W207

Pedestrian Detection

Evaluating the Performance of Various Machine Learning Algorithms

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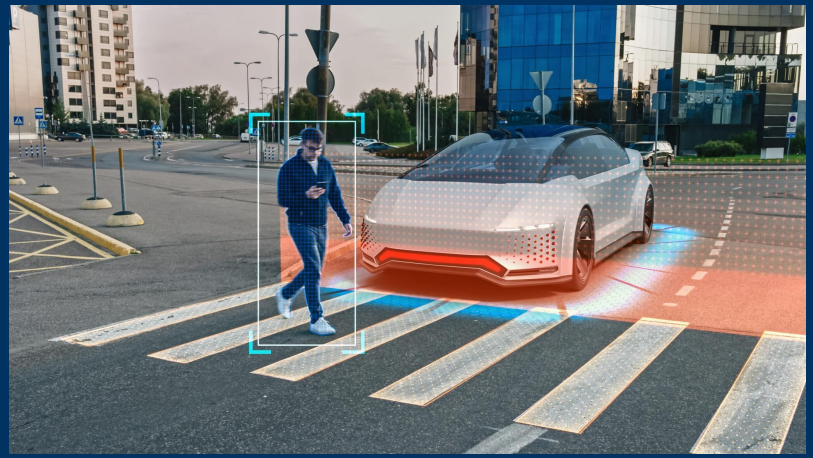
Motivation

Question: How effective are different machine learning models at identifying pedestrians on the street?

Motivation: Pedestrian detection is critical for the development of safe autonomous vehicles



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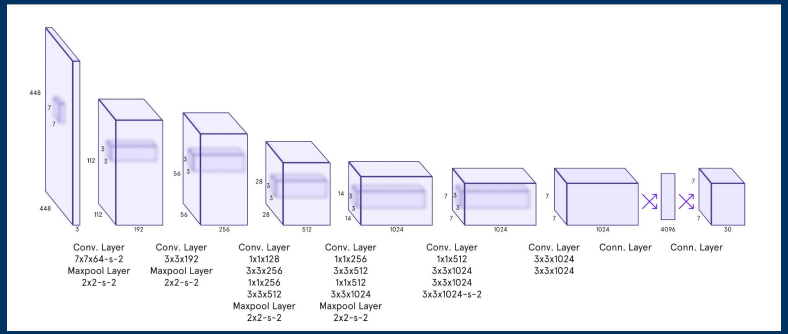
Motivation

Current Advancements:

- Very advanced algorithms such as YOLO and Faster R-CNN with advantages in different scenarios
  - E.g. GR-YOLO for pedestrian in crowded areas, YOLO-GW for fog or low light

Our Approach:

- Test the ability of machine learning algorithms to identify pedestrians and compare results with YOLO algorithm



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Data

- Collected from Waymo’s autonomous vehicles using 5 cameras and 5 lidars
- Has 11.8 million 2D bounding box annotations on camera images
    - Covers objects like vehicles, pedestrians, cyclists, and traffic signs
- Complements other datasets with:
    - 12.6 million 3D bounding boxes (lidar)
    - 3D semantic segmentation labels
- Good for object detection, tracking, and scene understanding for autonomous driving

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Data

- 799 scenes across San Francisco

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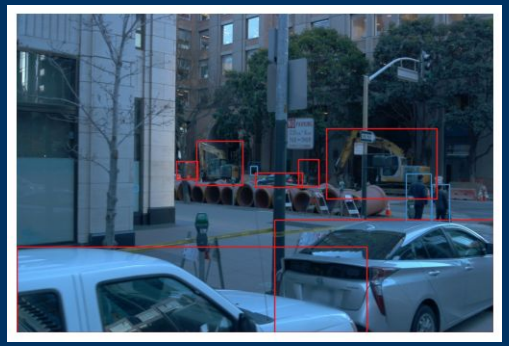
Data

Time	Left	Front	Right
15524401 95462613			
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Data

- Use the first 100 scenes in the dataset
- Randomly select 50 images in each scene
- Add image if having > 0.5% of the area with a pedestrian

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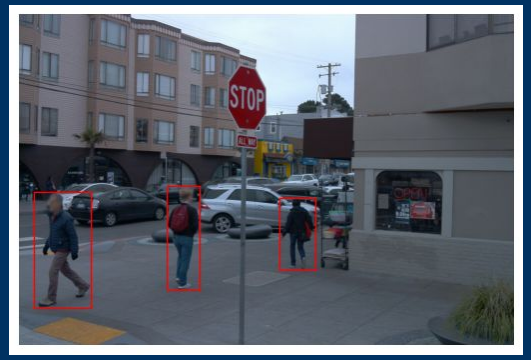
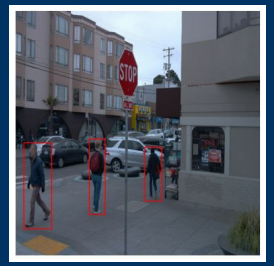
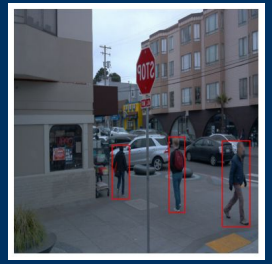
Data

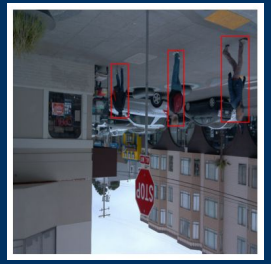




Resize (640x640)



Random Horizontal Flip



Random Vertical Flip

Random 90 ° Rotation

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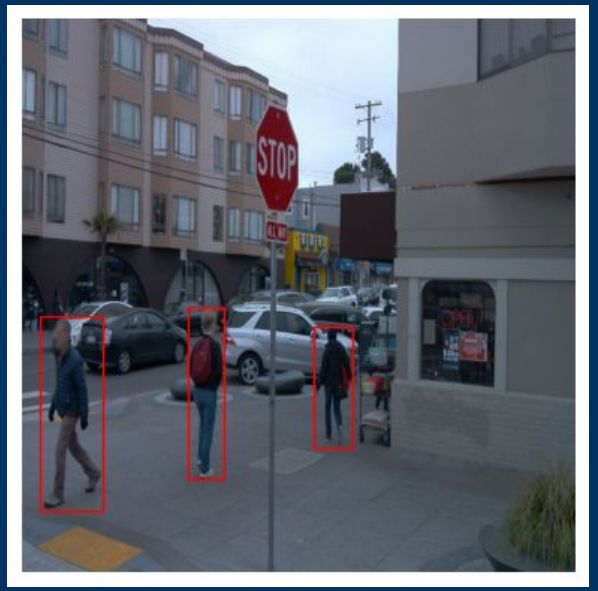
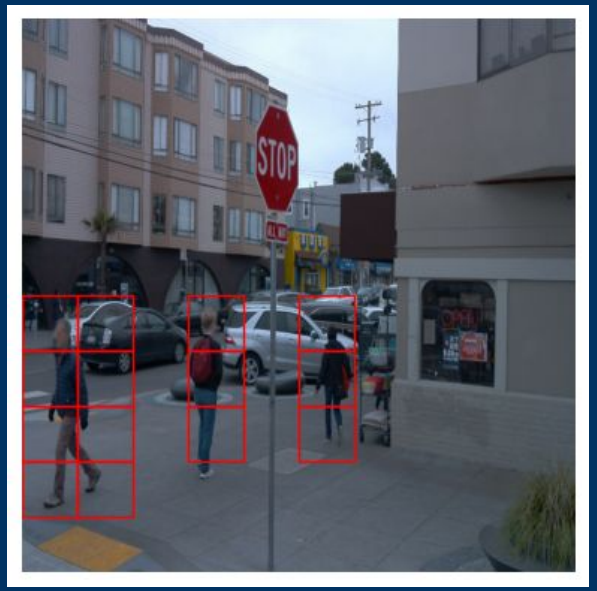
Data

- Transform images into grid of subimages (64x64 pixels each)
- Subimage is labeled as having a pedestrian if >25% of the subimage has a pedestrian bounding box





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Data

- Processed images were segmented with a grid pattern into sub-images
  - Only used for Logistic Regression and CNN
- However this created class imbalance
- So, we downsampled the negative class in the training and validation classes, and did not touch the final test

Figure: Positive class examples

	Training	Validation	Test	Test Final
Positive Images	3355	1102	1084	1858
Negative Images	6618	2222	2242	22042
Total	9973	3324	3326	23900

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Logistic Regression

Sklearn Model

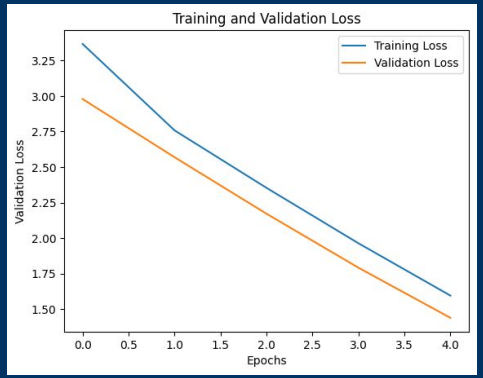
sklearn Logistic Regression Model

```
[17] # Build Logistic Regression Model Using SKlearn
     from sklearn.linear_model import LogisticRegression

     lr_model = LogisticRegression(max_iter=10)
     lr_model.fit(X_train_new_scaled, y_train_new)

     # Check Validation Accuracy
     accuracy_val = lr_model.score(X_val_new_scaled, y_val_new)
     print(f"Validation Accuracy: {accuracy_val}")
```

```
Validation Accuracy: 0.6585439229843562
```

Validation Accuracy = 0.65

Tensorflow Model



Validation Accuracy = 0.51

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Logistic Regression – Tensorflow

Sklearn Model Hyperparameters

- Batchsize=16
- Epochs=5
- Loss function: Binary Cross Entropy
- Optimizer: SGD

Logistic Regression – Analysis

- No spatial information due to flattening the data into a 1D array
- There are 12288 features which may cause high dimensionality

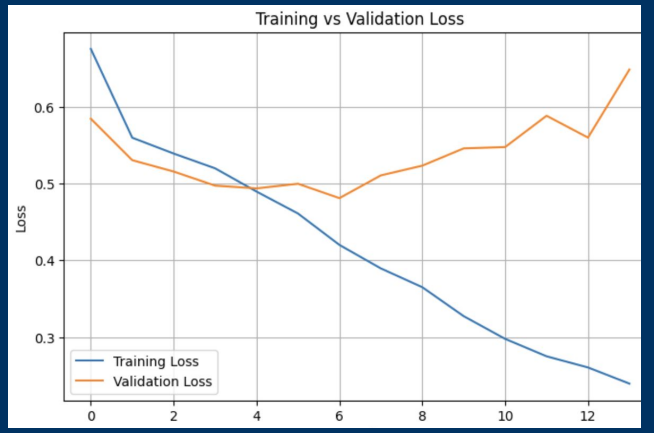
CNN

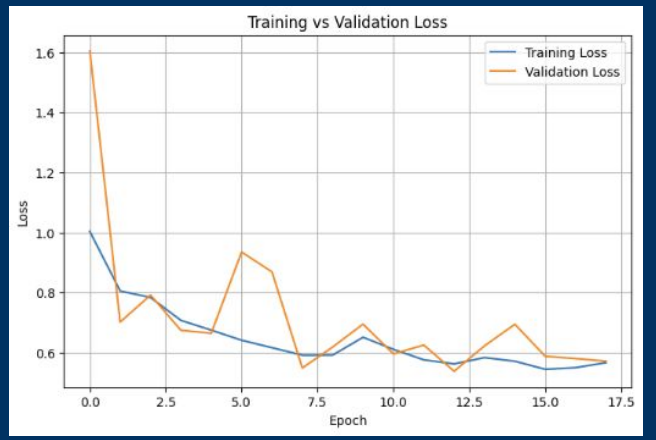
Baseline: Similar CNN architecture from Homework 10

- Early stopping (this time monitoring validation AUC instead of accuracy)
- Metrics: accuracy and AUC

Improved

- Incorporated BatchNorm layers
- More Conv2D + BatchNorm + Max Pooling layers
- More Dropout layers
- L2 Regularization





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CNN

Hyperparameters

- Batchsize=32
- Epochs=25
  - Early stopping restored weights from epoch 13
- Loss function: Binary Cross Entropy
- Optimizer: Adam

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 64, 64, 32)	896
batch_normalization (BatchNormalization)	(None, 64, 64, 32)	128
conv2d_1 (Conv2D)	(None, 64, 64, 32)	9,248
batch_normalization_1 (BatchNormalization)	(None, 64, 64, 32)	128
max_pooling2d (MaxPooling2D)	(None, 32, 32, 32)	0
dropout (Dropout)	(None, 32, 32, 32)	0
conv2d_2 (Conv2D)	(None, 32, 32, 64)	18,496
batch_normalization_2 (BatchNormalization)	(None, 32, 32, 64)	256
conv2d_3 (Conv2D)	(None, 32, 32, 64)	36,928
batch_normalization_3 (BatchNormalization)	(None, 32, 32, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 16, 16, 64)	0
dropout_1 (Dropout)	(None, 16, 16, 64)	0
flatten (Flatten)	(None, 16384)	0
dense (Dense)	(None, 128)	2,097,280
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 2,163,745 (8.25 MB)
Trainable params: 2,163,361 (8.25 MB)
Non-trainable params: 384 (1.50 KB)

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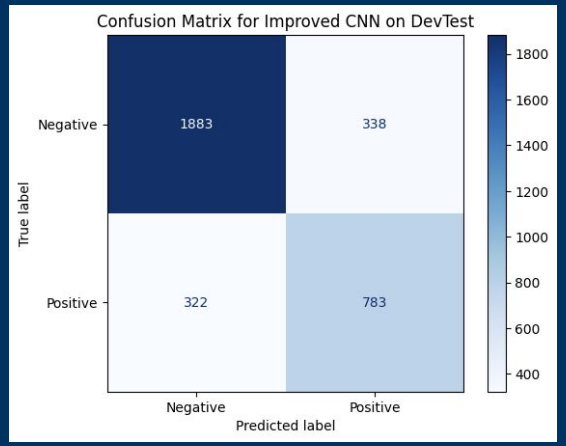
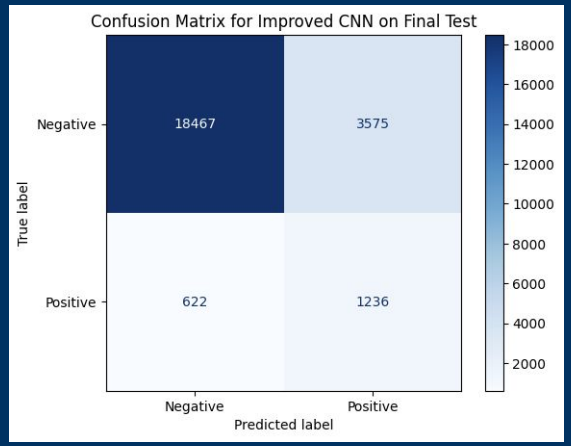
CNN Evaluation

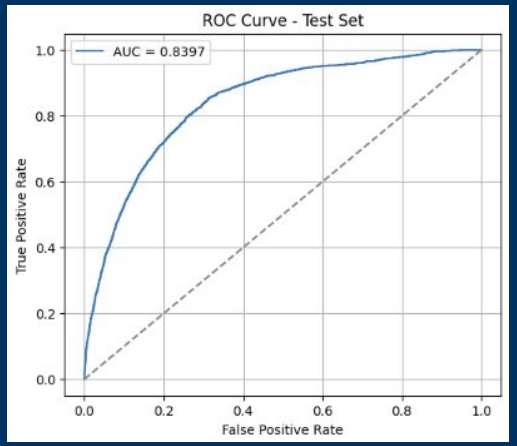
Improved model showed better generalizability

- Evaluation was similar in both test sets
- Great AUC value of 0.84
- FP rate was higher with final test set
- FN rate is biggest weakness in this application

```
Test Loss: 0.4434
Test Accuracy: 0.8244
Test AUC: 0.8396
```







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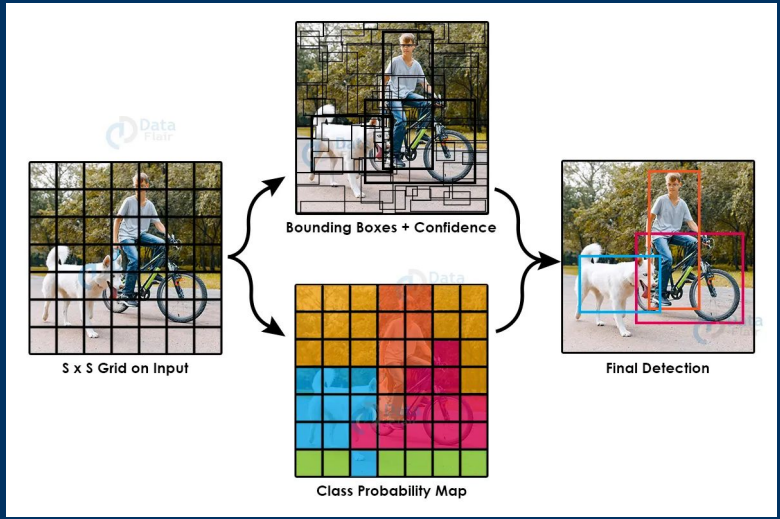
YOLO

- You Only Look Once (YOLO)
- Designed for object detection and classification using bounding boxes
- Pretrained on the PASCAL VOC dataset
- Compound Loss Function
    - box_loss: how far the box is from ground truth (both size and location)
    - cls_loss: The class prediction
    - obj_loss: The prediction confidence



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YOLO

Ground Truth

Predictions

box_loss	obj_loss	cls_loss	total
1.29	1.09	0.278	2.658

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YOLO

Batch Size	Epochs	Optimizer	Train Loss	Val Loss	Recall
8	5	SGD	0.083981	0.062203	0.67763
8	5	AdamW	0.096923	0.080926	0.41941
8	10	SGD	0.064414	0.046944	0.77632
8	10	AdamW	0.088209	0.066129	0.48054
16	5	SGD	0.085662	0.061643	0.66244
16	5	AdamW	0.093176	0.194419	0.52813
16	10	SGD	0.064542	0.044955	0.78456
16	10	AdamW	0.085590	0.064685	0.49178

- SGD better for finetuning than AdamW
- Larger batch size is generally better
- More epochs is marginally better

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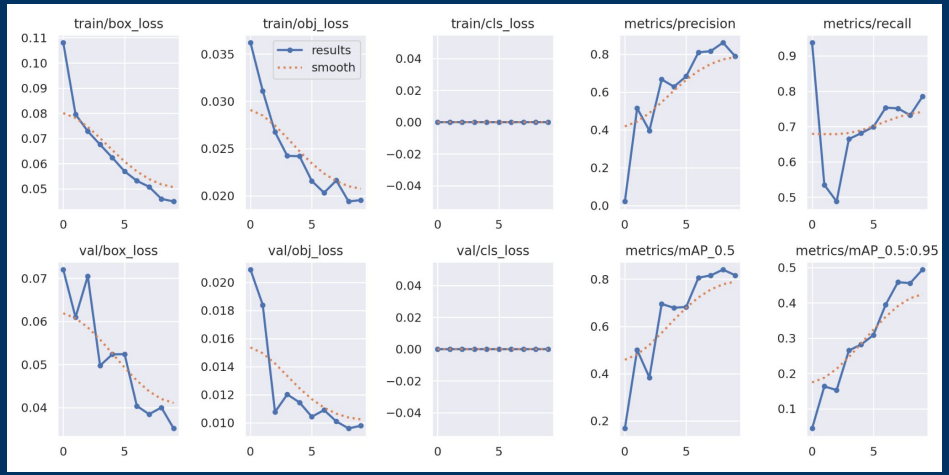
YOLO

- Loss consistently decreases over epochs
  - cls_loss is always 0 because we only have one class
- mAP (mean average precision) consistently increasing
- Recall was initially very high, decreased, then started improving again



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YOLO

Ground Truth

Predictions

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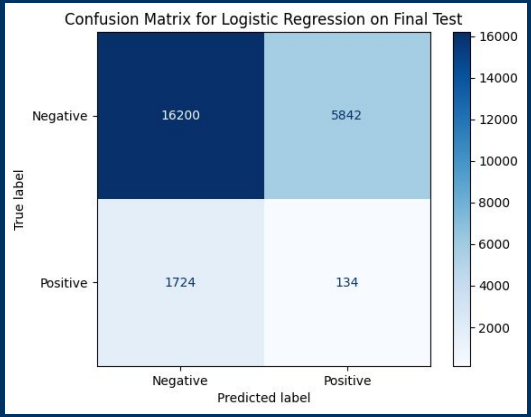
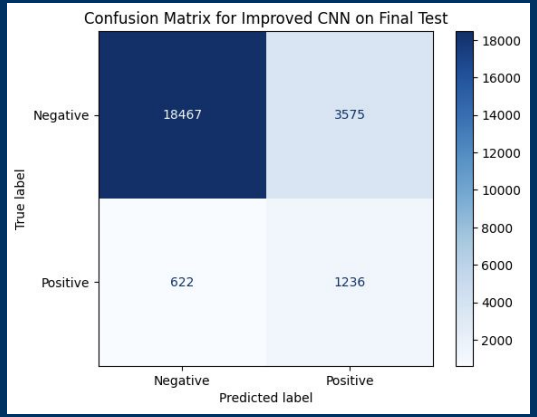
Conclusion

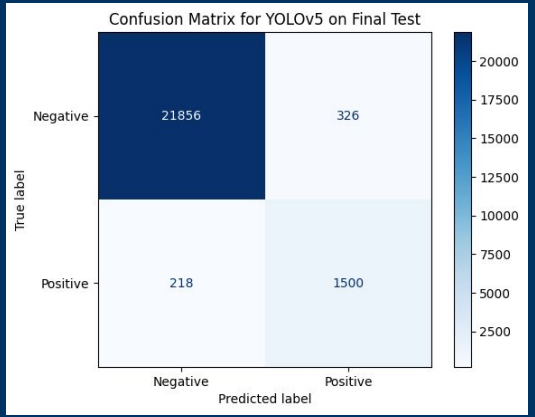
Logistic Regression:
Test Loss: 1.02
Test Accuracy: 0.683

CNN:
Test Loss: 0.4434
Test Accuracy: 0.8244
Test AUC: 0.8396

YOLO:
Test Loss*: 0.049308
Test Accuracy**: 0.977
Test AUC**: 0.9292







* YOLO uses a different loss function than LR and CNN methods
** Predictions from YOLO are bounding boxes which are then converted to similar format as the LR and CNN data for comparison purposes

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Future Directions

Model Improvements:

- Fine-tuning YOLO directly with Waymo Data
- Apply vision transformers, which have recently shown strong results in object detection tasks

Data and Preprocessing

- Incorporate the 3D lidar point clouds for richer feature sets and improved model accuracies, especially in occlusion-heavy or low-light scenarios

Other Object Detection Models

- Test other models such as Faster R-CNN, RetinaNet, and SSD

Thank you

Any questions?

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Contributions

Github:

Daniel Chung: I worked on the motivation slides, two of the data slides, future directions, and the CNN portion of coding and slides. I also used the functions Gautam provided to create the subimages for the Logistic Regression and CNN parts of the project.

Jacob Lu: I worked on the evaluation slide for the baseline and logistic regression slides of the final presentation. Additionally, I did additional preprocessing of the logistic regression and creating both the sklearn and TF logistic regression modeling/fitting.

Gautam Sai Yarramreddy: I worked on creating the dataset used in the LR, CNN, and YOLO models from the raw waymo data (both the bounding boxes and patches datasets). I also worked on creating the proper structure and datasets files needed for training the YOLOv5 model. I worked on finetuning and optimizing the hyperparameters on the YOLO model.