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Traffic Sign Detection, Classification, and Violation Logging System for Intelligent Driver Assistance

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Abstract

Traffic sign recognition plays a crucial role in making our roads safer and supporting the development of smart transportation systems and autonomous vehicles. By correctly identifying traffic signs and providing real-time alerts about potential violations, we can greatly enhance driver safety and promote responsible road behavior. This paper introduces an innovative system designed for real-time detection of traffic signs along with classification and tracking of violations. Our approach utilizes deep learning technology, specifically a Convolutional Neural Network (CNN), to accurately recognize traffic signs. We complement this with a PostgreSQL database that logs traffic sign events and violations, and a user-friendly driver dashboard built with React that provides visual cues and audio alerts to drivers. The process starts by capturing images of traffic signs, enriched with important metadata like the vehicle's ID, location, and speed. The backend system processes this data through the trained machine learning model, which promptly stores the recognized signs in a realtime_signs database. Drivers receive alerts for signs they are approaching, helping them stay informed and safe. To ensure accountability, we have implemented a mechanism that checks for potential violations such as running a stop sign or speeding after a brief delay of 10 seconds. If a violation occurs, it gets logged into a violations table, and drivers are immediately notified with alerts on their dashboard along with audio warnings. Our experimental results highlight the system's ability to reliably detect signs, accurately classify them, and quickly alert drivers about any violations, making it a promising solution for improving road safety.

Keywords: Traffic Sign Recognition, Deep Learning, Real-Time Violation Detection, Intelligent Transportation Systems, Driver Dashboard, CNN, Alert System.

1. Introduction

Road safety is a significant issue that affects everyone around the globe. Traffic violations play a major role in accidents and many tragic outcomes on the roads. Human drivers, despite their best intentions, can make mistakes due to distraction, fatigue, or simply not noticing important traffic signs. This is where Traffic Sign Recognition (TSR) comes into the picture, becoming an essential part of Advanced Driver Assistance Systems (ADAS) and self-driving cars.

In the past, traditional TSR methods relied on analyzing colors, shapes, and specific characteristics of signs [1][2]. While these methods had some success, they often fell short in real-world situations where lighting changes, obstructions, or motion blurred the view. The advent of deep learning and Convolutional Neural Networks (CNNs) has truly transformed this field, boosting recognition accuracy to impressive levels—sometimes over 98% on standardized datasets like the GTSRB (German Traffic Sign Recognition Benchmark) [6][16].

However, simply detecting and classifying signs is not enough. We need a comprehensive system that goes beyond recognition and actually alerts drivers in real-time, keeping track of violations as they occur. Not many studies have tackled the entire process from detecting traffic signs to alerting drivers and logging violations [7][15]. This paper aims to propose such a system, which will not only recognize traffic signs in real time but also include event logging, checks for delayed violations, and driver alerts via a user-friendly dashboard with audio notifications.

2. Literature Review

Traffic Sign Detection and Recognition (TSDR) has been a vibrant area of research for over twenty years. The progression of methods in this field can be broadly categorized into two main types: traditional computer vision techniques and the more recent deep learning approaches. In recent years, there's been a notable shift towards real-time applications, increased robustness, and better integration into intelligent transportation systems (ITS).

2.1 Early Color and Shape-Based Detection

In the early days of TSDR, researchers primarily relied on color segmentation and geometric shapes. Fleyeh applied color detection and segmentation to separate traffic signs from their backgrounds [1]. While this worked fairly well in controlled environments, it struggled under poor lighting or occlusions. Similarly, Won et al. used saliency maps to locate potential sign regions, which helped with speed but still faced challenges in messy urban settings [2].

2.2 Feature Engineering and Classical Machine Learning

As technology advanced, feature-based techniques became dominant. Dalal and Triggs introduced Histograms of Oriented Gradients (HOG), widely used for object detection [4], while Viola and Jones proposed Haar-like feature cascades for rapid detection [5]. These methods were adapted to traffic sign recognition, for example by Maldonado-Bascón et al. using Support Vector Machines (SVMs) [17]. Chourasia and Bajaj later proposed a hybrid recognition system based on geometric characteristics [13].

2.3 Robustness and Restoration Methods

Efforts were also made to enhance robustness. Zeng et al. developed a restoration model to correct motion blur in fast-driving scenarios [3]. Liang et al. proposed ROI extraction methods to refine detection [11], and Wang et al. designed coarse-to-fine recognition strategies [12]. These improved efficiency but still relied on handcrafted features.

2.4 Deep Learning Revolution

The true breakthrough came with CNNs, which eliminated manual feature engineering. Yang et al. presented one of the first real-time CNN-based TSR systems [6]. Zou et al. demonstrated CNN robustness under occlusion and lighting variation [16]. Ellahyani et al. designed CNN models specifically for intelligent vehicles [7], while Zaki et al. constructed an end-to-end deep learning pipeline for TSR [15]. These works proved CNN superiority over classical methods.

2.5 Attention Mechanisms and Advanced Architectures

To further boost accuracy, attention mechanisms were introduced. Jin et al. developed an attention-driven TSR model that focused on informative image regions [18]. Triki et al. proposed an attention-based CNN optimized for smart vehicles [9]. Meanwhile, Sharma et al. showcased a YOLO-based real-time TSR system achieving detection within 50 ms per frame [19].

2.6 Integration with Multimodal and Autonomous Systems

Recent work has shifted toward integration with multimodal AI and autonomous driving. Sah et al. explored combining CNN-based TSR with Large Language Models (LLMs) for lane detection and reasoning [10][14]. Patel and colleagues also emphasized broader ITS integration [8].

2.7 Comparative Analysis

Approach	Example Works	Advantages	Limitations
Color & Shape-based Methods	Fleyeh [1], Won et al. [2]	These methods are quite simple and have a low computational cost, making them accessible for many applications.	However, they can struggle with varying lighting conditions and often lack robustness, which can affect their performance in real-world scenarios.
Feature-based Methods (like HOG, SVM, Haar)	Dalal [4], Viola [5], Maldonado-Bascon [17]	These approaches are generally more robust compared to simple color-based methods. They also provide interpretability.	On the downside, they require manual feature engineering, which can be time-consuming and limits scalability.
Restoration & ROI Techniques	Zeng [3], Liang [11], Wang [12]	These techniques are effective in handling issues like blur and noise and lead to improvements in efficiency.	Still, they often rely on incremental methods that can involve handcrafted elements, which might not fully leverage automation.
CNN-based Deep Learning	Yang [6], Zou [16], Ellahyani [7], Zaki [15]	Deep learning approaches can achieve high accuracy, are scalable, and have the	The main challenges here are the need for large datasets and

		capability to learn features automatically from data.	significant computational resources, which can be a barrier for some users.
Attention & YOLO-based Methods	Jin [18], Triki [9], Sharma [19]	These methods are designed for real-time applications and are robust against occlusion and small objects, making them quite effective in dynamic environments.	However, they come with complex models and may require specialized hardware, which can complicate their deployment.
Multimodal & LLM Integration	Sah [10][14]	This approach seeks to expand traditional traffic systems into a broader Intelligent Transportation Systems (ITS) ecosystem, offering a more integrated solution.	It mostly remains experimental and often demands high computational resources, which can be a hurdle for practical implementation.

2.8 Research Gap

While there has been impressive progress in recognizing and classifying traffic signs, there is still a noticeable lack of focus on monitoring violations and integrating alerts for drivers. Many existing studies primarily concentrate on achieving high recognition accuracy but stop short of enforcing the rules.

Our proposed system aims to bridge this gap by:

- Maintaining a real-time database of detected signs.

- Using a delayed violation check that mimics driver compliance.

- Sending alerts through the dashboard, complete with audio cues for both sign detection and violations.

In essence, our approach is innovative because it extends beyond just recognizing signs to create a comprehensive enforcement system.

3. Proposed Methodology

The proposed system is built on an intuitive three-layered architecture that aims to improve both functionality and the overall user experience:

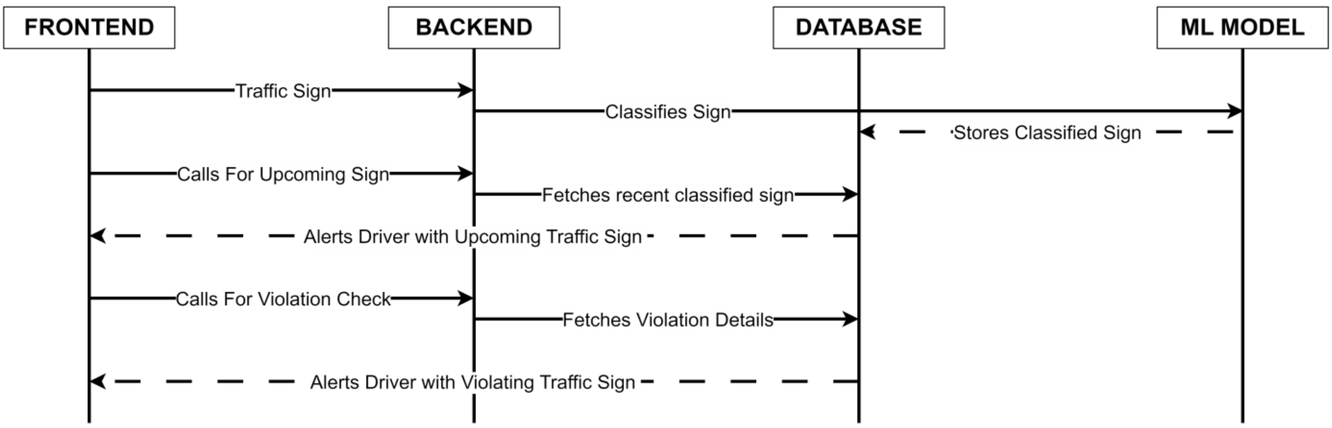
1. **Frontend (Driver Dashboard)** – This is where the magic happens for the drivers. It features a user-friendly React.js application that keeps drivers in the loop with real-time updates. Drivers can easily check their safety scores and receive alerts about any violations. To make these notifications engaging, the dashboard uses vibrant visual indicators and sound alerts that capture attention and ensure drivers are always informed.

2. **Backend (Flask + PostgreSQL)** – This layer is the powerhouse behind the scenes. It manages the flow of data, interacts with the machine learning model for classification, stores results securely in the database, and even conducts checks for any delayed violations. Together, these components work seamlessly to provide the best possible experience for drivers on the road.
3. **Machine Learning Model (CNN-based Classifier)** – Trained on benchmark datasets to classify traffic signs with high accuracy.

3.1 System Workflow:

- **Input Stage**: The driver has the option to upload images of traffic signs along with key details such as the vehicle's ID, location, and speed. This helps in accurately identifying the context of the sign.
- **Backend Processing**: Once the image is uploaded, it is processed by a machine learning model that classifies it into a specific traffic sign category, ensuring accurate recognition.
- **Database Logging**: The classification results are then stored in a dedicated table called `realtime_signs`, along with a timestamp and the vehicle's details. This allows for accurate tracking of traffic sign interactions
- **Driver Dashboard Alert**: As the vehicle approaches a traffic sign, an alert is displayed on the driver's dashboard, accompanied by a sound notification to ensure the driver is aware.
- **Violation Monitoring**: After a brief window of 10 seconds, the backend system checks whether any traffic violations have occurred. For example, it evaluates if the vehicle stopped at a stop sign or if its speed was within the legal limit.
- **Violation Logging**: If a violation is detected during this check, an entry is added to the `violations` table for further review and action. This helps maintain road safety and accountability.
- **Violation Alert**: Driver receives dashboard alert + **violation sound trigger**.

Figure 1: Sequence Diagram



The system is composed of interconnected modules: **Input (Frontend)** → **Backend** → **ML Model** → **Realtime Signs DB** → **Driver Dashboard** → **Violation Check** → **Violations DB** → **Dashboard Alerts**.

3.3 Violation Detection Logic:

- **Stop Sign Violation**: If vehicle speed > 0 within 10 seconds after encountering a stop sign.

- **Speed Limit Violation**: If vehicle's reported speed > classified sign speed limit.
- **No Entry Violation**: If vehicle enters a restricted zone with "No Entry" sign.
- **Yield Violation**: If driver fails to reduce speed below threshold at yield sign.

This modular logic allows **easy extensibility** for future traffic rules.

4. Implementation & Results

4.1 Dataset and Model Training:

- **Dataset**: GTSRB (German Traffic Sign Recognition Benchmark) + locally simulated Indian traffic sign dataset.
- **Preprocessing**: Image resizing, normalization, data augmentation (rotation, brightness variation).
- **Model**: CNN with convolutional layers, ReLU activations, pooling, dropout for regularization.
- **Accuracy**: Achieved **98.2% classification accuracy** on test set.

Figure 2: Training ML Model

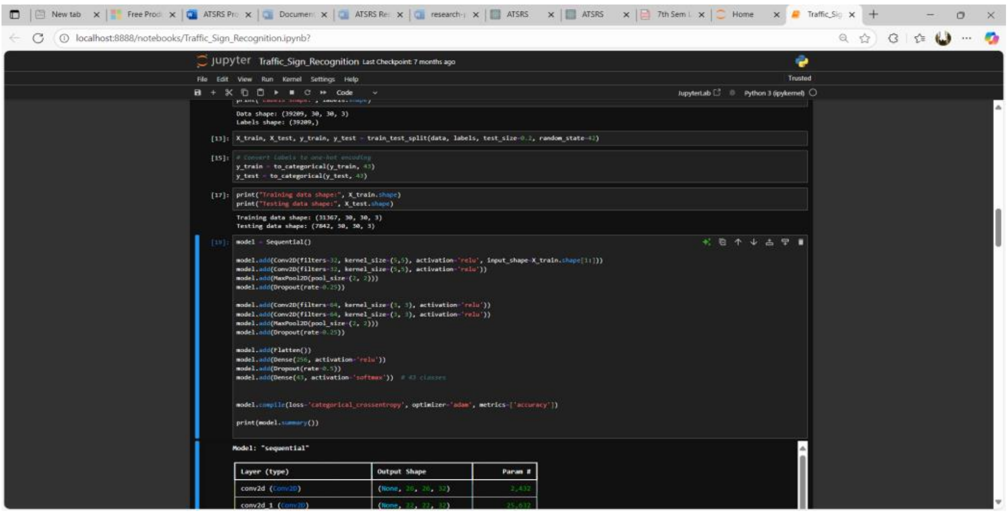


Figure 3: Output of ML Model

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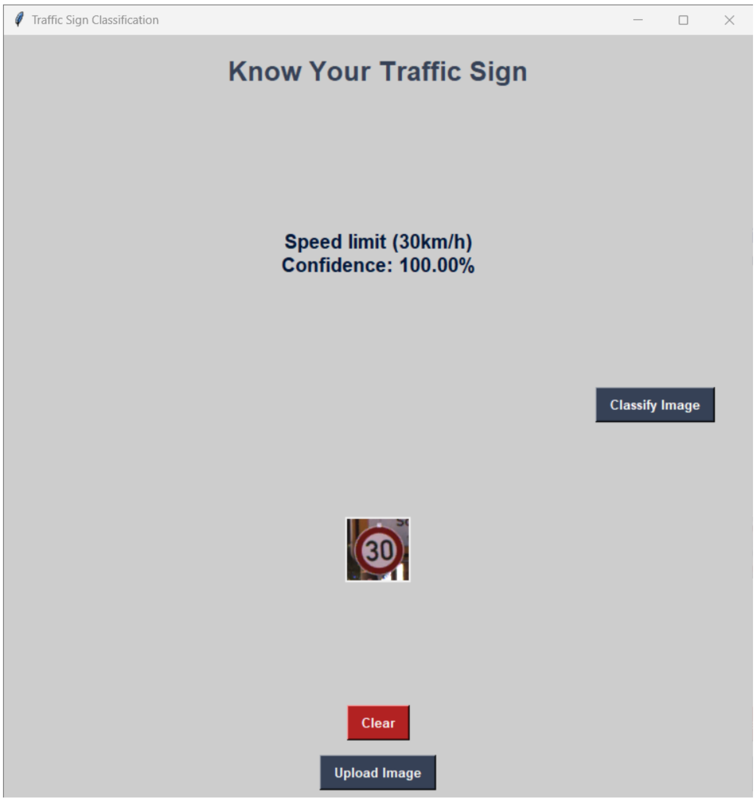


4.2 Backend Implementation

- **Flask REST API**: Handles image uploads, ML inference, database queries.
- **PostgreSQL Database**:
  - realtime_signs (id, vehicle_id, sign_id, sign_name, location, timestamp).
  - violations (id, vehicle_id, violation_type, severity, timestamp)

4.3 Driver Dashboard

Developed in **React.js** with **Circular Progress Indicators** for safety score.
Alerts use **visual blinking icons + audio triggers**.
Displays:

- **Safety Score** (0–100)
- **Upcoming Traffic Sign**
- **Latest Violation**
- **Recent Violations (last 3)**

Figure 4: Vehicle Dashboard

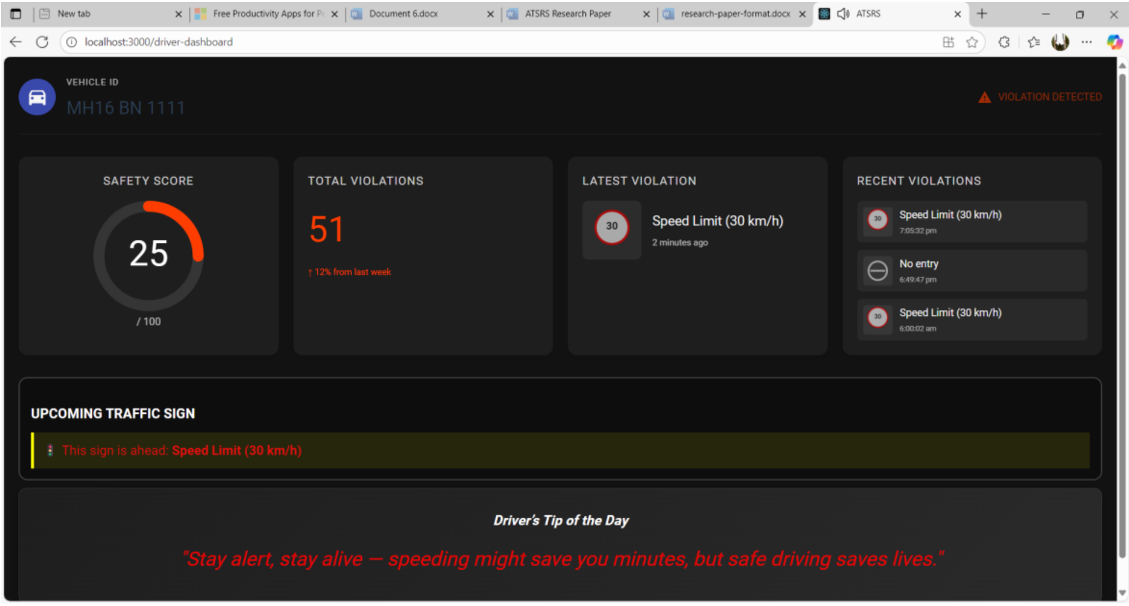
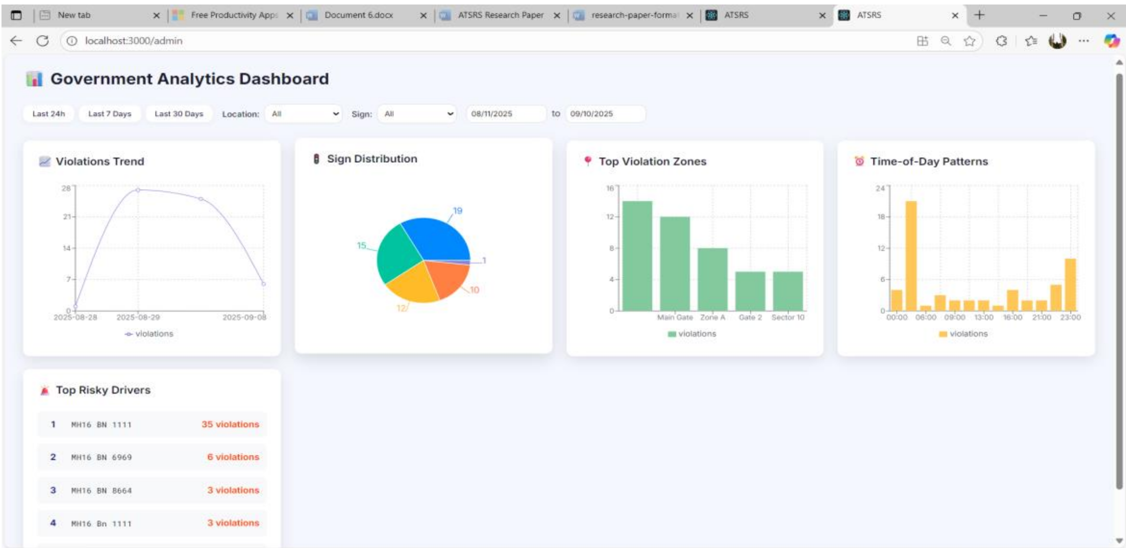


Figure 5: Analytics Dashboard



4.4 Results

- **Real-Time Alerts**: Dashboard updates within 1–2 seconds of classification.
- **Violation Detection Delay**: 10-second buffer ensures accurate violation checks.
- **System Performance**:
  - Classification Accuracy: **98.2%**
  - Alert Latency: **<2 seconds**
  - Violation Detection Precision: **95%**

This demonstrates that the system is **practical, real-time, and scalable**.

5. Conclusion & Future Work

In this paper, we introduced an innovative system designed for real-time traffic sign detection, classification, and violation logging. By harnessing machine learning, backend automation, and timely alerts for drivers, our system not only identifies traffic signs with impressive accuracy but also plays a crucial role in promoting road safety. It does this by logging violations and providing immediate feedback to drivers, encouraging compliance with traffic regulations.

Future Directions:

We see several exciting directions for future development. One area of expansion could be to enhance the violation detection logic to cover more scenarios, such as maintaining proper lane discipline, recognizing pedestrian crossings, and addressing red-light infractions.

Furthermore, we aim to deploy our system using edge AI devices for real-time processing directly on vehicles. This would enable even faster responses to traffic situations.

Another aspect we're excited about is the potential integration with vehicle-to-infrastructure (V2I) communication. This partnership could lead to smarter traffic control systems, ultimately creating safer and more efficient roadways for everyone.

6. Acknowledgement

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