Advancing Road Safety: YOLO-CNN Integration for Autonomous Vehicles

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***Abstract*—When it applies to self-driving vehicles, cost-effective and feasible alternatives have to be found for solving significant road safety challenges. Our investigation proposes an innovative technique by exploiting a Raspberry Pi device that has been equipped with sophisticated software and the sensors. Our approach excels in real-time hazard identification by integrating computer vision techniques and machine learning algorithms, which includes YOLO-based CNN for object recognition, animal detection, pothole detection, and traffic signboard and signal detection, alongside HSV for lane detection. Persistent advancement, fueled by continues inquiries and technical discoveries, promises effortless integration into mainstream transportation networks. This exhaustive tackle unlocks the door for greater adoption of autonomous driving technologies resulting in a major advancement in transportation safety regulations.**

***Index Terms*—Convolution Neural Network, YOLO, HSV, Self Driving cars, Levels of Automation, Artificial Intelligence, Machine Learning, Deep Learning.**

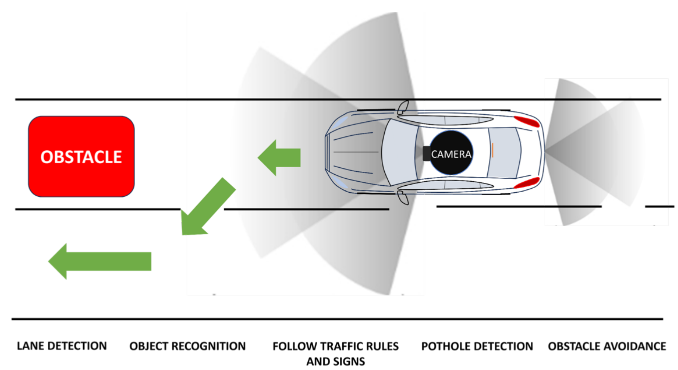

Fig. 1. Autonomous car

I. Introduction

The introduction of autonomous cars implies an important transformation in the transportation industry, without objectives being decreased journeys, expanding passenger convenience, and strengthening roadway security. Scholars understand that increased breakthroughs in technology and a change in perspective will be needed in order to prevent accidents, but classic vehicle security mechanisms for helmets or Brake have accomplished great progress. Modern technologies enable autonomous automobiles to understand what's going on on their own, decreasing or completely removing requirements for intervention from humans as well as offering possibilities for communities.

Strong sensory as well as computing capabilities are crucial for the eventual creation of autonomous cars. As the computer's brain for autonomous vehicles, the Raspberry Pi, a computer widely recognized for its ability to adapt and tiny footprint, analyses sensors info and runs complicated computations to regulate vehicle's behaviors [**?**]. These machines utilize a combination of deep learning, computer science, and machine learning techniques that serve well not simply in identifying things additionally in lane notice, people recognition, and traffic sign interpretation, amid other challenges.

Five phases, every reflecting distinct levels of automating and man interaction, have been employed to categorize the evolution of self-driving automobiles in succession. At the first level, frequently referred to as "hands-on," both the driver and the computerized device share control. Adaptive Cruise Control (ACC) and Parking Assistant are two instances of this cooperative control. As the machine learning algorithm evolves to Level 2, on occasion referred to as "hands-free," the driver has complete control of the automobile, including controlling steering, brakes, and growing faster,

although it might nevertheless be critical to make direct contact with the steering wheel if one wants to intervene instantaneously. The third stage, additionally referred to as

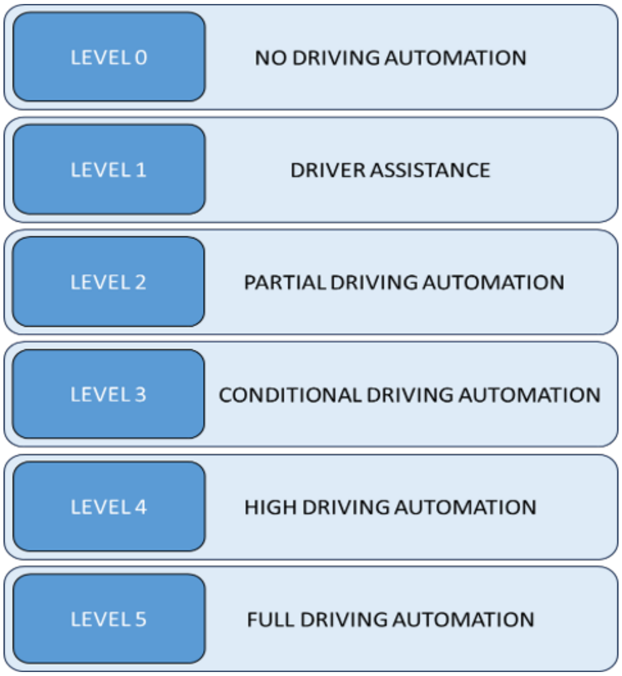

Fig. 2. Levels of autonomous driving in vehicles.

”eyes-off,” provides a higher level of autonomy by having a driver take care of other activities elsewhere driving, however immediate assistance is still needed within a predetermined period of time. Level 4, occasionally referred to as ”mind-off,” extends automation to moments in which a driver’s focus is no longer required for safety within preset zones or in instances which include impasse so the automobile has features with mechanisms to safely halt its trip whenever something is required. The final but not least, Level 5, sometimes referred to as ”steering-wheel optional,” signifies utter autonomy without of any sort of human interference in every scenario. Robo limousines represent a perfect illustration of these. These set levels establish an organized basis for knowing how self-driving transportation has grown while establishing the right equilibrium with developments in technology, security problems, legal constraints, and popular support. The scientific research on autos has made significant advancements, nevertheless there remains some need to be carried out on discovering efficient, affordable options. Limits in real-time detection of objects, precise navigation in dense locations, and effortless integration within normal public transit systems represent a number amongst these drawbacks. To address these hurdles, creative strategies and meticulous analysis must be used. Fueled by a desire for developments in autonomy cars, this paper features an in-depth analysis of an original use made integrating the Raspberry Pi computer mechanisms, complex codes, and instruments. Assessing the application of Raspberry Pi systems in autonomous automobiles, alleviating obstacles surrounding object recognition and highway safety, and presenting future research into Banana Pi-based technology for autonomous automobiles are the key objectives. Comprehensive examinations of the challenges facing technologies for autonomous driving, proposals for future research pathways to fill in recognised holes in literature, and insights into the approaches and techniques applied in earlier research attempts comprise some of the contributions. The layout of the paper is as follows: Background material on self-driving vehicle technologies gets examined in Section II. The third part addresses the procedures and strategies used in earlier studies. The challenges associated regarding technology for self-driving vehicles are outlined in Section IV. Future research directions are suggested in Section V, and the paper’s contribution to the field of autonomous vehicles have been highlighted in Section VI, that concludes the paper.

II. Related Work

To construct a wireless-operated car model, essential data points are crucial, gathered during the training process. Employing a VNC viewer facilitates remote control of the Raspberry Pi via Wi-Fi. The vehicle’s training progresses with the creation of a track, utilizing a Raspberry Pi camera to capture pixel data based on input commands (advance, stop, right, left). Subsequently, a dataset is compiled to train the neural network model, employing Convolutional Neural Networks (CNNs) known for precise object recognition. Unlike traditional neural networks, CNNs use images as input, making them ideal for classification tasks, providing accurate single-class labels for image outputs [1].This study employs two datasets, an online database and Lebanese road images, with over 1,000 images containing 2,000 potholes. YOLO (You Only Look Once) is highlighted for efficient object detection, with YOLOv4 claiming a 10 percent AP improvement and 12 percent speed boost over YOLOv3. The object detection pipeline includes informative region selection, challenging feature extraction due to diverse conditions, and classification using classifiers like DPM and SVM. Object detection architectures fall into classification-based (e.g., R-CNN) and regression-based (e.g., SSD, YOLO) types, addressing specific challenges in computer vision [2].The car processes a continuous image stream from Raspi Cam2, implementing image and video capture algorithms, frame-per-second calculation, and BGR to RGB conversion. Region of Interest (ROI) and perspective transformation enhance image analysis, followed by grayscale conversion and Canny edge detection. For lane detection, white pixel distances from the ROI’s left side determine turns, with Arduino UNO receiving corresponding commands. Machine Learning aids object detection using Cascade Classifier software on positive and negative samples. OpenCV methods identify target objects, and the distance formula calculates object proximity, controlling the car’s halt within a specified range via Arduino UNO commands [3]. This proposal introduces dual-backbone semantic segmentation network architectures, enhancing context capture while maintaining decisive output. Overcoming limitations of YOLOv3 in self-driving cars, the system integrates COCO and ADE20K datasets for Mask R-CNN, achieving improved accuracy and efficiency in instance and semantic segmentation [4].This study focuses on modeling autonomous vehicle driving behaviors using Probabilistic Logic Markov Decision Processes (MDP). The scenario involves decisions on maintaining speed, overtaking, or adjusting distance based on nearby vehicles. States are characterized by Boolean variables like free N, free NW, free W, and free SW, representing occupied or free regions around the vehicle. MDP-ProbLog efficiently declares state and action variables, e.g., "state fluent(free N)" and "action(keep distance)." [5]. The authors utilized advanced deep learning techniques, particularly the CenterNet framework, which improves object detection by employing triplets instead of pairs of keypoints. CenterNet addresses the limitations of CornerNet, enhancing precision and recall values and providing a global perspective of objects. Detectron2, built on Mask R-CNN, is a powerful deep neural network for cutting-edge object detection, featuring panoptic segmentation and dense-pose capabilities. YOLOv4, a state-of-the-art algorithm, ensures swift and precise detection, while EfficientDet adopts a single-stage detector pattern with efficient multi-scale feature fusion. These frameworks offer diverse approaches in object detection, catering to various requirements and priorities [6].

SL NO	TITLE	ALGORITHM
1	**Deep Learning Techniques for Obstacle Detection and Avoidance in Driverless Cars**	Convolutional Neural Networks (CNNs) algorithm
2	**Real-time Pothole Detection using Deep Learning**	YOLOv3 and Region-based segmentation algorithm
3	**Self-DrivingCar:UsingOpenCV2 and Machine Learning**	Haar Cascade Classifier, Canny Edge Detection algorithms.
4	**Exploiting the Joint Potential of Instance Segmentation and Semantic Segmentation in Autonomous**	Mask R-CNN and ADE20K Exception Algorithm.
5	**Probabilistic logic Markov decision processes for modeling driving behaviors in self-driving cars**	Convolutional neural network (CNN)
6	**Object Detection and Tracking Algorithms for Vehicle Counting: A Comparative Analysis**	SSD, YOLOv4, and R-CNN Algorithms
7	**SDR -Self Driving Car Implemented using Reinforcement Learning and Behavioral Cloning**	CARLA employs algorithms such as A* for path planning and PID for control in its versatile urban driving simulator
8	**Image recognition in self-driving cars using CNN**	Probabilistic Logic Markov Decision Processes
9	**Toward Attack Modeling Technique Addressing Resilience in Self-Driving Car**	Kalman Filter or Deep Learning Algorithms, System-Theoretic Accident Model and Processes and STAMP-Based Hazard Analysis
10	**An improved deep network-based scene classification method for self driving cars**	An improved Faster RCNN network with a residual attention block for local feature extraction.
11	**Fixed Settling Time Control for Self-Driving Car: Two-Timescales Approach**	Fixed settling time sliding mode control (FSTSMC) with barrier Lyapunov function,
12	**Pothole and plain road classification using adaptive mutation dipper throated optimization and transfer learning for self-driving cars.**	Adaptive Mutation Dipper Throated Optimization (AMDTO) for feature selection and optimization of Random Forest (RF) classifier and Optimized Hashing SMOTE for dataset balancing.
13	**Attacks on self-driving cars and their countermeasures: A survey.**	The ITS entities utilize IEEE802.11p and IEEE1609 standards, incorporating WAVE technology for V2V and V2I communication in self-driving cars.
14	**A Self-Driving Decision Making With Reachable Path Analysis and Interaction-Aware Speed Profiling**	A hierarchical Markov Decision Process-based
15	**Radars for Autonomous Driving: A Review of Deep Learning Methods and Challenges**	FMCW radars use a Fast Fourier Transform (FFT) to process frequency-shifted signals and obtain range, velocity, and angle measurements.

Fig. 3. Table

Introducing DRIVE-IT (Driving in Realistic Interactive Virtual Environments), our innovative approach revolutionizes the training, development, and validation of autonomous driving models. Utilizing CARLA (Car Learning to Act), an open simulator, DRIVE-IT offers free access to meticulously crafted urban environment assets, including diverse car models, structures, pedestrians, and street signs. Notably, it introduces a customizable sensor suite and dynamic environmental simulation, featuring high-quality 3D models and realistic weather conditions. Our study leverages state-of-the-art deep learning CNNs to translate raw pixels into precise steering commands, showcasing adaptability to diverse driving conditions. DRIVE-IT represents a significant advancement in autonomous vehicle research, setting new standards for realism and effectiveness in simulation-based training[7].This proposal suggests utilizing multiple layers of artificial neurons, forming neural networks known as nodes, for feature extraction in convolutional neural networks (CNNs). The initial layers capture minimal features like edges, while subsequent layers detect more complex features such as corners or combinational edges. Hidden layers in CNNs consist of convolutional, pooling, fully connected, and normalization layers, utilizing ReLU as the activation function. Backpropagation adjusts weights and errors for efficient learning. YOLO (You Only Look Once) represents real-time object detection, treating the problem as a regression task for spatially separated bounding boxes and class probabilities, predicted directly by single neural network nodes. Increased layers and networks enhance efficiency, particularly with larger datasets [8].

The proposed Severity-based Analytical Attack Model for Resilience (SAAMR) integrates concepts from existing frameworks like STRIDE, STAMP, PASTA, and CVSS, with a particular focus on Self-Driving Car (SDC) scenarios. SAAMR combines STAMP's feedback mechanisms for system disturbances with STRIDE's modification to address malicious attacks in SDC architectures. The SDC model is categorized into perception, decision-control, and action layers, following autonomy levels defined by the Society of Automotive Engineers (SAE). Employing the STAMP model, the study identifies potential failures in the SDC system, emphasizing the need for coordination and synchronization among multiple controllers. The study highlights the risks associated with lacking redundancy in control processes, using examples such as potential hazards from error-prone route selection due to failures in route control [9]. This proposal introduces a novel deep network architecture for scene classification in self-driving cars, comprising an upgraded Faster RCNN, an improved Inception V1 module, a feature fusion module, and a classification network. The Faster RCNN is enhanced with a spatial attention-based residual connection module, while the Inception V1 module incorporates a mixed activation function using ELU and Leaky ReLU. Pretrained on predefined representative objects, the Faster RCNN plays a key role in automating the detection of seven common traffic scene objects. The improved Inception V1 network outputs global features, and the feature fusion module seamlessly integrates local and global features, streamlining the scene classification process for self-driving cars across crosswalks, gas stations, parking lots, streets, and highways [10].This proposal introduces a control law for a two-time scale system, employing two distinct signals for fast and slow dynamics. The fixed-time Sliding Mode Control (SMC) with a barrier function is applied, ensuring convergence to sliding manifolds within a fixed time. The simulation, using CarSim and MATLAB, addresses the DLC problem in self-driving cars, implementing the proposed control for steering wheel angle. Results from E-Class Sedan simulations under varied conditions demonstrate the controller's robust performance in tracking global yaw references based on standard DLC trajectories. The study emphasizes the stability and effectiveness of the proposed control law across diverse scenarios [11].The proposed pothole detection method employs a ResNet-50 for feature extraction and introduces a novel binary particle swarm optimization algorithm (bPSDTO) for feature selection. Data augmentation and optimized SMOTE balancing are followed by hybrid particle swarm and dipper-throated optimization for feature optimization. The resulting features train a random forest model, further optimized with adaptive mutation dipper-throated optimization (AMDTO). The binary version (bAMDTO) adapts AMDTO for feature selection, demonstrating improved classification accuracy. This methodology integrates deep learning, optimization algorithms, and ensemble learning, advancing pothole detection in road image analysis. Model evaluation uses Stratified K-Fold Cross Validation [12].The structure of Intelligent Transportation Systems (ITS) is organized into three domains: the vehicle domain, Vehicle-to-Vehicle (V2V) domain, and infrastructure domain. Communication occurs through in-vehicle, V2V, V2I (Vehicle-to-Infrastructure), and I2V (Infrastructure-to-Vehicle) channels. Onboard Units (OBUs) in the vehicle domain facilitate communication, while the V2X system involves OBUs and Roadside Units (RSUs) for dynamic data exchange. Trusted Third Parties (TTP) and Trust Authorities (TAs) ensure secure connections. OBUs perform critical functions like wireless communication, information security, and reliable data transfer, contributing to applications such as junction accident warnings and incorrect driving alerts. The integration of OBUs, RSUs, and trusted entities forms a robust framework for efficient and secure communication in Intelligent Transportation Systems [13].In recent literature, autonomous vehicle decision-making algorithms are categorized into three main types: rule-based, graph-search, and sampling-based methods. Rule-based methods utilize traffic rules and finite state machines but lack adaptability to varying road conditions. Graph-search methods, including state lattice, elastic band, and A-star algorithms, optimize vehicle position sequences, while Markov Decision Process (MDP) considers uncertainties in traffic information. Sampling-based approaches, like the Rapidly-exploring Random Tree (RRT) algorithm, expedite sub-optimal decision-making. Collision-free decision-making involves assessing collision risk, with considerations for vehicle shapes, such as circular or rectangular approximations, each having associated limitations. Various studies explore and enhance these methodologies for effective autonomous driving [14].The study assessed safety implications of autonomous driving alert systems in three Tesla Model 3 vehicles across varied scenarios. Variability in alert consistency, system failures, and hands-free driving intervals was observed during highway driving. Lane departure tests revealed differences in emergency steering responses, raising safety concerns. Construction zone scenarios showed significant variations in obstacle handling and driver alerting. The findings underscore the need for standardized guidelines and improved system reliability in complex driving situations, contributing valuable insights for autonomous vehicle technology development [15].

III. Proposed Work

We present a comprehensive pathway for future endeavors as we progress in our attempt towards enhancing transportation safety with CNN Autonomous Vehicles based on YOLO. The fundamental concept of our proposed breakthroughs lies in the refinement and optimization of the Hue-Saturation-Value (HSV) method for lane detection, leveraging its accuracy and durability to improve vehicle navigation within defined lanes.

COMPONENTS	USES
Raspberry pi 4 B	Single-board computer for various applications, including IoT, robotics, and processing.
Raspberry Pi Camera Interface	Camera module designed for Raspberry Pi projects, enabling image and video capture.
Ultrasonic sensors	Measures distance using sound waves, often used in obstacle detection and navigation.
DC Voltage converter	Converts direct current (DC) voltage levels, useful for powering different components.
Motors	Converts electrical energy into mechanical motion, essential for moving parts in devices
Motor driver	Controls motors by providing power and direction, commonly used in robotics and automation.
12V dc Battery	Provides portable power for the vehicle.

Fig. 4. Components table

Building upon this crucial aspect, our project aims to go further into algorithmic improvements, particularly emphasizing the enhancement of the YOLO-based CNN for a variety of object detection possibilities. To achieve this, we are meticulously curating and training our model with a limited dataset, strategically chosen to increase accuracy. For animal detection, we focus on two specific animals—cow and dog—leveraging a focused dataset to enhance precision. Similarly, for traffic signboard detection, our dataset includes various signboards such as right turn, left turn, right U-turn, left U-turn, stop signal, no entry symbol, and hump detection. By training the model with these specific scenarios and symbols, we aim to enable the vehicle to accurately identify and respond to diverse traffic scenarios in real-time.

Additionally, our project addresses pothole detection by training the model with different scenarios and types of potholes, ensuring robust performance in detecting and avoiding road hazards. Utilizing the YOLO-based CNN algorithm, we meticulously train the model to effectively interpret and respond to various environmental cues, enhancing the vehicle's efficiency and accuracy in navigating dynamic road conditions.

Moreover, our future development plan emphasizes the seamless integration of ultrasonic sensors in conjunction with

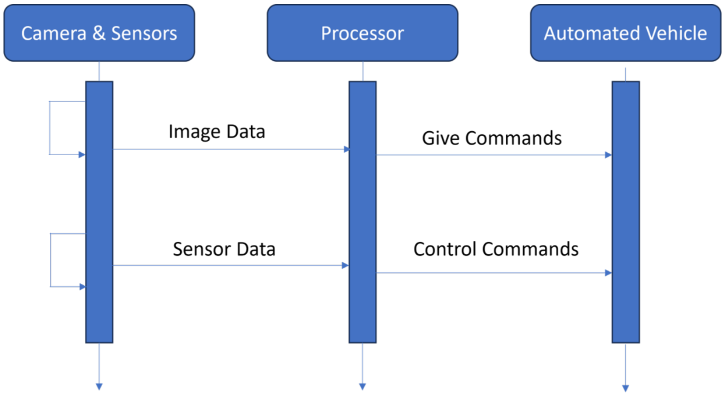

Fig. 5. Image and Sensor based Control

computational advancements, optimizing their deployment for precise obstacle detection and avoidance. To facilitate real-time decision-making and boost safety and dependability in a wide range of driving instances, we prioritize the meticulous positioning of sensors, advancement of data fusion methods, and integration of machine learning algorithms.

Furthermore, In addition to algorithmic advancements, we intend to establish an exhaustive structure for performance assessment and confirmation in our future work. Through extensive scenario-based testing and real-world deployment trials, we aim to validate the safety, dependability, and performance of our autonomous vehicle system under various traffic situations and environmental circumstances.

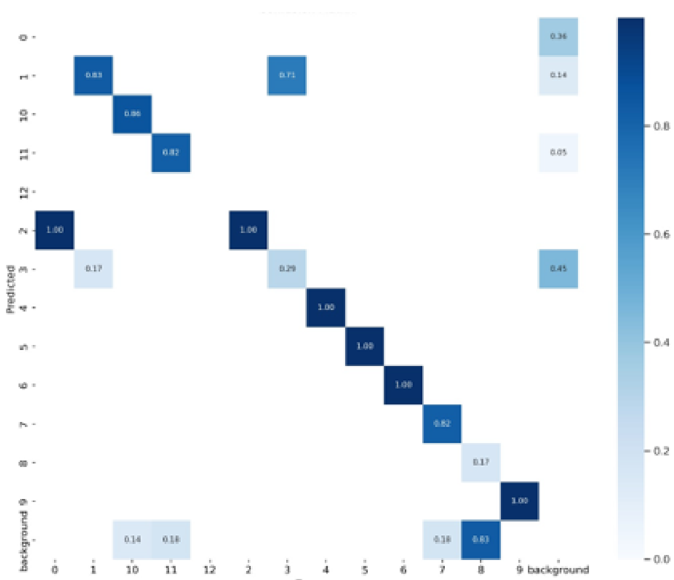

Fig. 6. Confusion Matrix

our project recognizes the broader societal benefits of autonomous driving technologies, including better road safety, reduced commute times, increased productivity, reduced expenditure on damages from accidents, and environmental friendliness through lower emissions. Additionally, self-driving cars offer a solution to parking problems in modern cities and the potential for better traffic discipline through improved law enforcement and speed management. Moreover, the potential for new car designs is vast, as self-driving cars may eventually function as self-guided train cars, offering passengers new ways to relax or stay entertained without the need for complicated driving tools.

Furthermore, In conclusion, our thorough future work path underscores an in-depth plan to improve the safety, effectiveness, and dependability of CNN Autonomous Vehicles based on YOLO. By leveraging the HSV algorithm for lane detection, enhancing object recognition capacity, meticulous dataset curation, and training methodologies, and considering the broader societal benefits, we aim to accelerate the integration of autonomous driving technologies into mainstream transportation networks, resulting in a safer, more efficient, and sustainable future of movement.

IV. Conclusion

In summary, our research ”Enhancing Transportation Safety with YOLO-based CNN Autonomous Vehicles” proposes a novel approach to enhance the security, effectiveness, and stability of self-driving vehicle technologies adhering to a careful analysis and integration of previous studies. Our system demonstrates enhanced perceptual capacities and guiding precision through rigorous developments such as the optimisation of YOLO-based CNN for object recognition and the improvement of the Hue-Saturation-Value (HSV) approach for lane detection. The smooth transition between DC motors and ultrasonic sensors improves our vehicle’s capacity to quickly and precisely detect and avoid obstacles.Our commitment to continuous assessment and development is made explicit in our intended future growth plan of action, which will guarantee the seamless integration of technology for autonomous vehicles into prevalent transportation networks. Our project, which focuses on sustainability, efficiency, and safety, unlocks the door for safer, smarter, and more efficient transportation networks, suggesting a bright future for movement.

References

[1] Sanil, Nischal, V. Rakesh, Rishab Mallapur, and Mohammed Riyaz Ahmed. “Deep learning techniques for obstacle detection and avoidance in driverless cars.” In 2020 International Conference on Artificial Intelligence and Signal Processing (AISP), pp. 1-4. IEEE, 2020.

[2] Shaghouri, Anas Al, Rami Alkhatib, and Samir Berjaoui. “Real-time pothole detection using deep learning.” arXiv preprint arXiv:2107.06356 (2021).

[3] Shoeb, Mohammed, Mohammed Akram Ali, Mohammed Shadeel, and Dr Mohammed Abdul Bari. “Self-Driving Car: Using Opencv2 and Machine Learning.” The International journal of analytical and experimental modal analysis (IJAEMA), ISSN 0886-9367.

[4] Usman, Mohammed, Mohammed Riyaz Ahmed, Raveendra Gudodagi, and Nitesh Kumar. “Exploiting the Joint Potential of Instance Segmentation and Semantic Segmentation in Autonomous Driving.” In 2023 International Conference for Advancement in Technology (ICONAT), pp. 1-7. IEEE, 2023.

[5] Avilés, Héctor, Marco Negrete, Rubén Machucho, Karelly Rivera, David Trejo, and Héctor Vargas. “Probabilistic Logic Markov Decision Processes for Modeling Driving Behaviors in Self-driving Cars.” In Ibero-American Conference on Artificial Intelligence, pp. 366-377. Cham: Springer International Publishing, 2022.

[6] Mandal, Vishal, and Yaw Adu-Gyamfi. “Object detection and tracking algorithms for vehicle counting: a comparative analysis.” Journal of big data analytics in transportation 2, no. 3 (2020): 251-261.

[7] Tippannavar, Sanjay S., S. D. Yashwanth, and K. M. Puneeth. “SDR–Self Driving Car Implemented using Reinforcement Learning and Behavioural Cloning.” In 2023 International Conference on Recent Trends in Electronics and Communication (ICRTEC), pp. 1-7. IEEE, 2023.

[8] Muppidi, Shreya. “Image recognition in self-driving cars using CNN.” International Journal of Science and Research Archive 9, no. 2 (2023): 342-348.

[9] Qurashi, Junaid M., Kamal Mansur Jambi, Fathy E. Eassa, Maher Khemakhem, Fawaz Alsolami, and Abdullah Ahmad Basuhail. “Toward Attack Modeling Technique Addressing Resilience in Self-Driving Car.” IEEE Access 11 (2022): 2652-2673.

[10] Ni, Jianjun, Kang Shen, Yinan Chen, Weidong Cao, and Simon X. Yang. “An improved deep network-based scene classification method for self-driving cars.” IEEE Transactions on Instrumentation and Measurement 71 (2022): 1-14.

[11] Khan, Rameez, Raja Amer Azim, Fahad Mumtaz Malik, Naveed Mazhar, Abid Raza, and Hameed Ullah. “Fixed Settling Time Control for Self-Driving Car: Two-Timescales Approach.” IEEE Access 10 (2022): 36518-36537.

[12] Alhussan, Amel Ali, Doaa Sami Khafaga, El-Sayed M. El-Kenawy, Abdelhameed Ibrahim, Marwa Metwally Eid, and Abdelaziz A. Abdelhamid. “Pothole and plain road classification using adaptive mutation dipper throated optimization and transfer learning for self-driving cars.” IEEE Access 10 (2022): 84188-84211.

[13] Chowdhury, Abdullahi, Gour Karmakar, Joarder Kamruzzaman, Alireza Jolfaei, and Rajkumar Das. “Attacks on self-driving cars and their countermeasures: A survey.” IEEE Access 8 (2020): 207308-207342.

[14] Song, Yuho, Sangwon Han, and Kunsoo Huh. “A Self-Driving Decision Making with Reachable Path Analysis and Interaction-Aware Speed Profiling.” IEEE Access (2023).

[15] Srivastav, Arvind, and Soumyajit Mandal. “Radars for Autonomous Driving: A Review of Deep Learning Methods and Challenges.” arXiv preprint arXiv:2306.09304 (2023).