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A Review on Artificial Intelligence for Autonomous Vehicle Behavior Prediction in Mixed Traffic Environment

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***Abstract*— This paper presents a comprehensive review of Artificial Intelligence (AI) techniques applied to autonomous vehicle (AV) behavior prediction in mixed traffic environments. The rapid advancement of AV technology, driven by AI, necessitates accurate prediction of surrounding vehicle behaviors for safe and efficient operation. The paper explores various machine learning and deep learning approaches, including Support Vector Machines, Random Forests, Convolutional Neural Networks, Long Short-Term Memory Networks, Graph Neural Networks, and Reinforcement Learning. These techniques demonstrate significant improvements in predicting and adapting to diverse road user behaviors, ultimately enhancing road safety. By analyzing the capabilities and limitations of these AI-powered solutions, this review aims to inform current applications and future advancements in AI-driven road safety.**

***Index Terms*—Autonomous Vehicles (AV's), Artificial Intelligence (AI), Behavior Prediction and Mixed Traffic Environments.**

I. Introduction

According to the World Health Organization (WHO), approximately 1.19 million people worldwide die annually as a result of road traffic crashes, with between 20 and 50 million sustaining non-fatal injuries [1]. Vulnerable road users, such as pedestrians, cyclists, and motorcyclists, face a significantly higher risk of fatalities compared to drivers of 4-wheel vehicles. Globally, while 30% of road deaths involve occupants of 4-wheel vehicles, pedestrians, powered two- and three-wheelers, and cyclists collectively account for 70% of fatalities. This significant difference highlights the urgent need for effective measures to enhance road safety for these vulnerable groups [2]. In Malaysia, the situation is also particularly concerning, with over 600,000 recorded road accidents and over 6,400 fatalities in 2023 alone [3].

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Motorcyclists are disproportionately affected, accounting for 65% of total fatalities [3]. Thus, these figures highlight the pressing need for effective strategies to reduce road traffic crashes and fatalities in the country.

Several contributing factors increase the risk and severity of road traffic crashes. One significant factor is speeding, which not only raises the likelihood of crashes but also worsens their consequences [4]. Additionally, driving under the influence of alcohol or other psychoactive substances significantly increases the risk of road traffic injuries [5]. The risk escalates with increasing blood alcohol concentration in the case of drink-driving, while drug-driving poses varying risks depending on the substance used. Furthermore, pedestrians struck by vehicles traveling at higher speeds also face significantly higher fatality rates [2]. The Global Status Report on Road Safety 2023 provides compelling evidence of the prevalence of risky driving behaviors [2]. Data from the report indicates that a significant percentage of drivers exceed the speed limit, with rates ranging from 1% to 66% across different countries. Additionally, drink driving remains a persistent problem, contributing to 10% of fatalities in 77 countries. The non-use of safety equipment, such as helmets [6], seat-belts [7], and child restraints [8], remains a significant concern. According to the report, 20% of drivers and 30% of passengers across multiple countries do not wear helmets, while 20% of drivers, 30% of front seat passengers, and 50% of rear seat passengers in various countries do not wear seatbelts. Furthermore, distracted driving, particularly mobile phone use [9], poses a significant risk, with studies reporting high rates of handheld phone use among drivers. A study by the Malaysian Institute of Road Safety Research revealed that human behavior is the primary cause of road crashes, followed by factors such as the design and condition of road infrastructure, as well as the condition of vehicles [10]. These behavioral factors, combined with other risk factors such as unsafe vehicles [11], inadequate road infrastructure [12] and post-crash care [13], and insufficient enforcement of traffic laws [14], contribute to the high incidence and severity of road traffic crashes. Recognizing and addressing these factors are crucial steps in reducing the incidence and severity of road traffic crashes and injuries.

Therefore, to address the growing concern of road safety, it is imperative to invest in AI-powered solutions. AI has the potential to revolutionize road safety by addressing the complex interplay of human behavior, vehicle dynamics, and environmental factors. AI-powered systems can analyze vast amounts of data from various sources, including traffic patterns, vehicle behaviors, and environmental conditions, to predict and prevent potential accidents. This includes predicting the behaviors of diverse road users within mixed traffic environments, where interactions between vehicles, pedestrians, and cyclists coexist on the road. By leveraging AI, we can develop more intelligent transportation systems that can adapt to real-time conditions and mitigate the risks associated with human error. AI plays a crucial role in enabling AV’s to navigate roads safely. For instance, AI algorithms can accurately detect and track various objects on the road, such as vehicles, pedestrians, cyclists, and road signs [15]. By combining data from multiple sensors, AI can create a more comprehensive understanding of the environment, improving the accuracy of object detection and tracking. Furthermore, AI can plan optimal paths for AV’s to follow, considering factors like traffic congestion, road conditions, and the presence of obstacles [16]. Additionally, AI can assess potential risks on the road and adjust the AV's behavior accordingly [17]. AI also controls the AV's steering and acceleration to maintain a safe trajectory and speed. In emergency situations, AI algorithms can quickly initiate maneuvers like braking or swerving to avoid accidents. Moreover, AI enables AV’s to understand and respond to human commands or questions through natural language processing [18]. Furthermore, AI can monitor the driver's state and intervene if necessary to prevent accidents [19]. Finally, AI can be trained to make ethical decisions in complex scenarios, such as choosing between hitting a pedestrian or colliding with another vehicle [20]. By integrating AI algorithms into AV control systems, these vehicles can proactively adjust their speed, trajectory, and response to surrounding conditions, thereby reducing the risk of collisions and improving overall road safety. AI-powered AV’s can make real-time decisions based on the behavior of other road users, anticipating potential hazards and taking evasive action if necessary.

This paper presents a comprehensive review of AI techniques applied to AV behavior prediction in mixed traffic environments. The study aims to identify effective AI algorithms for predicting the behavior of diverse road users, explore the potential of AI to mitigate road traffic fatalities and injuries, identify key challenges and opportunities associated with integrating AI into AV’s. By examining the capabilities and limitations of AI algorithms, this research seeks to provide insights into how AI-powered AV’s can contribute to enhanced road safety and inform future developments in this field.

II. AUTONOMOUS VEHICLE

While the rise of AV’s has gained prominence over the past two decades, their roots trace back to the early 20th century, beginning with Francis Houdina's 1925 remotely controlled car [21]. Houdina's vehicle, named Chandler, traveled about 19 kilometers in Manhattan but was interrupted by a collision. This marked one of the first attempts at creating an AV. Significant advancements occurred in the 1980s with German engineer Ernst Dickmanns, who converted a Mercedes-Benz van into an AV equipped with an integrated computer [21]. In 1987, this vehicle successfully navigated traffic-free streets at 63 kilometers per hour [21]. The 1990s saw further breakthroughs by Dickmanns, including a vehicle that traveled over 1,000 kilometers through Paris traffic in 1994 and another that journeyed autonomously between Munich and Copenhagen in 1995 [21]. These projects were part of the European Commission's Project Eureka, which provided substantial funding for AV research [21]. These milestones paved the way for the advanced AV technology we see today, demonstrating the long-standing human ambition to develop self-driving cars.

A. *AI as the Brain of Autonomous Vehicles*

Autonomous vehicles also known as self-driving cars or driverless cars, equipped with an intricate network of sensors and a powerful AI system, are revolutionizing transportation. The AI serves as the vehicle's intelligent brain, enabling it to navigate complex environments, interact with other road users, and safety. Fig. 1 shows the components of an autonomous vehicle [22]. It consists of various sensors and a central computer that work together to enable the vehicle to navigate and operate independently.

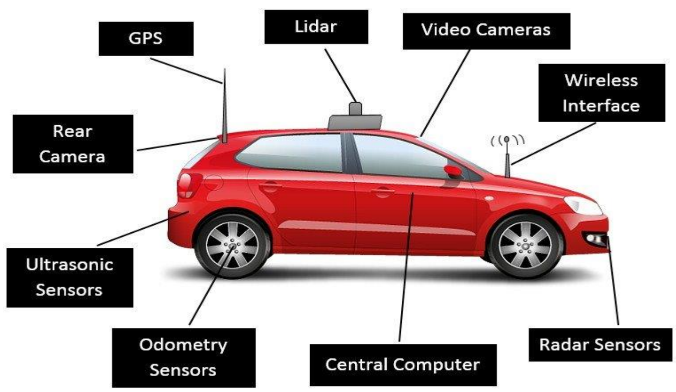

Fig. 1. Illustration of Autonomous Vehicle

1) *Sensor Integration and Data Processing*

By integrating data from a diverse array of sensors, the AI can build a comprehensive understanding of its surroundings. GPS provides a general location and reference to maps, allowing the AI to identify potential hazards like construction zones or traffic congestion [23]. LiDAR creates a 3D map, helping the AI accurately perceive objects, their distance, and their relative positions [24]. Video cameras analyze images to recognize objects, interpret traffic signs, and understand the behavior of other road users [25]. Rear cameras monitor vehicles behind, enabling the AI to anticipate potential lane changes or tailgating [26]. Ultrasonic sensors detect obstacles in close proximity, such as pedestrians or parked cars [27], while odometry sensors track the vehicle's position and velocity [28]. Radar sensors, even in low-visibility conditions, detect and track objects, crucial for predicting the behavior of other vehicles in crowded traffic [29].

2) Central Computer and Decision-Making

The central computer, housing the AI algorithms, processes data from these sensors to make informed decisions in real-time [30]. It integrates information from all sensors and uses AI to predict the behavior of other vehicles, plan the vehicle's path, and control its actions, such as steering, accelerating, and braking. The wireless interface enables V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure) communication, helping the vehicle anticipate potential hazards and make more informed decisions [31].

B. The Society of Automotive Engineers (SAE) Automation Levels

The Society of Automotive Engineers classification of driving automation levels as shown in Fig.2 provides a useful framework for understanding the progression towards fully AV's [32]. As technology advances, the automotive industry moves closer to achieving Level 5 autonomy, where vehicles are capable of operating in any condition without human intervention.

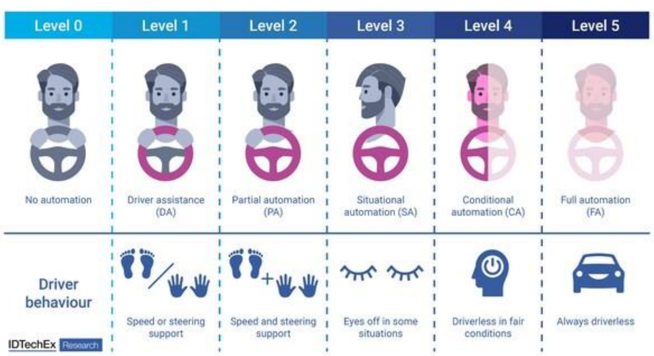

Fig.2. The Society of Automotive Engineers (SAE) Automation Levels

At Level 0 (No Automation), the driver is entirely responsible for all driving tasks, including steering, accelerating, braking, and parking. The vehicle offers no automated assistance beyond basic safety features like airbags and anti-lock brakes. This level represents traditional, human-driven vehicles.

Level 1 (Driver Assistance) introduces basic driver support systems. The vehicle can assist with either steering or acceleration/deceleration, but the driver must remain engaged and ready to take control at all times. Common features at this level include adaptive cruise control and lane departure warning.

Level 2 (Partial Automation) vehicles can control both steering and acceleration/deceleration in specific situations, but the driver must remain engaged and monitor the environment at all times. Advanced driver assistance systems (ADAS) like lane-keeping assist, automatic parking, and adaptive cruise control are prevalent at this level.

At Level 3 (Conditional Automation), the vehicle can perform all driving tasks in certain conditions and environments, but the driver must be ready to take control when the system requests. This level often involves features like traffic jam assist and highway pilot.

Level 4 (High Automation) vehicles can perform all driving tasks and monitor the environment in specific conditions or environments. The human driver does not need to intervene, but the system might not operate in all conditions. This level is suitable for autonomous taxis or delivery vehicles operating in defined geographic areas.

Level 5 (Full Automation) represents the pinnacle of autonomous driving, where the vehicle can perform all driving tasks in all conditions and environments that a human driver could handle. No human intervention is required. This level is the ultimate goal of AV development.

III. Literature Review

A. Machine Learning Approaches

1) Support Vector Machines (SVMs)

SVMs are a type of supervised machine learning algorithm that excel at classification tasks. In the context of AVs, SVMs can be used to predict the intentions and actions of other vehicles and pedestrians, enabling AVs to navigate safely and efficiently in mixed traffic environments.

In this study [33], A. Benterki et al. proposed two machine learning approaches for lane change prediction: Support Vector Machine (SVM) and Artificial Neural Network (ANN) to predict lane changes of surrounding vehicles on highways. The authors then compared the performance of these two models to determine which one was more effective for the task. The system uses features extracted from the NGSIM dataset containing detailed information on vehicle trajectories , such as longitudinal velocity, lateral velocity, longitudinal acceleration, lateral acceleration, distance to left marking, distance to right marking, yaw angle and yaw rate related to road. These features provide information about the vehicle's motion, position, and orientation relative to the road, which are all important factors in predicting lane changes. The SVM and ANN models are trained on the prepared dataset, which contains vehicle trajectory data with features and corresponding labels for lane change and lane keeping maneuvers. This training process involves the models learning patterns in the data to distinguish between different maneuver types. Once trained, the models are evaluated on a separate testing dataset to assess their performance. This involves comparing the models' predicted maneuver types with the actual known maneuver types in the testing data. Metrics like accuracy, recall, precision, and F1-score are used to evaluate the models' ability to correctly classify lane changes and lane keeping events.

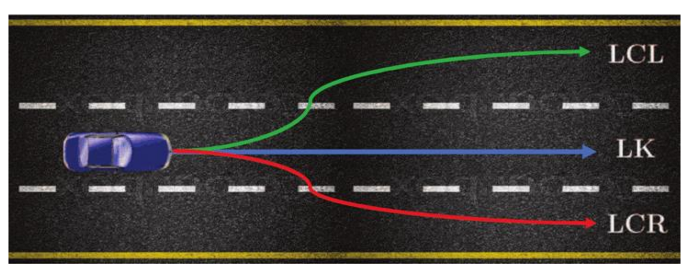

Fig 3: Lane Change and Lane Keeping Scenarios

The study successfully predicts lane changes using SVM and ANN. The SVM model achieved good performance reaching a prediction accuracy of 97.1%, with sensitivity, precision, and F1-score all at 95.7%. ANN achieved an accuracy of 98.8% and higher scores for the other metrics, but SVM was slightly faster in terms of prediction time. Overall, both methods demonstrated effective prediction capabilities due to the well-chosen features that captured vehicle dynamics and road structure.

The study by X. Wang et al. [34] investigates the enhancement of driver intention recognition by incorporating emotional factors using SVM theory. The first step involves collecting data on various aspects that influence driving behavior. This likely includes vehicle parameters such as speed, acceleration, pedal position, steering wheel angle, environmental factors such as road conditions, weather conditions, traffic density, and driver emotions such as indicators of emotions like fear, anger, or joy (potentially measured through physiological responses or surveys). The SVM algorithm is trained on a portion of the prepared data. After training, the SVM model is evaluated on a separate portion of the data (the testing set). The SVM model used in the study effectively recognized driver intentions, especially when considering emotional factors. It achieved high accuracy rates in both real and virtual driving scenarios for both speed changes and lane changes. Incorporating emotions significantly improved the model's accuracy, suggesting that understanding a driver's emotional state provides valuable insights into their likely intentions. While the model performed better with negative emotions, it still showed improvement with positive emotions compared to a model without emotional factors. The model's performance was consistent across different driving environments, indicating its potential for practical application.

S. Roy et al. [35] presents a robust vehicular control system equipped with various safety features, including collision detection, alcohol detection, seat-belt detection, and speed control. A key contribution of the study is the integration of SVMs with radial basis function kernels to classify and mitigate potential accidents. The system utilizes SVMs to analyze data from three sensors. Alcohol Sensor (MQ-3): Detects alcohol concentration in the driver's breath, Ultrasonic Sensor: Measures distance to nearby objects, and Vibration Sensor: Detects bumps and shakes. SVMs are trained on large datasets of sensor readings, each with features (e.g., alcohol concentration) and a corresponding class label (e.g., "Heavily Drunk"). Once trained, SVMs can classify new sensor readings. For instance, if a new alcohol sensor reading exceeds a certain threshold, the SVM will classify the driver as "Heavily Drunk." The SVM classifier achieves an impressive 95.8% accuracy in predicting accident likelihood based on vibration and ultrasonic sensor inputs. The alcohol detection system demonstrates 100% accuracy in distinguishing between heavily drunk and mildly drunk states, ensuring appropriate actions like engine disabling. Furthermore, the collision avoidance system effectively alerts drivers to potential collisions, reducing the risk of accidents. Overall, the study demonstrates the effectiveness of the proposed vehicular control system in mitigating road accidents through its accurate prediction of accident likelihood and timely alerts. The integration of SVMs and various sensors contributes significantly to the system's performance.

2) Random Forests

Random Forest is a powerful machine learning algorithm that can be effectively used for predicting the behavior of AVs in mixed traffic environments. By analyzing various factors such as vehicle positions, speeds, and road conditions, Random Forest can accurately anticipate the actions of other vehicles and pedestrians, enabling AVs to make informed decisions and navigate safely.

In the study, X. Gu et al. [36] introduces a data-driven approach using the Random Forest algorithm to predict lane changes. The authors use data from NGSIM dataset, which provides detailed information on vehicle positions, speeds, and accelerations. The raw data undergoes cleaning, filtering, and smoothing to ensure accuracy. For feature selection, the authors identify key factors that influence lane change decisions, such as vehicle speed, relative speed between surrounding vehicles, and distances between vehicles. A Random Forest model is built using the selected features and labeled data (lane change or no lane change). The model is trained on 80% of the data and tested on the remaining 20%. The result of the study indicates that the Random Forest-based lane change decision model achieved significant advancements in predicting vehicle behavior with high accuracy. When tested with sample data from the NGSIM dataset, the model accurately predicted vehicle lane change behavior in 97.72% of cases. Specifically, the accuracy was 98.22% for samples where vehicles maintained their lane and 97.22% for samples where vehicles changed lanes. Overall, the research paper shows that the Random Forest algorithm can be used to develop an accurate model for predicting lane-changing behavior of freeway vehicles. This model can be used to improve traffic flow and safety.

3) k-Nearest Cluster Neighbor (k-NCN)

k-NCN is an unsupervised learning technique that groups data points based on similarity. In recognition tasks such as image or pattern recognition, k-NCN aids in identifying similar instances or patterns within a dataset, facilitating classification or identification tasks. For AV’s, employing pattern recognition techniques such as k-NCN significantly enhances behavior prediction capabilities. By leveraging these techniques, AV’s can anticipate the behavior of surrounding entities and proactively take measures to avoid accidents, thereby improving road safety and navigation efficiency.

The study by Wahyono et al. [37] proposes a novel traffic sign recognition system for autonomous vehicles (AVs) called the k-NCN classifier. This approach aims to improve upon traditional k-Nearest Neighbor (k-NN) methods by addressing their limitations in terms of space and time requirements. The k-NCN classifier first converts images to a format that emphasizes red and blue colors, which are commonly used in traffic signs. It then uses the Maximally Stable Extremal Region (MSER) method to identify potential traffic sign regions, filtering out regions with unusual aspect ratios. Candidate regions are resized and processed using Histogram of Oriented

Gradients (HOG) features to capture their shape information. To reduce processing time, the training data is grouped into smaller clusters using k-means clustering. A distance function that considers both the mean and variance of feature values is used to compare unknown signs with these clusters. The unknown sign is classified based on the nearest cluster. The study demonstrates the effectiveness of the k-NCN classifier through evaluations on the German Traffic Sign Recognition (GTSR) database. The classifier achieves competitive classification rates while significantly reducing processing time compared to traditional k-NN. Additionally, implementation on real-world video data collected from an AV shows high detection and recognition rates, with a detection rate of 98.07%, recognition rate of 99.54%, and an average frame rate of 25 frames per second. The study demonstrates the effectiveness of the k-NCN classifier for real-time traffic sign recognition in autonomous vehicles. It achieves high detection and recognition rates while maintaining a fast processing speed.\

B. Deep Learning Approaches

1) Convolutional Neural Networks (CNNs)

CNNs are advanced algorithms primarily used for tasks like image recognition. In AV's, they analyze visual data from sensors to understand the environment. By extracting patterns, CNNs help AV's predict movements of nearby objects, enhancing safety on roads. Thus, CNNs are crucial for improving AV's' perception and decision-making abilities

Mohammad Yahya et al. [38] propose a novel method for object detection and recognition in autonomous vehicles, leveraging the power of deep learning as shown in Fig. 4. Their approach employs Fast R-CNN to accurately identify objects like cars, pedestrians, and traffic signs, thereby enhancing safety and driving assistance. To train their model, the researchers utilized the KITTI dataset and implemented data augmentation techniques to improve its generalization capability (prevent overfitting). Feature extraction was achieved using Gray-Level Co-occurrence Matrix (GLCM) for textural features and ResNet-50 for high-level features. Additionally, they employed Attention-guided Context Feature Pyramid Network (ACFPN) to effectively combine features from different levels, addressing challenges related to receptive field size and feature map resolution. For object detection and recognition, the Fast R-CNN approach was utilized, which selectively processes relevant regions, improving efficiency and providing accurate bounding boxes.

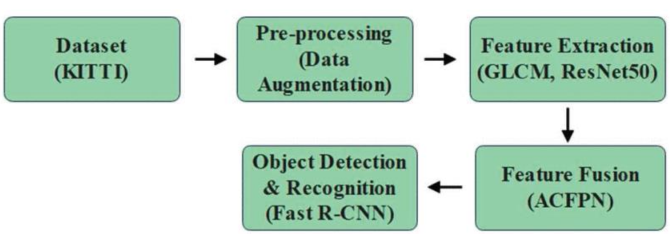

Fig. 4. Block Diagram for The Proposed Approach

The proposed method demonstrated superior performance compared to existing techniques like ShuffYOLOX, MobileYOLO, and S-DAYOLO in terms of Mean Average Precision (mAP), Model Complexity (Params), FLOPs, and Frames Per Second (FPS). Overall, this research proposes a promising approach for object detection and recognition in autonomous vehicles using Fast R-CNN and feature fusion techniques. The achieved high mAP and efficient model performance make it a valuable contribution to the field of autonomous driving.

Jung et al. [39] propose a system for real-time semantic segmentation in autonomous vehicles, utilizing a compressed CNN architecture and an energy-efficient hardware accelerator. The Depth-fused Trilateral Network (DTN), a compressed CNN architecture, leverages depth information and techniques such as dilated convolution and depthwise separable convolution to reduce network complexity. Notably, the DTN achieves a remarkable 94.73% accuracy on the KITTI Road dataset, significantly surpassing existing methods while reducing parameters and computation costs. To complement the DTN, the study introduces an energy-efficient CNN accelerator. This accelerator supports a variety of convolution operations, including pointwise, standard, depthwise separable, dilated, and transposed convolutions. By employing techniques like the dual-mode IFmap Holder and data path management, the accelerator enhances efficiency and achieves high throughput while consuming low power. Performance evaluations demonstrate the effectiveness of the combined system. The DTN's exceptional accuracy, coupled with the accelerator's energy efficiency, enables real-time semantic segmentation at impressive rates: 72.2 FPS for road segmentation and 37 FPS for multi-object segmentation. Overall, this work contributes to the development of real-time and low-power perception systems for autonomous vehicles.

O. Sharma et al. [40]. propose a novel CNN-STA-TF deep learning network for predicting the trajectory of autonomous vehicles on multi-lane highways. In this study, CNNs are used to analyze and understand the historical trajectories of vehicles. CNNs are designed to process and learn from image data, but they can also be adapted to handle time-based data like vehicle trajectories. The CNNs are used to extract features from the input data, such as relative positions, lane changes, and velocity changes. The proposed model achieves superior performance compared to existing RNN-based models in terms of accuracy and efficiency. The CNN-STA-TF model achieves a 10% reduction in Root Mean Square Error (RMSE) for predicting trajectories over a 5-second duration compared to state-of-the-art models. The model utilizes a Transformer-based encoder, which processes the entire input sequence at once, leading to faster prediction compared to RNN-based models that process data sequentially. The spatial attention network effectively captures the interactions between the target vehicle and its surrounding vehicles, leading to more accurate trajectory predictions. Overall, the study demonstrates the effectiveness of the CNN-STA-TF model for trajectory prediction of autonomous vehicles on multi-lane highways. This model has the potential to improve the safety and efficiency of autonomous driving systems.

2) Long Short-Term Memory Neural Networks (LSTMs)

LSTMs are neural networks designed for analyzing sequential data. LSTMs are also crucial for predicting behaviors in AV's. By analyzing sensor data, they anticipate the actions of nearby vehicles and pedestrians, enabling AV's to make informed decisions for safe navigation. Thus, LSTMs enhance AV's perception and decision-making abilities, contributing to improved road safety.

S. Qiao et al. [41] introduces a novel vehicle trajectory prediction model named AS-LSTM. This model effectively predicts future vehicle trajectories by leveraging social interactions and self-attention mechanisms. AS-LSTM takes historical trajectory data of surrounding vehicles as input, including their positions, velocities, and accelerations. The model processes this data using an LSTM encoder to capture temporal patterns, a self-attention mechanism to focus on relevant information, and an S-Pooling layer to understand vehicle interactions. Finally, the model decodes this processed information to predict the target vehicle's future trajectory. The AS-LSTM model, as described in the paper, demonstrates significant performance improvements in vehicle trajectory prediction compared to existing methods. This is primarily due to the incorporation of social interaction and self-attention mechanisms. The AS-LSTM model consistently achieved lower RMSE values across different prediction horizons (1s-5s) on both the NGSIM and HighD datasets. This indicates that the model's predictions were closer to the actual trajectories, demonstrating improved accuracy. The AS-LSTM model outperformed other models in predicting both horizontal and vertical positions. This suggests that the model was able to accurately capture the complex interactions between vehicles and the nuances of their movements in both longitudinal and lateral directions. Ablation studies revealed that both the self-attention mechanism and the S-Pooling layer contributed significantly to the model's performance. When used individually, these components reduced errors by 53% and 44%, respectively. Combined, they achieved a 39% error reduction. The S-Pooling layer, which captures social interactions, further enhanced the model's accuracy by 26% compared to using only the attention mechanism. This highlights the importance of considering vehicle interactions for accurate trajectory prediction. Overall, the AS-LSTM model demonstrates superior performance due to its ability to capture social interactions, where the s-pooling layer effectively models the influence of surrounding vehicles on the target vehicle's trajectory.

The research by Alsanwy et al. [42] investigated how well LSTM networks can predict motion signals in driving simulators. LSTMs are fed past vehicle data like acceleration, steering angle, and road conditions. The network then learns patterns from this data and predicts future motion signals. This method outperforms traditional Recurrent Neural Networks (RNNs) in terms of accuracy. LSTMs achieve a lower average error (RMSE) of 0.127 compared to RNNs at 0.149. Similarly, LSTMs have a lower average error rate (MAE) of 19.04% compared to RNNs at 26.0%. Finally, LSTMs show a stronger correlation (0.83) between predicted and actual values compared to RNNs (0.80). By demonstrating the superiority of LSTMs over RNNs in predicting motion signals, the study provides strong evidence for the potential of LSTMs to be used as a core component of autonomous driving systems.

The study by N. F. S. et al. [43] proposes an LSTM-based approach for autonomous vehicles to navigate highway merging safely. The researchers gathered data from two expert drivers performing highway merging maneuvers in a driving simulator. This data included various features like the vehicle's position, orientation, speed, and steering wheel angle. Five key features were selected to train the LSTM: longitudinal position, lateral position, yaw angle (vehicle's rotation), speed, and lateral distance to the highway guardrail. The network was trained to predict the optimal steering wheel angle for each time step based on the input features. The trained LSTM network acts as an "expert driver model." It takes real-time vehicle data as input and outputs the predicted steering angle. A PD controller uses this predicted angle as a reference to adjust the actual steering wheel angle of the vehicle in the simulator. The PD controller calculates the error between the desired and actual angles and applies proportional and derivative control to minimize this error. The system using the LSTM model successfully completed highway merging maneuvers in the simulator. It achieved an R-squared score of 0.82, indicating a strong correlation between the predicted and actual steering angles. The vehicle's trajectory closely resembled those of the expert drivers, demonstrating the ability to mimic their behavior. Advantages of using LSTM include mimicking expert drivers and handling complex maneuvers.

3) *Graph Neural Network (GNNs)*

GNNs are specialized neural networks that operate on graph-structured data. They analyze relationships between nodes and edges in a graph, enabling them to capture complex dependencies. In AV's, GNNs model interactions between vehicles, pedestrians, and objects on the road as a graph. By leveraging this structure, GNNs can predict future behaviors, enhancing AV navigation and safety.

In this research, Y. Wang et al. [44] focus on addressing the challenges associated with agent trajectory prediction in complex traffic scenarios. The authors aim to improve the accuracy of trajectory prediction while maintaining computational efficiency, essential for real-time applications in AV's. To achieve this goal, the authors propose VIF-GNN, a novel trajectory prediction framework that integrates the Virtual Interaction Force (VIF) concept with Graph Neural Networks (GNN). The VIF-GNN model uses a graph neural network (GNN) to capture the interactions between agents and lanes in a traffic scene. It first extracts features from raw data like location, velocity, and lane information. Then, it uses a subgraph encoder to transform these features into a format suitable for GNNs. Next, the global graph network, consisting of four attention layers, models various types of interactions: lane-lane, lane-agent, agent-agent, and global. Finally, the multi-modal decoder translates the learned graph representation into multiple possible future trajectories for the target agent.. Through extensive experiment VIF-GNN outperforms baseline models in both single and multi-modal trajectory prediction tasks. This is evident from achieving lower minimum Average Displacement Error (minADE) and minimum Final Displacement Error (minFDE) compared to LSTM, Transformer, VectorNet, TNT, and GOHOME models. VIF-GNN demonstrates the potential of using GNNs with VIF for accurate and efficient agent trajectory prediction in traffic scenarios. This can be crucial for autonomous vehicles to understand their environment and make safe decisions.

N. Pourjafari et al. [45] focus on addressing the critical challenge of collision avoidance at unsignalized intersections for AV's. The algorithm, executed in three sequential steps, utilizes LSTM and GNN models to predict vehicle trajectories, estimate safe traversal time windows, and calculate acceleration values to ensure safe passage through collision points while avoiding dangerous situations. The results presented in the paper demonstrate the effectiveness of the proposed algorithm through both qualitative and quantitative analyses. Qualitatively, the algorithm is shown to promote cautious driving behavior in AV's, even surpassing human-driven cars in certain scenarios. Through visualization and evaluation of four distinct intersection scenarios, the algorithm's ability to consider both immediate and subsequent collision points is highlighted. Quantitatively, the performance of the algorithm is evaluated using real-world data from the INTERACTION dataset. The future behavior predictor achieved an accuracy of 90.5%, outperforming the alternative approach which achieved 88%. Additionally, the algorithm was tested on 250 real-world scenarios, and the self-driving vehicle safely passed the intersection in all cases. These findings collectively demonstrate the effectiveness of the proposed algorithm and its potential to significantly improve the safety of autonomous vehicles at unsignalized intersections.

4) Double Deep Q Network (DDQN)

DDQN is an enhancement of the Deep Q-Network (DQN) algorithm used in reinforcement learning. It addresses the overestimation bias issue present in traditional Q-learning methods. By addressing the overestimation bias inherent in traditional Q-learning methods, DDQN provides more accurate estimations of action values. With DDQN, AV's can better anticipate and respond to dynamic traffic scenarios, ultimately improving their ability to navigate safely and efficiently.

The study conducted by X. Zhang et al. [46] resulted in the development of a hybrid DDQN model for AV lane-changing decisions. Their model demonstrated significant improvements over traditional DQN models, achieving higher success rates, better average rewards, and maintaining robust performance under varying traffic conditions. The training phase showcased the DDQN model's superiority in lane change decision-making, with success rates of 87.52%, 84.48%, and 81.43% for DDQN, DQN, and traditional DQN, respectively, underscoring its effectiveness over traditional DQN methods. Furthermore, analysis of average reward distribution revealed the DDQN model consistently outperformed its counterparts, achieving the highest average reward of 10.31 between rounds 2001 to 4000. In testing scenarios, the DDQN model continued to excel. In Scenario One, it exhibited a 0.9% and 3.6% higher success rate compared to DDQN and DQN, respectively, alongside superior average rewards, cumulative steps, and average speed, indicating enhanced decision-making and exploration capabilities. Similarly, in Scenario Two, despite increased traffic volume and adjusted parameters, the DDQN model maintained its superiority, achieving an 11.2% and 3.8% higher success rate compared to DDQN and DQN, respectively. These results highlighted the DDQN model's robustness and stability across diverse scenarios. Overall, the DDQN model consistently outperformed DDQN and DQN in terms of average success rate and reward in both scenarios, highlighting its efficacy in varying road conditions and traffic scenarios.

M. Dhinakaran et al. [47] aims to enhance the intelligence and decision-making capabilities of AV's through sophisticated algorithmic approaches. The research evaluates the performance of various DRL algorithms, including Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Trust Region Policy Optimization (TRPO). Notably, PPO demonstrates the highest success rate among the evaluated algorithms, achieving an impressive 82.6%. The study highlights the significant impact of optimization factors such as parameter tuning, exploration-exploitation balance, and reward shaping on navigation success. Parameter tuning emerges as a critical factor, substantially improving the success rate to 87.4%. Furthermore, the research emphasizes the importance of transfer learning in enhancing adaptability, with a remarkable generalization score of 92.3%. Safety modules are also implemented to enhance overall safety scores by 18.7%. These findings highlight the significance of algorithm selection and parameter optimization in optimizing navigation for AV's, providing valuable insights for future advancements in the field.

IV. DISCUSSIONS

A. Model-Related Challenges of Machine Learning in Autonomous Vehicles

While Support Vector Machines (SVMs), Random Forests, and k-Nearest Cluster Neighbor (k-NCN) offer promising approaches for AVs, each faces specific challenges that need to be addressed for successful implementation.

SVMs, while powerful tools for classification tasks, face several challenges when applied to AVs. In terms of data quality and quantity, the performance of SVMs heavily relies on the quality and quantity of training data. Real-world driving scenarios are diverse and complex, making it difficult to collect comprehensive datasets that cover all potential situations. For example, the NGSIM dataset used in [33] may not capture all possible driving scenarios, limiting the model's ability to generalize to unseen situations. In terms feature engineering, selecting and engineering relevant features is crucial for SVM performance. While the papers in [33], [34] mentioned using features like vehicle trajectory data, speed, acceleration, and distance to road markings, there may be other relevant features that were not considered. For instance, the presence of other vehicles in the blind spot or the driver's experience level could also influence lane change decisions. Furthermore, training and deploying SVMs on resource-constrained devices, such as AVs, can be computationally intensive. In real-time applications like lane change prediction, the SVM model may need to process a large amount of data and make predictions at high frequency, which can be challenging on devices with limited processing power. Addressing these challenges is crucial for the successful deployment of SVM-based solutions in autonomous vehicles. By carefully considering data quality, feature engineering and computational efficiency, researchers can develop more reliable and effective models for AV applications.

The study by X. Gu et al. [36] encountered several challenges when using Random Forest for lane change prediction. These challenges included data quality issues, such as noise and inconsistencies in the NGSIM dataset, and limited variety in the driving scenarios captured. Feature engineering also posed difficulties, as identifying the most relevant features and capturing complex feature interactions was challenging. Additionally, the risk of overfitting due to the complexity of Random Forest models and the need for balanced training data were concerns. Computational efficiency was another limitation, as training a large Random Forest model can be computationally expensive. Finally, the black box nature of Random Forest models made it difficult to understand the exact reasoning behind their predictions, which can be a challenge in safety-critical applications. Despite these challenges, the study successfully demonstrated the effectiveness of Random Forest for this task, highlighting its potential for use in autonomous vehicles.

k-NCN tackles pattern recognition tasks by grouping similar data points. However, as the number of features (dimensionality) increases, the curse of dimensionality can make it difficult for k-NCN to find meaningful relationships between data points. This can lead to degraded performance and increased computational cost. Techniques like Principal Component Analysis (PCA) can be used to reduce dimensionality, but this comes at the expense of losing some information. Moreover, k-NCN is sensitive to noise in the data, particularly if it affects the key features used for classification. Choosing the right features plays a crucial role in achieving accurate results. Noise reduction techniques like filtering can help mitigate the impact of noise on k-NCN's performance.

By recognizing these challenges and employing appropriate mitigation strategies such as data preprocessing, feature engineering, and careful model selection, we can harness the strengths of these machine learning algorithms and ensure the reliability and performance of AV systems.

B. Model-Related Challenges of Deep Learning in Autonomous Vehicles

Deep learning approaches like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), Graph Neural Networks (GNNs), and Deep Q-Networks (DQNs) offer significant promise. However, despite their strengths, deep learning approaches for autonomous vehicles face several challenges.

CNNs are well-suited for tasks like image recognition and object detection. However, they can be computationally expensive, especially for real-time processing in autonomous vehicles. Additionally, they require large amounts of labeled data and may struggle to generalize to new environments. For instance, the computational complexity of the model, due to the use of ResNet-50 and ACFPN, can limit real-time performance and increase power consumption [38]. Additionally, the model may struggle to generalize to new environments and could be vulnerable to adversarial attacks. Other than that, the CNN-STA-TF model, while efficient compared to RNN-based models, may still be computationally intensive, especially for real-time applications [40], due to the following factors such as the Transformer-based encoder used in the model processes the entire input sequence at once, which can be computationally demanding, especially for long input sequences, the spatial attention network, which captures interactions between the target vehicle and its surrounding vehicles, can also contribute to computational complexity, the CNN component of the model may still require significant computational resources for feature extraction, especially if it uses complex architectures, and autonomous vehicles often have strict real-time requirements, and the CNN-STA-TF model may need to be optimized further to meet these constraints. While the model demonstrates superior performance in terms of accuracy and efficiency compared to RNN-based models, it may still require specialized hardware or optimization techniques to ensure it can be deployed in real-time applications.

LSTM networks are effective for capturing long-term dependencies in sequential data. However, they can be computationally expensive and may suffer from the vanishing gradient problem. In autonomous vehicles, capturing long-term dependencies is crucial for understanding traffic patterns and predicting future vehicle behavior. For example, the computational complexity of the model proposed by S. Qiao et al. [41], due to the use of LSTMs, self-attention, and S-Pooling, can limit real-time performance and increase power consumption.

GNNs are designed to process graph-structured data, which can be useful for modeling the interactions between autonomous vehicles and other objects in their environment. However, constructing accurate and meaningful graphs can be challenging, and GNNs can become computationally expensive as the size of the graph increases. For ezample, the computational complexity of the proposed VIF-GNN model is primarily influenced by the following factors: Graph Size: The number of agents and lanes in the traffic scene directly affects the size of the graph, which in turn impacts the computational cost of the GNN. Larger graphs require more computations; GNN Architecture: The depth and width of the GNN layers determine the number of parameters and operations involved. Deeper and wider networks generally require more computational resources; VIF Calculation: The calculation of Virtual Interaction Forces involves computing pairwise distances and interactions between agents and lanes, which can be computationally expensive for large numbers of agents; and Feature Extraction: Extracting features from raw data can also contribute to the computational cost, especially if complex feature extraction techniques are used. To ensure both computational efficiency, researchers must carefully consider these factors when designing and training trajectory prediction models for autonomous vehicles.

Deep Q-Networks DQNs are a type of reinforcement learning algorithm that can be used for decision-making in autonomous vehicles. However, they can suffer from the overestimation bias and may be limited to discrete action spaces. Balancing exploration and exploitation is also a critical challenge in DQN-based learning. The DDQN model, introduced in [46], aims to address some of the limitations of traditional DQNs. While it offers improvements in terms of performance, it also comes with its own challenges. The DDQN model is generally more complex than traditional DQNs, requiring more computational resources and training time. There is also a risk of overfitting, where the model becomes overly specialized to the training data and struggles to generalize to new, unseen data. Moreover, the DDQN model's ability to generalize to new environments, particularly in rapidly changing traffic conditions, might be limited. Overall, while DQN and DDQN models show promise for AV lane-changing decisions, addressing the challenges associated with these techniques, such as overestimation bias, discrete action spaces, exploration-exploitation balance, complexity, generalization, data scarcity, and safety, is crucial for their successful deployment in real-world applications.

To address these challenges, researchers must focus on data augmentation, developing more efficient deep learning architectures, adversarial training, improving graph construction techniques, advancing reinforcement learning algorithms, utilizing hardware acceleration, and developing frameworks for safety and ethics in autonomous vehicles.

V. Conclusion

AI integration in AV's offers significant potential to enhance road safety in mixed traffic environments. This review examined various AI techniques for behavior prediction, including machine learning methods like Support Vector Machines (SVMs) and Random Forests, and deep learning techniques such as Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Graph Neural Networks (GNNs), and Double Deep Q Networks (DDQNs). These approaches improve AV's' ability to predict and adapt to diverse road user behaviors, enhancing decision-making and safety. Machine learning models like SVMs and Random Forests provide robust frameworks for predicting driving intentions. Deep learning methods, including CNNs and LSTMs, help analyze complex data for better response to dynamic traffic scenarios. GNNs and DDQNs further advance decision-making under uncertainty. Despite these advancements, human behavior's complexity and unpredictability pose ongoing challenges. Future research should incorporate multidisciplinary approaches and real-time data processing to improve prediction accuracy. Overall, AI-driven AV technology shows promise in reducing road traffic accidents and enhancing safety.

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