

Search Based Software Engineering for Testing Autonomous Cars

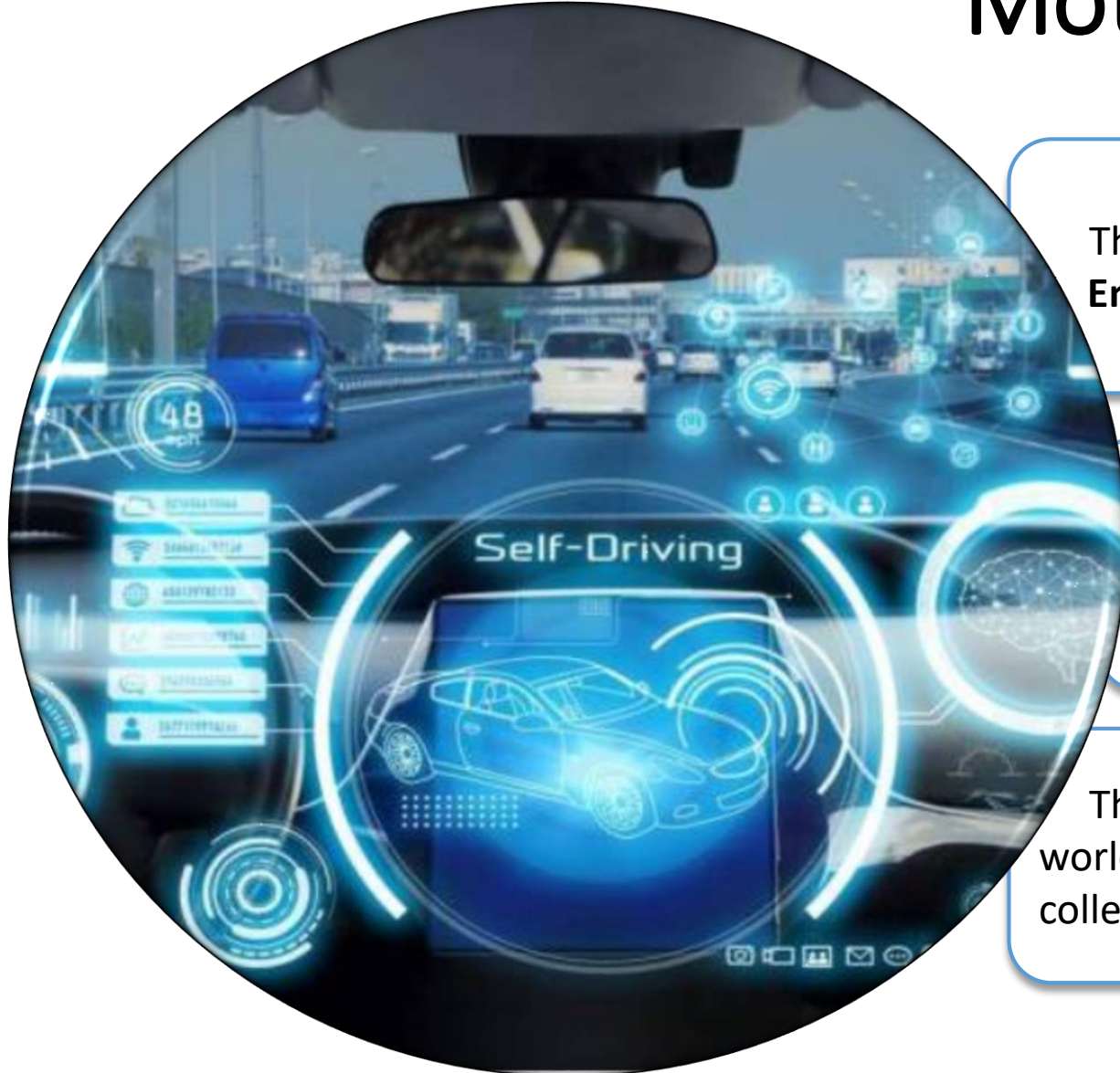
Train Generator:

Lane keeping functionality of self-driving cars

Team Members:

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Motivation



The main idea of the lane keeping functionality is derived from **End-to-end learning for lane keeping of self-driving cars**

In this paper, the model is trained using End-to-end approach by training with only camera images and steering angles

The model predicts the proper steering angles from the real world images. The huge amount of real world images are collected from **Comma.AI** dataset

Why BeamNG over Comma AI ?

BeamNG simulator



Proper scenarios can be generated with required complexity based on neural network architecture

Various road configurations and weather conditions can be simulated

The BeamNG provides a very realistic physics during car crashes

An extensive testing can be performed using BeamNG simulation

CommaAI dataset



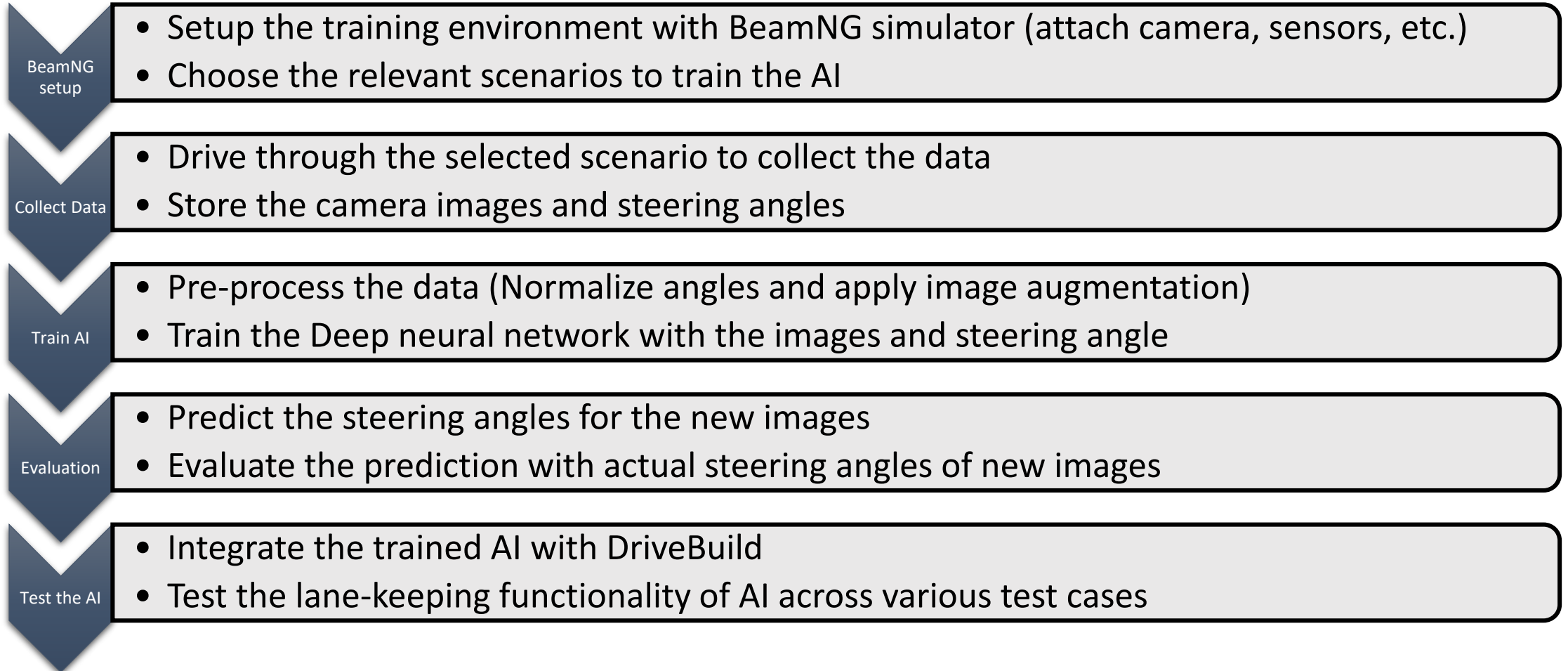
Includes real-world images with huge diversity and traffic participants which is too complex for simple architecture

Non-trainable images need to be identified and filtered

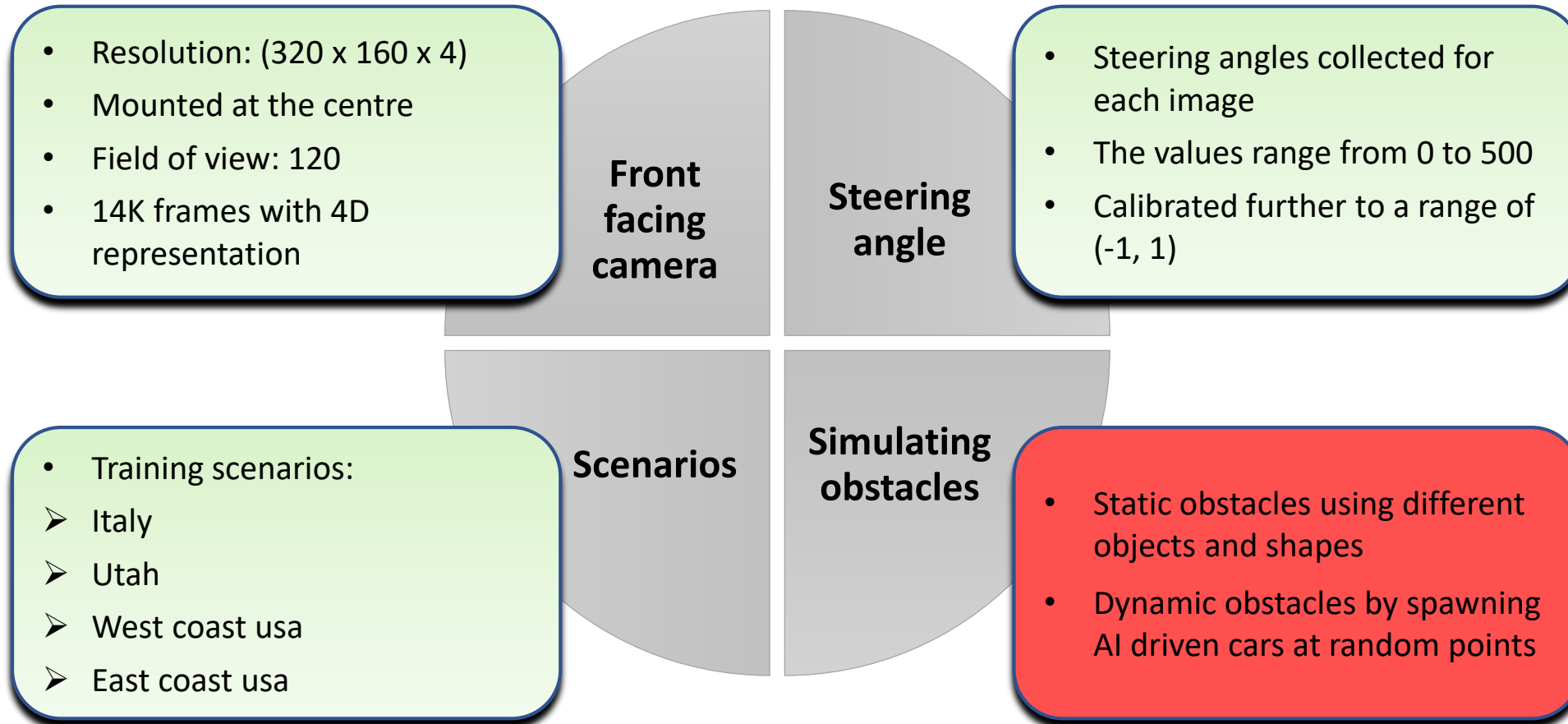
Needs complex neural network to train the AI

End-to-end approach might not be sufficient to accurately predict steering angles

The Proposed Approach



BeamNG Setup



This functionality is now removed since it is not used in the test cases of DriveBuild 5

Data collection

Initially, the ego car is driven manually to collect the data – (however, the results turned out to be bad since manually driving the car on the lane lead to inaccurate steering angles and hence the AI was trained with bad training data)

In order to overcome this difficulty, the BeamNG AI is used to drive through the defined scenarios

The BeamNG provides **drive_in_lane** functionality which can be used with an aggression level of 0.6 to accurately collect the training data without letting the BeamNG AI crash or drive too fast.

The camera images and corresponding steering angles are collected at a frequency of 20 Hz

Train AI

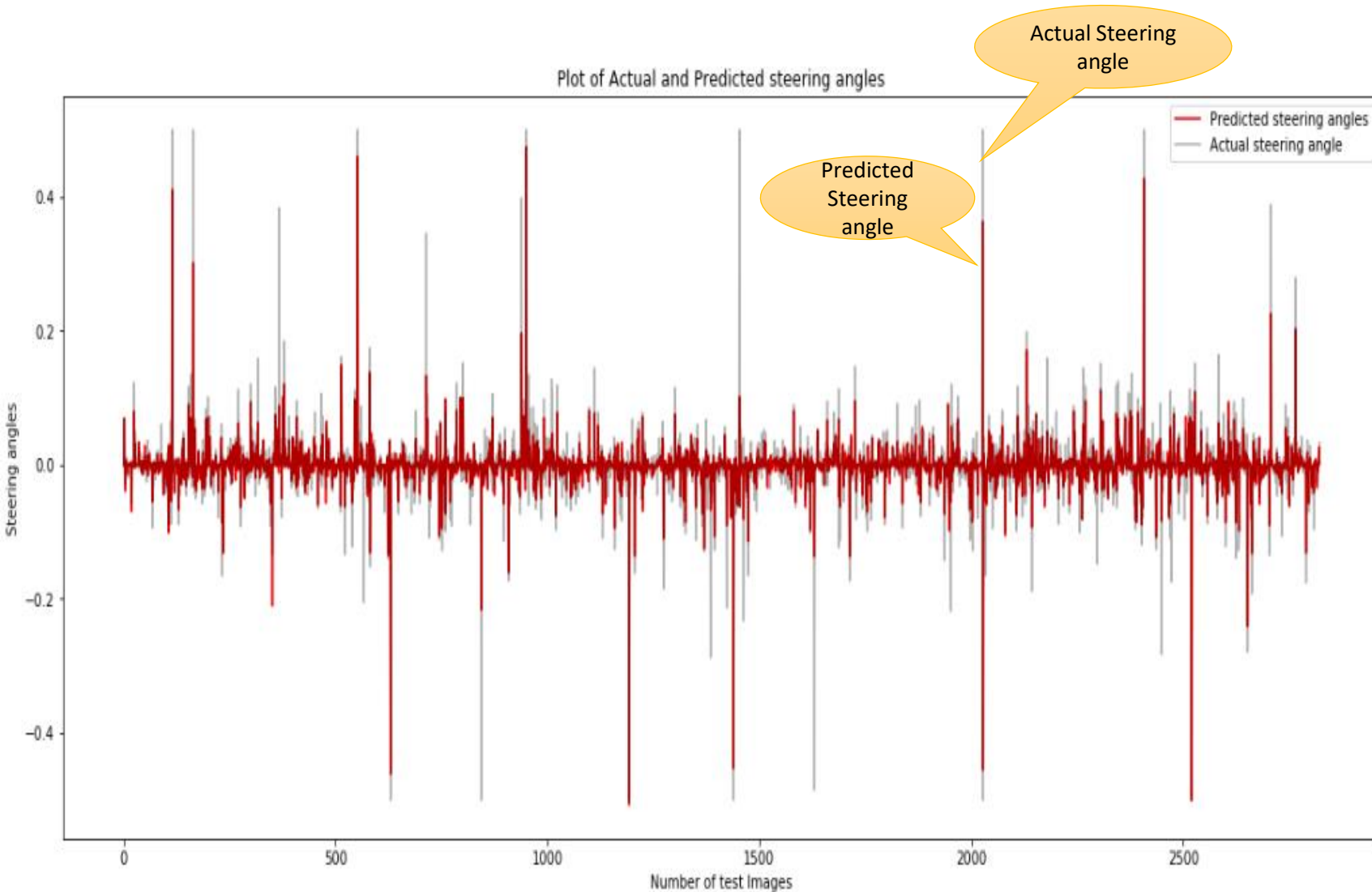
Pre-processing:

- The images are normalized from (0, 255) to (0, 1) to optimize the learning rate.
- The steering angles are normalized to (-1, 1).
- The training data is increased two-fold by applying horizontal flipping as an **Image augmentation** technique.

Training:

- The 6 layer deep Convolutional Neural Network is built to train the network with the randomly shuffled 11K image data and corresponding steering data.
- The model is trained for 80 epochs with Adam optimizer.
- The model predicts the steering angle for the given image.

Evaluation



Observations:

- From the plot, the predicted steering angle (dark red) appears to have a strong correlation with the actual steering angle
- The model needs improvement in predicting peak curves. Small to moderate steering angles appears to be closer to the actual steering angles

Integration with DriveBuild

- The Trained AI model is further integrated with the DriveBuild to test and evaluate the model with various test cases.
- The AI proves to be able to drive on the road without curves. However, it finds challenging to distinguish the road boundaries during the curvature since the AI is trained on the different road characteristics compared to test environment.

Effectiveness of the Results:

1. Since the DriveBuild scenarios are not identical to the trained scenarios in BeamNG, the AI finds it difficult to predict the accurate steering angles for road with turns.
2. In order to evaluate the AI effectively, the test cases similar to the trained AI scenarios need to be generated.

References and Further links

Train Generator Demo link:

<https://www.dropbox.com/s/i4bmr34yz0tylr/AI%20demo.mov?dl=0&fbclid=IwAR2HwXOaG3TsjqosaALDgzQcNIVLsttqg4GBTFgGxZYfGssKZjBr7W1CvjY>

- <https://github.com/commaai/comma2k19>
- <https://ieeexplore.ieee.org/abstract/document/7995975>
- <https://github.com/TrackerSB/DriveBuild>
- <https://github.com/BeamNG/BeamNGpy>