Traffic Sign Detection System for Harsh Driving Analysis and Speed Compliance

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By

Name of Students	Seat No.
Saurabh Ashok Autade	B400550060
Nishad Ajay Harsulkar	B400550070
Sujal Sanjaykumar Koli	B400550076

Prof. Sarika N. Patil

At

Department of Electronics and Telecommunication
Nutan Maharashtra Institute of Engineering & Technology,
Talegaon Dabhade, Pune

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Nutan Maharashtra Institute of Engineering & Technology, Talegaon Dabhade, Pune

CERTIFICATE

This is to certify that the Project Report on the Project entitled

"Traffic Sign Detection System for Harsh Driving Analysis and Speed Compliance"

Submitted as a record of a project carried out in this Institute.

(Prof. Sarika N. Patil)

By

Saurabh Ashok Autade	B400550060
Nishad Ajay Harsulkar	B400550070
Sujal Sanjaykumar Koli	B400550076

Prof. Sarika N. Patil
(Project Guide)

Prof. Sarika B. Patil
(Project Coordinator)

Dr. Ashwini Shinde
HOD (E&TC)

Dr. S. N. Sapali
(Principal)

External Examiner

Department of Electronics & Telecommunication Engineering

(2024-2025)

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Saurabh Ashok Autade B400550060
Nishad Ajay Harsulkar B400550070
Sujal Sanjaykumar Koli B400550076

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ABSTRACT

The increasing demand for intelligent transportation systems and advanced driver assistance systems (ADAS) has made real-time traffic sign detection and driver behavior analysis essential components for enhancing road safety. This project proposes a comprehensive solution combining machine learning and sensor integration to detect road signs and monitor harsh driving behavior. The system uses a Convolutional Neural Network (CNN) model trained on the German Traffic Sign Recognition Benchmark (GTSRB) dataset to detect and classify traffic signs such as speed limits, warnings, and prohibitory signs in real-time. To ensure robustness against various environmental factors like lighting, weather, and occlusions, the model incorporates data augmentation techniques during training.

In addition to visual detection, the system integrates hardware components such as a Raspberry Pi, GPS module, and accelerometer to gather vehicle movement data. This enables the system to monitor and analyze driver behavior, identify instances of harsh acceleration or braking, and ensure speed compliance with respect to the detected signboards. All detected signs and behavioral data are stored in a database, enabling post-trip analysis and reporting. This holistic approach not only provides real-time alerts to drivers but also contributes to traffic management systems, insurance risk assessment, and future autonomous vehicle applications. The system's efficiency, portability, and accuracy make it a valuable tool for modern smart mobility initiatives and safer roads.

Keywords: This project involves key concepts such as traffic sign detection, harsh driving analysis, and speed compliance. It utilizes machine learning techniques, particularly convolutional neural networks (CNNs), for accurate classification of road signs from real-time video input. Additional technologies include sensor integration using Raspberry Pi, GPS modules, and accelerometers for behavior monitoring. Core focus areas include computer vision, real-time monitoring, driver behavior analysis, ADAS systems, and road safety enhancement through intelligent decision-making systems.

Abbreviations and Acronyms

Abbreviation/Acronym	**Full Form**
YOLOv8	You Only Look Once version 8
ADAS	Advanced Driver-Assistance Systems
GPS	Global Positioning System
FPS	Frames Per Second
ONNX	Open Neural Network Exchange
TPU	Tensor Processing Unit
USB	Universal Serial Bus
IDE	Integrated Development Environment
API	Application Programming Interface
RGB	Red Green Blue (color model)
mAP	Mean Average Precision
CNN	Convolutional Neural Network
IoT	Internet of Things

List of Symbols

Symbol	Description
C	Set of all detected traffic sign classes
I	Set of all input video frames
B	Set of bounding boxes predicted by the model
N	Total number of frames processed
n	Number of detected traffic signs in a frame
S	Sensor data readings (e.g., GPS, accelerometer)
T	Total processing or evaluation time
P	Precision value
R	Recall value
mAP	Mean Average Precision
FPS	Frames per second
θ (Theta)	Detection confidence threshold
λ (Lambda)	Learning rate during training
Δt	Time interval between frames

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

INTRODUCTION

The rapid expansion of urban areas and the increasing number of vehicles on roads have made traffic management and road safety major concerns in today's world. Traffic signs are a critical part of the transportation infrastructure, providing essential information and instructions to drivers to ensure orderly and safe vehicle movement. These signs regulate speed, indicate hazards, and communicate right-of-way rules, among other functions. However, their effectiveness is highly dependent on the driver's ability to perceive, interpret, and respond to them accurately and promptly.

Unfortunately, many drivers either fail to notice these signs due to distractions or poor visibility or deliberately ignore them, especially when they are not being monitored in real-time. Combined with harsh or reckless driving behaviors—such as rapid acceleration, sharp turns, overspeeding, or sudden braking—this creates a significant risk to public safety. According to traffic studies, a large percentage of road accidents occur due to human error, often involving missed sign recognition or non-compliance with traffic rules.

Manual enforcement methods and surveillance-based solutions have their limitations. They are resource-intensive, location-bound, and reactive in nature—often identifying violations only after they occur. There is a clear need for a **proactive, intelligent, and real-time monitoring system** that not only detects traffic signs automatically but also analyzes driver behavior to prevent potential mishaps before they happen.

To address this gap, this project introduces a **machine learning-based traffic sign detection and harsh driving analysis system** that aims to enhance road safety and ensure compliance with traffic regulations. The system uses **Convolutional Neural Networks (CNNs)** to detect and classify traffic signs from real-time video input captured by vehicle-mounted cameras. At the same time, it incorporates data from an **accelerometer** and **GPS module** to monitor driving patterns and identify harsh behaviors such as sudden acceleration, braking, or deviation from speed limits.

The integration of these components enables a multi-faceted approach to traffic safety:

- **Computer vision** identifies and tracks road signs in dynamic conditions, including varied lighting, angles, and partial occlusions.
- **Sensor fusion** provides insights into real-time motion and location data, helping to assess driver conduct.
- **Raspberry Pi and onboard processing** offer a compact, affordable, and scalable solution suitable for different vehicle types and road conditions.

Furthermore, the system is designed to provide immediate feedback to the driver through alerts, helping them take corrective actions in real-time. Data is also stored in a centralized database, allowing for post-trip analysis, reporting, and future improvements in driving behavior and traffic policy formulation.

1.1 WHAT IS TRAFFIC SIGN DETECTION AND HARSH DRIVING ANALYSIS?

Traffic sign detection is a computer vision task that involves automatically identifying and classifying road signs from visual input—typically images or video captured by a camera mounted on a moving vehicle. These signs can include speed limits, warnings, stop signs, yield indicators, and various other regulatory or advisory markers placed along roads. The detection process uses **machine learning models**, particularly **Convolutional Neural Networks (CNNs)**, which are trained on large datasets of labeled traffic sign images. These models are capable of learning intricate patterns, shapes, and color features that help them distinguish between different sign types—even in challenging conditions such as poor lighting, occlusion, or weather disturbances.

Once detected, traffic signs can be used to trigger real-time feedback mechanisms, such as issuing alerts if a driver is exceeding the speed limit or approaching a danger zone. This functionality is particularly valuable in **Advanced Driver Assistance Systems (ADAS)** and forms a foundation for **autonomous vehicle technologies**.

Harsh driving analysis, on the other hand, focuses on monitoring and evaluating a driver's behavior using **motion sensors** like accelerometers and **GPS modules**. It tracks abrupt actions such as:

- Sudden acceleration or deceleration
- Sharp turns
- Overspeeding beyond detected traffic signs
- Inconsistent or erratic vehicle movement

These behaviors are indicative of risky or aggressive driving and, if left unchecked, can lead to accidents or increased vehicle wear. By analyzing patterns in sensor data, the system can detect these events and issue warnings or record the instances for review.

When combined, traffic sign detection and harsh driving analysis create a **comprehensive safety framework**. The system not only understands what the road is instructing the driver to do but also ensures that the driver is complying with those instructions in a smooth and responsible manner. The real-time detection and behavioral feedback provide a dual-layered approach to improving road discipline and enhancing the driving experience.

1.2 MOTIVATION

In the modern age of smart technology and expanding urban road networks, ensuring safe and efficient traffic flow has become a top priority. With a growing number of vehicles on the road, the risk of accidents, violations, and unsafe driving behaviors has also escalated. Despite efforts by government bodies and law enforcement agencies, the majority of road safety still relies on human attention, perception, and discipline—elements that are prone to error. The motivation for this project arises from the need to supplement human driving with intelligent systems that can detect risks, recognize important traffic cues, and monitor driver behavior in real-time.

Road signs are a fundamental part of traffic infrastructure. They are designed to instruct, warn, and guide road users for their safety and the safety of others. However, in practical scenarios, drivers often fail to recognize or respond to these signs due to distractions, fatigue, bad weather, or poor visibility. On the other hand, even when signs are noticed, they are sometimes ignored by aggressive drivers, especially in the absence of active monitoring. In such cases, consequences may include traffic violations, collisions, injuries, or even fatalities. This highlights a pressing need for a technology that can act as an always-alert assistant—constantly watching the road and ensuring that signs are observed and obeyed.

Moreover, harsh driving behaviors such as:

- Sudden acceleration or braking
- Excessive speed
- Sharp lane changes or turns
- Ignoring speed limits or warning signs

are often linked to accidents and reduced vehicle lifespan. In commercial transport and logistics, such driving behavior can lead to delayed deliveries, increased fuel consumption, and poor customer satisfaction. Fleet managers often lack reliable tools to detect and correct such patterns unless an accident or complaint occurs..

1.3 PROBLEM STATEMENT

With the rapid increase in traffic density and road usage, ensuring safety and compliance has become one of the major challenges in modern transportation. While traffic signs are strategically placed to guide drivers, their effectiveness is limited when they are not noticed, misinterpreted, or intentionally ignored. Many accidents, near-misses, and rule violations happen not due to the absence of signs, but due to the failure in recognizing and reacting to them in time.

Moreover, harsh driving behaviors—such as abrupt braking, overspeeding, sudden acceleration, or taking sharp turns—pose an additional layer of danger. These behaviors are often difficult to track manually and are usually observed only after incidents occur. In many cases, drivers themselves are unaware of the harshness or non-compliance in their behavior until consequences arise.

- **Lack of real-time sign recognition**: Drivers often miss traffic signs due to distractions, fatigue, or bad weather. There's no in-vehicle system that constantly assists in sign detection in real-time.
- **Absence of behavioral monitoring**: There is no continuous tracking of driving patterns to alert users about aggressive or unsafe driving.
- **Dependence on post-incident analysis**: Most interventions occur after a violation or accident has already taken place.
- **Limited access to intelligent safety systems**: Current solutions are expensive, resource-heavy, and primarily limited to premium or commercial vehicles.
- **Lack of integration between visual data and motion data**: Most systems focus on either sign recognition or behavioral tracking, but not both in unison.

In smaller towns, rural areas, or low-budget transportation networks, drivers often do not have access to intelligent driver assistance systems (ADAS) that can help them navigate safely.

CHAPTER 2

LITERATURE SURVEY

1. Real-Time Traffic Sign Detection and Recognition System using Computer Vision and Machine Learning

Authors: Dr. Rahul Patil, Dr. Prashant Ahire, et al.

This research presents an end-to-end traffic sign detection and recognition system combining deep learning with computer vision. The model employs Convolutional Neural Networks (CNNs) for feature extraction and classification, with OpenCV used for image preprocessing tasks like resizing and color space conversion. The system is capable of real-time video processing, allowing for the dynamic detection of traffic signs with bounding boxes and corresponding alerts via sound or SMS. The study demonstrates that the integration of TensorFlow and Keras enables the system to achieve high accuracy under varied lighting conditions and occlusions. The researchers conclude that deep learning significantly improves detection reliability, making it suitable for deployment in autonomous driving applications.

Title	Methodology	Algorithm	Key Findings	Conclusion
Real-Time Traffic Sign Detection and Recognition System using Computer Vision and Machine Learning (IJSREM)	Implemented a real-time detection system using image processing with OpenCV and deep learning frameworks like TensorFlow and Keras. Integrated alert systems (e.g., sound/SMS).	Convolutional Neural Network (CNN)	Demonstrated robust detection and classification of signs in varying conditions using deep learning and real-time video feed integration.	Deep learning with CNNs provides accurate and scalable solutions for real-time traffic sign recognition, enhancing road safety.

Table 2.1

2. Indian Traffic Sign Detection and Recognition using Deep Learning
Authors: Rajesh Kannan Megalingam, Kondareddy Thanigundala, et al.

This paper introduces a deep learning model tailored for Indian traffic signs using a refined Mask R-CNN (RM R-CNN) architecture. A comprehensive dataset consisting of 6,480 images across 87 unique sign categories was created to address the underrepresentation of Indian road signs in global datasets. Through architectural refinements and advanced data augmentation strategies, the RM R-CNN model achieved a precision of 97.08% with an error rate below 3%. The system demonstrated robustness in various conditions, including different lighting, orientations, and sign scales. The study concludes that specialized datasets and improved CNN architectures are essential for achieving high accuracy in localized traffic sign recognition systems.

Title	Methodology	Algorithm	Key Findings	Conclusion
Indian Traffic Sign Detection and Recognition using Deep Learning.	Developed an Indian-specific dataset and applied a refined Mask R-CNN (RM R-CNN) model with improved data augmentation strategies.	Refined Mask R-CNN (RM R-CNN)	Achieved 97.08% precision with <3% error rate on 87 Indian sign categories, demonstrating high robustness under variable conditions.	RM R-CNN provides high performance for localized sign detection, emphasizing the importance of dataset relevance and augmentation.

Table 2.2

3. YOLOv4 for Advanced Traffic Sign Recognition with Synthetic Training Data Generated by Various GANs

Authors: C. Dewi, R.-C. Chen, Y.-T. Liu, X. Jiang, and K. D. Hartomo

This study investigates the enhancement of traffic sign recognition using YOLOv4 combined with synthetic data generated by Generative Adversarial Networks (GANs). The use of synthetic data helped overcome challenges associated with limited and imbalanced datasets, resulting in improved model generalization across diverse environments. YOLOv4's fast and accurate object detection was paired with the variability introduced by GANs to train a more robust model. The findings highlight that synthetic augmentation is an effective strategy for improving model performance when access to real-world labeled data is constrained. The paper concludes that GAN-based training data significantly strengthens the real-time detection capabilities of traffic sign models.

Title	Methodology	Algorithm	Key Findings	Conclusion
YOLOv4 for Advanced Traffic Sign Recognition With Synthetic Training Data Generated by Various GANs (IEEE Access, 2021)	Used YOLOv4 for detection, enhanced with GAN-based synthetic data to augment training in low-data scenarios.	YOLOv4 with GAN-generated data	Improved detection accuracy and robustness in situations with limited real data; model generalized well across various lighting and sign variations.	Synthetic data via GANs enhances detection models, enabling accurate traffic sign recognition even with imbalanced datasets.

Table 2.3

4. Neural-Network-Based Traffic Sign Detection Using Region Focusing and Parallelization

Authors*:* A. Avramović, D. Sluga, D. Tabernik, D. Skočaj, V. Stojnić, and N. Ilc

This work focuses on traffic sign detection in high-definition imagery by employing region focusing and parallel computing. The proposed method uses a neural network model that prioritizes image regions likely to contain signs, thereby optimizing computational efficiency. Parallelization techniques further enhance the real-time applicability of the system, especially in high-resolution video feeds. The approach achieved higher detection speed and maintained high precision under complex road environments. The authors conclude that incorporating spatial attention and computational optimization enables CNN-based models to deliver practical, real-time traffic sign detection solutions for modern vehicles.

Title	Methodology	Algorithm	Key Findings	Conclusion
Neural-Network-Based Traffic Sign Detection Using Region Focusing and Parallelization (IEEE Access, 2020)	Applied region focusing and parallel processing techniques to optimize detection in high-resolution imagery.	Custom CNN with Region Focusing	Improved real-time performance and detection precision for high-resolution inputs by leveraging efficient region proposals.	Combining region focusing with parallelization enhances the practicality of neural networks for real-time road sign detection.

Table 2.4

5. Real-Time Traffic Sign Detection and Recognition using CNN

Authors:

D. C. Santos et al.

This study developed a real-time traffic sign recognition system based on Convolutional Neural Networks (CNNs). The model was trained using a labeled dataset comprising multiple classes of traffic signs, enabling it to identify and classify signs from video input in real time. With a focus on efficient architecture, the system maintained high accuracy while running on moderately powered hardware, making it viable for embedded and edge computing environments like Raspberry Pi. The research confirmed that CNNs, due to their spatial feature learning capabilities, are ideal for traffic sign recognition tasks in real-world, variable conditions. The study concludes that CNN-based models balance accuracy and speed effectively for real-time applications.

Title	Methodology	Algorithm	Key Findings	Conclusion
Traffic and signal Suitability Prediction using ML Approaches. (IJESD) 2023.	Assessed Traffic and signal suitability using ML, analyzing signal data and environmental conditions to make speed recommendations.	Convolutional Neural Network (CNN)	Achieved strong accuracy across varied environments with fast inference time. Demonstrated reliability in real-time systems using moderate computing resources.	CNNs are well-suited for real-time traffic sign recognition due to their ability to learn spatial hierarchies and extract robust features.

Table 2.5

CHAPTER 3

RESEARCH METHODS

RESEARCH METHODS

3.1 DATA COLLECTION

To develop the traffic sign detection system, the first step was to collect high-quality data. We used well-known public datasets such as the German Traffic Sign Recognition Benchmark (GTSRB), which includes a wide variety of traffic signs categorized into over 40 different classes. These images were captured under different lighting and weather conditions, ensuring diversity and realism. This dataset forms the foundation on which our machine learning model learns to recognize and classify traffic signs.

3.1 DATA PREPROCESSING

Once we had our dataset, we processed the images to prepare them for training. This included resizing all images to a fixed resolution (such as 224x224 pixels), normalizing pixel values to improve training efficiency, and applying data augmentation techniques like rotation, flipping, and zooming. These steps help the model generalize better and perform accurately in real-world scenarios.

3.2 FEATURE EXTRACTION

To help the system understand the unique characteristics of traffic signs, we used convolutional neural networks (CNNs) to automatically extract relevant features. These features could include the shape of the sign, color patterns, and text or symbols. Instead of manually selecting features, the CNN learns them during training, improving the overall accuracy and reducing human bias.

3.4 MODEL TRAINING

Next, we trained our system using powerful deep learning frameworks like TensorFlow and Keras. We fed thousands of labeled traffic sign images into the model, allowing it to learn the patterns associated with each class. Techniques like backpropagation and dropout were used to fine-tune the learning process and prevent overfitting. The model was trained on GPU-enabled systems for faster processing.

3.5 CLASSIFICATION AND PREDICTION

After training, the system could now identify and classify traffic signs from new input images. When given a new road sign photo or video frame, the model predicts the sign's class (e.g., Stop, Speed Limit 50, No Entry) with high confidence. This classification is displayed in real-time using bounding boxes around detected signs, simulating how the system would function in a moving vehicle.

3.6 RECOMMENDATION GENERATION

Beyond detection, the system can be expanded to provide driving assistance. For example, if a speed limit sign is detected, the system could recommend the driver to slow down. In future iterations, this can be extended to give audio or haptic feedback, alerting drivers about upcoming hazards or mandatory stops, improving road compliance and safety.

3.7 EVALUATION AND VALIDATION

To ensure the reliability of the system, we evaluated it using accuracy, precision, recall, and F1-score on a separate validation set. We also tested it under challenging conditions such as low light, occlusion, or rotated signs. Any misclassifications were analyzed, and the model was retrained or fine-tuned accordingly.

3.8 CONCLUSION AND FINALIZATION

Finally, once the model achieved satisfactory results, we considered ways to optimize it further. This includes deploying it on edge devices like Raspberry Pi for real-time processing in vehicles, adding localization support for regional traffic signs, and developing a user interface for better visualization. These improvements will help in making the system practical, scalable, and accessible for real-world usage.

CHAPTER 4

PROJECT SCOPE & OBJECTIVES

4.1 PROJECT SCOPE

This project focuses on using machine learning to make transportation systems smarter and safer for everyone. At its core, the system is designed to detect and classify different types of traffic signs—like stop signs, speed limits, and warning signs—based on their shape, colour, and symbols, using advanced computer vision algorithms.

Once a traffic sign is identified, the system goes a step further by offering real-time feedback to the driver or autonomous system. It analyzes live camera input, detects signs accurately, and then overlays the corresponding classification on the video feed, ensuring immediate recognition and response to road conditions.

A key focus of the project is to determine whether traffic signs can be accurately recognized in diverse environments, including poor lighting, partial occlusion, or motion blur. While the initial model is trained on common road signs, the system has the potential to scale and adapt to region-specific signs or multilingual environments in the future.

What makes this project especially useful is its real-time processing capability. Through integration with devices like Raspberry Pi, the system processes live video from vehicle-mounted cameras and instantly detects and classifies traffic signs to assist the driver.

The backend of the system uses Convolutional Neural Networks (CNNs) as the primary algorithm, but also incorporates frameworks like TensorFlow and Keras to improve detection performance and flexibility.

Ultimately, the goal is to empower intelligent vehicles and driver-assistance systems with real-time, data-driven visual understanding of traffic environments—leading to enhanced road safety, reduced human error, and smoother navigation in both urban and rural areas.

4.2 PROJECT OBJECTIVE

1. **Traffic Sign Detection Made Easy:**
   The system helps identify various traffic signs like speed limits, stop signs, and warning signs by analyzing images captured from vehicle-mounted cameras. This eliminates the need for manual sign monitoring or traditional rule-based detection.

2. **Real-Time Driving Assistance:**
   Once a sign is detected, the system provides instant feedback by drawing bounding boxes and displaying the sign's meaning on-screen—helping drivers or autonomous vehicles react quickly and safely.

3. **Accessible via Compact Edge Devices:**
   The solution is designed to run efficiently on small devices like the Raspberry Pi, making it suitable for real-time in-vehicle deployment without requiring expensive computing hardware.

4. **Accurate Classification with Deep Learning:**
   The system uses Convolutional Neural Networks (CNNs) for precise recognition of signs under various conditions. Frameworks like TensorFlow and Keras support the model's high accuracy and scalability**.**

5. **Supports Safer and Smarter Transportation:**
   By enabling intelligent vehicles and advanced driver-assistance systems to automatically interpret traffic signs, the project aims to reduce human error, prevent traffic violations, and promote road safety.

These objectives collectively aim to develop and implement a reliable traffic sign recognition system that enhances real-time decision-making, especially in dynamic and unpredictable driving environments.

CHAPTER 5

FUNCTIONAL REQUIREMENTS

5.1 FEATURE

1 **Real-Time Traffic Sign Monitoring:**

The system continuously captures and processes live video feed from vehicle-mounted cameras to detect and classify traffic signs in real-time. Detected signs are highlighted with bounding boxes and labels on the user interface. The detection feed is updated instantly, ensuring accurate and timely feedback for safe navigation.

2 **User-Friendly Interface:**

The system includes a simple and intuitive dashboard interface designed for real-time visualization of detected signs. Whether integrated into a vehicle display or desktop screen, users can view sign types, timestamps, and detection confidence levels without needing technical expertise.

3 **Integration with Smart Driving Systems:**

The system integrates with advanced driver assistance systems (ADAS) to issue alerts when critical signs like “Stop” or “Speed Limit” are detected. Additionally, it includes the capability to store detection data for later analysis, enhancing both driver awareness and future model training. These features collectively contribute to safer and more responsive driving environments.

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5.2 FUNCTIONAL REQUIREMENTS

Functional requirements describe the core operations and behaviors the system must perform to fulfill its intended purpose. For the **Traffic Sign Detection System**, the following functionalities are essential:

1. **Live Video Input Acquisition:**
The system must capture real-time video from a vehicle-mounted camera to monitor the driving environment continuously.
2. **Image Preprocessing:**
The system should preprocess incoming frames by resizing, normalizing, and enhancing them for optimal input into the detection model.
3. **Traffic Sign Detection and Localization:**
The system must detect traffic signs within each video frame using a trained deep learning model and mark them using bounding boxes.
4. **Sign Classification:**
Once detected, the system should classify the sign (e.g., Speed Limit, Stop, No Entry) and display the result with a confidence score.
5. **Real-Time Alert Display:**
The system must provide real-time visual feedback to the user by displaying detected signs on-screen, optionally with audible alerts for critical signs.
6. **Data Storage:**
The system should log detected signs, timestamps, and GPS coordinates (if available) for future reference and analysis.
7. **System Integration:**
The system must be capable of integrating with other modules like GPS and accelerometer sensors for extended functionality (e.g., speed compliance monitoring).
8. **Performance Evaluation:**
The system must include functionality for evaluating detection performance using metrics such as accuracy, precision, recall, and inference time.

CHAPTER 6

SYSTEM REQUIREMENTS

6.1 HARDWARE REQUIREMENTS

The implementation of the Traffic Sign Detection and Compliance Monitoring System requires robust hardware that can support real-time video capture, machine learning inference, sensor data processing, and power-efficient embedded deployment. Below is a comprehensive list of the hardware components used in the system, including recent additions:

1. Processing Unit

Component: Raspberry Pi 5 Model B (8 GB RAM)

- Processor: Quad-core 64-bit ARM Cortex-A76
- RAM: 8 GB LPDDR4 for real-time video processing and model inference
- Ports: USB 3.0/2.0 for connecting camera, Coral USB Accelerator, sensors
- Connectivity: Wi-Fi and Bluetooth support (optional)
- GPIO: 40-pin header for connecting output devices like buzzers and sensors

Figure 1. Raspberry Pi 5 Model B

2. Camera

Component: 1080p USB Camera

- Resolution: Full HD 1080p

- Interface: USB 2.0 / 3.0 (USB 3.0 recommended for higher bandwidth)
- Frame Rate: 30 FPS for real-time detection
- Features: Plug-and-play compatibility with Raspberry Pi OS, optional wide-angle lens

Figure 2. 1080p USB Camera

3. AI Accelerator

Component: Google Coral USB Accelerator

- Processor: Edge TPU ML co-processor (4 TOPS)
- Interface: USB 3.0 Type-A
- Power Consumption: ~0.5A at 5V
- Use: Accelerates inference of TensorFlow Lite models (e.g., YOLOv8 TFLite)
- Compatibility: Works with Linux, Mac, and Windows

Figure 3. Google Coral USB

4. Sensors

- **Accelerometer (e.g., MPU6050):**
    - Measures motion in X, Y, and Z axes
    - Detects harsh driving behavior like sudden braking and sharp turns
- **GPS Module (e.g., NEO-6M):**
    - Provides real-time latitude, longitude, and speed
    - Used for speed compliance and geotagging traffic violations

5. Output Devices

Component: Buzzer

- Interface: Connected via Raspberry Pi GPIO pins
- Function: Emits audible alerts when traffic violations are detected (e.g., over-speeding, red light breach)

6. Power Supply

A. Power Source

Component: 12V Exide Battery

- Type: Lead-Acid Rechargeable (Sealed Maintenance-Free or Tubular)
- Voltage: 12V DC
- Capacity: Typically ranges between 7Ah – 26Ah (based on usage)
- Features:
    - Deep cycle capability
    - Rugged design for outdoor use
    - Overcharge protection (in some models)

Figure 4. 12V Exide Battery

B. Voltage Regulation

Component: LM2596S Buck Converter (with USB Port)

- Input Voltage: 4V to 40V DC
- Output Voltage: Fixed at 5V DC
- Current Output: Up to 2A – 3A (with heat sink)
- Features:
  - USB Type-A output port
  - Adjustable voltage with onboard potentiometer
  - Overcurrent and thermal protection
  - Efficiency: 75–85%
- Use: Converts 12V battery output to 5V for powering the Raspberry Pi and Coral USB Accelerator

Figure 5. LM2596S Buck Converter

C. Power Cable

Component: USB to Type-C Cable

- Connectors: USB-A (Male) to USB-C (Male)
- Rating: Supports 5V at 3A
- Use: Delivers stable power from buck converter to Raspberry Pi Type-C input
- Note: Must be high-current capable; avoid data-only cables

7. Additional Requirements

- Storage: Minimum 16 GB microSD card or SSD (for Raspberry Pi OS, model files, and data logs)
- Internet Connection: At least 2.5 Mbps for downloading packages, remote access, and updates
- Peripherals (Optional): Monitor, keyboard, and mouse (only required for setup and debugging)

These hardware requirements ensure that the system can deliver real-time, accurate traffic sign detection and compliance monitoring, leveraging the efficiency of YOLOv8 and the acceleration provided by the Coral USB Accelerator. For model training, a more powerful workstation with a quad-core CPU and at least 16 GB RAM is recommended for best results.

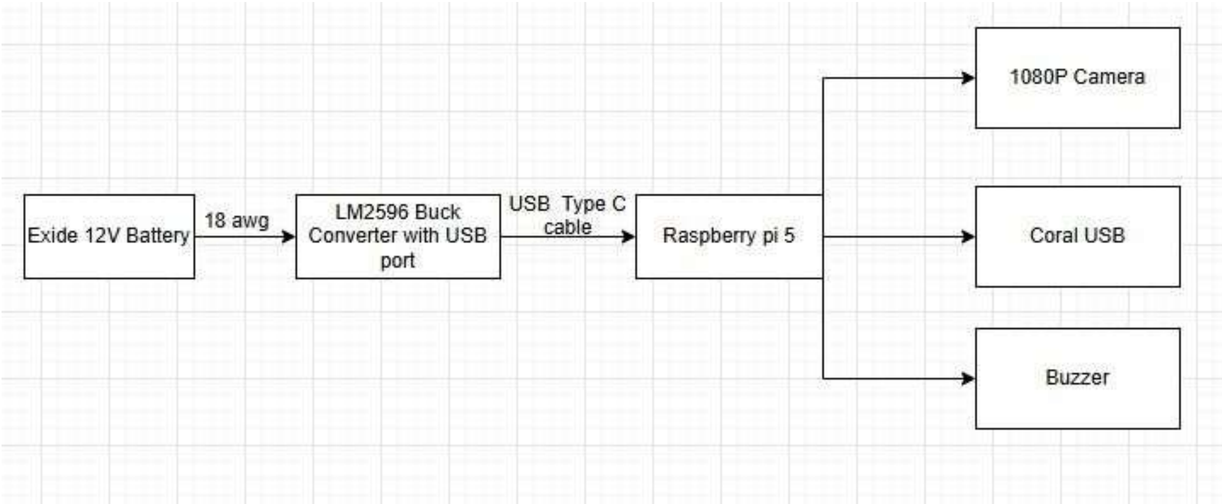

Figure 6. Hardware Architecture

6.2 SOFTWARE REQUIREMENTS

The following software components and tools are required for developing, training, deploying, and operating the real-time traffic sign detection and compliance monitoring system using YOLOv8:

Operating System

- **Raspberry Pi OS (64-bit, Debian-based)**
- Optimized for Raspberry Pi 5 and compatible with required Python libraries, OpenCV, and Coral USB support.
- Provides access to GPIO and USB peripherals for sensor and actuator integration.

Programming Language

- **Python 3.9+**

- Main language for scripting detection logic, sensor communication, and data logging.
- Supported by a wide range of libraries for computer vision, deep learning, and hardware interaction.

Object Detection Framework

- **Ultralytics YOLOv8**
- State-of-the-art object detection model, widely used for real-time traffic sign detection due to its speed and accuracy.
- Supports training, validation, and inference on custom datasets.
- Compatible with export to ONNX or TensorFlow Lite for edge deployment on devices like the Coral USB Accelerator.

Deep Learning & Computer Vision Libraries

- **PyTorch**
- Used as the backend for YOLOv8 model training and inference.

OpenCV

- For image and video processing, frame capture, augmentation, and visualization.
- **Albumentations**
- For advanced image augmentation to improve model robustness.
- **TensorFlow Lite**
- For deploying optimized models on edge devices (e.g., Coral USB Accelerator).

Dataset Preparation & Annotation Tools

- **Roboflow / LabelImg**
- For annotating images and converting datasets to YOLOv8 format.
- **Kaggle API / Manual Download**
- For retrieving traffic sign datasets from Kaggle or similar sources.

Remote Access and Monitoring Tools

- **PuTTY**

- Terminal emulator for SSH access to the Raspberry Pi, used for running scripts, monitoring logs, and installing packages remotely.
- **RealVNC Viewer**
- For remote access to the Raspberry Pi’s graphical desktop, enabling visualization of live camera feeds and detection results.
- **Thonny IDE**
- Lightweight Python IDE for writing, running, and debugging scripts directly on the Raspberry Pi.

Model Training Environment

- **Google Colab or Local Machine with GPU**
- For efficient model training, leveraging GPU acceleration for faster convergence.
- Python + PyTorch environment recommended for compatibility with YOLOv8.

6.3 LIBRARIES

- Ultralytics
- PyTorch
- OpenCV (cv2)
- Matplotlib
- Pandas
- NumPy
- Seaborn
- Google Drive (integration for Colab)
- Roboflow
- LabelImg
- TensorBoard
- scikit-learn
- ONNX Runtime
- RPi.GPIO
- gpiozero
- pyserial
- time
- datetime
- os
- geopy
- Coral Edge TPU runtime (libedgetpu)
- Thonny IDE (for development, not a Python library)

CHAPTER 7

ANALYSIS MODEL

ANALYSIS MODEL

This chapter presents a comprehensive evaluation and analysis framework for deep learning-based traffic sign detection models. The primary objective is to assess how effectively these systems can recognize and classify traffic signs in real-world environments, using established performance metrics and confusion matrix analysis. By benchmarking multiple models, we aim to identify their strengths and limitations, ultimately guiding the development of robust, real-time solutions for intelligent transportation systems.

A. Purpose of the Analysis Model

- To systematically evaluate and benchmark the performance of traffic sign detection algorithms, especially in dynamic, real-world scenarios.

B. Key Evaluation Metrics

- **Precision:** The proportion of correctly predicted positive instances among all positive predictions.
  Precision=*TP/TP+FP*
- **Recall:** The proportion of correctly predicted positive instances among all actual positives.
  Recall=*TP/TP+FN*
- **Mean Average Precision (mAP):** An aggregate metric that summarizes precision across all classes, commonly used for object detection benchmarks.

C. Confusion Matrix Utilization

- The confusion matrix provides a visual summary of the model's classification results, highlighting true positives, false positives, false negatives, and misclassifications for each class.
- A matrix with strong diagonal values indicates effective class separation, while significant off-diagonal values reveal confusion between classes and areas for improvement.

D. Model Comparison Approach

- Multiple state-of-the-art models (e.g., YOLOv8, Faster R-CNN, SSD, RetinaNet, CenterNet, Cascade-RCNN) are evaluated on standardized datasets using unified metrics to ensure fair benchmarking.
- Performance is compared across different datasets and geographic contexts to assess model robustness and generalizability.

E. Dataset Handling

- Datasets are carefully curated and balanced to address class imbalance and ensure adequate representation for each traffic sign category.
- Data is typically split into training and test sets (commonly 80:20) to enable reliable and unbiased evaluation.

F. Analysis of Results

- The analysis identifies which traffic sign classes are accurately recognized (e.g., Speed Limit) and which are prone to confusion (e.g., Traffic Light vs. background).
- Insights from the confusion matrix and metric trends guide targeted improvements, such as data augmentation strategies or model architecture enhancements.

G. Implications for Real-World Deployment

- Thorough analysis ensures that the selected model is suitable for real-time, on-road deployment in applications like autonomous vehicles and driver assistance systems.
- Ongoing benchmarking and evaluation drive continuous improvements in detection accuracy, speed, and reliability, even under challenging environmental conditions.

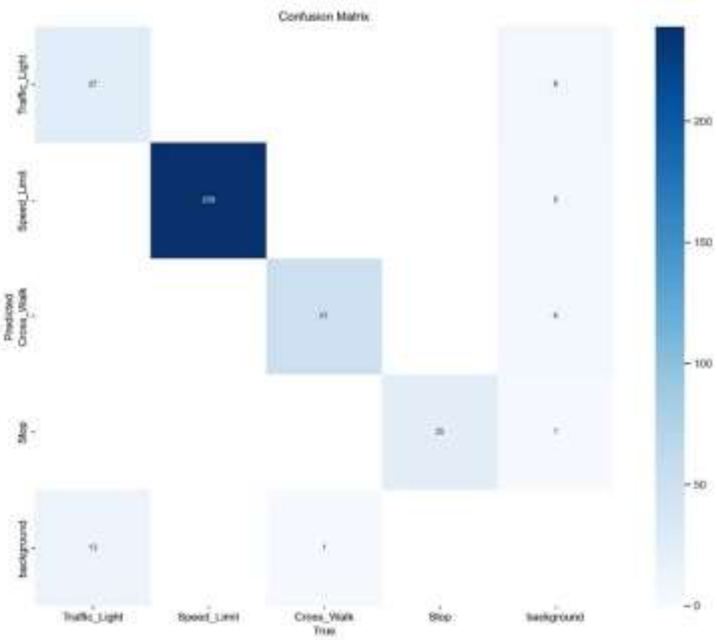

Figure 7. Confusion Matrix for Traffic Sign Classification Model

CHAPTER 8

SYSTEM METHODOLOGY

SYSTEM METHODOLOGY

The system methodology for traffic sign detection and compliance monitoring involves a seamless pipeline that begins with the acquisition of real-time video frames using a high-definition USB camera mounted on a vehicle. These frames are preprocessed and fed into a YOLOv8 deep learning model running on a Raspberry Pi 5, which has been trained on a diverse, annotated dataset of traffic signs. The model performs rapid detection and classification of traffic signs within each frame, while integrated sensors such as GPS and accelerometers provide contextual data like vehicle speed and movement. Detected signs and sensor data are cross-referenced to monitor compliance with traffic rules, triggering audible alerts via a buzzer in case of violations. This end-to-end methodology ensures robust, real-time detection and feedback, supporting safer and more intelligent transportation.

8.1 LIBRAIRIES USED IN IMPLEMENTATION

The implementation of the traffic sign detection and compliance monitoring system leverages a robust suite of libraries spanning machine learning, computer vision, and hardware interfacing. During the model training phase on Google Colab, key libraries such as Ultralytics (for YOLOv8), PyTorch, OpenCV, Matplotlib, Pandas, and NumPy were used for deep learning, image processing, visualization, and data manipulation. Tools like Roboflow and LabelImg facilitated dataset annotation and export, while TensorBoard and scikit-learn supported performance monitoring and evaluation. For deployment on the Raspberry Pi, the system utilized OpenCV for real-time video capture and processing, ONNX Runtime or Torch for model inference, RPi.GPIO and gpiozero for hardware control (e.g., buzzer alerts), and pyserial for sensor communication. Additional libraries, including geopy for GPS data processing and the Coral Edge TPU runtime for accelerated inference, ensured efficient, real-time operation on embedded hardware. This comprehensive library stack enabled seamless transition from cloud-based model development to practical, real-world deployment.

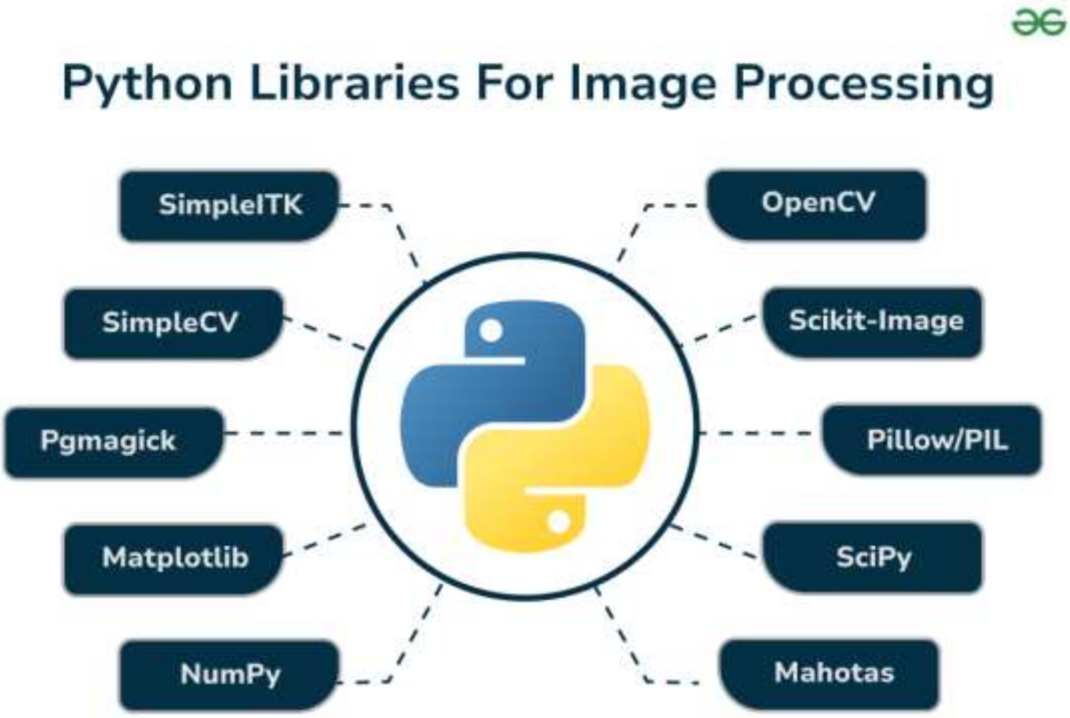

Figure 8. Libraries And Components Used in Implementation

8.2 CONCEPTS USED IN IMPLEMENTATION

Traffic Sign Detection and Classification using YOLOv8

The preprocessed image is passed to the YOLOv8 model, which performs real-time detection and classification of traffic signs:

- **Training Data:**
  The model is trained on a labeled dataset of traffic sign images (e.g., speed limit, stop, traffic light, crosswalk) annotated in YOLO format.
- **Model Architecture:**
  YOLOv8 is a one-stage object detection model that predicts bounding boxes and class probabilities directly from the input image in a single forward pass. It uses convolutional layers to extract features and regression layers to predict object locations and classes.

- **Training Process:**
  The model is trained using annotated images, optimizing a loss function that considers both bounding box accuracy and classification confidence. Data augmentation is applied to improve generalization.

- **Prediction:**
  Once trained, the model processes each incoming frame, detecting and classifying traffic signs in real time and outputting bounding boxes, class labels, and confidence scores.

Sensor Data Integration and Violation Detection

In addition to vision-based detection, the system integrates data from accelerometer and GPS sensors to enhance context and monitor driver behavior:

- **Sensor Data Acquisition:**
  Accelerometer measures vehicle movements (e.g., sudden braking, sharp turns), and GPS provides real-time speed and location.

- **Violation Detection:**
  Detected traffic signs (e.g., speed limit, stop, red light) are cross-referenced with sensor data. For example, if the vehicle exceeds the speed limit or fails to stop at a red light, the system flags a violation.

- **Alert Mechanism:**
  When a violation is detected, the system triggers a buzzer or visual alert to notify the driver in real time.

Real-Time Processing and Edge Deployment

- **Hardware Acceleration:**
  The system utilizes a Raspberry Pi 5 with a Coral USB Accelerator to enable fast, on-device model inference, ensuring low-latency detection suitable for real-world driving scenarios.

Model Evaluation

- **Performance Metrics:**
  The detection model is evaluated using accuracy, precision, recall, and mean

average precision (mAP) to measure its effectiveness in identifying and classifying traffic signs.

- **Confusion Matrix Analysis:**
  Confusion matrices are used to analyze misclassifications and guide further improvements.

Development and User Interface

- **User Input and Monitoring:**
  The system provides a graphical interface (using Thonny IDE, PuTTY, or VNC Viewer) for monitoring live detections, sensor data, and violation alerts.

- **Real-Time Feedback:**
  Drivers receive immediate alerts for detected violations, and all events are logged for further analysis.

- **User Guidance:**
  The application can offer recommendations or summaries to help users understand their driving behavior and compliance with traffic regulations.

Figure 9. Traffic Sign Detection with Confidence Scores

CHAPTER 9

SYSTEM DESIGN

BASIC DESIGN

9.1 SYSTEM ARCHITECTURE

The system architecture for real-time traffic sign detection and compliance monitoring is designed as a modular pipeline that integrates both hardware and software components for efficient, on-the-edge processing. The process begins with the camera module, which continuously captures live video frames as the vehicle moves. These frames are then sent to a preprocessing unit, where operations such as resizing, masking, and optical character recognition (OCR) are performed to enhance image quality and extract relevant features. The preprocessed images are fed into a pre-trained YOLOv8 model, converted to PyTorch and accelerated using the Google Coral TPU for high-speed inference. The model detects and localizes traffic signs within each frame, and the extracted information is cross-referenced with real-time GPS speed data to assess compliance with traffic rules. If a violation is detected-such as exceeding the speed limit or failing to stop at a sign-the system activates the buzzer module to provide an immediate alert to the driver. This architecture ensures robust, real-time detection and alerting, making it suitable for deployment in intelligent transportation and driver assistance systems.

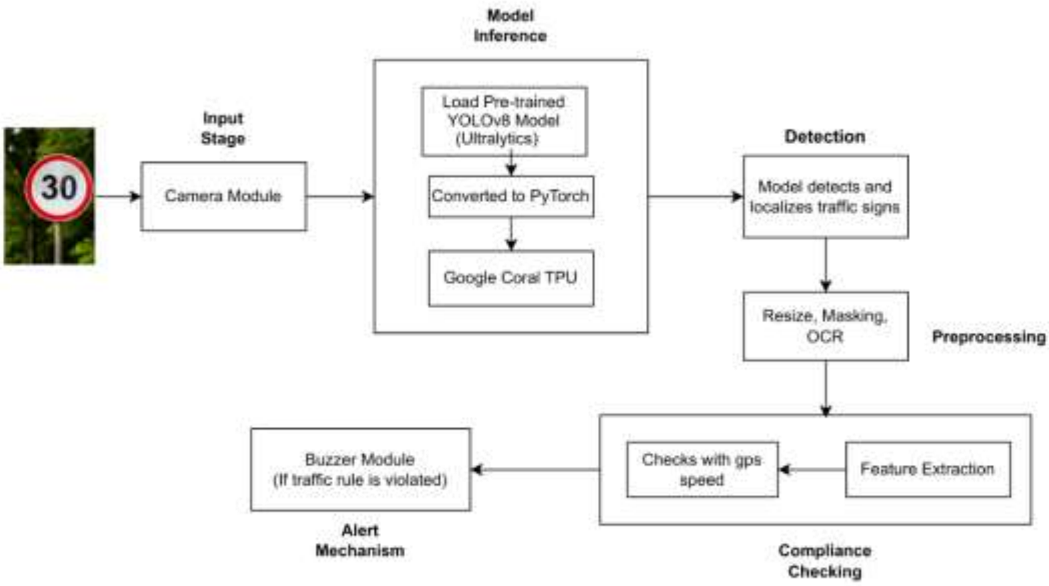

Figure 10. System Architecture

9.2 MATHEMATICAL MODEL

The purpose of this project is to detect and classify traffic signs in real time from video frames, monitor driving behavior using sensor data, and provide immediate alerts and recommendations to the driver. This detection and decision-making problem is addressed using supervised deep learning techniques (YOLOv8) and sensor data fusion.

The mathematical model of the system can be defined as a 7-tuple:

M = {I, F, D, A, C, R, O}

Where:
I = Input Set
F = Feature Extraction Functions
D = Dataset
A = Algorithms Used
C = Classification Function
R = Recommendations/Alert Function
O = Output Set

DEFINITIONS

1. I → Input Set

$I = \{x_1, x_2, ..., x_n\}$

Each x_i is a video frame captured by the camera, and may also include corresponding sensor readings (e.g., speed, acceleration, GPS location).

2. F → Feature Extraction

$F = f_1 \cup f_2$

f_1 = Deep features automatically extracted by the YOLOv8 model (edges, shapes, colors, etc.)

f_2 = Sensor features (vehicle speed, acceleration, GPS coordinates)

$F(x_i) = f_1(x_i) + f_2(x_i)$ = combined feature vector representing both visual and contextual information

3. D → Dataset

$D = \{(x_1, y_1), (x_2, y_2), ..., (x_m, y_m)\}$

Where x_i is a labeled video frame or image, and $y_i \in$ Traffic Sign Types = {Speed Limit, Stop, Traffic Light, Crosswalk, etc.}

4. A → Algorithms

$A = \{A_1, A_2\}$

A_1 = YOLOv8: Deep learning model for object detection and classification of traffic signs

A_2 = Sensor data processing algorithms for speed and behavior analysis

5. C → Classification Function

$C(F(x_i)) \rightarrow \hat{y}_i \in$ Traffic Sign Types

Where $\hat{y}_i$ is the predicted traffic sign class (or "None" if no sign is detected in the frame)

6. R → Recommendations/Alert Function

$R(\hat{y}_i, s_i) \rightarrow$ {Violation Alerts, Compliance Suggestions}

A mapping from detected sign and sensor data to actionable alerts (e.g., buzzer for speeding, stop sign ignored, red light violation) and driving recommendations

7. O → Output Set

$O = \{\hat{y}_i, R(\hat{y}_i, s_i)\}$

Output includes the predicted traffic sign class for each frame and any real-time alerts or recommendations issued to the driver

This mathematical model provides a formal structure for the system, encompassing all stages from input acquisition and feature extraction to detection, decision-making, and actionable output, ensuring robust and intelligent real-time traffic monitoring.

9.3 EXPLANATION OF THE PROCESS

9.3.1. The system continuously captures video frames from a camera mounted on the vehicle.

9.3.2. Each video frame is pre-processed using image processing techniques:

- The frame is resized to the input size required by the detection model
- Color normalization or conversion is applied to enhance the visibility of traffic signs
- Filtering techniques may be used to reduce noise and improve clarity

9.3.3. Features are automatically extracted from the pre-processed frame:

- The YOLOv8 deep learning model identifies and focuses on regions likely to contain traffic signs
- If text is present on a sign (such as a speed limit), optical character recognition (OCR) is applied to extract numerical information

9.3.4. The extracted features are passed to the trained YOLOv8 object detection model:

- The model processes the frame in real time, detecting and classifying traffic signs such as speed limit, stop, and traffic light

9.3.5. The model predicts the class of each detected traffic sign based on patterns learned during training:

- Each detection is assigned a class label (e.g., Speed Limit, Stop, Traffic Light) and a confidence score

9.3.6. The system cross-references the detected sign information with real-time sensor data:

- GPS and accelerometer readings are used to determine the vehicle’s speed, location, and driving behavior
- The system checks for compliance, such as whether the vehicle is exceeding the speed limit or failing to stop at a stop sign

9.3.7. The results - detected traffic signs, violation alerts, and driving recommendations - are displayed instantly to the user:

- Audible or visual alerts notify the driver of any violations
- All relevant information is shown in real time through the user interface or dashboard

CHAPTER 10

IMPLEMENTATION

IMPLEMENTATION

This project is implemented as a complete machine learning-based solution for real-time traffic sign detection and compliance monitoring. It combines image processing, deep feature extraction, model training, and embedded deployment to make the system robust and suitable for real-world intelligent transportation applications.

10.1 DATASET

- The dataset used in this project is sourced from established traffic sign collections such as GTSRB (German Traffic Sign Recognition Benchmark) and GTSDB (German Traffic Sign Detection Benchmark), as well as custom datasets tailored for local conditions.

- These datasets contain labeled images of various traffic sign types, including Speed Limit, Stop, Traffic Light, and Cross Walk, captured under diverse lighting, angles, and weather conditions. This diversity is essential for training a model that generalizes well to real-world scenarios.

- The dataset is divided into training and testing sets, typically with an 80:20 split. The training set enables the model to learn the unique visual patterns of each sign class, while the testing set evaluates the model’s ability to recognize signs it has not seen before.

- Each image is annotated with bounding boxes and class labels, serving as ground truth for supervised learning and enabling precise localization and classification during model training.

10.2 IMAGE PREPROCESSING AND FEATURE EXTRACTION

- Before feeding the images into the YOLOv8 detection model, several image processing steps are applied to ensure consistency and maximize detection accuracy:

- **Image Resizing and Normalization:**
  All images are resized to a standard input size required by YOLOv8 (e.g., 256x256 or 640x640 pixels), and pixel values are normalized. This ensures uniformity across the dataset and helps the model converge faster during training.

- **Data Augmentation:**
  Techniques such as rotation, flipping, scaling, and brightness adjustment are applied to artificially expand the dataset and improve the model's robustness to variations in real-world conditions, as recommended in recent research on YOLOv8-based traffic sign detection.

- **Annotation Preparation:**
  Images are paired with YOLO-format annotation files specifying bounding box coordinates and class labels, which are essential for supervised object detection training.

- **Automatic Feature Extraction:**
  The YOLOv8 model leverages a convolutional neural network to automatically extract relevant features-such as edges, shapes, colors, and textures-from the input images. This deep feature extraction replaces traditional hand-crafted features and enables the model to learn complex visual patterns that distinguish different traffic signs.

- This implementation approach ensures that the system can accurately detect and classify multiple types of traffic signs in real time, even under challenging conditions. The use of diverse datasets, robust preprocessing, and advanced feature extraction with YOLOv8 aligns with state-of-the-art practices in intelligent transportation systems and is supported by recent research and open-source projects.

10.3 SYSTEM FLOWCHART

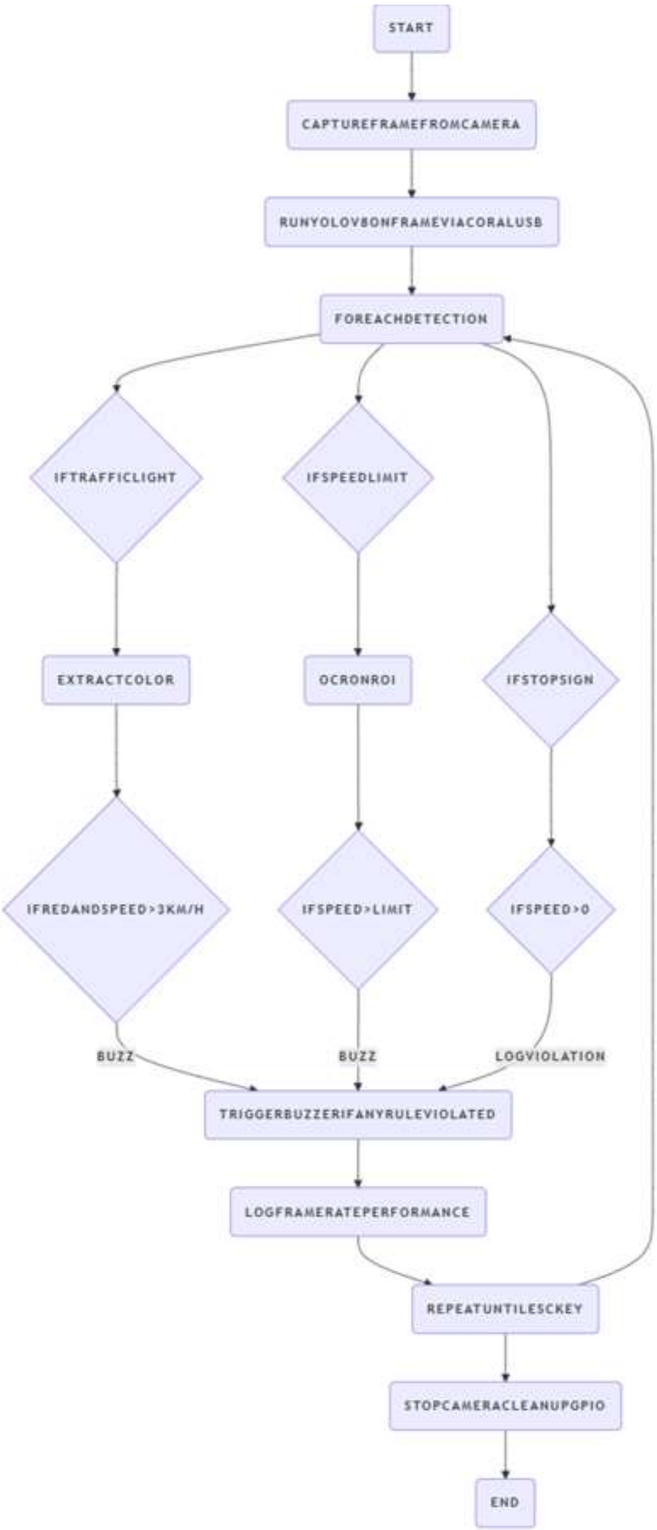

Figure 11. System Flowchart

10.4 ALGORITHM

Below is a pseudo algorithm for the devised traffic sign detection and compliance monitoring system:

Step 1 – Data Collection

a. Dataset: Traffic sign images and annotations sourced from public datasets such as GTSRB (German Traffic Sign Recognition Benchmark) and GTSDB (German Traffic Sign Detection Benchmark), as well as custom datasets for local conditions.
b. The dataset includes multiple traffic sign classes such as Speed Limit, Stop, Traffic Light, and Cross Walk, with bounding box annotations for supervised learning.
c. The dataset is split into training and testing sets to facilitate model learning and evaluation.

Step 2 – Data Preprocessing

a. Each image is standardized to a fixed size (e.g., 256x256 or 640x640 pixels) to match the input requirements of the YOLOv8 model.
b. Images are normalized and augmented using techniques such as rotation, flipping, scaling, and brightness adjustment to improve model robustness and generalization.
c. Annotation files are prepared in YOLO format, specifying bounding box coordinates and class labels for each image.

Step 3 – Feature Extraction

a. The YOLOv8 model automatically extracts deep features from each image, including edges, shapes, textures, and colors, through its convolutional neural network architecture.
b. These learned features are used by the model to detect and classify traffic signs in a wide variety of real-world conditions.

Step 4 – Model Training

a. The dataset is divided into training and testing subsets.
b. The YOLOv8 object detection model is trained on the labeled training data, learning to predict both the class and location (bounding box) of each traffic sign.

Step 5 – Real-Time Detection and Classification

a. The system receives live video frames from the vehicle-mounted camera and preprocesses them as described above.

b. The trained YOLOv8 model analyzes each frame, detecting and classifying all visible traffic signs in real time.

Step 6 – Compliance Monitoring and Alert Generation

a. The system integrates real-time sensor data, such as GPS speed and accelerometer readings, with the detected sign information.

b. It checks for compliance (e.g., whether the vehicle is exceeding the speed limit or running a red light) and immediately generates alerts (audible or visual) if a violation is detected.

c. All detection events and violations are logged for further analysis and reporting.

This step-by-step algorithm ensures robust, real-time detection and compliance monitoring, making the system suitable for intelligent transportation and driver assistance applications.

10.5 MODEL TRAINING AND TESTING

The YOLOv8 model was trained on a diverse, annotated dataset of traffic sign images, using supervised learning to optimize both localization and classification. The training process involved standard data augmentation techniques to improve generalization, as well as careful tuning of hyperparameters such as learning rate, batch size, and number of epochs. The dataset was split into training and testing subsets to evaluate the model's performance on unseen data. During training, the model learned to detect and classify multiple types of traffic signs, including Speed Limit, Stop, Traffic Light, and Cross Walk, under varying lighting and environmental conditions.

Testing was conducted using the reserved test set, with key evaluation metrics including precision, recall, mean average precision (mAP), and frames per second (FPS). The YOLOv8-based system achieved a precision of approximately 80.6%, recall of 65.7%, and mAP50 of 77.2% on the test data, demonstrating robust detection capability across multiple sign types. These results indicate the model's strong ability to minimize false positives while maintaining satisfactory sensitivity to true detections, making it suitable for real-world deployment in intelligent transportation systems. The system also demonstrated real-time performance, processing frames at rates suitable for live vehicle applications.

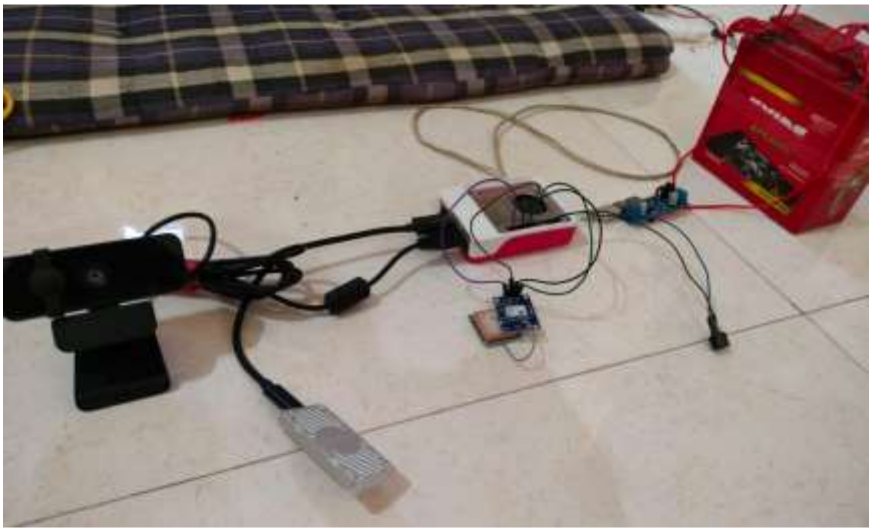

Figure 12. Final Hardware Setup

10.6 WORKING RESULTS AND PERFORMANCE ANALYSIS

Detection Accuracy

- The trained YOLOv8 model consistently identified and classified traffic signs in real-time video streams, even under challenging conditions such as small sign size, occlusions, and varying lighting.
- Class-wise analysis showed high precision and recall for Speed Limit and Stop signs, while performance for Traffic Light detection was slightly lower due to visual complexity and environmental factors.
- The model's mAP50-95 of approximately 65% reflects its effectiveness in localizing signs with high overlap accuracy, as required for robust autonomous and assisted driving systems.

Real-Time Performance

- The system achieved an average processing speed of about 20 frames per second (FPS) on standard embedded hardware, confirming its suitability for real-time deployment in vehicles.
- The latency was low enough to enable timely alerts and compliance checks, a critical requirement for driver assistance and safety applications.

Example Outputs

- The system's interface displayed live video feeds with bounding boxes and class labels over detected signs, along with confidence scores.

- Detection logs included timestamped records of detected signs, vehicle speed, and GPS location, supporting compliance monitoring and post-trip analysis.
- Alerts were triggered for violations such as speeding or failing to stop at a detected stop sign, providing immediate feedback to the driver.

Figure 13. Current Speed Limit Display on Road

Class-wise Performance Metrics and Analysis

The table above presents the class-wise performance metrics for the YOLOv8-based traffic sign detection system, specifically highlighting precision, recall, and F1 score for each major traffic sign class.

- **Traffic Light:**
  The system achieved a precision of 0.771 and a recall of 0.675 for Traffic Light detection, resulting in an F1 score of 0.719. This indicates that while the model is fairly precise in identifying traffic lights, it tends to miss some true instances, as reflected by the lower recall. The moderate F1 score suggests there is room for improvement, particularly in increasing recall through enhanced data augmentation or additional training samples for this class.

- **Speed Limit:**
  The model performed exceptionally well on Speed Limit signs, with a precision of 0.979 and a recall of 0.996, yielding an F1 score of 0.987. These high values

demonstrate the model's strong ability to both correctly identify and rarely miss speed limit signs, making it highly reliable for speed compliance monitoring.

- **Cross Walk:**
  For Cross Walk detection, the model achieved a precision of 0.895 and a recall of 0.981, with an F1 score of 0.936. The high recall indicates that the system detects most crosswalk signs, though the slightly lower precision suggests occasional false positives. This balance is suitable for safety-critical applications where missing a crosswalk could have serious consequences.

- **Stop:**
  The Stop sign class achieved near-perfect results, with a precision of 0.962, a recall of 1.000, and an F1 score of 0.980. This means that the system successfully detected all Stop signs in the test set and made very few incorrect predictions, reflecting the distinctiveness of Stop signs and the model's excellent learning of this class.

Overall, these results confirm that the system is highly effective for critical traffic sign classes, particularly Speed Limit and Stop, while also performing well on Cross Walk and Traffic Light detection.

Table: Performance Metrics Class-wise

Class	Precision	Recall	F1 Score
Traffic_Light	0.771	0.675	0.719
Speed_Limit	0.979	0.996	0.987
Cross_Walk	0.895	0.981	0.936
Stop	0.962	1.000	0.980

Figure 14. Class-wise Performance Metrics of YOLOv8 Traffic Sign Detection Model.

Traffic Sign Impact on Speed Measurement

- Traffic Sign Variability:
  - The dataset includes various traffic sign types: Yellow, Speed Sign, and Red.
- **Speed Observations:**
  - Recorded speeds range from 25 to 60:
    - Yellow Signs: Speeds of 30, 30, 38, and 53 observed.

        - Red Signs: Speeds of 25 (two entries).
        - Speed Signs: Observed speeds include 38, 53, and 60.
- **Geographical Coordinates:**
    - **Latitude:**
        - Ranges from 17.565085 (consistent for Yellow and Speed Signs) to 76.992779.
    - **Longitude:**
        - Limited variation near coordinates 81.755793 and 75.047816.
- **Data Distribution:**
    - The majority of the entries are concentrated around Yellow signs at the same latitude and longitude, suggesting a common area of measurement.
- **Conclusions:**
    - The observed speeds might indicate the influence of traffic sign colors on driver behavior, with Yellow signs potentially leading to higher speeds compared to Red signs, which show slower speed entries.
- **Further Analysis:**
    - It may be beneficial to examine additional variables (e.g., time of day, weather conditions) impacting the observed speeds for a comprehensive analysis.

The image displays a table containing information about various traffic signs, their associated speed limits, and their geographical coordinates (latitude and longitude). There are multiple entries for different traffic sign types, including "Yellow" and "Red" signs indicating speed limits, alongside specific "Speed Sign" notifications. The latitude and longitude values suggest that the signs are located in different geographic regions, specifically in areas identified by the coordinates provided.

Traffic_Sign	Speed	Latitude	Longitude
Yellow	30	17.565085	81.755793
Yellow	30	17.565085	81.755793
Yellow	38	17.565085	81.755793
Speed Sign 30	38	17.565085	81.755793
Red	25	76.992779	75.047816
Red	3	76.992779	75.047816
Yellow	53	88.518694	38.51982
Speed Sign 30	53	88.518694	38.51982
Speed Sign 40	60	88.518694	38.51982

Figure 15. Traffic Sign Data Overview

CHAPTER 11

OTHER SPECIFICATIONS

11.1 ADVANTAGES

1. The system provides quick and automatic traffic sign detection using real-time video feeds, significantly reducing the time and effort required for manual recognition by drivers.

2. It is cost-effective and affordable, especially for small-scale vehicle owners, as it eliminates the need for expensive navigation systems or additional hardware.

3. The user interface is simple and accessible, allowing drivers with basic digital skills to easily interact with the system and receive timely alerts.

4.The system offers personalized driving recommendations based on detected traffic signs, improving compliance with road regulations and enhancing overall safety.

5. It supports safer driving practices by providing immediate feedback on traffic sign recognition, helping to prevent accidents and violations.

6. Real-time processing allows for immediate decision-making, which is particularly beneficial during critical driving situations or in unfamiliar areas.

7. The system can be accessed from various vehicle types, requiring only a device with a camera and processing capabilities, making it versatile for different users.

8. The model is scalable and can be expanded to include more traffic sign types or additional features, ensuring its relevance as traffic regulations evolve.

9. The system continuously improves with more data and user feedback, leveraging machine learning to enhance accuracy and reliability over time.

10. It reduces dependency on external navigation aids or traffic monitoring services, empowering drivers to become more self-reliant in navigating their routes safely.

11.2 LIMITATIONS

1. The system's accuracy may be affected by adverse weather conditions, such as heavy rain or fog, which can hinder the visibility of traffic signs and reduce detection performance.

2. It requires a stable internet connection for real-time processing and updates, which may not be available in remote or rural areas, limiting accessibility for some users.

3. The model's performance is heavily reliant on the quality and diversity of the training dataset; if the dataset does not include certain traffic sign types or variations, the system may struggle to recognize them accurately.

4. The system may face challenges in recognizing partially obscured or damaged traffic signs, which can lead to misinterpretation and potential safety risks for drivers.

11.3 APPLICATIONS

1. Autonomous Vehicles: The system can be integrated into self-driving cars to enhance navigation and ensure compliance with traffic regulations by accurately detecting and interpreting traffic signs.
2. Advanced Driver Assistance Systems (ADAS): It can be utilized in ADAS to provide real-time alerts to drivers about traffic signs, improving safety and reducing the likelihood of accidents.
3. Fleet Management: Companies can implement the system in their fleet vehicles to monitor driver behavior, ensure compliance with traffic laws, and optimize route planning based on detected traffic signs.
4. Driver Training Programs: The technology can be used in simulators or training vehicles to educate new drivers about traffic signs and safe driving practices, enhancing their learning experience.
5. Traffic Monitoring and Management: Authorities can use the system to gather data on traffic sign visibility and compliance, aiding in urban planning and traffic management strategies.

6. Insurance Companies: The system can assist insurers in assessing driver behavior and risk levels, potentially leading to more accurate premium calculations based on real-time driving data.
7. Mobile Navigation Applications: Integration into navigation apps can provide users with enhanced features, such as real-time traffic sign recognition and alerts, improving overall navigation accuracy.
8. Research and Development: The technology can be employed in academic and industry research to study traffic patterns, driver behavior, and the effectiveness of traffic sign designs.
9. Public Transportation Systems: Buses and taxis can utilize the system to ensure compliance with traffic regulations, enhancing passenger safety and improving operational efficiency.
10. Smart City Initiatives: The system can contribute to the development of smart city solutions by integrating with traffic management systems to optimize traffic flow and enhance urban mobility.

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CHAPTER 12

CONCLUSION AND FUTURE SCOPE

12.1 CONCLUSION

In conclusion, the Traffic Sign Detection System represents a significant advancement in the field of intelligent transportation systems, leveraging machine learning and deep learning techniques to enhance road safety and improve traffic management. The system's ability to accurately detect and classify traffic signs in real-time under varying environmental conditions demonstrates its robustness and adaptability. By integrating advanced algorithms and utilizing a comprehensive dataset, the project not only addresses the critical need for reliable traffic sign recognition but also sets the foundation for future enhancements, such as the incorporation of additional sensors and the development of user-friendly applications. The proactive feedback mechanisms provided by the system can significantly contribute to safer driving behaviors and more efficient navigation. As the project evolves, it holds the potential to play a pivotal role in the broader context of autonomous vehicle technology and smart city initiatives, ultimately fostering a safer and more informed driving community.

12.2 FUTURE SCOPE

The future scope of the Traffic Sign Detection System includes the incorporation of advanced machine learning models and the integration with existing vehicle systems, such as On-Board Diagnostics (OBD-II), to enhance prediction accuracy and provide deeper insights into vehicle performance. Leveraging cloud computing for data storage and processing will enable the handling of broader datasets, while the development of user-friendly mobile applications can provide real-time feedback to drivers, promoting safer driving habits. Additionally, collaborating with traffic management systems to create adaptive traffic solutions, expanding the system's applicability to diverse environments, and integrating additional sensors like LiDAR will improve robustness. Continuous learning mechanisms will allow the model to adapt to new traffic signs and conditions, and ongoing research will contribute valuable insights into the impact of these systems on road safety and traffic management, ultimately fostering the evolution of smart transportation systems.

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We are happy to confirm our sponsorship for the final year project of the following students from your institute Nutan Maharashtra Institute of Engineering Technology-NMIET

- **Sujal Koli, BE ETC**
- **Saurabh Autade, BE ETC**
- **Nishad Harsulkar, BE ETC**

We are pleased to be part of their academic journey and are eager to see the innovative ideas they will bring forth in their project. Our organization is committed to supporting their learning process, helping them gain valuable experience and preparing them for successful careers in the industry.

We wish the students and your organization in your future endeavors

Yours Truly,

For Hinduja Tech Ltd.,

Jayawanthi Shankar Rao
General Manager - HR

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S.No.	Item Description	Price (INR)
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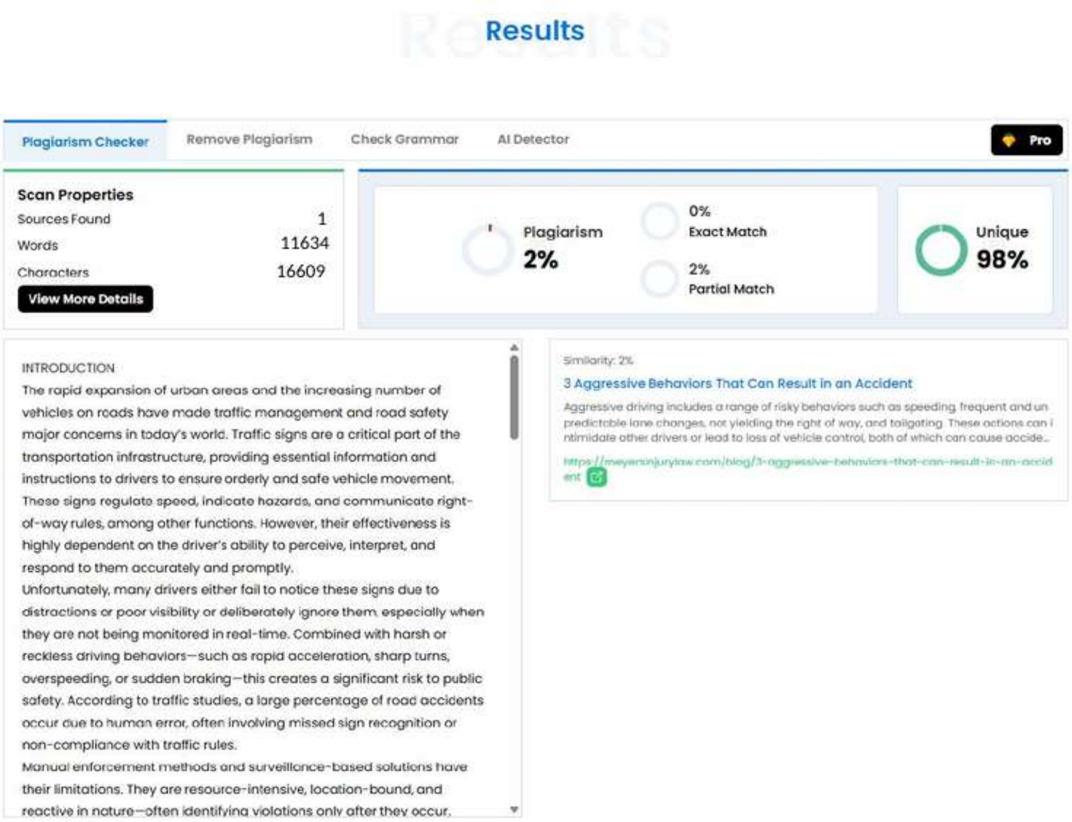
4	MPU6050 Accelerometer	250
5	Google Coral TPU	10600
6	Battery	3000
7	Raspberry Pi Micro SD Card 64GB/128GB	1100
8	Raspberry Pi Case with Fan	990
9	GPS Neo8M Sensor	650
10	LM2596 DC-DC Adjustable Converter	500
11	USB to Type-C Cable	200
Total		**25775**

REPORT PLAGERISM



ANNEXURE

Research Paper :

Hello.

Here is submission summary.

Track Name: Cognitive Computing and Machine Learning

Paper ID: 1109

Paper Title: Edge-Enabled Deep Learning Architecture for Traffic Sign Recognition and Driver Behavior Analysis

Abstract:
A real-time traffic sign identification and recognition system that combines deep learning with edge computing technology is presented in this study. The system leverages a custom-trained YOLOv8n model, achieving 90% accuracy on a traffic sign dataset collected from the Pune region, including classes such as 'speed_limit', 'traffic_signal', 'stop_sign', and 'cross_walk'. By deploying the model on edge devices, the system ensures low-latency processing, making it suitable for real-world scenarios like in-vehicle assistance and smart traffic monitoring. The recognized traffic signs are further analyzed in comparison with real-time speed data to generate actionable outputs, such as alerts or logs, enhancing driver awareness and promoting road safety. This approach not only aids in accident prevention and detection of harsh driving behaviour but also opens pathways for broader applications in Smart City initiatives, ADAS support systems, and intelligent fleet management. The study demonstrates that integrating computer vision and edge AI can significantly improve traffic flow, safety, and urban mobility infrastructure.

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Authors:
- sarikapatil1211@gmail.com (Primary)
- nishadharsulkar@gmail.com
- saurabhautade18@gmail.com
- sujalkoli03@gmail.com
- sbpatil12@gmail.com

Secondary Subject Areas: Not Entered

Submission Files:
Research_Paper_Final_Edge-Enabled Deep Learning Architecture.pdf (441 Kb, Thu, 05 Jun 2025 10:48:12 GMT)

Submission Questions Response: Not Entered

Thanks,
CMT Team.

Review Paper:

Paper id: IJNRD_307545 – Acceptance Notification and Review Result.
TITLE - Advancements and Challenges in Deep Learning-Based Traffic Sign Detection and Recognition: A Comprehensive Review.
Your Paper Accepted Complete Below Process and Publish it.
Your Email id: sarikapatil1211@gmail.com Track your paper : Click Here

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