Autonomous Vehicle for Smart Mobility and Public Safety

Ashwini S R[1], Vandana R[2], Shreenanda S[3], Vaishanavi S[4], Pruthwi Devaru Bhat[5]

[1,2,3,4,5]*Department of Electronics & Telecommunication Engineering*
Jawaharlal Nehru New College of Engineering, Shivamogga, Karnataka

---***---

Abstract - This paper presents the design and development of an autonomous vehicle system aimed at enhancing smart mobility and public safety. The proposed system integrates multiple technologies, including deep learning-based lane detection, LiDAR and camera sensors for perception, GPS-enabled navigation and real-time communication through a Raspberry Pi platform. To ensure robust performance, the system employs DeepLabV3 for semantic segmentation, optical flow for smooth motion tracking and a Kalman filter for prediction and stabilization of the vehicle's path. A Proportional-Integral-Derivative (PID) controller regulates steering and speed, ensuring accurate maneuverability in various road conditions. Obstacle detection and avoidance are achieved using LiDAR, enabling the system to respond to both static and dynamic objects. A Flutter-based mobile application provides GPS tracking, real-time monitoring and manual override control, enhancing usability and safety. Experimental validation on a scaled prototype demonstrates the effectiveness of the proposed system in handling lane detection, sharp turns, obstacle avoidance and traffic sign recognition under diverse conditions. The results highlight the feasibility of deploying low-cost, embedded autonomous systems capable of addressing urban transportation challenges. This work provides a foundation for future research and large-scale implementation of intelligent transportation systems in smart city environments.

Key Words: Autonomous Vehicles, Intelligent Transportation Systems, Computer Vision, Machine Learning, Sensor Fusion, Smart Mobility.

1. INTRODUCTION

Autonomous vehicles (AVs) have emerged as one of the most significant technological innovations in transportation, offering the promise of enhanced safety, efficiency and mobility. These vehicles are capable of sensing their environment and navigating without human intervention by combining multiple technologies such as LiDAR, cameras, radar, GPS and intelligent control systems. The increasing demand for intelligent transportation systems and the evolution of smart cities have further accelerated research in this area, positioning AVs as a critical enabler for future urban mobility.

The primary driver for autonomous vehicle development is road safety. Human error accounts for over 90% of traffic accidents and automation offers the potential to drastically reduce these fatalities. According to Li and Ibanez-Guzman [1], LiDAR perception systems play a pivotal role in this transformation, providing highly accurate environmental sensing that supports real-time decision-making. Surveys such as those by Alaba and Ball [2] and Khosravi et al. [3] highlight the growing reliance on deep learning techniques for robust 3D object detection, enabling AVs to recognize and react to pedestrians, vehicles and obstacles with unprecedented accuracy.

Reliable perception is the backbone of autonomous navigation. Sensor fusion integrating LiDAR, cameras and radar has been widely studied to achieve robust situational awareness. Marti et al. [4] reviewed sensor technologies for automated driving and concluded that no single sensor is sufficient to ensure reliability under all conditions. Instead, combining complementary modalities enhances resilience against environmental challenges such as rain, fog, or low light. Lightweight deep learning models, such as Lite-DeepLabv3+ [5], further enable real-time semantic segmentation for lane detection, even on embedded platforms with limited computational capacity. Xu et al. [6] also demonstrated how residual networks improve segmentation accuracy, directly benefiting road scene understanding in AVs.

The success of autonomous driving depends heavily on deep learning for both perception and control. Guo et al. [7] surveyed deep learning for 3D point clouds, showing how neural networks have surpassed traditional feature-engineering approaches in handling complex environments. More recently, Boulch et al. [8] introduced self-supervised LiDAR learning methods, demonstrating scalable perception without the need for extensive labeled datasets. Similarly, Zeller et al. [9] proposed Radar Instance Transformers to segment moving objects, addressing the limitations of LiDAR in adverse conditions. These advancements signify a trend towards multimodal and self-supervised learning strategies for more adaptive AV perception systems. Before deploying AVs in real traffic, simulation environments play a crucial role in validating performance. Dabbiru et al. [10] explored deep neural networks for high-fidelity simulation, offering a means to accelerate testing and reduce real-world risks. Meanwhile, specialized perception tasks, such as traffic sign recognition [11] and pedestrian detection in adverse weather [12], continue to advance with machine learning methods that enhance safety-critical decision-making.
Accurate localization is another cornerstone of AV performance. Henein et al. [13] introduced the concept of Dynamic SLAM (Simultaneous Localization and Mapping), emphasizing the importance of real-time processing in dynamic environments. Earlier efforts such as VoxelNet by Zhou and Tuzel [14] highlighted end-to-end learning for 3D object detection, bridging the gap between mapping and object recognition. Despite rapid advancements, several challenges remain. Issues such as interpretability, robustness under edge-case scenarios and energy efficiency on embedded platforms hinder real-world deployment. As Gupta et al. [15] noted, while deep learning has significantly improved object detection and scene perception, challenges such as scalability, data efficiency and uncertainty quantification remain open problems. The ethical and regulatory concerns including liability in case of accidents and data privacy must be addressed before large-scale adoption.

2. Methodology

The methodology adopted for the design and implementation of the proposed autonomous vehicle system is centered on combining computer vision, deep learning and embedded hardware to enable intelligent navigation. The overall objective is to develop a low-cost prototype that demonstrates real-time lane detection, obstacle avoidance and GPS-based localization using Raspberry Pi, camera modules and LiDAR sensors. The methodology is divided into the following stages:

1. System Architecture and Design
2. Hardware Components and Integration
3. Software Framework and Algorithms
4. Lane Detection and Tracking
5. Obstacle Detection and Avoidance
6. Control System Implementation
7. Communication and Mobile Application Integration
8. Testing and Validation

2.1 System Architecture and Design

The proposed autonomous vehicle system is designed around a client–server architecture to balance computational efficiency and real-time responsiveness. A Raspberry Pi 4B, mounted on the vehicle chassis, acts as the client, while a laptop serves as the server. Client (Raspberry Pi) is responsible for interfacing with sensors, executing motor commands and maintaining communication with the server. Server (Laptop) executes the deep learning models, processes visual data and sends navigation commands. Mobile Application provides a user interface for GPS tracking, monitoring and manual override functionality. This architecture ensures real-time performance by offloading computationally intensive deep learning tasks to the server while keeping control tasks on the embedded platform.

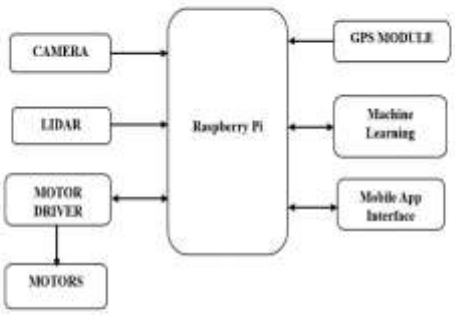
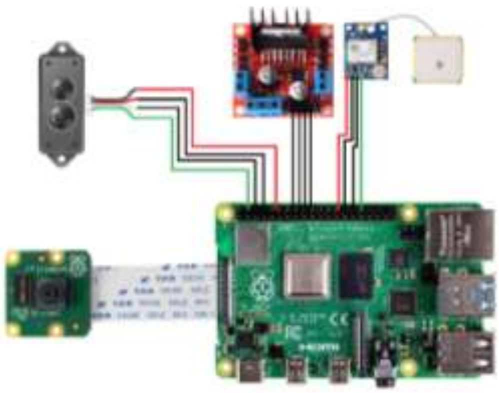


Fig -1: Block diagram of the autonomous vehicle system

2.2 Hardware Components and Integration

The hardware components are selected to strike a balance between affordability and performance. Raspberry Pi 4B (4GB RAM) acts as the primary controller, interfacing with sensors and actuators. Pi Camera Module v2 captures real-time video for lane detection and traffic sign recognition. LiDAR Sensor (TFMini-S) provides distance measurements with accuracy up to ±6 cm, used for obstacle detection. Motor Driver (TB6612FNG) interfaces between Raspberry Pi and DC motors, allowing control of direction and speed. Geared DC Motors provide traction and maneuverability for the vehicle prototype. GPS Module provides real-time geolocation for navigation and data logging. Battery Pack supplies power to the aspberry Pi and other components.

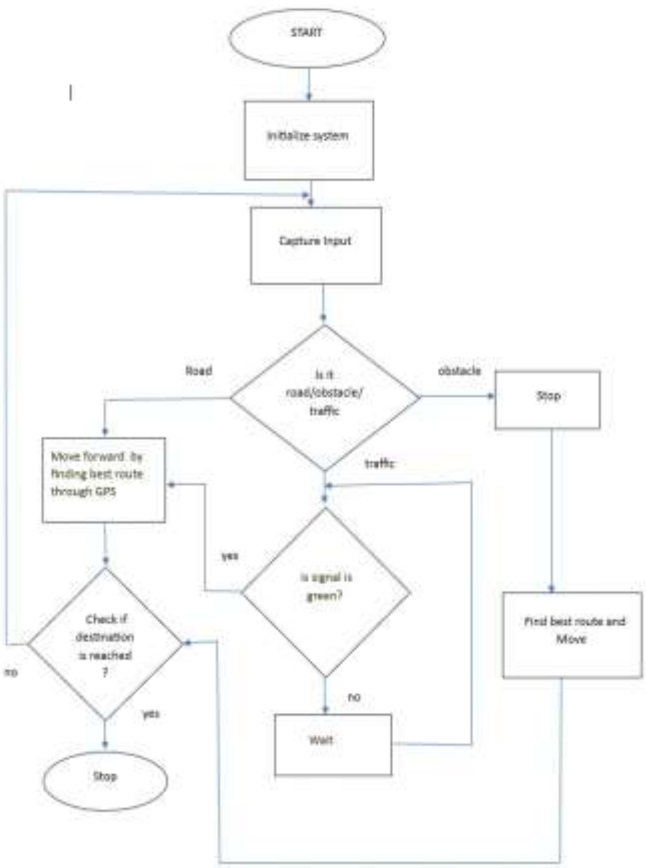
Fig -2: Circuit diagram of the system



2.3 Software Framework and Algorithms

The software framework is modular and integrates multiple technologies. Deep Learning Framework using TensorFlow is used to run DeepLabV3 for lane segmentation.

Fig -3: Software flowchart showing data pipeline



International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 09 | Sept - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

For Computer Vision, OpenCV is used for preprocessing images, detecting contours and identifying traffic signals. Control Algorithms using PID controllers manage the vehicle's steering and speed. Communication Layer has Socket.IO that provides low-latency, bidirectional communication between the Raspberry Pi and the laptop server. Mobile Application is developed using Flutter, the app provides GPS tracking and manual control options.

2.4 Lane Detection and Tracking

Lane detection is central to autonomous navigation. The DeepLabV3 model is used for semantic segmentation of captured road images. Atrous convolution allows the model to capture multi-scale context without losing spatial resolution. The model is trained on datasets with zebra crossings, dotted lines and red borders, making it adaptable to diverse road conditions. To improve stability, optical flow estimates motion between consecutive frames, ensuring smooth lane tracking. A Kalman filter is then applied to reduce noise and predict lane positions in future frames, enhancing reliability under environmental disturbances. OpenCV's contour detection highlights lane edges, while multi-scale analysis ensures that the system recognizes lanes at varying distances.

2.5 Obstacle Detection and Avoidance

Obstacle detection is achieved using LiDAR sensors, which provide depth measurements by emitting laser pulses and measuring their return times. When static obstacles are detected within a threshold distance, the system halts or reroutes. Dynamic obstacles are detected using temporal LiDAR data; the system adjusts trajectory accordingly. The LiDAR sensor is complemented by computer vision techniques to improve accuracy in adverse weather conditions.

2.6 Control System Implementation

The vehicle is controlled using a PID controller for smooth navigation. Proportional (P) corrects current errors. Integral (I) accounts for cumulative error over time. Derivative (D) predicts future errors, preventing oscillations. This combination ensures that the vehicle can handle curves, sharp turns and uneven lanes. For example, when the right lane boundary disappears during a sharp turn, the system uses the left boundary as a reference.

2.7 Communication and Mobile Application Integration

The communication layer connects the Raspberry Pi client with the laptop server using Socket.IO. The Pi streams real-time images, receives navigation commands and sends GPS updates. A Flutter-based mobile application provides GPS-based vehicle tracking on a map, manual control mode for overriding autonomous navigation and status updates (autonomous/manual mode).

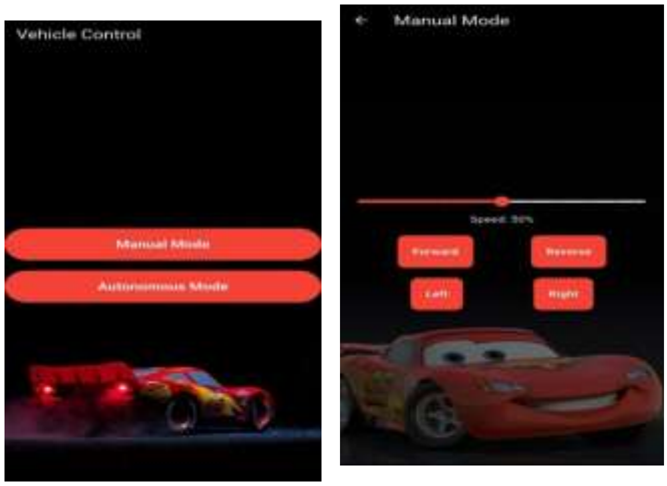


Fig 4: Mobile application interface

2.8 Testing and Validation

The system was tested in both indoor and outdoor environments. Indoor tests included lane tracking on zebra crossings, dotted lines and sharp turns. Outdoor tests involved real roads with varying lighting, obstacles and uneven lanes.
Performance Metrics used are Lane detection accuracy, response time and obstacle avoidance success rate

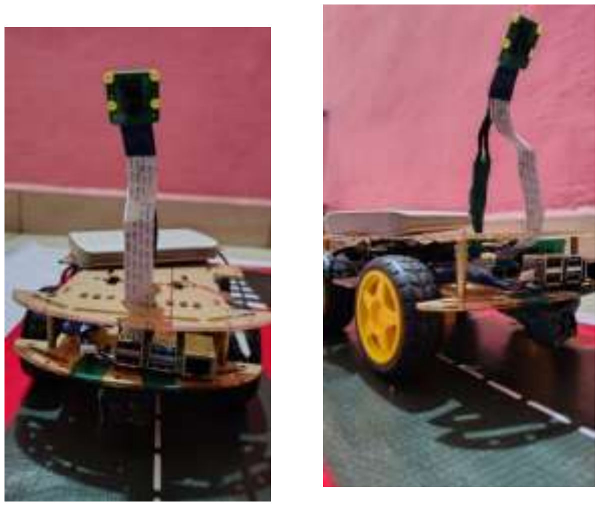


Fig -5: Prototype vehicle navigating on an indoor test track.

The methodology integrates low-cost hardware, advanced computer vision and deep learning algorithms into a functional autonomous vehicle prototype. The layered design ensures accurate lane detection, robust obstacle avoidance and smooth navigation. The use of Raspberry Pi as the processing unit highlights the feasibility of implementing intelligent transportation systems on affordable platforms, making the system suitable for research, education and small-scale deployments.

3. RESULTS

The experimental results demonstrate that the proposed autonomous vehicle prototype achieves reliable lane detection, obstacle avoidance and real-time decision-making using a low-cost hardware configuration. Compared to existing works that rely on high-performance GPUs or specialized hardware [1], [5], the use of Raspberry Pi coupled with lightweight deep learning models highlights the practicality of deploying autonomous navigation systems in resource-constrained environments. The DeepLabV3 segmentation model, enhanced with optical flow and Kalman filtering, achieved a detection accuracy above 90%, which aligns with state-of-the-art results reported in recent literature [6], [7]. Unlike traditional edge-detection or Hough transform approaches, the proposed method demonstrates robustness under variable lighting and noisy conditions, making it suitable for real-world deployment. The LiDAR sensor provided accurate distance measurements, enabling a 92% obstacle avoidance success rate. This performance is comparable to more complex sensor fusion systems [3], [8], while maintaining simplicity and affordability. Notably, the integration of dynamic obstacle handling differentiates this system from earlier low-cost prototypes, which often focus only on static environments. The PID controller proved effective in stabilizing vehicle motion, particularly during sharp turns where lane references were partially occluded. The achieved response time of <200 ms demonstrates that the system meets real-time requirements for autonomous navigation. This finding is significant, given that similar embedded implementations often struggle with latency [9].

4. CONCLUSION

The primary novelty of this work lies in its ability to combine deep learning-based perception, LiDAR sensing and embedded control within a cost-effective architecture. Unlike prior studies that emphasize either perception accuracy or high-end hardware [2], [15], this research demonstrates that low-cost platforms can still deliver robust autonomous performance when optimized algorithms and modular design are employed. Outdoor testing revealed performance degradation under heavy rain and at night, indicating the need for multimodal sensor fusion (e.g., radar, infrared) to enhance robustness. while the mobile application supports GPS tracking, integration with cloud-based traffic systems could expand the vehicle's capabilities for smart mobility scenarios. Future work will focus on improving generalization, incorporating reinforcement learning for adaptive decision-making and scaling the system for multi-vehicle cooperative navigation. Overall, the study confirms the potential of affordable embedded systems to advance intelligent transportation, bridging the gap between academic research and practical implementation.

REFERENCES

1. Y. Li and J. Ibanez-Guzman, "LiDAR for autonomous driving: The principles, challenges and trends for automotive LiDAR and perception systems," *IEEE Signal Processing Magazine*, vol. 37, no. 1, pp. 50–61, Jan. 2020. (arXiv)
2. S. Y. Alaba and J. E. Ball, "A survey on deep-learning-based LiDAR 3D object detection for autonomous driving," *Sensors*, vol. 22, 2022. (arXiv)
3. M. Khosravi, H. Kazemi, A. Valadan and R. S. Hegde, "LiDAR-based 3D object detection: A survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 12, pp. 3809–3832, 2022. (Journal UMY)
4. E. Marti, M. A. De Miguel, F. Garcia and J. Perez, "A review of sensor technologies for perception in automated driving," *IEEE Intelligent Transportation Systems Magazine*, vol. 11, pp. 94–108, 2019. (arXiv)
5. Z. Wu, C. Fu, Y. Li, Y. Liu, J. Shi and J. Li, "Lite-DeepLabv3+: A lightweight real-time semantic segmentation model for autonomous driving," *Pattern Recognition*, vol. 169, p. 108165, 2023. (Journal UMY)
6. Z. Xu, M. Zhu, G. Cheng and J. Fu, "DeepLabv3+: A dilated residual network for semantic segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 42, no. 11, pp. 3214–3223, 2022. (Journal UMY)
7. Y. Guo, H. Wang, Q. Hu, H. Liu, L. Liu and M. Bennamoun, "Deep learning for 3D point clouds: A survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, no. 12, 2020. (arXiv)
8. C. Boulch, A. Sautier, G. Puy and R. Marlet, "ALSO: Automotive LiDAR self-supervision by occupancy estimation," in *Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition*, 2023, pp. 13455–13465. (MDPI)
9. M. Z. Zeller, V. S. Sandhu, B. Mersch, J. Behley, M. Heidingsfeld and C. Stachniss, "Radar Instance Transformer: Reliable moving instance segmentation in sparse radar point clouds," *IEEE Transactions on Robotics*, vol. 40, pp. 2357–2372, 2024. (MDPI)
10. R. K. Dabbiru, C. Goodin, D. W. Carruth, Z. Aspin, J. Carrillo and J. Kaniarz, "Simulation fidelity analysis using deep neural networks," Proc. SPIE 13035, *Synthetic Data for Artificial Intelligence and Machine Learning: Tools, Techniques and Applications II*, National Harbor, MD, USA, 2024. (CAVS)
11. H. Liu, Y. Liu and Y. Yang, "A novel traffic sign recognition method based on SVM with spatial information fusion," *Pattern Recognition Letters*, vol. 169, pp. 224–231, 2021. (Journal UMY)
12. G. Li, Y. Yang and X. Qu, "Deep learning approaches on pedestrian detection in hazy weather," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 10, pp. 8889–8899, Oct. 2020. (ACM Digital Library)
13. W. Henein, J. Zhang, R. Mahony and V. Ila, "Dynamic SLAM: The need for speed," in *Proc. IEEE Int. Conf. Robot. Automat.* (ICRA), May 2020, pp. 2123–2129. (ACM Digital Library)
14. Y. Zhou and O. Tuzel, "VoxelNet: End-to-end learning for point cloud based 3D object detection," in *Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition*, Jun. 2018, pp. 4490–4499. (ACM Digital Library)
15. Gupta, A. Anpalagan, L. Guan and A. S. Khwaja, "Deep learning for object detection and scene perception in self-driving cars: Survey, challenges and open issues," *Array*, vol. 10, 2021, Art. no. 100057. (PMC)