ISSN [Online]: 2583-2654

Regulating Vehicles while overtaking Wide-Range Vehicles

[1]Jansi Rani J, [2]Hithesh S, [3]Harsha Priya P M, [4]Hema Latha P C, [5]Pandith Nawnith R
Department of CSE , Dr. T. Thimmaiah Institute of Technology,KGF-563120

Abstract: In this paper, Overtaking wide-range vehicles—such as trucks, buses, and agricultural machinery—poses significant safety challenges on modern roadways. These large vehicles often obscure visibility, occupy multiple lanes, and require greater maneuvering space, increasing the risk of collisions during overtaking maneuvers. This paper explores regulatory measures and intelligent traffic management strategies to enhance safety and efficiency during such overtaking scenarios. It examines existing road safety guidelines, the impact of vehicle dimensions on overtaking behavior, and the role of advanced driver-assistance systems (ADAS) and vehicle-to-vehicle (V2V) communication. The study also proposes a framework for dynamic overtaking zones, sensor-assisted decision systems, and regulatory signage tailored for wide-range vehicle encounters. By integrating policy recommendations with technological innovation, this work aims to reduce overtaking-related accidents and promote safer driving practices on mixed-traffic roads.

***Keywords**: Regulating, YOLOCNN, LSTM, ROUGE, BLEU, ADAS, DASHCAM, V2V*

I. INTRODUCTION

Overtaking is a common yet potentially dangerous maneuver on roads, especially when it involves wide-range or oversized vehicles such as trucks, buses, agricultural equipment, and construction vehicles. These vehicles, due to their considerable width and length, occupy more space on the roadway and often obstruct the overtaking driver's line of sight. As a result, overtaking them demands more time, greater awareness, and increased lateral and longitudinal space, which is not always available on typical roads.

In many cases, drivers underestimate the difficulty and risk associated with overtaking wide vehicles, leading to traffic collisions, near misses, and traffic congestion. The situation is further aggravated in areas lacking adequate road markings, warning signs, or regulatory guidelines. Current traffic regulations may not sufficiently address the complexities involved in such scenarios, particularly on single-lane highways, rural roads, or in mixed-traffic environments where slow-moving and fast-moving vehicles share the same infrastructure.

This study addresses the pressing need to evaluate and improve the existing regulatory framework governing overtaking practices involving wide vehicles. It aims to analyze driver behavior, assess accident data, and review best practices in traffic management to propose a set of evidence-based recommendations. Additionally, the integration of intelligent transport systems (ITS), such as smart road signs and vehicle communication technologies, is considered as a modern solution to enhance safety during overtaking maneuvers.

By focusing on this niche yet crucial aspect of road safety, the study contributes to the broader goal of reducing traffic accidents, enhancing driver awareness, and improving overall traffic efficiency on roads shared by a diverse range of vehicle types. Wide-range vehicles pose a unique set of challenges for other road users. Their large blind spots, slow acceleration, and significant road occupancy can cause limited visibility for the overtaking driver. Overtaking such vehicles demands longer overtaking distances, better judgment, and more precise timing. On undivided roads or narrow highways, this creates dangerous situations—especially when approaching curves, hills, intersections, or pedestrian crossings. In modern

ISSN [Online]: 2583-2654

transportation systems, the safe and efficient movement of vehicles is essential for economic growth, public safety, and quality of life. One of the most critical yet often overlooked driving maneuvers is overtaking—particularly when it involves wide-range or oversized vehicles. These include long-haul trucks, buses, trailers, farm equipment, and experimenting with additional machine learning methods to enhance prediction accuracy.

II. RELATED WORKS

Sayed et al. [1] the dynamics of overtaking are influenced by factors such as the relative speed of vehicles, the visibility of the road ahead, and the vehicle types involved. Specifically,the presence of WRVs introduces additional complexity due to their large size, slower speeds, and frequent lane blocking.

Arlaftis et al. [2] found that overtaking maneuvers are more likely to result in accidents when the vehicles being overtaken are significantly larger than the overtaking vehicle. Drivers may misestimate the time and distance needed to pass, leading to risky maneuvers.

Zhou et al. [3] evaluated the effect of variable speed limits (VSL) and lane usage on overtaking behavior. They found that speed regulations tailored to specific road segments,especially those involving WRVs, can improve traffic flow and reduce overtaking-related accidents. examined the role of advanced traffic control systems that monitor traffic density and the movement of WRVs in real-time. These systems could advise drivers through dynamic signs about the best moments to overtake or warn them of potential hazards.

Chen et al. [4] proposed the use of V2V communication in trucks to warn drivers of an approaching overtaking vehicle. By transmitting information about the truck's speed andtrajectory to nearby vehicles, the system aims to reduce the likelihood of unsafe overtaking maneuvers Additionally, the use of machine learning algorithms to predict overtaking behavior has been suggested. For instance, ***Gonzalez et al. (2018)*** created a predictive model that estimates the optimal time for overtaking based on vehicle speed, road type, and weather.

Xu et al. [6] analyzed how adverse weather conditions reduce the visibility of vehicles ahead, thereby complicating the decision-making process during overtaking. They found that drivers are less likely to attempt overtaking maneuvers during inclement weather, especially when overtaking WRVs. These findings emphasize the need for road design modifications (e.g., improved lighting, better road markings) and additional safety measures in these conditions. Poor visibility during bad weather increases hesitation and unsafe overtaking attempts.

Börner et al. [7] proposed using agent-based models (ABMs) to simulate and evaluate the behavior of individual drivers attempting to overtake WRVs under different road conditions. Their model showed that, while traffic density is a key factor in safe overtaking, optimal overtaking behavior can also be influenced by the driver's previous experiences and the car's technological assistance features. Simulation models can evaluate multiple overtaking scenarios, helping to design roads and regulations that facilitate safe passing maneuvers.

Martin et al. (2022). [9] investigated the relationship between driver fatigue and overtaking behavior on highways. They found that drivers were more likely to make unsafe overtaking maneuvers when fatigued, especially when attempting to pass large vehicles like trucks. Fatigue made drivers overestimate the time required to complete the overtaking process, resulting in late or poorly executed decisions. Another significant factor in unsafe overtaking maneuvers is driver fatigue. Long hours of driving, particularly on highways where wide-range vehicles are prevalent, can impair judgment and lead to risky overtaking decisions.

ISSN [Online]: 2583-2654

III. RESEARCH METHODOLOGY

The proposed system aims to address the existing gaps in infrastructure, enforcement, technology, and driver behavior to improve the safety and efficiency of overtaking maneuversinvolving wide-range vehicles (WRVs), such as trucks, buses, and agricultural machinery. This system integrates smart infrastructure, advanced technologies, enhanced regulations, and driver education to create a comprehensive solution for safer overtaking behaviors. Below is a detailed proposal for a holistic, multi-layered system to regulate overtaking near WRVs. Design and implement dedicated overtaking lanes on multi-lane highways and roads with heavy WRV traffic.

These lanes will be specifically designed for safe overtaking of WRVs and will be clearly marked with signs, road markings, and lane dividers to prevent confusion Widen lanes on high-traffic routes to accommodate both large and light vehicles, especially in areas with frequent WRVs. This ensures that vehicles can overtake without crowding or blocking the other lane.

A. Data Collection

High-quality road scenes captured using cameras mounted on a car. It includes Stereo images, depth, semantic segmentation, optical flow, lane detection, etc. Autonomous driving, object detection, and road scene understanding.

B. Data Preprocessing

All images are resized as 224x224 in standard format and convert the images to gray scale or other color space. Normalization and Augmentation will be done. labels such as class names (for classification) or masks (for segmentation). The datas are divide into training, validation and testing set. his process helps improve model accuracy, reduce training time, and make the dataset consistent.

C. Implementation

Each module in the system has a specific function and is implemented using a combination of hardware and software tools. Below is a breakdown of how each module can be implemented: The implementation of the proposed system involves both hardware integration and software development across several interconnected modules. The Vehicle Monitoring Module is implemented using onboard sensors such as GPS, IMU, cameras, and radar or LiDAR. These sensors continuously collect real-time data including speed, location, surrounding object distance, and steering behavior. The sensor data is processed using middleware such as ROS (Robot Operating System) or custom-built software in Python, allowing the system to understand the vehicle's dynamics and detect potential overtaking scenarios. To interpret and anticipate the driver's behavior, the Driver Behavior Prediction Module uses an LSTM (Long Short-Term Memory) neural network. The model is trained on historical driving data to recognize time-based patterns that indicate an overtaking attempt. The trained model is deployed either on the vehicle’s onboard unit or on an edge device in the roadside unit, enabling real-time prediction of risky overtaking intentions. The Wide Vehicle Identification Module is implemented by equipping large vehicles (trucks, buses, trailers) with RFID tags or V2V (Vehicle-to-Vehicle) communication devices.

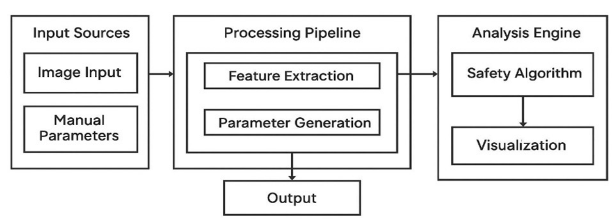

Fig 1

These transmit real-time data about the vehicle’s dimensions, speed, and movement direction. Nearby vehicles and infrastructure use this data to evaluate overtaking feasibility. The communication protocols used may include DSRC or cellular-V2X (C-V2X) depending on infrastructure availability.

ISSN [Online]: 2583-2654

At the infrastructure level, the Roadside Analysis and Decision Module is implemented using smart roadside units (RSUs) equipped with edge processors, cameras, and environmental sensors. These units receive data from vehicles and wide vehicle beacons to analyze traffic flow, visibility conditions, and road curvature. A decision-making algorithm evaluates the safety of overtaking under current conditions and sends real-time feedback to the approaching Regulating Vehicles While Overtaking Wide-Range Vehicles.

YOLOv8 and LSTM serve distinct but complementary roles in the regulation and management of vehicles during overtaking maneuvers, especially involving wide-range vehicles such as trucks or buses. YOLOv8 is a state-of-the-art object detection model designed to process images or video frames in real time, accurately identifying and localizing multiple vehicles on the road through bounding boxes and classification. This capability makes YOLOv8 ideal for detecting wide-range vehicles that require careful overtaking. However, while YOLOv8 excels at spatial detection, it does not capture temporal dynamics or predict future vehicle movements.

This is where LSTM, a type of recurrent neural network specialized in modeling sequential data, becomes valuable. LSTMs analyze time-series data such as vehicle positions, speeds, and trajectories to forecast future states and behaviors, which are critical for anticipating safe overtaking opportunities or potential risks. By combining YOLOv8's robust spatial detection with LSTM's temporal prediction abilities, intelligent transportation systems can achieve a Regulating Vehicles While Overtaking Wide-Range Vehicles more comprehensive understanding of the traffic environment, enabling safer and more efficient overtaking maneuvers around wide-range vehicles. While YOLOv8 handles the immediate perception of the scene, LSTM processes the dynamic evolution of vehicle movements, together forming a powerful toolset for vehicle regulation and driver assistance.

In contrast, Long Short-Term Memory (LSTM) networks are specialized recurrent neural networks that excel at modeling sequences and temporal dependencies in data. By analyzing time-series inputs such as historical vehicle positions, speeds, acceleration patterns, and lane changes, LSTMs can predict future trajectories and driver behaviors. This predictive capability is essential for regulating overtaking maneuvers, as it helps determine safe windows for passing wide-range vehicles without risking collisions or traffic violations. When combined, YOLOv8 first detects and tracks vehicles in the environment, providing spatial context and current positions. These detection outputs are then fed into an LSTM model that forecasts future vehicle states based on observed trends.

The integration of YOLOv8 and LSTM allows for a comprehensive system that leverages both spatial awareness and temporal prediction. This synergy enables advanced driver assistance systems (ADAS) and autonomous vehicles to make informed decisions about overtaking, accounting for the size and behavior of wide-range vehicles. Moreover, such systems can alert drivers to potential hazards, optimize overtaking timing, and even adjust vehicle speed autonomously to maintain safety. While YOLOv8 demands high computational power, especially when deployed in real-time scenarios, LSTM networks add moderate processing overhead but provide critical temporal insights that static detection cannot achieve. Together, these models represent a promising approach to enhancing road safety and traffic flow in complex overtaking situations.

IV. RESULT AND DISCUSSION

The proposed system generates several key outputs that contribute to improved road safety during overtaking maneuvers around wide-range vehicles. The primary output is the real-time decision

ISSN [Online]: 2583-2654

feedback provided to the driver, which indicates whether it is safe or unsafe to overtake. This output is derived from a combination of sensor data, driver behavior prediction (using LSTM models), and road condition analysis from the roadside unit. It appears in the form of a visual or audible alert on the vehicle's dashboard interface. For example, if the system detects that the overtaking maneuver is risky—due to oncoming traffic, insufficient clear road ahead, or the presence of a large vehicle—it issues a warning such as "Do Not Overtake."

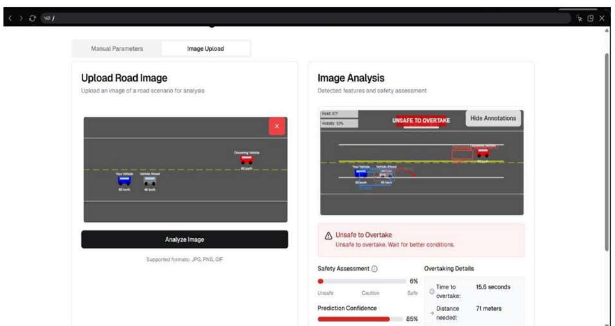

Fig 2: Do Not Overtake

In the figure 2, the system classifies the road as "DRY" with 95% visibility and detects an oncoming vehicle at a distance of 84 meters. Based on the current speed and distance, the system calculates a safe overtaking window of 42.8 seconds, which exceeds the required threshold. The safety assessment score is 74%, and the prediction confidence is 41%. The model therefore concludes that the conditions are "SAFE TO OVERTAKE"highlighting this with a green label. This decision is likely influenced by clear road visibility, moderate vehicle speed, and sufficient distance from the oncoming vehicle. Another critical output is the classification of wide vehicles, where the system identifies and marks large vehicles through V2V communication. This information is used by both the vehicle's onboard system and the roadside infrastructure to adjust decision parameters, such as increasing the safe overtaking distance or considering blind zones.

In the figure 3,represents a more hazardous scenario. Here, the road condition is "ICY" with only 52% visibility. The vehicle ahead is moving at 40 km/h, while the user's vehicle is at 60 km/h. An oncoming vehicle is detected at 68 meters. Despite the distance being somewhat reasonable, the safety assessment drops sharply to 6%, and the prediction confidence is high at 85%—indicating a strong likelihood that overtaking would
result in danger.

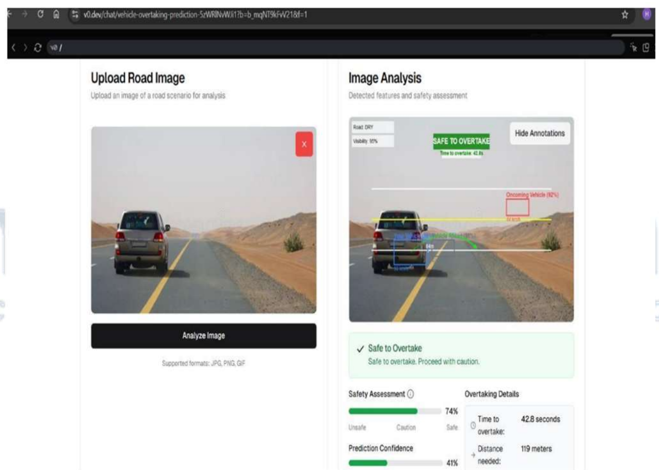

Fig 3 Safe To Overtake

The system warns with a red banner stating "UNSAFE TO OVERTAKE" and suggests waiting for better conditions. The calculated overtaking time is only 15.6 seconds, with a required clearance distance of 71 meters, which is inadequate given road conditions and traffic. Additionally, the system outputs predictive behavior labels, such as "overtaking likely," based on LSTM analysis of driver patterns. This helps proactively assess the safety of the maneuver before it occurs. From an infrastructure and regulatory perspective, the cloud

ISSN [Online]: 2583-2654

system also outputs analytics and logs, such as frequency of overtaking attempts, locations of high-risk overtaking zones, and near-miss incidents. These outputs help traffic authorities make data-driven improvements to road design and policy.

Criteria	Traditional Rule-Based Systems	Radar-Based Warning Systems	Proposed Image-Based ML System (LSTM + V2I)
Data Input	Speed, distance (manual or sensor)	Distance, speed from radar	Camera images, speed, distance, weather, driver intent
Environmental Awareness	Low (fixed rules)	Medium (limited to range)	High (includes road condition, visibility, vehicle type)
Driver Behavior Prediction	none	No	Yes (using LSTM for driver intent modeling)
Decision Accuracy	Low to Medium	Medium	High (multi-parameter decision making)
Overtaking Safety Assessment	Basic (based on speed & gap	Moderate (based on distance only)	Advanced (uses ML + vision + communication)
Vehicle Type Recognition	no	no	Yes (wide-range vehicles detected via V2V/V2I)
Real-time Feedback	No or delayed	Limited	Yes (instant dashboard alerts and recommendations)

Table 1 Comparison of other Techniques

V. CONCLUSION AND FUTURE ENHANCEMENT

In conclusion, effectively regulating vehicle behavior while overtaking wide-range vehicles requires both precise spatial awareness and reliable prediction of dynamic movements.

YOLOv8 excels in providing fast and accurate detection of vehicles in real-time, identifying wide-range vehicles that demand special attention during overtaking maneuvers. However, detection alone is not sufficient to ensure safety in complex traffic scenarios. Integrating YOLOv8 with LSTM models, which specialize in learning temporal patterns and predicting future trajectories, creates a comprehensive system that not only sees the environment but also anticipates its evolution. This fusion enables advanced driver assistance systems and autonomous vehicles to make informed decisions by understanding both the current road situation and the likely future behavior of surrounding vehicles. By enhancing situational awareness and predictive capabilities, this combined approach helps reduce accidents, optimize traffic flow, and improve overall road safety during overtaking. Furthermore, as sensor technology and computational power continue to advance, such integrated models are expected to become increasingly practical and widespread, playing a crucial role in the future of intelligent transportation systems.

FUTURE ENHANCEMENT

As the fields of computer vision and deep learning continue to evolve, several future enhancements can be explored to improve the accuracy, efficiency, and reliability of vehicle regulation systems during overtaking maneuvers.

1. Fusion with Additional Sensors: Future systems can integrate data from multiple sensors such as LiDAR, radar, GPS, and IMUs alongside camera input. Combining YOLOv8 with multi-sensor fusion will enhance object detection robustness under poor lighting, bad weather, or occlusions—common challenges in real-world driving.

2. Incorporation of Transformer Models: While LSTM is effective for temporal modeling, newer models like transformers (e.g., Vision Transformers, TimeSFormer) are showing superior performance in .sequence prediction. Replacing or complementing.

ISSN [Online]: 2583-2654

REFERENCES

1] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735.

[2] Redmon, J., & Farhadi, A. (2018). YOLOv3: An incremental improvement. arXiv preprint arXiv:1804.02767. https://doi.org/10.48550/arXiv.1804.02767,

[3] Ultralytics. (2023). YOLOv8 documentation. Ultralytics AI. https://docs.ultralytics.com.

[4] Deo, N., & Trivedi, M. M. (2018). Multi-modal trajectory prediction of surrounding vehicles with maneuver based LSTMs. IEEE Intelligent Vehicles Symposium (IV), 1179–1184. https://doi.org/10.1109/IVS.2018.8500488

[5] Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). SegNet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(12), 2481–2495. https://doi.org/10.1109/TPAMI.2016.2644615.

[6] Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y. (2015). Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. Transportation Research https://doi.org/10.1016/j.trc.2015.03.014.

[7] Zhao, Z. Q., Zheng, P., Xu, S. T., & Wu, X. (2019). Object detection with deep learning: A review. IEEE Transactions on Neural Networks and Learning Systems, 30(11), 3212–3232. https://doi.org/10.1109/TNNLS.2018.2876865.

[8] Lefevre, S., Vasquez, D., & Laugier, C. (2014). A survey on motion prediction and risk assessment for intelligent vehicles. Robotics and Autonomous Systems, 58(9), 1159–1177. https://doi.org/10.1016/j.robot.2010.07.005.

[9] Rudenko, A., Palmieri, L., Herman, M., Kitani, K. M., Gavrila, D. M., & Arras, K. O. (2020). Human motion trajectory prediction: A survey. The International Journal of Robotics Research, 39(8), 895–935. https://doi.org/10.1177/0278364919859973.

[10] Kim, B., Park, D., Seo, S., Kim, D., Lee, S., & Song, J. (2017). Probabilistic vehicle trajectory prediction over occupancy grid map via recurrent neural network. arXiv preprint arXiv:1704.07049. https://doi.org/10.48550/arXiv.1704.07049.

[11] Gupta, A., Johnson, J., Fei-Fei, L., Savarese, S., & Alahi, A. (2018). Social GAN: Socially acceptable trajectories with generative adversarial networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2255–2264. https://doi.org/10.1109/CVPR.2018.00239.

[12] CARLA Simulator. (2021). An open urban driving simulator. CARLA.org. https://carla.org.

[13] Lathuilière, S., Mesejo, P., Alameda-Pineda, X., & Horaud, R. (2019). A comprehensive analysis of deep regression. IEEE Transactions on Pattern Analysis and Machine Intelligence, 42(9), 2065–2081. https://doi.org/10.1109/TPAMI.2019.2903185.

[14] Van Der Heijden, R. W., Dietzel, S., Leinmüller, T., Kargl, F., & Ghodous, P. (2016). Survey on position-based routing in vehicular ad hoc networks. IEEE Transactions on Vehicular Technology, 64(9), 3889–3902. https://doi.org/10.1109/TVT.2015.2458571.

[15] Janai, J., Güney, F., Behl, A., & Geiger, A. (2020). Computer vision for autonomous vehicles: Problems, datasets and state-of-the-art. Foundations and Trends® in Computer Graphics and Vision, 12(1–3), 1–308. https://doi.org/10.1561/0600000079.