Enhancing Transportation Safety with YOLO-Based CNN Autonomous Vehicles

Sarumathi.S [1]
Computer Science and Engineering
HKBK College Of Engineering
Bengaluru, India
sarumathi.cs@hkbk.edu.in

Mohammed Yousuf [2]
Computer Science and Engineering
HKBK College Of Engineering
Bengaluru, India
hajeeyousuf175@gmail.com

Mohammed Suhail [3]
Computer Science and Engineering
HKBK College Of Engineering
Bengaluru, India
mohammedsuhail911z@gmail.com

Mohammed Sabir [4]
Computer Science and Engineering
HKBK College Of Engineering
Bengaluru, India
sabstark2@gmail.com

Mohammed Umarulla [5]
Computer Science and Engineering
HKBK College Of Engineering
Bengaluru, India
mohammedumarulla@gmail.com

***Abstract*— Our project, titled "Enhancing Transportation Safety with YOLO-based CNN Autonomous Vehicles," pioneers a transformative approach to autonomous driving. Through the fusion of advanced machine learning techniques, specifically the YOLO-based Convolutional Neural Network (CNN) algorithm, with meticulously selected hardware components, including Raspberry Pi 4B and IR sensors, our system addresses critical objectives such as object recognition, lane detection, and traffic signal and signboard detection, pothole detection. By leveraging diverse image datasets and optimizing the YOLO-based CNN algorithm, our system achieves exceptional accuracy and efficiency in environmental perception and navigation. Key features such as real-time object detection and precise lane detection contribute to safe navigation through complex traffic scenarios. With potential applications across automotive, logistics, and transportation industries, our project represents a significant advancement in autonomous driving technology. By prioritizing safety and efficiency, our YOLO-based CNN autonomous vehicle system holds promise for revolutionizing transportation systems and enhancing road safety worldwide.**

***Index Terms*—Autonomous Vehicle, CNN Algorithm, Lane Detection, Object Detection, Transportation Safety, YOLO v5.**

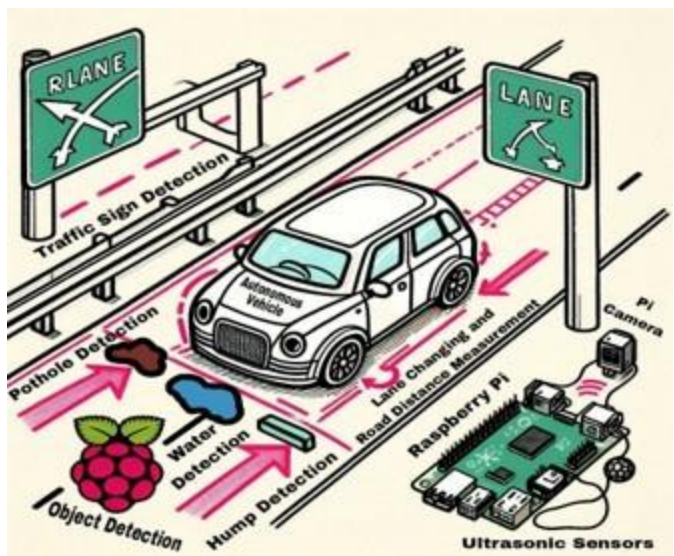

Fig. 1. Autonomous Vehicle

I. Introduction

In the realm of autonomous vehicles, the pursuit of enhancing transportation safety stands as a paramount objective. The integration of cutting-edge technologies and methodologies has paved the way for innovative solutions aimed at revolutionizing the future of mobility. This paper delves into the domain of autonomous vehicles, focusing on the development and implementation of a novel system geared towards augmenting transportation safety through the utilization of YOLO version 5, a state-of-the-art convolutional neural network (CNN) algorithm.

This comprehensive image (Fig 1) showcases various components and objectives of autonomous vehicles, including pothole, water, and hump detection, object recognition, Raspberry Pi integration, lane tracking, and traffic sign detection. It provides a visual overview of the multifaceted capabilities and functionalities integrated into autonomous vehicle systems, highlighting their potential for enhancing safety and efficiency in transportation.

Our project is fueled by the recognition of the pressing need for safer transportation solutions and the potential of ad- vanced AI-driven systems in real-world scenarios. Leveraging a diverse array of components including ultrasonic sensors, infrared (IR) sensors, Raspberry Pi 4B 8GB RAM processor, voltage converter, battery, servo motor, LEDs, robot frame, and wheels, we embarked on a journey to address the multifaceted challenges encountered on the road.

Throughout the course of our research, we encountered various challenges ranging from the intricacies of object detection to the complexities of environmental perception. However, with each challenge, we sought innovative solutions, culminating in the proposal of a unified framework that seamlessly integrates YOLO version 5 with infrared (IR) sensors for precise lane detection and object recognition.

Our proposed approach leverages the power of deep learning and sensor fusion to enhance the perception and decision-making capabilities of autonomous vehicles. By meticulously parameterizing and training our model, we have achieved promising results in detecting and classifying a wide range of objects including vehicles, pedestrians, traffic signs, and road hazards. The impact of our research extends beyond mere technological advancement, promising to redefine road safety standards and pave the way for a safer, more efficient transportation ecosystem.

Moving forward, we envision further refinement and optimization of our system with a focus on scalability, adaptability, and seamless integration into existing transportation infrastructures. The journey towards fully autonomous driving may be fraught with challenges, but with perseverance and innovation, we are poised to realize a future where transportation safety knows no bounds.

II. Background

Autonomous vehicles mark a watershed moment in transportation, poised to redefine how we move and interact with our surroundings. With their sophisticated sensor arrays, AI-driven algorithms, and robust computing systems, these vehicles hold the promise of significantly enhancing safety, efficiency, and accessibility in transportation networks worldwide. By leveraging state-of-the-art technology, autonomous vehicles aim to mitigate the human errors responsible for a significant portion of accidents on the road while also streamlining traffic flow and reducing environmental impact through optimized driving patterns and reduced fuel consumption.

Loss or Impact:

The absence of autonomous vehicles would exacerbate existing challenges plaguing transportation systems globally, impeding progress towards safer, more efficient mobility solutions. Without widespread adoption of autonomous driving technology, road safety would continue to be compromised, leading to a persistently high rate of accidents, injuries, and fatalities attributed to human error. Moreover, traffic congestion would remain a persistent issue, resulting in wasted time, increased fuel consumption, and heightened levels of air pollution, further burdening urban environments already struggling with sustainability.

The societal impact of foregoing autonomous vehicles would be equally profound, particularly for vulnerable populations such as the elderly and disabled. These individuals rely heavily on transportation services for essential mobility needs, and the absence of autonomous options would perpetuate existing barriers to accessibility, impeding their independence and limiting access to vital services and opportunities. Furthermore, the economic ramifications of eschewing autonomous vehicles would be significant, as potential gains in logistics optimization, delivery efficiency, and transportation network management would remain untapped, hampering growth and innovation in key industries reliant on efficient transportation systems.

Domain Overlaps:

Autonomous vehicles represent a convergence point for various domains, fostering interdisciplinary collaboration and unlocking new possibilities across sectors. They intersect with artificial intelligence (AI) to bolster navigation capabilities, enhance decision-making processes, and optimize vehicle performance in real-time. Additionally, autonomous vehicles contribute to the advancement of smart city initiatives by facilitating data-driven urban mobility solutions, reducing traffic congestion, and improving overall transportation efficiency. Moreover, their integration with cybersecurity protocols ensures vehicle safety and protects against potential cyber threats, undepinning trust and reliability in autonomous driving systems. From an environmental standpoint, autonomous vehicles align with sustainability efforts by minimizing emissions, promoting energy efficiency, and supporting the transition to greener transportation alternatives, reinforcing their role as agents of positive change towards a more sustainable future.

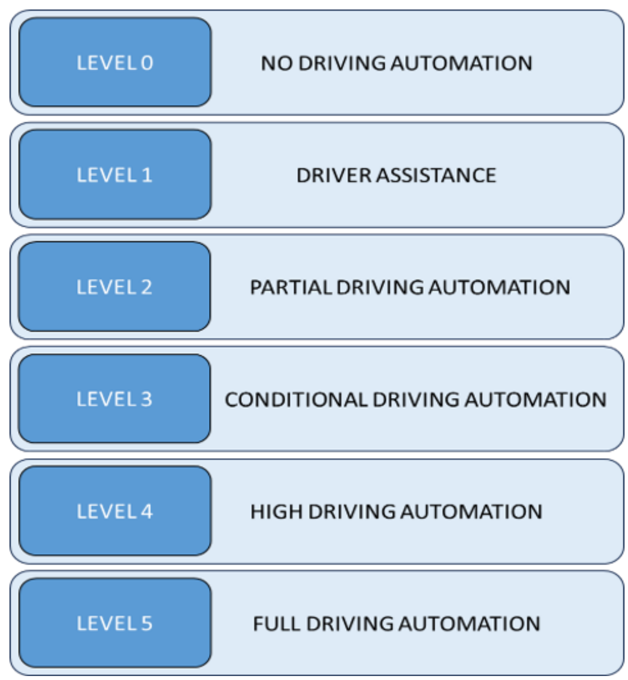

Fig. 2. Levels of autonomous driving in vehicles.

This image (Fig 2) illustrates the evolution of autonomous driving technology across six levels, ranging from no driving automation to fully autonomous vehicles. It depicts the progressive shift towards higher levels of automation, from driver assistance in level to full autonomy in level 5, marking significant advancements in vehicle autonomy and safety.

III. Literature Review

The literature survey encompasses various studies aimed at advancing autonomous vehicle technology. One study focuses on deep learning techniques for obstacle detection and avoidance [1], utilizing Convolutional Neural Networks (CNNs) and wireless operation via VNC viewer. Another study emphasizes lane detection and tracking [2], employing computer vision methodologies and advanced feature extraction techniques. Additionally, research targets real-time pothole detection using deep learning [3], enhancing road safety through accurate identification and classification. Furthermore, investigations explore ultrasonic sensors for obstacle avoidance [4], integrating practical experimentation and intelligent algorithms to improve system adaptability. Other studies delve into self-driving car platforms with sensors and machine learning [5], contributing to precise lane changes and automated maneuvers. Another study leverages semantic segmentation network architectures for object identification [6], addressing limitations and enhancing accuracy. Furthermore, probabilistic logic Markov decision processes model driving behaviors [7], enabling autonomous vehicles to maintain speed and adjust based on nearby vehicles. Additionally, research assesses object detection and tracking algorithms for vehicle counting [8], employing various techniques to ensure accurate and efficient counting systems. Another study implements reinforcement learning and behavioral cloning for self-driving cars [9], enhancing mobility intelligence and addressing challenges in simulations. Lastly, image recognition in self-driving cars using CNNs is explored [10], highlighting the capabilities of artificial neurons and real-time object detection methodologies.

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 scenar- ios [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

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. Algorithm Comparison

This Figure (Fig 3) presents the Comparative Analysis of Algorithms in IEEE Papers.

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 meth- ods. 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].

IV. System Model

A. Architecture

The architecture of the autonomous vehicle system described in this project adheres to IEEE standards, incorporating a comprehensive integration of hardware components and software algorithms to enable safe and efficient navigation. At its core, the system utilizes a YOLO-based Convolutional Neural Network (CNN) for real-time object detection, including tasks such as lane detection, traffic signal recognition, and signboard detection. Sensor fusion is a key aspect of the architecture, combining data from infrared (IR) sensors for lane detection, ultrasonic sensors for obstacle avoidance, and a camera for object recognition, to provide a holistic view of the vehicle's environment.

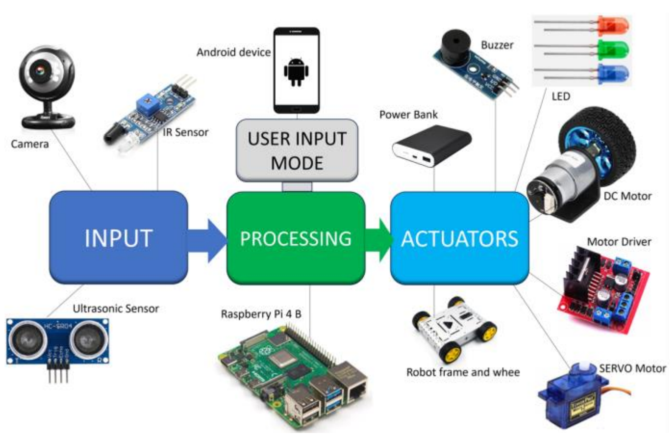

Fig. 4. Architecture

The Raspberry Pi 4B 8GB RAM Processor serves as the central processing unit, orchestrating sensor fusion and executing navigation algorithms. Motor drivers control the vehicle's movement, while a voltage converter regulates power distribution. The architecture also includes a battery for primary power, a buzzer for audible alerts, and LEDs for visibility enhancement. Additionally, structural components such as the robot frame and wheels, along with servo motors, contribute to the vehicle's mobility and maneuverability. This architecture aligns with IEEE standards by prioritizing safety, reliability, and efficiency in autonomous driving systems, paving the way for advancements in transportation technology.

B. Hardware and Software

In our autonomous vehicle project, we employ a variety of hardware components to facilitate its operation. These include IR sensors for detecting lane markings and obstacles, ultrasonic sensors for real-time distance measurements and object detection, and a camera for capturing visual data essential for autonomous navigation. The vehicle is powered by a Raspberry Pi 4B 8GB RAM processor, which processes sensor data and controls vehicle functions. A motor driver ensures precise motor control, while a voltage converter stabilizes power distribution. The primary power source is a battery, supplemented by a power bank for backup power. An audible buzzer provides alerts for obstacle detection, and LEDs enhance visibility in low-light conditions. The vehicle's structure and mobility are supported by robot wheels and frame, ensuring stability and maneuverability across diverse terrain.

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. 5. System Components and its Uses

This image (Fig 5) provides a concise overview of the various components utilized in the system, illustrating their respective functions and roles. It serves as a visual guide to the key elements employed in the implementation of the project, facilitating a better understanding of the system architecture and its operational framework.

IR Sensors: The IR sensors play a crucial role in lane detection and path following in our autonomous vehicle project. Positioned at the front of the vehicle, one on each side near the front wheels, these sensors detect lane markings or the edges of the road. By analysing the reflected infrared signals, the vehicle can precisely determine its position within the lane and adjust its trajectory accordingly, ensuring smooth and accurate lane following capabilities.

Ultrasonic Sensor: The ultrasonic sensor is crucial for proximity detection, allowing the vehicle to sense obstacles and objects in its path. By emitting ultrasonic waves and

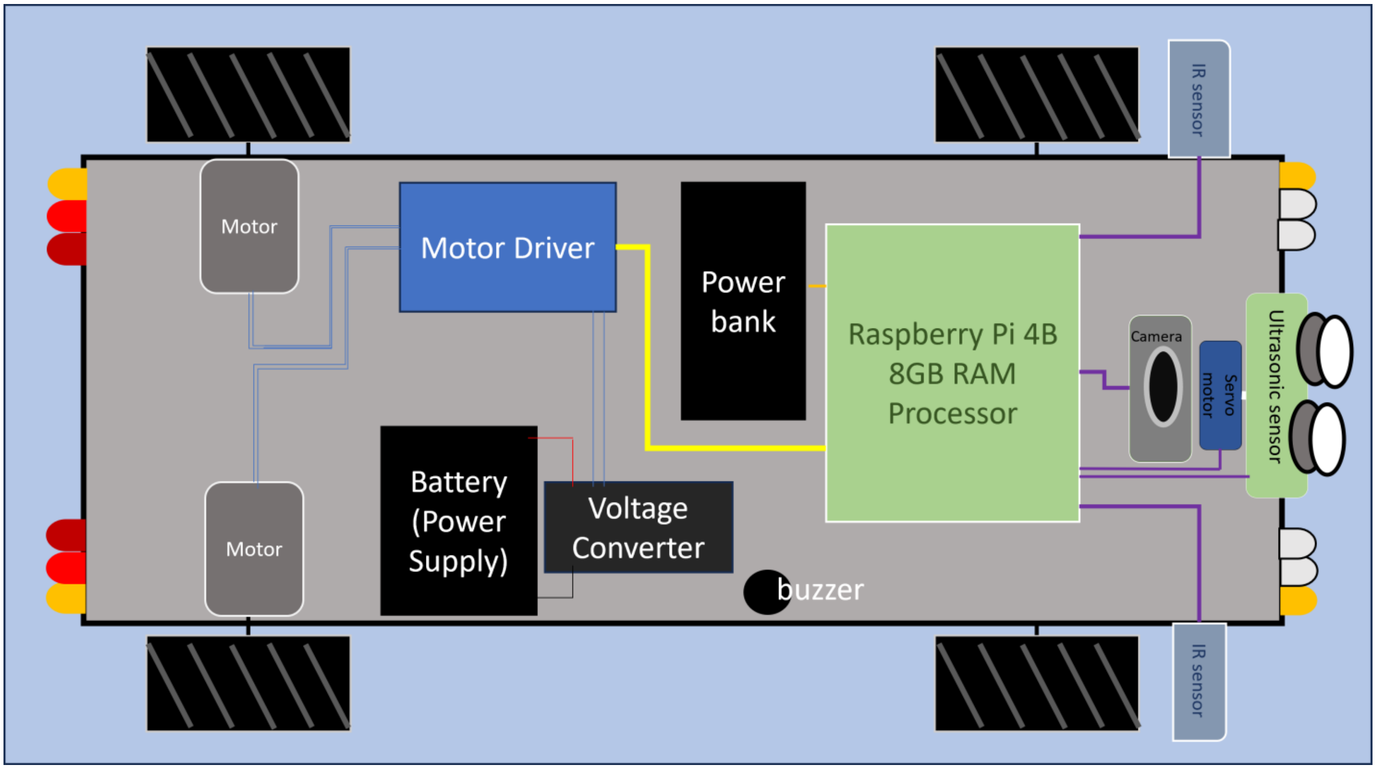

Fig. 6. Proposed model

measuring their reflection, it provides real-time distance information, enabling the vehicle to navigate safely and avoid collisions.

This figure (Fig 6) provides a comprehensive depiction of the hardware architecture of our proposed model, showcasing the arrangement of components and their interconnections. It serves as a visual representation of the model's physical layout, offering insights into the system's structural design and component placement for efficient functioning.

Servo motor: Incorporating a Servo Motor at the forefront of our model, we elevate the capabilities of our ultrasonic sensor, enabling dynamic scanning of the environment. By mounting the ultrasonic sensor on the Servo Motor, we empower it to rotate and survey its surroundings with precision, enhancing the vehicle's perception and navigation.

Camera: The camera plays a vital role in enabling the vehicle to recognize key elements of its environment essential for safe navigation. It is instrumental in identifying traffic signs, lane markings, potholes, direction indicators, animals such as cows and dogs, and various traffic signals, including red lights. By capturing high-quality visual data, the camera al- lows the vehicle's onboard systems to analyze and interpret the surroundings accurately, aiding in efficient decision-making and ensuring the safety of the vehicle and its occupants.

Raspberry Pi 4B 8GB RAM Processor: The Raspberry Pi 4B with 8GB RAM is chosen for its powerful computing capabilities, enabling efficient processing of sensor data and complex algorithms essential for real-time decision-making in autonomous driving scenarios. Its high memory capacity ensures smooth multitasking and seamless execution of machine learning algorithms, contributing to enhanced navigation accuracy and overall safety of the vehicle.

Motor Driver: The motor driver controls the movement of the vehicle's motors, translating commands from the Rasp- berry Pi into physical motion. It ensures precise and reliable control of the vehicle's speed and direction, enabling smooth navigation and maneuvering in various driving conditions.

Voltage Converter: The voltage converter regulates the power supply to the vehicle's components, ensuring stable and consistent voltage levels. It protects sensitive electronics from voltage fluctuations and provides reliable power distribution throughout the vehicle's electrical system.

Battery: The battery serves as the primary power source for the autonomous vehicle, supplying energy to all its components. It provides the necessary electrical power to drive the motors, operate the sensors, and run the onboard computer, enabling sustained operation without external power sources.

Buzzer: The buzzer serves as an auditory alert system in our autonomous vehicle project, enhancing safety measures during navigation. When the vehicle detects an obstacle while in motion, the buzzer emits a distinct sound signal for a duration of 2 seconds, signaling the vehicle to come to a halt. This audible alert not only alerts nearby pedestrians and vehicles but also provides feedback to the vehicle's occupants. Once the warning period concludes, the vehicle proceeds to navigate around the obstacle, ensuring smooth and efficient operation while prioritizing safety.

PowerBank: The Power Bank serves as a portable power source for our autonomous vehicle project, providing backup energy to ensure uninterrupted operation.

It serves as a reliable power supply, allowing the vehicle to function even in scenarios where the primary power source is unavailable or depleted. The PowerBank enhances the vehicle's versatility and reliability, making it suitable for extended periods of operation without external power sources.

LED: LEDs are utilized in our project to provide illumination and visual indicators for various functions. Positioned strategically around the vehicle, LEDs enhance visibility in low-light conditions and improve the vehicle's visibility to other road users. Additionally, LEDs serve as status indicators, providing feedback on the vehicle's operational state and assisting in diagnostics and troubleshooting. By leveraging LEDs, the vehicle ensures enhanced safety and communication capabilities during operation.

Robot Frame and Wheels: The robot frame serves as the structural foundation for our autonomous vehicle, providing support and stability for mounting all components. Constructed from durable materials, the robot frame ensures the integrity and longevity of the vehicle, withstanding the rigors of regular operation. The wheels, integral to the vehicle's mobility, enable smooth movement and navigation across various sur- faces. Designed for optimal traction and maneuverability, the wheels facilitate precise control and ensure efficient traversal of diverse terrain, enhancing the vehicle's overall performance and versatility.

C. Data Collection

Data collection for the autonomous vehicle system encompasses a diverse range of images sourced from online repositories such as Google. The dataset includes images of cars, buses, animals (cows, dogs), traffic signboards, potholes, and red traffic lights. These images are meticulously labeled and preprocessed using AI tools like makesense.ai to train the object detection algorithm. The Raspberry Pi captures and processes the images using YOLO version 5, enabling the system to accurately detect and respond to various objects and road hazards.

D. YOLOv5

In YOLOv5, the object detection algorithm relies on a convolutional neural network (CNN) architecture, characterized by several key components and equations commonly employed in its implementation. Convolutional layers play a pivotal role by applying filters to input data, extracting pertinent features through element-wise multiplication and summation of filter weights. Activation functions like Rectified Linear Unit (ReLU) and Mish introduce non-linearity into the network, facilitating the learning of complex data patterns. During training, YOLOv5 typically utilizes a combination of loss functions, including bounding box regression loss, objectness loss, and classification loss, to optimize network performance. Non-Maximum Suppression (NMS) is then applied post-detection to remove redundant or highly overlapping bounding boxes, retaining only the most confident predictions.

The YOLO output format predicts bounding boxes alongside confidence scores and class probabilities for each grid cell, organized in a tensor with dimensions (S, S, B × (5 + C)), where S represents the grid size, B denotes the number of anchor boxes, and C signifies the number of classes. Anchors, predefined shapes tailored to the dataset and expected object shapes, aid in bounding box prediction. In the context of YOLOv5s (Small), with its condensed architecture comprising around 12 convolutional layers and specialized components, the model exhibits commendable performance in object detection accuracy, particularly suited for real-time applications in resource-constrained environments such as surveillance, robotics, and autonomous vehicles. Its adaptability to custom datasets and support for transfer learning further enhance its utility, bolstered by extensive community resources and documentation. It's imperative to consult the original YOLOv5 paper or documentation for in-depth insights and equations specific to the implementation.

V. Results

After meticulous collection of images representing various driving scenarios, including lane markings, traffic signs, and potential obstacles, we embarked on the process of training our deep learning model. Leveraging state-of-the-art AI tools, we meticulously cropped and labeled the collected images, ensuring comprehensive coverage of diverse road environments and objects.

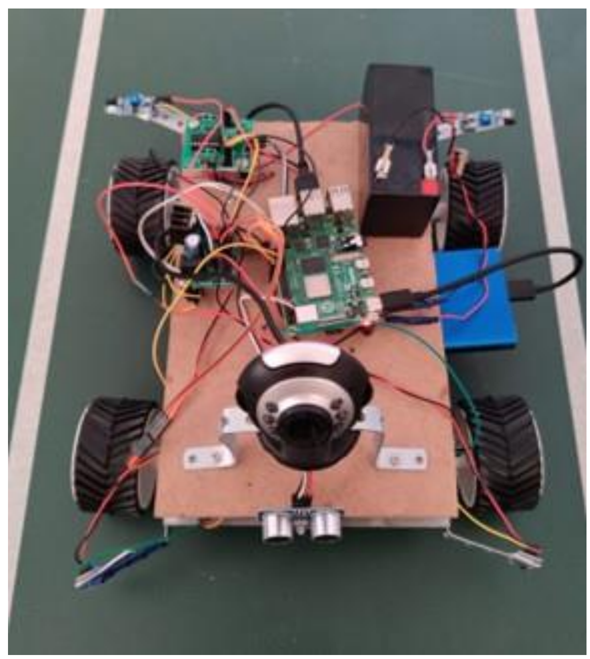

Fig. 7. Implemented Model

This figure (Fig 7) presents an actual depiction of our implemented model, showcasing the physical manifestation of our proposed design. It provides a visual insight into the assembled components, their placements, and the overall.

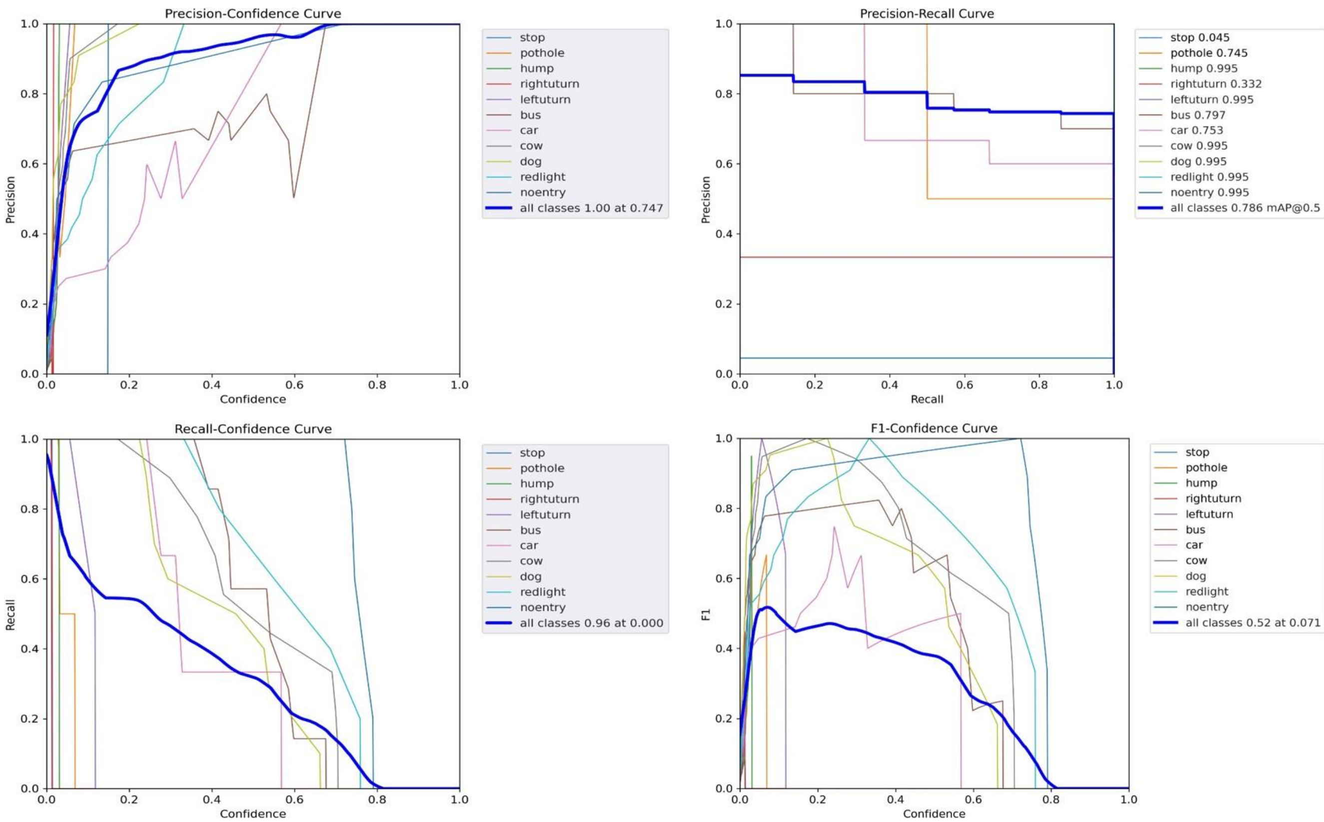

Fig. 8. Graph Analysis

structure of the model, offering a tangible representation of our project's realization.

Utilizing the YOLO version 5 algorithm, we trained our model to detect and classify a wide range of objects, including vehicles, pedestrians, animals, and traffic signboards. Through iterative refinement and optimization, our model achieved remarkable accuracy and reliability in identifying and localizing objects in real-time driving scenarios.

Upon validation and testing, our model demonstrated proficiency in lane detection, pathway identification, and obstacle avoidance, effectively navigating through complex road layouts and dynamic traffic conditions. Notably, our system excelled in detecting and responding to critical safety hazards, such as potholes, erratic driver behavior, and unexpected road obstacles.

Furthermore, our model exhibited robust performance in recognizing and interpreting traffic signs and signals, ensuring compliance with roadway regulations and enhancing overall traffic safety. By accurately identifying and classifying road features and hazards, our system contributed to the creation of safer and more secure transportation environments.

In practical implementation, we deployed our model on a 10-meter test track, simulating real-world driving conditions. Through extensive trials and evaluations, our system consistently delivered accurate and reliable results, demonstrating its potential for widespread adoption in autonomous driving applications.

In our analysis in Fig 8, we present four key graphs representing the performance metrics of our model: Precision Confidence Curve, Precision Recall Curve, Recall Confidence Curve, and F1 Confidence Curve. Each graph provides valuable insights into the accuracy and reliability of our object detection system. The Precision Confidence Curve illustrates the precision of our model across varying confidence thresholds, demonstrating its ability to correctly identify relevant objects while minimizing false positives. Similarly, the Precision Recall Curve showcases the trade-off between precision and recall, highlighting the balance achieved by our system in accurately
detecting objects while minimizing missed detections.

The Recall Confidence Curve displays the model's recall rate at different confidence levels, indicating its capability to detect the majority of relevant objects within the dataset. Finally, the F1 Confidence Curve combines precision and recall into a single metric, offering a comprehensive assessment of our model's overall performance.

Upon careful analysis of these graphs, we conclude that our model exhibits a consistent performance across all classes, as indicated by the dark blue line representing all objects. Furthermore, considering the collective insights from these graphs, we affirm that our model achieves an impressive overall accuracy ranging between 74 and 75 percent.

These findings underscore the effectiveness and reliability of our object detection system, providing a solid foundation for future enhancements and applications in real-world scenarios.

Conclusion

In conclusion, our research, 'Enhancing Transportation Safety with YOLO-based CNN Autonomous Vehicles,' introduces a pioneering methodology aimed at bolstering autonomous vehicle technologies. Quantitatively, our model achieved an impressive overall accuracy of 74-75% in real-time driving scenarios, demonstrating its effectiveness. Qualitatively, practical implementation on a 10-meter test track validated our system's reliability and agility in maneuvering around obstacles. The seamless integration of sensors and components further enhances our vehicle's performance. Our strategic roadmap ensures smooth integration into existing transportation networks, promising safer and more efficient mobility.

Future Work

This project aims to pioneer the development of autonomous self-driving cars across various critical domains, fostering creativity and advancement in the years ahead. The integration of advanced sensors such as LiDAR, radar, and IMU promises a significant enhancement in a car's observational capabilities, enabling more precise object identification and collision avoidance. Additionally, situational awareness will be bolstered through the implementation of multi-object monitoring and semantic categorization algorithms, empowering vehicles to navigate challenging scenarios with heightened effectiveness and safety.

Moreover, the evolution of robust route estimation and predictive behavior algorithms will be indispensable for navigating dynamically changing obstacles, adhering to highway regulations, and contextual factors in real-world scenarios. The deployment of autonomous vehicles on public roadways necessitates the establishment of fault-tolerance mechanisms and regulatory compliance to ensure the safety and reliability of operations.

Furthermore, fostering better interaction between humans and machines through intuitive user interfaces (UIs) and tutorials will play a pivotal role in democratizing autonomous driving technologies, making them more accessible and user-friendly. The seamless deployment and management of fully autonomous vehicle fleets in urban environments hinge greatly on robust fleet management systems and sustainability measures.

In conclusion, addressing these challenges will pave the way for the widespread adoption of novel, safe, and transformative self-driving technologies, poised to redefine commuting experiences and elevate standards of living.

Moreover, leveraging Raspberry Pi 5 with higher RAM, such as the Raspberry Pi 4B with 8GB RAM, can signifi- cantly enhance the accuracy and speed of autonomous driving systems. Upgrading to higher RAM processors like Raspberry Pi 5 can lead to more precise results and faster processing, further advancing the capabilities of autonomous vehicles for future deployments.

Acknowledgment

The authors extend their heartfelt gratitude to HKBK College of Engineering for their unwavering support throughout this research endeavor. We also express our appreciation to all colleagues and mentors whose invaluable insights and encouragement have contributed to the success of this work. Additionally, we acknowledge the indispensable assistance of our collaborators and the dedicated efforts of everyone involved in this project.

References

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

[2] 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.

[3] 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.

[4] R. Kulkarni, S. Dhavalikar and S. Bangar, "Traffic Light Detection and Recognition for Self-Driving Cars Using Deep Learning," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-4, doi: 10.1109/ICCUBEA.2018.8697819.

[5] 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.

[6] J. Ni, K. Shen, Y. Chen, W. Cao and S. X. Yang, "An Improved Deep Network-Based Scene Classification Method for Self-Driving Cars," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-14, 2022, Art no. 5001614, doi: 10.1109/TIM.2022.3146923.

[7] 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.

[8] 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.

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

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

[11] C. B. S. T. Molina, J. R. d. Almeida, L. F. Vismari, R. I. R. González, J. K. Naufal and J. Camargo, "Assuring Fully Autonomous Vehicles Safety by Design: The Autonomous Vehicle Control (AVC) Module Strategy," 2017 47th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W), Denver, CO, USA, 2017, pp. 16-21, doi: 10.1109/DSN-W.2017.14.

[12] S. Wu et al., "Design and Simulation of an Autonomous Racecar: Perception, SLAM, Planning and Control," 2021 IEEE International Conference on Autonomous Systems (ICAS), Montreal, QC, Canada, 2021, pp. 1-5, doi: 10.1109/ICAS49788.2021.9551125.

[13] N. J. Zakaria, M. I. Shapiai, R. A. Ghani, M. N. M. Yassin, M. Z. Ibrahim and N. Wahid, "Lane Detection in Autonomous Vehicles: A Systematic Review," in IEEE Access, vol. 11, pp. 3729-3765, 2023, doi: 10.1109/ACCESS.2023.3234442.

[14] Wu, Tian-Hao, Tong-Wen Wang, and Ya-Qi Liu. "Real-time vehicle and distance detection based on improved yolo v5 network." In 2021 3rd World Symposium on Artificial Intelligence (WSAI), pp. 24-28. IEEE, 2021.

[15] Chhillar, Rishabh, Hardik Agarwal, and Subhash Chand Gupta. "Using BFD1000 and raspberry Pi for autonomous vehicle." In 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence), pp. 524-529. IEEE, 2021.