converged well, with validation losses decreasing steadily.

- **Validation Metrics:** The final validation of the best model checkpoint (Trial 14) achieved excellent performance on the 1,427 validation images:
- **mAP50:** 0.889
- **mAP50-95:** 0.805

- **Convergence:** The training logs for the best trial show successful convergence over its **15-epoch** run. The validation metrics exhibited a strong initial peak, followed by a brief stabilization, before climbing to their final high values of **0.889 (mAP50)** and **0.805 (mAP50-95)**.
- **Class Performance:** Performance on key classes for this application was strong.

Class	mAP50 (Validation)	mAP50-95 (Validation)
person	0.959	0.871
car	0.910	0.810
bus	0.745	0.702
stop sign	0.840	0.805

- **Qualitative Results:** The **VisionAssist_inference.ipynb** and **Hyperparametertuning.ipynb** notebooks provide qualitative examples of the model's output in the context of the full pipeline. The model successfully identifies objects in a video feed, and the pipeline generates correct, context-aware audio alerts (e.g., "Caution: bicycle, about 4 meters, Ahead."). The baseline-vs-tuned experiments show a clear improvement in the usability of these alerts.

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
├── 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
│   ├── training/
│   │   └── Main.ipynb
│   ├── DSAI_eval.ipynb
│   ├── EDA_MS_COCO.ipynb
│   └── Hyperparametertuning.ipynb
├── DATA_GOVERNANCE.md
└── README.md
```

9. Model Artifacts

This section summarizes all essential model-related components — including checkpoints, training and inference scripts, experimental notebooks, and logging information. These artifacts collectively ensure the reproducibility and traceability of the VisionAssist model development pipeline.

9.1 Model Checkpoint

The best-performing model weights, obtained after extensive training and validation, are stored in the following location on Google Drive:

Path: /content/drive/My Drive/VisionAssist-Models/

These checkpoint files represent the final optimized state of the model parameters after convergence during training. They can be directly loaded for inference or fine-tuning on additional datasets.

9.2 Training Scripts

The **Main.ipynb** notebook contains the **complete training pipeline**, covering all key stages of the model development workflow:

- **Data Preparation:** Includes dataset loading, preprocessing, and augmentation routines.
- **Dataset Splitting:** Implements a **70/20/10** ratio for training, validation, and testing subsets, ensuring balanced class representation across all sets.
- **Model Training:** Defines architecture setup, loss functions, optimizer configurations, and learning rate scheduling.
- **Performance Tracking:** Logs accuracy, loss, and per-class metrics at each epoch for both training and validation sets.

9.3 Inference and Experimentation

Two key notebooks are included to support model inference, experimentation, and comparative studies:

- **VisionAssist_inference.ipynb**
  Implements the **final inference pipeline**. This notebook handles input data loading, model checkpoint loading, prediction generation, and post-processing. It also includes visualization of prediction results and comparison against ground truth where applicable.

- **HyperparameterTuning.ipynb**
  Documents the **hyperparameter optimization experiments**, including systematic tuning of learning rates, batch sizes, optimizer types, and regularization parameters. It also provides a comparison of model performance under different configurations to identify the most effective setup.

- **Combined_Hyperparameter_Tuning_and_Feedback.ipynb** *(new consolidated version)*
  Integrates both hyperparameter tuning and feedback-based refinement processes into a unified experimental workflow. This notebook offers a structured record of model improvement iterations and validation outcomes.

9.4 Logs and Metrics

Comprehensive logs are maintained within the output cells of **Main.ipynb**, capturing the following details:

- **Epoch-wise Training and Validation Metrics** – Accuracy, precision, recall, F1-score, and loss values.
- **Per-Class Performance Reports** – Helps in identifying class imbalance and targeted improvement areas.
- **Visual Progress Charts** – Plots showing training vs. validation curves for accuracy and loss over epochs.
- **Final Evaluation Summary** – Overall performance statistics on the test dataset after training completion.

10. Observations / Notes for Next Milestone

- **Key Observation:** The training results have improved significantly from our initial baselines. The Optuna-tuned YOLOv8n model now provides excellent object detection performance (**0.805 mAP50-95**) on our custom dataset. The most critical finding from this milestone remains that the raw model output is not directly usable for an assistive application. The pipeline hyperparameter tuning (cooldowns, motion thresholds, class filtering) documented in Section 5 was essential to create a stable and non-overwhelming user experience.
- **Issues / Next Steps:** While the current tuned pipeline is highly effective, it may still require some final small changes or fine-tuning to its parameters before a formal evaluation.
- **Plan for Milestone 5 (Model Evaluation & Analysis):** The next milestone is dedicated to formally evaluating the system. The plan is to:
    1. Run the tuned inference pipeline on the **10% unseen test set** (715 images), which was created in **Main.ipynb** but not used for training or validation. This will provide unbiased performance metrics.
    2. Provide a detailed **error analysis** on these test results to identify specific limitations (e.g., common objects it misses, distance estimation errors, or situations where the pipeline logic fails).
    3. Discuss the system's overall **limitations and possible improvements** in preparation for real-world user testing.
    4. Perform the motion and distance calibration experiments described above and populate the parameter metrics table.
    5. Prepare a small user trial with 3-4 visually impaired volunteers for subjective evaluation of alert clarity, response time and usability. This will enable combining automated metrics and real-user feedback to prioritize changes before deployment.

Closing Notes:

We have extended Milestone-4 to not only clarify system architecture but to rigorously optimize it. Critically, we moved beyond simple observation-based tuning to reproducible, empirical procedures.

Model Optimization: The YOLOv8n detector was successfully fine-tuned using an automated Optuna hyperparameter search, improving its performance from a baseline of 0.836 mAP50 to a superior 0.889 mAP50.

Pipeline Tuning: We systematically tuned non-neural parameters (like motion thresholds and alert cooldowns) to solve specific usability issues, transforming raw detections into a stable assistive tool.

The document now presents a fully tuned system ready for the formal user-centric evaluation planned for Milestone 5. It also details design changes, such as the exclusion of certain prospective technologies, with clear justifications based on our empirical findings.

11. 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	Approved
JIVRAJ SINGH SHEKHAWAT	Approved
BALASURYA K	Approved
PRASHASTI SARRAF	Approved
Karan Patil	Approved

Name	Contribution	Signature	Date
TANUJA NAIR (21f1000660)	**- Inference Pipeline Architecture** **- Empirical Model Benchmarking and Validation** **- Lightweight Distance and Motion Algorithm Optimization** **- POC Creation**	Tanuja Nair	04/11/2025
BALASURYA K (22f3002744)	**- Show latency by start vs end time by tweaking params for inference code** **-Combined_Hyperparameter_Tuning_and_Feedback.ipynb** **-Model Artifacts (section 9) prepared** **- Initial POC Creation**	Balasurya	04/11/2025
PRASHASTI SARRAF (21f1001153)	**-**	Prashasti Sarraf	04/11/2025
JIVRAJ SINGH SHEKHAWAT (22f3002542)	**- Yolo Model Finetuning with Optune** **- Yolo Models Latency Comparison** **- Readme Changes**	Jivraj Singh Shekhawat	04/11/2025
KARAN PATIL (22f2001061)	- **Milestone 4 documentation**	Karan Patil	04/11/2025