

IoT based Speed Control and Accident Avoidance using AI Road Sign Detection System

Dr. S. Kamalathiyagarajan, Kalidhsan S, Kavikuamr VJ, Sathish S, Manish S

Professor, Department of Electrical and Electronics Engineering

Students, Department of Electrical and Electronics Engineering

Anjalai Ammal Mahalingam Engineering College, Thiruvavur, TamilNadu, India

Abstract: *The project aims to enhance vehicle safety on Indian roads through a traffic sign detection system powered by the YOLO deep learning architecture. The system is trained and validated using the Indian Traffic Sign Recognition dataset, ensuring high accuracy and relevance to local traffic conditions. YOLO's powerful feature extraction and classification capabilities enable the real-time detection and recognition of various traffic signs, facilitating immediate responses to dynamic road environments.*

Real-time video processing allows the system to instantly identify and classify traffic signs as vehicles navigate through different areas. Upon detecting a traffic sign, integrated vehicle controls automatically adjust speed, promoting safer driving and minimizing the risk of accidents for both drivers and pedestrians. The system is engineered to withstand challenging conditions such as low lighting, adverse weather, and partially obscured or damaged signs, ensuring consistent and reliable performance. Extensive real-world testing across diverse Indian traffic scenarios optimizes system robustness and practical applicability.

These tests help fine-tune the model for performance under complex conditions, improving its ability to handle the unique characteristics of Indian roads. The proposed system bridges the gap between advanced traffic management and local road safety needs, contributing to reduced accidents and enhanced driving experiences.

Keywords: traffic sign detection

I. INTRODUCTION

Road safety remains a pressing issue in India, where diverse traffic conditions, inconsistent driver behavior, and a complex array of traffic signs contribute to an unpredictable driving environment. With rapid urbanization and increasing vehicle density, Indian roads have become more challenging to navigate safely. According to the Ministry of Road Transport and Highways, a significant percentage of accidents occur due to drivers' failure to recognize or obey traffic signs. This alarming trend underscores the need for innovative solutions to mitigate risks, improve road safety, and reduce human error. One such solution is the integration of advanced driver-assistance systems (ADAS), which utilize artificial intelligence to enhance vehicular and pedestrian safety.

This project introduces a traffic sign detection system specifically designed for Indian roads, leveraging the capabilities of deep learning algorithms, particularly YOLO (You Only Look Once), to ensure rapid and accurate traffic sign recognition in real-time scenarios. The YOLO algorithm is well-suited for real-time applications due to its speed and accuracy. Unlike traditional object detection methods that rely on region-based approaches, YOLO employs a single neural network to process an image and predict bounding boxes and class probabilities simultaneously. This approach significantly reduces computational overhead and makes real-time detection feasible, which is crucial for driving applications where split-second decisions can prevent accidents. By processing live video feeds from a vehicle's onboard camera, the system can instantly detect and classify traffic signs, providing timely alerts to the driver. Additionally, the system can be integrated with vehicle control mechanisms to enable automatic speed adjustments, ensuring compliance with road safety regulations.



A key aspect of this project is the use of the Indian Traffic Sign Recognition dataset to train the model. This dataset encompasses a comprehensive collection of traffic signs found across India, including standard regulatory signs, warning signs, and unique regional variations. The inclusion of region-specific signs ensures that the system is well-versed with the intricacies of Indian roadways, where sign designs, placements, and visibility conditions vary widely. By training the model on diverse data, the system is equipped to handle real-world complexities, recognizing signs accurately even in challenging environments. Real-time traffic sign detection has profound implications for road safety, as it enables vehicles to adapt dynamically to changing road conditions. The ability to detect speed limits, stop signs, pedestrian crossings, and other critical indicators ensures that drivers remain aware of their surroundings and make informed decisions.

II. LITERATURE SURVEY

This study by J. Wang, Y. Chen, Z. Dong, and M. Gao presents an enhanced version of the YOLOv5 deep learning model, specifically designed for real-time multi-scale traffic sign detection. Traffic sign recognition is crucial for intelligent transportation systems, autonomous vehicles, and driver assistance technologies, as it enables efficient and accurate interpretation of road signs under varying environmental conditions. The authors improve upon the standard YOLOv5 architecture by optimizing its feature extraction capabilities, enhancing its ability to detect traffic signs of different sizes, orientations, and lighting conditions. The proposed model incorporates several key modifications to the original YOLOv5 network.

First, an improved backbone network with enhanced feature fusion techniques is introduced, allowing better detection of small and distant traffic signs. Second, the model integrates attention mechanisms to focus on critical regions of an image, improving detection accuracy by filtering out background noise and irrelevant objects. Third, the authors refine the anchor box selection strategy, enabling the model to handle multi-scale variations more effectively. These enhancements significantly boost detection performance while maintaining real-time processing speeds, making the model suitable for deployment in autonomous vehicles and smart transportation infrastructure.

The research employs a large-scale traffic sign dataset for training and evaluation, demonstrating superior accuracy and robustness compared to traditional object detection methods. Experimental results indicate that the improved YOLOv5 model outperforms baseline YOLOv5 and other deep learning-based approaches in terms of precision, recall, and mean average precision (mAP). Notably, the model achieves high detection rates even in challenging conditions such as occlusions, low lighting, and motion blur. One of the standout features of this approach is its real-time processing capability. The optimized network structure ensures that the model can run efficiently on edge computing devices, including embedded systems in vehicles and roadside infrastructure.

In this study, R. K. Megalingam et al. present a deep learning-based approach for detecting and recognizing Indian traffic signs, addressing the unique challenges posed by India's diverse road conditions, varying sign designs, and complex traffic scenarios. The research highlights the importance of accurate and efficient traffic sign recognition for intelligent transportation systems, autonomous driving, and advanced driver-assistance systems (ADAS). Unlike standardized traffic signs in Western countries, Indian traffic signs exhibit variations in shape, color, and language, making detection and classification a challenging task. The proposed system leverages convolutional neural networks (CNNs) to effectively identify traffic signs in real-world scenarios. The model is trained on a comprehensive dataset of Indian traffic signs, covering regulatory, warning, and informational signs.

The deep learning pipeline consists of multiple stages, including image preprocessing, feature extraction, classification, and real-time deployment. The researchers enhance model performance by incorporating data augmentation techniques, improving robustness against occlusions, poor lighting, and motion blur. Additionally, transfer learning is applied using pre-trained deep learning models, allowing efficient feature learning from large-scale datasets. Experimental results demonstrate that the model achieves high accuracy in detecting and classifying Indian traffic signs, outperforming traditional machine learning-based approaches. The study also benchmarks the model against popular object detection architectures, such as YOLO and Faster R-CNN, showcasing superior performance in terms of precision, recall, and inference speed.



A key strength of the system is its adaptability to real-time applications, enabling seamless integration into in-vehicle systems and smart city infrastructure. The lightweight nature of the model allows deployment on edge computing devices, ensuring real-time processing without reliance on cloud-based solutions. The study also discusses the potential applications of this technology, including its integration with vehicle-to-infrastructure (V2I) communication networks. By enabling real-time traffic sign recognition, the system can assist drivers in making informed decisions, reduce human errors, and improve road safety.

This study by S. Saxena et al. focuses on enhancing traffic sign detection in complex and unconstrained environments using an improved version of the YOLOv4 object detection model. In real-world traffic scenarios, especially in urban and semi-urban areas, traffic signs often appear in challenging conditions such as occlusions, varying lighting, motion blur, and background clutter. The proposed model aims to improve detection accuracy and robustness in such challenging settings, ensuring reliable recognition for autonomous driving systems and intelligent transportation networks. The authors build upon the YOLOv4 framework by incorporating multiple optimizations.

One of the key improvements is the integration of an attention mechanism, which helps the model focus on relevant regions of an image while filtering out distractions such as billboards, pedestrians, and vehicles. Additionally, the model utilizes an advanced feature pyramid network (FPN) and path aggregation network (PAN) to enhance multi-scale feature extraction, improving detection performance across small and distant traffic signs. To further optimize precision and recall, the researchers refine the anchor box selection strategy, making the model more adaptable to diverse traffic sign sizes and orientations. A large-scale traffic sign dataset, consisting of images captured in diverse environmental conditions, is used to train and evaluate the model. Experimental results show that the improved YOLOv4 model achieves higher accuracy than conventional object detection methods, including standard YOLOv4 and Faster R-CNN.

The model demonstrates superior performance in detecting partially obscured, faded, and low-contrast traffic signs, making it well-suited for deployment in real-world conditions. Moreover, the system maintains real-time processing speeds, ensuring its applicability in autonomous vehicles and roadside infrastructure. One of the standout features of this research is its adaptability to edge computing environments. The optimized model can be deployed on low-power devices, such as embedded AI chips in vehicles and traffic monitoring systems, reducing reliance on cloud-based processing. This makes it a practical solution for intelligent transportation systems that require real-time decision-making capabilities.

This study by R. Sharma, V. Kukreja, and V. Kadyan presents a deep learning-based approach for the classification of Hispa disease in rice plants using convolutional neural networks (CNNs). Rice Hispa (*Dicladispa armigera*) is a major pest that affects rice crops, leading to significant yield losses in various agricultural regions. Early and accurate detection of this disease is crucial for timely intervention and effective pest control measures. Traditional methods of disease identification rely on manual inspections by experts, which can be time-consuming, labor-intensive, and prone to human error. This research leverages CNNs to automate and enhance the accuracy of disease detection, providing an efficient solution for precision agriculture. The proposed system employs a deep CNN model trained on a dataset of rice leaf images exhibiting symptoms of Hispa disease.

The model consists of multiple convolutional layers for feature extraction, followed by pooling layers to reduce dimensionality while preserving essential patterns. A fully connected layer at the end classifies images into diseased or healthy categories. To enhance the performance of the model, the researchers utilize data augmentation techniques such as rotation, scaling, and contrast adjustments, ensuring robustness against variations in lighting conditions, leaf orientations, and background noise. The study evaluates the model's performance using various metrics, including accuracy, precision, recall, and F1-score.

Experimental results demonstrate that the CNN-based approach achieves high classification accuracy compared to traditional machine learning techniques such as support vector machines (SVM) and random forests. Additionally, the model is optimized for real-time deployment, enabling farmers and agricultural experts to detect Hispa disease using mobile applications or embedded systems in smart farming equipment. One of the significant contributions of this research is its potential application in real-world agricultural scenarios. By integrating the model with Internet of Things (IoT)-enabled drones or field cameras, real-time disease monitoring can be achieved at a large scale. This



approach not only helps in early disease detection but also assists in precision pesticide application, reducing excessive chemical use and promoting sustainable farming practices.

This study by G. Zhang, Y. Peng, and H. Wang introduces an advanced road traffic sign detection method using the RTS R-CNN instance segmentation network. Accurate traffic sign detection is critical for autonomous driving systems, intelligent transportation infrastructure, and advanced driver-assistance systems (ADAS). The research focuses on improving detection accuracy and robustness, particularly in challenging environments characterized by poor lighting, occlusions, and background clutter. Traditional object detection models often struggle with small-scale and partially obstructed traffic signs, making it essential to develop more sophisticated approaches for real-world deployment. The proposed method builds upon the Faster R-CNN framework, integrating an instance segmentation module to enhance object localization and classification accuracy.

The RTS (Road Traffic Sign) R-CNN network incorporates a region proposal network (RPN) optimized for traffic sign detection, ensuring precise bounding box predictions. Additionally, a multi-scale feature extraction strategy is employed to improve recognition capabilities for both near and distant signs. The segmentation module enables pixel-wise classification, allowing the system to differentiate traffic signs from overlapping or similar background objects. To evaluate the model's effectiveness, the authors use a large-scale traffic sign dataset, including images captured in varying weather and road conditions. Experimental results show that the RTS R-CNN method outperforms conventional object detection approaches such as YOLO and Faster R-CNN in terms of precision, recall, and mean average precision (mAP). The segmentation capability significantly reduces false positives and enhances recognition accuracy, making it a viable solution for intelligent vehicle systems.

Furthermore, the model demonstrates real-time processing capabilities, ensuring its suitability for deployment in autonomous vehicles and smart city applications. A key advantage of this approach is its ability to maintain high detection accuracy even under adverse conditions. By leveraging deep learning-based segmentation, the system effectively distinguishes traffic signs from visually complex backgrounds, such as urban environments with multiple overlapping objects.

his study by Z. Liu, D. Li, S. S. Ge, and F. Tian addresses the challenge of detecting small traffic signs within large images, a crucial task for autonomous driving, smart transportation, and intelligent vehicle systems. Small traffic signs often appear in complex road environments where factors such as motion blur, occlusions, varying lighting conditions, and background clutter can significantly hinder detection accuracy. Traditional object detection methods struggle with small-scale objects due to limited feature representation, making it essential to develop specialized approaches for improving detection robustness. The authors propose a novel detection framework designed to enhance the identification of small traffic signs in high-resolution images. Their method employs a region-based detection approach combined with multi-scale feature extraction to improve localization accuracy.

By refining feature representation, the framework ensures that small traffic signs are effectively distinguished from surrounding objects, reducing false positives and enhancing classification performance. The model integrates an adaptive feature fusion strategy, allowing the detection system to capture fine-grained details of small-scale traffic signs while maintaining efficiency in processing large images. To evaluate the performance of their approach, the researchers conduct extensive experiments using large-scale traffic sign datasets that include images captured under various weather and road conditions. The results demonstrate that their method outperforms conventional object detection algorithms, including Faster R-CNN, SSD, and YOLO, particularly in cases where traffic signs are distant, partially occluded, or displayed at extreme viewing angles.

The proposed system achieves superior precision, recall, and mean average precision (mAP), highlighting its effectiveness in real-world traffic scenarios. One of the significant contributions of this research is its ability to improve detection accuracy while maintaining computational efficiency. The authors emphasize that their model can be integrated into intelligent transportation systems and autonomous vehicles to enhance traffic sign recognition and road safety. Additionally, they explore the potential for further improvements through the adoption of transformer-based architectures, which offer superior feature extraction capabilities, and self-supervised learning techniques to reduce reliance on large annotated datasets.



This study by Z. Zhang, Z. Xie, J. Sun, X. Zou, and J. Wang introduces an advanced traffic sign detection framework based on a cascaded R-CNN architecture with multiscale attention mechanisms. Accurate traffic sign detection is essential for intelligent transportation systems, autonomous vehicles, and advanced driver-assistance systems (ADAS). However, real-world traffic environments present numerous challenges, including varying sign sizes, imbalanced datasets, occlusions, and environmental conditions such as poor lighting and adverse weather. The authors propose a cascaded R-CNN model that enhances detection performance by incorporating a multiscale attention mechanism to improve feature extraction across different levels of image resolution. The model is designed to address the issue of imbalanced sample distribution, which is common in traffic sign datasets where small, rare, or partially occluded signs are underrepresented.

To mitigate this challenge, the researchers introduce a novel sampling strategy that balances the dataset, ensuring improved recognition of both frequent and rare traffic sign categories. A key innovation in this approach is the use of a multiscale attention module, which enhances the model's ability to focus on important image regions while filtering out background noise. This feature significantly improves detection accuracy, especially for small and distant traffic signs. Additionally, the cascaded structure of the R-CNN framework refines region proposals in multiple stages, leading to precise bounding box predictions and reduced false positives. The model also employs a feature pyramid network (FPN) to enhance small-object detection by aggregating multi-resolution features.

The effectiveness of the proposed model is evaluated on large-scale traffic sign datasets, demonstrating superior performance compared to traditional detection methods, such as Faster R-CNN, SSD, and YOLO. The experimental results show that the cascaded R-CNN achieves higher precision, recall, and mean average precision (mAP), particularly in challenging scenarios involving occlusions and varying sign sizes. The multiscale attention mechanism ensures robustness against cluttered backgrounds and enhances detection reliability under real-world conditions.

This study by R. Sharma, V. Kukreja, and Sakshi presents a deep learning-based approach for detecting the severity of mustard downy mildew disease. Early and accurate disease detection is crucial for precision agriculture, as it helps farmers take timely preventive measures to reduce crop losses and optimize yield. Traditional disease identification methods, such as manual inspection and biochemical analysis, are often time-consuming, subjective, and require expert intervention. Deep learning models provide an automated and efficient alternative for disease classification, ensuring real-time monitoring and early intervention. The authors propose a convolutional neural network (CNN)-based deep learning framework for mustard downy mildew disease detection. The model is trained on a dataset containing images of mustard leaves with varying levels of disease severity, allowing it to differentiate between healthy and infected crops.

By leveraging deep feature extraction, the proposed approach enhances classification accuracy and provides an efficient method for assessing disease progression. The study explores different preprocessing techniques, such as contrast enhancement and noise reduction, to improve model performance and robustness. A key innovation of this research is the integration of a severity classification system, enabling farmers to assess the extent of infection and take appropriate countermeasures. The model classifies disease severity into multiple categories, ranging from mild to severe, using a combination of deep feature learning and data augmentation techniques. Additionally, the researchers employ transfer learning with pre-trained models to improve classification accuracy while minimizing computational costs.

To evaluate the effectiveness of their approach, the authors conduct experiments using standard performance metrics such as accuracy, precision, recall, and F1-score. The results indicate that the proposed deep learning model outperforms traditional machine learning algorithms and achieves high classification accuracy even under varying lighting conditions and leaf orientations. Furthermore, the study highlights the potential for real-time implementation of the model through mobile applications or edge computing devices, making it accessible for farmers in remote areas.

This study by V. Baliyan, V. Kukreja, V. Salonki, and K. S. Kaswan presents a deep learning-based approach for detecting and classifying the severity levels of Corn Gray Leaf Spot (GLS) disease. GLS is a fungal infection that significantly impacts maize crop yield, making early and accurate detection essential for effective disease management. Traditional manual inspection methods are often labor-intensive, subjective, and prone to errors. The authors propose an automated, data-driven approach leveraging deep learning techniques to enhance disease diagnosis in precision



agriculture. The proposed model employs a convolutional neural network (CNN) architecture to classify GLS severity into multiple levels, enabling farmers and agronomists to make informed decisions regarding disease management.

The researchers preprocess images using contrast enhancement, noise reduction, and data augmentation techniques to improve model robustness and generalization. Transfer learning with pre-trained deep learning models is also explored to enhance classification accuracy while minimizing computational complexity. A key contribution of this research is the use of a severity grading system that categorizes infected leaves based on lesion size, shape, and distribution. This enables precise assessment of disease progression, which is crucial for determining appropriate treatment measures. The model is trained and validated using a dataset containing images of maize leaves collected under diverse environmental conditions, ensuring high adaptability to real-world agricultural scenarios.

To evaluate the effectiveness of the proposed approach, the authors employ performance metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that the deep learning model outperforms traditional machine learning techniques and provides reliable severity classification, even in challenging conditions such as poor lighting and occlusions. The findings highlight the potential of AI-driven solutions in revolutionizing plant disease detection and management.

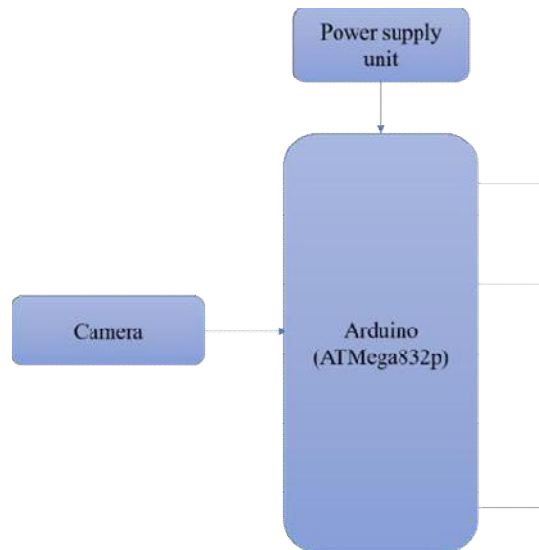
This study by R. Ayachi, M. Afif, Y. Said, and M. Atri presents a deep learning-based traffic sign detection system designed for real-world applications in Advanced Driver Assistance Systems (ADAS). Accurate and efficient traffic sign detection is critical for ensuring road safety, supporting autonomous vehicles, and enhancing intelligent transportation systems.

Traditional traffic sign detection methods often struggle with challenges such as occlusions, varying lighting conditions, motion blur, and complex backgrounds. This research addresses these issues by leveraging deep learning techniques to improve detection robustness and accuracy. The authors propose a deep convolutional neural network (CNN)-based model tailored for real-time traffic sign detection. The framework integrates a multi-stage processing pipeline that includes image preprocessing, feature extraction, and classification. A key component of this approach is the implementation of a region proposal network (RPN) optimized for detecting small and partially obstructed traffic signs. Additionally, the model employs multi-scale feature learning, ensuring accurate recognition across different sign sizes and perspectives. A significant contribution of this study is the adaptation of the deep learning model for real-world driving conditions, where traffic signs may be affected by adverse weather, poor illumination, and background clutter. The researchers conduct extensive experiments using a large-scale dataset of traffic signs captured under diverse environmental settings. The evaluation results demonstrate that the proposed model outperforms traditional object detection algorithms such as Faster R-CNN, SSD, and YOLO in terms of precision, recall, and mean average precision (mAP). The model's high detection accuracy and low false positive rate make it suitable for deployment in ADAS and autonomous driving systems.

The study also highlights the potential integration of the proposed system with vehicle-to-everything (V2X) communication networks, allowing real-time updates and enhanced decision-making for autonomous vehicles. Future research directions include optimizing the model for energy-efficient edge computing, implementing transformer-based architectures for improved feature representation, and developing self-supervised learning techniques to reduce reliance on extensive labeled datasets.



III. BLOCK DIAGRAM



IV. HARDWARE COMPONENTS

Arduino UNO:

- Type: Microcontroller board based on ATmega328P.
- Role: Acts as the brain of the system. It reads inputs from switches and the ultrasonic sensor, processes them, and controls.

Feature:

- Microcontroller: ATmega328P
- Operating voltage: 5V
- Input voltage: 7-12V
- Flash memory: 32KB
- SRAM: 2KB



Fig 1. Arduino

Power Supply:

- Type: Dual Output Linear Voltage Regulator Power Supply Module.
- Role: Converts 12V AC/DC input to regulated +5V and +12V DC outputs.
- Feature: Provides both +5V (via 7805) and +12V (via 7812) regulated outputs.



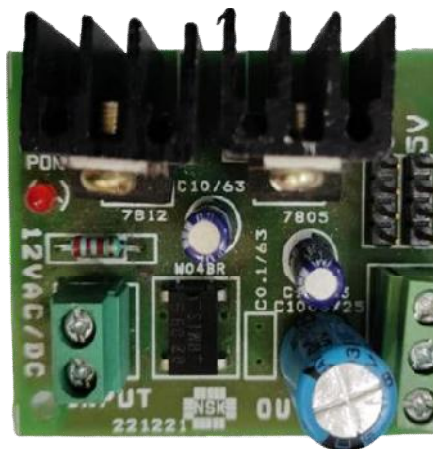


Fig 2. Power Supply

L293D Motor Drive:

- Type: Dual H-Bridge Motor Driver Module (L298N).
- Role: Controls direction and speed of two DC motors or one stepper motor.
- Feature: Supports both onboard 5V regulation and external 5V input options.

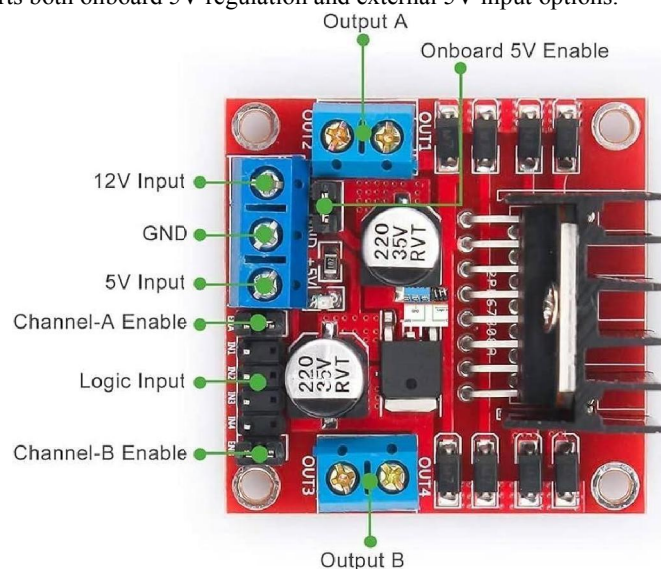


Fig 3. L293D Motor Drive

BUZZER:

- Type: Piezoelectric Buzzer.
- Role: Produces sound or beep in response to electrical signal.
- Feature: Operates typically with low voltage (3V–12V) for alert or notification signals.



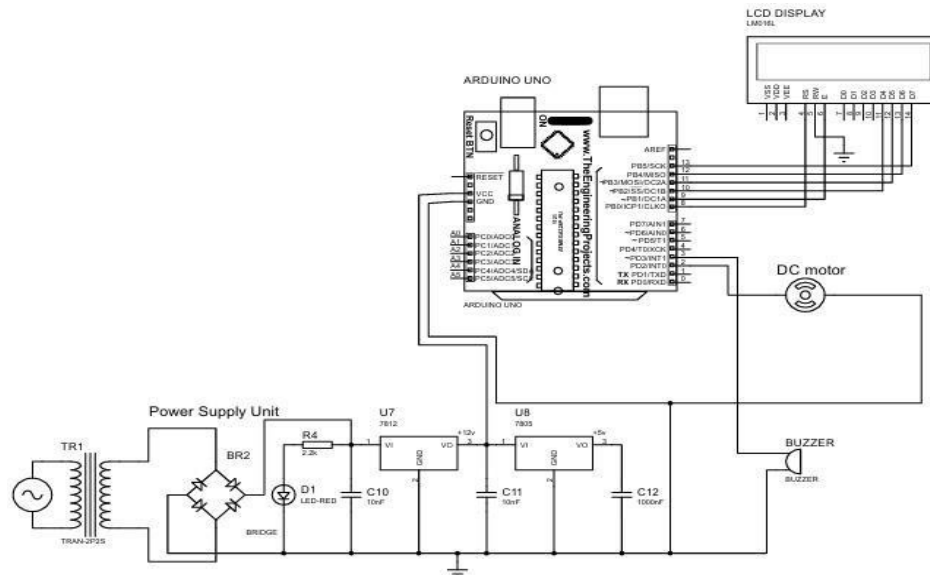


Fig 4. Buzzer

LIQUID CRYSTAL DISPLAY:

- Type: 16x2 Alphanumeric LCD Display Module.
- Role: Displays characters and basic symbols in embedded systems.
- Feature: Supports parallel interface with 16 pins, typically uses HD44780 controller.

V. CIRCUIT DIAGRAM



EXPLANATIONS

The circuit diagram illustrates a microcontroller-based system using the Arduino Uno to control an LCD display, a DC motor, and a buzzer, powered through a regulated power supply. The power supply section consists of a step-down transformer (TR1) that converts AC voltage to a lower AC voltage, which is then rectified by the bridge rectifier (BR2). The filtered DC voltage is regulated by voltage regulators U7 (7812) and U8 (7805) to provide +12V and +5V outputs, respectively. Capacitors C10, C11, and C12 (10 μ F and 1000 μ F) are used for voltage smoothing, while R4 (330 Ω) limits current to the LED indicator (D1), which confirms power status. The Arduino Uno controls the system using several digital pins. An LCD display (16x2) is connected as follows: RS to pin 7, E to pin 6, and data lines D4-D7 connected to pins 5, 4, 3, and 2, respectively. The RW pin is grounded. This configuration allows 4-bit communication between the Arduino and the LCD.

A DC motor is connected via a motor driver (not shown explicitly in the circuit), controlled by a designated digital pin, typically pin 9 or 10. The buzzer is connected to digital pin 8, which triggers sound alerts based on logic programmed into the Arduino.

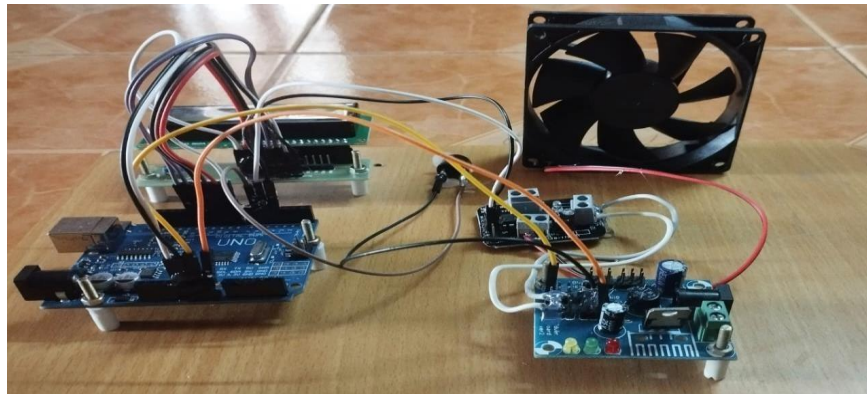


The VCC and GND pins of the Arduino are powered by the +5V and ground from the regulator output. The circuit ensures effective control and display functionality for embedded applications such as automation, monitoring, or alert systems.

VI. PROPOSED SYSTEM

The proposed traffic sign detection system is designed to enhance vehicle safety on Indian roads by leveraging the powerful deep learning architecture YOLO (You Only Look Once). Given the increasing concerns over road safety due to the complexity of Indian traffic conditions, including diverse vehicle types, unpredictable driver behaviors, and an extensive range of traffic signs, this system aims to mitigate accidents caused by the failure to recognize or obey traffic regulations. The Ministry of Road Transport and Highways has reported that a significant percentage of road accidents result from misinterpretation or ignorance of traffic signs, highlighting the urgent need for an advanced, AI-driven solution. To address this challenge, the system utilizes YOLO's efficient object detection capabilities to achieve real-time traffic sign recognition, ensuring immediate responses to dynamic road environments.

The system is trained and validated using the Indian Traffic Sign Recognition dataset, which comprises a comprehensive collection of traffic signs commonly found across the country. This dataset ensures the model is highly relevant to local traffic conditions and can accurately classify a wide range of signs, including speed limits, pedestrian crossings, school zones, and hazard warnings. Real-time detection is critical for autonomous or semi-autonomous vehicles to adjust their behavior based on the detected traffic signs, thereby improving road safety and reducing human error. The implementation of YOLO in traffic sign detection is particularly advantageous due to its ability to perform simultaneous object detection and classification at high speeds without compromising accuracy.



VII. SOFTWARE MODULE REQUIRED

1. ARDUINO UNO USAGE:

- Used Arduino Uno as the primary microcontroller for interfacing with hardware components.
- Programmed in Arduino C/C++ to control sensors, actuators, and data transmission.

2. PYTHON SOFTWARE CODE:

- Developed Python scripts for data processing, visualization, and communication with Arduino via serial port.
- Used libraries like PySerial for serial communication and Matplotlib/Pandas for handling and displaying data.

ADVANTAGES:

- Enhances road safety by providing real-time detection and classification of traffic signs, reducing human error and accident risks.
- Uses the YOLO deep learning model for fast and accurate sign recognition, ensuring rapid vehicle responses.



to changing traffic conditions.

- Automatically adjusts vehicle speed and triggers braking mechanisms, improving compliance with traffic rules and preventing potential collisions.
- Handles low lighting, adverse weather, and occluded signs using advanced image preprocessing and data augmentation techniques.
- Reduces driver workload by providing automated alerts and real-time decision- making assistance for traffic sign interpretation.
- Integrates seamlessly with vehicle control units and ADAS, enabling smoothoperation within connected vehicle environments and smart transportation systems.
- Integrates seamlessly with vehicle control units and ADAS, enabling smoothoperation within connected vehicle environments and smart transportation systems.

VIII. CONCLUSION

The implementation of a traffic sign detection system using YOLO deep learning architecture marks a transformative step toward enhancing road safety in India. By addressing critical issues such as misinterpretation of traffic signs, delayed driver responses, and unpredictable traffic conditions, this system significantly reduces accident risks. Its ability to process real-time video feeds, detect traffic signs instantly, and trigger immediate vehicle responses ensures a proactive approach to accident prevention.

The use of the Indian Traffic Sign Recognition dataset enhances the model's accuracy and adaptability, ensuring that it performs reliably under diverse road conditions. The integration of advanced image preprocessing techniques and cloud-based learning further optimizes detection accuracy, making the system highly efficient in real- world scenarios. Extensive testing across urban and rural environments ensures robustness, providing a reliable solution that functions effectively under various environmental challenges.

Additionally, the system's compatibility with ADAS and vehicle control mechanisms offers a scalable and cost-effective solution for automotive safety enhancement. As the demand for intelligent transportation systems grows, this traffic sign detection system paves the way for future innovations in autonomous driving and smart mobility.

By reducing human error, improving traffic law compliance, and enabling better traffic management, the system contributes to a safer and more organized road network. Ultimately, this initiative bridges the gap between AI-driven technology and practical road safety solutions, making Indian roads safer for all users.

REFERENCES

- [1]. J. Wang, Y. Chen, Z. Dong and M. Gao, "Improved YOLOv5 network for real-time multi- scale traffic sign detection", Neural Comput. Appl, vol. 35, no. 10, pp. 7853- 7865, Apr. 2023.
- [2]. R. K. Megalingam, K. Thanigundala, S. R. Musani, H. Nidamanuru and L. Gadde, "Indian traffic sign detection and recognition using deep learning", International Journal of Transportation Science and Technology, vol. 12, no. 3, pp. 683-699, Sep. 2023.
- [3]. S. Saxena, S. Dey, M. Shah and S. Gupta, "Traffic sign detection in unconstrained environment using improved YOLOv4", Expert Syst. Appl, vol. 238, pp. 121836, Mar. 2024.
- [4]. R. Sharma, V. Kukreja and V. Kadyan, "Hispa Rice Disease Classification using Convolutional Neural Network", 2021 3rd International Conference on Signal Processing and Communication (ICPSC), pp. 377-381, May 2021.
- [5]. G. Zhang, Y. Peng and H. Wang, "Road Traffic Sign Detection Method Based on RTS R- CNN Instance Segmentation Network", Sensors, vol. 23, no. 14, Jul. 2023.



- [6]. Z. Liu, D. Li, S. S. Ge and F. Tian, "Small traffic sign detection from large image", Applied Intelligence, vol. 50, no. 1, pp. 1-13, Jan. 2020.
- [7]. Zhang, Z. Xie, J. Sun, X. Zou and J. Wang, "A Cascaded R-CNN With Multiscale Attention and Imbalanced Samples for Traffic Sign Detection", IEEE Access, vol. 8, pp. 29742-29754, 2020.
- [8]. R. Sharma, V. Kukreja and and Sakshi, "Mustard Downy Mildew Disease Severity Detection using Deep Learning Model", 2021 International Conference on Decision Aid Sciences and Application DASA 2021, pp. 466-470, 2021.
- [9]. Baliyan, V. Kukreja, V. Salonki and K. S. Kaswan, "Detection of Corn Gray Leaf Spot Severity Levels using Deep Learning Approach", 2021 9th International Conference on Reliability Infocom Technologies and Optimization (Trends and Future Directions) ICRITO 2021, 2021.
- [10]. R. Ayachi, M. Afif, Y. Said and M. Atri, "Traffic Signs Detection for Real-World Application of an Advanced Driving Assisting System Using Deep Learning", Neural Process. Letters, vol. 51, no. 1, pp. 837-851, Feb

