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Autonomous Vehicle Lane-Changing System using Light GBM

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Abstract

Traffic dynamics and autonomous vehicle navigation depend heavily on lane-changing behaviour. This paper introduces a machine learning-based method to predict lane-changing intentions using vehicle trajectory data and driver behaviour analysis. Our model achieves high accuracy while maintaining computational efficiency by utilizing the Gaussian Mixture Model (GMM) for driver behaviour clustering and LightGBM for lane-change classification. The system incorporates feature engineering, and hyperparameter optimization to improve prediction reliability. Our experimental results show that the suggested method significantly increases lane-change prediction accuracy, making it appropriate for real-time intelligent transportation systems. This project uses Pygame for visualization and LightGBM for decision-making to simulate an autonomous lane-changing car in real time. The simulation simulates actual traffic situations, with the autonomous car using trained machine learning models to assess the environment and decide whether to change lanes. Using factors such vehicle speed, acceleration, time-to-collision, relative velocity, and driving style—all of which are categorized using a Gaussian Mixture Model (GMM)—a pre-trained LightGBM model powers the decision-making process and forecasts the need for lane changes. This project offers insights into the viability and practical implementation issues of automated lane-changing technology.

Keywords: *Autonomous vehicle, Lane change, Gaussian Mixture Model (GMM), LightGBM, Pygame, Realtime Simulation.*

1. Introduction

1.1. Autonomous Vehicles

Self-driving automobiles, sometimes referred to as autonomous vehicles, are outfitted with sophisticated sensors, artificial intelligence, and control systems that enable them to travel and function without the need for human assistance. These cars sense their environment, identify impediments, and make judgments while driving in real time by using technology like LiDAR, radar, cameras, and GPS. Autonomous driving is classified into different levels (0-5) based on the extent of automation, ranging from driver assistance to full autonomy. By increasing mobility, lowering traffic, and improving road safety, autonomous vehicle development seeks to increase accessibility and efficiency in transportation.

1.2. Lane Changing in Autonomous Vehicles

In order to maintain efficiency and safety, lane change is a crucial component of autonomous driving that calls for exact decision-making. In order to identify surrounding traffic, evaluate gaps, and anticipate other drivers' intentions, autonomous cars rely on sensors like LiDAR, radar, and cameras. On the basis of variables including vehicle speed, acceleration, Time Headway (THW), and Modified Time to Collision (MTTC), machine learning models, such as Light GBM and deep learning networks, assist in forecasting lane-change intentions. Three crucial processes are involved in a good lane change: decision-making (figuring out if a change is required), trajectory planning (figuring out

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a safe route), and execution (smoothly switching to the new lane without getting into an accident). The capacity of autonomous vehicles to make human-like lane-change judgments while preserving safety and traffic flow is further improved by cutting-edge methods like reinforcement learning and driver behaviour modeling. [1]

1.3.Challenges in Lane Changing for Autonomous Vehicles

- **Uncertainty in Surrounding Vehicle Behavior:** It is difficult to predict human drivers' intentions (such as abrupt lane changes or aggressive driving). Making dangerous manoeuvres might result from misjudging a vehicle's behaviour.
- **Real-Time Decision Making:** Autonomous systems need to be able to quickly analyse a variety of elements, such as road conditions, gaps, acceleration, and vehicle speed. Lane changes may not be executed on schedule if there are computational delays.
- **Handling Dense and High-Speed Traffic:** It can be challenging to identify a safe lane change in dense traffic. Even little errors in judgment can lead to crashes when driving at high speeds.
- **Sensor Limitations and Environmental Factors:** The accuracy of LiDAR, radar, and cameras can be impacted by unfavourable weather conditions, such as fog, rain, or snow. Inaccurate lane detection may result from obscured objects (such as big trucks) and poor road markers.
- **Ethical and Legal Considerations:** Ethical issues must be taken into account while making decisions in crucial situations, such as preventing an accident. varied nations have varied laws governing autonomous lane changes.

1.4.Uncertainty in Surrounding Vehicle Behavior

A major obstacle to automated lane change is uncertainty in surrounding vehicle behaviour, since human drivers behave in unpredictable ways depending on their own driving habits, outside influences, and road conditions. There are many different types of drivers. Some are aggressive and change lanes abruptly without signalling, while others are extremely careful and slow down before changing lanes. Prediction becomes even more difficult when turn signals are used inconsistently because many drivers don't communicate their intentions, which forces autonomous systems to rely on indirect indicators such lateral movement, changes in acceleration, and possible impediments up ahead. Unpredictable or last-minute lane changes brought on by impatience, missing exits, or traffic circumstances give an autonomous car less time to react, which raises the possibility of crashes. Additionally, it is challenging for an AI-based system to forecast a human driver's next action because human drivers respond differently to external inputs including weather, pedestrian crossings, and merging traffic. Because uncommon or infrequent driving behaviours, like road rage or reversing on a highway, are hard to measure and predict, modelling human behaviour is still a challenging undertaking. Autonomous cars employ sophisticated machine learning models and driver behaviour analysis to forecast driver intent, sensor fusion methods to integrate information from LiDAR, cameras, and radar, and real-time decision-making algorithms to continuously adjust lane-change tactics in order to reduce these uncertainties. [4]

1.5.Real-Time Decision Making

The ability of autonomous cars to assess their surroundings, anticipate any dangers, and carry out safe lane changes or manoeuvres in a matter of milliseconds is known as real-time decision-making. In order to guarantee safe and easy navigation in changing traffic situations, this procedure combines sensor fusion, artificial intelligence (AI), and control algorithms. In order to identify other cars, pedestrians, road signs, and lane markings, autonomous cars constantly gather information from a variety of sensors, including LiDAR, cameras, radar, and ultrasonic sensors. AI-based perception models are then used to process this sensor data in order to categorize objects, calculate their speeds, and forecast their future motions. By anticipating the actions of other cars, machine learning algorithms and predictive models enable the autonomous system to plan lane changes, braking, or acceleration while lowering hazards. The car must also make decisions based on a number of parameters, including speed limits, traffic laws, road curvature, and possible impediments. Adapting swiftly to unforeseen circumstances, like abrupt lane changes by other vehicles, unexpected pedestrian crossings, or unfavourable weather conditions that impair sight and road traction, is an essential component of real-time decision-making. Autonomous cars employ sophisticated control algorithms, like Reinforcement Learning and Model Predictive Control (MPC), to make dynamic judgments in order to manage these situations. All things considered, autonomous cars need real-time decision-making to be safe, effective, and dependable. This lowers the chance of accidents and enables them to handle challenging traffic situations with little assistance from humans. [9]

2. Related Works

The research on the Lane Change Safety Prediction Model for Automatic Driving a Long Short-Term Memory (LSTM) neural network is used in Based on LSTM (2024) [1] to forecast vehicle trajectories from time-continuous driving behaviour data. By improving forecast accuracy, this method guarantees safer lane changes under a variety of driving circumstances, including emergency braking. Future developments will try to increase model accuracy, accommodate unforeseen driving circumstances, and include increasingly intricate multi-vehicle interactions. The Machine Learning-Based Vehicle Intention Trajectory Recognition and Prediction for Autonomous Driving (Yu, Hanyi, et al. 2024), presented at the 7th ICAACE IEEE Conference, adopts a CNN-LSTM model [2] to obtain a high prediction accuracy of 98.66%. In complex traffic situations, this approach outperforms standard models and improves decision-making by accurately capturing human driving patterns. The model will be optimized for real-time systems in the future, and real-time data feedback will be incorporated for increased accuracy. In order to minimize emergency braking, minimize collision likelihood, and optimize lane-change requests for a more comfortable driving experience, the Directional Lane Change Prediction Using Machine Learning Methods [3] (Ardakani, Mostafa, and Timothy Bonds. August 2023) study, which was published in the Journal of Applied Engineering Science, makes use of K-Nearest Neighbour (KNN), Artificial Neural Networks (ANN), and Deep Reinforcement Learning (DRL). UAV integration for real-time traffic data collection and increased judgment accuracy are examples of future improvements. Vehicle sensor data and machine learning algorithms including KNN, ANN, and DRL are used in the Safe Data-Driven Lane Change Decision Using Machine Learning in Vehicular Networks (Naja R. August 2023) study, which was published in the Journal of Sensor and Actuator Networks [4], to forecast lane-change judgments. By lowering crash rates and emergency braking, the study shows increased safety. UAV integration for real-time data collecting and improving reinforcement learning reward functions are examples of future work. The Lane-Exchanging Driving Strategy for Autonomous Vehicles via Trajectory Prediction and Model Predictive Control (Chen, Yimin, et al. May 2022) [5] study, published in the Chinese Journal of Mechanical Engineering, integrates a Gaussian Mixture Model (GMM) with Model Predictive Control (MPC) for trajectory prediction. This approach improves safety by taking into account the dynamic interactions between neighbouring and autonomous vehicles. Expanding the study to include multiple vehicle interactions and enhancing adaptability to different driving situations are the goals of future research. The Integration of GNSS and INS In order to estimate vehicle positions during GNSS failures, the LightGBM model, which is based on Machine Learning LightGBM Model for Vehicle Navigation (Li, Bangxin, et al. May 2022) [6], published in Applied Sciences, integrates GNSS and INS data. The method cuts down on training time while increasing position accuracy. Future enhancements will include real-time validation for dynamic vehicle navigation systems and noise reduction in INS data. The Prediction of Driver Lane-Changing Behaviour According to a Deep Learning

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(Wei, Cheng, Fei Hui, and Asad J. Khattak. April 2021) [7] study that was published in the Journal of Advanced Transportation, lane changes may be classified with 93.5% accuracy using a hybrid Seq2Seq RNN and fully linked network. To increase forecast accuracy and flexibility, the study recommends adding more variables, such as vehicle type and road conditions. The Deep Learning-Based Vehicle Behaviour Prediction for Autonomous Driving Applications: A Review (Mozaffari, Sajjad, et al. August 2020) [8], published in IEEE Transactions on Intelligent Transportation Systems, examines input representations, machine learning techniques, and deep learning advantages. It highlights the superior performance of deep learning models in predicting vehicle behaviour. Future enhancements focus on multimodal prediction, environmental awareness, and integrating traffic rules into models. Artificial Intelligence for Predicting Vehicle Behaviour: A Hybrid Method ANN and LSTM networks trained on the NGSIM dataset are used to forecast lane shifts 2.2 seconds ahead of time, according to Manoeuvre Classification and Trajectory Prediction (Benterki, Abdelmoudjib, et al. March 2020) [9], published in IEEE Access. This technique improves the safety of autonomous vehicles by offering high accuracy with few errors. The dataset will be enlarged, driver behaviour will be examined, and predictions will be applied to urban settings in future research. Reproducing Kernel Hilbert Space (RKHS) is used in the Continuous Behavioural Prediction in Lane-Change for Autonomous Driving Cars in Dynamic Environments (Dong, Chiyu, and John M. Dolan. November 2018) [10] to continually forecast lane-change trajectories while collecting vehicle interactions. When compared to baseline techniques, it exhibits reduced prediction errors. Future research aims to extend the model's applicability to dynamic contexts and address problems brought on by a lack of training data.

3. Proposed Model

The figure 1 illustrates a structured approach to predicting lane-changing behaviour using machine learning techniques. It begins with a dataset containing vehicle movement information, which undergoes preprocessing and feature engineering to extract key attributes such as speed, acceleration, and gap distance. After preprocessing, a Gaussian Mixture Model (GMM) is applied to classify driving behaviour into different categories like cautious, neutral, or aggressive. This behavioural information, along with other engineered features, is then fed into a LightGBM model, a powerful gradient boosting algorithm, to predict whether a vehicle will change lanes. By incorporating driver behaviour analysis through GMM, the model improves the accuracy of lane change prediction, making it more effective for autonomous driving applications. Figure 1 shows Proposed Model [11]

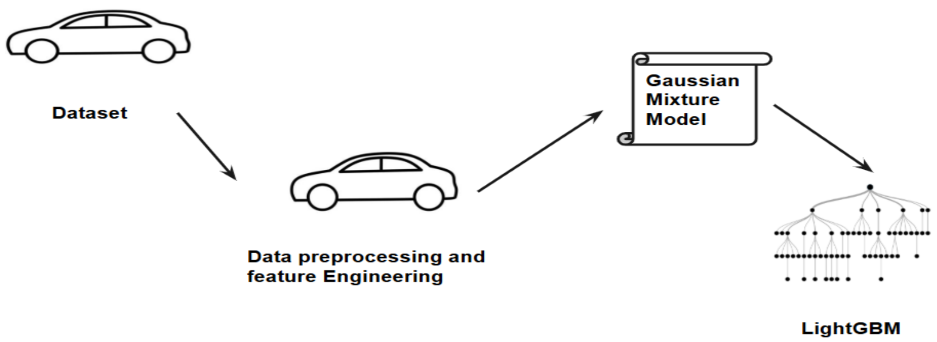

Figure 1 Proposed Model

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3.1.Dataset

The NGSIM I-80 dataset is a popular traffic dataset that offers comprehensive vehicle trajectory information gathered from a section of California's Interstate 80 (I-80). At high temporal and spatial resolutions, it contains data on lane changes, vehicle positions, accelerations, and speeds. Research on autonomous driving benefits greatly from this dataset, which is especially useful for examining lane-changing behaviours, vehicle interactions, and traffic flow dynamics. Models for lane-change prediction, driving behaviour analysis, and intelligent transportation systems are developed and assessed by researchers using this dataset. The data's real-world nature and great precision make it perfect for machine learning applications in autonomous car decision-making.

3.2. Data Preprocessing

In the preprocessing stage of the project, the raw NGSIM I-80 dataset was first cleaned to ensure data quality. This involved removing any missing or inconsistent entries and filtering out irrelevant data that did not contribute to the analysis. The dataset was then sorted and aligned based on vehicle IDs and timestamps to maintain temporal consistency. Duplicate records were removed, and necessary columns were selected for the modeling phase. Finally, the data was normalized using standard scaling techniques to bring all features to a similar scale, which is crucial for improving the performance and convergence of machine learning algorithms. This cleaned and structured dataset was then ready for further analysis and modeling. [13]

3.3. Feature Engineering

To increase the performance and interpretability of the lane change prediction model, numerous high-level features were engineered from the pre-processed NGSIM I-80 dataset. These features are critical in representing vehicle interactions, dynamic driving behaviour, and temporal movement patterns. The following features were derived. [12]

3.3.1. Gap

The longitudinal (X-axis) distance between a vehicle and the one directly ahead of it in the same lane.

$$Gap_i = x_{\{preceding\}} - x_{\{subject\}}$$

The gap helps measure how much free space a vehicle has in front. Smaller gaps can imply discomfort or a potential safety risk, which often leads a driver to consider a lane change to maintain speed or avoid tailgating.

3.3.2. Time Headway (THW)

The amount of time it would take for the subject vehicle to reach the preceding vehicle if it continues at its current speed.

$$THW = \frac{Gap}{v}$$

where v is the velocity of the subject vehicle. THW is a critical safety metric. A low THW indicates aggressive driving and increases the risk of a rear-end collision. Vehicles with low THW are more likely to change lanes to avoid unsafe following conditions.

3.3.3. Modified Time to Collision (MTTC)

An advanced version of Time-To-Collision (TTC) that accounts for both the relative velocity and relative acceleration between the subject and the preceding vehicle.

$$MTTC = \frac{-\Delta v - \sqrt{(\Delta v)^2 + 2 \cdot \Delta a \cdot Gap}}{\Delta a}$$

$$v = v_{subject} - v_{preceding}$$
$$\Delta a = a_{subject} - a_{preceding}$$

Unlike THW, MTTC considers deceleration and dynamic conditions, making it more reliable in stop-and-go traffic or when vehicles are accelerating or braking. A smaller MTTC indicates imminent collision risk, prompting lane changes.

3.3.4. Jerk

The rate of change of acceleration over time. It represents how suddenly a vehicle is changing its acceleration profile.

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$$Jerk_t = a_t - a_{t-1}$$

High jerk values are often signs of abrupt manoeuvres like sudden braking or aggressive acceleration. Such behaviours typically precede lane changes in response to traffic or to avoid perceived hazards.

3.3.5. Relative Distance (Distance to Previous Position)

The Euclidean distance the vehicle has travelled since the previous frame, based on both X and Y coordinates.

$$Distance = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$$

This spatial measurement helps identify micro-movements in both longitudinal and lateral directions. An increase in lateral distance (Y-axis change) can signal an ongoing or attempted lane change.

3.4. Models

3.4.1. Gaussian Mixture Model (GMM)

Using characteristics like velocity, acceleration, time headway (THW), time-to-collision (MTTC), and jerk, GMM is used in this project to classify drivers into various driving styles. These characteristics show how the car behaves dynamically and how the driver makes decisions while driving. GMM is appropriate for clustering behavioural patterns that are naturally present in the driving data because it does not require labelled data. Based on its movement profile, each vehicle is given a "Driving Style" label—such as aggressive, moderate, or cautious—by applying GMM. By allowing lane-change decisions to take into account not only external traffic conditions but also the driver's internal tendency or aggression, this extra feature improves the accuracy of the model. The Gaussian Mixture Model is a probabilistic unsupervised learning technique that models the data as a mixture of several Gaussian distributions. It assumes that each data point belongs to a cluster with a certain probability, enabling soft clustering — particularly useful in modeling uncertain and overlapping driving behaviours.

3.4.2. Light GBM (Light Gradient Boosting Machine)

LightGBM is a high-performance gradient boosting framework that constructs decision trees leaf-wise, resulting in higher efficiency and faster training than conventional boosting techniques. In this project, a variety of engineered features, such as vehicle speed, acceleration, gap to the previous vehicle, relative velocity and acceleration, THW, MTTC, and the driving style output from the GMM model, are used to identify the driver's intention to change lanes in real-time using LightGBM. The selection of LightGBM was based on its capacity to effectively manage feature interactions, support parallel learning, and handle large datasets. When deciding when the car should change lanes to prevent collisions and preserve smooth flow, the car can make precise and timely decisions thanks to its predictive power. The use of LightGBM allows the system to respond dynamically to evolving traffic conditions, providing a robust backbone for intelligent behaviour modelling in autonomous or assisted driving simulations.

3.4.3. Why Light GBM no other algorithms?

Based on the performance metrics shown in the table 1, LightGBM was chosen for the project due to its exceptional balance of accuracy, precision, recall, and training efficiency. Among all the models evaluated—LSTM, SVM, XGBoost, and LightGBM—LightGBM demonstrated consistently high performance across all three lane change intention types: Lane Keeping (LK), Right Lane Change (RLC), and Left Lane Change (LLC). Notably, it achieved an overall accuracy of 98.32%, which is nearly as high as XGBoost's 98.47%, but with significantly lower training time (496.4 seconds) compared to XGBoost's 3880.7 seconds and SVM's 33819.3 seconds. Additionally, LightGBM achieved perfect recall (100%) for LLC and high recall for RLC (99.93%), which is crucial in a real-time system where missing a lane change decision could lead to unsafe outcomes. It also maintained very high precision, minimizing false positives in predictions. These results indicate that LightGBM offers both high predictive accuracy

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and computational efficiency, making it a highly suitable model for a real-time lane change prediction system. Its ability to handle large datasets and support rapid inference further justified its selection for this simulation project.[3] Table 1 shows Performance Metrics of Different Models

Table 1 Performance Metrics of Different Models

Model	Type	Precision	Recall	Accuracy	Training time(s)
LSTM	LK	90.10%	96.21%	95.33%	992.3
	RLC	97.83%	95.78%		
	LLC	97.79%	93.73%		
SVM	LK	88.31%	97.29%	94.21%	33819.3
	RLC	97.23%	93.46%		
	LLC	96.88%	92.10%		
XGBoost	LK	95.79%	99.88%	98.47%	3880.7
	RLC	99.93%	97.97%		
	LLC	99.96%	97.50%		
LightGBM	LK	99.91%	94.89%	98.32%	496.4
	RLC	97.89%	99.93%		
	LLC	97.34%	100%		

4. Experimental Results and Analysis

4.1.Performance Metrics

To adequately assess machine learning algorithms, choosing the right performance criteria is crucial. In this work, we primarily used precision (P), accuracy (A), recall (R), and F1-score (F1) as performance indicators. The precision, which indicates how many of the positive predictions are accurate, is computed by Equation (19). It ranges from 0 to 1.

Precision:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score:

$$\text{F1-Score} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

4.2. Result

The performance of the proposed lane change prediction model given in table 2, as evaluated on the test data, demonstrates strong results. The model achieved an overall accuracy of 91.46% and an impressive ROC-AUC score of 0.9708, indicating excellent capability in distinguishing between lane-keeping and lane-changing manoeuvres. The classification report further highlights a precision of 0.97 and recall of 0.89 for class 0 (lane-keeping), and a precision of 0.83 and recall of 0.96 for class 1 (lane change). This indicates that the model is highly effective at correctly identifying vehicles that intend to change lanes, which is critical for safety in autonomous driving. The macro and weighted averages of precision, recall, and F1-score all hover around 0.91–0.92, showcasing balanced performance across classes. The confusion matrix also reveals a strong number of true positives and true negatives, with relatively fewer misclassifications. Overall, the results demonstrate the robustness and reliability of the LightGBM model integrated with Gaussian Mixture Model-based feature clustering in predicting lane changes in real-time scenarios. [14]

4.3. Real Time Simulation

The dynamic, interactive real-time lane change simulation module for this project was made with Pygame and simulates highway driving behaviour, with a focus on making intelligent lane changes. This simulation aims to evaluate and illustrate the performance of the LightGBM-based lane change intention prediction model in real-world driving situations. (Refer to Fig-2)

4.4.Simulation Environment

The dynamic, interactive real-time lane change simulation module for this project was made with Pygame and simulates highway driving behavior, with a focus on making intelligent lane changes. This simulation aims to evaluate and illustrate the performance of the Light GBM-based lane change intention prediction model in real-world driving situations.

4.5.Player Car Behavior

The lane-change prediction model is used to govern the behavior of the ego vehicle, which is represented by the player automobile (blue). It starts in the center lane and dynamically changes its behavior according to model forecasts and traffic flow. The automobile maintains a constant speed, but based on a forecast made by the trained Light GBM model, it may choose to change lanes to prevent possible collisions or increase driving safety.

4.6.Surrounding Vehicles

Other moving vehicles (red automobiles) with arbitrary beginning positions and speeds in various lanes are introduced into the game. These cars continuously travel down the screen to replicate actual traffic situations. To cut down on computing overhead while still producing intricate driving scenarios, the number of nearby cars is restricted to a manageable level (for example, four). [15]

4.7.Feature Extraction in Real Time

For every simulation frame, the system produces real-time features. These consist of the player's speed, acceleration, relative velocity and acceleration, time headway (THW), minimum time to collision (MTTC), jerk, and distance to vehicles in front of them (gap). The driver's behaviour style is estimated using these features and then supplied into a pre-trained Gaussian Mixture Model (GMM), which is then used as an input for lane change prediction. Table 2 shows Model Output

Table 2 Model Output

Lane Change	Accuracy	Precision (Class 0)	Recall (Class 0)	F1-Score (Class 0)	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)
0	96.24%	0.944033	0.965123	0.954461	0.975510	0.960443	0.967918
1	98.84%	0.983228	0.988451	0.985833	0.991987	0.988343	0.990162

4.8.Lane Change Decision Making

The LightGBM model is used to determine whether a lane change is required (1) or not (0) after the real-time features have been retrieved and scaled using a pre-fitted StandardScaler. The system uses a bespoke logic to check the safety conditions in neighbouring lanes and prevent crashes if a lane change is advised (ensuring no surrounding vehicle is too close). Lane changes are only permitted when they are safe and required, which reflects a human-like approach to decision-making.

4.9.Purpose and Contribution

The suggested intelligent lane changing system is validated and proof-of-concepted using the real-time simulation. It enables testing of the model's safety, accuracy, and reactivity in a reactive and visually interpretable setting. For upcoming research on autonomous driving systems, this type of simulation can be extended to incorporate sensor data or reinforcement learning methods.

Conclusion

This project presents an intelligent lane-changing system for autonomous vehicles using a combination of Gaussian Mixture Models (GMM) for driver behaviour classification and LightGBM for accurate lane change prediction. Leveraging real-world NGSIM I-80 data, feature engineering, and real-time simulation with Pygame, the system demonstrates high precision, recall, and overall performance in predicting safe and timely lane changes. The integration of behaviour-based modeling with efficient machine learning techniques ensures practical viability for real-time intelligent transportation systems, offering valuable insights for the future of autonomous driving technology.

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