Embedded Safety System for Autonomous Vehicles

Jennifer C Saldanha[1], Prakash S H[2], Jithesh[3], Guruprasad[4], Rachana[5]
[1]*Assistant Professor, St. Joseph Engineering College Mangalore, India*
[2,3,4,5] *St. Joseph Engineering College Mangalore, India*

***Abstract*—The research provides a reliable embedded safety system to improve the situational awareness and stability of autonomous vehicles. This project combined real-time object and pedestrian detection using the YOLO algorithm, speed identification, and blind spot monitoring using ultrasonic sensors. These functions are deployed on embedded systems like Raspberry Pi and ESP32, activating advanced control measures such as PWM-based speed control and LED-based risk alerts. The camera module can capture road imagery for detection and classification; the speed limit is observed with image processing and OCR technique and the ultrasonic sensor continuously observes blind areas. OCR model obtains speed limit information and allows real-time vehicle speed control. This prototype testing under various road situations presented high accuracy and consistency in object recognition, speed customization, and blind spot alerts. The project presents minimal delay and informed choices in a real-time environment. Long-term upgrades will be prioritised incorporating sensor fusion, V2X communication, and IMU-based pose correction to improve safety in a challenging traffic environment.**

***Index Terms*—Autonomous Vehicles, Pedestrian detection YOLO, Object Detection, OCR, PWM, Raspberry Pi, ESP32, Sensor Fusion, V2X Communication, IMU Pose Correction.**

I. INTRODUCTION

Implementing advanced detection systems and monitoring techniques aims to improve road safety and the driving experience of autonomous vehicles. This system combines the blind spot monitor, speed limit recognition, and real-time object and pedestrian detection. Using advanced technology guarantees traffic regulation and avoids possible hazards. The system integrates embedded devices like Raspberry Pi, ESP32, and ultrasonic sensors with machine learning algorithms. This system reduces accidents and provides a better experience for both human and autonomous cars.

In autonomous vehicles, object and pedestrian detection is the most important and plays a very crucial part. Using detection algorithms like YOLO and single-shot multi-box detectors, detect the object and pedestrians effectively [1]. Spotting pedestrians with compact design and low power consumption can efficiently boost pedestrian safety [2]. This system uses the pre-trained YOLO model. The speed recognized is also important in autonomous vehicles while they are moving. If the speed is detected, the vehicle is controlled to that speed, which plays a very significant role. This project includes an ultrasonic sensor for the blind spot monitor and PWM for speed control, less complicated than traditional approaches [3].

Blind Spot Detection (BSD) is a crucial component of autonomous vehicles and guarantees the safety of the driver. Another important factor is choosing a sensor based on its accuracy, economy, adaptability, and efficiency. [10]. In the vehicle in particular, some angles are not visible to the driver and cannot be watched directly or in the mirror in those particular areas called blind spots. BSD helps drivers identify vehicles or objects in their blind spots by using an ultrasonic sensor. This sensor monitors the environment continuously. If the vehicle finds it, it gives an LED indication to the driver.

In this project, one of the objectives is blind spot detection using an HC-SR104 ultrasonic sensor. The placement of the ultrasonic sensor will play a crucial role in the BSD [7]. The most hazardous situation during a lane change occurs when a driver fails to detect vehicles in the blind spot. To ensure safe driving, it is crucial to closely monitor the blind spot or blind area [8]. The transmitting angle of the wave and receiving back the signals are also important. The ultrasonic sensor continuously transmits and receives signals back from the object, and it indicates the driver with an LED.

II. LITERATURE ANALYSIS

This literature review explores recent advancements in Vehicle safety, focusing on trends, research themes, and the effectiveness of technologies like object detection, vehicle avoidance, and automated braking, especially under challenging conditions. It emphasizes sensor integration, algorithms, and real-time processing in enhancing vehicle safety and highlights the current state.

Chengji Liu; Yufan Tao; Jiawei Liang; Kai Li; Yihang Chen 2018[1] The researchers developed an object detection technique based on the YOLO model, training a generative model with degraded images. Experiments show that using deteriorated images enhances feature learning, improves performance in complex scenes, increases average detection precision, and results in a more robust, generalizable model.

Zhiheng Yang;Jun Li;Huiyun Li (2018) [2] A new pedestrian detection system based on Darknet is proposed, using optimized anchor boxes and a pedestrian-specific deep CNN. It processes images of any size, outputting bounding box coordinates and pedestrian scores. Experiments show it meets real-time and accuracy requirements for low-speed autonomous driving.

S Arun Prakash, Aravind Mohan R, Rahul M Warrier, R Arun Krishna, Sooraj Bhaskar A, Aswathy K Nair (2018) [3] A system is proposed to trace a vehicle's location and control its speed based on the area's speed limit. The digital environment was developed in LabView, with hardware implemented using Arduino. GPS coordinates provided the speed limit, sent via Bluetooth to Arduino, which then controlled the vehicle’s speed using PWM.

Shinpei Kato; Shota Tokunaga; Yuya Maruyama; Seiya Maeda; ManatoHirabayashi; Yuki Kitsukawa; Abraham Monrroy; Tomohito Ando; Yusuke Fujii; Takuya Azumi (2018) [4] Autoware on Board is a new embedded Autoware profile for autonomous vehicles on the Drive PX2 platform, using ARM cores and Tegra GPUs. It is the first publicly available version with quantified performance, showing up to 3× higher latency than high-end PCs.

HU Xin, MING Pingliang1, WEI Xuezhou2, Wuhan (2017) [5] The study proposed mathematical models for operation modes and structural traits of a DC motor. Using a thyristor-based double closed-loop control, it effectively limits startup armature current and stabilizes motor speed. The approach can be further developed for complex industrial applications.

Hai Wang and Yijie Yu, Yingfeng Cai, Xiaobo Chen, Long Chen, and Qingchao Liu (2020) [6] Deep learning algorithms for road vehicle detection were compared using the KITTI dataset, evaluated by recall, precision, average precision, and FPS. Real street scenes were used to assess their practical effectiveness.

Muhammad Herman Jamaluddin, Ahmad Zaki Shukor, Muhammad Fahmi Miskon, Fariz Ali@Ibrahim and Muhammad Qamarul Arifin Redzuan (2016) [7] An Arduino UNO and SRF04 ultrasonic sensor system was tested in two experiments: with a static car and a moving car at constant speed, both with the sensor placed above the rear tire. Results show this placement effectively detects vehicles in the blind spot.

Kyeong-Hoon Jung, Kang Yi (2015) [8] A method is proposed to estimate a detected car’s trajectory in the blind spot by analyzing pose changes in rear-view images using multi-class HOG with SVM and adjusted ROI windows. It reduces complexity by eliminating motion estimation, with minimal impact on recall and precision.

Eduardo Arnold;Omar Y. Al-Jarrah;Mehrdad Dianati;Saber Fallah;David Oxtoby;Alex Mouzakitis (2019) [9] proposed a review of the state-of-the-art of 3D object detection within the context of autonomous vehicles. We analyzed sensor technologies with their advantages and disadvantages and discussed standard datasets. The reviewed works were categorized based on sensor modality: monocular images, point clouds, and fusion.

Ann Zenna Sajan, G R Gnana King (2021) [10] advanced a shot at pedestrians, which facilitates passengers go the road safely with none coincidence from excessive-pace cars. The automobile’s pace control and horn sound in those zones, which may run on Raspberry Pi. The machine used Open computer imaginative and prescient as an image processing software program machine to scale back the rate of the moving vehicles when they reached the zebra lines.

III. METHODOLOGY

The embedded safety system for self-driving cars suggested in the paper includes four main functions: detection of objects and people in the vehicle's front and recognition of speed limits with necessary speed modifications, blind spot vigilance, and accurate control of a DC motor via Pulse Width Modulation (PWM). Detection of objects and people utilises a camera and ultrasound sensors connected to a Raspberry Pi, where deep learning algorithms such as You Only Look Once (YOLO) are employed to maximise accuracy. Once a potential threat is detected, the system instantly sends an emergency stop command to the vehicle control unit for immediate action.

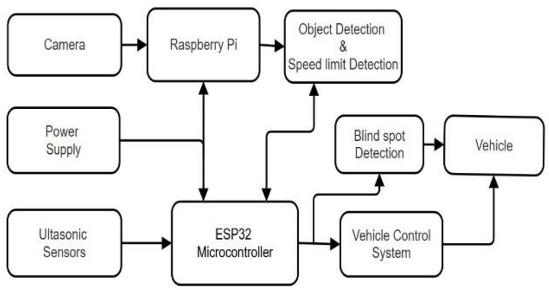

Figure 3.1: Block Diagram

A camera attached to a vehicle recognizes road signs in order to register the speed limit, which is processed sequentially in OpenCV and neural networks. As a result, speed limit signs are read and the speed is adjusted in real-time by changing the PWM signals fed to the DC motor. Moreover, blind spot vigilance uses a combination of sensors to provide an additional layer of monitoring and real-time alerts to improve safety and minimize visibility-related accidents.

The Camera captures the video feeds concerning the vehicle. This data is forwarded to the Raspberry Pi (CPU), which passes the images through deep learning and computer vision processes. It identifies objects such as people and other vehicles. When an obstacle is identified, the Raspberry Pi processes the information and gives certain instructions to the Vehicle control system that changes the speed, and direction or applies brakes to the vehicle. At the same time, the Ultrasonic Sensor picks up nearby obstacles especially those positioned at the vehicle's blind spots. This sensor is connected to the ESP32 Module, which calculates the distance and warns of possible dangers. The control system acknowledges the alarm from the Blind Spot Detection and governs the vehicle to change its position safely. All components rely on a Power Supply Unit to ensure power efficiency as they function with a high energy output. The VCS receives and makes decisions from data coming from the camera and ultrasonic sensor to perform driving actions, for example, slowing down, or speeding.

A. Component Systems

- Raspberry Pi 4

The Raspberry Pi 4, developed by the Raspberry Pi Foundation, is a single-board computer. It includes an SoC with an integrated ARM Cortex-A72 CPU and a Broadcom Video Core VI GPU. The Raspberry Pi 4 functions as a main processing unit to receive data from multiple sensors as well as to control all the peripherals of the system [18].

- ESP-32

The embedded microcontroller ESP-32 is well known for its intricate features like combining Bluetooth and Wi-Fi alongside remarkable processing power, while consumption of energy is minimal. For these reasons, it is widely used in remote monitoring and control systems with single-board computers [18].

- Camera

For intelligent navigation in real-time, cameras provide visual data for execution which is pivotal for speed and tasks pertaining to object detection. modules capture video sequences and deploy in deep learning algorithms such as the YOLO model for object recognition and classification. In this way, the camera system is capable of detecting traffic signs, and obstacles, and makes decisions all autonomously without human intervention [17][18].

a) YOLO

YOLO (You Only Look Once) is one of the best object detection models and most appropriate for real-world applications. YOLO was developed by Joseph Redmon and it outperforms other models like region-based Convolution Neural Networks (R-CNN) because of its lesser processing time. YOLO applies a single neural network to the entire image at once to predict each label and bounding box. YOLO achieves real time performance up to 155 frames per second (fps), and although a bit of accuracy is sacrificed, it is well worth the speed. Such scenarios where rapid and accurate object detection is required, are where it excels most.

Three basic principles are the building blocks for the YOLO framework. It uses a singular CNN that predicts multiple bounding boxes and their probabilities of each class simultaneously. Secondly, the input image is treated as a regular grid and each cell is responsible for detecting objects whose centers fall into the cell. Finally, YOLO computes the coordinates, dimensions, and confidence score of each detected object using bounding box regression. This design allows YOLO to conduct detection in a simple, computationally light, and streamlined manner.

b) Estimation of Distance

The approach employs the pinhole imaging model for estimating distances while enhancing it with the vehicle pose information. The method uses a monocular camera system where the distance (Z) is defined as the focal length (f) of the camera, the mounting height (H), and the object's vertical position on the image plane.

Project image coordinates onto real distances, the dimensions of the pixels and the position of the optical center of the camera must be considered. Additionally, disturbances like vibrations, road slopes, and variations in the pitch and roll angles are compensated for by the vehicle pose information from an Inertial Measurement Unit (IMU). This approach dynamically modifies the extrinsic parameters of the camera during movement, such as the position of the vanishing line, changing the distance estimation formula. The vertical dimension scaling factor. With the integration of pose corrections, this approach has been found to enhance the precision of the distance estimation when the system is deployed in complex terrains such as slopes and rough terrains. This technique works especially well for accurately detecting nearby cars.

B. Speed Limit Detection

Autonomous cars use advanced image processing, sensors, and live video surveillance to recognize and react to varying speed limit areas. As a car travels, onboard cameras take several photos of the road surroundings and look for pre-specified patterns in terms of shape, colour, and text. These pictures are analyzed with deep learning algorithms like YOLO (You Only Look Once), which can identify and classify different road signs correctly in real time. When a speed limit sign is identified, Optical Character Recognition (OCR) programs like Tesseract pick up the numeric value, for example, "50 km/h".

This pulled speed limit is communicated to the control system of the car, where the speed of the car is automatically controlled to remain within legal and safety limits. The system adjusts continuously as new signs are encountered, staying safe in all conditions during the trip.

In optical character recognition (OCR) in advanced driver-assistance systems (ADAS), the application is of particular importance in recognizing speed limit signs. The technology enables the system to extract numeric speed limits from images captured and translate them into actionable, machine-readable text for vehicle response in real time.

1. Image Capturing The system starts by a camera capturing images or video frames of road signs. These visual inputs are forwarded to the onboard processing unit, where the OCR system starts processing the data for information on speed limits.

2. Preprocessing The captured image is pre-processed before text recognition in order to enhance accuracy. Methods like deskewing straighten tilted text, despeckling eliminate noise due to environmental conditions like rain or dust, edge smoothing clarifies numerals, and colour and contrast adjustments make the speed limit text clear against the background.

3. Text Recognition the OCR system then recognizes the numeric characters through two primary techniques. Pattern matching relates identified shapes with preserved numeral templates, whereas feature extraction targets structural features such as curves, edges, and loops to identify the most probable digit.

4. Interpretation and post-processing Following recognition, the recognized speed limit is verified by comparison with typical values

C. PWM-Based Speed Control

Motors are driven by electrical signals rather than direct speed values; we utilize Pulse Width Modulation (PWM) to regulate the amount of power supplied to the motor. The speed PWM map is a predefined mapping that connects specific speed values (in km/h) to corresponding PWM duty cycle values. For instance, a speed of 10 km/h corresponds

to a PWM value of 5, while 100 km/h maps to 50. This proportional relationship helps simplify the control logic, allowing the system to easily convert detected speed limits into PWM signals for motor control.
In the process of implementation, after detecting a speed limit, whether it is through object detection through a camera, the appropriate PWM value is fetched from the dictionary. A Raspberry Pi or microcontroller with a motor driver module like the L298N interfaces with the motor. The PWM value, which is a square wave signal with a variable duty cycle, defines the speed of the motor by controlling the duration it remains "on" during each repetition of the cycle. For instance, if the duty cycle is 50%, the motor allows power to be sent for half of the cycle which would enable the motor to turn at moderate speed.

D. Blind Spot Detection
In this project, the specific value is set for the object detection. If the object is detected within the range, the system triggers the warning. the outside range object is ignored by the sensor. If the object is detected within the set range on the left side, the left ultrasonic sensor will detect the object, and the system will activate the left LED. Similarly, if an object is detected on the right side the right LED will turn on. The ultrasonic sensor operates continuously, constantly transmitting sound waves and measuring the return echoes. This allows the system to monitor the blind spot in real time. The LED turn on only when an object is detected within the specified range, ensuring that the driver is alerted to the presence of other vehicles or obstacles in the blind spot. The formula is used to measure the distance to the object

Sound speed=340 m/sec

$$D = S * T / 2 \quad (1)$$

Where D= Distance
T= Time
S= Speed

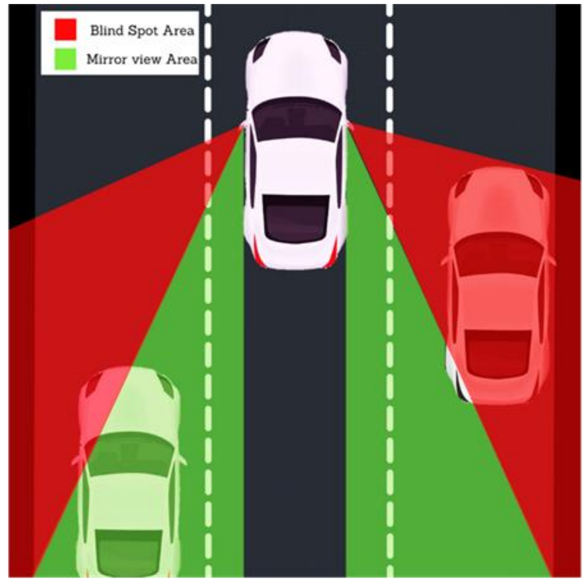

Figure 3.2 Blind Spot Areas

Figure 3.2 shows the blind spots of a car, which are indicated by red regions, where the driver cannot see other cars in the side mirrors. The mirror view zones, which are viewable through the side mirrors of the car, are indicated by green areas. This map shows the areas where more sensors, such as ultrasonic sensors, could help increase driver safety and visibility.

E. Model View

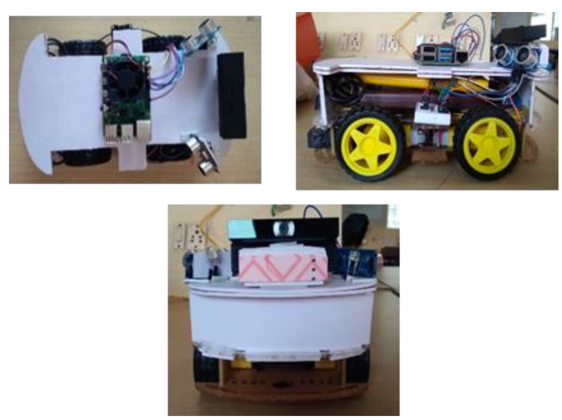
Figure 3.3: Vehicle Prototype

Figure 3.3 shows the prototype of our autonomous vehicle from three different angles, highlighting key components. The top view reveals the Raspberry Pi, camera, and sensors with wiring. The side and front views show the chassis, motor driver, battery pack, and sensor placement. These angles help visualize the hardware integration and overall design.

IV. RESULTS AND DISCUSSION

The vehicle uses a front camera to capture real-time video processed by the YOLO system to recognize objects such as cars, pedestrians, traffic signs and other objects. Comfortable objects come with boxes and are given trust. The system also appreciates the distance to each object and helps the vehicle adapt its speed to avoid collisions and maintain a safe distance. It recognizes speed limit signs and automatically adjusts the vehicle's speed accordingly.

A. Object and Pedestrian Detection

The project uses a camera associated with the Raspberry PI for pedestrian and object recognition. The photos are analyzed with the Yolo algorithm, known for its real-time speed and accuracy. Yolo divides all photos into grids and recognizes and classifies objects. This allows vehicles to quickly recognize pedestrians, vehicles and street observations, allowing for immediate decisions such as stopping or slowing down. During testing, the model showed high accuracy and was suitable for autonomous navigation.

Figure 4.1 The Object Is Detected Outside the Line

In autonomous vehicles, the security system recognizes objects and locations within lanes. In the photo, a mobile phone outside the lane with a green bounding box with a 3.51 m 0.0% mobile phone is marked in the lane. The dotted yellow and red lines indicate the track boundary and ensure that the object is outside the root. Additionally, the display showed that the vehicle was transparent, there was no lane stream, and no speed limit signs were found

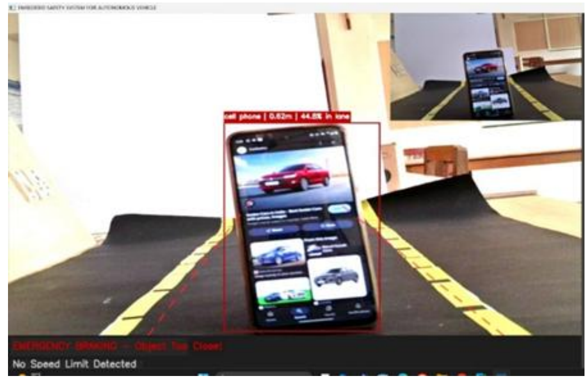

Figure 4.2 The Object Is Detected Inside the Line

The camera recognizes the phone as a barrier to miniature roads. The system identifies the object based on computer vision, estimates its distance (0.62 meters) and finds it is in the lane (44.8%). The object is too tight, causing emergency braking alert and simulates how autonomous cars respond in real scenarios to prevent collisions.

B. Speed Limit Detection

The system's speed limit detection ensures traffic compliance by adjusting vehicle speed based on road signs. A camera captures speed signs, which are processed using OpenCV, YOLO, and Tesseract OCR to extract speed values. Once identified, a command is sent to the DC motor to adjust speed. Tests showed the system reliably recognized speed signs and dynamically adjusted speed, confirming its effectiveness.

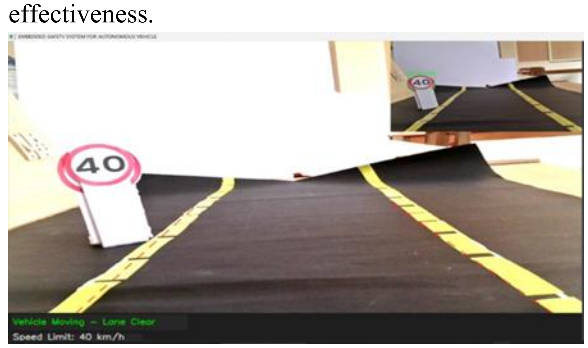

Figure 4.3: Speed Limit Detected

The image shows the output of an autonomous vehicle's onboard safety system using camera input. It detects road signs and lane markings, identifying a "40 km/h" speed limit sign, displayed in the lower-left corner. Yellow lane lines and red dashed tracking lines indicate active lane detection, helping keep the vehicle within safe boundaries. The display status "Vehicle Moving – Lane Clear" confirms the vehicle is in motion with no obstructions ahead. This demonstrates the system's real-time ability to recognize road signs and track lanes for safe navigation.

C. Blind Spot Monitoring

To prevent blind spot accidents, the system uses ultrasonic sensors to detect objects outside the camera's view. These sensors emit sound waves and calculate object distance based on the return time. If an object is within a danger zone, a warning LED is triggered. This feature is especially useful during lane changes to avoid collisions with approaching vehicles. Testing showed high detection accuracy and low false positives, making it a vital safety feature for autonomous driving. In the blind spot area, an approaching object triggers the detection system, activating the corresponding LED to alert the driver.

Figure 4.4 Blind Spot Detected

D. Distance Estimation Accuracy

The object distance estimate system's accuracy is demonstrated in this graph. The Y-axis displays the estimated distance determined by the system, while the X-axis displays the actual distance to the object (in meters). A diagonal line (y = x) should ideally form between the estimated and actual values. A divergence in the prediction is indicated by any departure from this line. The accuracy of the system's distance estimate method increases with the proximity of the depicted points to the diagonal.

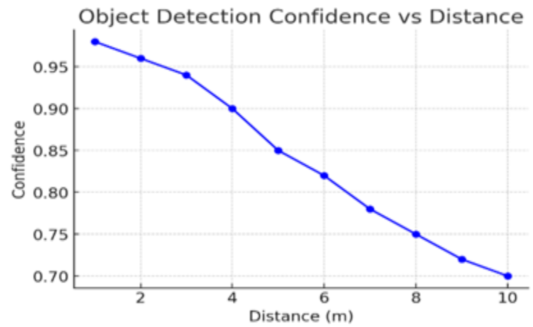

Figure 4.5 Object Detection graph

E. System Latency in Driving Scenarios

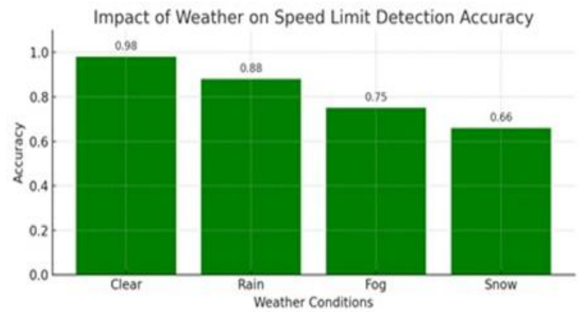

Figure 4.6 Detection Accuracy Comparison for Different Weather Conditions

The system's latency under different driving conditions is seen in this bar graph. The Y-axis shows the system response time in seconds, while the X-axis identifies the various scenarios: clear, rain, fog, and snow weather. For safety-critical activities, a lower latency means a faster system response. Particularly in difficult circumstances like bad weather, the graph aids in determining where the system operates effectively and where enhancements are required.

F. Speed Vs PWM Signal Mapping

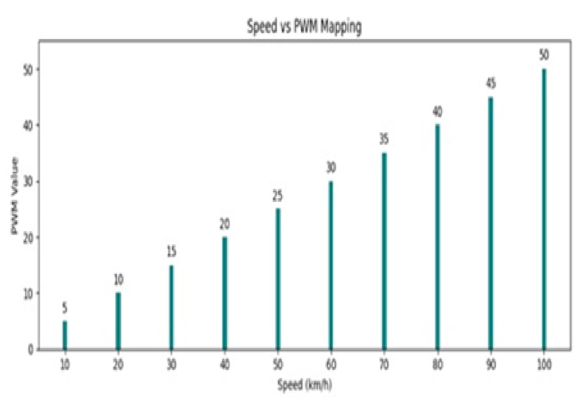

Figure 4.7 Speed vs PWM Signal Mapping

This graph shows how the vehicle's speed is translated into motor control signals using Pulse Width Modulation (PWM). The X-axis represents speed in kilometres per hour (km/h), and the Y-axis shows the corresponding PWM values. Both the line and bar versions of the graph depict a linear relationship, where PWM increases proportionally with speed. This clear and consistent mapping is crucial for embedded systems to control motor speed effectively and ensures smooth acceleration and deceleration in real time.

V. CONCLUSION

The Autonomous Vehicle Embedded Safety System offers an all-encompassing solution to boost road safety through the incorporation of intelligent detection, monitoring, and responding mechanisms. Through integrating real-time object and pedestrian detection, adaptive speed control, and blind spot monitoring, the system is able to dramatically decrease the chances of accidents. Its capacity for timely decision-making and real-time feedback guarantees not only adherence to road regulations but also safety for all road users. This comprehensive strategy sets the stage for autonomous driving that is safer, smarter, and more dependable.

REFERENCES

[1] C. Liu, Y. Tao, J. Liang, K. Li, and Y. Chen, "Object detection based on YOLO network," 2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China, 2018, pp. 799-803,

[2] Zhiheng Yang, Jun Li, and Huiyun Li, "Real-Time Pedestrian Detection for Autonomous Driving," in *Proceedings of the 2018 International Conference on Intelligent Autonomous Systems*, 2018, pp. 1-6, doi: 10.1109/EPSCICON.2018.8379569

[3] S. A. Prakash, A. Mohan R, R. M. Warrier, R. A. Krishna, S. Bhaskar A, and A. K. Nair, "Real Time Automatic Speed Control Unit for Vehicles," in Proceedings of the 2018 International Conference on Power, Signals, Control and Computation (EPSCICON), Thrissur, India, 2018, pp. 1-6, doi: 10.1109/EPSCICON.2018.8379569

[4] S. Kato, S. Tokunaga, Y. Maruyama, S. Maeda, M. Hirabayashi, Y. Kitsukawa, A. Monrroy, T. Ando, Y. Fujii, and T. Azumi, "Autoware on Board: Enabling Autonomous Vehicles with Embedded Systems," in Proceedings of the 2018 ACM/IEEE 9th International Conference on Cyber-Physical Systems (ICCPS), Porto, Portugal, 2018, pp. 287-296, doi: 10.1109/ICCPS.2018.00038.

[5] X. Hu, P. Ming, and X. Wei, "Analysis and Comparison of Various Speed Control Strategies on the Performance of DC Motor," in Proceedings of the 2017 IEEE International Conference on Mechatronics and Automation (ICMA), Takamatsu, Japan, 2017, pp. 2016-2021, doi: 10.1109/ICMA.2017.8016127.

[6] H. Wang, Y. Yu, Y. Cai, X. Chen, L. Chen, and Q. Liu, "A Comparative Study of State-of-the-Art Deep Learning Algorithms for Vehicle Detection," in Proceedings of the 2019 IEEE Intelligent Transportation Systems Conference (ITSC), Auckland, New Zealand, 2019, pp. 330-337, doi: 10.1109/ITSC.2019.8917159.

[7] M. H. Jamaluddin, A. Z. Shukor, M. F. Miskon, F. Ali@Ibrahim, and M. Q. A. Redzuan, "An Analysis of Sensor Placement for Vehicle’s Blind Spot Detection and Warning System," *Journal of Telecommunication, Electronic and Computer Engineering*, vol. 8, no. 7, pp. 101-106, 2016

[8] K. H. Jung and K. Yi, "Determination of Moving Direction by the Pose Transition of Vehicle in Blind Spot Area," in *Proceedings of the 2015 IEEE International Symposium on Consumer Electronics (ISCE)*, 2015, pp. 1-4, doi: 10.1109/ISCE.2015.7363654

[9] Shnain, Saif Kamil, et al. "Developing Vehicles Blind Spot Sensors Using Arduino to Avoid Parking Accidents." 2024 35th Conference of Open Innovations Association (FRUCT). IEEE, 2024

[10] S. S. G. Bagi, H. G. Garakani, B. Moshiri, and M. Khoshnevisan, "Sensing Structure for Blind Spot Detection System in Vehicles," in 2019 IEEE International Conference on Vehicular Electronics and Safety (ICVES), Cairo, Egypt, 2019, pp. 1–6, doi: 10.1109/ICVES.2019.8906328.

[11] C. Xiong, C. Wang, W. Ma, and Y. Shan, "Traffic Sign Detection and Recognition Based on

Convolutional Neural Networks," in 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), Changsha, China, 2016, pp. 1377–1381, doi: 10.1109/FSKD.2016.7603374

[12] D. Feng, C. Haase-Schütz, L. Rosenbaum, H. Hertlein, C. Gläser, F. Timm, W. Wiesbeck, and K. Dietmayer, "Deep multi-modal object detection and semantic segmentation for autonomous driving: Datasets, methods, and challenges," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 3, pp. 1341–1360, Mar. 2021, doi: 10.1109/TITS.2020.2972974.

[13] E. Zadobrischi and M. Negru, "Pedestrian detection based on TensorFlow YOLOv3 embedded in a portable system adaptable to vehicles," in *Proc. 15th Int. Conf. on Development and Application Systems (DAS)*, Suceava, Romania, 2020, pp. 21–23, doi: 10.1109/DAS49615.2020.9108944.

[14] Ramteke, A. Y., et al. "Blind Spot Detection for Autonomous Driving Using RADAR Technique." *Journal of Physics: Conference Series*. Vol. 2763. No. 1. IOP Publishing, 2024.

[15] McLachlan, S., Neil, M., Dube, K., Bogani, R., Fenton, N., & Schaffer, B. (2021). Smart automotive technology adherence to the law:(de) constructing road rules for autonomous system development, verification and safety. *International Journal of Law and Information Technology*, *29*(4), 255-295.

[16] N. S. Hegde and M. G, "Review on AI-Driven Automation for Autonomous Vehicles," Recent Trends in Artificial Intelligence & Its Applications, vol. 3, no. 2, pp. 19–28, May–Aug. 2024.

[17] S. A. Atone, A. S. Bhalchandra, and P. H. Bhagat, "Moving object detection with an IP camera," in *Proc. 2nd Int. Conf. on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2018, pp. 1081–1083, doi: 10.1109/ICCONS.2018.8663070.

[18] E. Zadobrischi and M. Negru, "Pedestrian detection based on TensorFlow YOLOv3 embedded in a portable system adaptable to vehicles," in *Proc. 15th Int. Conf. on Development and Application Systems (DAS)*, Suceava, Romania, 2020, pp. 21–23, doi: 10.1109/DAS49615.2020.9108944.