Université de Sfax
TUNISIE

المدرسة الوطنية للالكترونيك والاتصالات بصفاقس
ECOLE NATIONALE D'ELECTRONIQUE ET DES TETECOMMUNICATIONS DE SFAX

Data Engineering and Decisional System

End of The Year Project :

AI in Self Driving Cars

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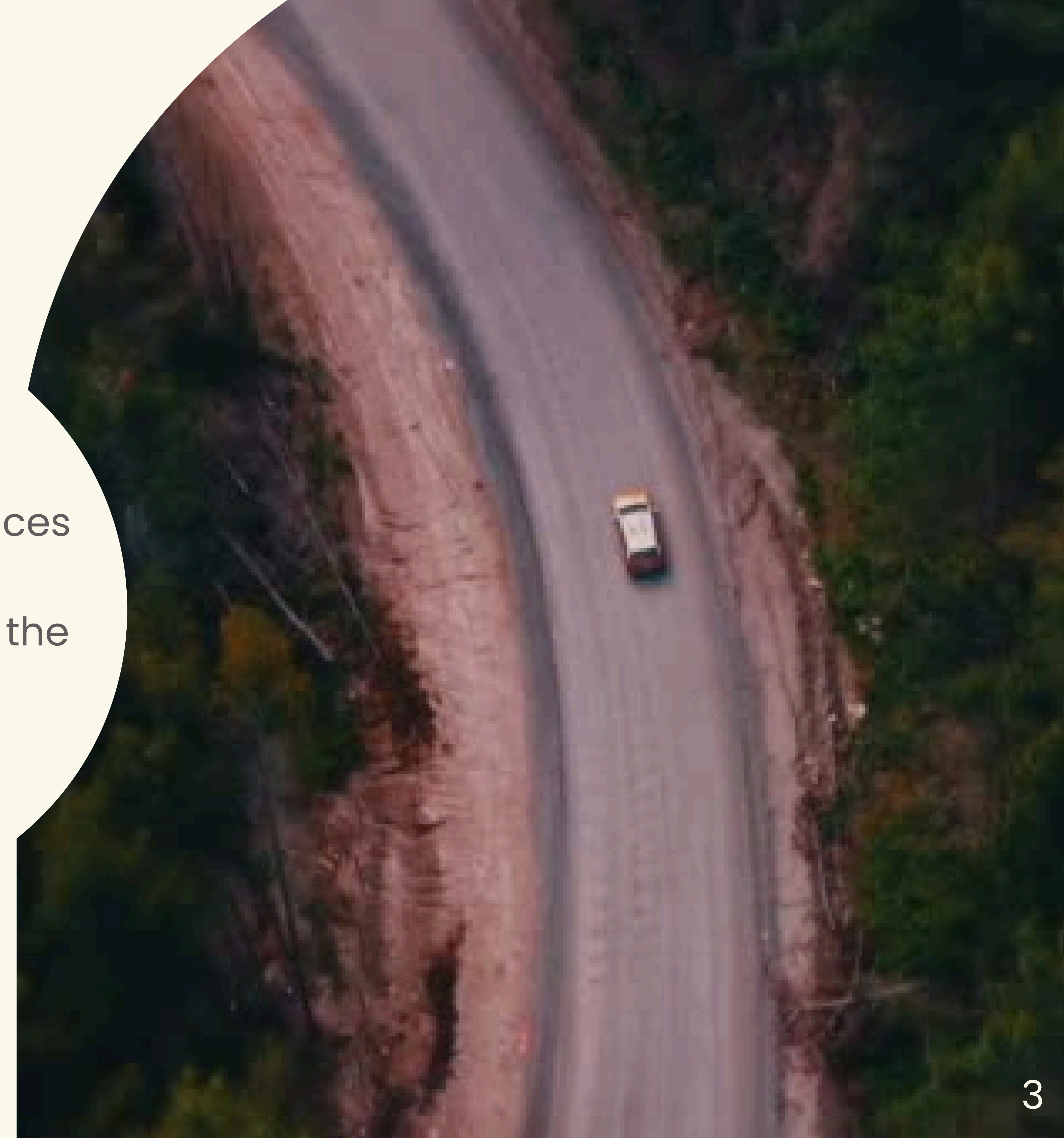
Introduction

Integrating Reinforcement Learning and Semantic Segmentation, our project enhances self-driving cars' decision-making and perception abilities. By visualizing results in the CARLA simulator



Motivations and Goals

- Advancing Road Safety and Accessibility
- Achieving robust object detection
- Enhancing decision-making

Project Context

Our project focuses on overcoming major hurdles in perception and navigation, to enhance transportation safety and efficiency

Project Context

CARLA Simulator

”Car Learning to Act”"

CARLA, the simulator we rely on, offers a comprehensive suite of Python APIs such as carla.Actor.
With features like dynamic weather simulation and traffic generation, it provides a realistic testing environment crucial for our research in autonomous vehicles.

Used Technologies

Reinforcement Learning in Simulated Environments

Harnessing Reinforcement Learning in simulated environments, our project empowers autonomous agents to learn dynamically, refining decision-making through trial and error.

Used Technologies

Reinforcement Learning in Simulated Environments

Episode : loop of Steps

Step Demonstartion

Action Space : Input

Variables : Steering Wheel and Throttle

Simulation

The car's interaction with the enviroment

Evaluate (Stable Baseline3)

Rewards and Penalties

Adapt and Learn

Adjust the Variables

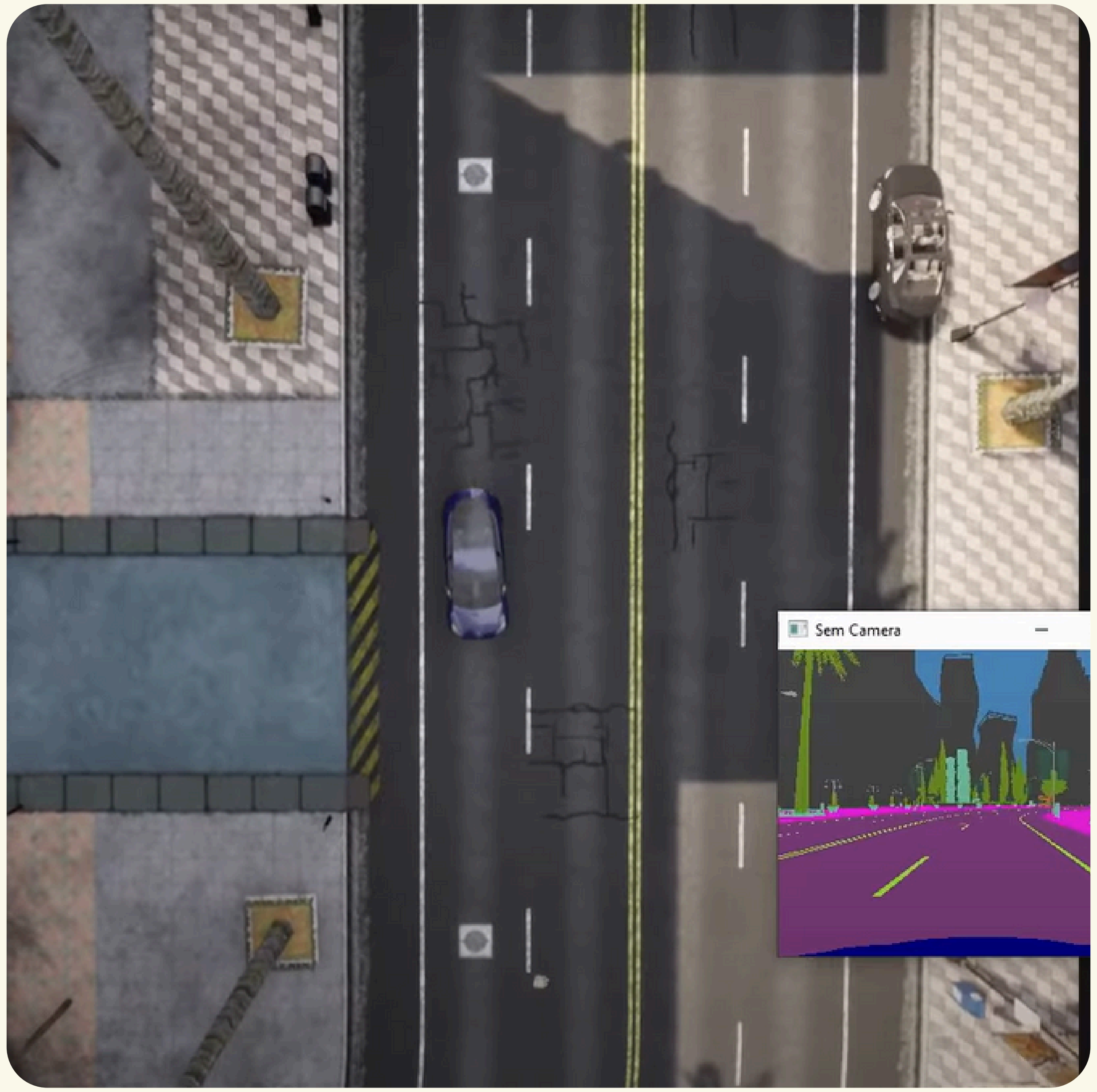
Observation Space : Output

Go through another step

Used Technologies

Reinforcement Learning in Simulated Environments

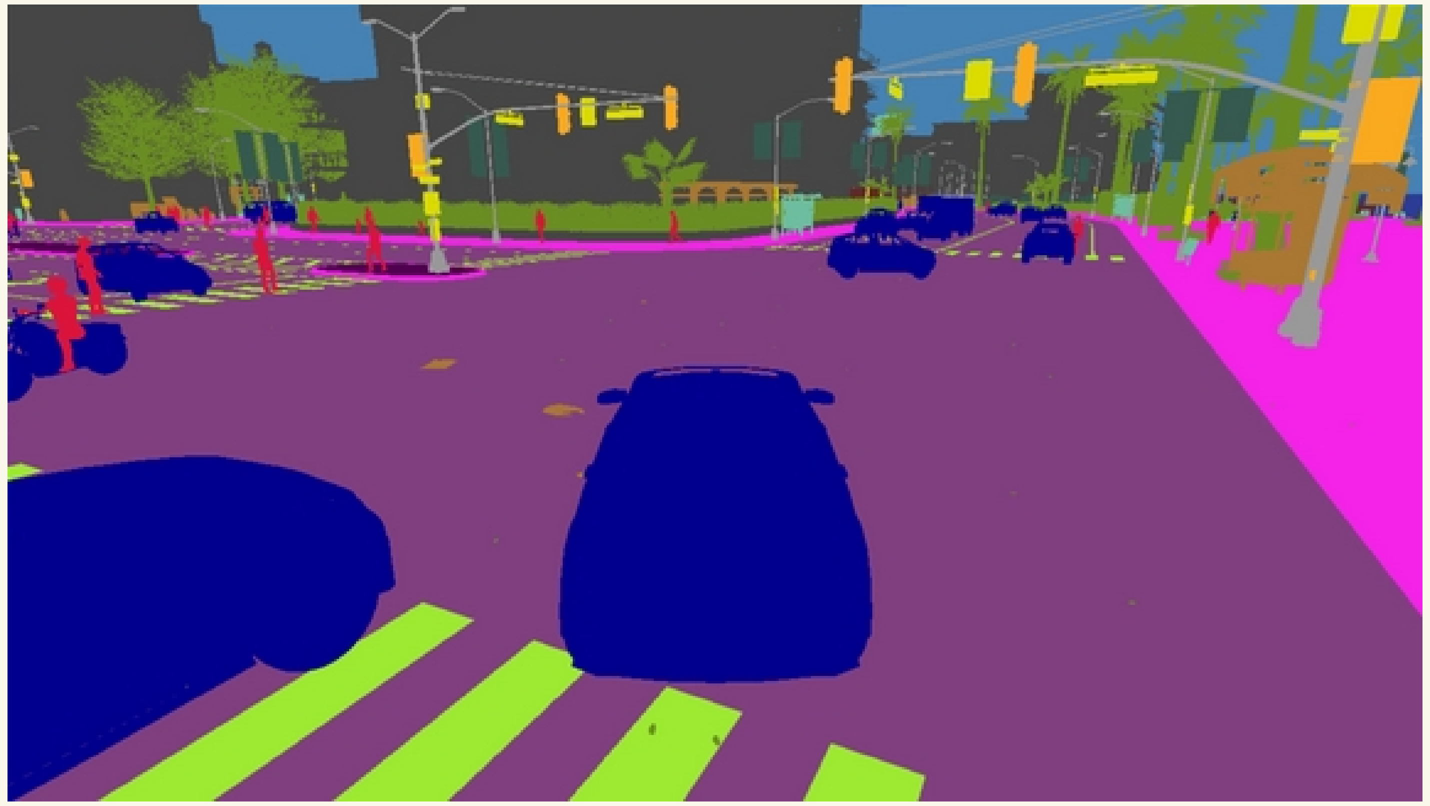
Observation Space



Used Technologies

Semantic Segmentation

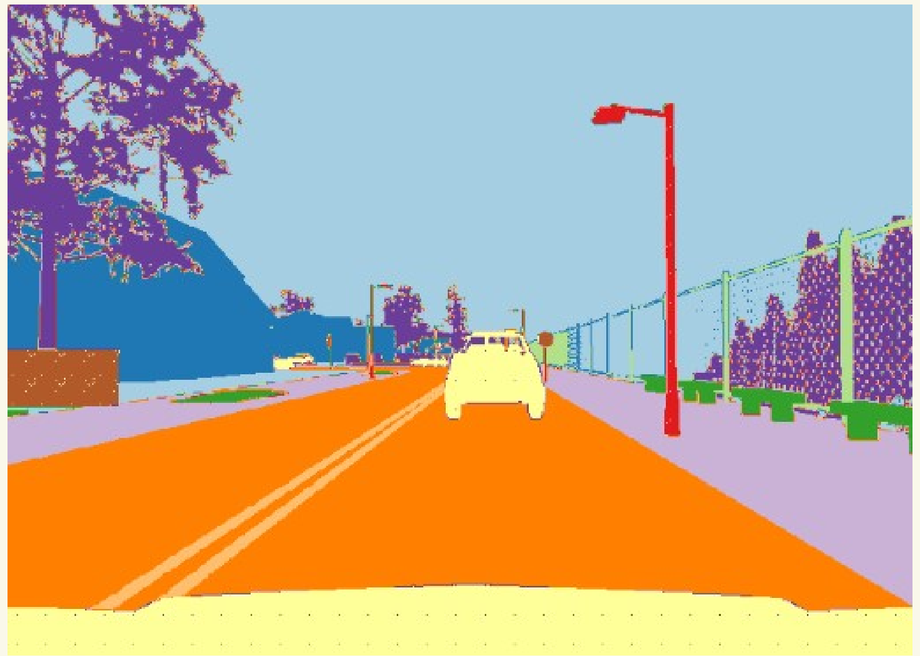
- Enabling precise understanding of the environment.
- Lane Following Model
- Empower autonomous cars to interpret surroundings accurately, ensuring safe navigation and informed decision-making.



Used Technologies

Dataset Overview

- Sourced from the CARLA self-driving car simulator.
- Contains 5000 RGB consecutive images and corresponding 5000 semantic segmentation images.



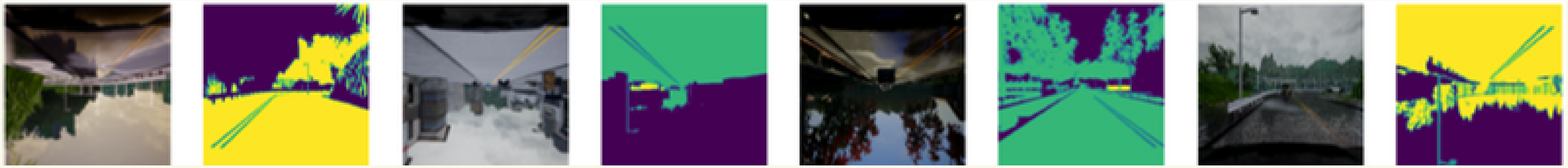
- Encompasses diverse scenes and objects labeled with categories like buildings, fences, people, vehicles, and traffic signs.
- Captured under various weather conditions during simulated car journeys.

Used Technologies

Data Preparation

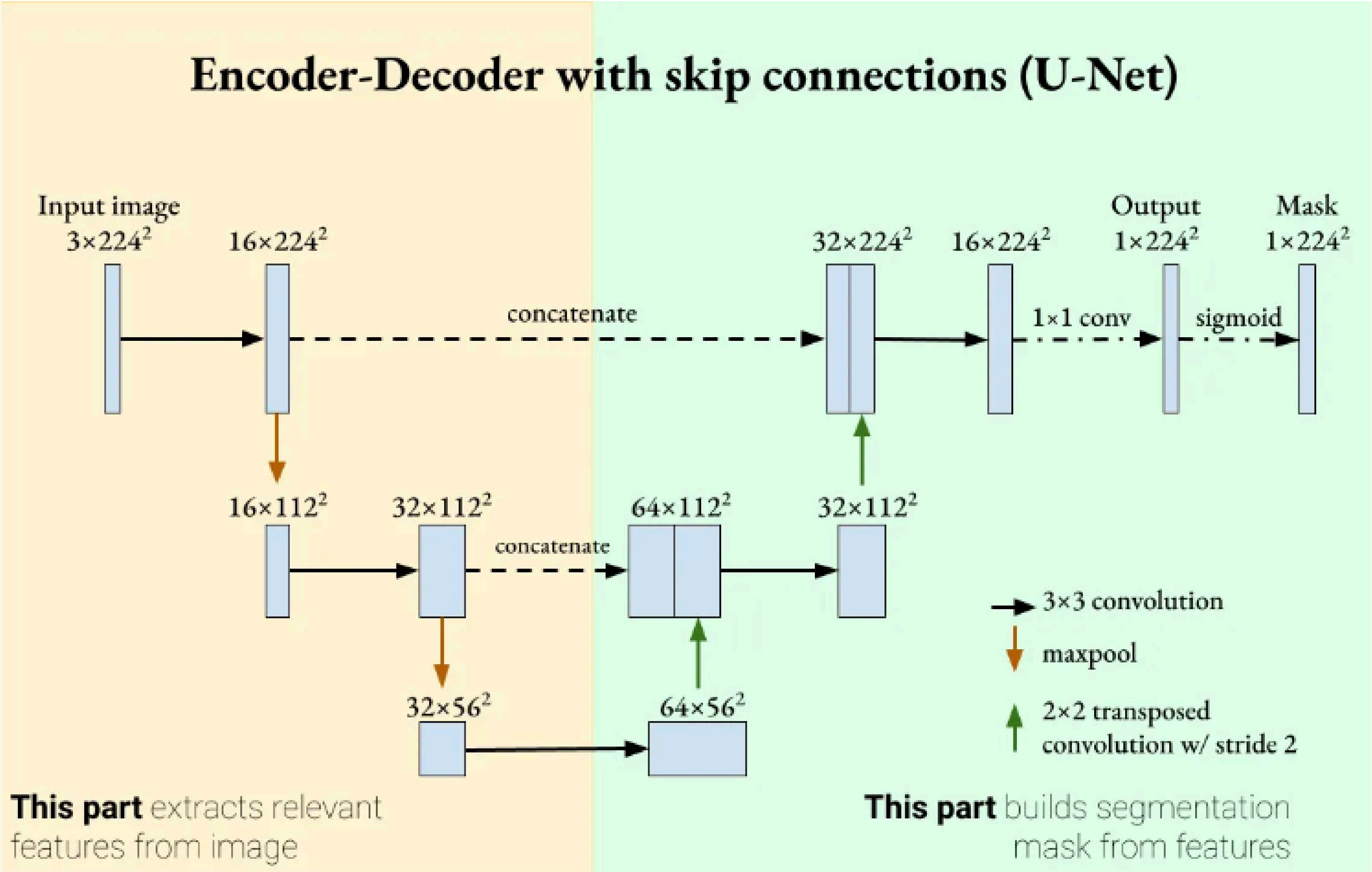
- Transform image and mask paths into arrays by decoding image files.
- Converting them to floating-point type, resizing them, and ensuring binary mask arrays.

- Data augmentation is a technique to expand the size and diversity of a training dataset .
- Zoom augmentation , noise augmentation ,random rotations.



Used Technologies

Model architecture and training

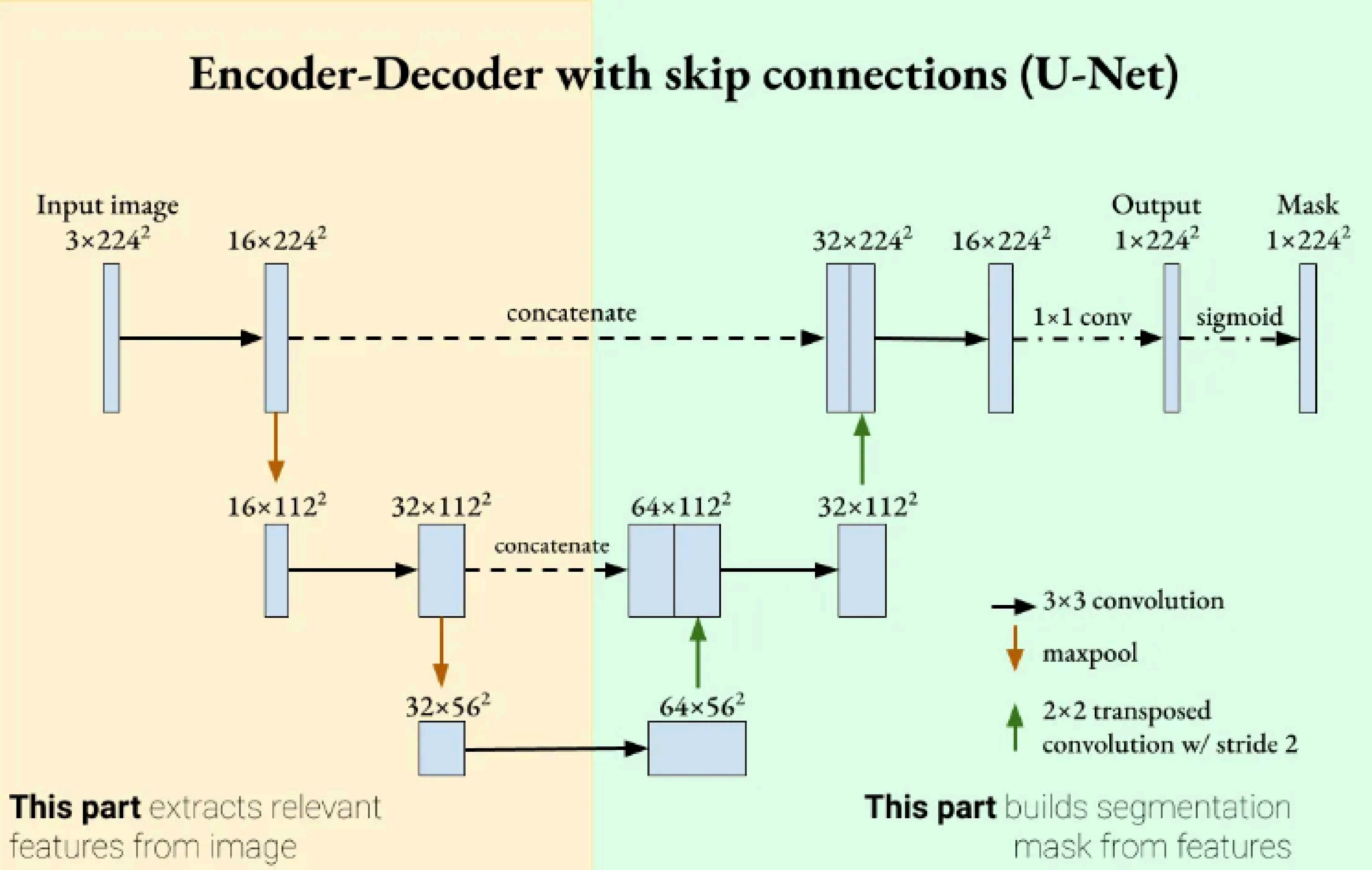


The U-Net architecture consists of an encoder and a decoder , resembling a "U" shape.

Used Technologies

Model architecture and training

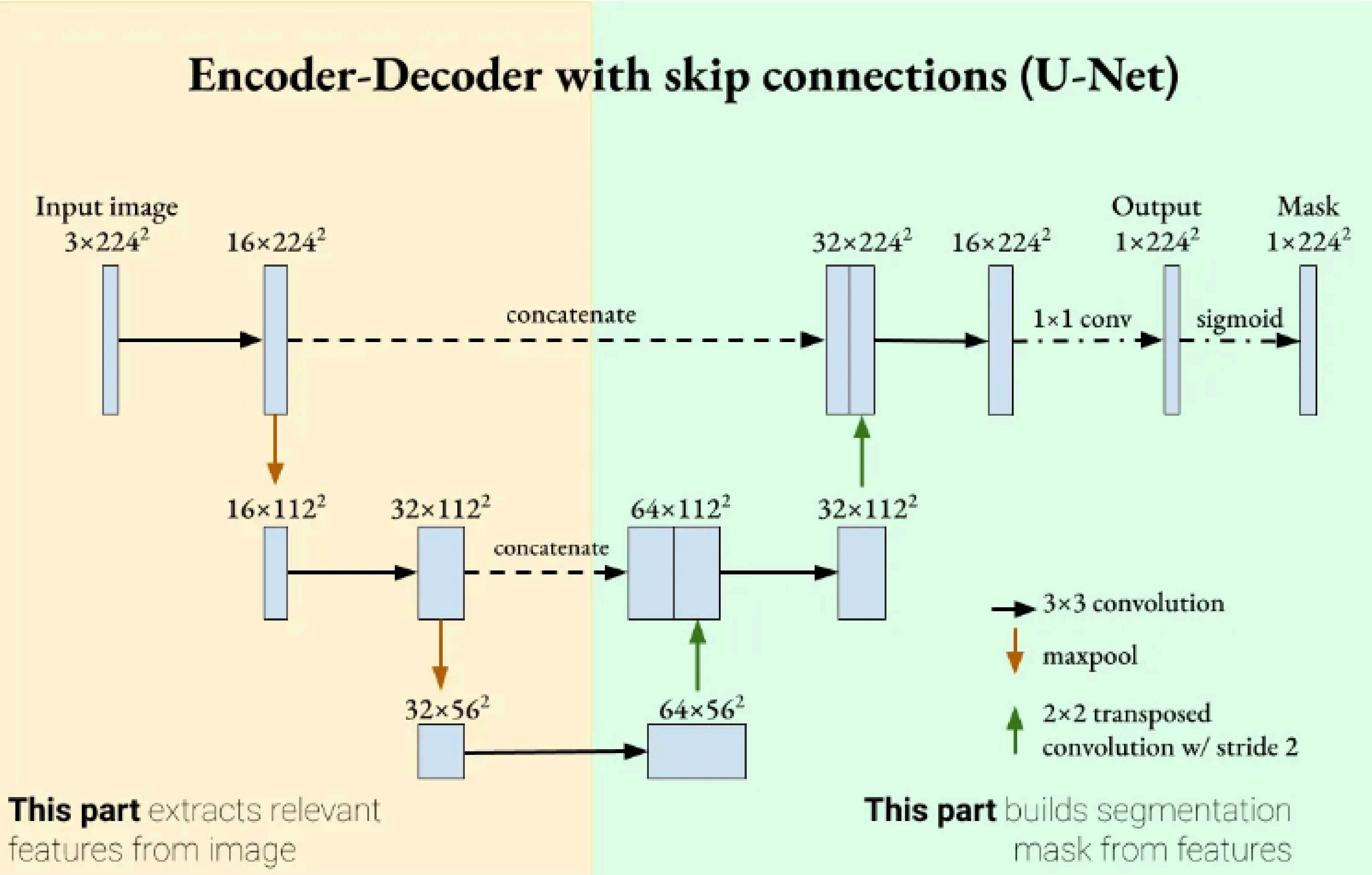
- **main role :** Feature Extraction from the input image.
- **Encoder Structure:** consists of convolutional layers followed by max-pooling operations.
- **Max-Pooling:** to downsample and reduce the spatial dimensions of the feature maps .
- A non-linear activation function like **ReLU** is applied to introduce non-linearity into the network.



Used Technologies

Model architecture and training

- **Decoder Functionality:** builds segmentation mask from feature maps.
- Restoring spatial details lost during downsampling .
- **Skip connections :** containing high resolution spatial information and detail-rich features.
- **Final Convolutional Layer:** produces segmentation masks

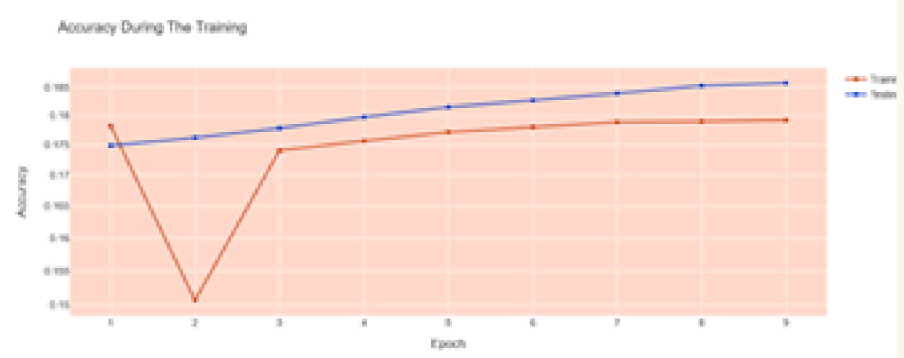


Used Technologies

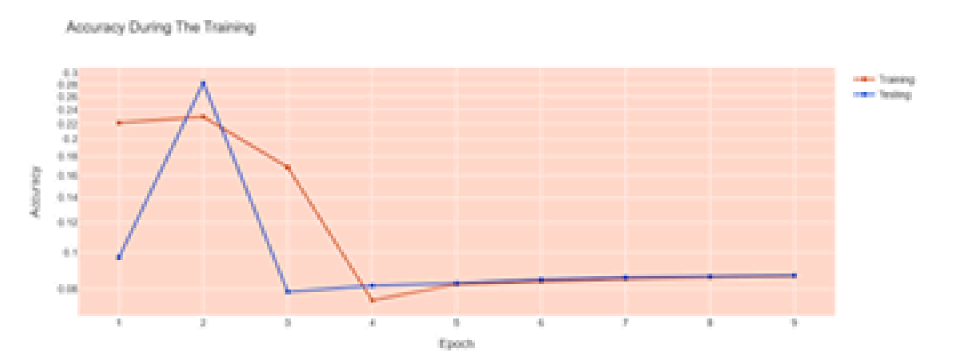
Model architecture and training

Model 1:

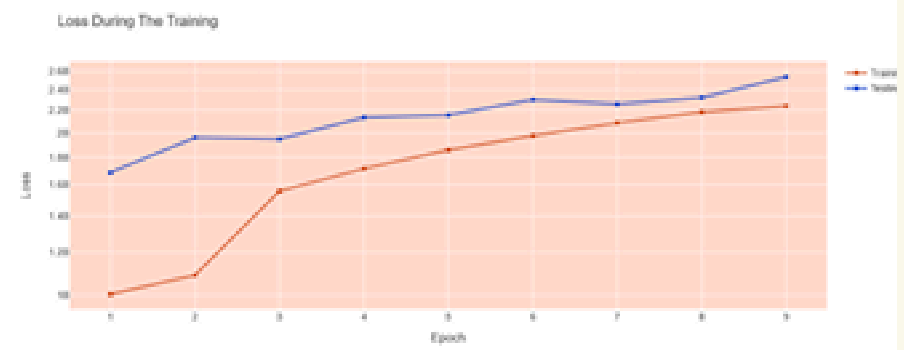
- was based on the classic U-Net structure
- ReLU activation function,dropout probability of 0.3,max pooling with a (2, 2) pool size
- Lack of significant improvement in initial model performance despite data augmentation.
- Importance of refining hyperparameters to improve model performance.



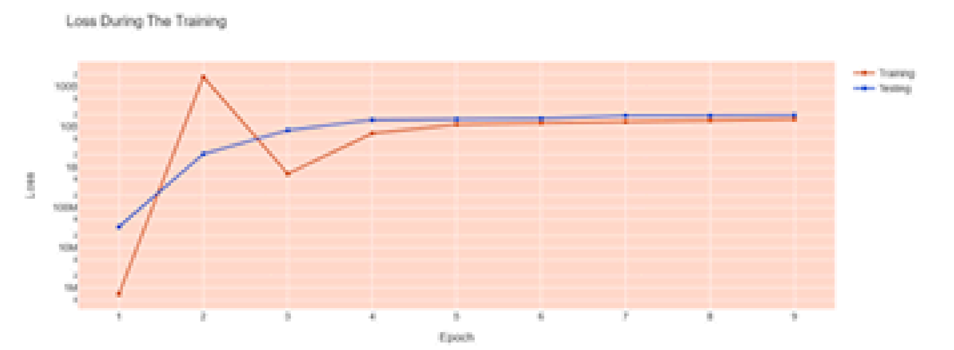
(a) Training and Testing Accuracy of Initial Model before data augmentation



(b) Training and Testing Accuracy of Initial Model after data augmentation



(c) Training and Testing Loss of Initial Model before data augmentation



(d) Training and Testing Loss of Initial Model after data augmentation

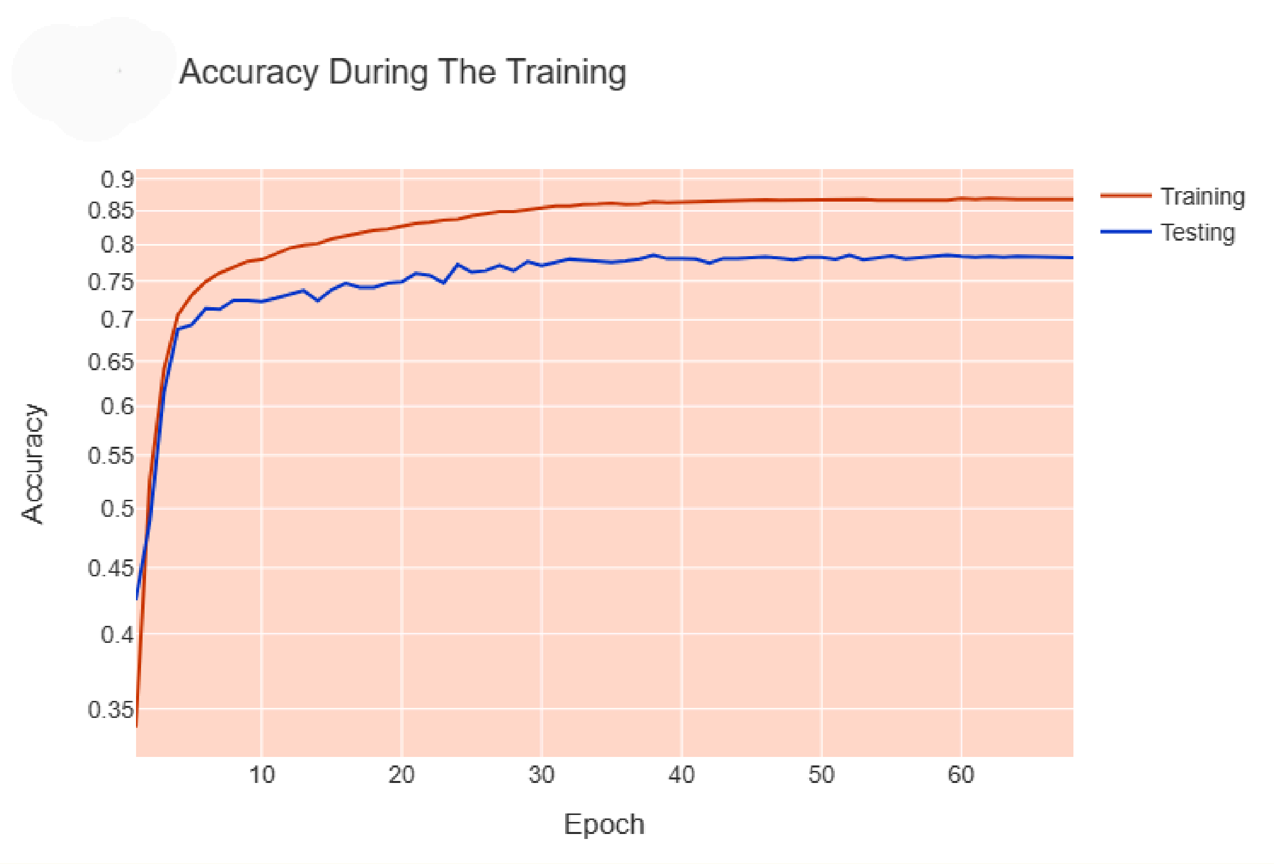
graphs comparing initial model performance pre and post data augmentation.

Used Technologies

Model architecture and training

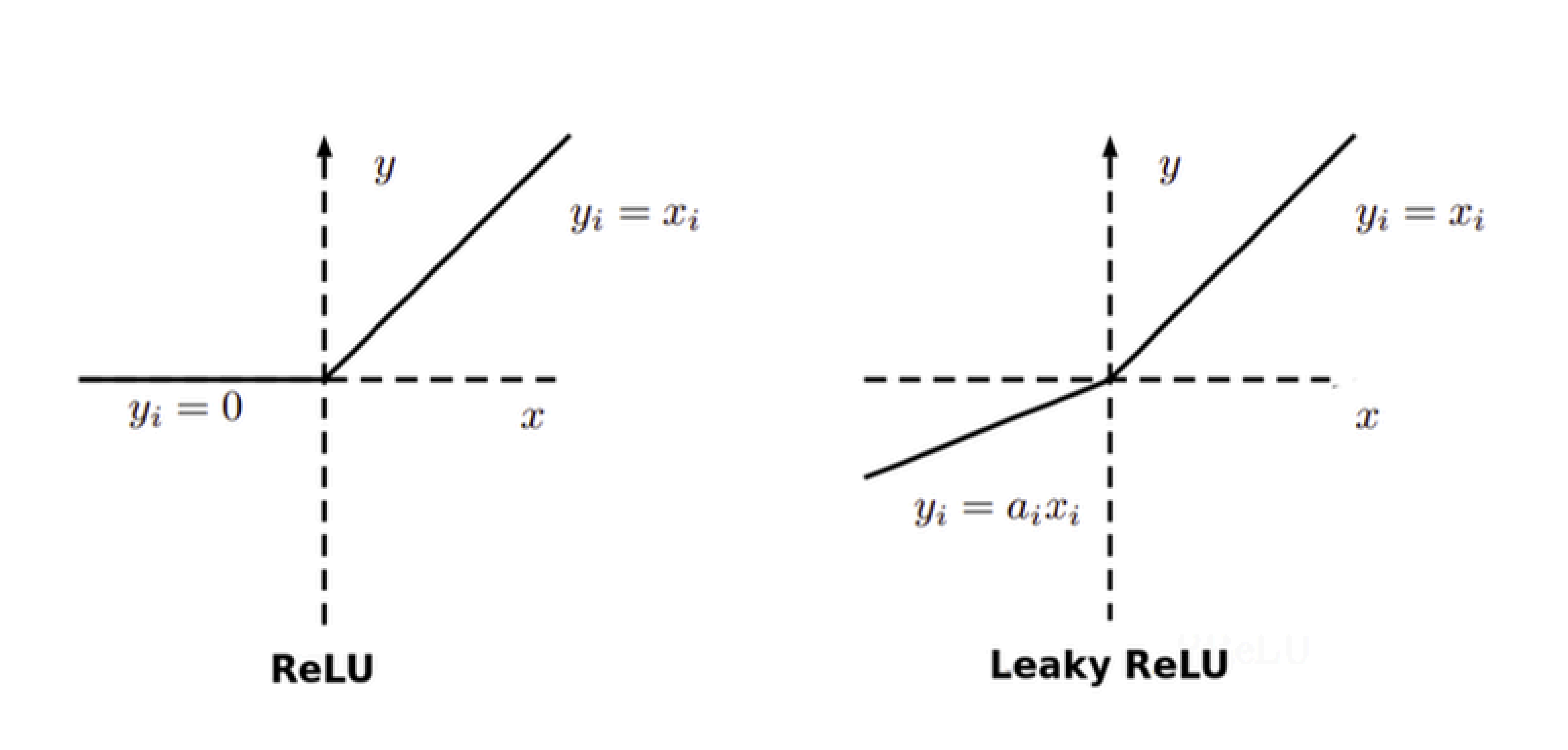
Model 2:

- Development based on Model 1 foundation.
- Integration of Batch Normalization as a hyperparameter.
- Batch Normalization applied after each convolutional layer in both contracting and Expanding Paths.
- The model learns the patterns in the training data too well
- The testing accuracy does not increase as much as the training accuracy.
- A large gap between the training loss and testing loss indicates that the model may be overfitting.



Used Technologies

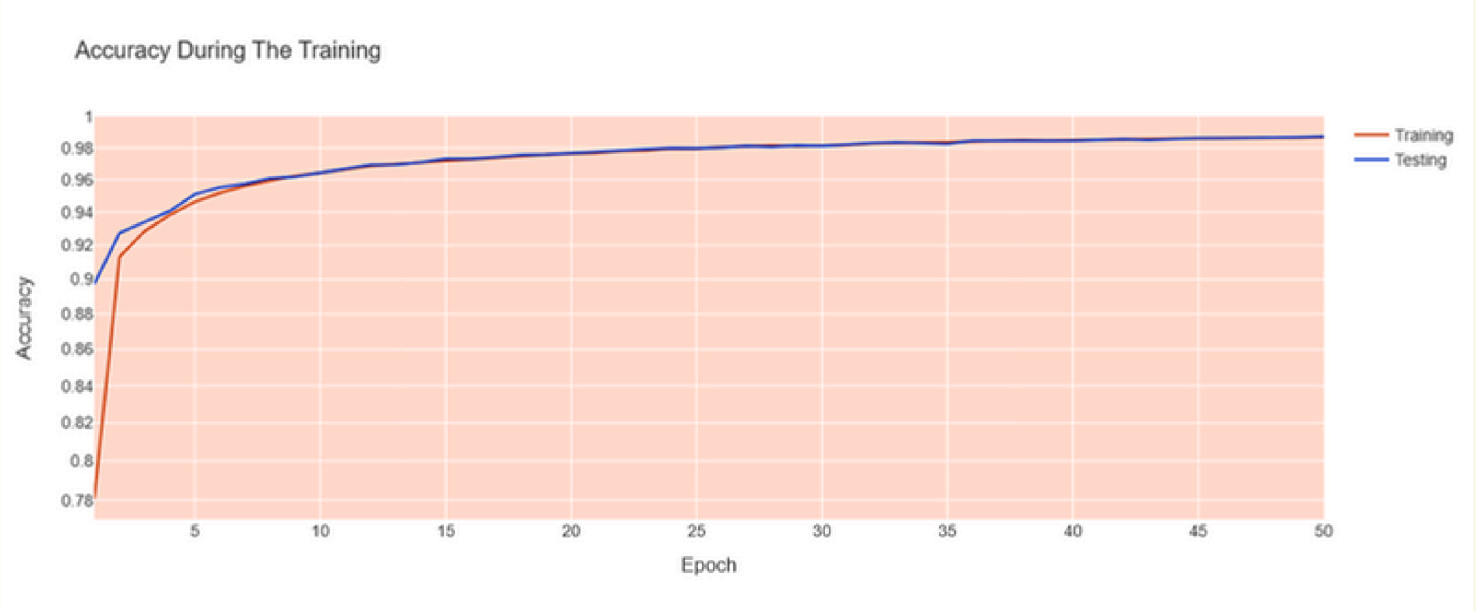
Model architecture and training



- **Relu :** accelerates training by avoiding “the vanishing gradient” problem.
- **Leaky Relu :** addresses the "dying ReLU" problem by allowing a small, non-zero gradient for negative inputs

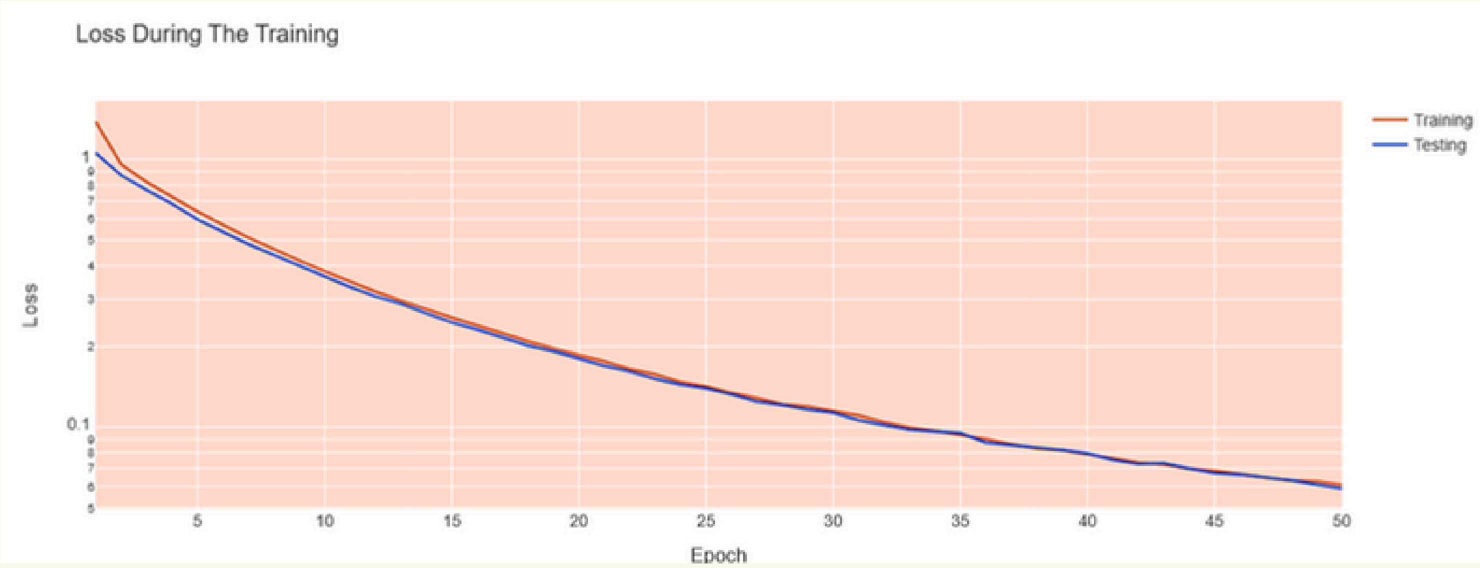
Used Technologies
Model architecture and training

Model 3:



- Objective : improved training stability compared to Models 1 and 2.

- Replacement of the standard ReLU activation function with Leaky ReLU



- Significant performance improvements , attaining a training accuracy of 0.98 and testing accuracy of 0.98

Used Technologies

Model Evaluation

- A remarkable similarity, indicating accurate identification and classification of semantic features by the model.
- The close resemblance between predicted and ground truth segmentations provides compelling evidence of the model's effectiveness and reliability in semantic segmentation tasks.

Used Technologies

Model Evaluation

	Class	Recall	Precision	Specificity	IoU	TDR	F1-Score
0	All Classes	0.93	0.95	1.0	0.89	0.93	0.94
1	Class 1	1.0	0.99	1.0	0.99	1.0	0.99
2	Class 2	0.99	0.98	1.0	0.97	0.99	0.98
3	Class 3	0.91	0.82	1.0	0.76	0.91	0.86
4	Class 4	0.9	0.93	1.0	0.84	0.9	0.91
5	Class 5	0.65	0.81	1.0	0.56	0.65	0.72
6	Class 6	0.9	0.96	1.0	0.86	0.9	0.93
7	Class 7	0.99	0.99	1.0	0.98	0.99	0.99
8	Class 8	1.0	1.0	1.0	1.0	1.0	1.0
9	Class 9	0.99	0.98	1.0	0.97	0.99	0.98
10	Class 10	0.95	0.98	1.0	0.94	0.95	0.96
11	Class 11	1.0	1.0	1.0	0.99	1.0	1.0
12	Class 12	0.96	0.94	1.0	0.9	0.96	0.95
13	Class 13	0.85	0.94	1.0	0.81	0.85	0.89

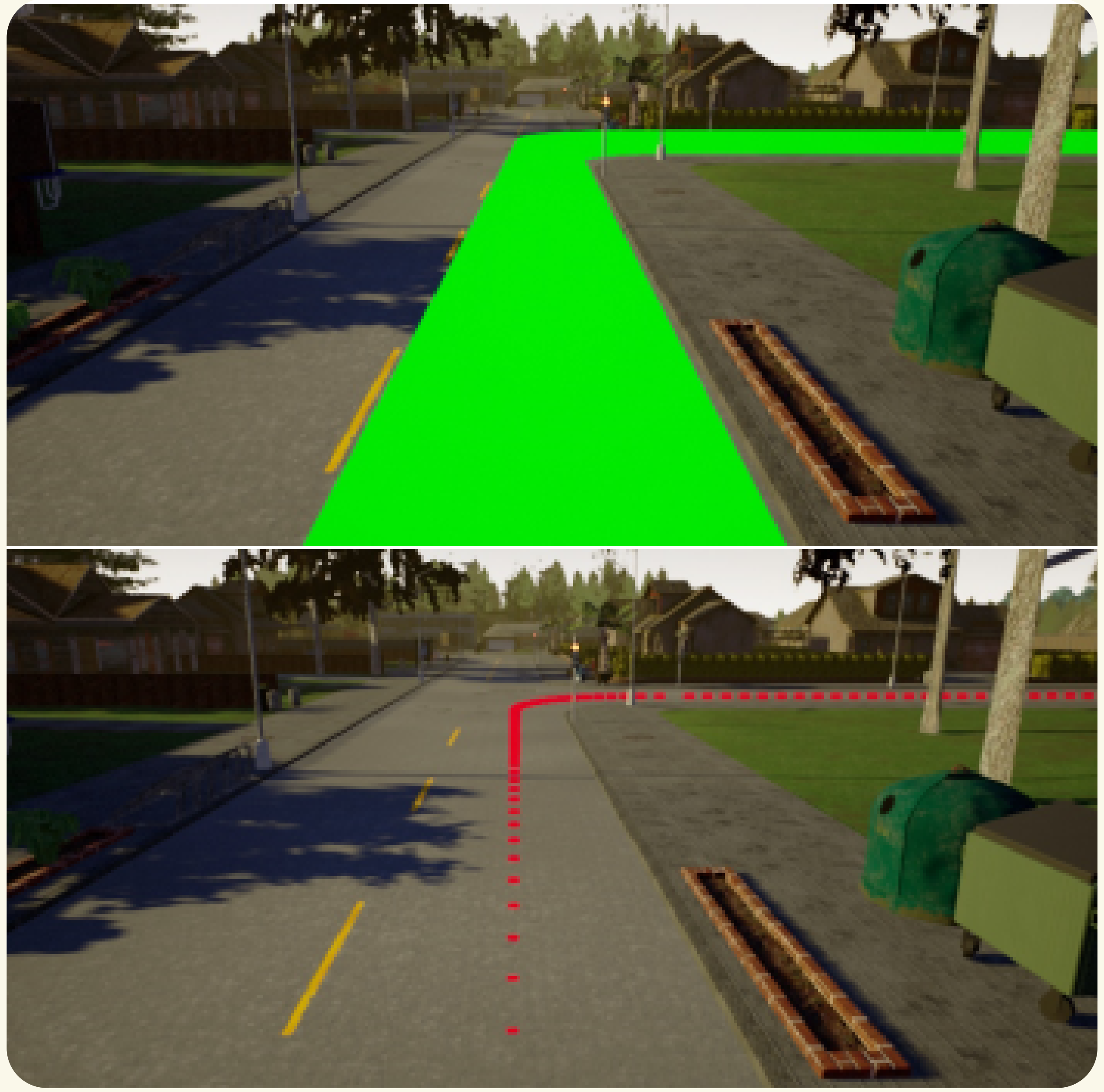
evaluate predicted images of the training dataset

	Class	Recall	Precision	Specificity	IoU	TDR	F1-Score
0	All Classes	0.89	0.94	1.0	0.85	0.89	0.91
1	Class 1	1.0	0.99	1.0	0.99	1.0	0.99
2	Class 2	0.98	0.98	1.0	0.96	0.98	0.98
3	Class 3	0.89	0.81	1.0	0.74	0.89	0.85
4	Class 4	0.86	0.91	1.0	0.8	0.86	0.88
5	Class 5	0.4	0.82	1.0	0.37	0.4	0.54
6	Class 6	0.8	0.92	1.0	0.75	0.8	0.86
7	Class 7	0.99	0.99	1.0	0.98	0.99	0.99
8	Class 8	1.0	1.0	1.0	1.0	1.0	1.0
9	Class 9	0.99	0.98	1.0	0.97	0.99	0.98
10	Class 10	0.95	0.98	1.0	0.93	0.95	0.96
11	Class 11	1.0	1.0	1.0	0.99	1.0	1.0
12	Class 12	0.95	0.92	1.0	0.88	0.95	0.93
13	Class 13	0.77	0.93	1.0	0.73	0.77	0.84

evaluate predicted images of the testing dataset

Experimentation and Results

Testing and Validation with CARLA



Experimentation and Results

DEMO VIDEO

The project challenges

- The car exhibited unconventional behaviors, such as aimless turning and slow driving to complete the step and earn the reward.

- Uncertainty in selecting specific data augmentation techniques for our dataset.

- Certain augmentation techniques led to overfitting issues in our model.

Conclusion and perspectives

- **Conclusion :** Our project has made good progress in combining reinforcement learning and semantic segmentation for autonomous driving.

- **Perspectives :** Looking forward, we aim to make our model better at making quick decisions in real time. We also want to explore using advanced sensors like LiDAR and radar to help our agents understand their surroundings better.

Thank you for your attention!