Department of
Computer Science & Engineering

Thesis Title:
Integrative Trajectory Forecasting for Autonomous Vehicles in Mixed Traffic Environments

Supervised By:
Md Rakibul Haque
Lecturer,
Dept. of Computer Science & Engineering, RUET.

Presented By:
Md. Nazmul Hossain
ID : 1803170

Topic Outline

- Introduction
- Literature Review
- Challenges
- Objectives
- Methodology
- Dataset Details
- Results & Performance Analysis
- Conclusion
- Limitations & Future Work
- References

Introduction

- Trajectory refers to a path that a vehicle moves through space over time.

- For of an autonomous vehicle, trajectory not only the route but also it’s motion—speed, acceleration, and direction etc.

Fig – 1: Some Trajectories of Various Vehicle [7].

Introduction (CONT'D)

- Mixed traffic environment consists of different types of road users, such as pedestrians, bicycles, motorcycles, cars, and buses, share the same space and interact with each other.

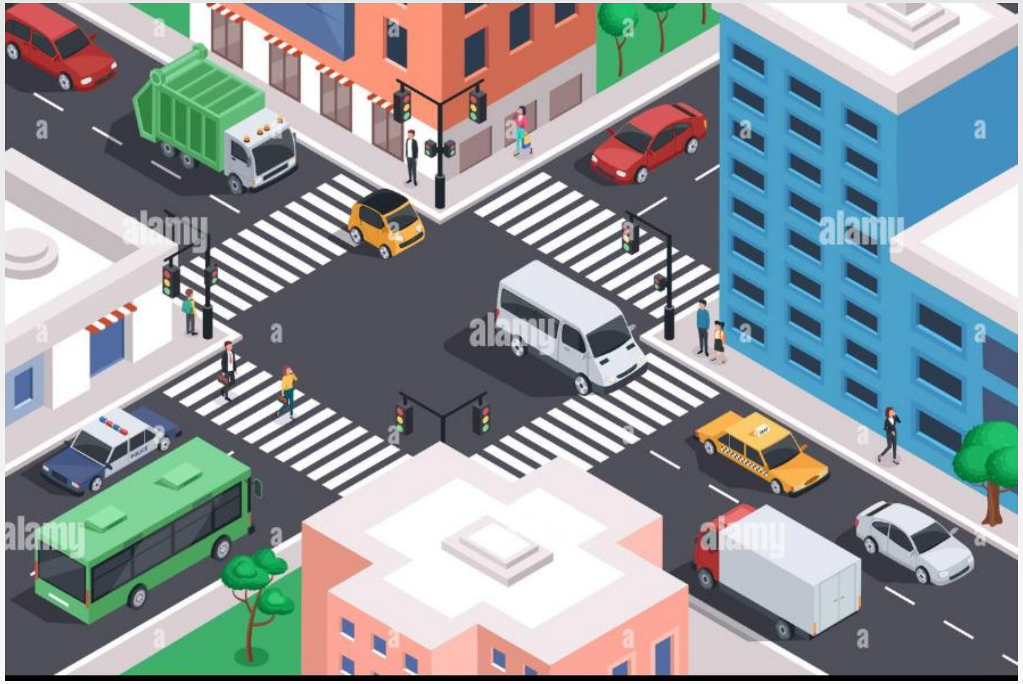

Fig – 2: Mixed Traffic Environment [1].

TrafficPredict: Trajectory Prediction for Heterogeneous Traffic-Agents [2]

Performances:

- Using previous state-of-the-art approaches in accuracy for trajectory prediction in heterogeneous traffic.
- Offer real-time performance without assumptions about traffic conditions or the number of agents.

Limitations:

- The accuracy varies with traffic conditions and the historical data available.
- Future improvements will consider additional constraints such as lane directions, traffic signals, and rules.

Interactive Trajectory Prediction for Autonomous Driving via Recurrent Meta Program Induction Network [3]

Performances :

- Here, behavior estimation based on historical observation of all related cars including the target car and surrounding cars.
- Also achieving lower mean error rates in trajectory prediction for both longitudinal and lateral directions.

Limitations:

- Future developments are needed for a more advanced generator and observer structure to further reduce prediction errors and to extend the framework to more general scenarios, such as turns at intersections and highway merging.

Literature Review (CONT'D)

TraPHic: Trajectory Prediction in Dense and Heterogeneous Traffic Using Weighted Interactions [4]

Performances :

- It is LSTM-CNN based hybrid network, where consider the fast moving vehicle by increase their weights.

Limitations:

- It is designed for dense heterogeneous traffic scenarios, it is not effective for sparse traffic.
- Here, do not use any batch normalization and dropout.

Challenges

Work on Urban Areas Consists of Mixed Traffics

Considering Driver Dynamic Behavior and Turning Radius

Reduce Prediction Error

Objectives

- Deals with mixed traffic environment consists of various cars, bicycles, bikes, buses, pedestrians etc. in an urban areas.

- Considering driver dynamic behavior and turning radius.

- Also increasing the accuracy of the model is an obligatory part of my work.

Methodology

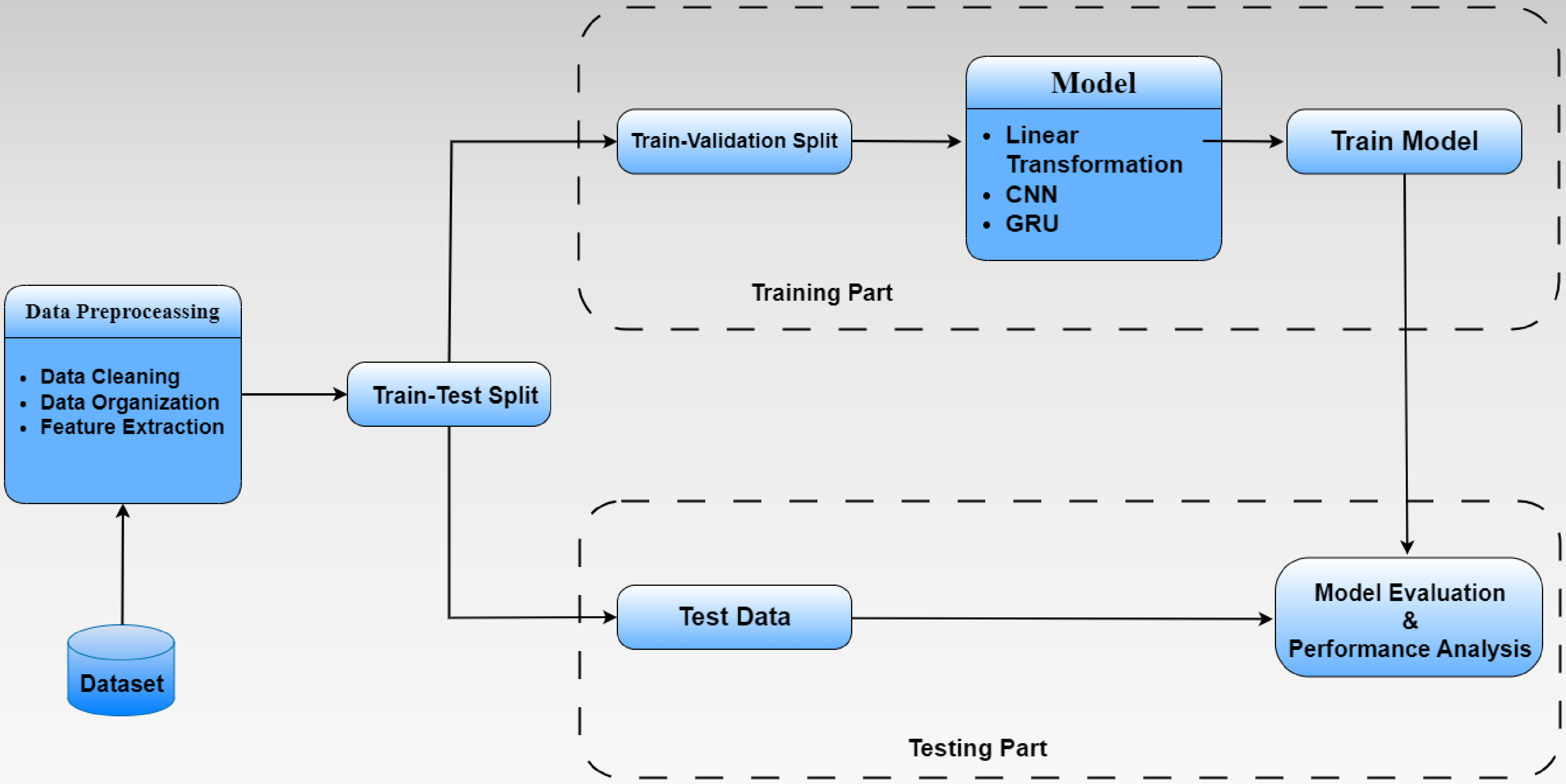

Fig – 3: Methodology.

Methodology (CONT'D)

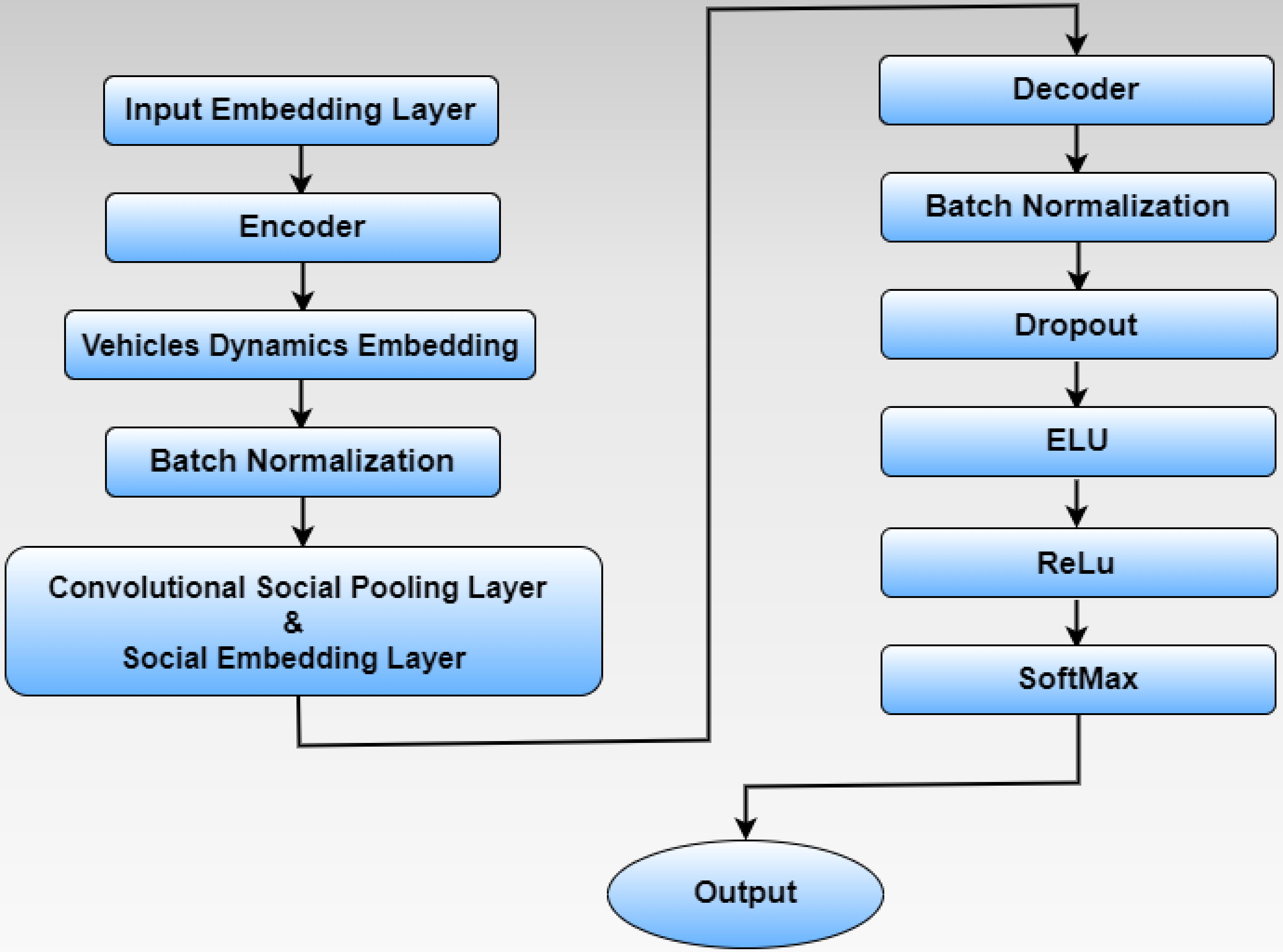

Fig – 4: Model Flow Chart.

Methodology (CONT'D)

Model Architecture

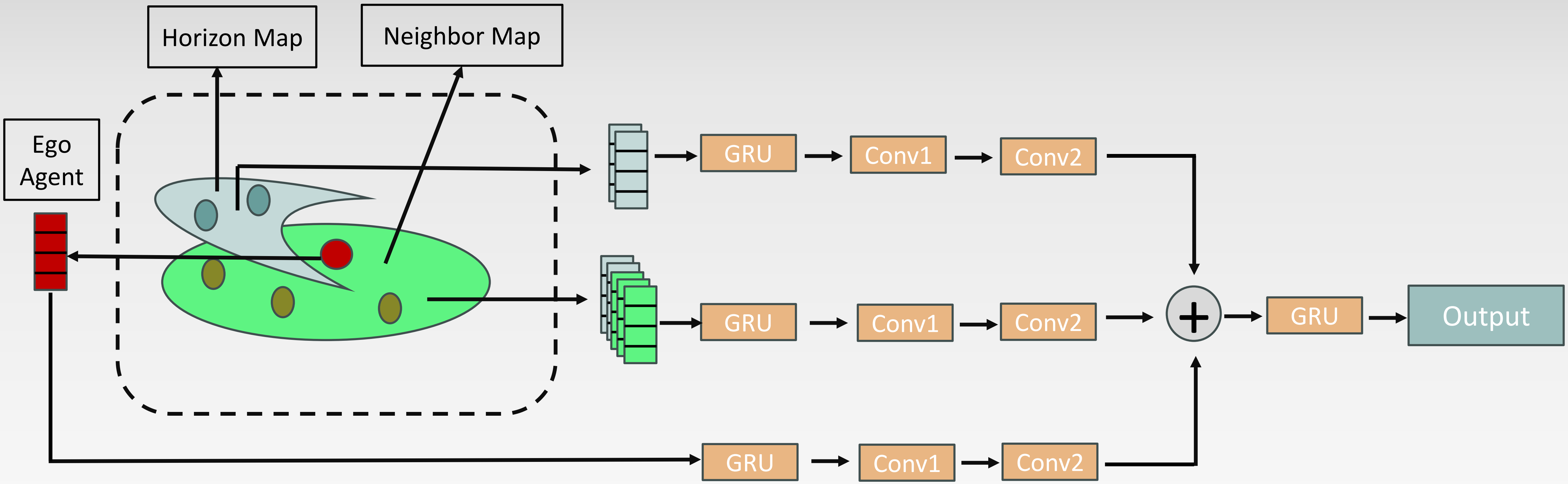

Fig – 5: GRU-CNN Architecture

Dataset Details

Dataset Name: NGSIM (Next Generation Simulation) Dataset

Source: The NGSIM dataset originates from the Next Generation Simulation (NGSIM) program, a project by the U.S. Department of Transportation (DOT) [5]

Data Collection: The NGSIM dataset was obtained through the utilization of tower-mounted cameras, providing a bird's-eye perspective for data collection.

No. of Frames: 10.2×10^3

Density: 1.85×10^3 per km

Visibility: 0.548 km

Average Instances per frame

Agent	Avg. Instance
Car	981.4
Bike	3.9
Track	28.2

Dataset Details (CONT'D)

Attributes Details: NGSIM dataset has 25 Attributes. Some of them described below –

Attributes	Details
Positional Data	It represents the spatial position of an object in a frame.
Motion Data	It represents the speed, acceleration etc. of a vehicle.
Vehicle Information	It represents the vehicle id, type, shape, heading etc.
Time Data	It represents the timestamps of a frame capture.

Results & Performance Analysis

- We implemented the model with the NGSIM Dataset –

Average Displacement Error (ADE)	**2.86164**
Final Displacement Error (FDE)	**5.19008**

Operation	Value (s)
Data Loading Time	0.418
Training Time	30961.05
Testing Time	119.77

Results & Performance Analysis

➢ **Average Training Loss vs Epoch Curve –**

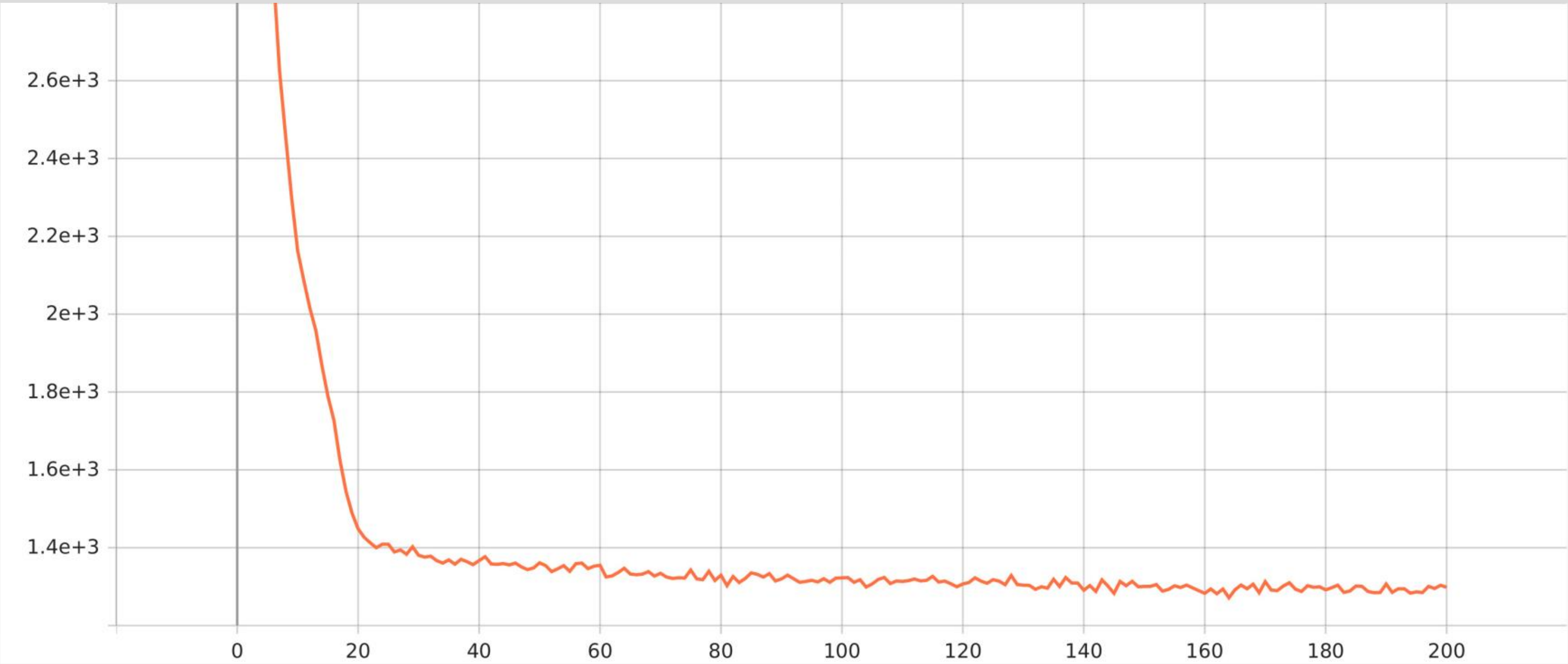

Figure - : Average Training Loss vs Epoch Curve.

Results & Performance Analysis

➢ **Average Validating Loss vs Epoch Curve –**

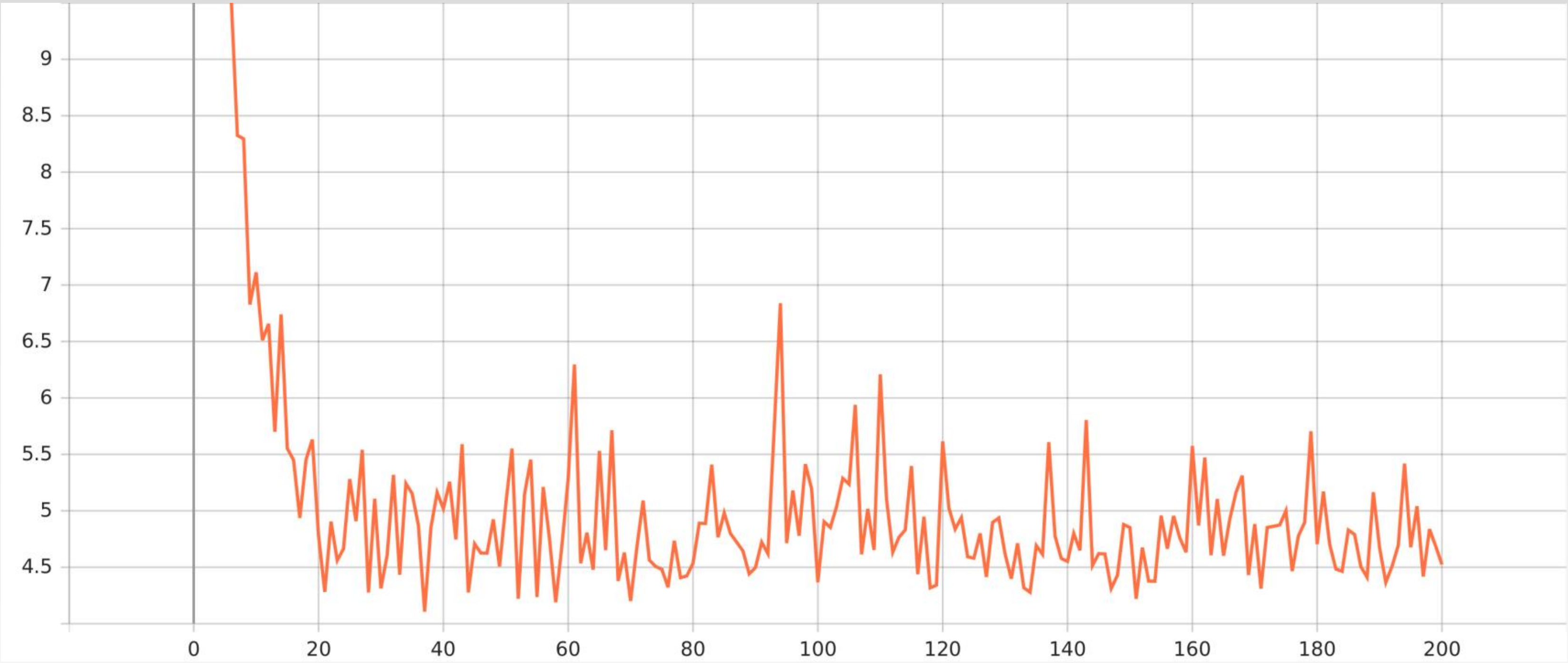

Figure - : Average Validating Loss vs Epoch Curve.

Results & Performance Analysis

➢ **Comparison of previous works with our model using NGSIM dataset –**

Model	ADE	FDE
RNN-ED [7]	6.86	10.02
S-LSTM [8]	5.73	9.58
S-GAN [9]	5.16	9.42
CS-LSTM [10]	7.25	10.05
TraPHic [4]	5.63	9.91
Our Model	**2.86**	**5.19**

Conclusion

In conclusion, our study presents a novel trajectory forecasting model tailored to the NGSIM dataset. Leveraging a custom-designed GRU-CNN architecture, we achieved promising results on trajectory forecasting, which is helpful for autonomous vehicle or advance driver assistance system.

- Utilized GRU for temporal dependency analysis and CNN for capturing dynamic driver behavior and turning radius.

- Use batch normalization and dropout for reduce overfitting.

- Evaluated our model against existing methodologies, showcasing superior performance metrics.

Limitations & Future Work

Our Model outperform in dense heterogeneous traffic scenarios, but limiting its effectiveness in sparse or homogeneous traffic conditions. So in future a more generalized model can be develop.

Acknowledging the limitations of the NGSIM dataset, future work may involve utilizing datasets with higher density and greater heterogeneity.

References

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Thank You

Q & A