Heaven's Light is Our Guide

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

Rajshahi University of Engineering & Technology, Bangladesh

Integrative Trajectory Forecasting for Autonomous Vehicles in Mixed Traffic Environments

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RUET, Rajshahi

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CERTIFICATE

This is to certify that this thesis report entitled ***“Integrative Trajectory Forecasting for Autonomous Vehicles in Mixed Traffic Environments ”*** *submitted by* ***Md. Nazmul Hossain, Roll:1803170*** *in partial fulfillment of the requirement for the award of the degree of Bachelor of Science in Department of Computer Science & Engineering of Rajshahi University of Engineering & Technology, Bangladesh is a record of the candidate own work carried out by him under my supervision. This thesis has not been submitted for the award of any other degree.*

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ABSTRACT

This research addresses the crucial challenge of predicting vehicle trajectories in urban environments, a key factor for autonomous vehicle navigation. By accurately forecasting the movements of surrounding traffic agents, autonomous vehicles can make informed decisions to navigate complex traffic scenarios safely and efficiently. This work introduces a novel trajectory prediction model that leverages the strengths of gated recurrent units (GRUs) and convolutional neural networks (CNNs). This model is specifically designed for dense, heterogeneous traffic conditions, where diverse traffic agents interact frequently. Extensive evaluation on standard datasets demonstrates the model's superiority over existing methods in predicting trajectories within dense, mixed traffic scenarios. The model's effectiveness is acknowledged to have limitations in sparse or homogeneous traffic situations. Despite this, the proposed model represents a significant advancement in autonomous navigation systems. By effectively capturing dynamic driver behaviour and considering turning radius variations, the model enhances the safety and efficiency of autonomous vehicles in urban environments. Further research is encouraged to explore potential refinements and adaptations of the model to diverse traffic scenarios. This continued development will ultimately contribute to the creation of robust and reliable autonomous vehicle navigation systems.

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Chapter 1

Introduction

1.1 Introduction

Vehicle trajectory, delineating the path and dynamics of a vehicle including speed and acceleration, is fundamental in understanding its lateral positional relationship with respect to highway geometry [1]. This positional relationship often changes due to driver steering behavior, particularly evident when vehicles navigate curves. In the intricate landscape of modern traffic scenarios, the accurate prediction of a vehicle's trajectory holds paramount importance for intelligent vehicles to navigate safely and efficiently. Real-time trajectory prediction enables intelligent vehicles to adapt their maneuvers based on the dynamic states of preceding vehicles, enhancing overall safety and efficiency [1]. In the realm of autonomous vehicles (AVs), trajectory prediction serves as a crucial component akin to eyesight, enabling AVs to foresee the future movements of surrounding objects. This technology empowers AVs to navigate safely by anticipating the paths of pedestrians, vehicles, and other elements, thereby facilitating proactive collision avoidance and maneuver planning [2]. Trajectory prediction influences decision-making processes for lane changes, braking, and acceleration, providing foresight that contributes to smoother traffic flow and proactive traffic management. Ultimately, accurate trajectory prediction forms the bedrock of safety, reliability, and efficiency in the future of autonomous transportation [3]. In a mixed traffic environment encompassing various road agents such as cars, buses, trucks, bicycles, pedestrians, and even animals, predicting trajectories becomes a multifaceted challenge [4]. This necessitates the consideration of driver behavior and turning radius to accurately anticipate and navigate through diverse traffic scenarios.

1.2 Trajectory of a vehicle

The direction of a vehicle is a multifaceted concept including its spatial facilitates, speed, speeding up, and indeed twitch, all fastidiously depicted as capacities of time [5]. It typifies the complicated exchange between the vehicle's development and the transient measurement, giving a comprehensive understanding of its way through space over a assigned period. In the setting of independent vehicles, direction arranging develops as a foremost endeavor, looking for to chart the most ideal course for the vehicle's route from its show area to a foreordained goal [6]. This arranging handle unfurls in the midst of a complex web of contemplations, where different variables such as deterrents, winning activity conditions, and the inborn flow of the vehicle come into play. By unpredictably analyzing these components, direction arranging calculations endeavor to strike a sensitive adjust between effectiveness, security, and consolation, guaranteeing a consistent and strong travel for the independent vehicle. Moreover, the centrality of vehicle direction modeling expands past the domain of independent driving, serving as a foundational foundation for the improvement of urban brilliant administrations. Through fastidious examination and modeling of vehicle directions, analysts and professionals pick up important bits of knowledge into optimizing transportation frameworks, improving security measures, and invigorating the in general effectiveness of urban landscapes. By leveraging progressed computational methods and real-world information, direction modeling encourages the recreation and forecast of vehicle developments, empowering partners to expect and relieve potential challenges proactively. Moreover, this granular understanding of vehicle directions empowers the refinement of urban foundation and transportation approaches, cultivating economical and flexible urban situations competent of obliging the advancing needs of cutting-edge society. In substance, the direction of a vehicle rises above simple spatial development, epitomizing a wealthy embroidered artwork of worldly elements and vital decision-making. As independent vehicles proceed to multiply and reshape the texture of urban versatility, the craftsmanship and science of direction arranging and modeling will stay vital apparatuses in the journey for more secure, more astute, and more effective transportation frameworks.

1.3 Autonomous Vehicle - AV

The concept of self-driving vehicles, also known as autonomous cars, has undergone a long evolutionary journey since initial tests in the early 20th century [7]. Advancements in automation technology have revolutionized various sectors of human life, including agriculture, healthcare, transportation, manufacturing, and information technology. Recent years have witnessed significant progress in autonomous vehicle research, with both tech giants like Waymo Google, Uber, and Tesla, as well as traditional automakers like Renault, Toyota, Audi, and Volvo, contributing to the development of Level-3 autonomous cars [8]. Looking ahead, the future of autonomous vehicles envisions manufacturing processes driven by Internet of Things (IoT) technologies, tailored to meet user requirements and ensuring safety and comfort in transportation systems for passengers and cargo alike. The continuous acquisition and updating of data are vital for the seamless operation of autonomous vehicles, with IoT and Artificial Intelligence (AI) playing pivotal roles in facilitating the exchange of information among devices. This review paper explores the various technologies and methodologies employed in autonomous vehicles, addressing existing gaps in research through comprehensive literature surveys.

1.4 Advanced Driver Assistance System - ADAS

Progressed Driver-Assistance Frameworks are electronic frameworks that help the driver while driving the vehicle by giving exact perusing of the information collected from street environment utilizing different hardware to guarantee street security. When planned with a secure human-machine interface, they are aiming to increase driver security and generally street security. Most mishaps happen due to human mistakes which can be effectively dodged by the utilize of fake insights along with electronic innovation. The ADAS are expecting to maintain a strategic distance from street mischances which ordinarily occur due to human blunder by utilizing electronic innovation. The utilize of this kind of framework in vehicles is awesome for applications like daze spot observing, lane-keep help and forward collision caution. The utilize of ADAS is a most to guarantee street security and appropriate activity management [9]. Advanced driver-assistance frameworks (ADAS) are advances that help drivers with the secure operation of a vehicle. Through a human-machine interface, ADAS increment car and street security. ADAS utilizes robotized innovation, such as sensors and cameras, to identify adjacent impediments or driver blunders, and react appropriately. ADAS can empower different levels of independent driving [10].

1.5 Mixed Traffic Environments

Blended activity situations allude to roadways where different sorts of vehicles share the same space, counting conventional human-driven vehicles, bikes, cruisers, people on foot, and progressively, independent vehicles. These situations show interesting challenges and elements due to the contrasting speeds, sizes, behaviors, and vulnerabilities of the distinctive street. To explore complex urban activity securely and productively, independent vehicles must make mindful forecasts in connection to encompassing traffic-agents (vehicles, bikes, people on foot, etc.). A challenging and basic assignment is to investigate the development designs of diverse traffic-agents and anticipate their future directions precisely to help the independent vehicle makes sensible route decision [11]. Productive activity control can reduce activity clog, decrease fuel utilization, and move forward activity security. With the improvement of communication and robotization innovations, it is customary. vehicles (RVs), associated vehicles (CVs), and associated and mechanized vehicles (CAVs) will coexist on urban streets in the close future [12]. Heterogeneity is one of those characteristics which separate activity conditions of a creating nation from other created countries. The heterogeneity which speaks to the differing qualities among vehicle categories is suspected to have antagonistic impacts on path teach, blockage potential, and street users' safety.

1.6 Overview

This thesis work delves into the critical realm of trajectory forecasting, particularly in the context of autonomous vehicles and advanced driver-assistance systems (ADAS). The motivation behind this research stems from the increasing prominence of self-driving cars and the indispensable role of accurate trajectory prediction in ensuring their safe and efficient operation. The study begins with an exhaustive review of existing literature and related works in the field, seeking to identify gaps, challenges, and opportunities for innovation. Drawing insights from this review, a comprehensive dataset containing trajectory data is meticulously collected and curated, comprising crucial information such as positional data, motion data, vehicle information, and timestamps for data collection. Leveraging various state-of-the-art techniques and methodologies, a novel model is developed to forecast trajectories with precision and reliability. This model is designed to incorporate intricate patterns and dynamics observed in real-world driving scenarios, including complex traffic interactions, environmental factors, and driver behaviors.

Through rigorous experimentation and testing, the performance of the developed model is evaluated across diverse scenarios and datasets, shedding light on its strengths, limitations, and potential areas for improvement. The analysis of results not only serves to validate the effectiveness of the proposed model but also provides valuable insights into the broader implications of trajectory forecasting in modern civilization. From enhancing road safety and traffic management to enabling seamless integration of autonomous vehicles into urban environments, the impact of accurate trajectory prediction extends far beyond individual vehicles, shaping the future of transportation and mobility.

1.7 Motivation

The motivations behind the study on trajectory prediction of vehicles in urban areas are multifaceted and address several critical aspects of autonomous vehicle technology and its integration into real-world settings.

Safety Enhancement: The primary motivation lies in improving the safety of autonomous vehicles operating in mixed traffic environments. By accurately predicting the trajectories of other road users, such as human-driven vehicles, cyclists, and pedestrians, autonomous vehicles can proactively anticipate and respond to potential collision scenarios.

Human-Autonomous Vehicle Interaction: In mixed traffic environments, human drivers often rely on implicit communication cues, such as eye contact and hand gestures, to negotiate interactions with other road users. Autonomous vehicles must be able to interpret and respond to these social cues effectively to navigate safely and smoothly. Therefore, the thesis aims to develop interactive trajectory prediction models that enable autonomous vehicles to anticipate and adapt to the behavior of human road users, fostering more natural and intuitive interactions on the road.

Traffic Flow Optimization: Effective trajectory prediction algorithms can contribute to optimizing traffic flow and reducing congestion in mixed traffic environments. By accurately forecasting the movements of different vehicles and anticipating potential bottlenecks or conflicts, autonomous vehicles can adjust their trajectories dynamically to minimize disruptions and maintain smooth traffic flow, thereby enhancing overall efficiency and mobility.

Real-World Deployment Challenges: Despite significant advancements in autonomous vehicle technology, deploying these vehicles in real-world environments poses numerous challenges, including unpredictable human behavior, complex traffic scenarios, and varying environmental conditions. By addressing the specific challenges of trajectory prediction in mixed traffic environments, the thesis aims to develop practical solutions that can facilitate the safe and efficient integration of autonomous vehicles into diverse urban and suburban settings.

Regulatory and Policy Implications: The successful deployment of autonomous vehicles hinges not only on technological advancements but also on regulatory frameworks and policy decisions that govern their operation. By providing insights into the capabilities and limitations of interactive trajectory prediction models, the thesis can inform policymakers and regulatory agencies in developing standards and guidelines for the safe and responsible deployment of autonomous vehicles in mixed traffic environments.

Overall, the thesis on interactive trajectory prediction of autonomous vehicles in mixed traffic environments is driven by the overarching goal of advancing the state-of-the-art in autonomous vehicle technology and accelerating the transition towards safer, more efficient, and more sustainable transportation systems. By addressing key challenges and opportunities in trajectory prediction, the research contributes to realizing the full potential of autonomous vehicles in reshaping the future of mobility.

1.8 Objective of the Thesis

The objectives of the thesis on trajectory prediction of vehicles in urban areas are designed to address the complexities and challenges inherent in the integration of autonomous vehicles into real-world settings. These objectives encompass both technical advancements and practical applications, aimed at enhancing the safety, efficiency, and usability of autonomous vehicle technology in mixed traffic environments. The key objectives include:

- Develop Accurate Trajectory Prediction Models: The primary objective is to develop advanced machine learning and predictive modeling techniques capable of accurately forecasting the trajectories of diverse road users, including human-driven vehicles, cyclists, and pedestrians. These models should incorporate factors such as historical data, environmental conditions, and social interactions to improve prediction accuracy and reliability.

- Enhance Human-Autonomous Vehicle Interaction: Another objective is to enhance the interaction between autonomous vehicles and human road users by developing intuitive and socially-aware trajectory prediction algorithms. This involves analyzing and interpreting human behavior cues, such as gestures, eye contact, and body language, to anticipate and respond to the intentions of other road users effectively.

- Improve Safety and Collision Avoidance: A key objective is to improve safety and collision avoidance capabilities of autonomous vehicles through proactive trajectory prediction and risk assessment. By accurately identifying potential collision scenarios and hazardous situations in advance, autonomous vehicles can take preemptive actions, such as adjusting speed or changing lanes, to mitigate risks and ensure safe navigation in mixed traffic environments.
- Optimize Traffic Flow and Efficiency: The thesis aims to optimize traffic flow and reduce congestion in mixed traffic environments by developing trajectory prediction models that facilitate smoother interactions between autonomous vehicles and other road users. By dynamically adjusting trajectories based on real-time traffic conditions and congestion patterns, autonomous vehicles can contribute to improving overall traffic efficiency and mobility.
- Validate and Evaluate Performance: An essential objective is to validate and evaluate the performance of the developed trajectory prediction models through extensive simulations and real-world testing scenarios. This involves assessing prediction accuracy, responsiveness, and reliability under diverse environmental conditions and traffic scenarios to ensure the robustness and effectiveness of the proposed approaches.

Overall, the objectives of the thesis are aligned with the overarching goal of advancing the state-of-the-art in autonomous vehicle technology and facilitating the seamless integration of autonomous vehicles into diverse urban and suburban landscapes. By addressing these objectives, the research contributes to realizing the potential benefits of autonomous vehicles in improving road safety, traffic efficiency, and mobility for society as a whole.

1.9 Challenges

The primary focus of this thesis revolves around the intricate task of trajectory prediction within a diverse and dynamic mixed traffic environment. This environment comprises various types of road agents, including but not limited to buses, trucks, motorcycles, pedestrians, and even animals. In addition to these diverse entities, the presence of traffic infrastructure elements such as traffic lights, traffic signs, and speed breakers further complicates the prediction task.

The challenges inherent in this scenario stem from the complex interactions and behaviors exhibited by the different road agents. Each type of agent possesses its own set of movement patterns, intentions, and responses to external stimuli. For instance, buses and trucks may have slower acceleration and deceleration rates compared to motorcycles, while pedestrians and animals exhibit unpredictable movements.

Furthermore, the dynamics of traffic signs and signals add another layer of complexity. Deciphering the intentions of road agents in response to these signals, such as stopping at a red light or yielding at a stop sign, requires a nuanced understanding of traffic rules and behavioral norms.

The ultimate goal of this thesis is to develop robust prediction models capable of accurately forecasting the trajectories of various road agents within this heterogeneous environment. These predictive capabilities are crucial for the successful implementation of autonomous driving systems and Advanced Driver Assistance Systems (ADAS). By effectively anticipating the movements of surrounding agents, autonomous vehicles can make informed decisions to ensure safe and efficient navigation through mixed traffic scenarios.

1.10 Thesis Organization

The report is organized into 6 chapters including this chapter: ***Introduction*** where all the related topics are discussed which are needed for understanding the research work. The outline of rest of the works are organized as follows:

Chapter 2

Topic-Background Study

This chapter explores various deep learning models, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), and others, in the context of trajectory prediction. It also elucidates the significance of trajectory prediction within a business context.

Chapter 3

Topic - Literature Review

This chapter encompasses a range of topics related to vehicle trajectory prediction, including studies on predicting vehicle trajectories, the heterogeneous composition of traffic, different methodologies employed for trajectory prediction, and the role of autonomous vehicles in this domain.

Chapter 4

Topic - Materials & Methodology

This chapter discusses the dataset and the proposed methodology. It also includes a detailed description of data pre-processing, proposed architecture.

Chapter 5

Topic - Result & Performance Analysis

This chapter analyses the experimental result and performance of the proposed architecture along with the comparis with related works. The metrics which were used to evaluate our model is also described here.

Chapter 6

Topic - Conclusion

Through this chapter, the research work has been concluded. This article gives a summary of my research's findings. I have also tried to make an effort to highlight limitations and potential future work areas of my work.

1.11 Conclusion

In this chapter, we've provided a comprehensive overview of the study to come, offering a preliminary look at the tasks that lie ahead. Through our discussion, we've highlighted the inspiration behind the research, articulated the objectives we seek to accomplish, and identified the challenges that will be further explored in subsequent chapters. By laying this groundwork, we’ve set the stage for a more in-depth examination of the motivations driving our inquiry, the specific goals we aim to achieve, and the obstacles we anticipate encountering. This introductory discussion serves as a foundation upon which we will build a deeper understanding of the complexities inherent in our research domain and the strategies required to address them effectively.

Chapter 2

Background Study

2.1 Introduction

The background study serves as a cornerstone in any thesis endeavor, laying the foundation for informed exploration and analysis. Deep learning, a pivotal subset of artificial intelligence, empowers computers to glean insights from data through the crafting of sophisticated algorithms and models. Within this realm, various deep learning architectures have emerged as potent tools for trajectory prediction, notably LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), adept at handling time series data. Furthermore, CNN (Convolutional Neural Networks) are leveraged for feature extraction, facilitating nuanced understanding of complex datasets. Beyond the technical nuances, this chapter delves into the broader implications of trajectory prediction on autonomous vehicles and driver assistance systems, elucidating the profound business impact and societal implications inherent in these advancements. Through this comprehensive exploration, we aim to provide a holistic understanding of the intricate interplay between deep learning methodologies and their real-world applications in trajectory prediction.

2.2 Deep Learning Model

Deep learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), have revolutionized various domains, including image processing, natural language processing, and autonomous driving. These models employ multiple layers of interconnected nodes to learn intricate patterns and representations from large datasets, enabling them to achieve state-of-the-art performance in tasks like image recognition, language translation, and trajectory prediction. By leveraging techniques like backpropagation and gradient descent, deep learning models iteratively adjust their internal parameters to minimize prediction errors and improve accuracy. Some advance deep learning model described below–

2.3 Long Short-Term Memory - LSTM

Long short-term memory (LSTM) arrange is a repetitive neural organize (RNN), pointed at managing with the vanishing angle issue display in conventional RNNs. Its relative cold-heartedness to crevice length is its advantage over other RNNs, covered up Markov models and other grouping learning strategies. It points to give a short-term memory for RNN that can final thousands of timesteps, hence ”long short-term memory” [13]. A common LSTM unit is composed of a cell, an input entryway, an yield gate [14].and a disregard gate [15]. The cell recollects values over self-assertive time interims and the three entryways control the stream of data into and out of the cell. Disregard doors choose what data to dispose of from a past state by relegating a past state, compared to a current input, a esteem between 0 and 1. A (adjusted) esteem of 1 implies to keep the data, and a esteem of 0 implies to dispose of it. Input doors choose which pieces of modern data to store in the current state, utilizing the same framework as disregard doors. Yield entryways control which pieces of data in the current state to yield by allotting a esteem from 0 to 1 to the data, considering the past and current states. Specifically yielding pertinent data from the current state permits the LSTM organize to keep up valuable, long-term conditions to make forecasts, both in current and future time-steps.

2.4 Gated Recurrent Units - GRU

Gated Recurrent Units (GRUs) are a powerful tool in the world of recurrent neural networks (RNNs) designed to tackle a major hurdle: the vanishing gradient problem. This problem prevents standard RNNs from learning long-term relationships within sequences of data [16]. Introduced in 2014 by Kyunghyun Cho et al., GRUs overcome this limitation using a gating mechanism, similar to Long Short-Term Memory (LSTM) networks [16]. These gates act as intelligent filters, deciding which information from the past to remember (long-term memory) and how much of the current input to integrate. GRUs hold a distinct advantage over LSTMs:

their streamlined architecture. With fewer parameters, GRUs often train faster and require less computational power. This makes them a compelling choice for various applications that rely on sequential data, like natural language processing (NLP). In NLP tasks like machine translation, GRUs excel at understanding the context within a sequence of words, leading to more accurate translations [17]. Similarly, they play a vital role in speech recognition, where they model the sequential nature of speech, aiding in tasks like automatic speech-to-text conversion. Even in time series forecasting, GRUs can be employed to analyze past data points and predict future trends, such as stock prices or weather patterns [17]. With their ability to capture both short-term and long-term dependencies while maintaining efficiency, GRUs have become a popular choice for various tasks that involve sequential data analysis.

2.5 Convolutional Neural Networks - CNN

Convolutional Neural Networks (CNNs) are a powerful architecture within deep learning specifically designed to excel at tasks involving image and grid-like data [18]. Unlike standard neural networks, CNNs leverage a unique structure that incorporates convolutional layers. These layers employ filters that slide across the input data, extracting features like edges, shapes, and patterns. By stacking multiple convolutional layers, CNNs can progressively learn increasingly complex features, ultimately leading to robust image recognition capabilities [19].
A key advantage of CNNs lies in their ability to exploit the spatial relationships between pixels within an image. This inherent understanding of spatial locality allows CNNs to achieve superior performance in tasks like image classification, where the goal is to identify the objects present in an image [19]. Their success extends beyond static images, as CNNs can also be applied to video analysis, where they can track object movement and identify activities within video sequences [20]. Furthermore, CNNs have found applications in other grid-like data domains, such as medical image analysis and natural language processing tasks that involve analyzing sequences of words with a focus on their positional context within a sentence [20]. With their exceptional feature extraction capabilities and ability to leverage spatial relationships, CNNs have become a cornerstone of various computer vision and image analysis applications. Convolutional Neural Networks (CNNs) are a powerful architecture within deep learning specifically designed to excel at tasks involving image and grid-like data [18]. Unlike standard neural networks, CNNs leverage a unique structure that incorporates convolutional lay-

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2.6 Business Impact on Trajectory Prediction

The business impact of trajectory prediction encompasses a multitude of factors that extend far beyond technical considerations, significantly influencing various industries and sectors.

- Autonomous Vehicles (AVs): Trajectory prediction plays a pivotal role in the development and deployment of autonomous vehicles. Accurate predictions enable AVs to anticipate and adapt to the movements of other road agents, ensuring safer navigation and reducing the risk of accidents. This, in turn, enhances public trust in autonomous technology and accelerates its adoption, driving growth in the AV market.

- Transportation and Logistics: In the realm of transportation and logistics, trajectory prediction optimizes route planning, resource allocation, and scheduling. By forecasting the movements of vehicles, pedestrians, and other road agents, businesses can streamline operations, minimize delivery times, and maximize efficiency in supply chain management.

- Smart Cities and Urban Planning: Trajectory prediction contributes to the development of smart cities by informing urban planning initiatives and traffic management strategies. By analyzing traffic patterns and predicting future trajectories, city planners can design more efficient road networks, reduce congestion, and enhance overall mobility within urban environments.

- Insurance and Risk Management: The ability to accurately predict trajectories enables insurance companies to assess and mitigate risk more effectively. By incorporating trajectory data into risk models, insurers can offer more tailored policies, adjust premiums based on individual driving behaviors, and ultimately reduce claims payouts, leading to improved profitability.

- Retail and Advertising: Trajectory prediction has applications in retail and advertising, particularly in the realm of location-based marketing. By analyzing the movement patterns of individuals, businesses can deliver targeted advertisements and promotions based on their predicted trajectories, enhancing customer engagement and driving sales.

- Public Safety and Law Enforcement: Law enforcement agencies leverage trajectory prediction to enhance public safety and security. By anticipating potential traffic violations, accidents, or criminal activities, authorities can deploy resources more efficiently, enforce traffic regulations, and respond proactively to emerging threats.

In summary, trajectory prediction has far-reaching implications across various domains, driving innovation, efficiency, and safety in diverse industries. By harnessing the power of predictive analytics, businesses and policymakers can unlock new opportunities for growth, sustainability, and societal advancement.

2.7 Conclusion

The background study chapter provides a comprehensive overview of the foundational concepts and technologies underpinning trajectory prediction. Through an exploration of various deep learning models such as LSTM, GRU, and CNN, alongside an examination of their applications in predicting time series data, the chapter underscores the critical role of machine learning in trajectory forecasting. Furthermore, the discussion delves into the business impact of trajectory prediction across different sectors, highlighting its significance in autonomous vehicles, transportation, logistics, smart cities, insurance, retail, advertising, public safety, and law enforcement. By elucidating the diverse applications and implications of trajectory prediction, the chapter underscores its transformative potential in driving innovation, efficiency, and safety across industries. Overall, the background study serves as a foundational framework for understanding the significance of trajectory prediction, laying the groundwork for subsequent chapters to delve deeper into the methodology, implementation, and outcomes of trajectory forecasting in real-world scenarios.

Chapter 3

Literature Review

3.1 Introduction

Within this literature review, an exploration unfolds surrounding the trajectory prediction of vehicles through the analysis of trajectories pertaining to diverse road agents, including buses, cars, and pedestrians. This examination traverses the landscape of machine learning and deep learning methodologies such as RNNs, CNNs, LSTMs, GANs, among others, employed for this purpose. Emphasizing the critical role of appropriate predictor variables, the review delves into discussions concerning potential advancements in predicting vehicle trajectories under varied conditions. Furthermore, it delves into the exploration of various optimization techniques, enriching the discourse surrounding this pivotal aspect of vehicular trajectory prediction.

3.2 Related Works

Rohan Chandra et al.[21] introduces a novel LSTM-CNN hybrid network for trajectory prediction in dense traffic scenarios. The paper addresses the limitations of existing models by incorporating factors such as velocity, turning radius, and local density to enhance prediction accuracy. By leveraging the strengths of both CNNs and LSTMs, the proposed model achieves a significant 30% improvement in accuracy on dense datasets, particularly showcasing its effectiveness on a new Asian urban dataset. Unlike traditional approaches, this model can handle heterogeneous road agents without explicit behavior assumptions, making it versatile for various traffic conditions.The paper contributes to the field by bridging the gap in accurate trajectory forecasting, especially in dense traffic environments. While existing datasets like ApolloScape and NGSIM simulations offer diverse scenarios, this paper's approach provides a unique perspective on traffic prediction. By drawing inspiration from RNNs and LSTMs for sequence modeling, the model showcases the potential of combining different neural network architectures for more effective traffic prediction. However, the paper acknowledges limitations in the application of generative models like VAEs and GANs due to challenges in back-propagation during training. Despite this, the successful utilization of generative models for trajectory prediction in pedestrian crowds and sparse traffic scenarios demonstrates the paper's innovative contributions to the field.

In the study conducted by Yuexin Ma et al.[11], a novel LSTM-based algorithm for predicting trajectories of heterogeneous traffic agents in urban environments. The main contribution lies in proposing a new approach to handle trajectory prediction scenarios where different types of traffic agents, such as vehicles, bicycles, and pedestrians, interact with each other. To model these interactions, the authors introduce a 4D graph structure that captures spatial and temporal relationships between agents, as well as similarities and differences between agent categories. The proposed architecture consists of two main layers: an instance layer and a category layer. The instance layer aims to capture the movements and interactions of individual agents using LSTM networks and attention mechanisms. The category layer, on the other hand, learns the movement patterns and similarities of agents within the same category, providing guidance to refine the predictions for individual instances. By integrating information from both layers, the algorithm can leverage the collective knowledge of agent interactions and category-specific patterns. To facilitate research in this area, the authors have collected and released a new large-scale trajectory dataset in urban traffic, featuring various traffic agents and interactions. Experimental results on this dataset demonstrate improved accuracy compared to previous state-of-the-art methods, with about 20% improvement in average displacement error and final displacement error. Despite these contributions, the paper acknowledges some limitations. The accuracy of the proposed method may vary based on traffic conditions and the duration of observed past trajectories. Additionally, the method does not explicitly consider constraints such as lane directions, traffic signals, and traffic rules, which could potentially further improve prediction accuracy. The evaluation is also limited to a specific urban environment, and the performance may need to be validated in different traffic scenarios and environments. Furthermore, the paper does not provide a detailed comparison of computational efficiency and scalability with other methods, nor does it discuss the potential challenges in extending the method to handle a larger number of traffic agent categories or more complex interactions. Overall, the paper presents a novel approach for trajectory prediction in heterogeneous traffic scenarios, contributing to modeling spatial and temporal relationships, learning category-specific patterns, and providing a new dataset for evaluation. However, there are opportunities for further improvements and validations in different traffic environments and conditions.

In a study carried out by Chiyu Dong, et al.[22], presents a novel approach for predicting the trajectory of surrounding vehicles in autonomous driving scenarios. The authors highlight the importance of accurately predicting the future trajectories of neighboring vehicles for autonomous cars to interact and cooperate effectively in complex driving situations such as lane changes and merging. The paper provides a comprehensive literature review of existing methods for interactive trajectory prediction and cooperative driving, categorizing them into rule-based, optimization-based, and probabilistic/learning approaches. The authors critique the limitations of these methods, such as the lack of consideration for interactions among vehicles, the need for manually designed probabilistic models and reward functions, and the inability to handle continuous action spaces or sequential information effectively. The authors propose a Recurrent Meta Induction Network (RMIN) framework to address these shortcomings. The RMIN is based on the Conditional Neural Process (CNP), which uses a set of demonstration examples and an additional observation as inputs to predict the corresponding output. However, the original CNP does not consider the sequential information in the inputs due to permutation invariance requirements. The RMIN overcomes this limitation by replacing the original demonstration sub-net with a recurrent neural cell, allowing it to capture sequential information in the historical trajectories of surrounding vehicles. The proposed method is evaluated on real trajectory data from the NGSIM dataset, specifically focusing on lane-change scenarios. The results demonstrate that the RMIN outperforms traditional kernel methods and the original CNP in terms of mean error in both longitudinal and lateral trajectory prediction. The authors attribute this improvement to the RMIN's ability to capture sequential information and the use of a fully connected network as the generator, which explicitly models the relationships among positions in the predicted trajectory. Overall, the paper presents a novel and effective approach for interactive trajectory prediction in autonomous driving scenarios, addressing the limitations of existing methods and demonstrating its superiority through experimental results on real-world data.

In the study of Ernest Cheung,[23] a comprehensive writing audit, covering considers on driving behaviors from the areas of social brain research and transportation inquire about. These things have characterized drivers based on their levels of forcefulness and carefulness, regularly connecting these behaviors with components such as driver age, identity characteristics, and reactions to surveys. Be that as it may, the creators highlight the requirement for an approach that can recognize driver behaviors exclusively from sensor information, as would be required for independent driving systems. The creators at that point examine earlier work related to direction highlights, independent car route, and adjustment to human driver behaviors. They distinguish restrictions in existing strategies, such as the failure to handle nonstop activity spaces, the requirement for physically outlined probabilistic models and remunerate capacities, and the need of thought for consecutive data in trajectories. To address these confinements, the creators propose a novel set of direction highlights, counting a path taking after metric and a relative speed metric, that can be effortlessly extricated from vehicle directions. They conduct an expanded web-based client ponder to build up a data-driven mapping between these highlights and six driver behaviors: forcefulness, carelessness, debilitating behavior, carefulness, cautiousness, and timidity. Through figure investigation, the creators distinguish a inactive variable that summarizes these behaviors and can be utilized to degree the level of mindfulness required when driving close other vehicles. They join this mapping, called the Direction to Driver Behavior Mapping (TDBM), into an existing independent driving calculation, AutonoVi, to empower more secure real-time route by maintaining a strategic distance from possibly unsafe drivers. The paper presents exploratory comes about illustrating the viability of the proposed approach in terms of made strides direction expectation exactness and more secure route choices compared to standard strategies.

The study of Fang-Chieh Chou et al.[24] presents a deep learning approach for predicting the future motion of vulnerable road users (VRUs) like pedestrians and bicyclists for autonomous driving applications. It builds upon recent work using rasterized images of the surrounding context as input to convolutional neural networks (CNNs) for motion prediction. Traditional approaches for VRU motion prediction have relied on hand-crafted models like the social force model and Inverse Reinforcement Learning that attempt to encode interactions between actors and obstacles. However, the need to manually design features makes them difficult to scale to complex environments. Many recent deep learning methods have applied recurrent models like LSTMs for motion prediction, incorporating factors like neighboring actor interactions through pooling or attention mechanisms. Some work has included static scene context by concatenating CNN features from scene images with actor states. However, most prior work does not fully leverage rich map data available in autonomous driving. A key novelty of this paper is encoding high-definition map data like lane geometry, crosswalks, and traffic light states directly into the rasterized input images. The authors explore several variations of the rasterization pipeline and their impact, such as pixel resolution, rotating the frame to the actor's perspective, and different schemes for encoding map elements. On the modeling side, the paper proposes a new efficient CNN architecture called FastMobileNet designed for fast inference speed on GPUs. It also introduces a spatial feature fusion technique to combine the rasterized context with other actor state features like velocity and acceleration. Through extensive experiments, the authors demonstrate the benefits of their approach over baselines like unscented Kalman filters and Social-LSTM models, both in terms of prediction accuracy and inference speed. They also provide insights into which rasterization choices are most impactful for VRU prediction.

Stephanie Lefevre et al.[25] observes the problem of estimating a driver's intended maneuver at road intersections for applications like advanced driver assistance systems and autonomous driving. It focuses on incorporating contextual information from digital maps and handling uncertain observations. Previous work on maneuver intention estimation can be broadly categorized into discriminative and generative approaches. Discriminative methods like learning prototype trajectories from data are limited in generalizing to arbitrary intersections. Generative approaches explicitly model the process between intention and vehicle behavior, but often do not leverage map context. Some works have used probabilistic representations like Bayesian filters, probabilistic finite state machines, and hierarchical hidden Markov models to model maneuver evolution. However, they either do not utilize map information or only consider topological characteristics like lane connectivity. The European PReVENT-INTERSAFE project incorporated intersection topology but not geometry for probabilistic intention estimation. On the other hand, modeling approaches based on Gaussian processes have included geometric context like road borders but assume accurate lane-level positioning which may not be realistic. In contrast, the proposed approach uses a Bayesian network to probabilistically combine uncertain observations of the vehicle's behavior (position, orientation, turn signal) with both topological information like lane connectivity as well as geometric characteristics like lane shapes and paths extracted from a detailed digital map representation.

In a study carried out by Haicheng Liao et al.[26] a novel trajectory prediction model called GaVa (Graph Attention for Vehicle Anticipation) for autonomous vehicles in mixed-autonomy traffic environments. Traditional approaches to trajectory prediction have largely relied on computational methods like time-series analysis. In contrast, GaVa incorporates findings on how human drivers allocate visual attention based on factors like speed, proximity, and orientation. It introduces an "adaptive visual sector" mechanism that mimics how a driver's central field of view dynamically adjusts with speed. The paper reviews prior work using deep learning for trajectory prediction, including Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Graph Neural Networks (GNNs). Models combining CNNs and LSTMs or utilizing multi-head attention have shown promising results. Research on visual behavior in driving is also covered, such as how a driver's visual field changes with speed, with slower speeds allowing a broader focus. Eye-tracking studies have confirmed drivers concentrate on the central region for vehicle control but shift attention for maneuvers like lane changes. The proposed GaVa model contains several novel components inspired by this prior work: a Context-Aware Module for capturing temporal dependencies, an Interaction-Aware Module using CNNs and Graph Attention Networks to model spatial interactions between agents, a Vision-Aware Module incorporating an adaptive visual sector based on speed, and a Priority-Aware Module using a Transformer encoder-decoder for multi-trajectory prediction. The authors evaluate GaVa on the NGSIM, HighD, and MoCAD datasets, outperforming state-of-the-art baselines by at least 15.2%, 19.4%, and 12.0% respectively across prediction horizons. Ablation studies validate the importance of components like the Interaction-Aware and Vision-Aware Modules.

3.3 Conclusion

Previous literature reviews have predominantly concentrated on vehicle trajectory prediction, often employing a range of deep learning models and technologies for this purpose. Additionally, there exists literature exploring driver's behavior and intentions while operating a vehicle, with a particular emphasis on the dynamics of different road agents. Nevertheless, much of the existing research tends to be narrowly focused on specific tasks within these domains. Recognizing this gap, I have formulated and executed my proposed methodology to offer a comprehensive approach to address these issues.

Chapter 4

Proposed Methodology & Implementation

4.1 Introduction

In the pursuit of accurately predicting the trajectories of road agents based on their temporal coordinates, the utilization of advanced deep learning techniques becomes imperative. Recurrent Neural Networks (RNNs) stand out as a formidable choice due to their innate ability to handle time series data efficiently. Specifically, the Gated Recurrent Unit (GRU), a variant of RNN, emerges as a pivotal component in our predictive framework. Moreover, the incorporation of Convolutional Neural Networks (CNNs) enhances our predictive capabilities by extracting pertinent features from the dataset. This fusion of GRU and CNN architectures synergistically harnesses both temporal and spatial information, thereby enriching the predictive capacity of our model. To further refine our predictive framework, we employ linear transformations for encoding and decoding, ensuring optimal information preservation throughout the prediction process. Additionally, meticulous preprocessing of the dataset is undertaken to organize homogeneous objects into structured numpy arrays. This preprocessing step not only enhances data organization but also lays a solid foundation for subsequent modeling endeavors. Furthermore, the creation of trajectory and track arrays facilitates comprehensive data management and analysis, enabling seamless integration into our predictive pipeline. By adopting this meticulously crafted methodology, we aim to optimize model performance and elevate the accuracy and reliability of trajectory predictions.

4.2 Methodology

In the proposed methodology, we embrace a holistic approach to forecast the trajectories of diverse road agents. The journey commences with the collection of a meticulously curated dataset, followed by rigorous preprocessing procedures to refine and enhance its quality. Subsequently, we embark on the quest to identify salient features latent within the dataset, essential for informing our predictive model. To facilitate comprehensive analysis and experimentation, we partition the dataset into distinct subsets tailored for various objectives. Leveraging a custom deep learning model, meticulously tailored to the intricacies of the problem domain, we undertake the model training process. Once trained, the model undergoes rigorous testing, wherein its predictive capabilities are put to the ultimate trial. Through meticulous evaluation methodologies, we assess and quantify the performance of the model, shedding light on its efficacy and potential for real-world deployment. The intricate workflow, beautifully depicted in Figure.-4.1, showcases the seamless execution of these steps.

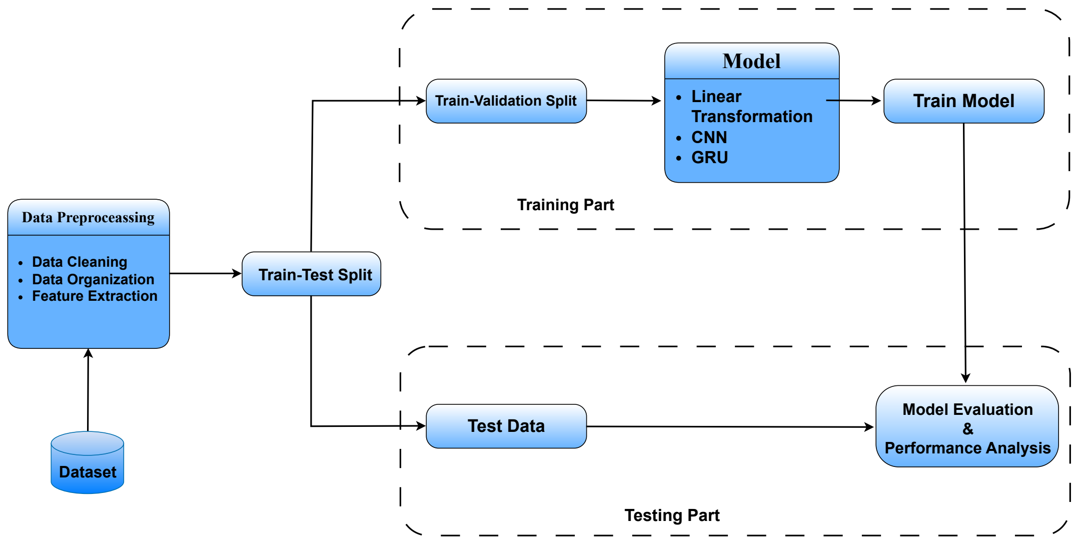

Figure 4.1: Proposed Methodology.

4.3 Dataset Descriptions

This study utilized the Next Generation Simulation (NGSIM) dataset for trajectory prediction. Here's a detailed description of the NGSIM dataset with its statistical size, source, attributes:

- **Source:** The NGSIM dataset originates from the Next Generation Simulation (NGSIM) program, a project by the U.S. Department of Transportation (DOT) [27].
- **Data Collection:** The NGSIM dataset was obtained through the utilization of tower-mounted cameras, providing a bird's-eye perspective for data collection. The NGSIM program involved collecting real-world traffic data on four different highway locations in the United States [27]. Table-4.1 shows the location of data collection at U.S.

Table 4.1: NGSIM Dataset Locations.

Code	**Location**
US 101	Los Angeles
I-80	Emeryville, California
US 50	Nevada
I-66	Virginia

- **Attributes Details:** The NGSIM dataset includes various attributes for each vehicle, providing a comprehensive picture of the traffic scenario. Here are some key attributes:
  - Positional Data: This category encompasses the X and Y coordinates, measured in meters, which denote the spatial location of vehicles within the traffic environment.
  - Motion Data: Motion data includes parameters such as speed and acceleration, both crucial for understanding vehicle dynamics. Speed, measured in meters per second, indicates how fast a vehicle is moving along its trajectory, while acceleration, measured in meters per second squared, signifies the rate of change of speed over time.
  - Vehicle Information: This category provides details about the vehicles themselves, including lane identification and vehicle type. Lane identification specifies the lane within which a vehicle is traveling, offering insights into lane-specific behaviors. Vehicle type categorizes vehicles into different classes (e.g., car, truck), which may influence their movement patterns and behaviors.

– Time Data: Time data consists of timestamps associated with each observation or data point collected during the study. These timestamps provide temporal context, indicating when each observation was recorded. Time data is essential for analyzing temporal patterns, sequences of events, and dynamics over time within the traffic environment.

- **Statistical Analysis:** The dataset comprises approximately 10.2×10^3 frames, each capturing a snapshot of the traffic environment. The visibility, estimated at 0.548 km, indicates the approximate length of visible road in meters from the camera's perspective. With a density of 1.85×10^3 per kilometer[21], the dataset reflects the concentration of road agents within the observed area. It encompasses three distinct types of road agents, each exhibiting varying behaviors and characteristics. Table-4.2 provides insight into the average number of instances of each agent per frame, offering a quantitative overview of their prevalence within the dataset.

Table 4.2: Average Instances per frame [21].

Agent	Avg. Instance
Car	981.4
Bike	3.9
Track	28.2

4.4 Dataset Preprocessing

Data preprocessing is a crucial step in preparing raw data for analysis, particularly in the context of machine learning applications. This process involves several key steps to enhance the quality and suitability of the data for specific analytical tasks. Let's break down the preprocessing steps described in your content:

- Removing Null Values: The initial step involves identifying and removing null or missing values from the NGSIM dataset. Null values can introduce inconsistencies and inaccuracies in the data, potentially affecting the performance of machine learning models.

- Filtering Objects by Type: The data is further preprocessed by filtering out specific classes of objects based on their type of attribute. This typically involves segregating objects into categories such as vehicles, bikes/motorcycles, and humans. Separate arrays are then created to store trajectories for each class, enabling focused analysis on types of road agents.

- Storage of Preprocessed Data: The preprocessed trajectory data is stored in NumPy binary files, providing an efficient and structured format for subsequent analysis. These files encapsulate the cleaned and transformed data, ensuring its integrity and accessibility for machine learning tasks.

- Creation of Track Arrays: Additionally, numpy arrays are generated to create tracks for specific types of road agents. This involves aggregating the positions of a particular object in each frame of the dataset, enabling the reconstruction of its trajectory over time. These track arrays provide valuable context for understanding the movement patterns and behaviors of different road agents.

- Calculation of Distance and Vehicle Attributes: Various metrics, such as distance from the ego vehicle to other vehicles, length, speed, and acceleration of vehicles, are calculated as part of the preprocessing pipeline. These metrics offer insights into the spatial relationships and dynamics of vehicles within the environment, enriching the dataset with additional features for machine learning analysis.

- Data Saving: Finally, the preprocessed data, including trajectory arrays, track arrays, and calculated vehicle attributes, is saved to files for future reference and analysis. This ensures the preservation of the processed data in a structured and accessible format, ready for utilization in machine learning models and experiments.

By following these preprocessing steps, the raw NGSIM dataset is transformed into a cleaned, organized, and enriched dataset, primed for effective analysis using machine learning techniques.

4.5 Feature Extraction

The technique used to extract features in this thesis work is primarily based on calculating the distances and positions of surrounding obstacles relative to the main object (e.g., vehicle) in each trajectory. Here's a general overview of the feature extraction process:

- Identifying Surrounding Objects: For each frame of the trajectory, identifies nearby objects or obstacles within the environment. These could include other vehicles, pedestrians, or any other relevant entities. Here, only consider the 39 surrounding objects.

- Calculating Relative Positions: Once the surrounding objects are identified, compute the relative positions of these objects with respect to the ego agent (e.g., the vehicle of interest). This typically involves calculating the differences in x and y coordinates between the main object and each surrounding object. dx = x coordinate of ego agent - x coordinate of surrounding objects dy = y coordinate of ego agent - y coordinate of surrounding objects

$$dx = X_{\text{ego agent}} - X_{\text{surrounding objects}} \tag{4.1}$$

$$dy = Y_{\text{ego agent}} - Y_{\text{surrounding objects}} \tag{4.2}$$

- Calculating Distances: After determining the relative positions, compute the distances between the ego agent and each surrounding object. This is done using formula squared distance as follows –

$$distance = dx^2 + dy^2 \tag{4.3}$$

- Organizing Features: The extracted features, such as distances and positions, are then organized into different categories based on their spatial relationships (e.g., left-top, left-bottom, center -top, center-bottom, right-top, right-bottom) with respect to the ego agent.

- Feature Representation: Finally, the extracted features are represented in a structured format, here uses numpy arrays, and stored for further analysis or processing.

4.6 Training, Validation and Testing Set

In this scenario, the goal is to effectively manage trajectory data by partitioning it into distinct subsets for training, validation, and testing purposes. The process begins by aggregating trajectory data from multiple files, ensuring a comprehensive dataset for analysis. To maintain data integrity, trajectories are segregated based on unique vehicle identifiers, ensuring that each subset retains the complete trajectory history of individual vehicles.

Following this, a train-test split is performed to allocate data for training and testing the machine learning models. Here, 80% of the data is assigned to the training set, while the remaining 20% is reserved for testing. However, to further enhance model performance and prevent overfitting, the training set undergoes additional partitioning. Approximately 12.5% of the training data is set aside as a validation set, serving as an independent dataset to fine-tune model parameters and evaluate its performance during training. Table-4.3 shows the percentage of train, validation and test set slitting.

Table 4.3: Percentage of Train, Validation and Test Set Splitting.

<table>
<tr><td colspan="3">Dataset</td></tr>
<tr><td colspan="2">Train Set</td><td>Test Set</td></tr>
<tr><td colspan="2">80%</td><td rowspan="3">20%</td></tr>
<tr><td>Train Set</td><td>Validation Set</td></tr>
<tr><td>87.5%</td><td>12.5%</td></tr>
</table>

To facilitate efficient data management and analysis, trajectory and track data structures are constructed for each subset. These structures enable the organization and storage of trajectory information, ensuring easy access and manipulation during model development and evaluation. Finally, the partitioned data is saved in both text and NumPy binary formats, providing flexibility and compatibility for subsequent machine learning tasks.
Overall, this meticulous partitioning process ensures that trajectory data is appropriately utilized for training, validation, and testing machine learning models, ultimately enhancing their accuracy and reliability in real-world applications.

4.7 Model Architecture

In this section, we introduce our innovative network architecture designed for trajectory prediction within dense and heterogeneous traffic environments. In the context of heterogeneous traffic, the objective is to forecast trajectories, representing temporal sequences of spatial coordinates for a given road agent. Predicting temporal sequences demands models capable of capturing temporal dependencies within data, such as Gated Recurrent Units (GRUs). However, traditional GRUs operate independently for each road agent, failing to learn dependencies or relationships among heterogeneous agents. To address this limitation, we integrate Convolutional Neural Networks (CNNs) to identify interactions among different road agents. By combining CNNs with GRUs, our architecture learns locally significant relationships, both spatially and temporally, among heterogeneous road agents. Figure-4.2 shows the model architecture.

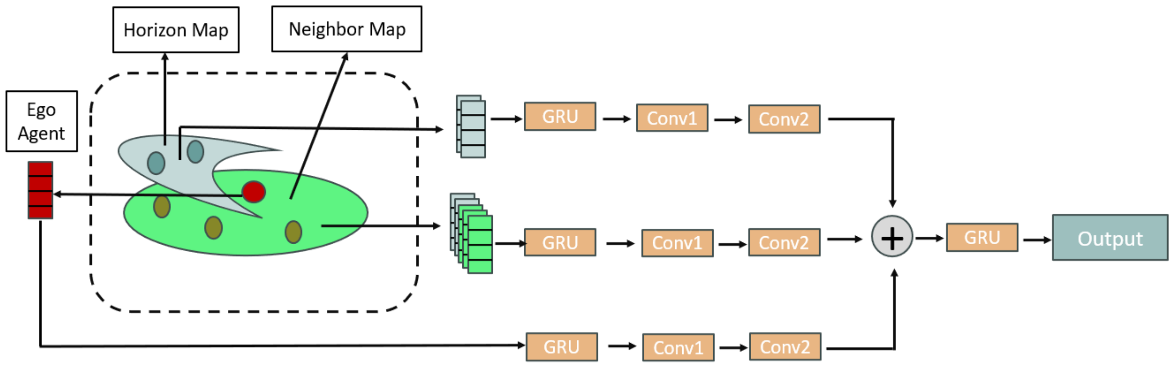

Figure 4.2: Model Architecture.

The architecture comprises three map:

1. Horizon Map: Processes embeddings of agents within the ”horizon” or semi-elliptical region ahead of the target agent. These embeddings traverse Fully Connected (FC) layers and GRUs to construct a ”horizon map”.

2. Neighbor Map: Handles embeddings of agents neighboring the target agent. Similar to the horizon layer, these embeddings pass through FC layers and GRUs to form a ”neighbor map”.

3. Ego Agent: Focuses on the embedding of the target agent itself, processing it through FC and GRU layers.

This integrated approach enables our model to effectively capture intricate interactions and dependencies among heterogeneous road agents, thereby enhancing trajectory prediction accuracy in complex traffic scenarios.

4.8 Model Flow Chart

In this study, describe the purpose of each layer in the provided neural network architecture. Figure-4.3 illustrate the model flow chart of proposed architecture.

1. Input Embedding: The purpose of these layers is to transform the input features into a lower-dimensional space, which helps in capturing essential information and reducing the complexity of the model.

2. Encoder: This layer encodes the temporal sequence of input features, capturing the dependencies and patterns over time in the trajectory data.

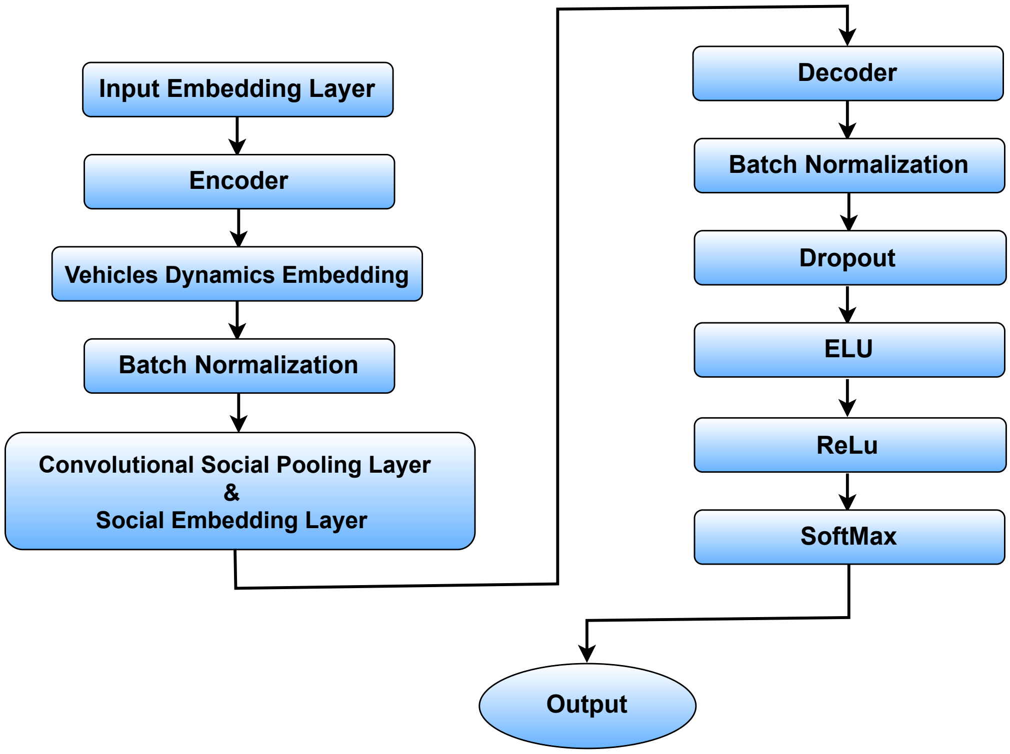

Figure 4.3: Model Flow Chart.

3. Vehicle Dynamics Embedding: This layer extracts a representation of vehicle dynamics from the encoded features, providing insights into the dynamic behavior of the agents.

4. Batch Normalization: Batch normalization layers normalize the activations of the previous layer, making training more stable and accelerating convergence by reducing internal covariate shift.

5. Optional Behavioral Modification: If enabled, this layer adjusts the weights of the encoder GRU's hidden vectors based on additional information, potentially enhancing the model's performance in capturing specific behaviors.

6. Convolutional Social Pooling and Embedding: These layers capture social interactions among agents in the scene by applying convolutional operations followed by max-pooling. They help the model understand the spatial relationships and interactions among different agents.

7. Decoder: This layer decodes the encoded features and predicts future trajectories based on the learned representations. It generates sequential outputs while considering contextual information from the encoder and social embeddings.

8. Output Layers: These layers produce the final predictions of the model. They generate outputs such as position coordinates and maneuver classes, enabling the model to forecast the future trajectories of road agents.

9. Dropout: Dropout regularization is applied to prevent overfitting by randomly dropping a fraction of the neurons during training, promoting the generalization of the model.

10. Activation Functions: These functions introduce non-linearity into the model and transform the outputs into suitable formats, such as probabilities for categorical predictions or positive values for continuous predictions.

4.9 Activation Function

These functions introduce non-linearity into the model and transform the outputs into suitable formats, such as probabilities for categorical predictions or positive values for continuous predictions.

4.9.1 ReLU

The Rectified Linear Unit (ReLU) activation function, introduced by Nair and Hinton [28], is a piecewise linear function that replaces negative inputs with zero, while leaving positive inputs unchanged. ReLU has become widely used due to its simplicity, computational efficiency, and effectiveness in alleviating the vanishing gradient problem. It helps mitigate issues associated with sigmoid and tanh activations by enabling faster convergence during training. ReLU has been instrumental in the success of deep neural networks, providing improved performance in various tasks such as image classification, object detection, and natural language processing [28]. Figure-.4.4 shows the graph–

4.9.2 ELU

The Exponential Linear Unit (ELU) activation function, proposed by Clevert et al.[30], is an extension of the Rectified Linear Unit (ReLU) activation. It addresses the vanishing gradient problem by allowing negative values, facilitating smoother gradients. For negative inputs, ELU applies an exponential function, preventing the gradient from vanishing, thus aiding faster convergence during training. ELU maintains sparsity benefits of ReLU and enhances learning in

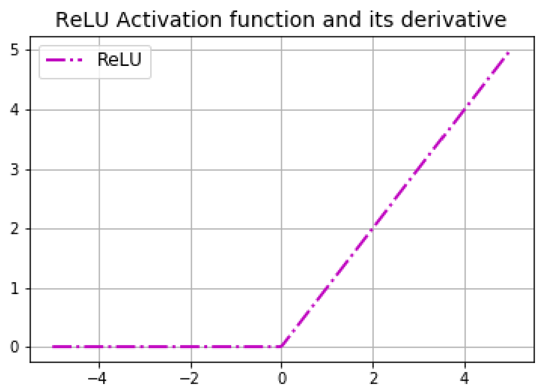

Figure 4.4: ReLU Activation Function [29].

deep neural networks. It has become popular due to its improved convergence properties and efficient gradient propagation [30]. Figure-4.5 shows the graph–

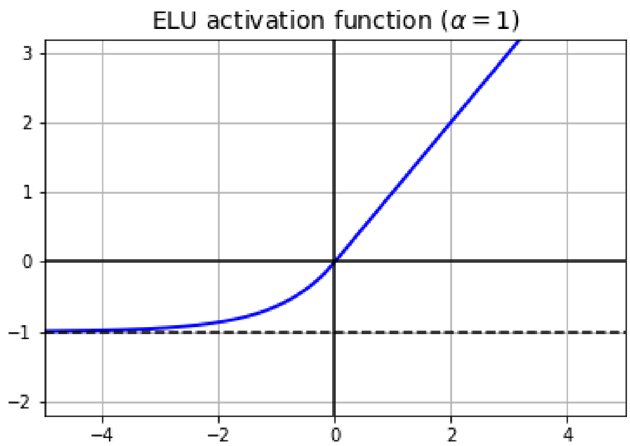

Figure 4.5: ELU Activation Function [29].

4.9.3 SoftMax

The softmax activation function, proposed by Bridle in 1990 [31], is commonly used in classification tasks to convert raw output scores into probability distributions. It computes the probability of each class being the correct classification by exponentiating the input scores and normalizing them across all classes. Softmax ensures that the output probabilities sum up to one, making it suitable for multi-class classification problems. It is particularly useful in neural network architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for generating probabilistic outputs for classification tasks [31]. Figure-4.6

shows the graph–

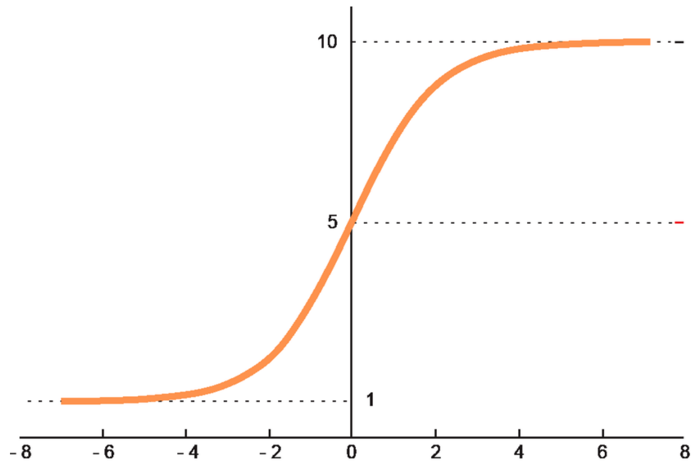

Figure 4.6: SoftMax Activation Function [32].

4.10 Conclusion

This chapter comprehensively addresses the foundational components pivotal to our proposed deep learning methodology, emphasizing dataset characteristics, data pre-processing techniques, feature extraction methodologies, and the creation of training and testing sets. Furthermore, it delves into detailed insights regarding the architecture of the hybrid model, shedding light on the composition and functionality of individual layers. By elucidating these essential elements, this chapter provides a comprehensive understanding of the methodological framework underpinning our approach. Through meticulous dataset description, rigorous pre-processing protocols, and sophisticated feature extraction strategies, we ensure the robustness and efficacy of our model. Additionally, the delineation of training and testing set creation methodologies underscores the meticulousness applied in model evaluation. Moreover, the exposition of model layer information offers valuable insights into the inner workings and structural intricacies of our hybrid architecture. Overall, this chapter serves as a conclusive synthesis of the methodological framework, laying the groundwork for subsequent experimental investigations and analytical assessments.

Chapter 5

Result & Performance Analysis

5.1 Introduction

This chapter delves into an in-depth exploration of performance indicators for our model, providing a detailed analysis of results and performance. We examine various metrics and indicators to evaluate the effectiveness of the model, including validation curves and graphs that offer insights into its performance. Moreover, we conduct a comprehensive comparative analysis between our model and previous works, aiming to showcase the advancements and improvements achieved. By comparing performance metrics and model behaviors, we elucidate the strengths and potential areas for further enhancement. Throughout this chapter, we present our findings derived from the evaluation of the model. These findings offer valuable insights into the model's capabilities, limitations, and overall effectiveness in trajectory prediction tasks. By synthesizing the results and performance analyses, we aim to provide a comprehensive understanding of the model's performance landscape and its significance in the broader context of trajectory prediction research.

5.2 Model Performances

The evaluation of a model encompasses a diverse range of parameters and experimental results, each offering unique insights into its performance. Below, we delve into the experimental findings and analyze the model's performance across various metrics and parameters.

5.2.1 Average Training Loss vs Epoch Curve

The average training loss vs. epoch curve is a graphical representation commonly used in machine learning to track the progression of the model's performance during the training process. It visualizes how the average loss, which quantifies the disparity between the model's predictions and the actual targets, evolves over successive training epochs. In Figure-5.1 shows the average training loss vs. epoch curve of our developed model.

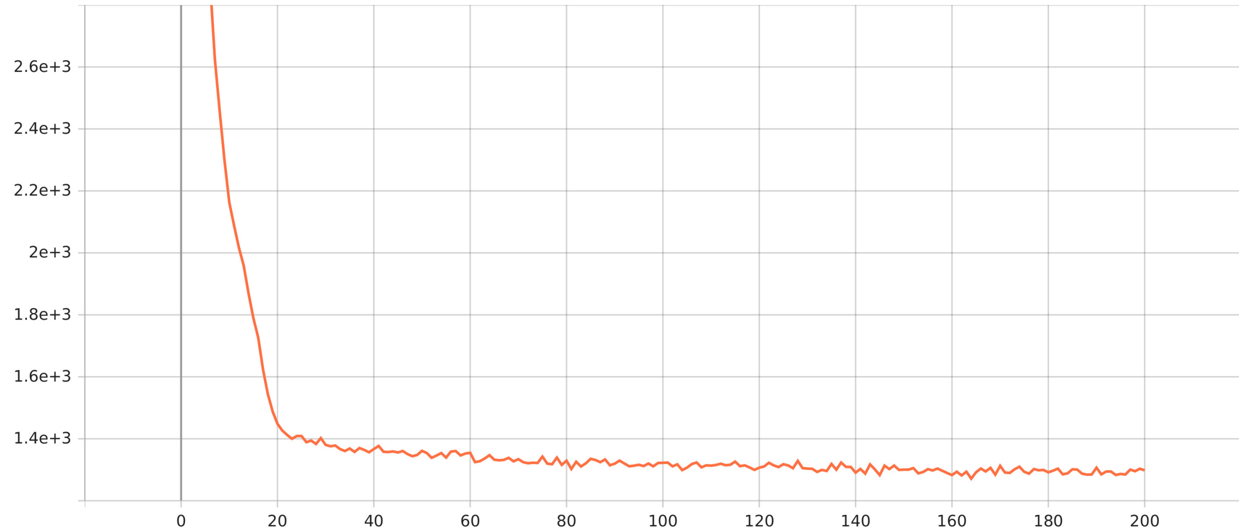

Figure 5.1: Average training loss vs epoch curve.

5.2.2 Average Validating Loss vs Epoch Curve

The validating average loss is a metric used to evaluate the performance of a machine learning model during the validation phase. Similar to the training loss, it quantifies the disparity between the model's predictions and the actual targets, but it is computed using a separate validation dataset rather than the training data.In Figure-5.2 shows the average training loss vs. epoch curve of our developed model.

5.3 Confusion Matrix

To evaluate the effectiveness of models in trajectory prediction, several commonly used metrics such as ADE and FDE are employed. Before delving into the intricacies of these evaluation metrics, it's essential to grasp their fundamental definitions.

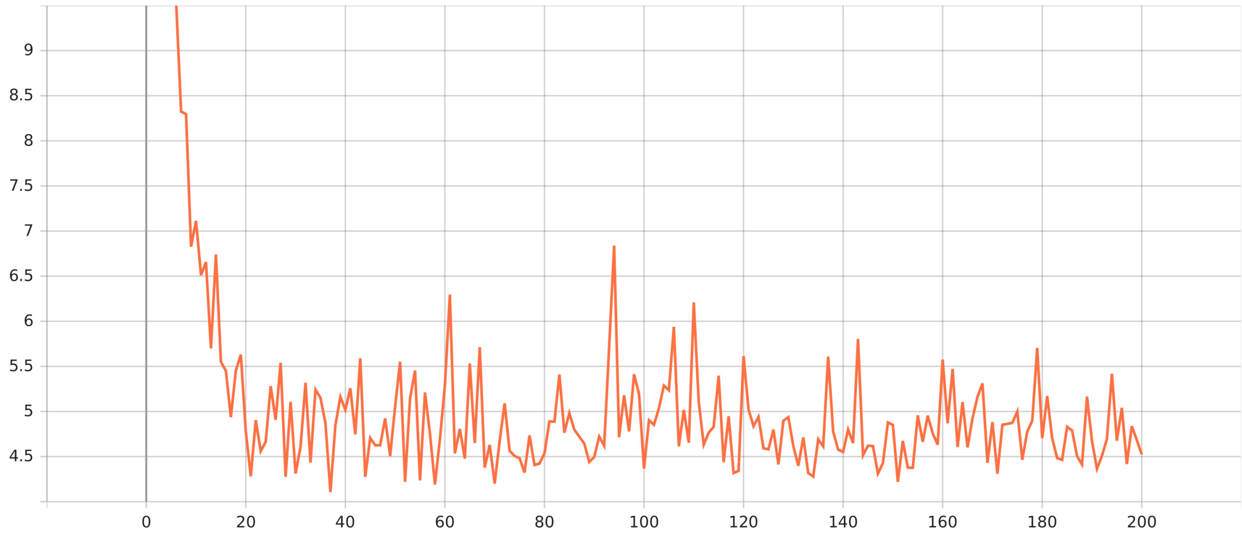

Figure 5.2: Average validating loss vs epoch curve.

1. Average Displacement Error (ADE): ADE serves as a metric for assessing the accuracy of trajectory predictions. It quantifies the overall deviation between the predicted positions and the actual positions at each time step throughout the prediction horizon. Calculated as the Root Mean Square Error (RMSE), ADE provides a comprehensive measure of how closely the predicted trajectory aligns with the actual trajectory over time.

$$ADE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x^i_{\text{predicted}} - x^i_{\text{actual}})^2 + (y^i_{\text{predicted}} - y^i_{\text{actual}})^2} \tag{5.1}$$

2. Final Displacement Error (FDE): FDE focuses specifically on the accuracy of trajectory predictions at the final time step of the prediction horizon. It measures the RMSE distance between the final predicted position (i.e., the position at the end of the predicted trajectory) and the corresponding true location. FDE offers valuable insights into the precision of predicting the endpoint of the trajectory compared to the actual endpoint.

$$FDE = \sqrt{(x_{\text{predicted, final}} - x_{\text{actual, final}})^2 + (y_{\text{predicted, final}} - y_{\text{actual, final}})^2} \tag{5.2}$$

In summary, these metrics offer a quantitative means to assess the performance of models by comparing predicted points with actual ground truth data points. Understanding these metrics lays the groundwork for comprehending their significance in evaluating the effectiveness of trajectory prediction models.

5.3.1 Experimental Result

We conducted training of the network over 200 epochs employing the Adam optimizer, a batch size of 32, and a learning rate of 0.001 on Kaggle utilizing the GPU P100 accelerator. The resulting performance metrics are presented in Table 5.1, showcasing the experimental outcomes. Additionally, Table 5.2 provides insights into the time required for training, further elucidating the model's performance characteristics.

Table 5.1: Experimental Result.

Parameter	**Value**
Average Displacement Error (ADE)	2.86
Final Displacement Error (FDE)	5.19

Table 5.2: Time Required for Model Execution.

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

5.3.2 Comparison Methods

In this study, we compare our developed model with existing models [21], all evaluated using the NGSIM dataset:

- RNN-ED (Seq2Seq): An RNN encoder-decoder model widely used in vehicle motion and trajectory prediction [33].
- Social-LSTM (S-LSTM): An LSTM-based network incorporating social pooling of hidden states to predict pedestrian movements in groups [34].
- Social-GAN (S-GAN): A hybrid LSTM-GAN network designed to forecast movements for large human crowds [35].

- Convolutional-Social-LSTM (CS-LSTM): A variant of S-LSTM integrating convolutions into the architecture described in to predict movements in sparse highway traffic [36].
- TraPHic: A LSTM-CNN based model specifically tailored for trajectory forecasting [21].

Table-5.3 illustrate a comparison various existing model to our developed model.

Table 5.3: Comparison of ADE and FDE for different models.

Model	**ADE**	**FDE**
RNN-ED	6.86	10.02
S-LSTM	5.73	9.58
S-GAN	5.16	9.42
CS-LSTM	7.25	10.05
TraPHic	5.63	9.91
Our Model	**2.86**	**5.19**

In our model, we address the nuanced dynamics of vehicle drivers by incorporating their dynamic behavior and considering the turning radius of vehicles, crucial factors often overlooked in prior approaches. Our model employs a GRU-CNN hybrid network, leveraging the strengths of GRU in handling shorter sequences and less complex temporal data. Unlike existing methods such as S-LSTM and S-GAN, which focus on predicting trajectories in top-down crowd scenarios, our model learns weighted interactions tailored to the shape, dynamic constraints, and behaviors of involved agents. Additionally, while CS-LSTM treats all agent interactions equally and TraPHic omits batch normalization and dropout, we employ 1D and 2D batch normalization alongside dropout regularization, enhancing model robustness and generalization. Consequently, our model outperforms prior methods by effectively capturing intricate agent interactions and yielding superior trajectory predictions, thus demonstrating its efficacy in diverse traffic scenarios.

5.4 Conclusion

This chapter emphasizes the use of evaluation metrics to analyze the performance of the model. Through comparisons with previous models, our model demonstrates superior performance.

We delve into various aspects including training and validation curves, training loss curves, and evaluation metrics such as average displacement error and final displacement error. By examining these metrics, we gain insights into how well the model generalizes to unseen data and how accurately it predicts trajectories. The training and validation curves provide a visual representation of the model's learning progress and its ability to generalize to new data. Meanwhile, the training loss curve illustrates how effectively the model minimizes errors during training. Furthermore, the evaluation metrics, including average displacement error and final displacement error, offer quantitative measures of the model's performance. These metrics enable us to assess how closely the predicted trajectories align with the actual trajectories, providing a comprehensive understanding of the model's predictive capabilities. Overall, our analysis showcases the effectiveness of the proposed model and highlights its superiority over previous approaches. By leveraging evaluation metrics and visualizations, we provide a thorough evaluation of the model's performance, paving the way for future advancements in trajectory prediction research.

Chapter 6

Conclusion & Future Works

6.1 Introduction

This concluding chapter offers a succinct overview of the entire research endeavor, encapsulating key aspects such as the problem domain, prior studies, the innovative contributions made, experimental analyses, and the derived conclusions. It serves as a comprehensive wrap-up, summarizing the journey from inception to findings. Furthermore, this chapter provides a brief glimpse into potential future directions for further research. By outlining avenues for future exploration and development, it sets the stage for continued advancements in the field, building upon the foundation laid by the current study.

6.2 Summary

Previous research endeavors focused on forecasting trajectories of road agents amidst dense traffic scenarios, often yielding average displacement errors exceeding 5. Our study marks a departure from this trend by achieving a notable reduction in this metric to 2.86, indicating substantial improvement. Additionally, we succeeded in minimizing the final displacement error to 5.19. Our approach, rooted in a GRU-CNN model, intricately considers driver behavior, intention, and turning radius. Tailored for mixed traffic environments, our model demonstrates versatility in accommodating various road agents. Overall, our developed model presents a promising solution to trajectory prediction challenges in complex traffic settings, showcasing significant enhancements in displacement error reduction. This research signifies a pivotal advancement in trajectory forecasting methodologies, paving the way for more accurate and reliable predictions in diverse traffic conditions.

6.3 Conclusion

Through this research, our GRU-CNN model showcased effective performance on the NGSIM dataset, substantially reducing prediction errors compared to prior studies. By synthesizing insights from existing literature on trajectory prediction, we gained valuable knowledge and critically analyzed their methodologies. Leveraging this understanding, we developed a comprehensive model that accounts for diverse factors such as driver behavior, intention, turning radius, vehicle dynamics (e.g., speed, acceleration), and vehicle shape and headings. Preprocessing the NGSIM dataset facilitated feature extraction, which served as input for our model. The results demonstrated significant improvements, with an Average Displacement Error (ADE) of 2.86 and a Final Displacement Error (FDE) of 5.19, surpassing the performance of previous works utilizing the NGSIM dataset. This culmination underscores the efficacy of our approach in advancing trajectory prediction accuracy, thereby contributing to the broader landscape of intelligent transportation systems.

6.4 Limitation

While our proposed model showed promising results in trajectory prediction, it is important to acknowledge its limitations. One significant limitation is the use of the NGSIM dataset, which has certain constraints. Despite offering high visibility, the dataset lacks heterogeneity and has low density. Heterogeneity, characterized by the diversity of agents in the dataset, and density, representing the number of traffic agents per kilometer, are crucial factors influencing model performance. Additionally, the NGSIM data, collected from tower-mounted cameras providing a bird's eye view, do not reflect the driver's perspective.

Furthermore, our model's design is tailored to dense heterogeneous traffic scenarios, limiting its effectiveness in sparse or homogeneous traffic conditions. Additionally, modeling heterogeneous constraints necessitates detailed knowledge of the shapes and sizes of various road agents, which can be challenging to obtain.

Moreover, despite the GRU model's improvements over traditional RNNs in mitigating the vanishing gradient problem, it still struggles with retaining information over long sequences.

This limitation may hinder the model's ability to capture intricate patterns and subtle nuances in the data effectively. These constraints highlight the need for further research and the exploration of alternative approaches to address these challenges in trajectory prediction tasks.

6.5 Future Works

Addressing the limitations highlighted in this study opens avenues for future research in trajectory prediction. One potential direction is to explore datasets that offer greater heterogeneity and higher density than the NGSIM dataset. This could involve collecting data from diverse urban environments with varying traffic compositions and densities, providing a more comprehensive understanding of real-world scenarios.

Additionally, future work could focus on developing models specifically tailored to sparse or homogeneous traffic conditions. By incorporating features and mechanisms that adapt to different traffic environments, such models could enhance prediction accuracy across a wider range of scenarios.

Furthermore, efforts to improve the GRU model's performance over long sequences are warranted. Exploring advanced architectures or incorporating attention mechanisms could help mitigate the challenges associated with information retention in extended sequences, enabling more accurate predictions of complex traffic patterns.

Moreover, addressing the limitations of modeling heterogeneous constraints requires innovative approaches to gather detailed information about road agents' shapes and sizes. Utilizing advanced sensing technologies or leveraging crowd-sourced data could facilitate the acquisition of comprehensive datasets for training and evaluation.

Overall, future research endeavors should aim to develop robust trajectory prediction models that are adaptable to diverse traffic conditions, effectively capture complex patterns, and overcome the limitations inherent in current methodologies. By addressing these challenges, advancements in trajectory prediction can contribute to safer and more efficient transportation systems.

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