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Vehicle Trajectory Prediction Using Deep Learning for Advanced Driver Assistance Systems and Autonomous Vehicles

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Abstract—Vehicle trajectory prediction is essential for advanced driver assistance systems (ADAS) and autonomous vehicles (AVs), playing a crucial role in collision avoidance, path planning, and traffic control. Traditional models often overlook the variability in driver behavior, particularly in braking patterns, which significantly impacts trajectory predictions. Our study introduces an improved trajectory prediction model that uses Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks while considering driver braking patterns along with vehicle dynamic information. The models' accuracy is evaluated in a simulated environment that replicates real-world driving conditions. This environment captures comprehensive vehicle dynamics data, encompassing critical parameters such as position, rotation, acceleration, speed, and braking patterns. To ensure a realistic and varied dataset, data were meticulously gathered from 17 drivers, each utilizing a driving simulator equipped with the Euro Truck Simulator software. The model was implemented and validated using Python 3.9, Google Colab, and Scikit-learn, selected for their robustness in deep learning applications. Our results indicate that incorporating braking patterns significantly improves position predictions, outperforming the existing models based solely on vehicle dynamic data. This was evident by a notable decrease in Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) when braking patterns were incorporated. This advancement strengthens trajectory prediction systems for ADAS and AVs, enhancing operational safety.

Keywords— *Vehicle Trajectory Prediction, Braking Patterns, Autonomous Vehicles, Deep Learning Algorithms, Road Safety*

I. INTRODUCTION

Vehicle trajectory prediction is a pivotal element in the evolution of Advanced Driver Assistance Systems (ADAS) and Autonomous Vehicles (AVs), playing a vital role in enhancing transportation safety and efficiency. Accurate prediction of trajectories of human-driven vehicles is fundamental for effective collision avoidance, path planning, and traffic management [1]. The increase in sensing technologies, including GPS, LIDAR, and cameras, has resulted in abundant high-quality data on dynamic vehicle behaviour. Consequently, researchers have turned to deep

learning techniques to harness this data for accurate vehicle trajectory prediction [2], [3].

In recent years, deep learning has exhibited substantial potential in vehicle trajectory prediction [4], [5]. Deep learning models, particularly Long Short-Term Memory (LSTM) models, have adeptly captured intricate patterns and trends in data, yielding precise predictions of a vehicle's future trajectory [6] and motion [7]–[10]. A notable advantage of deep learning-based models lies in their capability to handle time series data, a critical aspect for capturing the sequential nature of vehicle positions [11]. Numerous studies have highlighted the efficacy of deep learning models for vehicle trajectory prediction. For instance, Benterki et al.[5] introduced a model that uses LSTM and Gated Recurrent Network (GRU) to predict vehicle trajectories based on historical GPS data and vehicle dynamics. The model demonstrated robust performance when evaluated on the publicly available Next-Generation Simulation (NGSIM) dataset, comprising real-world traffic data collected from various US highways as part of the NGSIM program by the Federal Highway Administration (FHWA) [12]. Similarly, Yang et al. [13] devised a model employing LSTM-RNNs for long-term trajectory prediction, leveraging vehicle dynamics and historical GPS data, and reported high accuracy with the NGSIM dataset.

Previous research on trajectory prediction has predominantly utilized the NGSIM dataset to forecast vehicle trajectories [6], [14], [15]. However, these models' dependency on the NGSIM dataset confines their predictive scope to highway scenarios, neglecting the intricate dynamics of roundabouts and intersections within urban environments. We have developed a CNN-LSTM model to overcome existing limitations, trained across various road scenarios. This model has demonstrated precise trajectory prediction capabilities [16], [17]. However, an aspect not previously included is considering human driver behaviour in the predictive process. Drivers are not just operators executing commands; they actively engage with and respond to the dynamic road environment, processing information and making decisions influenced by a complex mix of internal and external factors. For instance, driving braking patterns reflect

the geometry of the road, underscoring their necessity in vehicle trajectory prediction models. Human behaviour, especially braking patterns, has effectively captured a driver's behaviour and intentions [18], [19]. In their trajectory prediction study on takeover behaviour, Yu et al. [20] have incorporated the binary status of braking lights (on or off), a feature typically indicative of a vehicle's parking status rather than the actual braking pressure. Yet, comprehensive integration of the entire range of braking patterns for predicting vehicle trajectories and driving behaviour in various scenarios remains unexplored. Our study aims to fill this gap to provide a more accurate trajectory prediction. To fulfill this, an experiment involving 17 participants using a driving simulator was conducted [21]. Driving simulators vary in their complexity, with some featuring sophisticated motion cueing algorithms designed to offer a natural driving experience to the users [22]–[32]. Vehicle data and driver braking patterns for diverse scenarios were collected using a stationary driving simulator and the Euro Truck Simulator software. The proposed method adopts LSTM and GRU networks, which have proven effective in Trajectory prediction [5], [13]. The LSTM and GRU models feature layers designed to capture long-term temporal patterns, crucial for forecasting future vehicle positions. The dataset encompasses a variety of driving scenarios, including left turns, lane changes, and interactions at intersections, thereby extending the model's applicability across diverse conditions rather than being limited to isolated cases. Such a method improves the model's ability to generalize and maintain robust performance, marking a significant advancement in the effort to create more encompassing and dependable vehicle trajectory prediction systems within the domain.

This paper is structured in the following manner: Section II explores the research approach, including the procedure for collecting data, data preprocessing techniques, and the model proposed for predicting vehicle trajectories. The effectiveness of the proposed model in making precise predictions is examined in Section III. Section IV concludes the paper with final remarks.

II. METHODOLOGY

This section outlines the methods used for data collection, describes the proposed model, details the data preprocessing and preparation steps, introduces the performance metrics used in the study, and explains the implementation of the LSTM and GRU models proposed.

A. Data Collection

This study utilised a Next Level Racing Motion Platform V3 to create an environment resembling real-world driving conditions, enhancing the participant experience [21]. The motion functionality of the platform was deactivated throughout the research to maintain uniformity among the participants and mitigate the risk of motion sickness due to unforeseen movements. For a more genuine driving experience, the Logitech G920 Driving Force Racing Wheel was employed to simulate actual steering and braking actions [33]. The chosen simulation environment for this project was the Eurotruck driving simulator, which had been adapted for car simulations [34]. Additionally, future research will explore the integration of a Universal Motion Simulator and a Motion Cueing Algorithm [35]–[44]. A triple-screen monitor setup provided participants a 180-degree visual field, facilitating



Fig. 1. The setup of the experiment.

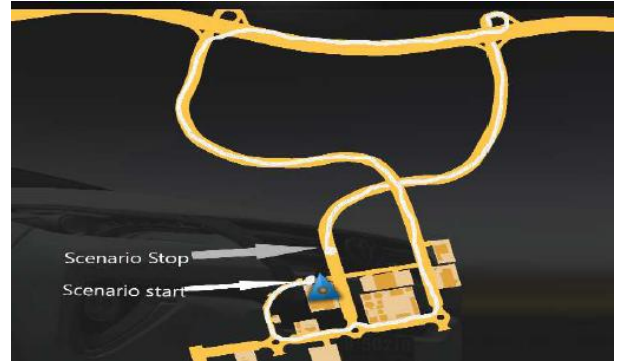


Fig. 2. The driving road map utilized in this study.

natural head movements and deeper immersion in the virtual setting. The experimental setup is shown in Fig. 1 [16].

Vehicle dynamics information, including longitudinal, vertical, and latitudinal positioning, rotation, acceleration, speed, and braking patterns, was gathered for all participants using the Eurotruck driving simulator software. The research included 25 healthy participants aged 19 to 40, with an average age of 32.7 and a standard deviation of 8.96. Each participant had previous driving experience and held a valid driver's license. Including participants with prior driving experience was essential to guarantee their understanding of basic driving principles. Before the study, these individuals completed questionnaires about their driving history and demographic information. They were also evaluated for motion sickness susceptibility using the Simulator Sickness Questionnaire (SSQ) [45]–[48]. The study did not include participants susceptible to motion sickness [49] or with significant vision impairments. The research was conducted with the endorsement of the Human Ethics Advisory Groups (HEAGs) at Deakin University. During the experiment, drivers navigated from one location to another using a map. This map showcased a range of road conditions, such as highways, roundabouts, intersections, and turns, as shown in Fig. 2 [16].

B. Model Description and Hyperparameters

LSTM:

LSTMs, a subset of Recurrent Neural Networks (RNNs), excel in learning and retaining long-term dependencies. First introduced by Hochreiter and Schmidhuber [50]. LSTMs have undergone various enhancements. These networks are widely recognized for their effectiveness across numerous applications. RNNs are constructed from a sequence of repetitive neural network modules. In standard RNNs, this module often comprises a simple structure like a single tanh layer. However, LSTMs deviate in their structure, adopting a

chain-like form but with a more complex repeating module. Rather than having just one neural network layer, an LSTM module includes four interacting layers. The core components of a basic LSTM unit encompass an input gate, an output gate, and a forget gate. These elements enable the LSTM cell to retain information for an extended period. The input and output gates are instrumental in managing the influx and release of data from the LSTM cell. The three memory cell gates are operated according to the eqs. (1)-(6) at each time step t .

$$f_t = \sigma(W_f \cdot [h_t - 1, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_t - 1, x_t] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_t - 1, x_t] + b_C) \quad (3)$$

$$C_t = f_t * \tilde{C}_t - 1 + i_t * \tilde{C}_t \quad (4)$$

$$O_t = \sigma(W_O \cdot [h_t - 1, x_t] + b_O) \quad (5)$$

$$h_t = O_t * \tanh(C_t) \quad (6)$$

where f_t , i_t , and O_t are the activation functions of the forget, input and output gates at each time step t , respectively. W_f , W_i , W_C , W_O , b_f , b_i , b_C , and b_O are their respective weights and biases. $\tilde{C}_t$ is the candidate value for the memory cell state C_t at time t and x_t and h_t are the memory cell input and final output, respectively.

GRU:

GRU (Gated Recurrent Unit), like LSTM, is designed for sequential data processing. Its ability to selectively retain or discard information over time stands out. What sets GRU apart from LSTM is its simpler architecture, which involves fewer parameters. This makes GRU easier to train and enhances its computational efficiency. The primary distinction between GRU and LSTM lies in their handling of memory. In LSTM, a distinct memory cell state is controlled by three gates - the input, output, and forget gates.

Fig. 3 shows the GRU unit architecture. Conversely, GRU replaces this memory cell state with a "candidate activation vector." Two gates govern the updating of this vector: the reset gate and the update gate using eqs. (7)-(10)

$$r_t = \sigma(W_r \cdot [h_t - 1, x_t] + b_r) \quad (7)$$

$$u_t = \sigma(W_u \cdot [h_t - 1, x_t] + b_u) \quad (8)$$

$$\tilde{C}_t = \tanh(W_C \cdot [r_t * u_t - 1, x_t]) \quad (9)$$

$$C_t = r_t * h_t - 1 + (1 - z_t) * \tilde{C}_t \quad (10)$$

where r_t , u_t , are the reset gate and update gate each time step t , respectively. W_r , W_u , b_r , b_u are their respective weights and biases. $\tilde{C}_t$ is the candidate value for the memory cell state C_t at time t . x_t and h_t are the memory cell input and final output, respectively.

This study configures the GRU and LSTM models with specific hyperparameters: The LSTM and GRU layer have 14 units, indicating a model capable of capturing complex patterns. The activation function is 'tanh', normalising neuron outputs to a range between -1 and 1. A dense layer with 3 neurons follows the LSTM layer for output mapping. The model's performance is measured using the Mean Squared Error loss function, and optimisation is carried out using the

Adam algorithm. The training process involves 10 epochs, each processing the training dataset once. The batch size is set

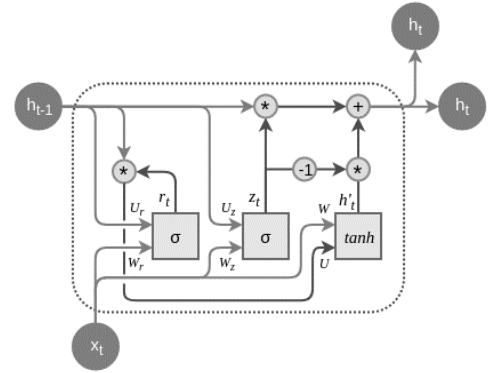


Fig. 3. The structure of the GRU.

to 1, meaning the model updates after each training example. Verbosity is at level 1, providing essential training progress details. Early stopping is employed to prevent overfitting, monitoring the validation loss and stopping the training if there's no improvement in this loss for 10 consecutive epochs. These hyperparameters are crucial in defining the model's learning process and ability to generalise from the training data. The manually optimised hyperparameters for the LSTM and GRU models are summarised in Table I.

C. Data Preprocessing and Preparation

In this research, 25 participants were initially recruited. However, after detailed screening, eight individuals were found to have visual impairments and a tendency to experience motion sickness, leading to their exclusion. This resulted in a reduced sample size of 17 participants. Before inputting into the model, the data gathered from these participants underwent preprocessing, which involved aligning, formatting, and standardising the data. The alignment step was crucial to ensure data comparability, where the X, Y, and Z positions on the map were used to accurately locate each subject's data points. The final dataset consisted of 50,949 samples divided into different portions for training, validation, and testing. Specifically, 70% (35,664 samples) was used for training, 20% (10,190 samples) for validation, and the remaining 10% (5,095 samples) for evaluating the model's performance.

Data Standardisation:

The Z Score, or Standard Score, is a method used to standardise the values of an attribute into a consistent range. This standardisation is a crucial preprocessing step in statistical analysis, machine learning, and deep learning, as it minimises the effects of varying scales and ranges among data points. This process involves transforming each data point by subtracting the mean of the distribution and then dividing by

TABLE I
THE HYPERPARAMETERS OF THE INVESTIGATED MODELS

hyperparameter	Value
LSTM and GRU Layer	14
Activation	Tanh
Dense Layer	3
Loss Function	Mean Square Error
Optimizer	Adam
Epochs	10
Batch Size	1
Verbosity	1
Early Stopping Monitor	Validation loss
Early Stopping Patience	10

the standard deviation. Such standardisation leads to improved accuracy and generalisation in models. After aligning, formatting, and standardising the data, it was combined by concatenating the datasets from each subject, allowing for integrating multiple subjects' data into the model.

Transforming Data for Supervised Learning:

The initial step following data importation is to verify that the data are correctly formatted and structured, enabling effective learning by the model. In our study, the goal is to train a model capable of leveraging 500 historical data points (equivalent to 25 seconds) to make accurate predictions about the signal 5 seconds into the future. We utilize a sliding window of 500 past samples as the model's historical data to forecast one future time step. After making a prediction for the next time step, the model adjusts by shifting one step forward, allowing for continuous, auto-recursive forecasting. This involves incorporating the predicted 500th time step back into the input, repeating this cycle throughout the dataset's duration. Equations 11 and 12 provide an illustration of the initial input-output sequence respectively.:

$$\begin{bmatrix} P_{x0} & P_{y0} & P_{z0} & a_{x0} & a_{y0} & a_{z0} & r_{x0} & r_{y0} & r_{z0} & s_1 & b_1 \\ P_{x1} & P_{y1} & P_{z1} & a_{x1} & a_{y1} & a_{z1} & r_{x1} & r_{y1} & r_{z1} & s_2 & b_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ P_{x499} & P_{y499} & P_{z499} & a_{x499} & a_{y499} & a_{z499} & r_{x499} & r_{y499} & r_{z499} & s_{500} & b_{500} \end{bmatrix} \quad (11)$$

Here P_{xi} , P_{yi} , P_{zi} : denote the vehicle's X, Y, and Z position coordinates at the i th timestep. While a_{xi} , a_{yi} , and a_{zi} specify the acceleration components in the X, Y, and Z directions. Moreover, r_{xi} , r_{yi} , and r_{zi} represent the angular displacements or rotations around the X, Y, and Z axes and s_i represent the overall vehicle speed. For the driver control inputs b_i represent the braking patterns at the i th timestep. Braking patterns are represented as a signal ranging from zero to one, indicating the amount of pressure the driver applies, and are incorporated into the model. The output is represented by:

$$[P_{x500} \ P_{y500}] \quad (12)$$

Following the model's training phase, it is evaluated using a set of test data. The model is tasked with predicting 100 future timesteps, equivalent to a prediction span of 5 seconds. Subsequently, the predicted data are transformed back to their original format for a direct comparison against the real data, serving as a measure to gauge the model's accuracy and effectiveness.

D. Performance Metrics

The model's performance is evaluated using three key metrics: Root Mean Square Error (RMSE), Pearson's Correlation coefficient (r), and Mean Absolute Error (MAE). RMSE measures the standard deviation of prediction errors, indicating how close predictions are to actual values. Pearson's r assesses the linear relationship between predicted and actual values, with positive or negative values indicating direct or inverse relationships, respectively. MAE provides an average magnitude of prediction errors, offering a straightforward representation. Together, these metrics comprehensively assess the model's accuracy and predictive capability.

III. RESULTS AND DISCUSSIONS

This section provides a detailed comparison of the proposed LSTM and GRU models for predicting vehicle trajectories, including the consideration of driver braking patterns. The comparison begins with an assessment of the computational requirements for training the proposed models.

It then rigorously evaluates the models' precision in predicting vehicle movements, using RMSE, MAE, and r as the primary measures of effectiveness.

A. Computational Load Performance and Analysis

The models were developed using Python version 3.9 and were constructed on Google Colab, a cloud computing service that enables the execution of Python code in a Jupyter notebook setting. This platform provides access to a Tesla K80 GPU, equipped with 12 GB of memory, facilitating enhanced computational capabilities. During the training, it was noticed that there were some differences in computational demands between LSTM and GRU models, especially when incorporating braking patterns. The standard LSTM model required a total training time of 2,997 seconds (299.7 seconds per epoch), while adding braking patterns increased this to 3,043 seconds (304.3 seconds per epoch), indicating the additional complexity of the data. With its more straightforward structure, the GRU model showed greater efficiency, completing training in 2,890 seconds (289.0 seconds per epoch) for the standard model and 2,903 seconds (290.3 seconds per epoch) with braking patterns. This suggests that GRUs are more adept at handling complex data with better computational efficiency, making them suitable for resource-constrained environments requiring complex data processing.

B. Trajectory Prediction Performance

Table II provides a comparison of how well the proposed deep-learning models can predict vehicle trajectory, taking into account both vehicular data and drivers' braking patterns. This comparison specifically looks at the accuracy of predicting vehicles' longitudinal and lateral positions using both LSTM and GRU models.

Table II illustrates that the LSTM model performs better than the GRU in predicting vehicle trajectory. This is evident from its lower RMSE (0.47 longitudinal, 0.80 lateral) and MAE (0.41 longitudinal, 0.72 lateral) compared to the GRU's RMSE (1.10 longitudinal, 1.40 lateral) and MAE (0.94 longitudinal, 1.38 lateral). At the same time, both maintain a high correlation coefficient ($r = 0.99$).

Incorporating braking patterns significantly enhances the predictive accuracy of both models. The LSTM+B model shows a marked improvement, with RMSE reducing to 0.34 (longitudinal) and 0.53 (lateral) and MAE to 0.29 (longitudinal) and 0.50 (lateral). The GRU+B model also exhibits improved accuracy, which is evident from the reduced RMSE (0.39 longitudinal, 0.42 lateral) and MAE (0.36 longitudinal, 0.33 lateral). All models' correlation coefficient remains consistently high ($r = 0.99$).

Meanwhile, Figs. 4a-b shows the prediction results for both models using only vehicle dynamics data and Figs. 4c-d illustrate the prediction results for LSTM and GRU, but with the inclusion of braking patterns to vehicle dynamics. Fig. 5

TABLE II
THE PERFORMANCE OF THE PROPOSED MODELS

Category	Vehicle trajectory (positions) prediction					
	Longitudinal Position			Lateral Position		
	RMSE	MAE	r	RMSE	MAE	r
LSTM	0.47	0.41	0.99	0.80	0.72	0.99
GRU	1.10	0.94	0.99	1.40	1.38	0.99
LSTM+B	0.34	0.29	0.99	0.53	0.50	0.99
GRU+B	0.39	0.36	0.99	0.42	0.33	0.99

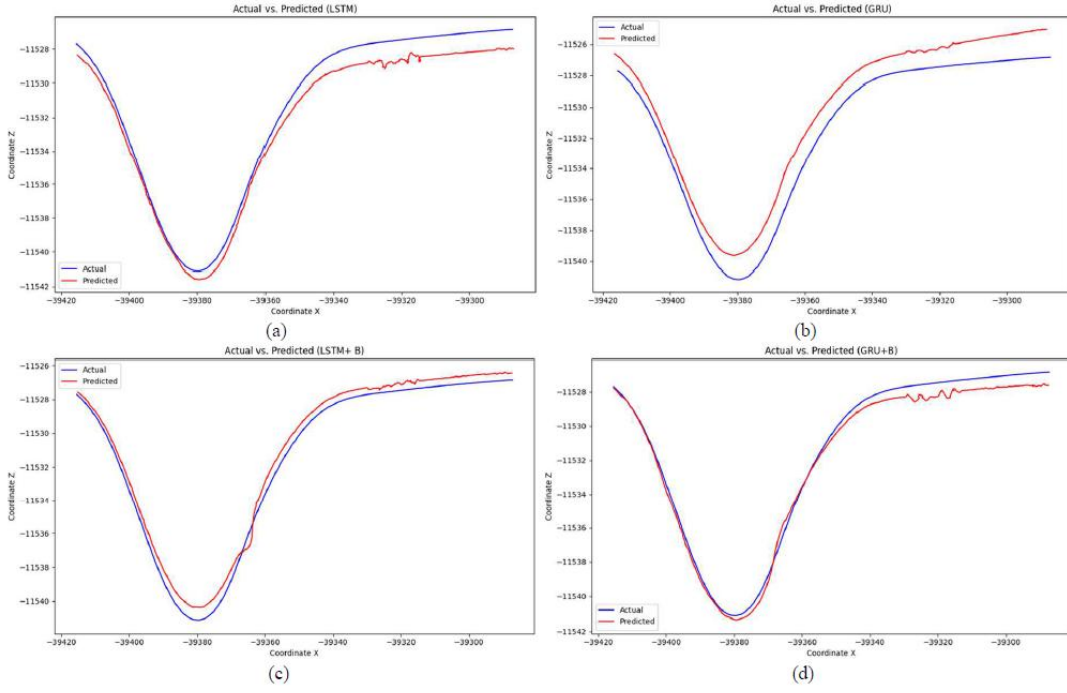


Fig. 4. The prediction results for (a): LSTM model using vehicle dynamics data; (b) GRU model using vehicle dynamics data; (c): LSTM model using braking patterns +B; (d) GRU model using braking patterns +B; l

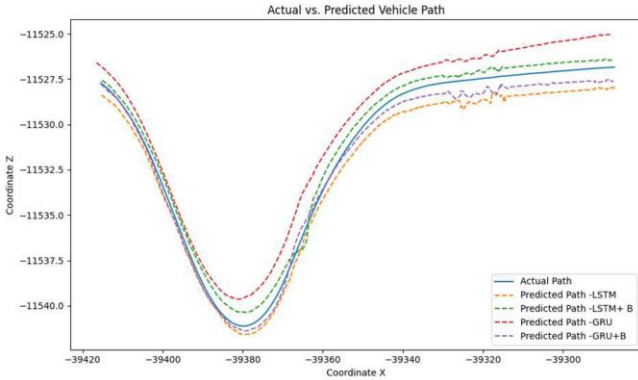


Fig. 5. The prediction results for LSTM and GRU models using braking patterns +B and only vehicle dynamics data..

compares these predictions, and it is clear from the visual representation that incorporating braking patterns significantly enhances the accuracy of the predictions.

These results suggest that while the LSTM model is inherently more accurate in vehicle trajectory prediction than the GRU model, adding braking patterns as a feature significantly enhances both models' performance. The LSTM, both standard and with braking patterns, consistently demonstrates lower RMSE and MAE values, indicating its higher precision in trajectory prediction. The GRU models, particularly with the inclusion of braking patterns, show notable improvement, although not to the same extent as the LSTM models.

The high correlation coefficients across all configurations affirm the strong linear relationship between the predicted and actual trajectory values, indicating the reliability of these models in trajectory prediction tasks. The enhanced performance with braking patterns underscores the importance of considering driver-specific behaviours in trajectory prediction models, especially for applications like

advanced driver assistance systems (ADAS) and autonomous vehicles (AVs) [51]–[53], where accuracy and reliability are paramount.

IV. CONCLUSION

In conclusion, this study introduces a novel approach to vehicle trajectory prediction essential for improving driver assistance systems and autonomous vehicles. This is to address the problem associated with the existing vehicle trajectory prediction models, which were solely based on vehicle dynamic information.

Our approach integrates driver braking patterns into LSTM and GRU network models while still considering vehicle dynamic data such as position, rotation, acceleration and speed. This integration has notably improved the accuracy of both longitudinal and lateral position predictions. This enhancement addresses the shortcomings of traditional trajectory prediction models by incorporating driver behaviour variability, an aspect often overlooked in previous models. This advancement in trajectory modelling not only increases the accuracy of predictions but also makes a substantial contribution to the field of vehicular technology, with a particular focus on enhancing safety and operational efficiency. Data for this study was collected from 17 drivers using a driving simulator. The validation was conducted using Python 3.9 and Google Colab. The results show that including braking patterns in LSTM and GRU models along with vehicle dynamic data enhances prediction accuracy, demonstrating the importance of driver-specific behaviours in trajectory modelling, especially for ADAS and AV applications.

In upcoming research, enhancing our trajectory prediction model's accuracy and robustness will involve integrating supplementary data sources, such as physiological [54], [55] and environmental factors. Additionally, we will explore further prediction techniques to optimize the performance of the proposed model [56]–[65]. Developing comprehensive and context-aware models is pivotal in adapting to various

driving environments and scenarios. This would significantly enhance the safety and operational efficiency of advanced driver assistance systems and autonomous vehicles, aligning with the ongoing evolution in this dynamic field of transportation technology. Moreover, the implementation of advanced motion simulation technologies equipped with the latest motion cueing algorithms [66]–[74] will be a focal point for subsequent studies. This strategy aims to significantly enhance the fidelity of simulated driving experiences, thus improving the efficacy of testing and validation for trajectory prediction models in conditions that closely mimic real-world driving situations. Beyond this, the exploration of other trajectory prediction techniques will also be prioritized to evaluate their comparative effectiveness against the method proposed in the current research.

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