SHELTERAID

PUBLIC HEALTH RESOURCES MAP

Final Presentation - August 6, 2024 (Section 6)

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Project Page

Project Team

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Project Manager, SME, Product Manager, Dataset Generation

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Application Developer, Dataset Generation

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EDA Lead, ML Engineer, Model Evaluator, Dataset Generation

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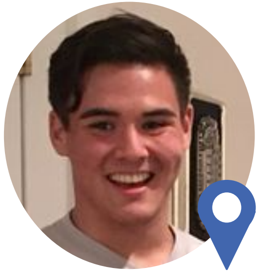


Lead ML Engineer, Model Deployment, Data Infrastructure

Mission Statement: *ShelterAID Public Health Resources Map uses computer vision technology to help improve safety and public health outcomes for people living in unsheltered homelessness.*

Problem & Project Overview

Problem

It's hard to help people experiencing unsheltered homelessness if you **can't find them**.

Solution

ShelterAID helps public health agencies **find, count, and support** people living in unsheltered homelessness in their cities.

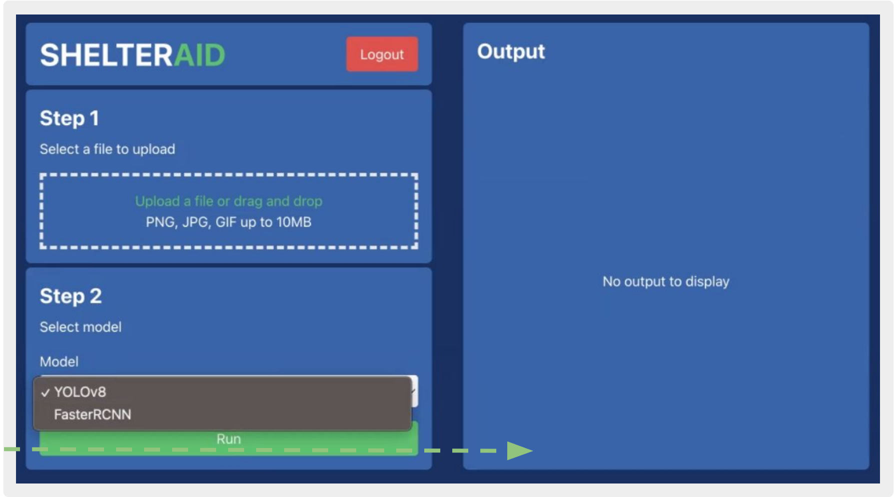
MVP

We will provide a web application that allows credentialed users to input a satellite image, then run the model to **detect shelters** in the image.

MVP Demo

- Simple proof-of-concept application that allows a user to:
  - **Upload** a satellite image
  - **Select** parameters and run the model
  - **Return** an image with detected shelter locations
- Users can answer the question:

How many shelters are in this image/location?



Dataset Generation

No dataset existed or could be located → First project team task was creating one

Step 1: Find

Search GoogleEarth for encampments and individual shelters

- Used HUD Point-in-Time Count data to select cities
- Used public data, partner data, and news to help locate camps

Step 2: Create

Screenshot at regular interval heights above the ground

- Overall range 200m - 2,000m above sea level
- 204 images from five states, 14 cities

Step 3: Label

Annotated and processed using Roboflow

- 1,740 annotations (1,455 shelters, 285 camps)
- Documented definitions/guidelines and peer-reviewed

Step 4: Export

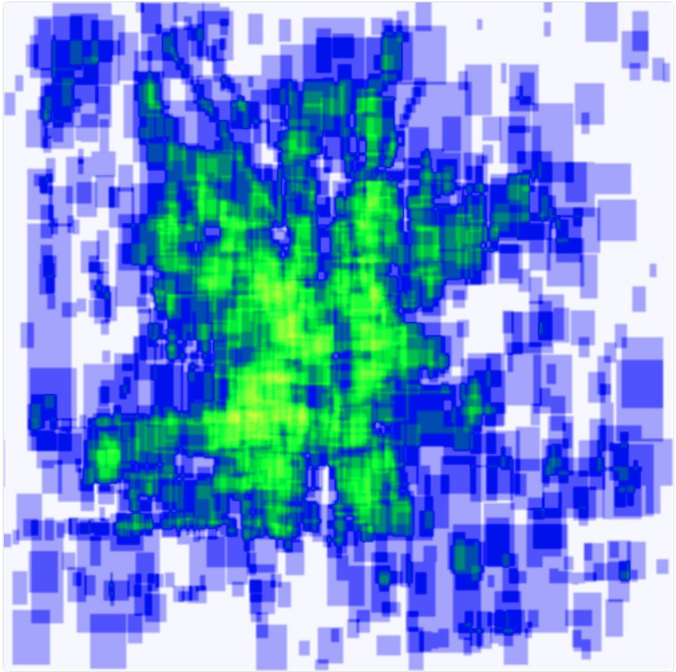
Assigned splits and exported in various formats

- 153 train/41 validate/10 test
- YOLOv7pytorch and YOLOv8

Exploratory Analysis

Shelters vary in size, shape, color, orientation, location w/in surrounding context, visibility/occlusion, and many other factors.

Annotations Heatmap



Sample Labeled Shelters

Modeling Approach

Trained four models, all leveraging transfer learning by building on existing models that were pretrained for object detection.

Model 1

Faster RCNN Baseline

- Faster RCNN + MobileNet backbone pretrained on COCO dataset
- Replaced classification head with custom FasterRCNN predictor
- 10 epochs in batches of 4

Model 2

Faster RCNN Tuned

- Faster RCNN + MobileNet backbone pretrained on COCO dataset
- Hyperparameter tuning (grid search)
- Preprocessing and augmentation steps

Model 3

YOLOv7

- YOLOv8 model trained on the COCO dataset
- 100 epochs, auto-batching
- Cosine learning rate adjustment

Model 4

YOLOv8

- YOLOv8 model trained on the COCO dataset
- 100 epochs, auto-batching
- Cosine learning rate adjustment
- Resized images (stretch to 640X640)

Evaluation Strategy

True Positives Defined by Intersection Over Union (IoU) Threshold

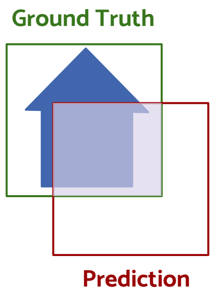
- IoU = Compares ground truth bounding box to predicted bounding box (“how correct is this prediction?”)
- True Positive: IoU over 0.25 (25% overlap)

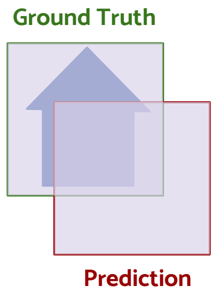
Primary Evaluation Metric: Recall

- Recall = (True Positives) / (True Positives + False Negatives)
- We are prioritizing reducing the number of false negatives, allowing for some false positives:
    - ShelterAID’s goal is to FIND encampments
    - False negatives result in vulnerable people never receiving aid
    - False positives result in resources temporarily deployed to the wrong location

Secondary Evaluation Metric: Precision

- Precision = (True Positives) / (True Positives + False Positives)



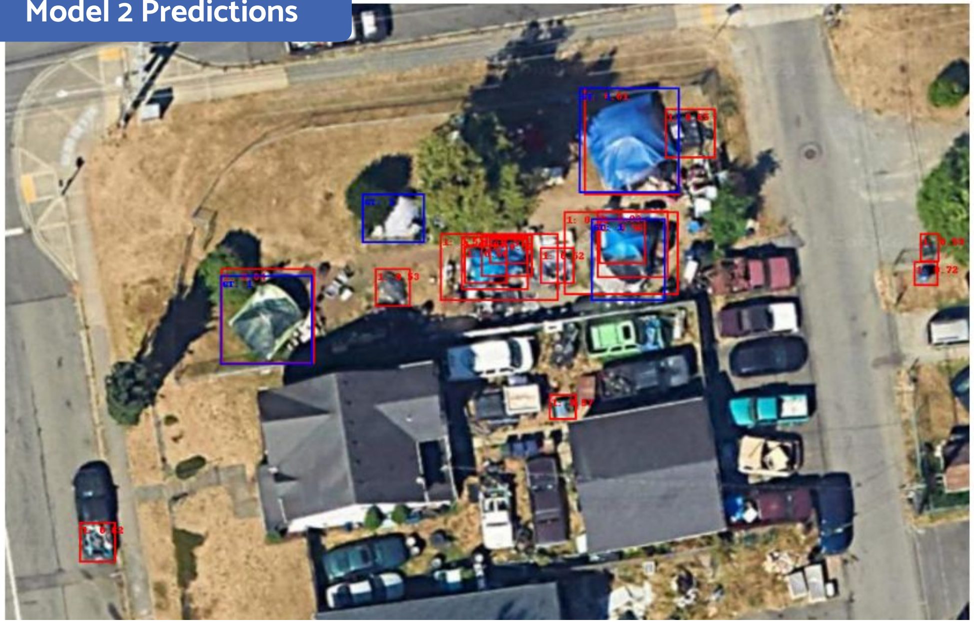


Model 2 Performance: Faster RCNN

Moderate Recall + Low Precision

- Recall: **0.40**
- Precision: **0.10**
- Fairly effective at identifying shelters, but many false positives from re-identifying the same shelter many times
- Re-identifications (especially those at the wrong size) are likely reducing precision

Model 2 Predictions



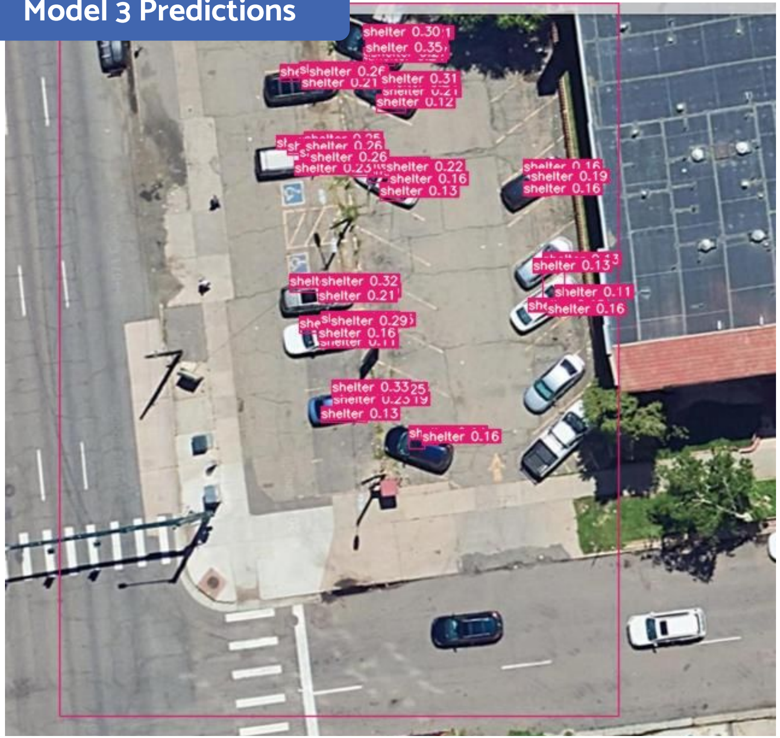
Ground Truth Prediction

Model 3 Performance: YOLOv7

Poor recall + Poor Precision

- Recall: **0.0007**
- Precision: **0.00332**
- Most often predicted zero shelters
- Predictions were very far off from labels
- Possible reason: the model may have been trained exclusively on at-level images (as opposed to aerial imagery)

Model 3 Predictions



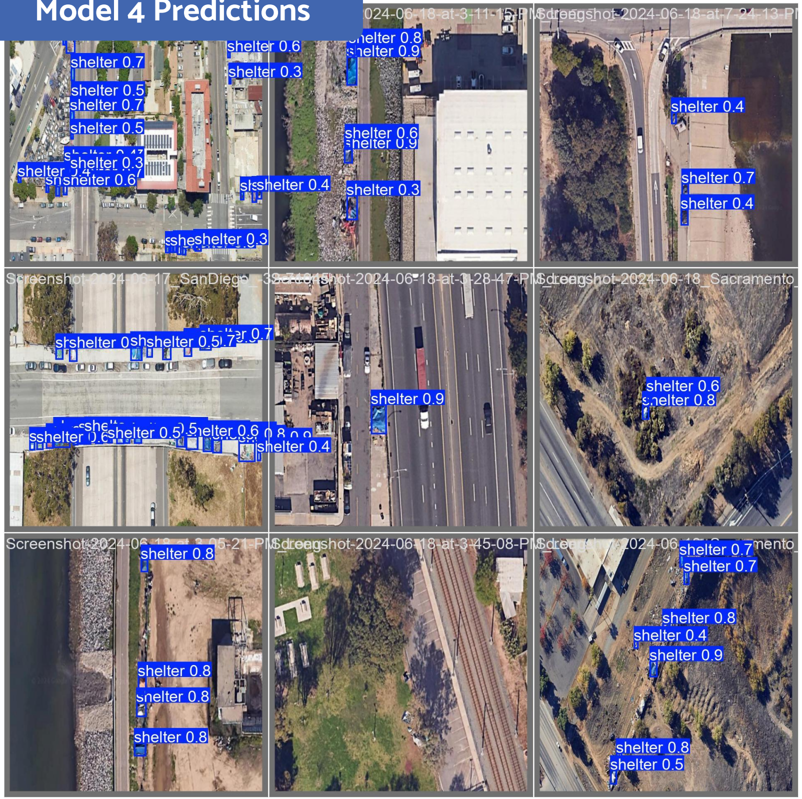
Prediction

Model 4 Performance: YOLOv8

Moderate Recall + Moderate Precision

- Recall: **0.483**
- Precision: **0.552**
- Often finds most of the shelters in an image, and successfully identifies large clusters (if not always precisely)
- Sometimes mis-identifies debris
- Great at finding tents, less successful at identifying tarp shelters

Model 4 Predictions



Prediction

Model 4 Performance: YOLOv8

Ground Truth

Model 4 Predictions

Model 4 Performance: YOLOv8 Test Set

Ground Truth (9 Shelters)

Ground Truth (8 Shelters)

Results:

- 6 true positives
- 3 false negatives
- 2 false positives (or are they?)
- Images with tree canopy coverage were especially hard to label correctly

Model Performance

Evaluated all four models with these metrics.

Model 1

Faster RCNN Baseline

- Recall: **0.331**
- Precision: **0.154**

Performance Summary:

- Many false positives
- Repeat re-identification

Model 2

Faster RCNN Tuned

- Recall: **0.40**
- Precision: **0.10**

Performance Summary:

- Many false positives
- Repeat re-identification
- Degraded precision

Model 3

YOLOv7

- Recall: **0.0007**
- Precision: **0.00332**

Performance Summary:

- Very poor performing
- Often zero predictions

Model 4

YOLOv8

- Recall: **0.483**
- Precision: **0.552**

Performance Summary:

- Improved recall and precision
- Very good at certain shelter types

Technical Challenges

1

Encampments vs. Shelters

- Initially planned two classes: shelter, encampments
- Encampments were very difficult to concretely define
- Models aso performed very poorly for encampments
- Reassessed the problem and primary user need ⟶ decided to drop encampments and move ahead with one class

2

Model Performance

- First round recall < 40%
- Many missed shelters, many overlapping predictions on same shelter, erratic encampment predictions
- Tested other models and attempted to train from scratch.
- Assessed metrics and primary use case ⟶ adjusted IoU from 50% to 25%

3

Limited Dataset

- 204 total images, 1,455 labeled shelters ⟶ likely not enough
- Tested this by downsampling our final model (YOLOv8) by 30%, performance decreased ⟶ more data collection could lead to further improvement

Roadmap Items

1

Additional Model Improvement

- Additional tuning
- Additional experimentation with augmentation and preprocessing steps
- Test additional pretrained models

2

Additional Data Collection

- Collect more data using iterative, strategic, feedback loop, including:
  - Assess model performance
  - Analyze gaps
  - Collect more data
  - Train new model
  - Assess model performance
  - Etc.

3

Product Expansion (Sat Imagery)

- Build infrastructure to ingest large satellite imagery w/geocoding
  - Tile image
  - Run model on each tile
  - Return predictions
  - Geocode predictions
  - Return addresses and descriptive statistics (counts, etc.)

Project Mission

ShelterAID Public Health Resources Map uses computer vision technology to help **improve safety and public health outcomes for people living in unsheltered homelessness**.

Our products will help public health agencies **find, count and better support** people in vulnerable groups. We will vigorously defend against any future uses of our product that may cause harm.

FIND
Find people experiencing unsheltered homelessness in their communities.

COUNT
Estimate the size of the unsheltered population and measure trends over time.

SUPPORT
Provide needed resources and support quickly, especially in emergencies.

Image source

Thank you

Lizzie Friend | Slack: Lizzie Friend

Emanuel Mejia | Slack: Emanuel Mejia

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Zach Zimmerman | Slack: Zachary Zimmerman

Special thanks to our classmates, instructors Korin and Puya, and to the Denver Department of Public Health & Environment for providing guidance, data, and expertise.

Appendix: Dataset Details / Users & Use Cases / Project Page

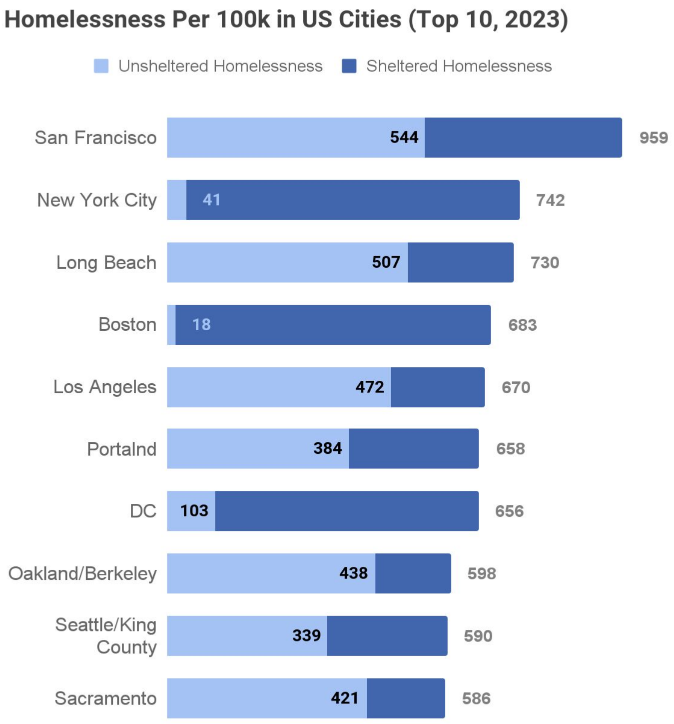
Appendix: Dataset Details

- 204 total images
- 22 total nulls (goal 10%)
- 14 cities
- 5 states
- Heights from sea level ranging from 200m-2,000m
- Taking into account varying city elevations, most were between 200-550m above ground
- Varied heights within each city

City/Area	State	Height (sea level)	Positives	Nulls	Total
Denver/Boulder	Colorado	1,600-2,000m	44	4	**48**
Seattle/Tacoma	Washington	250-550m	38	3	**41**
Los Angeles	California	200-500m	19	3	**22**
SF/Oakland/Berk	California	200-450m	18	2	**20**
Long Beach	California	200-500m	18	2	**20**
San Diego	California	200-500m	16	2	**18**
Portland	Oregon	250-550m	11	2	**13**
San Jose	California	200-500m	7	1	**8**
Sacramento	California	200-500m	7	1	**8**
Phoenix	Arizona	400-750m	4	2	**6**
Total		-	182	22	204

Appendix: Target User & Use Cases

- In the US there are **50** state health departments, over **3,000** county departments, and many municipal programs.
- Our product will be targeted toward programs in areas that have **urban centers** *and* large **unsheltered populations**, including:
  - Encampment **assessment teams** who strive to visit all encampments in a city to ensure safety for its residents
  - Communicable disease **epidemiologists** who need to conduct rapid investigations during outbreaks
  - **Immunization** teams and **mobile healthcare** vans who bring services to people who need them
  - **Agency directors** who need to advocate for increased funding for new or expanded support programs
  - Housing programs who provide **emergency shelters** in extreme heat or cold.



Homelessness in US Cities and Downtowns