Vehicle Auto Steering Using Deep Learning

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Outline

- Introduction
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- Approach
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Introduction

- Concepts of deep learning and convolutional neural networks are applied to teach the computer to drive car autonomously
- CNN methodology has been implemented for the estimation of steering angle
- Images from the front mounted car cameras (input to CNN) are fed into a CNN which then computes a proposed steering command
- Once trained, the network can generate steering angles from the video images of a single center camera

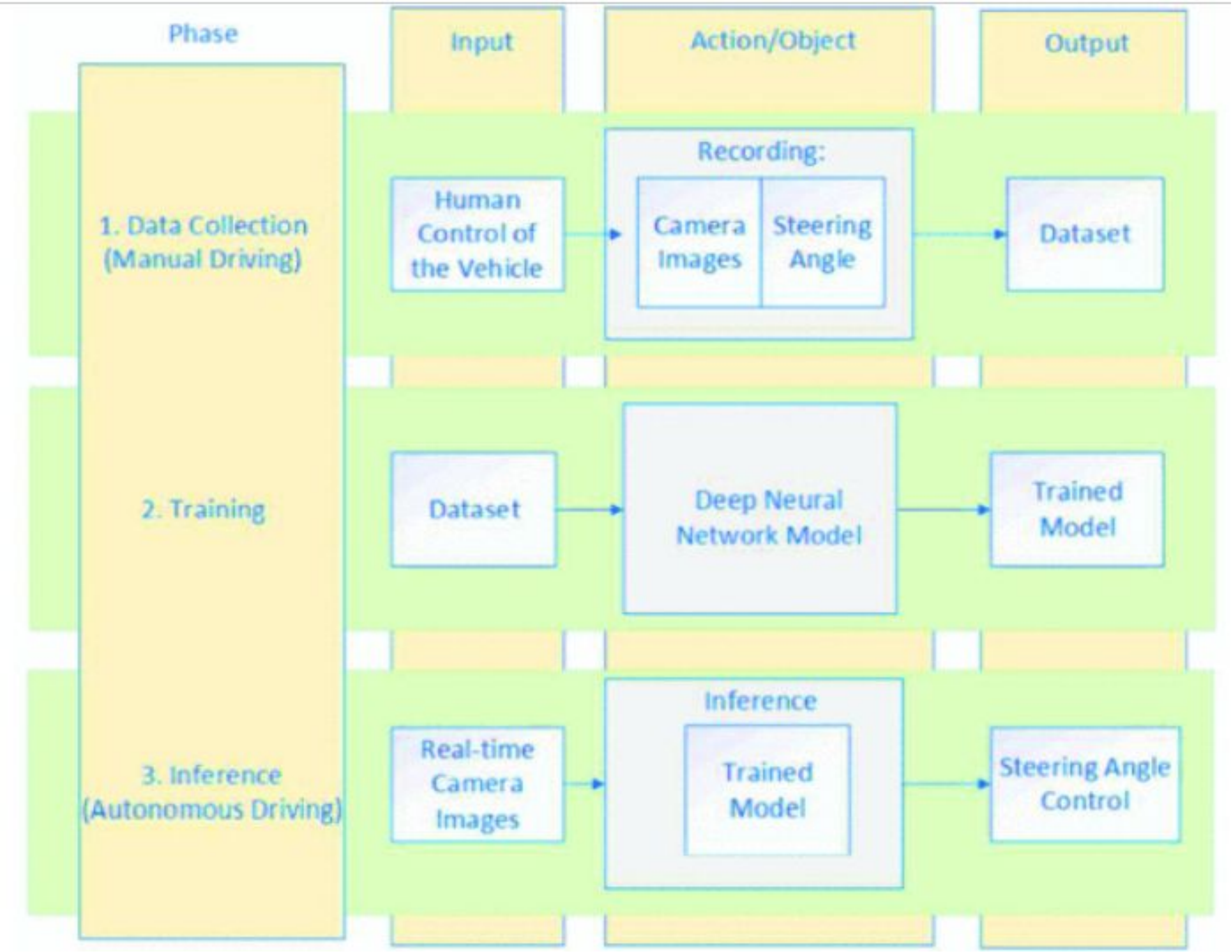
Softwares Used

- The data collection is performed using Udacity self-driving car simulator designed by Unity (game engine)
- VSCODE and Google Colab for scripting and model training
- Python Socketio and flask libs to connect the trained model to the simulator

Approach

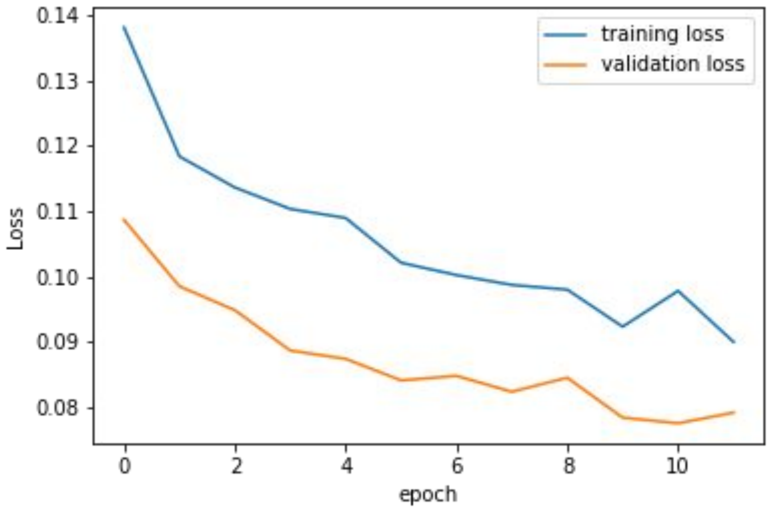
- Udacity open source car simulator is used for data generation. It provides two options: training mode and autonomous mode
- For preparing the deep neural network, pictures are procured from all of the three cameras - centre, left, and right
- Image augmentation is done on the raw data set, to increase the number of images and for the model to easily adapt to different types of images to learn
- Zoomed, Panned, brightness altered, mirrored images are generated from the original images using batch generator
- The deep neural network for independent driving is prepared on this dataset and can anticipate the directing point
- At last, this prepared model is utilized for inference, that is a continuous execution of the independent vehicle in a similar stimulator environment

Approach


Phase
Input
Action/Object
Output
1. Data Collection (Manual Driving)
Human Control of the Vehicle
Recording:
Camera Images
Steering Angle
Dataset
2. Training
Dataset
Deep Neural Network Model
Trained Model
3. Inference (Autonomous Driving)
Real-time Camera Images
Inference
Trained Model
Steering Angle Control

Results and Evaluation

- Training and validation loss during model training phase was 0.098 and 0.0716 respectively
- With less training data, better results are obtained when car is run on first track (other than unseen track)
- To overcome overfitting problem, drop out technique is implemented

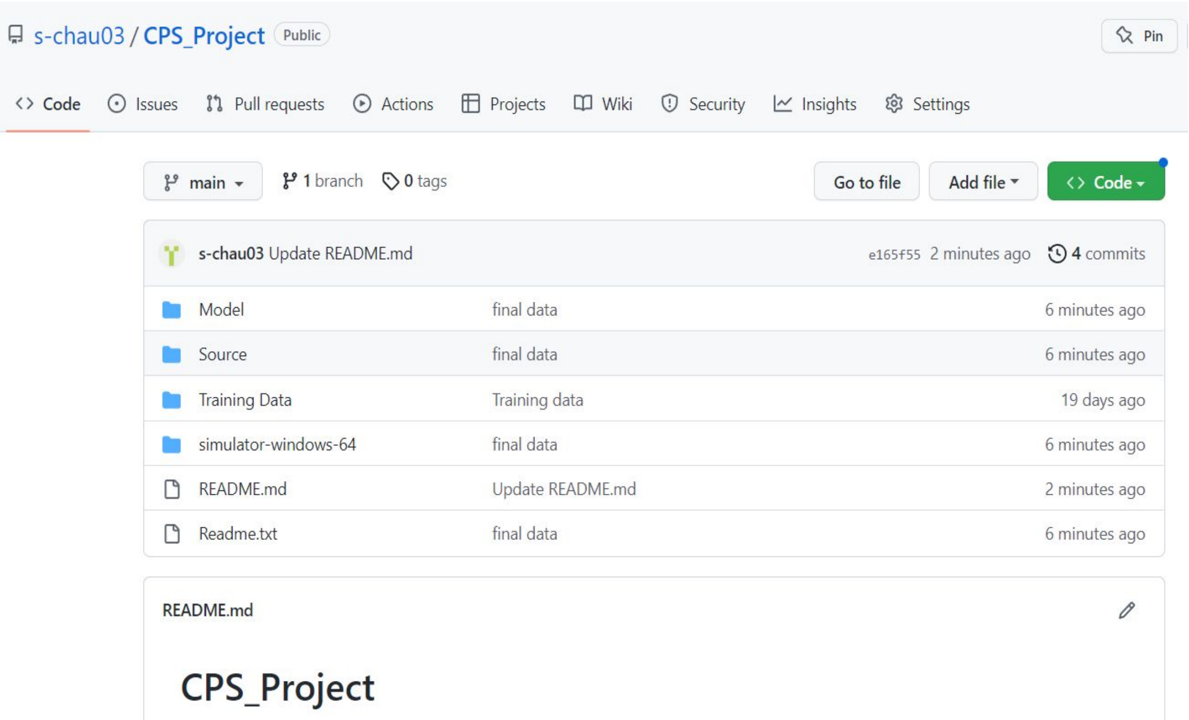


Results and Evaluation

```
<ipython-input-33-115b913bba99>:1: UserWarning: `Model.fit_generator` is deprecated and will be r
  h = model.fit_generator(batch_generator(X_train, y_train, 100, 1),
Epoch 1/12
100/100 [==============================] - 189s 2s/step - loss: 0.1387 - val_loss: 0.1124
Epoch 2/12
100/100 [==============================] - 187s 2s/step - loss: 0.1302 - val_loss: 0.0955
Epoch 3/12
100/100 [==============================] - 202s 2s/step - loss: 0.1168 - val_loss: 0.0882
Epoch 4/12
100/100 [==============================] - 184s 2s/step - loss: 0.1102 - val_loss: 0.0906
Epoch 5/12
100/100 [==============================] - 182s 2s/step - loss: 0.1065 - val_loss: 0.0794
Epoch 6/12
100/100 [==============================] - 183s 2s/step - loss: 0.1060 - val_loss: 0.0783
Epoch 7/12
100/100 [==============================] - 183s 2s/step - loss: 0.1000 - val_loss: 0.0775
Epoch 8/12
100/100 [==============================] - 183s 2s/step - loss: 0.0998 - val_loss: 0.0797
Epoch 9/12
100/100 [==============================] - 183s 2s/step - loss: 0.0982 - val_loss: 0.0786
Epoch 10/12
100/100 [==============================] - 181s 2s/step - loss: 0.0964 - val_loss: 0.0729
Epoch 11/12
100/100 [==============================] - 182s 2s/step - loss: 0.0975 - val_loss: 0.0757
Epoch 12/12
100/100 [==============================] - 181s 2s/step - loss: 0.0898 - val_loss: 0.0716
```

Github Code Repository

- https://github.com/s-chau03/CPS_Project



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