Car Parts Segmentation for Insurance Companies

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Introduction

Several insurance companies specialize in customer service for car damages. For now, this task has been done manually. However, as it is tedious and time consuming, we were interested in automating this step.
With the expansion of Artificial Intelligence, customers would ideally send a picture of their car and have a Deep Learning algorithm assess its damage, for more efficient and faster response rate and assessment.
In order to achieve this, the DL algorithm first needs to be able to segment the different car parts from an image, which was our focus in this project.

Dataset

- For training and validation, we used the dataset provided by Deloitte. It consisted of 2001 orange cars, 835 black cars and 168 photos, out of which 30 were considered as testing data.
- We were provided with numpy arrays of the images and their segmentation.
- We were also provided with landscape images, that were proven useful for the data augmentation task (see methods).

Color	Description	Class Value	Color Values
No color	Background	0	NA
Orange	Hood	10	(250, 149, 10)
Dark Green	Front Door	20	(19, 98, 19)
Yellow	Rear Door	30	(249, 249, 10)
Cyan	Frame	40	(10, 248, 250)
Purple	Rear Quarter Panel	50	(149, 7, 149)
Light Green	Trunk Lid	60	(5, 249, 9)
Blue	Fender	70	(20, 19, 249)
Pink	Bumper	80	(249, 9, 250)
No Color	Rest of Car	90	NA

Table 1: Car Colors and Descriptions

Model Architecture

We decided to build a custom U-Net architecture for our DL model.

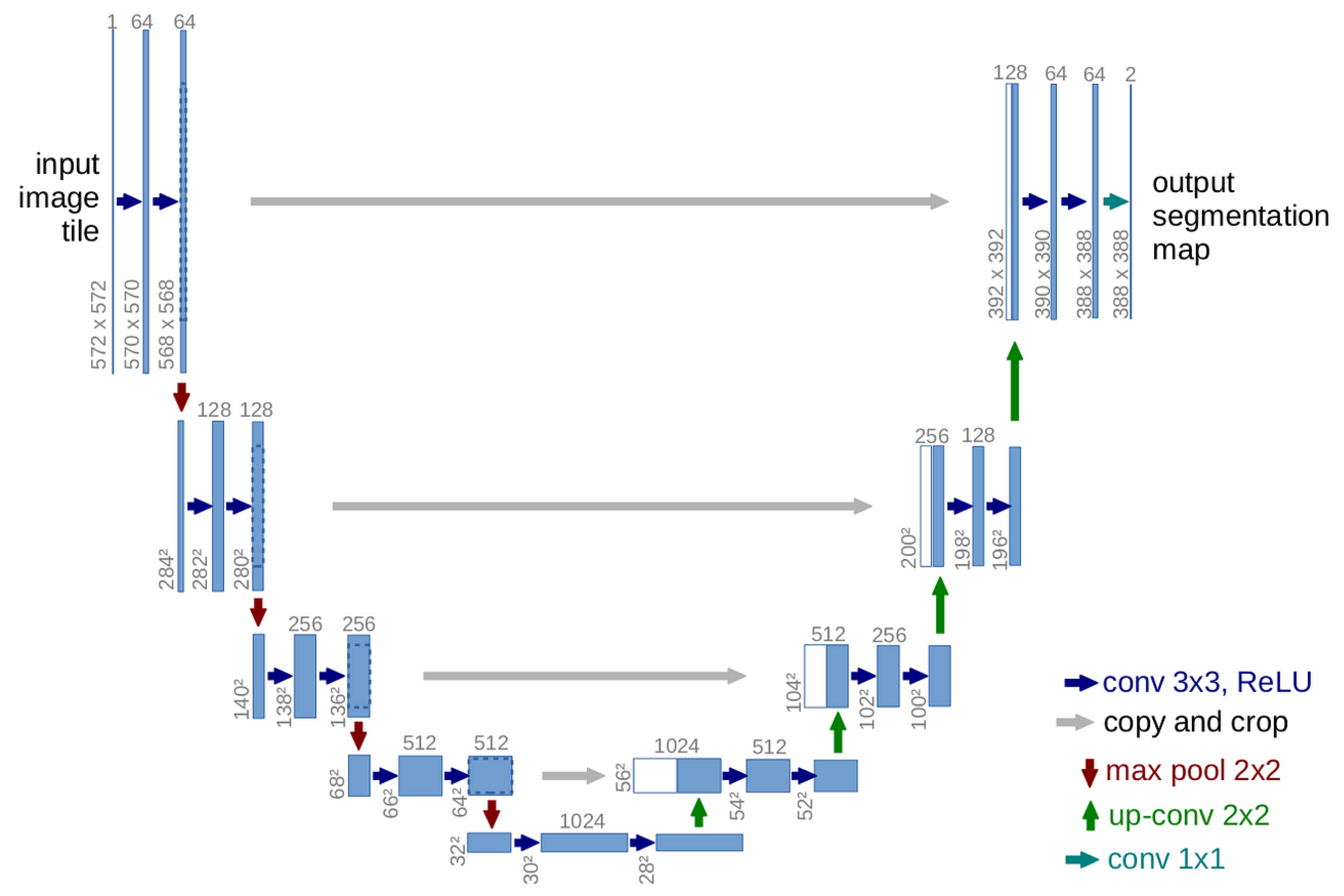

Figure 1: Classic U-Net architecture.

Methods

- Pixel class prediction in the numpy arrays.
- Hyperparameter tuning: betas for ADAM, learning rate, strides.
- Dynamic change of learning rate.
- Data augmentation.

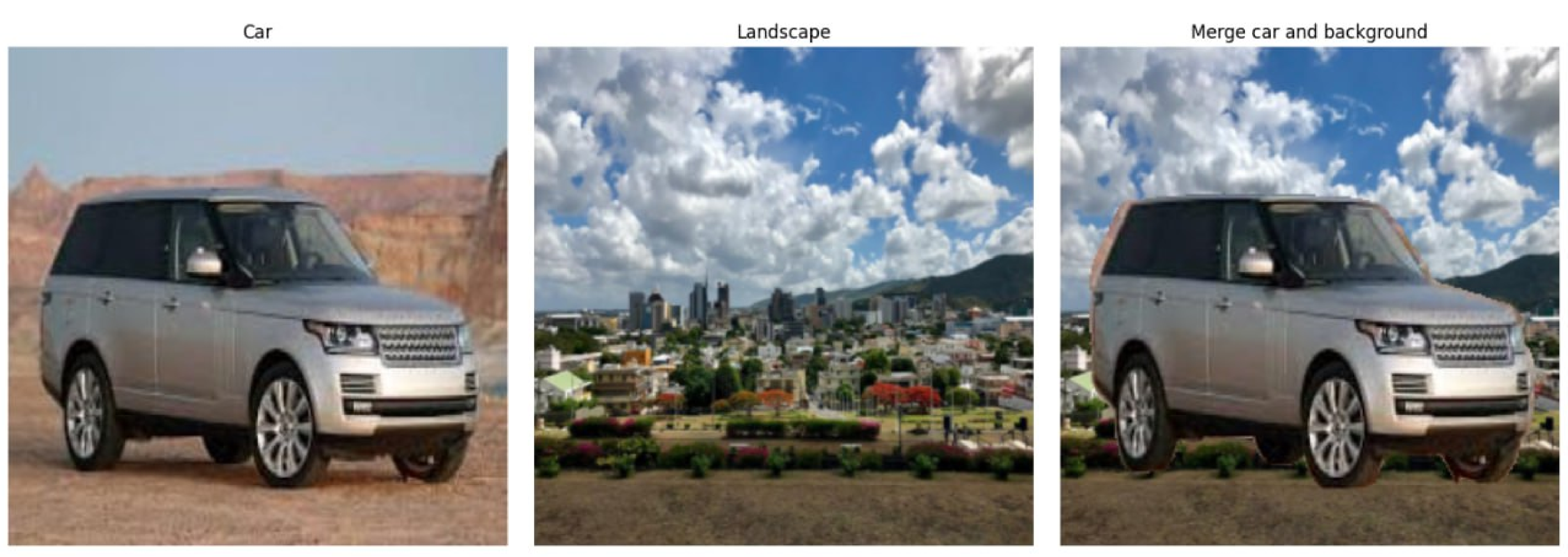

Figure 2: Augmented data

Model performance Results (Cross Entropy Loss)

We trained our model with 35 epochs and a batch size of 4.

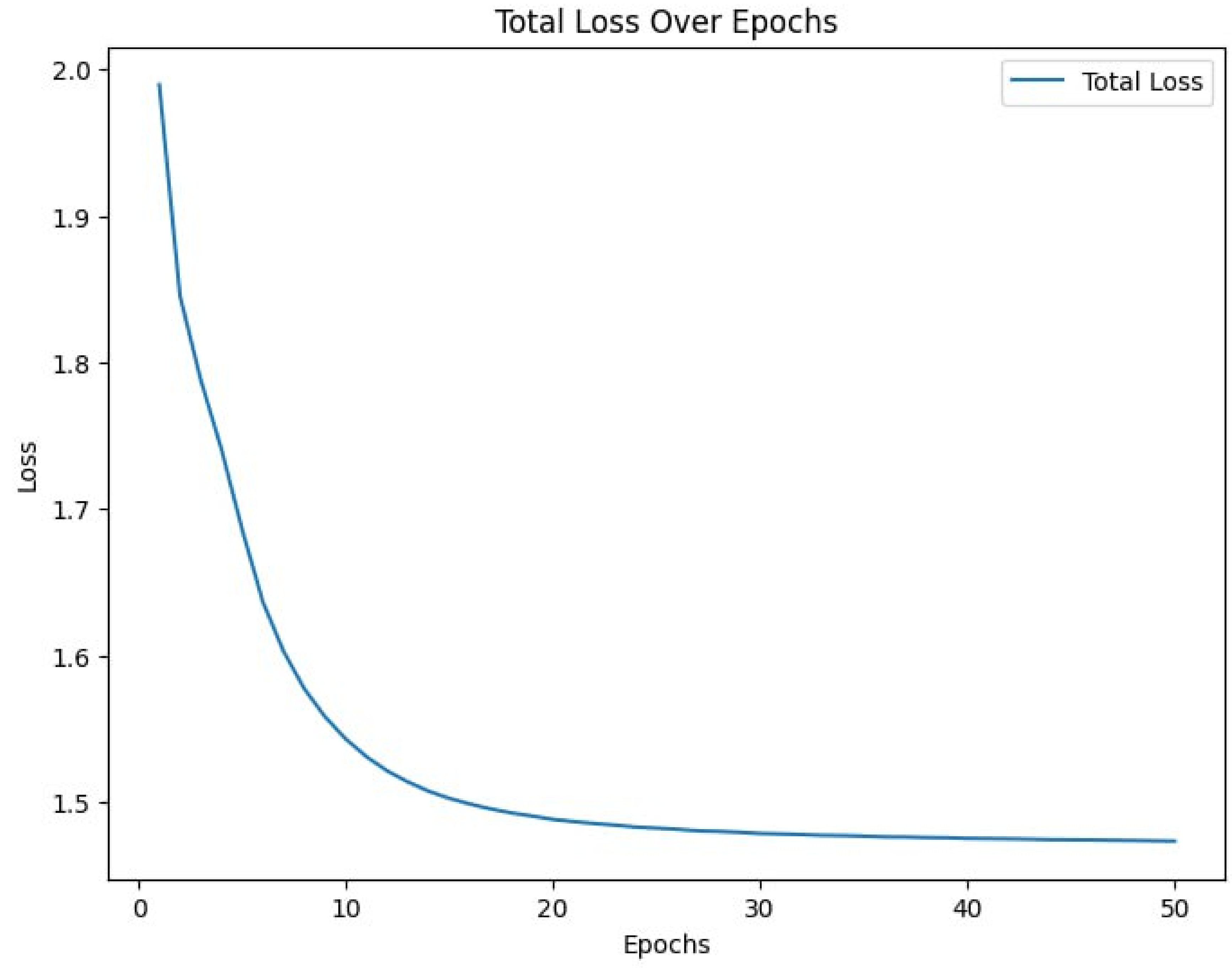

Figure 3: Evolution of Cross Entropy Loss.

At about 35 epochs, we attained a loss inferior to 1.5 .

Model Performance Results For Each Type of Car

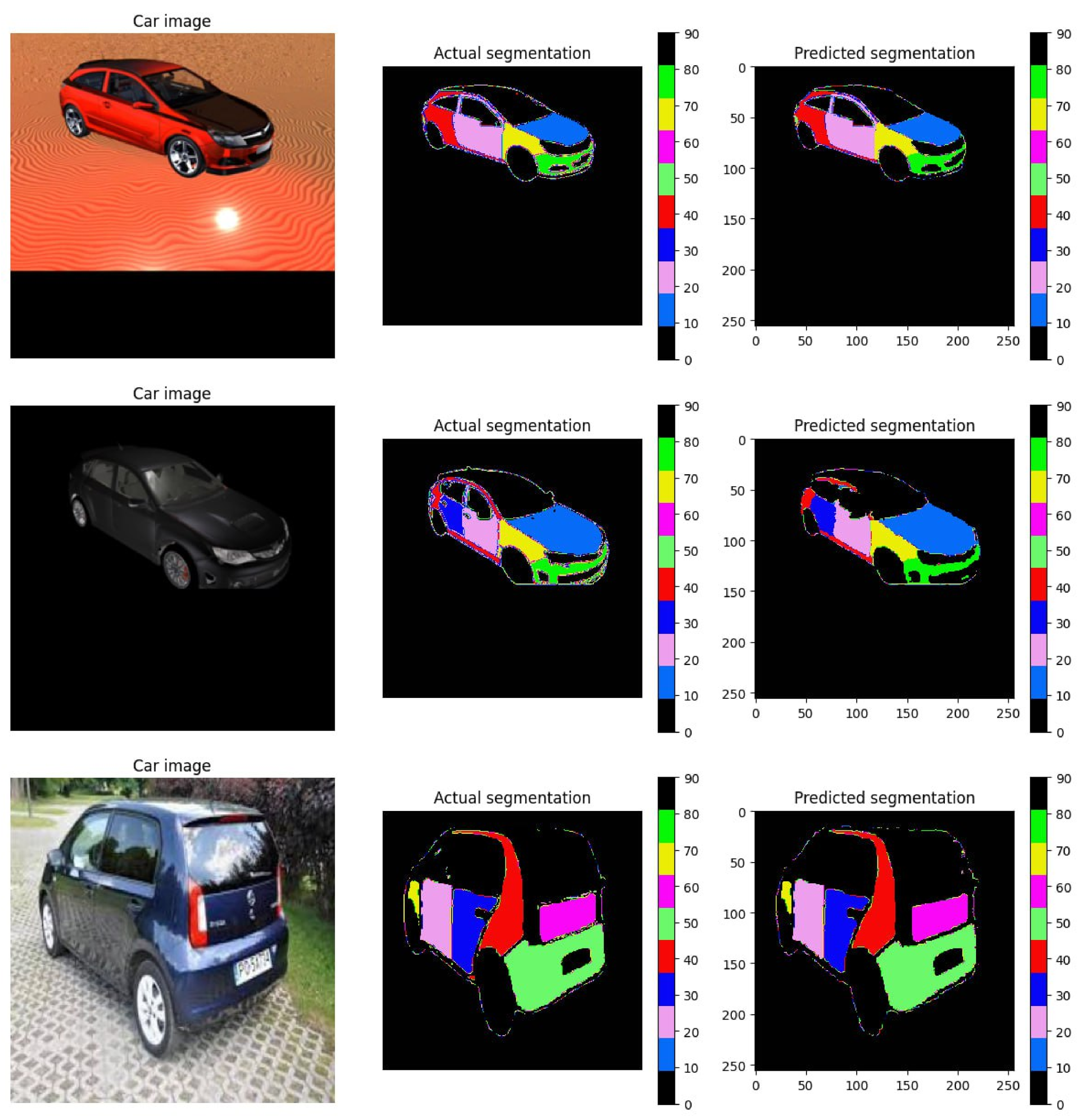

Figure 4: Performance of our model.

Conclusion and Outlook

- Our model performs well on the test data, precisely segmenting the parts of a car in an image.
- our model works well with both the black and/or orange dataset as well as with our augmented dataset using the different landscapes.
- The performance can be improved by adding noise, rotations, and data transformation techniques in general to the dataset.
- Future work involves assessing the damage of a car after segmentation.

Acknowledgements

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References

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