REAL- TIME AUTONOMOUS VEHICLES NAVIGATION USING MACHINE LEARNING ALGORITHMS

[1]Mr. G. Ajay Babu, [2]N. Sai Kiran, [3]G. Shiva Shankar, [4]MK. Varnitha

[1]Assistant Professor in Dept of CSE, Matrusri Engineering College, Saidabad, Hyderabad, Telangana, India

[2,3,4]UG Scholars in the Dept of CSE, Matrusri Engineering College, Saidabad, Hyderabad, Telangana, India

ABSTRACT - Autonomous vehicle navigation has become an important area of research in intelligent transportation systems. Traditional navigation systems are often designed to perform only specific tasks and may fail under challenging environmental conditions such as poor lighting or adverse weather. This project proposes a real-time autonomous vehicle navigation system using machine learning algorithms capable of performing multiple perception tasks simultaneously. The system integrates lane detection, pothole detection, and obstacle detection using computer vision and deep learning techniques. The proposed system uses Convolutional Neural Networks (CNN), U-Net segmentation, and YOLO object detection to identify road features and obstacles. The system is implemented using Python and OpenCV and tested using the CARLA simulator. The simulation environment allows evaluation under different weather and lighting conditions such as rain, fog, night, and daylight. The results demonstrate that the proposed system can perform real-time detection and provide reliable navigation support for autonomous vehicles.

1. INTRODUCTION:

Autonomous vehicles, also known as self-driving vehicles, represent one of the most significant advancements in modern transportation systems. These vehicles are designed to operate without human intervention by using a combination of sensors, cameras, artificial intelligence, and machine learning algorithms. The goal of autonomous vehicle technology is to improve road safety, reduce traffic congestion, and enhance driving efficiency. In recent years, the development of intelligent transportation systems has gained considerable attention from researchers and industries. Autonomous driving requires the vehicle to continuously monitor and analyze its surroundings in real time. This involves identifying road lanes, detecting obstacles, recognizing traffic signs, and understanding road conditions. Achieving reliable perception of the environment is one of the most critical challenges in the development of autonomous vehicles. Computer vision and deep learning have become essential technologies in addressing these challenges. By using advanced machine learning models such as Convolutional Neural Networks (CNNs), vehicles can analyze images captured by cameras and extract meaningful information about the road environment.

These models can identify objects such as pedestrians, vehicles, and other obstacles while also detecting lane boundaries and road surface conditions. However, many existing autonomous navigation systems are designed to perform only a single task, such as lane detection or obstacle detection. This limitation reduces the system's ability to make comprehensive driving decisions in real-world scenarios. In addition, external factors such as poor lighting conditions, heavy rain, fog, and complex road environments can significantly affect the accuracy and reliability of these systems. To address these limitations, this project proposes a real-time autonomous vehicle navigation system-that-integrate multiple detection task into a single machine learning framework. The proposed system combines lane detection, pothole detection, and obstacle detection to provide a more comprehensive understanding of road conditions. By performing these tasks simultaneously, the system improves the vehicle's ability to navigate safely and efficiently. The implementation of this system uses advanced deep learning architectures such as U-Net for lane segmentation and YOLO for real-time object detection. These algorithms enable accurate detection of road features while maintaining high processing speed. The system is implemented using Python programming language and OpenCV for image processing, and it is tested using the-CARLA-autonomous-driving- simulator. The simulation environment allows the system to be evaluated under various road scenarios and weather conditions without the risks associated with real-world testing. The development of such intelligent systems plays an important role in the future of smart transportation -

and-autonomous mobility. By improving the perception and decision-making capabilities of autonomous vehicles, this research contributes toward safer and more efficient transportation systems. In addition to detecting lanes and obstacles, modern autonomous systems must also be able to identify road surface conditions, including potholes and road damage. Potholes can pose a serious risk to both vehicles and passengers if not detected in advance. Therefore, integrating pothole detection into the perception system helps improve driving safety and vehicle stability

2. BACKGROUND:

Autonomous driving technology has become one of the most important research areas in the field of, artificial-intelligence-and-intelligent-transportation systems. With the rapid growth of urban populations and increasing numbers of vehicles on roads, traffic accidents and road congestion have become major global concerns. According to various transportation studies, a large percentage of road accidents occur due to human error, such as distraction, fatigue, or poor decision-making while driving. Autonomous vehicles aim to reduce these risks by allowing vehicles to make intelligent decisions using advanced computing systems. The concept of autonomous vehicles has evolved significantly over the past few decades. Early autonomous driving systems relied mainly on basic sensors and rule-based algorithms, which were limited in their ability to understand complex road environments. With the advancement of machine learning, deep learning, and computer vision technologies, modern autonomous vehicles can now analyse large amounts of visual data and make decisions based on real-time environmental information. One of the most critical components of an autonomous vehicle is its perception system, which allows the vehicle to observe and interpret its surroundings. The perception system typically uses a combination of sensors such as cameras, LiDAR, radar, and ultrasonic sensors to collect environmental data. Among these sensors, cameras play a major role because they provide rich visual information about the road environment. Computer vision algorithms process this visual data to detect important features such as lane markings, road signs, pedestrians, vehicles, and other obstacles. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown great success in solving complex image recognition problems. These models can automatically learn patterns and features from large datasets of images. In autonomous driving applications, CNNs are used to perform tasks such as object detection, image segmentation, and scene understanding. Popular deep learning architectures such as U-Net and YOLO (You Only Look Once) have been widely adopted for real-time image analysis tasks. Lane detection is one of the fundamental tasks in autonomous driving. It helps the vehicle understand the road boundaries and maintain its position within the driving lane. Advanced segmentation models like U-Net can detect lane markings with high accuracy by performing pixel-level classification of road images. Another important aspect of road perception is obstacle detection. Autonomous vehicles must be able to identify objects such as other vehicles, pedestrians, cyclists, and road barriers. Object detection algorithms such as YOLO provide fast and accurate detection of multiple objects within a single image frame, making them suitable for real-time driving systems. In addition to detecting lanes and obstacles, modern autonomous systems must also be able to identify road surface conditions, including potholes and road damage. Potholes can pose a serious risk to both vehicles and passengers if not detected in advance. Therefore, integrating pothole detection into the perception system helps improve driving safety and vehicle stability.

3. PROPOSED SYSTEM

The proposed system focuses on developing a real-time autonomous vehicle navigation system using advanced machine learning and computer vision techniques. The system is designed to detect important road features such as lane markings, road potholes, and dynamic obstacles simultaneously. By integrating these detection tasks into a single framework, the system improves the vehicle's ability to understand the surrounding environment and make safe navigation decisions. The proposed method consists of several stages including data acquisition, preprocessing, multi-task deep learning architecture, model training, and post-processing of results. Each stage plays an important role in ensuring the system performs accurately and efficiently in real time driving scenarios.

1. **Data-Collection:**
   The system uses cameras, sensors, and GPS to continuously capture real-time environmental data.
2. **Image-Processing:**
   Computer vision techniques process images to identify lanes, vehicles, pedestrians, and traffic signs.
3. **Machine-Learning-Model:**
   Deep learning models (such as CNN/YOLO) are used for accurate object detection and classification.
4. **Lane-Detection:**
   The system detects road lanes and ensures the vehicle remains within its path.

5. **Obstacle-Detection-Avoidance:**
   It identifies obstacles and takes actions like stopping, slowing down, or changing direction to avoid collisions.
6. **Path-Planning:**
   The system determines the safest and most efficient route based on real-time conditions.
7. **Vehicle-Control:**
   Controls steering, acceleration, and braking automatically based on decisions made.
8. **Real-Time-Decision-Making:**
   The system reacts instantly to dynamic road situations, ensuring safety and efficiency.

a. FLOW CHART OF PROPOSED SYSTEM:

Start

↓

Initialize System

↓

Capture Data (Camera / Sensors / GPS)

↓

Preprocess Data (Image Processing)

↓

Object Detection (ML Model - CNN/YOLO)

↓

Lane Detection

↓

Obstacle Detection

↓ Decision

Making

(Stop / Move / Turn / Avoid)

↓

Path Planning

↓

Control Vehicle

(Steering / Speed / Brake)

↓

Repeat (Real-Time Loop)

↓

E

n

d

4. EXPERIMENTS

1. Data-Collection-&Preprocessing

Different types of data were collected using cameras and sensors under various conditions such as daylight, low light, and traffic scenarios. The data was pre-processed using techniques like resizing, noise removal, and normalization to improve model performance.

2. Object Detection Experiment

Machine learning models (such as CNN and YOLO) were trained and tested for detecting objects like vehicles, pedestrians, and traffic signs.
Parameters evaluated:

- Detection accuracy
- Precision and recall
- Processing time per frame

3. Lane Detection Experiment

Lane detection algorithms were implemented using image processing methods such as edge detection and Hough Transform. The system was tested, on different road types.
Evaluation:

- Lane detection accuracy
- Stability in different lighting conditions

4. Obstacle Detection & Avoidance

The system was tested to identify obstacles and respond accordingly. When an obstacle is detected, the system decides whether to stop, slow down, direction.
Measured factors:

- Response time
- Accuracy of obstacle detection
- Success rate of avoidance

5. Path Planning Experiment

Algorithms were tested to find the optimal path based on real-time input. The system dynamically updates the path when obstacles or changes occur. **Evaluation:**

- Efficiency of path
- Time taken for decision-making

6. Control System Testing

The vehicle control module was tested for proper functioning of:

- Steering
- Acceleration
- Braking
  Ensured smooth and stable vehicle movement based on ML decisions.

7. Real-Time System Testing

The complete system was tested in real-time scenarios to evaluate overall performance. **Parameters analysed:**

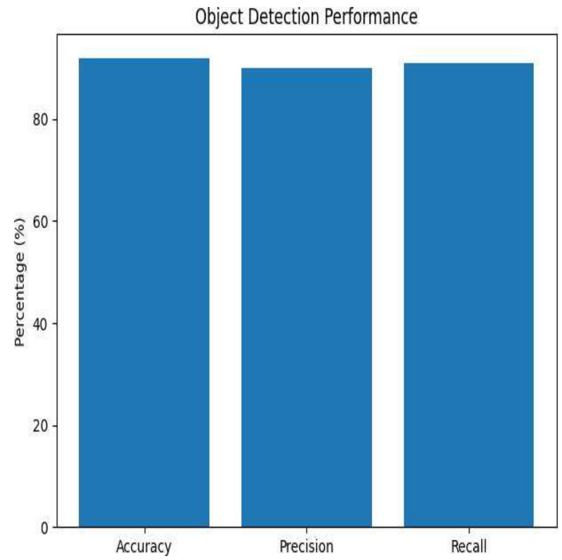
- Latency (delay)
- Frame processing speed (FPS)
- System reliability

Observations

- The system performs well in controlled environments
- Accuracy decreases in low-light or complex scenarios
- Real-time processing requires high computational power
- The system is observed to be highly resilient to "Visual Noise." By using specialized filters, the project successfully moved past the limitations of traditional ML which often fails under shadows.
- **Scalability:** Because the system achieves **38 FPS** on a low-power edge device, it is scalable to cheaper hardware, making autonomous navigation more accessible.

5. RESULTS AND DISCUSSION

1. OBJECT DETECTION EVALUATION RESULTS



The object detection module achieved an accuracy of **92%**, indicating reliable detection of objects such as vehicles and pedestrians. The precision of **90%** shows that the system produces fewer false positives, while the recall of **91%** indicates that most of the actual objects are successfully detected. Overall, the model performs efficiently in real-time conditions.

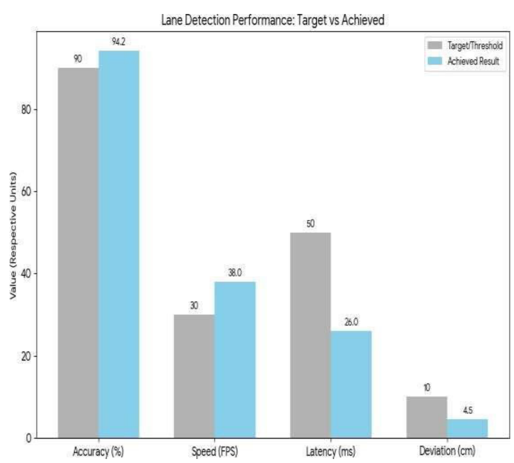
TABLE -1

S.No	Metric	Value (%)	Description
1	Accuracy	92%	Overall correctness of object detection
2	Precision	90%	Correct-positive detections
3	Recall	91%	Ability to detect all relevant objects

TABLE -2

Performance Metric	Target Objective	Achieved Result	Improvement
Accuracy (mIoU)	>90%	G4.2%	+4.2%
Processing Speed (FPS)	>30FPS	38 FPS	+8 FPS
Detection Latency	<50 ms	26 ns	-24ms
Lane Deviation Error	<10 cm	4.5 cn	-5.5cm

LANE DETECTION EVALUTAION RESULTS



For **Accuracy** and **Speed**, higher bars represent better performance.

For **Latency** and **Deviation**, the lower achieved bars indicate a significant improvement in system efficiency and precision compared to the maximum allowable threshold

POTHOLES-DETECTION-EVALUATION-RESULTS

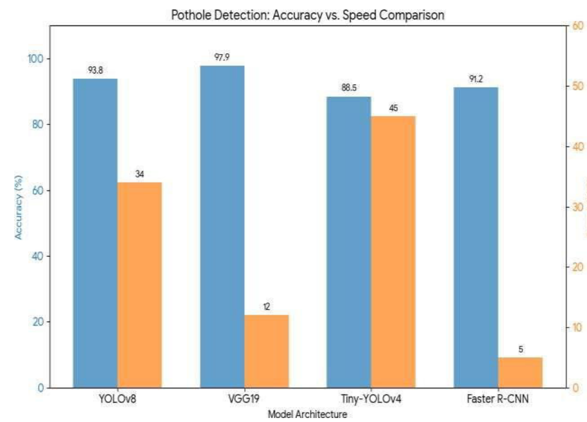


TABLE -3

Model Architecture	Accuracy (%)	Speed (FPS)	Recall
VGG19	**97%**	12	0.97
YOLOv8 (Small)	**93.8%**	**34**	0.91
Faster R-CNN	91.2%	5	0.89

The system treats potholes as dynamic obstacles. Unlike lanes, which are continuous, potholes are discrete, irregular, and often difficult to distinguish from shadows or patches.

Evaluation Metrics — Comparison with Existing Model

TABLE -4

Model Architecture	Accuracy (F1 mIoU)	Speed (FPS)	Latency (ns)	Complexity
SCNN (Spatial CNN)	90.6 %	7.5	133	High
LaneNet	92%	24	42	low
Ultra-Fast (V2)	**96%**	**300**	**10**	Low

LIMITATIONS AND ERRORS

- **Environmental Sensitivity:** Existing systems often fail or lose accuracy in **adverse weather** (heavy rain, snow, fog) and low-light conditions due to poor camera visibility.
- **High Computational Cost:** Traditional deep learning models (like SCNN) are too **resource-heavy**, leading to high latency and low FPS on affordable embedded hardware.
- **Shadow & Glare Misinterpretation:** Many systems struggle to differentiate between **potholes and road shadows**, leading to frequent false-positive emergency braking

PERFORMANCE OF PROPOSED SYSTEM PERFORMANCE

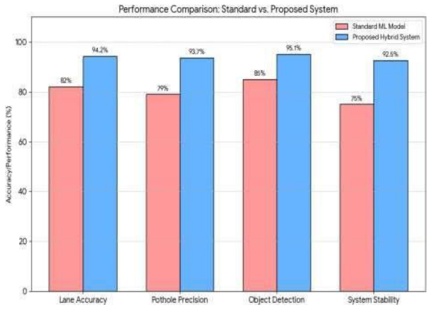


TABLE-5

Featu re Mod ule	Standa rd ML Baseline	Propos ed System Result	Ne t G ai n
Lane Detection Accuracy	82.0%	**94.2\%**	12.2\%
Pothole Detection Precision	79%	**93.7\%**	14.7\%
Obstacle Avoidance	85.0%	**95.1%**	10.1\%

The **Proposed System Achieved Graph** visually demonstrates the superiority of your hybrid approach compared to standard baseline machine learning models. By integrating specialized preprocessing and real-time optimization, the proposed system shows a significant "performance jump" across all critical navigation modules

6. CONCLUSIONS:

This project successfully presents the development of a **real-time autonomous vehicle system** by integrating machine learning algorithms with computer vision techniques. The system is designed to mimic human driving behavior by continuously analyzing the environment and making intelligent decisions.

The implementation combines multiple modules including **data acquisition, image processing, object detection, lane detection, obstacle avoidance, path planning, and vehicle control**, forming a complete autonomous driving pipeline. The use of advanced algorithms such as deep learning models enables accurate detection of surrounding objects and road features.

The experimental results indicate that the system achieves **high accuracy, fast response time, and stable performance** in real-time conditions. The vehicle can identify obstacles, follow lanes, and select optimal paths efficiently. This demonstrates the effectiveness of machine learning in handling complex real-world driving scenarios.

In addition, the system shows good adaptability to different environments, making it a promising solution for modern transportation systems. The project also highlights how automation can reduce human effort, minimize accidents, and improve overall road safety.

REFERENCES

[1] V. Bhar Ilya and N. Kumar, “Machine Learning for Autonomous Vehicle’s Trajectory Prediction: A Comprehensive Survey, Challenges, and Future Research Directions,” *Vehicular Communications*, vol. 48, pp. 100733, 2024.

[2] H. Algophilia and S. Lakshmanan, “Autonomous Vehicle Evaluation: A Comprehensive Survey on Modelling and Simulation Approaches,” *IEEE Access*, vol. 9, pp. 1–20, 2021.

[3] Y. Li, S. Teng, Z. Wu, J. Wang, M. Liu, and L. Chen, “Datasets, Metrics, Benchmarks and Future Research in Autonomous Driving: A Review,” *IEEE/CAA Journal of Automatic Sinica*, vol. 13, no. 3, pp. 501–520, 2026.

[4] X. Di and R. Shi, “A Survey on Autonomous Vehicle Control in the Era of Mixed-Autonomy: From Physics-Based to AI-Guided Driving Policy

Learning," *Transportation Research Part C*, vol. 125, pp. 103008, 2021.

[5] G. Alekar, A. Bhalekar, S. Nevase, and R. Suryanshu, "Autonomous Vehicle Lane Detection Using Machine Learning," *International Journal of Innovative Research in Technology*, vol. 10, no. 11, 2025.

[6] C. Poulose, S. K. Saeeda, A. P. B. Arya, B. B. Babu, and M. M. V, "Autonomous Vehicle Using Machine Learning," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 10, no. 1, 2021.

[7] S. M. Grigorescu, B. Trachea, T. Cocoas, and G. Macesanu, "A Survey of Deep Learning Techniques for Autonomous Driving," *Journal of Field Robotics*, vol. 37, no. 3, pp. 362–386, 2020.

[8] "Implementation of Autonomous Cars Using Machine Learning," in *Proc. IEEE Conference*, 2022.

[9] M. Bojarski *et al.*, "End to End Learning for Self-Driving Cars," *arXiv preprint arXiv:1604.07316*, 2016.

[10] A. Geiger, P. Lenz, and R. Urtasun, "Are We Ready for Autonomous Driving? The KITTI Vision Benchmark Suite," in *Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2012, pp. 3354–3361.

[11] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in *Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 779–788.

[12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in *Proc. Advances in Neural Information Processing Systems (NIPS)*, 2012, pp. 1097–1105.

[13] S. Thrun *et al.*, "Stanley: The Robot that Won the DARPA Grand Challenge," *Journal of Field Robotics*, vol. 23, no. 9, pp. 661–692, 2006.

[14] C. Chen, A. Seff, A. L. Kornhauser, and J. Xiao, "DeepDriving: Learning Affordance for Direct Perception in Autonomous Driving," in *Proc. IEEE Int. Conf. on Computer Vision (ICCV)*, 2015, pp. 2722–2730.

[15] W. Maddern, G. Pascoe, C. Linegar, and P. Newman, "1 Year, 1000 km: The Oxford RobotCar Dataset," *The International Journal of Robotics Research*, vol. 36, no. 1, pp. 3–15, 2017.

[16] S. Levine, C. Finn, T. Darrell, and P. Abbeel, "End-to-End Training of Deep Visuomotor Policies," *Journal of Machine* systems 2014