Semantic Segmentation for Self Driving Cars

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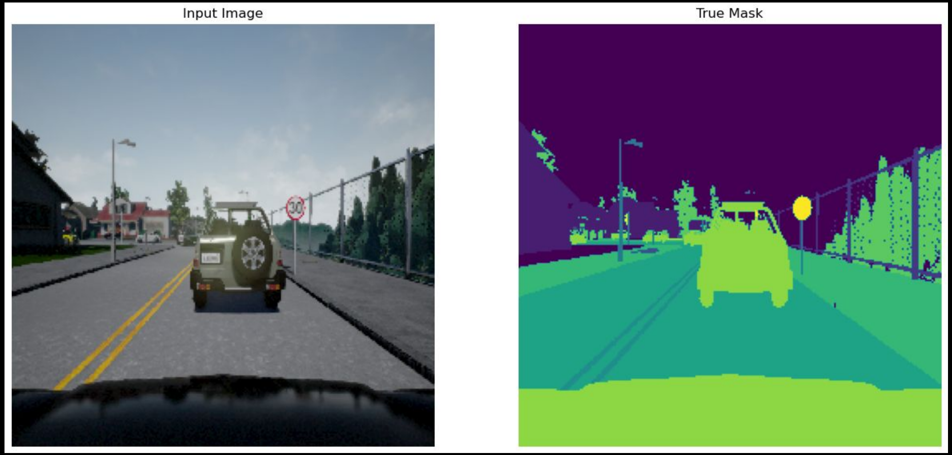
Business Understanding

Autonomous driving technologies have experienced incredible growth as electric vehicles become more mainstream. More robust systems are needed in order to prevent accidents.

Our goal is to create a model that is proficient at classification of roads, vehicles, signage, and other environmental elements.

Data

- ➔ Images come from CARLA simulator
- ➔ 5000 images, 5000 masks
- ➔ Older version with 13 classes

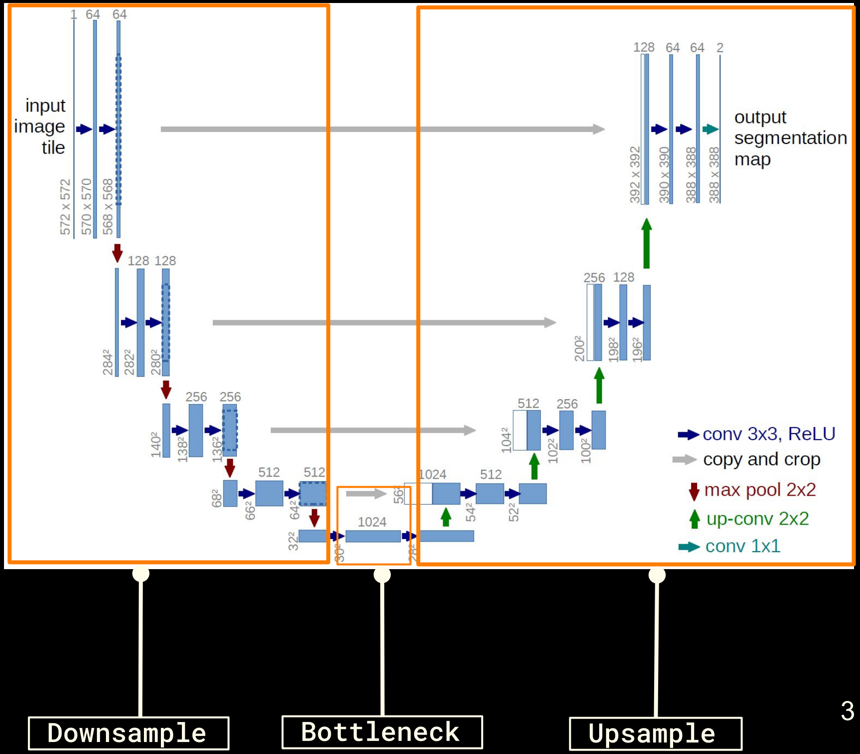


Value	Tag	Converted color
0	Unlabeled	(0, 0, 0)
1	Building	(70, 70, 70)
2	Fence	(190, 153, 153)
3	Other	(250, 170, 160)
4	Pedestrian	(220, 20, 60)
5	Pole	(153, 153, 153)
6	Road line	(157, 234, 50)
7	Road	(128, 64, 128)
8	Sidewalk	(244, 35, 232)
9	Vegetation	(107, 142, 35)
10	Car	(0, 0, 142)
11	Wall	(102, 102, 156)
12	Traffic sign	(220, 220, 0)

U-Net Architecture

- Special type of CNN that has a U shape
- Downsample extracts features from input, decreases resolution of image
- Bottleneck stops downsampling, passes info to upsample blocks
- Upsample increases resolution of image, uses skip connections to prevent info loss during downsample

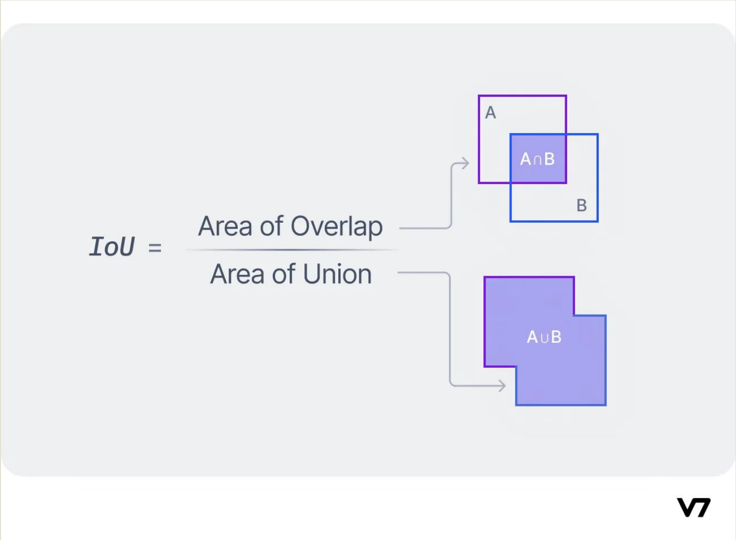
[1]

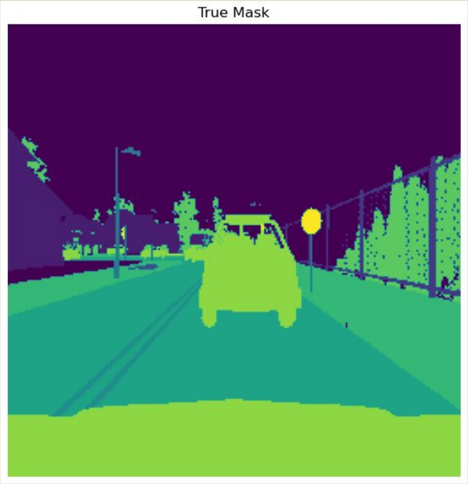


Metrics

- Accuracy is not a great measure for semantic segmentation
- Mean Intersection over Union is much better

[2]



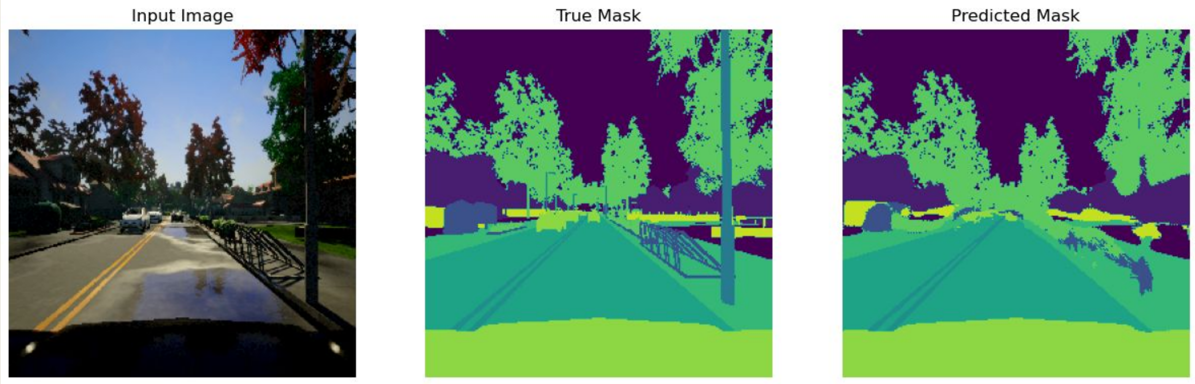


Baseline

- Decent prediction for a beginning model

- Simple architecture, lacked features for more robust learning

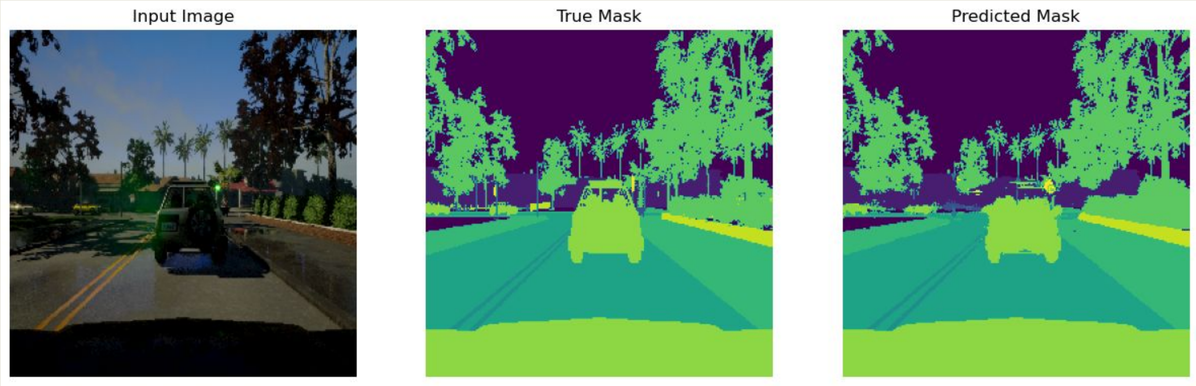
- Struggles on smaller objects



Conv2DTranspose

- Considerably better segmentation of smaller objects, but still struggles

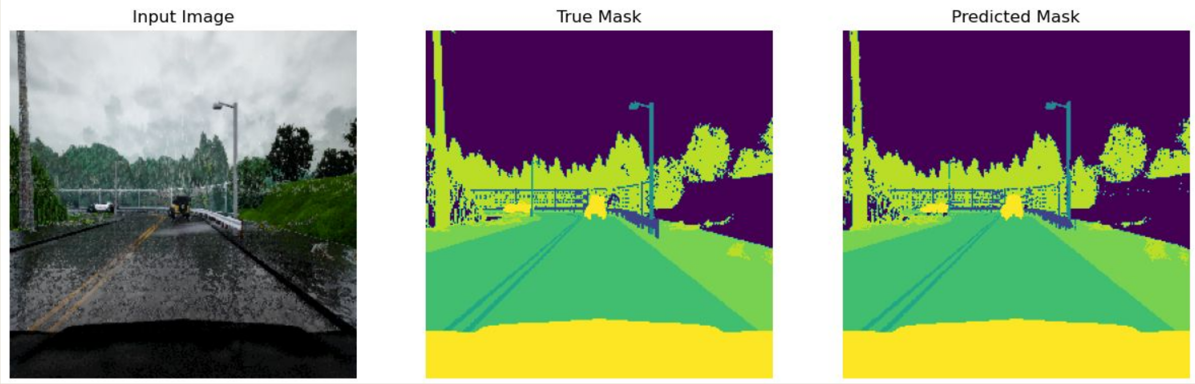
- Added regularization, activation functions to improve learning



Upsampling2D

- Similar output compared to second model, but fares better on smaller objects

- Very similar architecture as previous model, replaced with simpler deconvolution



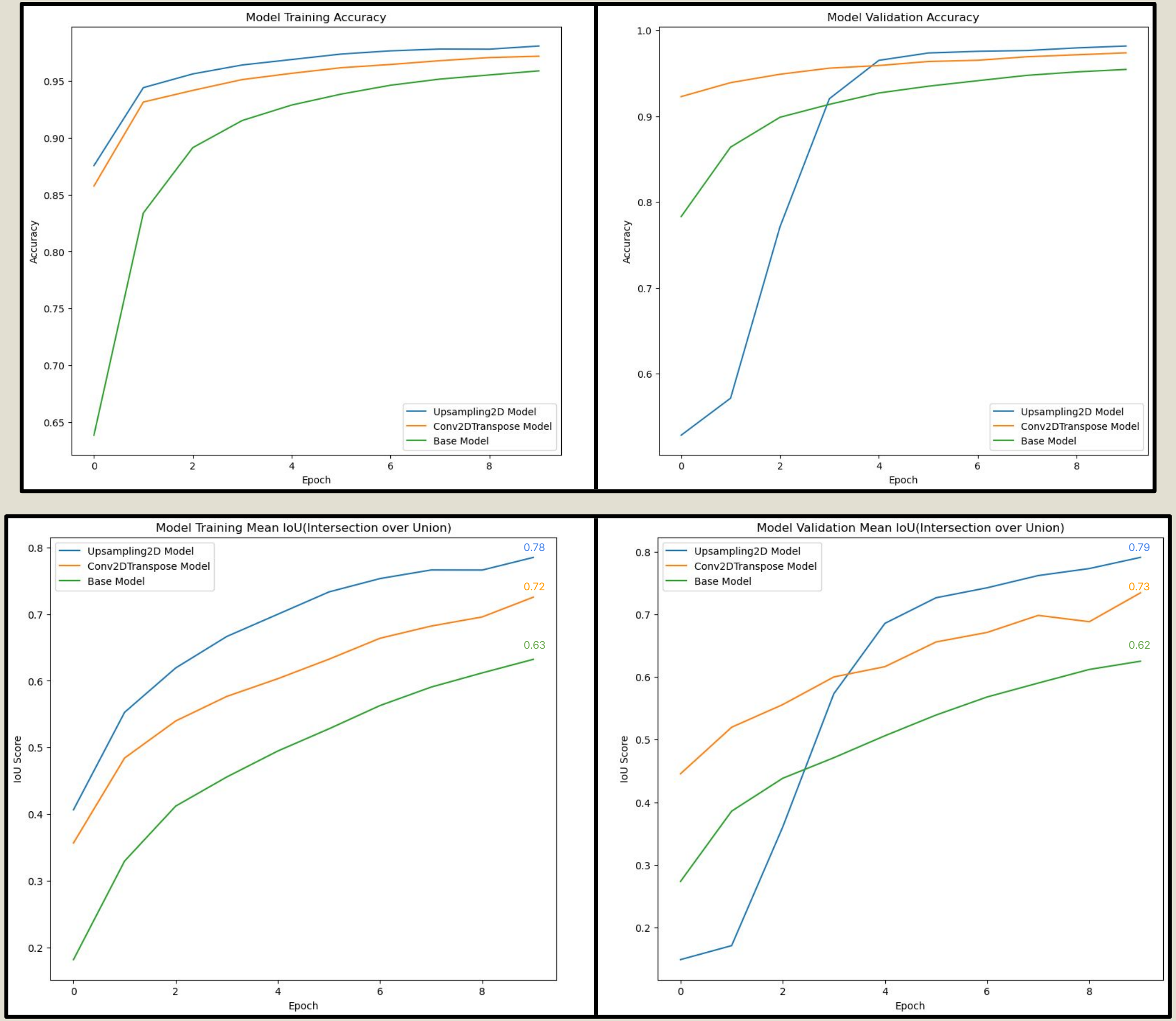
Performance

- According to accuracy, all models performing very well

- Using a better metric, baseline struggles to keep up with other models

- Upsampling2D is best performing model

- Only ran for 10 epochs, could do better with more time

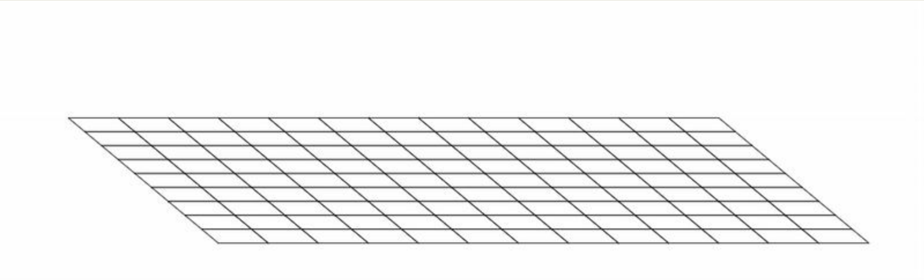


Conv2DTranspose

- Despite being more complex than Upsampling2D, performed worse

- Frequently creates artifacts from filters overlapping unevenly across output

[3]

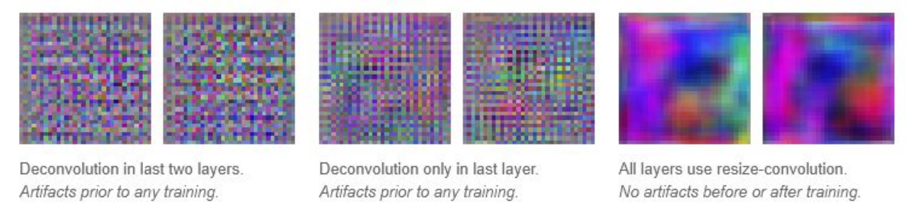


Upsampling2D+Conv2D

- Uses simpler interpolation methods like nearest neighbor

- Separates upsampling and feature transformation steps

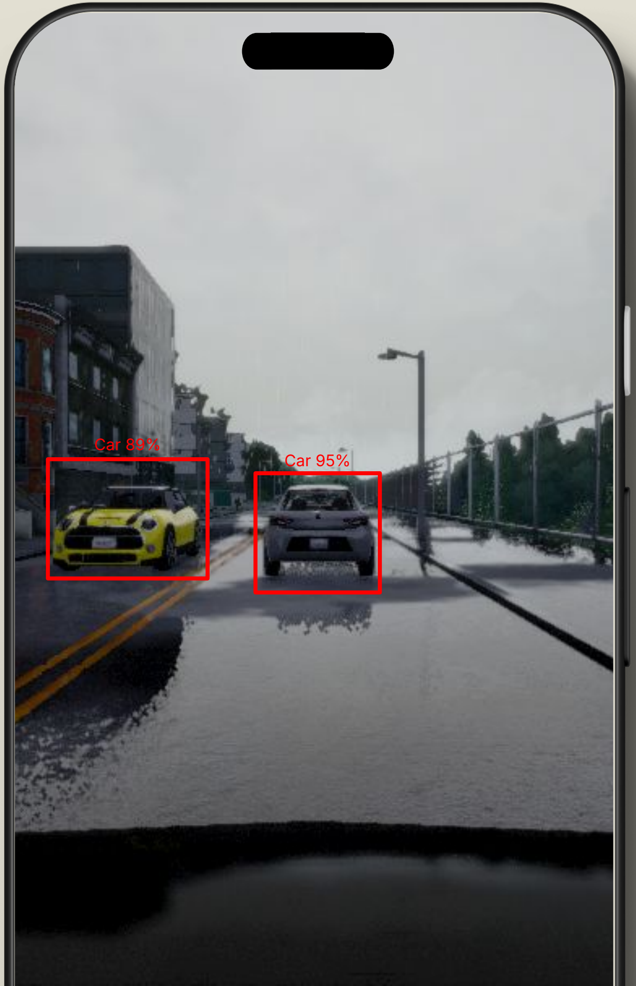
[3]



Next Steps

- Evolve model to work on video segmentation

- Create lightweight app to allow user to submit images, viewing output



References

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