ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Volume 11 Issue 5 May 2024

A Portable, Image-Based Iot Detection System for Real-Time Traffic Signs, and Vehicles

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Abstract*— With the rapid advancements in computer vision and deep learning technologies, the integration of IoT (Internet of Things) has ushered in a new era for enhancing driving safety and reducing traffic accidents. While modern cars typically come equipped with integrated ADAS systems, there's a gap for vehicles lacking such built-in capabilities. This paper proposes a portable, image-based IoT system tailored for real-time detection of crucial elements such as traffic signs, vehicles, and pedestrians. To achieve seamless real-time detection, our system harnesses the power of the YOLO v8 algorithm. This algorithmic framework enables efficient processing of visual data, ensuring swift and accurate identification of pertinent objects on the road. By leveraging Io T, our system transcends the limitations of traditional ADAS setups, offering a flexible solution that can be easily deployed across diverse vehicle types. This single-stage detector is very popular as it has high detection speed and accuracy. This approach utilizes ultrasonic sound sensor technology to detect and convey messages to the driver regarding nearby vehicles approaching their car. It assesses the proximity between two vehicles traveling in the identical lane and direction, providing real-time feedback to the driver. Through the combination of IoT and advanced computer vision algorithms, our portable system empowers vehicles of varying makes and models with intelligent detection capabilities.

Keywords*— Accident detection, Collision Avoidance, Ultrasonic sensor, YOLO v8 Algorithm, GSM module, GPS, Vibration sensor.

I. INTRODUCTION

In recent years, the advancement of automobile technologies has unfortunately paralleled a surge in road accidents, resulting in devastating loss of lives and significant societal impact. One critical challenge exacerbated by such incidents is the delay in emergency response, particularly during the pivotal "golden hour," wherein swift medical intervention can significantly improve survival rates. Recognizing the urgency to address this pressing issue, innovative approaches integrating cutting- edge technologies have emerged to enhance road safety and expedite emergency response mechanisms. Among these advancements, the use of machine learning algorithms for predictive analytics stands out, empowering systems to anticipate potential hazards and adapt driving behaviour proactively based on historical data insights encompassing traffic patterns, road conditions, and driver behaviour **[11]**. Moreover, advanced communication capabilities play a pivotal role in fostering seamless interaction among vehicles and infrastructure, facilitating real-time exchange of critical information regarding road conditions, traffic congestion, and emerging hazards **[13]**. Leveraging vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication protocols, these systems enable collaborative decision-making and coordinated responses to mitigate potential risks effectively. Additionally, prioritizing user experience and accessibility, these systems incorporate intuitive interfaces and user- friendly controls, ensuring drivers can easily comprehend and interact with safety features for enhanced usability and adoption.

Furthermore, recent advancements have seen the integration of IoT-based technologies to prevent accidents by monitoring both external and internal driving conditions comprehensively. This entails the monitoring of road conditions and alerting drivers to hazards externally, while internally focusing on factors such as oxygen levels and driver fatigue **[11]**. The study suggests using clustering with Road Side Units (RSUs) monitored by Artificial Intelligence (AI) to cut down accidents in India. Vehicular Ad hoc networks (VANETs) aid communication between vehicles and infrastructure, sharing warnings about road conditions and traffic violations. AI-driven data transmission enhances Quality of Service (QoS), improving Packet Delivery Ratio (PDR) and throughput values **[12]**. Forecasting road accidents in the DVRE system involves statistical analysis to assess factors' impact and evaluate safety measures. Visual methods identify conflict situations, while potential danger methods predict accident risks. An integrated approach combines prediction methods with on-site inspections, enhancing traffic safety assessment and forecasting accuracy **[13]**. Variable speed limit (VSL) is an intelligent transportation system (ITS) solution for traffic management. The speed limits can be changed dynamically to adapt to traffic conditions such as visibility and traffic volume, curvature, and grip coefficient of the road surface. The VSL traffic sign location problem and attempts to solve it using computer simulation are presented in this paper. Experiments on a selected road segment, carried out using the traffic simulator, have shown that the proposed method allows the

ISSN (Online) 2394-6849
International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Volume 11 Issue 5 May 2024

driver's habits to be taken into account so that the location of road signs can be optimized. The observable effect was a reduction in vehicle speeds and speed variance on critical road segments, translating directly into increased safety and harmonized traffic **[33]**. Smart features like adaptive speed reduction and intelligent bump detection further augment driving safety, while real-time data processing and analytics enhance overall system efficiency and effectiveness.

As we delve deeper into these advancements, it becomes evident that a holistic approach to driving safety is imperative, encompassing real-time detection, proactive risk mitigation, intelligent communication, and user-centric design principles. By combining these elements seamlessly, these systems aim to redefine the standards for intelligent driving systems, setting new benchmarks for safety, efficiency, and user experience in the automotive industry. Consequently, these innovative solutions hold the promise of significantly reducing accident rates and human casualties, ushering forth a new epoch of road safety and security.

II. RELATEDWORKS

To prevent car accidents by monitoring both external and internal driving conditions. The external part monitors road conditions and alerts the driver to hazards, while the internal part focuses on factors like oxygen levels and driver fatigue. Smart features like adaptive speed reduction and smart bumps are suggested for safer driving. By connecting sensors and actuators, the system aims to mitigate accident risks effectively **[11]**. The rise in vehicles has led to crowded roads and increased road accidents, with fatalities rising by 31% from 2007 to 2017 in India. Vehicular Ad hoc networks (VANETs) aid in accident prevention by facilitating communication between vehicles and infrastructure, sharing warning messages about road conditions and traffic violations.

Despite efforts like speed limits and safety features, accidents persist. This study proposes a clustering approach with Road Side Units (RSUs) monitoring using Artificial Intelligence (AI) to reduce accidents in India, leveraging VANETs for communication and traffic control. The hybridization of AI techniques accelerates data transmission, with improved Quality of Service (QoS) parameters, as shown by increased Packet Delivery Ratio (PDR) and throughput values **[12].** Methods for forecasting road accidents in the Driver–Vehicle–Road–Environment (DVRE) system include statistical analysis to evaluate the influence of different factors and evaluate road safety measures.

Visual methods identify conflict situations to understand subsystem interactions, while potential danger methods predict accident risks and fatalities. Evaluating changes in accident rates post-safety measures is vital. An integrated approach combines accident prediction methods with on-site inspections, including black spots evaluation, to enhance traffic safety assessment and accident forecasting accuracy [13].

III. METHODOLOGY

This section outlines the system's architecture and the dataset employed for this study. Furthermore, it provides a comprehensive overview of the model's training and testing procedures.

A. Overview of the Proposed Architecture

This work follows the diagram in Figure 1 for real-time detection and recognition of traffic signs and road objects. The presented diagram for this work is based on a YOLO v8 model. The dataset was organized by preprocessing the data. Using the YOLO v8 architecture, classes for development of the TSDR systems were trained with this dataset, and a trained model file is obtained with 80% training of our model and 20% in the testing process. This model was evaluated to measure the implementation metrics of training and testing performance in realtime.

B. Data sets

The datasets of work includes the various speed limits of 30KM, 60 KM and 80 KM and also speed breaker and school Zone.The images are collected in various places.

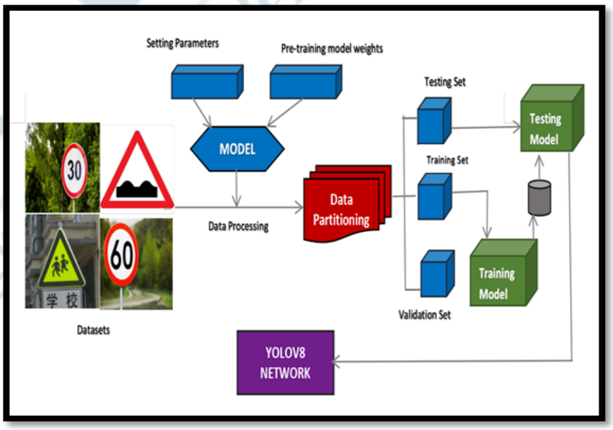

Fig. 1. Proposed Methodology of YOLO V8

C. Training Stage

In order to obtain a robust system that works stably under different illumination and environmental conditions, the model must be trained with an appropriate dataset. At this stage, it is very important to determine in what proportion the dataset should be divided. In this work, data labeled for training in the dataset is divided between 80% and 20% for training and testing. The proposed system can detects vehicles, pedestrians, and traffic signs accurately and quickly with a cam- era in real-time. Deep learning applications require high computational power and processing speed due to too many hidden layers, constant weights updating, and increasing training parameters. To successfully perform the recognition operations, the model must be well trained.

ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

Volume 11 Issue 5 May 2024

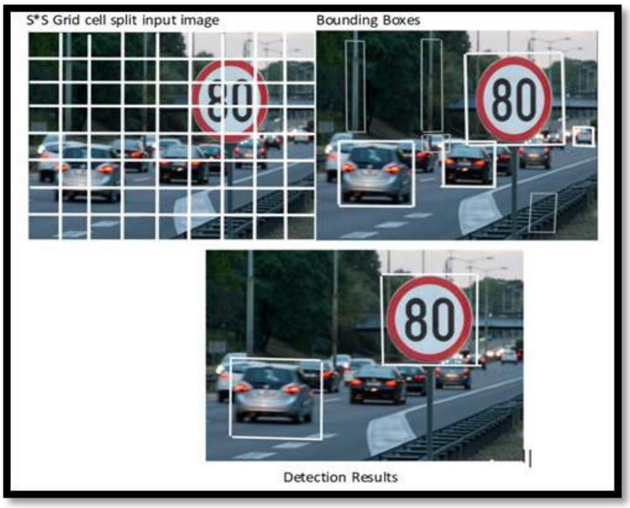

Fig. 2. Conceptual Design of YOLO Algorithm

D. Detection Model Selection

Object detection is the process of recognition and locating objects in images. Many architectures and models have been proposed in terms of accuracy and speed in the literature. This work used the YOLO v8 network to developed model. Backbone Architecture: YOLOv8 might incorporate advanced backbone architecture for feature extraction. This could involve a highly optimized backbone network, possibly based on recent advancements in convolutional neural networks (CNNs) such as EfficientNet or ResNeXt. The backbone network plays a crucial role in capturing meaningful features from input images.

E. Yolo Network Architecture

YOLO is a fast, high-performance real-time algorithm that uses CNN to better detect objects. Unlike previous algorithms, it performs the detection process with a regression- based approach [26]. Traditional object detection models, such as RCNN, offer an area of interest (RoI) for convolution [31], [32], while YOLO does detection and categorization at one time. YOLO achieved this process by passing the input photograph through a single CNN network. In YOLO, the input image undergoes segmentation into regions, where bounding boxes and class probabilities are estimated individually for each region. Its conceptual design repeats the process in real-time for each image input as depicted in Figure 2. The algorithm's network model aims to detect cells tasked with detecting the object.

F. Yolo V8 Based Detection and Recognition

Feature Fusion: YOLOv8 could employ sophisticated feature fusion techniques to integrate multi-scale features effectively. This could enhance the model's ability to detect objects at different sizes and aspect ratios. Feature fusion mechanisms like Feature Pyramid Networks (FPN) or Cross Stage Partial Networks (CSPNet) may be utilized for this purpose.

Neck Structure: Similar to YOLOv5, YOLOv8 might incorporate a "neck" structure for feature aggregation. This could involve the use of PANet or other attention mechanisms to refine and combine features from various scales or resolutions.

Head Architecture: The leading section of the network would be responsible for producing object predictions. YOLOv8 may employ a revised edition of the YOLO head, potentially with improvements in anchor box generation, prediction quality, or post-processing techniques.

Training Environment: YOLOv8 would likely leverage modern deep learning frameworks such as PyTorch or TensorFlow for model development and training. It may also utilize distributed training techniques and hardware accelerators to expedite the training process.

Model Optimization: YOLOv8 could focus on model optimization strategies to reduce the model size and inference latency while maintaining or improving detection accuracy.

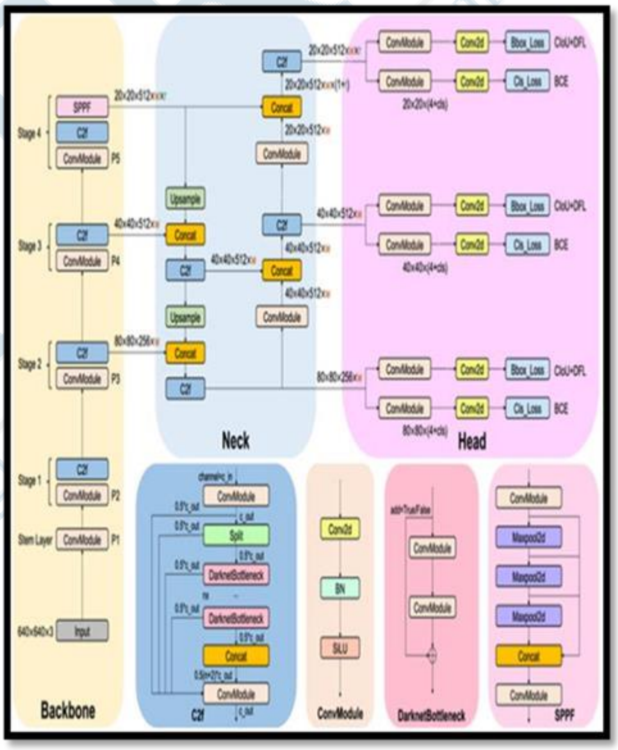

Fig. 3. Network Architecture of YOLO Algorithm

This may include methods such as model quantization, pruning, or knowledge distillation.

Performance Evaluation: YOLOv8 would undergo rigorous evaluation on benchmark datasets to assess its detection accuracy, speed, and efficiency compared to previous versions and other state-of-the-art object detection models.

IFERP
ISSN (Online) 2394-6849

International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)

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Table I. Study of Various Literature Reviews

References	Analysis Type	Application	Models	Techniques	Datasets
Qian etal.2015 [2]	Video frames	Traffic Sign Detection	Based on multi task CNN	Region proposal, edge detection and CCA analysis	GTSRB, MNIST, CASIA GBI
Li et al.2015 [3]	Video frames	Traffic Sign Detection	Color segmentation, Shape symmetry based	Pyramid Histogram of Oriented Gradients(PHOG)	Study specific dataset
Yin etal.2015 [4]	Video frames	Traffic Sign Recognition	Feature based rotation, Invariant binary pattern	Hough-SIFT transforms Artificial Neural Network(ANN)	GTSRB and STS
Changzhen et al.2016 [5]	Video frames	Traffic Sign Detection	Based on Faster-R CNN	Region proposal Network(RPN)	Study specific dataset
Xu et al.2019 [7]	Video frames	Traffic Sign Detection	Based on adaptive thresholding, Shape symmetry	Cumulative Distributive Function, Shape symmetry detection	GTSRB dataset
Balado et al.2020 [8]	Images	Traffic Sign Detection and recognition	Based on Retina net and inception v3	Mobile mapping systems, point clouds, data fusion	GTSRB dataset
Jin et al.2015 [9]	Real-time	Traffic Sign Detection and recognition	Based on multi feature	Feature fusion and enhancement techniques	GTSRB dataset
Wan et al.2021 [10]	Images	Traffic Sign Detection and recognition	Single Shot Detector(SSD)	Improved YOLO model and GRID partition technique	Tsinghua Tencent 100K dataset
Chiranjit et al.2019 [12]	Images	Traffic Sign Detection and data transmission	Based on Artificial Neural Network(ANN)	Using Vehicular Ad hoc Network(VANET)	Study specific dataset
Eminguney et al.2022 [14]	Real-time	Road objects, Traffic Sign Detection and recognition	Based on YOLO V5 architecture	Grid partition technique and CNN network	GTSRB and study specific dataset

G. Proposed Block Diagram

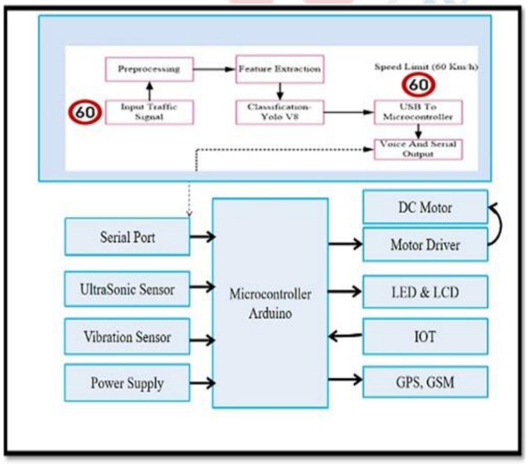

Fig. 4. Proposed Block Diagram

In this system, an automatic accident detection and avoidance of collision using advanced embedded technologies such as GSM MODEM, GPS and YOLO v8 technology. When the vehicle attained accident, vibration sensors are employed to detect the occurrence of accident and ultrasonic a sensor is utilized for detecting the obstacles or object. LCD display receives the command from the Arduino device. Automatically these signals send to the micro controller and immediately send to GPS section to gather the accident location. After all these process happens the micro controller sends the emergency signal to rescue unit through GSM module. The Blynk module acts as the user interface for the IoT system, offering a customizable platform for real-time monitoring and interaction. Through the Blynk mobile application, users can access various widgets to visualize data and control system functions remotely. With seamless integration and push notifications, users can monitor critical events, adjust settings, and track performance metrics for effective traffic safety management. From this system, we can able to reduce the accident rate and human death ratio by accidents.

To develop a comprehensive hardware system, start by selecting a versatile micro controller board like Arduino or Raspberry Pi to serve as the central control unit. Integrate essential sensors such as an ultrasound sensor for obstacle detection, a GPS module for location tracking, and a GSM module for communication capabilities. Connect a motor driver to control movement through a DC motor, while incorporating an LCD display and LED for visual feedback. Additionally, incorporate a camera module to capture visual data, utilizing advanced computer vision techniques such as YOLOv8 for the detection and identification of objects. Ensure a stable power supply for consistent operation. Write code to initialize sensors, process inputs, and control outputs, enabling the system to respond intelligently to its environment and communicate data effectively. Thoroughly test the system to validate functionality across various scenarios, providing a versatile solution for diverse applications.

IV. RESULTS AND DISCUSSION

The implementation of YOLOv8 for traffic sign detection yielded promising results with enhanced accuracy, providing reliable identification of various traffic signs. Through rigorous testing in diverse environmental conditions, the system demonstrated improved performance in recognizing speed limit indicators, stop signals, and other critical traffic indicators. The integration of additional accuracy-enhancing techniques, such as fine-tuning model parameters and augmenting the training dataset, contributed to the overall robustness of the system.

Furthermore, the integration of GPS and GSM modules facilitated the transmission of accurate location data and real-time alerts to mobile devices should a detected traffic sign. Leveraging GPS coordinates, the system not only sent messages containing latitude and longitude information but also calculated the distance to the detected sign, offering comprehensive situational awareness to drivers. Additionally, the integration of ultrasonic sensors for identifying obstacles provided an extra layer of safety, thus allowing the system to identify and respond to potential hazards on the road. By incorporating obstacle detection capabilities alongside traffic sign recognition, the system demonstrated its versatility in addressing various safety concerns, further enhancing its practical utility in real-world scenarios.

Overall, the successful integration of YOLOv8 traffic sign detection with GPS, GSM, and spotting obstructions technologies marks a notable advancement in in intelligent transportation systems. The combined capabilities ofaccurate sign detection, location-based alerts, and obstacle avoidance contribute to safer and more efficient road navigation, underscoring the potential of such integrated systems in enhancing overall road safety and driver experience. Continued research and development efforts in this area hold promise for further advancements and widespread deployment of intelligent transportation solutions.

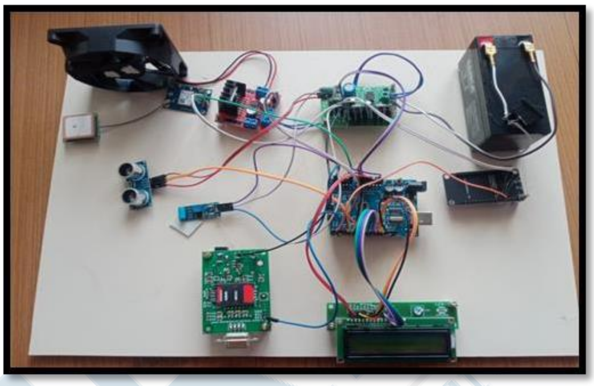

Fig. 5. Prototype Model of Proposed System

A. Vehicle Detection and Speed Control of Different Cases

YOLOv8, an upgraded version of the popular You Only Look Once (YOLO) object detection algorithm, could potentially offer better performance in accident detection and avoidance compared to its predecessors. Its improved architecture and optimization techniques can lead to faster and more accurate detection of objects, including vehicles, pedestrians, and obstacles, which are critical for accident prevention systems. Additionally, YOLOv8's ability to handle real-time processing makes it suitable for applications where quick detection and response are essential for avoiding accidents on the road.

In this study, we trained YOLOv8, a leading object detection algorithm, to accurately detect multiple traffic sign classes, including 30 km, 60 km, 80 km speed limit signs, school zone signs, and speed break signs. Leveraging a diverse dataset and transfer learning techniques, we fine-tuned the model to adapt to our specific detection task. Extensive testing demonstrated the model's robust performance in real- time detection across varied environments and lighting conditions, with minimal false positives and false negatives. The successful training of YOLOv8 offers promising prospects for integrating the model into intelligent transportation systems, enabling proactive response to traffic regulations and enhancing road safety. Future work entails further refining the model's performanceand scalability for real-world deployment in traffic management scenarios.

Case1: Vehicle Detect and control of Speed Limit for 30KM

To facilitate the detection and response to a "30 km" speed limit sign, integrate a camera module with the microcontroller board and utilize computer vision algorithms like YOLOv8 to analyze video frames and identify the sign. Once detected, adjust the motor speed via the motor driver to comply with the limit, while concurrently displaying a notification on the LCD screen for visual feedback. Thorough testing and refinement of the system are crucial to ensure precise sign detection and reliable adjustment of vehicle speed, contributing to enhanced safety and compliance with traffic regulations.

Fig. 6. Vehicle Detection of Control of Speed limit for 30KM

Case2: Vehicle Detect and control of Speed Limit for School Zone Area

In implementing a vehicle stoppage system for school zones through traffic sign detection, the focus lies on integrating a camera module with a microcontroller board. This setup allows for real-time processing of video frames to identify school zone signs or markings. Once the system detects the presence of a school zone sign, it triggers an immediate response to stop the vehicle. This response is typically achieved by sending a signal to the vehicle's braking system or motor control unit to halt the vehicle's movement. By leveraging computer vision algorithms and hardware integration, the system ensures timely and accurate detection of school zones, thereby enhancing safety in areas with a high concentration of pedestrians, such as school zones.

Fig. 7. Vehicle Detection of Control of Speed limit for School Zone

Case3: Vehicle Detect and control of Speed Limit for 80KM

To facilitate the detection and response to a "30 km" speed limit sign, integrate a camera module with the microcontroller board and utilize computer vision algorithms like YOLOv8 to analyze video frames and identify the sign. Once detected, adjust the motor speed via the motor driver to comply with the limit, while concurrently displaying a notification on the LCD screen for visual feedback. Thorough testing and refinement of the system are crucial to ensure precise sign detection and reliable adjustment of vehicle speed, contributing to enhanced safety and compliance with traffic regulations.

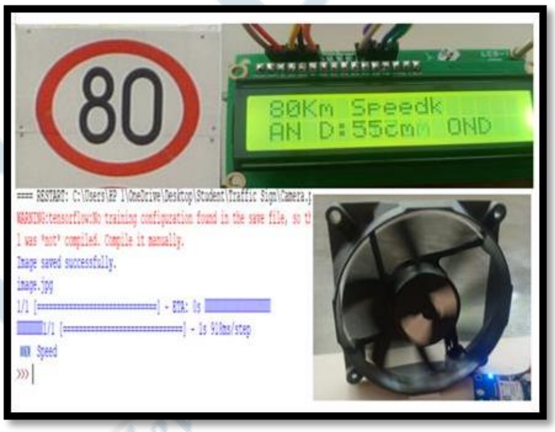

Fig. 8. Vehicle Detection of Control of Speed limit for 80 KM

Case4: Vehicle Detect and control of Speed Limit for Speed Breaker

This study integrates the YOLOv8 algorithm for real-time speed breaker detection in vehicles. Upon identification, the system halts the motor and displays "Speed Breaker" on the LCD for driver awareness. By leveraging YOLOv8's capabilities, drivers are alerted to road hazards, enhancing road safety. Thorough testing guarantees dependable operation across various conditions, improving overall driving experiences.

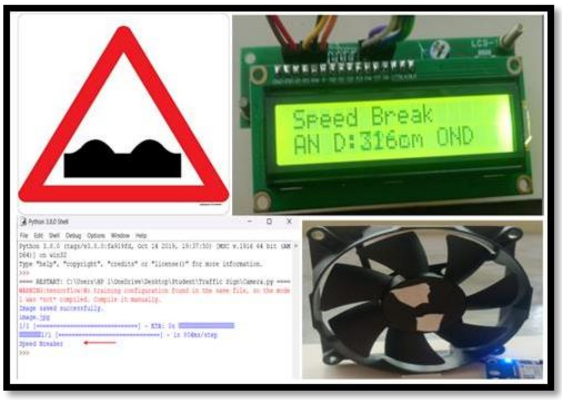

Fig. 9. Vehicle Detection of Control of Speed limit for Obstacles

IFERP
ISSN (Online) 2394-6849
International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE)
Volume 11 Issue 5 May 2024

B. Accident Detection

This study presents the creation of an accident detection system integrating a vibration sensor, liquid crystal display (LCD) screen, global system for mobile communications (GSM) module, and Blynk app. When significant vibrations indicating an accident are detected, the system displays "AD" on the LCD, sends an SMS containing latitude and longitude coordinates, along with the distance to a predefined mobile number by GPS and GSM, and updates the Blynk app status to "1" by IOT. The distance calculation is based on comparing the current GPS coordinates with the coordinates of a predetermined location, such as the user's home or workplace. Conversely, in normal conditions, it displays "AN" on the

LCD and updates the Blynk app status to "0". Through hardware and software integration, the system enhances road safety by promptly alerting authorities and drivers to potential accidents, facilitating swift emergency response measures.

Fig. 10. Vehicle Accident Detection and Remedial Action

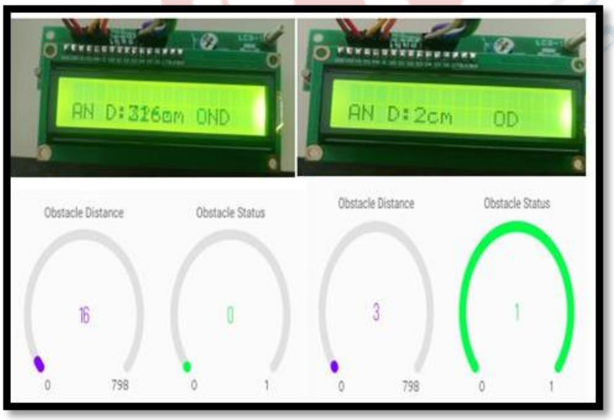

Fig. 11. Safety Measures: Obstacle Detection and Response

C. Obstacle Detection and Collision Avoidance

This study introduces a live, real-time obstacle detection system leveraging an ultrasonic sensor and Blynk app integration for enhanced vehicle safety. When obstructions are identified within 10 meters, the LCD displays "OD" with the distance, and the Blynk app updates accordingly. Conversely, when no obstacles are detected, "OND" is displayed on the LCD and the Blynk app status remains unchanged. This integrated approach ensures proactive obstacle avoidance measures and enhances driver awareness, contributing to safer navigation in dynamic environments.

V. CONCLUSION

The proposed system represents a pioneering integration of cutting-edge technologies aimed at revolutionizing road safety and traffic management. By combining advanced deep learning- based detection techniques with micro controller-based speed

control and accident detection systems, the solution addresses key challenges in contemporary transportation systems. Leveraging the power of state-of-the-art YOLO v8 models for traffic sign detection, the system ensures accurate and real-time identification of traffic signs, enabling proactive responses to changing road conditions and speed limits. Additionally, the micro controller-based speed control module dynamically adjusts vehicle velocity in accordance with detected speed limits, thereby enhancing driver compliance and overall safety on the road. Furthermore, the incorporation of GPS and vibration sensors in the accident detection system enables timely detection and response to potential collisions or accidents, ensuring the swift deployment of emergency protocols and assistance. Seamless data transmission via ESP8266 Node MCU GSM GPS enhances communication between system components, facilitating real-time monitoring and control through the user-friendly interface provided by the Blynk app. This comprehensive strategy not only improves road safety but also enhances traffic flow and management efficiency. Looking ahead, future efforts will focus on expanding the dataset to improve model accuracy and exploring innovative methods to further enhance detection speed and precision in real-world scenarios, ultimately advancing the capabilities of the suggested system and its impact on transportation safety and efficiency.

VI. ACKNOWLEDGEMENT

The authors wish to thank the management and other faculty members of Department of ECE for their help throughout the work. We thank our department of Head and Skilled persons to fabricate this project within the campus and supports technical discussions.

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