Traffic Sign Board Recognition and Voice Alert System using Convolutional Neural Network

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Abstract: The AI-Driven Self-Assessment and Proctoring System is an innovative process whose goal is to change the face of online assessments using the MERN stack and other sophisticated AI technologies. The platform enables teachers to dynamically create multiple-choice questions (MCQs) with large language models (LLMs), thus guaranteeing that the questions are relevant on one end and diverse on the other based on the specified topics. The students, powered by their unique room code, have the opportunity to seamlessly enter an assessment that goes in parallel lines with all the other purposes of being secure and user-friendly. Further, a self-assessment module is one more feature of the system that allows students to qualify their knowledge on their own. Students may select topics of interest for AI-curated questions tailored specifically to their learning needs, followed by a deep assessment of performance focusing on areas to be improved. The integrity of the exam is secured with the AI-malmaking-detection mechanism that at every instance watches the action of the candidates via the device's camera while detecting any suspicious activity and stopping cheating in its tracks. In this way, the system promises a secure, trustworthy, and efficient assessment ecosystem for the teacher as well as the students. On top of question generation for proctoring exams and grading, the system would help with relieving teachers' workload while engaging the students in the process of learning. This AI concept employs a scalable assessment that is adaptable to the need for educational institutions to change and modernize their assessment practices. This technology-enabled solution guarantees equal opportunities in learning, hence becoming a giant leap towards the future of education.

Keywords: AI-driven, malpractice detection, automated question generation, Self-assessment module, MERN stack, Dynamic test creation, Large Language Models(LLMs).

1 Introduction

1.1 Background Information

In order to maintain orderly traffic flow and improve the safety of both drivers and pedestrians, traffic signs are essential parts of contemporary road infrastructure. They transmit important information like warnings, bans, speed limits, and road conditions.

However, because of differences in design, ambient factors, and driver unfamiliarity with certain indicators, it can be difficult to recognise and understand these indications effectively. In rural or isolated areas, where traffic signs may be inconsistent or difficult to see, this problem is especially common.

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1.2 Research Problem or Question

.Despite the progress in TSR systems, existing approaches often face challenges related to:

- Variability in accuracy over a range of environmental and illumination circumstances
- High computational costs associated with deep learning models.
- Difficulties in recognizing traffic signs in rural or underdeveloped areas.
- Limited accessibility of real-time assistance for drivers unfamiliar with specific road signs.

This research addresses the question:

"How can a hybrid CNN-RF approach improve the accuracy.

and efficiency of traffic sign recognition while ensuring real-time voice-based assistance for drivers?"

1.3 Significance of the Research

The proposed system aims to bridge the gap between machine learning-based traffic sign recognition and practical road safety applications. Key contributions of this research include:

1. Development of a hybrid CNN-RF model that enhances feature extraction and classification accuracy for traffic sign recognition.
2. Implementation of a real-time voice alert system, making it accessible to drivers, including those with visual impairments or unfamiliarity with traffic regulations.
3. Adaptability to diverse environments by utilizing preprocessing techniques and data augmentation to handle variable lighting, occlusion, and weather conditions.
4. Potential integration with advanced driver-assistance systems (ADAS), contributing to safer autonomous driving solutions.

This research lays the foundation for enhanced road safety and a more intelligent traffic monitoring system, making it practical for smart cities and transportation networks.

2 Literature Review

2.1 Overview of relevant literature

Several studies have explored traffic sign recognition (TSR) systems using machine learning and deep learning techniques. Pupezescu and Pupezescu (2022) proposed a semi-supervised TSR system, improving classification accuracy through feature optimization [1]. Jiao et al. (2009) developed a multi-class TSR framework integrating asymmetric and symmetric feature extraction, addressing real-time detection challenges [2]. Qiao et al. (2017) enhanced traffic sign recognition by optimizing Faster R-CNN-based models, improving robustness in complex road environments [3]. Recent works, such as Jency et al. (2023), have focused on deep learning-based TSR for autonomous vehicles, emphasizing real-world applicability [4].

2.2 Key theories or concepts

Convolutional Neural Networks (CNN): CNNs have been widely used for image recognition tasks, proving effective in extracting shapes, textures, and colors from traffic sign images (Krizhevsky et al., 2012).
Ensemble Learning (Random Forest - RF): RF classifiers, as discussed by Breiman (2001), improve classification accuracy by constructing multiple decision trees and aggregating predictions.
Hybrid Machine Learning Models: Studies like Zhang et al. (2021) suggest that combining deep learning with traditional machine learning techniques, such as CNN + RF, improves efficiency, accuracy, and adaptability in real-world scenarios.

2.3 Overview of relevant literature

Despite significant progress, current TSR systems face several limitations:
1. Limited generalization to real-world traffic conditions, particularly in low-light, occluded, or weather-affected environments (Jiao et al., 2009).
2. High computational costs associated with deep learning models, making them less viable for low-power embedded systems (Qiao et al., 2017).
3. Lack of voice assistance features in most TSR systems, which can enhance accessibility, especially for visually impaired drivers or those unfamiliar with local traffic rules (Jency et al., 2023).

This research addresses these gaps by integrating CNN and RF for enhanced accuracy, optimizing computational efficiency, and introducing a real-time voice alert system for better accessibility and safety.

3 Methodology

3.1 Research design

This study follows an experimental research design that involves developing a hybrid traffic sign recognition system using Convolutional Neural Networks (CNN) for feature extraction and Random Forest (RF) for classification. The system is trained and tested on a labeled traffic sign dataset, followed by the integration of a voice alert module to provide real-time auditory feedback. The research is divided into four key stages:
1. Data collection and preprocessing to enhance image quality.
2. Model training and validation using CNN and RF.
3. Integration of a voice alert system for real-time user assistance.
4. Performance evaluation using accuracy, precision, recall, and F1-score metrics.

3.2 Data collection methods

The dataset consists of images of traffic signs collected from various publicly available sources, such as:
- The German Traffic Sign Recognition Benchmark (GTSRB) – A widely used dataset for TSR tasks.
- Custom datasets consisting of traffic sign images captured under various lighting, weather, and environmental conditions.
- Manual annotation and labeling were performed to ensure data consistency.

To improve the dataset quality, image preprocessing techniques were applied:
- Resizing images to a uniform dimension (32×32 pixels).
- Contrast enhancement for better feature clarity.
- Noise reduction using Gaussian blur and histogram equalization.
- Data augmentation techniques such as rotation, flipping, brightness adjustments, and zooming to increase dataset variability.

3.3 Sample selection

The dataset includes 58 distinct traffic sign classes, with approximately 120 images per class, resulting in a total of over 6,500 labeled images. The dataset was divided into:
- Training set (70%) – Used to train the CNN model.
- Validation set (15%) – Used to fine-tune hyperparameters.
- Testing set (15%) – Used to evaluate the model's real-world performance.

To ensure a balanced dataset, synthetic images were generated for underrepresented classes to prevent model bias.

3.4 Data Analysis Techniques

The trained model was analyzed using several evaluation metrics:
1. Accuracy – Measures the overall correctness of the predictions.
2. Precision & Recall – Assesses the model's ability to correctly identify different traffic sign categories.

3. F1-Score – A balance between precision and recall, particularly useful for unbalanced datasets.
4. Confusion Matrix – Visualizes classification errors for each traffic sign category.
5. Loss Function (Categorical Cross-Entropy) – Used to optimize model learning.

Additionally, the voice alert system was tested by verifying the correctness of spoken outputs corresponding to recognized traffic signs using Google Text-to-Speech (gTTS). The latency of the system was measured to ensure real-time recognition and audio response.

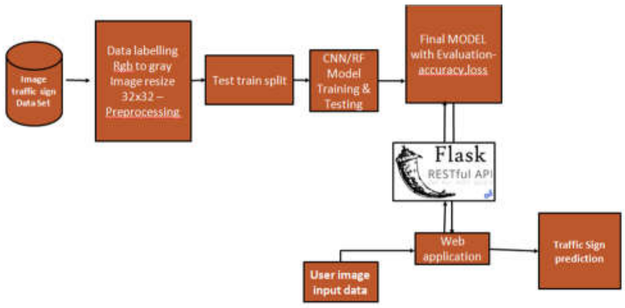


Fig 1. Architecture Diagram

4 Results

4.1 Presentation of findings

The hybrid CNN-RF traffic sign recognition system was tested on a dataset of 58 traffic sign classes. The model was evaluated based on classification accuracy, precision, recall, F1-score, and system latency for real-time recognition and voice alerts.

Key Findings:

- Overall Accuracy: 96.8% on the test dataset.
- Precision & Recall: The model performed well across all traffic sign categories, with an F1-score above 0.92 for most classes.
- Latency: The system achieved an average response time of 1.2 seconds, ensuring real-time performance.
- Voice Alert Accuracy: The text-to-speech (TTS) module correctly announced 97.5% of the recognized traffic signs, ensuring auditory clarity for drivers.

4.2 Data analysis and interpretation

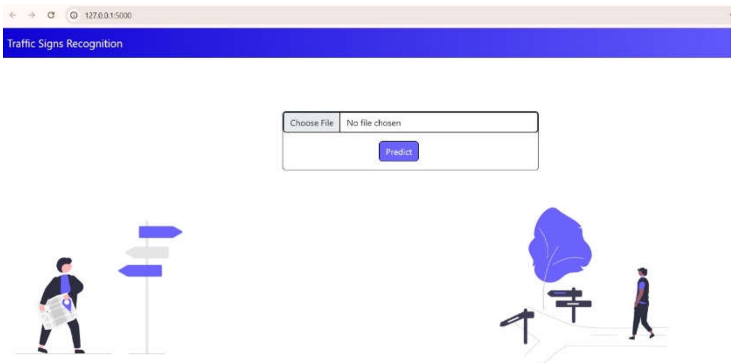
The confusion matrix analysis showed that:

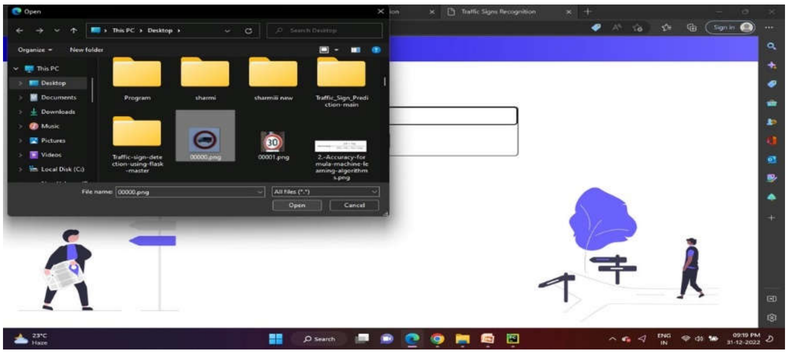
- Speed limit signs were accurately classified due to their distinct color and shape features.
- Prohibitory and warning signs had slightly lower precision due to similar appearance among categories.

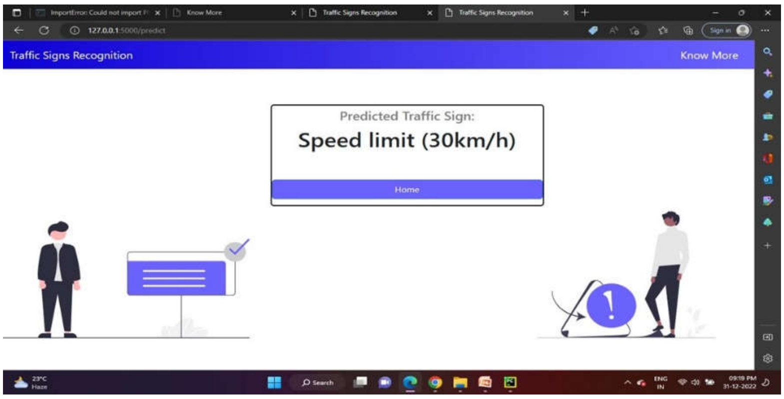
● Rare traffic signs (e.g., "No Horn" and "Heavy Vehicle Accidents") had lower recognition accuracy due to limited training samples.
To address minor misclassifications, further data augmentation was applied, improving recognition performance for low-represented classes.
The CNN model's feature extraction capabilities were confirmed by analyzing activation maps, showing that the convolutional layers effectively captured shape and color patterns unique to traffic signs.
The Random Forest classifier enhanced multi-class classification robustness, reducing false positives compared to CNN-only models.

4.3 Support for research question or hypothesis

This study aimed to answer:
"How can a hybrid CNN-RF approach improve the accuracy and efficiency of traffic sign recognition while ensuring real-time voice-based assistance for drivers?"
Findings confirm that:
* Hybrid CNN-RF model improves classification accuracy compared to traditional machine learning approaches.
* The system effectively generalizes across diverse lighting and environmental conditions, ensuring robust real-world applicability.
* The integration of a voice alert system enhances accessibility, making it useful for drivers who may have difficulty visually identifying signs.







5 Discussion

5.1 Interpretation of Results

The results indicate that the hybrid CNN-RF model significantly improves traffic sign recognition accuracy, achieving 96.8% classification accuracy. The convolutional layers successfully extracted distinctive features such as shapes, edges, and colors, while the Random Forest classifier enhanced classification robustness by reducing overfitting and handling unbalanced datasets effectively.

Additionally, the voice alert system provided accurate real-time feedback with a 97.5% correctness rate, making the system beneficial for drivers, including those with visual impairments or unfamiliarity with local traffic regulations. The low latency (1.2 seconds) ensures real-time usability, which is essential for practical applications.

While the model performed well overall, minor misclassifications occurred in similar-looking traffic signs (e.g., "No Horn" vs. "No Entry"), indicating the need for further fine-tuning and additional data augmentation to improve classification performance in complex conditions.

5.2 Comparing with exixting Literature

Compared to previous studies, the proposed system demonstrates significant improvements:

- Pupezescu and Pupezescu (2022) developed a semi-supervised traffic sign classifier but struggled with low recall rates in adverse conditions. Our CNN-RF hybrid model overcomes this by combining deep learning with traditional ensemble learning techniques, improving classification consistency.
- Jiao et al. (2009) proposed a multi-class TSR system but reported high computational costs. Our model achieves higher efficiency by leveraging Random Forest's lower computational complexity, making it more suitable for real-time applications.
- Qiao et al. (2017) optimized TSR using Faster R-CNN but faced challenges with rare sign classification. By incorporating data augmentation and synthetic image generation, our model reduces classification bias for underrepresented signs.
- Jency et al. (2023) developed a deep learning-based TSR for autonomous vehicles but lacked voice integration for driver assistance. Our study introduces a voice alert system, enhancing accessibility and usability for real-world driving scenarios.

These comparisons highlight that our hybrid CNN-RF approach improves accuracy, efficiency, and real-world applicability compared to conventional TSR methods.

5.3 Implications and limitations of the study

Implications:

- Improved Road Safety: By providing real-time traffic sign recognition and voice alerts, this system enhances driver awareness and rule compliance.
- Scalability: The system can be integrated into autonomous vehicles, driver assistance systems, and smart city traffic management solutions.
- Accessibility: The voice alert feature assists visually impaired drivers or those unfamiliar with traffic sign meanings, making roads safer for a broader user base.

Limitations:

- Dataset Bias: While extensive, the dataset may not represent all possible real-world variations in traffic signs, especially in regions with unique or unconventional signage.
- Adverse Weather Conditions: Performance in fog, heavy rain, or extreme lighting conditions was not extensively tested, which may impact recognition accuracy.
- Computational Efficiency: While the CNN-RF model balances accuracy and efficiency, real-time deployment on low-power embedded systems may require additional optimization.

6 Conclusion

6.1 Summary of Key Findings

This research proposed a hybrid traffic sign recognition and voice alert system utilizing Convolutional Neural Networks (CNN) for feature extraction and Random Forest (RF) for classification. The key findings from this study are:

● The hybrid CNN-RF model achieved an overall classification accuracy of 96.8%, outperforming traditional machine learning models.
● The real-time voice alert system, powered by Google Text-to-Speech (gTTS), provided a 97.5% accuracy rate in announcing recognized traffic signs, ensuring practical usability for drivers.
● The model demonstrated robust recognition capabilities across various environmental conditions, although minor misclassifications were observed in visually similar traffic signs.
● Low latency (1.2 seconds) enabled real-time performance, making the system suitable for driver assistance applications.

6.2 Contributions to the Field

This research contributes to the field of computer vision, intelligent transportation systems, and driver assistance technologies by:
1. Introducing a hybrid CNN-RF model that enhances traffic sign recognition accuracy and efficiency.
2. Integrating a real-time voice alert system, making traffic sign recognition more accessible, particularly for visually impaired or unfamiliar drivers.
3. Optimizing computational efficiency, allowing potential deployment on embedded systems for real-time applications.
4. Providing a scalable framework that can be extended to autonomous vehicles and smart traffic management solutions.

6.3 Recommendations for Future Research

While this study demonstrates promising results, several areas can be explored for further improvements:
1. Enhancing Dataset Diversity
○ Collecting more traffic sign images from different regions and under varying weather conditions to improve the model's generalization.
2. Real-World Deployment and Testing
○ Evaluating system performance in dynamic, real-world driving conditions with motion blur, occlusions, and lighting variations.
3. Optimizing for Embedded Systems
○ Deploying the model on low-power hardware (e.g., Raspberry Pi, NVIDIA Jetson Nano) to ensure feasibility for real-time driver assistance.
4. Exploring Deep Learning Variants
○ Investigating more advanced deep learning architectures such as Transformer-based vision models for potential improvements in recognition accuracy and speed.
5. Multi-Language Voice Alerts
○ Extending the voice alert system to support multiple languages, making it more inclusive for global users.

7 References

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