International Journal of Computer Science and Mechatronics
A peer reviewed international journal | Article available at http://ijcsm.in | SJIF 8.726
©smsamspublications.com | Vol.12.Issue.5. 2026.ISSN: 2455-1910

Improving Self Driving Cars Safety Analysis Using Artificial Intelligence

S. Haritha[1], S. Yuvaraj, G[2]. Sabeena Gnana Selvi[3]
Project Students, Assistant Professor,
Department of CSE Sathyabama Institute of Science and Technology, Chennai, India

***Abstract*—**The goal of this project is to create a sophisticated lane and obstacle detection system that will increase the safety of self-driving automobiles. While the obstacle detection system detects and monitors any risks like other cars or pedestrians, the lane detection system makes sure the car stays in its lane by recognizing lane borders in real-time. The car may maneuver more skillfully by integrating both technologies, guaranteeing safe lane-keeping and accident avoidance. Enhancing vehicle control and adapting to changing road conditions are the main goals of this strategy, which is crucial for autonomous driving. The ultimate objective is to aid in the advancement of safer self-driving technology, which will lower the probability of collisions and improve driving safety in general, even in challenging situations.

Keywords—*autonomous vehicles, Autonomous cars, obstacle detection, lane detection Avoiding collisions, Navigation in real time, systems for driver assistance, computer vision, traffic safety, processing images, deep learning for controlling vehicles, Object detection, edge detection, Improvement of safety*

I. INTRODUCTION

When it comes to autonomous vehicle technology, one of the most important factors is safety. It is crucial that these vehicles be able to safely recognize and respond to lane boundaries as well as potential impediments because they traverse intricate road conditions. By combining two essential elements—lane detection and obstacle detection— this study seeks to improve the safety of autonomous vehicles. To provide safe and effective navigation, the lane detection system assists the vehicle in keeping its position within the lane, while the obstacle detection system detects possible hazards such as other vehicles, pedestrians, and other obstructions.

The lane detection system analyzes the road surface and recognizes lane markings using computer vision techniques. The system can precisely identify lane margins and direct the motion of the car by processing pictures and video in Realtime. This is accomplished by techniques like region of interest (ROI) masking and edge detection, which enable the system to concentrate on the pertinent portions of the road, cutting down on pointless calculations and enhancing performance. To lower the chance of drifting or crashes, the car can then modify its steering to keep it in the center of the lane.

The project incorporates an obstacle detection module in addition to lane detection to assist the vehicle in recognizing and avoiding possible hazards. The system can identify obstructions in the vehicle's path, such as other cars, people or debris, by utilizing sophisticated image processing techniques and object detection algorithms. This feature, which allows the vehicle to alter its trajectory in real time, is essential for collision avoidance. A more complete safety solution is made possible by the integration of lane and obstacle detection systems, which offers a strong foundation for improving the dependability and security of autonomous vehicles.

II. LITERATURE SURVEY

In recent years, there has been a lot of interest in the use of AI in autonomous vehicles, especially in terms of improving vehicle safety. Numerous research examines how AI technologies affect self-driving cars, primarily focusing on how they might enhance lane and obstacle detection systems. AI-based models have demonstrated efficacy in safety management using software modeling techniques that improve the performance of self-driving systems, per a comprehensive review by Abbasi and Rahmani [2]. More research has been done on the security and dependability of these systems, and case studies on Open Pilot and other technologies have shown encouraging outcomes in terms of guaranteeing safe vehicle operation [3]. Advances in artificial intelligence (AI) in the field of autonomous vehicles are also making it simpler for these systems to identify impediments and drive safely in challenging situations [5][7].

Numerous research has examined the use of deep learning and machine learning algorithms to improve object recognition and avoidance capabilities, which are crucial to the security of self-driving cars. Convolutional neural networks (CNNs) have been highlighted as a means of enhancing car safety systems, such as the incorporation of voice recognition for improved driver assistance [14]. Furthermore, one of the most important areas for improving autonomous vehicle capabilities has been identified as the use of deep learning in obstacle detection and avoidance [16]. The dependability of these technologies is also continuously assessed, with research focusing on their practical performance and the developments required to get completely autonomous driving without human assistance [13][8]. These results imply that deep learning and artificial intelligence are crucial for enhancing the usefulness and safety of driverless cars.

SUMMARY OF LITERATURE SURVEY.

Significant improvements in safety and obstacle detection systems are highlighted in the linked research on artificial intelligence (AI) in autonomous cars. Convolutional neural networks (CNNs) and other deep learning and artificial intelligence (AI) approaches have proved crucial in improving lane detection and real-time hazard detection, ensuring that cars can safely drive in challenging surroundings. In autonomous driving systems, studies have shown the security and dependability of AI-based technologies like Open Pilot. Current research is concentrating on how well these technologies work in the actual world and how they integrate with obstacle detection. Furthermore, the development of completely autonomous vehicles that can operate safely and independently of humans has been largely fueled by advances in machine learning algorithms, such as those for object identification and driver support.

III. PROPOSED METHODOLOGY

A. *Problem Statement*

The need for improved safety and navigational capabilities in autonomous vehicles through real-time lane and obstacle recognition is the issue this project attempts to solve. Although self-driving technologies have advanced significantly, it is still difficult to ensure safe and effective vehicle operation in dynamic conditions, such as properly following lanes and identifying obstructions. Vehicle safety may be jeopardized by current systems' inability to handle complicated road conditions, fluctuating lighting, and unexpected hazards. By combining lane detection and obstacle avoidance approaches, this research seeks to provide an integrated system that would improve autonomous vehicles' perception of their environment and allow them to make better driving judgments in real time.

B. *Objectives*

1. **Build a Sturdy Lane recognition System:** The main objective is to develop a lane recognition system that can reliably recognize road lane markers in a range of driving scenarios. This entails managing difficulties such as changing illumination conditions (day/night), different types of road surfaces (concrete, asphalt), and weather elements (rain, fog, shadows). To detect and track lanes, the system uses computer vision and image processing algorithms to process real-time video data from cameras.

2. **Combine Obstacle Detection and Avoidance:** This project aims to combine lane detection with an obstacle detection system that can recognize possible hazards or items (such as pedestrians, other cars, or debris) in the path of the vehicle. To identify and track impediments and initiate the proper avoidance actions, the obstacle detection system will use a variety of sensor inputs, including cameras, LIDAR, and ultrasonic sensors, as well as sophisticated algorithms, such deep learning.
3. **Enhance Autonomous Vehicle Safety:** In the end, the main goal is to help make autonomous vehicles safer and more dependable overall. This research aims to lower the probability of accidents brought on by environmental variables, bad road conditions, or human mistake by enhancing lane-keeping and obstacle-avoidance skills. The vehicle's capacity to make safe driving judgments will be greatly enhanced by faster detection and reaction times, opening the door for a wider use of autonomous driving technology.
4. **Test and Assess the System:**
The system will undergo extensive testing on a range of roadways, including highways, rural roads, and urban streets. The correctness, dependability, and responsiveness of the system will all be assessed. The efficacy of the system will be evaluated using performance indicators like failure rates, latency, and detection accuracy. Additionally, the study will involve controlled physical testing and simulations.

C. Data Acquisition

To guarantee thorough environmental awareness, the lane and obstacle detection system's data acquisition process gathers information from a variety of sensors. High-definition video frames from the front of the car are captured by cameras, which serve as the main input for lane detection. To record lane boundaries, road markings, and adjacent cars, these cameras are installed on the windshield. By scanning the environment around the vehicle and identifying items like cars, people, and road obstacles, LIDAR sensors give 3D point cloud data, which is crucial for precise obstacle recognition. For short-range obstacle detection, especially in low-speed scenarios like parking, ultrasonic sensors are used. By helping with lane tracking and vehicle positioning, GPS and IMU data make sure the car stays in its lane and travels the right path.

1. **Gathering Datasets for Lane Detection** The algorithms for lane detection are trained and validated using datasets including the BDD100K, Simple Lane Detection Dataset, and Culhane dataset. Numerous road circumstances, such as varying illumination, weather, and road kinds, are included in these datasets. Installing cameras, LIDAR, and other sensors on a car to record driving footage in real time is another way to acquire custom data. Data is annotated to mark lane markers in the captured frames, and this enables the system to handle scenarios that might not be reflected in the open- source datasets.
2. **Gathering Datasets for Obstacle Identification** Open- source datasets such as the Waymo Open Dataset, nosecones, and the KITTI Vision Benchmark Suite are used to teach obstacle detection. Various obstacles, including bicycles, cars, people, and road furniture, are represented by labeled 3D point cloud data from LIDAR and camera photos in these databases. To ensure that obstacles are identified in real-world scenarios, unique data gathering is carried out to gather information using LIDAR, cameras, and ultrasonic sensors, much like lane detection. To identify items according to their nature and placement in the environment, the data is annotated.

3. Augmenting Data

The dataset is subjected to data augmentation techniques to enhance the model's generalization and resilience. These methods include adding simulated weather effects like fog and rain, rotating, varying brightness, and random cropping. Better performance in real-world situations where driving circumstances might change quickly is ensured by augmentation, which aids the model in learning to detect lanes and obstacles under various settings.

IV. PROPOSED WORKFLOW 1. Gathering and Preparing Data

Data collection from a variety of sensors, including cameras,
LIDAR, ultrasonic sensors, and GPS, is the first step in the project. While LIDAR and ultrasonic sensors provide 3D point cloud data for obstacle detection, cameras record video frames for lane detection. To manage noise, enhance quality, and standardize the data for additional analysis, preprocessing is done. To

improve the dataset by adding differences in weather, illumination, and road conditions, this step also involves data augmentation.

2. Module for Lane Detection

A lane detection technique is applied to the preprocessed camera frames. To recognize lane markers, the system uses deep learning-based approaches like Convolutional Neural Networks (CNNs) or image processing techniques like edge detection and Hough Transform. The technology then ensures lane conformance by tracking the vehicle's position within the lane once the lane borders have been set. The position of the car with relation to the road's lanes is provided by this real- time module.

3. Module for Obstacle Detection

The project uses computer vision techniques, including object identification algorithms (such YOLO and Faster RCNN), to detect obstacles in the route of the vehicle. To identify items like cars, pedestrians, or roadblocks, the algorithm examines the video frames. Potential risks are identified by calculating each object's location, distance, and categorization in relation to the vehicle. Throughout the video frames, the identified objects are noted and followed.

4. Training and the Model

The model uses sophisticated object identification methods like YOLO (You Only Look Once) for obstacle detection and deep learning algorithms like Convolutional Neural Networks (CNNs) for lane detection. Labeled datasets, which include annotated frames with lane markers and other obstructions, are used to train these models. The models are designed to function well in real-time settings, exhibiting low latency and excellent accuracy. After being trained independently, the lane and obstacle detection modules are combined into a single system.

5. Control and Decision-Making

The decision-making process decides how the vehicle should react to its surroundings based on the combined data from the two modules. For instance, the car's navigation system modifies its course or notifies the driver if an impediment is found within a critical range. In a similar vein, the control system will intervene to bring the car back within the lane lines if it veers out of it. To deal with more complicated situations, the decision-making process can be either rule based or applied using machine learning models like reinforcement learning.

V. TECHNOLOGY

1. Computer Vision

The system can process video frames and extract pertinent information about the road surroundings thanks to computer vision, which is at the heart of this research. For tasks like lane detection and picture preprocessing, OpenCV is widely used. The method separates lane borders from extraneous visual information by employing Canny Edge Detection, Gaussian blur, and grayscale video frame conversion. The Hough Line Transform method recognizes and extrapolates lane markers to provide a continuous and unambiguous visual path for navigation, while the region of interest (ROI) is specified using masks to focus solely on road sections.

2. Using Deep Learning to Identify Obstacles Deep learning models are used in the project to recognize and categorize barriers in real time. For object detection, algorithms like Faster R-CNN (Region-based Convolutional Neural Network) and YOLO (You Only Look Once) are used. These frameworks can quickly and accurately identify cars, people, and other obstacles by evaluating each video frame. The performance of the detection system is further improved while training time is reduced by utilizing transfer learning with pre-trained models. By using Convolutional Neural Networks (CNNs) for feature extraction, the system can identify intricate patterns like the size, texture, and form of barriers.

3. Language of Programming

Python is the main programming language used for this project because of its many machine learning and image processing libraries. Development is streamlined by libraries like OpenCV, TensorFlow, Kera's, and NumPy. Python is also favored due to its ease of integration with computer vision tasks and interoperability with deep learning frameworks.

4. Algorithms for Image Processing

Lane and obstacle detection relies heavily on several image processing algorithms. By identifying regions with notable intensity variations, Canny Edge Detection efficiently highlights lane borders and locates the edges in an image. These edges are joined using the Hough Transform technique to create continuous, straight lines that serve as lane markings. To ensure effective processing and a lower computational load, region masking is utilized to limit analysis to regions of the video feed, such as the road.

5. Training and Optimizing Models

Using annotated data and supervised learning approaches, the deep learning model is trained. By adapting pre-trained models, such YOLOv3 or Faster R-CNN, to the project specific dataset, transfer learning is used to drastically cut down on training time. By optimizing variables such as learning rate, batch size, and epoch count, hyperparameter tuning raises the accuracy and efficiency of the model. The model's performance is assessed using metrics like mean Average Precision (mAP) and Intersection over Union (IoU).

5. Region Masking:

A key preprocessing method in computer vision, region masking is particularly useful for applications such as autonomous car lane recognition. By eliminating extraneous regions like the sky, buildings, or surrounding terrain, the main goal is to concentrate solely on the region of interest (ROI), such as the road. This is accomplished by establishing a precise geometric region that roughly corresponds to the location of lane markers in the frame. This region is typically a polygonal form, such as a trapezoid. The ROI pixels are then set to white (1) and the remaining pixels to black (0) to form a binary mask. By applying this mask to the frame, the targeted area is isolated, therefore obliterating the rest of the image.

Figures and Tables **System Architecture:**

The lane and obstacle detection project's system architecture is made to process live video feeds to guarantee autonomous cars navigate safely. To extract, process, and interpret visual information from the surroundings, the architecture is made up of several sequential modules that cooperate. Usually from a camera installed on the car, the input layer records the video stream. Preprocessing is done on this raw video to enhance the data's quality and applicability. Important preprocessing techniques include applying Gaussian blur to minimize noise, turning the image to grayscale for simplicity, and highlighting important boundaries in the frame with edge detection methods like the Canny Edge Detector.

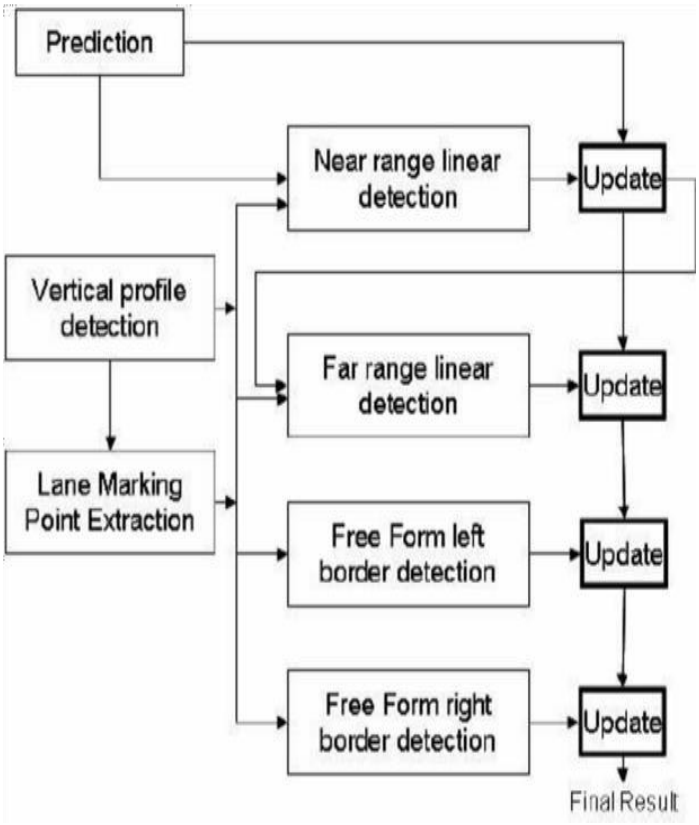


Fig 1 System Architecture

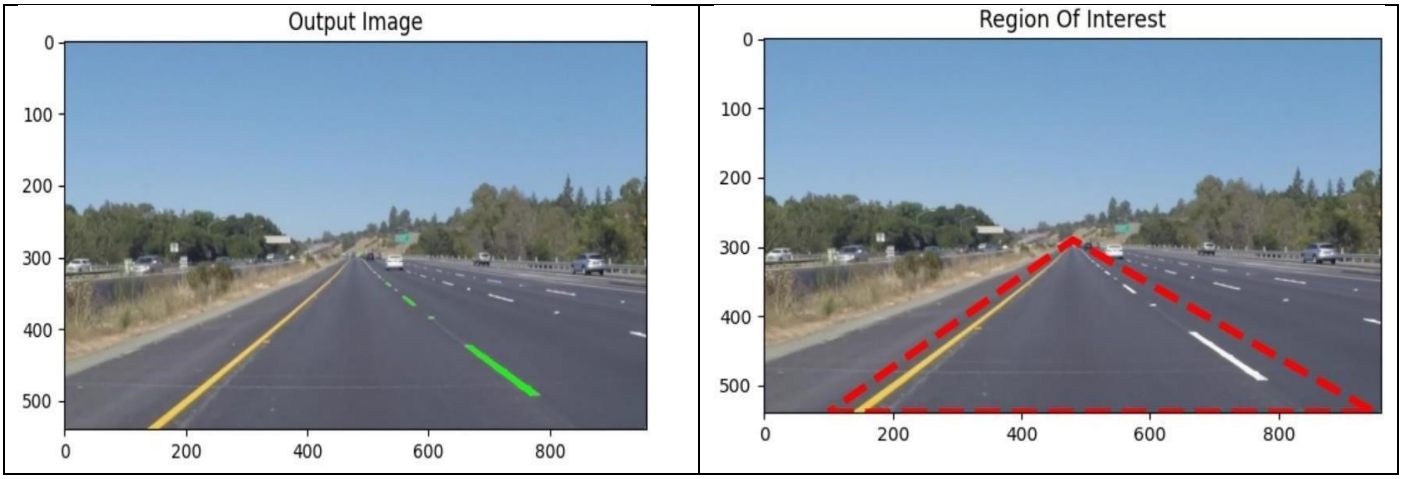
Following the completion of preprocessing, the system uses region masking to separate the ROI, keeping the attention on the road ahead. To detect and categorize things on the road, obstacle detection uses deep learning models like YOLO (You Only Look Once), while lane detection uses the Hough Line Transform to determine lane borders. After processing, the data is incorporated into a decision-making module that determines the best course for the car by analyzing obstructions and lane markings. The system's ability to function effectively in real-time and provide vital insights for safe and independent navigation is ensured by its modular architecture. Numerous autonomous driving applications can benefit from its scalability, resilience, and ability to adjust to changing road and environmental circumstances.

Acknowledgment

We would like to sincerely thank our advisers and mentors for their crucial support and direction during this endeavor. Their knowledge and perceptions were crucial to the creation and effective deployment of the lane and obstacle detection system. We also want to express our gratitude to our colleagues for their helpful criticism and cooperation, which enabled us to improve our strategy. Finally, we acknowledge that this project would not have been possible without the usage of open-source tools and frameworks.

VI RESULTS AND DISCUSSION

Using computer vision techniques, the suggested system successfully combines lane and obstacle detection, producing accurate and dependable real-time outputs. The system proved to be highly accurate in identifying obstacles using the YOLO deep learning model and lane borders using the Hough Line Transform during testing on a variety of road conditions. By effectively removing extraneous details from the frames, the region masking technique improved the focus on important road elements. The system's resilience and versatility are demonstrated by its capacity to manage a variety of illumination and environmental conditions, such as mild rain and shadows.



However, in severe weather situations where visibility is significantly decreased, like heavy rain or fog, the performance is affected. Overlapping barriers present another difficulty and can sometimes result in incorrect classifications. The system's overall performance shows considerable promise for improving autonomous vehicle safety despite these drawbacks. Accuracy and resilience may be further increased by future developments, such as adding more training data or honing the obstacle detection algorithm. The project also emphasizes how crucial effective algorithms and real-time processing are to guaranteeing smooth autonomous navigation.

VII CONCLUSION

The lane and obstacle detection system is a good example of how deep learning and computer vision techniques can be used for autonomous navigation. The system addresses important safety issues for self-driving cars by precisely recognizing lane lines and spotting impediments in real time.

Despite certain drawbacks, the project provides a solid basis for future studies and advancements in autonomous car technology. To improve driving efficiency and road safety, this work adds to the continuous developments in intelligent transportation systems.

REFERENCES

[1] *A Systematic literature review about the impact of artificial intelligence on autonomous vehicle safety*. (2020, December 1). IEEE Journals & Magazine | IEEE Xplore.
[2] https://ieeexplore.ieee.org/abstract/document/8892611/
[3] Abbasi, S., & Rahmani, A. M. (2023). Artificial Intelligence and software modeling
[4] Approaches in Autonomous Vehicles for Safety Management: A Systematic review. *Information*, *14*(10), 555. https://doi.org/10.3390/info14100555
[5] Alsubaei, F. S. (2022). Reliability and Security analysis of
[6] Artificial Intelligence-Based Self-Driving Technologies in Saudi Arabia: a case study of OpenPilot. *Journal of Advanced Transportation*, *2022*, 1–25. https://doi.org/10.1155/2022/2085225
[7] Bhavana, S., Kolachala, R., Kotamarti, S., & Rao, T. V. N. (2024). AI Advancements in Self-
[8] Driving Vehicle Technology. In *Advances in computational intelligence and robotics book series* (pp. 149–174). https://doi.org/10.4018/979-8-3693-4252-7.ch008
[9] Biggi, G., & Stilgoe, J. (2021). Artificial Intelligence in Self- Driving Cars Research and Innovation: A Scientometric and Bibliometric analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3829897
[10] Chandavarkar, N. D., & S, N. P. (2023). SWOT analysis on

[11] AI-based self-driving car companies. *International Journal of Management Technology and Social Sciences*,
[12] 89–102. https://doi.org/10.47992/ijmts.2581.6012.0291
[13] *Deep learning for safe autonomous driving: current challenges and future directions*. (2021, July 1). IEEE Journals & Magazine | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/9284628/
[14] *Evolution of machine learning algorithms for enhancement of Self-Driving Vehicles Security*. (2022, November 19). IEEE Conference Publication IEEE Xplore.https://ieeexplore.ieee.org/abstract/document/10088396/
[15] Gupta, S., Upadhyay, D., & Dubey, A. K. (2019).
[16] SelfDriving car using artificial intelligence. In *Lecture notes in mechanical engineering* (pp. 521–533). https://doi.org/10.1007/978-981-13-6577-5_49
[17] Manoharan, S. (2019). AN IMPROVED SAFETY ALGORITHM FOR ARTIFICIAL INTELLIGENCE ENABLED PROCESSORS IN SELF DRIVING CARS.
[18] *Journal of Artificial Intelligence and Capsule Networks*,
[19] *2019*(2), 95–104. https://doi.org/10.36548/jaicn.2019.2.005
[20] Muqeet, M. A., Mohiuddin, R., Thaniserikaran, A., Ahmed, I., Subrahmanyam, K. A., & Podapati, A. (2022, February 9).
[21] *Self-Car Driving using Artificial Intelligence and Image Processing*. https://journal.ijresm.com/index.php/ijresm/article/view/173 3
[22] Ni, J., Chen, Y., Chen, Y., Zhu, J., Ali, D., & Cao, W.
[23] (2020). A survey on Theories and Applications for SelfDriving Cars based on Deep Learning methods. *Applied*
[24] *Sciences*, *10*(8), 2749. https://doi.org/10.3390/app10082749
[25] *Reliability of Self-Driving cars: When can we remove the safety driver?* (2023, August 1). IEEE Journals & Magazine | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/10056924/
[26] Totakura, V., Vuribindi, B. R., & Reddy, E. M. (2021). Improved Safety of Self-Driving Car using Voice Recognition through CNN. *IOP Conference Series Materials Science and Engineering*, *1022*(1), 012079. https://doi.org/10.1088/1757-899x/1022/1/012079
[27] Yan, H. (2022). Vehicle Safety-Assisted Driving Technology based on computer artificial Intelligence environment. *Computational Intelligence and Neuroscience*, *2022*, 1–10. http://doi.org/10.1155/2022/4390394
[28] Zaghari, N., Fathy, M., Jameii, S. M., Sabokrou, M., & Shahverdy, M. (2020). Improving the learning of self-driving vehicles based on real driving behavior using deep neural network techniques. *The Journal of Supercomputing*, *77*(4),
[29] 3752–3794. https://doi.org/10.1007/s11227-020-03399-4
[30] Bautista, C. & University Óbuda, Doctoral School of Safety and Security Sciences, Institute of Next-Technologies, Budapest, Hungary. (2022). SELF-DRIVING CARS WITH
[31] MARKOVIAN MODEL-BASED SAFETY ANALYSIS. In *XXVIII Skup TRENDOVI RAZVOJA: "UNIVERZITETSKO OBRAZOVANJE ZA PRIVREDU" (*p. 394).http://www.trend.uns.ac.rs/stskup/trend_2022/radovi/T4.1/T4. 1-6.pdf
[32] Chen, K., Li, Y., Zhang, W., Liu, Y., Li, P., Gao, R., Hong,
[33] L., Tian, M., Zhao, X., Li, Z., Yeung, D., Lu, H., & Jia, X. (2024, April 16). *Automated evaluation of large Vision-Language models on self-driving corner cases*. arXiv.org. https://arxiv.org/abs/2404.10595
[34] Dusarlapudi, K., Sudhakar, K., Ranjani, A. P., Chennupati, P., & Gummadi, J. (2022). Design and Implementation of ML-Based Pothole Detection System with Telegram Notification. *International Conference on Sustainable and Innovative Solutions for Current Challenges in Engineering & Technology*, 559–567. Springer Nature Singapore.

[35] Dusarlapudi, K., Sudhakar, K., Chennupati, P., & Gummadi, J. (2022). Sustainable Approach for Pothole Detection--A Machine Learning Implementation. *7th International Conference on "Economic Growth and Sustainable Development: Emerging Trends"*, 7(1), 1–7.

[36] Sireesha, T., & Sudhakar, K. (2015). Multi Vehicle Tracking Locking and Speed Control Based on GCM and GPS Modules. *International Journal of Computer Science & Mechatronics-IJCSM*, 1(1).

[37] Prakash, J., Sengottaiyan, N., Anbukaruppusamy, Sudhakar, K., & Mahaveerakannan, R. (2022). RG Technique to Reduce the Fuel Consumption and Co2 Emission in VANET. *International Conference on Computing, Communication, Electrical and Biomedical Systems*, 167–180. Springer International Publishing.

[38] Kalyan, D., Sudhakar, K., Sai, P. P. V., & Krishna, J. G. (2023). Model Based Design Accelerometer Control system in EV-ECU For HIL Testing. *2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, 150–154. IEEE.

[39] Kattupalli, S., Sunayana, K., Sravya, G., Priyanka, K., & Parimala, K. (2018). An Accident / Incident Reporting Device using IoT. *International Conference on Contemporary Engineering & Technology - ICCET2018*, 2(1), 99.

[40] Dusarlapudi, K., Goutham, O. M., Kasukurthi, R., Simha, M. C., Amarnadh, D., & Sudhakar, K. (2024). Design and Implementation of Smart Interface for Next-Gen Monitoring in EV's. *2024 4th International Conference on Sustainable Expert Systems (ICSES)*, 84–89. IEEE.

[41] Tiruvuri, C. S., Dusarlapudi, K., Sudhakar, K., Krishna, J. S. V. G., Ranjani, A. P., & Sai, P. P. V. (2023). The Dashboard Infrastructure of Electric Vehicles with IoT and Wireless Power Transfer System. *2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*. IEEE.

[42] Sudhakar, K., Rajyalakshmi, K. G., Aruna, J. B. S., Vivek, A., & Devi, O. R. (2024). Forest Fire Prediction and Mitigation using Machine Learning and OpenCV. *International Conference Engineering, Social-Sciences, And Humanities (IC-ESSU-2024)*, 4(1).

[43] Dusarlapudi, K., Sudhakar, K., Krishna, J. G., Teja, K. S., & Sai, N. V. (2024). Cost-effective retrofit electric vehicle solutions empowered by IoT dashboard integration. *Intelligent Computation and Analytics on Sustainable Energy and Environment*, 334–341. CRC Press.

[44] Cui, A., Casas, S., Sadat, A., Liao, R., & Urtasun, R. (2021). *LookOut: Diverse Multi-Future Prediction and Planning for Self-Driving*.

[45] http://openaccess.thecvf.com/content/ICCV2021/html/Cui_Lo okOut_Diverse_Multi-

[46] Future_Prediction_and_Planning_for_Self- Driving_ICCV_2021_paper.html

[47] *Explainable Artificial Intelligence for Autonomous Driving: A Comprehensive Overview and field Guide for future research directions*. (2024). IEEE Journals & Magazine | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/10604830/