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# A secure and intelligent framework for autonomous driving : Enhancing vehicle trajectory prediction with LSTM-XGboost model

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## Abstract

Autonomous driving, particularly when it involves smart decision-making and path planning in dynamic settings such as highways, presents far greater challenges compared to navigating static environments. This research paper investigates the effectiveness of various machine learning models in predicting the trajectories of surrounding vehicles, focusing on the personalized framework using LSTM-XGboost model. In this research, we have categorized the vehicles NGSIM dataset into Traditional, Moderate, and Aggressive driving styles to assess model performance using RMSE and MAE metrics across different prediction horizons (1- 5 seconds). The results demonstrate that the LSTM-XGboost model consistently outperforms other baseline models, including GNN, LSTM, GBM-LSTM, and ARIMA, in all vehicle categories. Notably, the personalized LSTM-XGboost model, tailored to specific vehicle categories, yields significantly better prediction accuracy compared to the overall dataset. This research highlights the potential of advanced machine learning models for improving vehicle trajectory predictions and underscores the importance of vehicle categorization for enhancing model performance.

***Subject Classification:*** *Primary 93A30, Secondary 49K15.*

***Keywords:*** *Autonomous driving, Vehicle trajectory prediction, Secure communication systems, Intelligent transportation, LSTM-XGboost.*

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## 1. Introduction

Navigating urban environments securely is a formidable challenge for self driving systems due to the complex nature of traffic scenarios that involve a diverse array of participants, including vehicles and pedestrians. Precisely modeling, understanding, and predicting the behaviors of these participants are crucial for enhancing the security, path planning, and control of self driven vehicles [1]–[4]. Traditional approaches to vehicle trajectory prediction often rely on kinematic models or physics-based simulations. While these methods have been instrumental in advancing the field, they may fail to capture the intricate and stochastic nature of real-world driving behaviors [5]-[6].

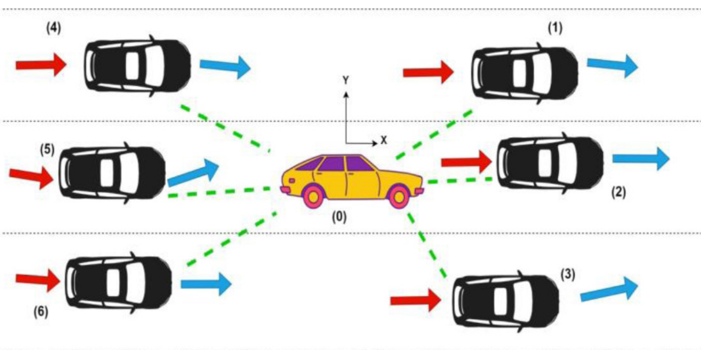


**Figure 1**

**Driving scenario of the vehicles on road.**

As illustrated in Figure 1, the vehicle painted yellow is designated as the ego vehicle with index (0), while the vehicles colored black, indexed from (1 to 6), represent the surrounding vehicles. The historical trajectory is depicted by the red line, whereas the blue line indicates the model's predicted trajectory. The interactions among ego & surrounding vehicle are shown by green colored dashed line. [7]

In recent years, data-driven approaches leveraging machine learning techniques have gained significant traction in addressing the complexities of vehicle trajectory prediction [3]-[7]. However, existing data-driven methods often lack the capability to effectively model the temporal dependencies and individualized patterns inherent in vehicle trajectory data. To address these limitations, this study proposes a novel framework that synergistically combines the strengths of LSTM networks and XGboost models for estimating the future path of the surrounding vehicles. LSTM networks, a variant of recurrent neural networks, are highly effective at recognizing sequential dependencies and analyzing temporal patterns, which makes them ideal for tasks that involve predicting trajectories of vehicles [8]. The synergistic combination of LSTM networks and XGboost models in our proposed framework allows for the simultaneous modeling of temporal dependencies and driver-specific patterns, finally increasing the accuracy and reliability of the trajectory predictions.

## 2. Literature Review

In recent times, deep learning methods have shown remarkable success in addressing the complex task of vehicle trajectory prediction.

Zhao [9] proposed a multi-stream LSTM network that incorporates various input modalities, including vehicle kinematics, road geometry, and surrounding vehicle information. However, their study did not explicitly consider personalized modeling or driver-specific characteristics.

Yuan et al. [10] introduced a driver-aware LSTM model that incorporates driver identity information into the network architecture. Their approach achieved promising results on public datasets, suggesting the potential benefits of personalized modeling for trajectory prediction.

Ensemble learning techniques have been explored to further enhance prediction performance. Xin and Zhang [11] developed a hybrid framework that combines LSTM networks with gradient boosting decision trees (GBDTs). However, their study did not incorporate personalized modeling or address the variability in driving styles.

Hu [12] discussed a personalized trajectory forecast model that combines LSTM networks with Gaussian mixture models (GMMs). Their framework models individual driving styles allowing for personalized trajectory predictions. While this approach accounts for personalization, it may struggle to capture complex, nonlinear relationships in trajectory data effectively.

Jiang [13] introduced an XGboost-based model for vehicle trajectory prediction, leveraging various handcrafted features and spatial-temporal information. Their approach demonstrated promising results on public datasets but did not explicitly consider personalized modeling or incorporate temporal dependencies using deep learning techniques.

While the existing work in this area offers important insights and contributions, there remains a need for much efficient framework that seamlessly integrates personalized modeling, captures temporal dependencies, and leverages the strengths of both deep learning and ensemble learning techniques. Our proposed approach aims to bridge this gap by combining LSTM networks and XGboost models, enabling accurate and personalized trajectory predictions for autonomous driving applications.

## 3. Experimentation

The figure 2 outlines a framework for vehicle trajectory prediction using a series of steps, including data preprocessing, driving style recognition, model training (LSTM and XGboost), and ensembling.

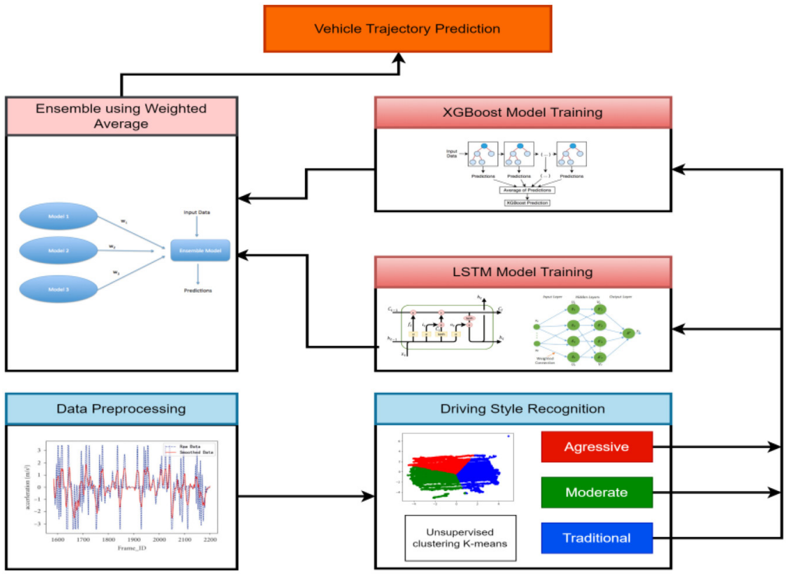


**Figure 2**

**Proposed framework to predict the trajectory of the nearby vehicles**

**Data Preprocessing:** Data preprocessing involves normalization and noise reduction, typically using techniques such as z-score normalization and moving average filters. The normalization can be mathematically represented as:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{1}$$

Where $x_i$ represents the original value, μ denotes the mean of dataset, and the standard deviation is denoted by σ. For noise reduction, a simple moving average might be applied:

$$MA_t = \frac{1}{k} \sum_{n=t-k+1}^{t} x_n \tag{2}$$

Where, $MA_t$ denotes the moving average at certain time t, $x_n$ denotes the data points, and k refers to the number of periods considered in the moving average.

**Driving Style Recognition:** Unsupervised clustering using K-means can be described as minimizing the sum of squares within-cluster. The objective function J is given by:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n_j} \left\| x_i^{(j)} - c_j \right\|^2 \tag{3}$$

In equation 3, k represents the number of clusters, $n_j$ refers to the number of observations in j-th cluster, $x_i^{(j)}$ are the data points in j cluster, and $c_j$ represents the centroid of cluster j.

**Model Training using LSTM & XGboost:** The LSTM cell operations include gates that regulate the flow of information. The key operations within an LSTM unit can be mathematically described as:

$$\text{Forget Gate:} \quad f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$

$$\text{Input Gate:} \quad i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

$$\text{Output Gate:} \quad o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$\text{Cell State Update:} \quad C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{7}$$

$$\text{Output:} \quad h_t = o_t * \tanh(C_t) \tag{8}$$

XGboost involves creating multiple decision trees and boosting weaker learners. The updating of the model uses the following gradient boosting framework:

$$\theta^{(t+1)} = \theta^{(t)} - \eta \sum_{i=1}^{n} \nabla_{\theta^{(t)}} L(y_i, f^{(t)}(x_i)) \tag{9}$$

where L is the loss function, $\nabla_{\Theta}^{(t)} L$ is the gradient of the loss, η is the learning rate, $y_i$ are the target values, and $f^{(t)}$ is the prediction of the model at iteration t.

**Ensemble using Weighted Average:** An ensemble model is created using a weighted average of the predictions from multiple models (LSTM & XGboost). The final ensemble prediction is a weighted sum of individual model outputs, optimized based on model performance:

$$\hat{y} = \sum_{m=1}^{M} w_m \hat{y}_m \tag{10}$$

where $\hat{y}_m$ are the predictions from each model and $w_m$ are the weights corresponding to the model's performance, satisfying

$$\sum_{m=1}^{M} w_m = 1 \tag{11}$$

**Vehicle Trajectory Prediction:** The final step involves using the ensemble model to predict the vehicle trajectory error. The predictions from LSTM and XGboost models, along with the ensemble's aggregated output, provide a robust estimation of the trajectory errors.

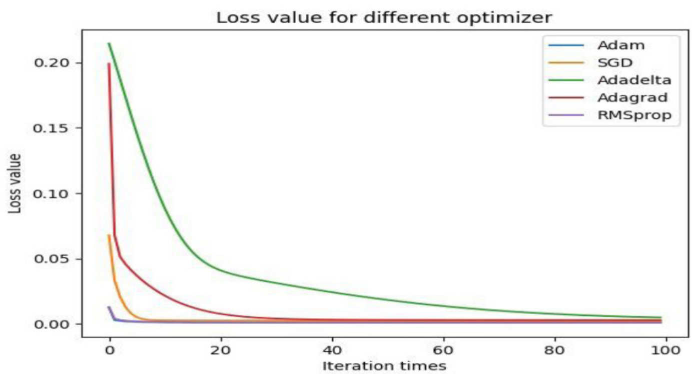


**Figure 3**

**Loss value versus iteration time for various optimizers**

Figure 3 illustrates the loss values for different optimizers. The graph shows that Adam converges the fastest and reaches the lowest loss value in the least amount of time. RMSProp also converges quickly but not as fast as Adam. SGD and Adagrad show moderate convergence speeds. Adadelta has the slowest convergence and the highest loss value. The rapid convergence and minimal loss value of Adam make it the most effective optimizer among the ones compared.

## 4. Results

The following table 1 summarize the prediction performance of various models for vehicle trajectory prediction across different vehicle categories: Traditional, Moderate, and Aggressive, using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics. The models compared are Graph Neural Network (GNN), Long Short-Term Memory (LSTM), Gradient Boosting Machine with LSTM (GBM-LSTM), Autoregressive Integrated Moving Average (ARIMA), and the proposed LSTM-XGboost.

**Table I**

**Comparative performance metrics of various models across prediction horizons in Traditional, Moderate, Aggressive & Aggregate vehicle category**

| Vehicle Category (Traditional) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Models** | **Prediction Horizon (RMSE)** | | | | | **Prediction Horizon (MAE)** | | | | |
| | **1 s** | **2 s** | **3 s** | **4 s** | **5 s** | **1 s** | **2 s** | **3 s** | **4 s** | **5 s** |
| **GNN** | 0.25 | 0.28 | 0.27 | 0.26 | 0.23 | 0.21 | 0.24 | 0.23 | 0.22 | 0.19 |
| **LSTM** | 0.1 | 0.1 | 0.09 | 0.1 | 0.1 | 0.08 | 0.08 | 0.07 | 0.08 | 0.08 |
| **GBM-LSTM** | 0.08 | 0.08 | 0.08 | 0.09 | 0.08 | 0.04 | 0.04 | 0.04 | 0.05 | 0.05 |
| **ARIMA** | 0.05 | 0.1 | 0.15 | 0.21 | 0.26 | 0.04 | 0.09 | 0.13 | 0.18 | 0.23 |
| **LSTM-XGboost** | 0.04 | 0.03 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| **Vehicle Category (Moderate)** | | | | | | | | | | |
| **Models** | **Prediction Horizon (RMSE)** | | | | | **Prediction Horizon (MAE)** | | | | |
| | **1 s** | **2 s** | **3 s** | **4 s** | **5 s** | **1 s** | **2 s** | **3 s** | **4 s** | **5 s** |
| **GNN** | 0.5 | 0.47 | 0.45 | 0.46 | 0.46 | 0.45 | 0.42 | 0.41 | 0.41 | 0.42 |
| **LSTM** | 0.28 | 0.21 | 0.18 | 0.16 | 0.16 | 0.14 | 0.11 | 0.1 | 0.09 | 0.1 |
| **GBM-LSTM** | 0.03 | 0.06 | 0.06 | 0.07 | 0.07 | 0.02 | 0.04 | 0.03 | 0.04 | 0.04 |
| **ARIMA** | 0.04 | 0.08 | 0.12 | 0.16 | 0.2 | 0.03 | 0.07 | 0.1 | 0.14 | 0.17 |
| **LSTM-XGboost** | 0.02 | 0.02 | 0.03 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 |

| Vehicle Category (Aggressive) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Models** | **Prediction Horizon (RMSE)** | | | | | **Prediction Horizon (MAE)** | | | | |
| | **1 s** | **2 s** | **3 s** | **4 s** | **5 s** | **1 s** | **2 s** | **3 s** | **4 s** | **5 s** |
| **GNN** | 0.2 | 0.2 | 0.19 | 0.18 | 0.18 | 0.18 | 0.18 | 0.17 | 0.17 | 0.16 |
| **LSTM** | 0.13 | 0.12 | 0.11 | 0.1 | 0.1 | 0.1 | 0.09 | 0.09 | 0.08 | 0.08 |
| **GBM-LSTM** | 0.1 | 0.11 | 0.11 | 0.1 | 0.1 | 0.06 | 0.06 | 0.07 | 0.06 | 0.06 |
| **ARIMA** | 0.06 | 0.12 | 0.18 | 0.25 | 0.31 | 0.05 | 0.11 | 0.16 | 0.21 | 0.27 |
| **LSTM-XGboost** | 0.04 | 0.05 | 0.05 | 0.04 | 0.04 | 0.02 | 0.03 | 0.02 | 0.02 | 0.02 |

| Vehicle Category (Aggregate Dataset) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Models** | **Prediction Horizon (RMSE)** | | | | | **Prediction Horizon (MAE)** | | | | |
| | 1 s | 2 s | 3 s | **4 s** | **5 s** | **1 s** | **2 s** | **3 s** | **4 s** | **5 s** |
| **GNN** | 0.31 | 0.3 | 0.28 | 0.28 | 0.28 | 0.3 | 0.28 | 0.27 | 0.27 | 0.27 |
| **LSTM** | 0.11 | 0.12 | 0.12 | 0.11 | 0.11 | 0.11 | 0.1 | 0.1 | 0.1 | 0.1 |
| **GBM-LSTM** | 0.1 | 0.1 | 0.09 | 0.09 | 0.1 | 0.05 | 0.05 | 0.05 | 0.04 | 0.05 |
| **ARIMA** | 0.08 | 0.1 | 0.12 | 0.2 | 0.3 | 0.05 | 0.09 | 0.12 | 0.15 | 0.25 |
| **LSTM-XGboost** | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |

As depicted in the table 1, key findings of the result obtained are:

(a) Superior Performance of LSTM-XGboost: Across all vehicle categories and prediction horizons, the LSTM-XGboost model consistently outperforms other models. It achieves the lowest RMSE and MAE values, indicating higher accuracy in predicting the path of the vehicles around the autonomous vehicle. For instance, in the Traditional category, LSTM-XGboost maintains an RMS error of 0.03 metre and an MA error of 0.02 metre for prediction horizon of 1-5 second, significantly outperforming GNN, LSTM, GBM-LSTM, and ARIMA.

(b) Effectiveness of Vehicle Categorization: In the traditional Vehicle category LSTM-XGboost achieves the best output with the lowest RMS error of 0.03 m and MA error of 0.02 m. In moderate vehicles category, the model maintains excellent performance with an RMS error of 0.02 m and MA error of 0.02 m, demonstrating its robustness across varying vehicle behaviors. In aggressive vehicles category, the model continues to show superior accuracy with an RMSE & MAE of 0.04 m & 0.02 m respectively. When considering the entire dataset, LSTM-XGboost still outperforms other models with an RMSE of 0.04 m and an MAE of 0.03 m but less effective compared with categorized driving styles.

## 5. Conclusion & Future Scope

This research highlights the effectiveness of predictive models in vehicle trajectory forecasting, emphasizing a personalized LSTM-XGboost framework for secure autonomous driving. Our findings confirm that LSTM-XGboost surpasses models like GNN, LSTM, GBM-LSTM, and ARIMA across Traditional, Moderate, and Aggressive driving styles, achieving the lowest RMSE and MAE values for highly accurate predictions. The categorization of vehicles based on driving behavior significantly enhanced predictive accuracy, enabling reliable trajectory forecasting essential for safe autonomous systems. Future work could incorporate adaptive learning for continuous model updates, ensuring sustained accuracy amid evolving driving patterns, road conditions, and traffic. Integrating real-time data streaming could further enhance autonomous vehicle applications.

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