Tab Content for Homeless Encampment Detection Web App

"Why?" Tab Content

Understanding Homelessness Through Technology

Homelessness has become an increasingly visible crisis in many urban areas, particularly in major cities like San Francisco, Los Angeles, and San Diego. Accurate monitoring and mapping of homeless encampments is crucial for:

- **Effective resource allocation**: Helping city officials and service providers direct aid where it's most needed
- **Timely intervention**: Enabling faster response to emerging encampments and changing patterns
- **Trend analysis**: Understanding the evolution of homelessness in different areas over time
- **Service coordination**: Improving collaboration between different agencies and organizations

Traditional monitoring methods rely heavily on manual surveys, which are labor-intensive, time-consuming, and often lag behind rapidly changing conditions on the ground. Manual surveys may also be inconsistent due to differences in reporting methodologies and observer interpretation.

Bridging the Technology Gap

While satellite imagery has been used in previous research to identify encampments from an aerial perspective, this approach has significant limitations:

- Overhead images miss encampments under trees, bridges, or overhangs
- Satellite imagery is often not updated frequently enough to track dynamic changes
- Details that help distinguish temporary camping from homeless encampments may not be visible from above

Our project addresses these limitations by leveraging street-level imagery to detect encampments from the ground perspective, providing a more comprehensive view that complements existing satellite-based approaches.

An Educational Tool for Stakeholders

This tool serves as both a practical application and an educational resource for:

- **Researchers**: Demonstrating the potential of computer vision in addressing social challenges
- **Surveyors & Data Collectors**: Providing a technological complement to ground-level observation
- **Government Authorities**: Offering data-driven insights for policy development and resource allocation
- **Service Providers**: Helping to identify areas where outreach and assistance may be needed

Our goal is not to replace human judgment or intervention, but to enhance it by providing a technological tool that can process large amounts of visual data quickly and consistently, helping stakeholders make more informed decisions about how to address homelessness in their communities.

"Our Process" Tab Content

Model Selection and Development

Our homeless encampment detection system uses a **Fast R-CNN** (Region-based Convolutional Neural Network) model that was selected after extensive testing and comparison with other state-of-the-art object detection models:

- **YOLO** (You Only Look Once): Offered faster detection speed but lower accuracy for our specific use case
- **Mask R-CNN**: Provided instance segmentation capabilities but with higher computational complexity
- **DeepLabV3+**: Offered semantic segmentation but struggled with distinguishing multiple nearby encampments

Fast R-CNN emerged as the optimal solution, balancing accuracy and computational efficiency. The model uses a two-stage detection approach, first identifying regions of interest and then classifying their contents, which proved particularly effective for detecting encampments in complex urban scenes.

Addressing Class Imbalance

A major challenge in developing our model was the inherent imbalance in our dataset—encampments are relatively rare objects in street-level imagery compared to common urban objects like cars and buildings. To overcome this, we tested several strategies:

- **Loss reweighting**: Assigning higher importance to the encampment class during training
- **Class-aware sampling**: Ensuring that each training batch contained examples of encampments
- **Data augmentation**: Creating synthetic training examples through image manipulation

Our best results came from combining all three approaches, with **mosaic and mixup augmentation** providing particularly significant improvements. These techniques create composite images by:

- **Mosaic augmentation**: Stitching together four different images into a single training example (shown in example images)
- **Mixup augmentation**: Blending images together by taking weighted combinations of them

This approach allowed our model generalize for varied conditions, significantly improving its ability to detect them in real-world settings across different contexts

[img-1]

Model Performance

Our Fast R-CNN model with combined strategies achieved:

- Overall F1 score of approximately 80%
- mAP@50 (mean Average Precision) of 80%

Interestingly, we found that the model performs better on data from San Francisco and Los Angeles than from San Diego. This regional variation highlights the importance of diverse training data and suggests that urban characteristics may affect detection performance.

Our Fast R-CNN model for the scope of (LA and SF) achieved:

- Overall F1 score of 94%
- mAP@50 (mean Average Precision) of 95%
- Strong performance in detecting for encampments specifically as well as homeless carts.

Mask R-CNN	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average F1	0.7877	0.7965	0.8072	0.788
mAP50	0.7907	0.7968	0.8093	0.7859
IoU	0.5262	0.5657	0.5674	0.5845

Fast R-CNN	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average F1	0.782	0.792	0.7651	0.7974
mAP50	0.7807	0.7911	0.7759	0.793
IoU	0.5556	0.5347	0.5355	0.5919

YOLO	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average F1	0.332	0.553	0.363	0.256
mAP50	0.431	0.543	0.412	0.432
IoU	0.185	0.249	0.19	0.199

DeeplabV3+	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average F1	0.3701	0.3448	0.3185	0.2752
IoU	0.7411	0.6456	0.6928	0.3267

[Img-2]

F1 Fast R CNN	People	Encampments	Cart	Bike
Scenario 1	0.8587	0.7096	0.6357	0.9239
Scenario 2	0.8732	0.6817	0.7109	0.9022
Scenario 3	0.8587	0.6519	0.6475	0.9022
Scenario 4	0.8587	0.7745	0.6541	0.9022

mAP@50 Fast R CNN	People	Encampments	Cart	Bike
Scenario 1	0.8587	0.6976	0.6428	0.9239
Scenario 2	0.8804	0.679	0.7029	0.9022
Scenario 3	0.8587	0.6782	0.6645	0.9022
Scenario 4	0.8587	0.7433	0.6678	0.9022

[Img-3]

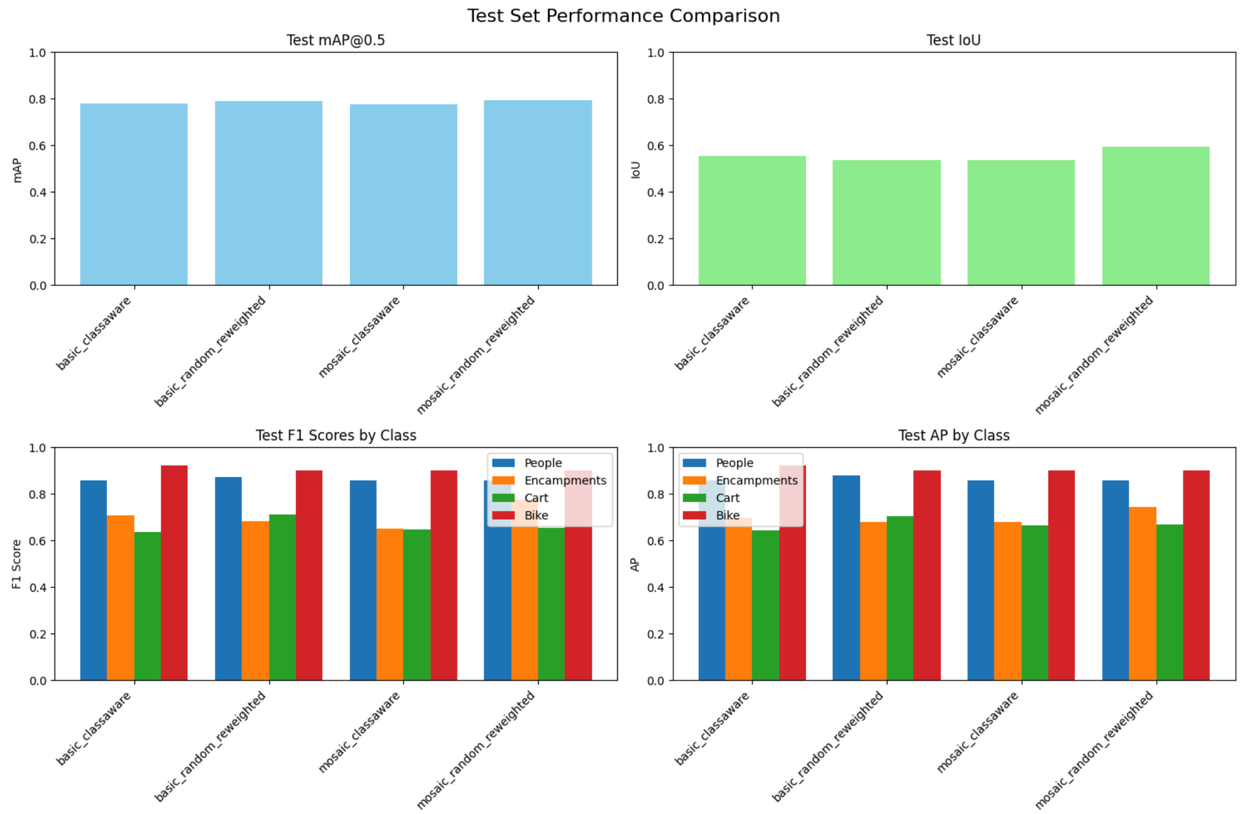
Fast R-CNN Trained on a Subset of Data (SF and LA street view images only)

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average F1	0.94185	0.833675	0.94	0.927625
mAP50	0.94685	0.829775	0.94965	0.929275
Average IoU	0.424	0.208	0.4583	0.4382

F1	People	Encampments	Cart	Bike
Scenario 1	0.9245	0.8807	0.9811	0.9811
Scenario 2	0.9057	0.5422	0.9434	0.9434
Scenario 3	0.8868	0.9298	0.9811	0.9623
Scenario 4	0.9057	0.918	0.9434	0.9434

Average Precision	People	Encampments	Cart	Bike
Scenario 1	0.9245	0.9007	0.9811	0.9811
Scenario 2	0.9057	0.5266	0.9434	0.9434
Scenario 3	0.9057	0.9495	0.9811	0.9623
Scenario 4	0.9057	0.9246	0.9434	0.9434

[Img-4]



[Img-5]

Disclaimer and Best Practices

Important considerations when using this tool:

1. **Confidence thresholds**: We recommend setting confidence thresholds above 0.75 to minimize false positives. The sliders in the main interface allow you to adjust these thresholds separately for each class.
2. **Model limitations**: While our model achieves high accuracy overall, it may occasionally:
   - Generate "hallucinations" (false positives) in areas with few objects or people
   - Miss encampments that are partially obscured or have unusual appearances
   - Perform differently across geographic regions based on training data distribution
3. **Human verification**: This tool is designed to assist human decision-making, not replace it. All detections should be verified by human experts before being used to inform policy or resource allocation decisions.

4. **Ethical use**: This technology should be employed to help connect unhoused individuals with services and resources, not for enforcement actions that may further marginalize vulnerable populations.
5. **Ongoing development**: We continue to refine the model by expanding our training dataset and improving our augmentation techniques. Future iterations will address regional performance differences and enhance detection accuracy.

By using this tool responsibly and with an understanding of its capabilities and limitations, stakeholders can gain valuable insights into the distribution and characteristics of homeless encampments in urban areas.