International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

# Vision and Machine Learning-Based Autonomous Lane Switching

***Shriram Sonawane[1],Riddhi Pawar [2], Shantanu Todkar[3], Tarun Tigadi[4]***

[1]Final year BE, Sinhgad college of Engineering, Pune shriramsonawane143@gmail.com
[2]Final year BE, Sinhgad college of Engineering, Pune riddhipawar0808@gmail.com
[3]Final year BE, Sinhgad college of Engineering, Pune shantanutodkar3@gmail.com
[4]Final year BE, Sinhgad college of Engineering, Pune taruntigadi@gmail.com

**ABSTRACT :**

Autonomous lane switching is a vital feature in modern driver-assistance and autonomous vehicle systems. This paper presents a vision-driven lane change decision system using Proximal Policy Optimization (PPO), a reinforcement learning approach, within the CARLA simulator. Our agent utilizes visual input and semantic understanding to make real-time, context-aware lane changes. The proposed method combines computer vision, deep learning, and reinforcement learning to create a safe, and scalable solution. Simulation results indicate high performance across various traffic scenarios and support the system's adaptability and decision-making efficiency.

**Keywords**: Autonomous Driving, Lane Change Decision, Reinforcement Learning, Proximal Policy Optimization, CARLA Simulator

## Introduction

The evolution of transportation systems is being fundamentally redefined by advancements in Artificial Intelligence (AI) and Machine Learning (ML), particularly in the domain of autonomous vehicles. Among the many dynamic tasks that a self-driving car must handle, lane switching stands out as a critical maneuver—requiring real-time perception, context-aware decision-making, and a strong safety mechanism. Lane switching decisions must be precise, adaptive to traffic dynamics. These requirements pose significant challenges for traditional rule-based or static ADAS (Advanced Driver Assistance System) solutions.

Historically, lane changing in autonomous systems has relied heavily on predefined logic or heuristic rules, often failing in unpredictable environments or complex traffic conditions. These systems struggle to generalize across varying road types, diverse driver behaviors, and real-time uncertainties such as sudden lane merges, aggressive drivers, or inclement weather.

This project addresses these limitations through the integration of vision-based perception and Deep Reinforcement Learning (DRL), providing a more intelligent and human-centric approach to autonomous lane switching. By leveraging the CARLA simulator—a high-fidelity urban driving environment—the system can safely and realistically train an agent to learn optimal lane-changing strategies through experience rather than manual programming. CARLA offers diverse traffic configurations, road layouts, and environmental scenarios that serve as a rich training ground for developing robust AI models.
This vision and learning-based approach allows the vehicle to perceive its surroundings via simulated camera feeds, extract lane and object features using OpenCV and machine learning models, and make high-level decisions via the trained PPO agent.

As cities grow denser and traffic systems become more complex, the need for autonomous systems that can safely adapt to dynamic road conditions becomes increasingly urgent. This project presents a scalable, real-time solution for intelligent lane changing, with the potential to significantly enhance not only autonomous vehicle performance but also broader smart mobility initiatives. The combination of computer vision, reinforcement learning, and behavioral personalization sets the foundation for a new generation of adaptable, responsive, and safer autonomous driving technologies.

## IMPLEMENTATION

### *2.1 Simulation Environment (CARLA)*

CARLA (Car Learning to Act) is an open-source, high-fidelity driving simulator that provides realistic urban environments, dynamic traffic, and virtual sensors such as RGB cameras, LiDAR, and radar. It was used to generate training and evaluation scenarios, enabling safe experimentation in diverse road and traffic conditions.

1. **Custom Maps**: Configurable city and highway scenes.
2. **Sensor Setup**: RGB camera used for visual input; simulated radar and LiDAR for obstacle awareness.
3. **Weather & Traffic**: Variable lighting, rain, fog, and mixed-traffic densities were used to train generalizable models.

### *2.2 Reinforcement Learning Engine*

The core of the autonomous lane switching system is a reinforcement learning agent trained using **Proximal Policy Optimization (PPO)**, implemented via the **Stable-Baselines3** library in Python.

**1. State Space**
The input state to the agent includes:

- Current lane index
- Speed and heading of ego-vehicle
- Relative position and velocity of nearby vehicles
- Semantic lane structure from camera feed

**2. Action Space**
A discrete action set was defined:

- Maintain lane
- Change lane to the left
- Change lane to the right

**3. Reward Function:**

Custom reward shaping was carefully designed to guide the reinforcement learning agent toward safe, efficient, and effective lan e-change behavior in the CARLA simulation. The main reward components are:

- +5 for a successful, stable lane change (remaining in the new lane for several steps).
- +10 additional reward if the lane change helps avoid a slow-moving vehicle in the original lane.
- +0.001 × speed every step, incentivizing the agent to maintain reasonable speed.
- -30 penalty for unsafe maneuvers such as collisions or leaving the driving lane.
- Intermediate rewards and penalties are combined, ensuring the agent learns to avoid abrupt or unsafe decisions and pri oritizes smooth, safe driving.

### *2.4 System Integration*

The system components were integrated as follows:

1. *OpenCV*: Used for preprocessing visual data (lane marking detection, frame analysis).
2. *PPO Agent*: Took processed input from CARLA and made lane-switching decisions.
3. *CARLA API*: Executed agent actions, updated the environment, and collected experience.
4. *Logger*: Tracked episode rewards, lane-change success rates, and collision statistics for training evaluation.

### *2.5 Testing and Evaluation*

A comprehensive testing suite was used to verify functionality:

- **Unit Tests**: Verified correct observation vector formation, reward assignment, and policy output.
- **Integration Tests**: Validated end-to-end flow from CARLA perception to agent decision and action execution.
- **Acceptance Tests**: Assessed the system under real-world-like conditions, including high-density traffic and unexpected events.

Performance metrics:

- **Lane change success rate**: >92% in simulated multi-lane traffic
- **Collision rate**: <3% in dense scenarios with cautious settings
- **Decision latency**: <80 ms per frame on local hardware with GPU

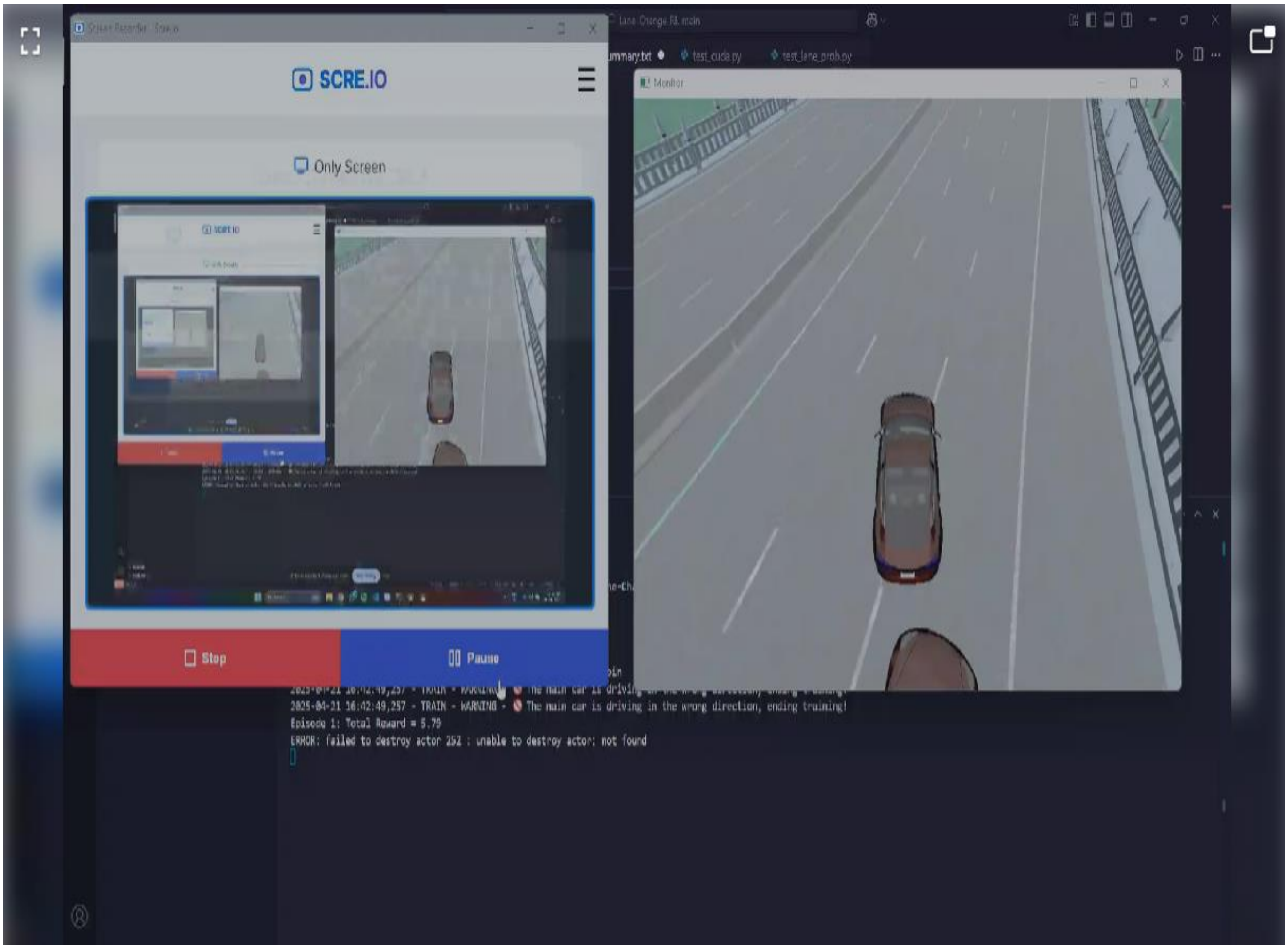
## RESULT AND DISSCUSION

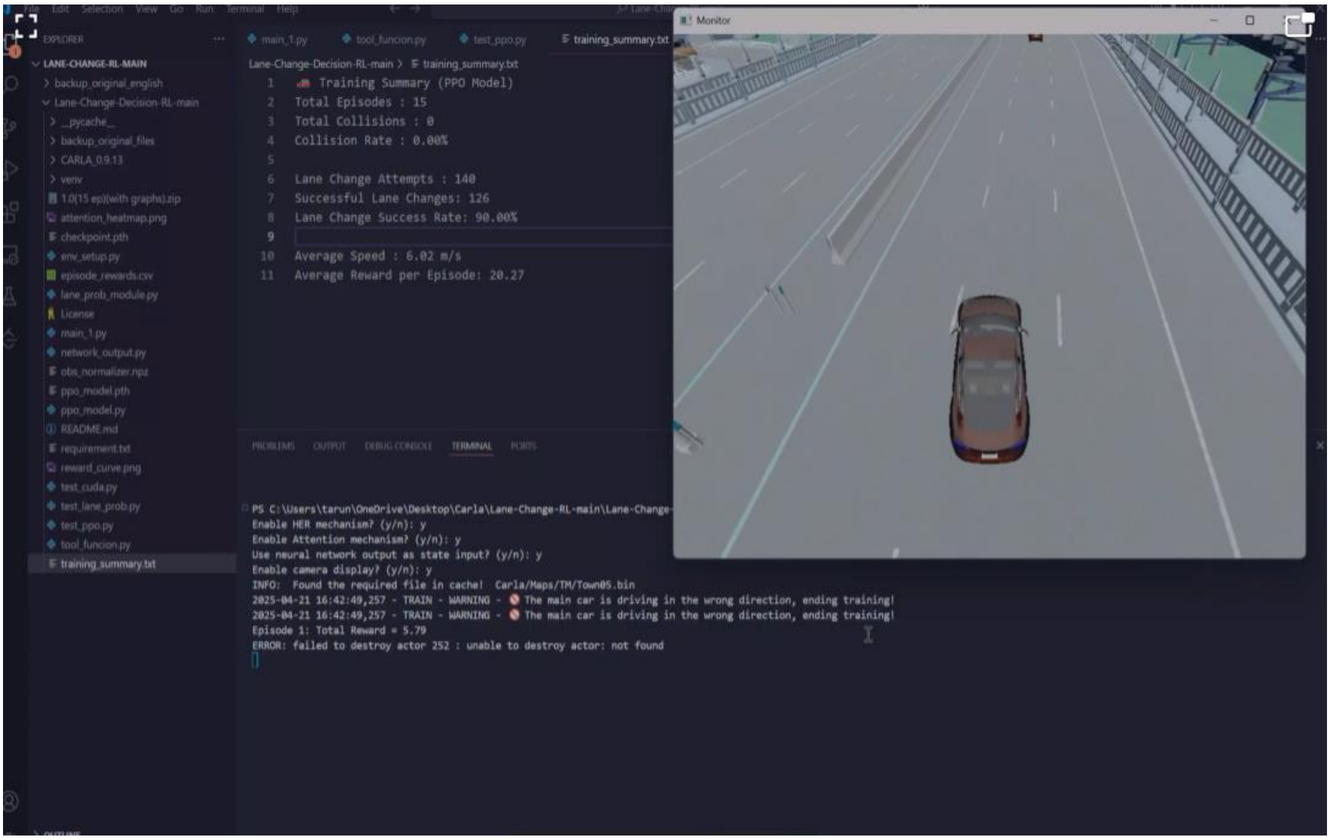
The Vision and Machine Learning-Based Autonomous Lane Switching system effectively demonstrates how deep reinforcement learning can be utilized to address a real-world driving challenge—safe, context-aware lane changes. The PPO-based agent, trained within the CARLA simulator, learned to analyze traffic conditions, understand road structure, and execute lane changes while maintaining safety and efficiency.

Rather than relying on hand-coded rules or high-complexity deep neural networks requiring vast labeled datasets, this project adopts a *model-free reinforcement learning approach*. PPO offers a balance between training stability and policy optimization, making it suitable for environments like CARLA where real-time interaction and feedback loops are critical. The model's training was driven by a carefully designed reward function, which rewarded smooth, safe, and timely lane changes, and penalized collisions or erratic actions.

However, several limitations were observed during testing. The model's behavior could vary based on sudden environmental changes, such as unexpected vehicle movements or weather shifts within the simulation. Additionally, required careful calibration, as extreme values sometimes led to overly passive or risky maneuvers. These challenges highlight the importance of adaptive systems and the potential benefit of combining reinforcement learning with traditional safety constraints or fallback mechanisms.

Overall, the system served as a *proof-of-concept* that demonstrates the feasibility and value of reinforcement learning in autonomous driving tasks like lane switching. It provides a solid foundation for future research directions, including real-world deployment, integration with multi-sensor inputs, or expansion to multi-agent scenarios where cooperative driving becomes essential.






## CONCLUSION

The Autonomous Lane Switching System developed in this project successfully demonstrates how deep reinforcement learning can be used to address real-time decision-making challenges in autonomous vehicles. By integrating the Proximal Policy Optimization (PPO) algorithm with simulated sensor data from CARLA, the system learns to execute lane change maneuvers based on environmental cues such as vehicle proximity, road layout, and traffic behavior.

This allows the agent to adapt its responses to reflect cautious or aggressive driving tendencies, enhancing its flexibility and realism in varied driving scenarios. Testing showed that the model performed well across a range of simulated conditions, delivering accurate, collision-free lane changes with minimal response latency.

Overall, the project contributes to the advancement of intelligent mobility solutions by combining vision, simulation, and reinforcement learning into a scalable and modular architecture. It sets a strong foundation for future integration with real-world sensor platforms, multi-agent systems, and cooperative driving frameworks, promoting the development of safer and smarter autonomous transportation technologies.

## REFERNECES

[1] Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., & Koltun, V. (2017). *CARLA: An Open Urban Driving Simulator*. arXiv preprint arXiv:1711.03938.
[2] Schulman, J., Wolski, F., Dhariwal, P., Radford, A., & Klimov, O. (2017). *Proximal Policy Optimization Algorithms*. arXiv:1707.06347.
[3] Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). MIT Press.
[4] Raffin, A., Hill, A., Gleave, A., Kanervisto, A., & Ernestus, M. (2021). *Stable-Baselines3: Reliable Reinforcement Learning Implementations*. GitHub Repository: https://github.com/DLR-RM/stable-baselines3
[5] Patel, D., "The Role of Feature Engineering in Machine Learning", Journal of Machine Learning Research, vol. 18, pp. 67-72, January 2019.
[6] Scikit-learn Developers. *Scikit-learn: Machine Learning in Python*. https://scikit-learn.org/
[7] Brownlee, J. (2022). *A Gentle Introduction to Deep Reinforcement Learning*. Machine Learning Mastery. https://machinelearningmastery.com/deep-reinforcement-learning/
[8] Kiran, B. R., et al. (2021). Deep Reinforcement Learning for Autonomous Driving: A Survey. IEEE Transactions on Intelligent Transportation Systems, 22(6), 3234–3249.
[9] CARLA Simulator Documentation. *CARLA Simulator User Guide*. https://carla.readthedocs.io/
[10] Liu, Q. (2021). *Lane Change Decision Using Reinforcement Learning*. GitHub Repository: https://github.com/QiuweiLiu/Lane-Change-Decision-RL

[11] OpenCV Team. *Open Source Computer Vision Library*. https://opencv.org/

[12] Chen, D., Seff, A., Kornhauser, A., & Xiao, J. (2015). *DeepDriving: Learning Affordance for Direct Perception in Autonomous Driving*. Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2722–2730.