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Traffic Sign Recognition System

Yalla Lokesh Kumar[1], Dr. T. Siva Ramakrishna[2]
[1]*Master of Computer Applications, Department of Computer Science and Engineering, University College of Engineering Kakinada (UCEK), JNTU Kakinada, Andhra Pradesh, India*
[2]*Associate Professor, Department of Computer Science and Engineering, University College of Engineering Kakinada (UCEK), JNTU Kakinada, Andhra Pradesh, India*

Abstract: Traffic sign detection and recognition have become essential components of intelligent transportation systems and Advanced Driver Assistance Systems (ADAS) due to the increasing need for road safety and automated driving. Conventional traffic sign recognition approaches based on handcrafted features and traditional image processing techniques often struggle to achieve high accuracy under varying environmental conditions such as poor lighting, occlusions, motion blur, and complex backgrounds. To overcome these limitations, this work presents a Traffic Sign Detection and Recognition System Using Convolutional Neural Networks (CNN), designed to accurately detect and classify traffic signs from input images. The proposed framework utilizes computer vision techniques for image preprocessing, including resizing, normalization, and image enhancement, followed by deep learning-based feature extraction and classification using a Convolutional Neural Network (CNN). The CNN automatically learns discriminative visual features such as shapes, colors, and patterns from traffic sign images, eliminating the need for manual feature engineering. The system is trained and evaluated using the German Traffic Sign Recognition Benchmark (GTSRB) dataset, which contains more than 50,000 labeled images belonging to 43 different traffic sign classes. A user-friendly interface is developed using Streamlit, enabling users to upload traffic sign images or capture images through a webcam for real-time prediction. The trained model classifies the detected traffic sign and displays the predicted class along with the confidence score. Experimental results are evaluated using Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and Training Performance Metrics, demonstrating the effectiveness of the proposed CNN-based framework for accurate and reliable traffic sign recognition. The developed system contributes to improving road safety and can be effectively integrated into intelligent transportation systems, driver assistance technologies, and autonomous vehicle applications.

Keywords: Traffic Sign Detection, Traffic Sign Recognition, Convolutional Neural Network (CNN), Deep Learning, Computer Vision, Image Classification, GTSRB Dataset, Streamlit, Intelligent Transportation Systems (ITS), Advanced Driver Assistance Systems (ADAS), Autonomous Vehicles.

I. INTRODUCTION

Road safety continues to be a global challenge as traffic accidents cause a large number of injuries and deaths every year. Traffic signs are essential elements of road infrastructure because they communicate important information, including speed regulations, warning notices, prohibited actions, and mandatory directions. Drivers rely on these signs to make safe and informed decisions while traveling. However, recognizing traffic signs in real-world environments is not always easy. Factors such as poor lighting, unfavorable weather, motion blur, faded signboards, obstacles blocking visibility, and complex surroundings can reduce recognition accuracy. Incorrect or delayed identification of traffic signs may increase the likelihood of traffic violations and road accidents. For this reason, developing automated systems that can recognize traffic signs accurately has become an important research focus.

Recent developments in Artificial Intelligence (AI), Computer Vision, and Deep Learning have transformed the field of image analysis. Modern AI models are capable of identifying and classifying traffic signs automatically with minimal human involvement. Among various deep learning architectures, Convolutional Neural Networks (CNNs) have proven to be highly effective for image classification because they learn visual patterns directly from image data instead of relying on manually designed features. By extracting information such as edges, colors, textures, and shapes, CNN-based models provide reliable recognition performance and are increasingly being adopted in intelligent transportation applications and driver assistance technologies. Although considerable progress has been made, several existing traffic sign recognition systems still face challenges when deployed in real-world scenarios. Variations in illumination, blurred images caused by vehicle movement, partially covered signs, and distracting backgrounds often reduce the effectiveness of these models. Furthermore, many conventional techniques depend on handcrafted feature extraction methods, which may not accurately represent the complex appearance of traffic signs under different environmental conditions.

These shortcomings emphasize the need for more adaptive recognition systems that can automatically learn robust image features and maintain consistent performance across diverse road situations.

To overcome these challenges, this study presents a Traffic Sign Detection and Recognition System developed using a Convolutional Neural Network (CNN) and trained on the German Traffic Sign Recognition Benchmark (GTSRB) dataset. The proposed system follows a complete workflow that includes image preprocessing, feature extraction, and traffic sign classification to identify 43 different categories of traffic signs. A Streamlit-based graphical interface has also been developed, allowing users to upload traffic sign images or capture them through a webcam for instant prediction. The application displays both the predicted traffic sign class and its confidence score, making the system suitable for real-time use. The proposed framework offers an efficient, scalable, and accurate solution that can contribute to Advanced Driver Assistance Systems (ADAS), Intelligent Transportation Systems (ITS), and future autonomous driving applications.

The remaining sections of this paper are organized as follows. Section II reviews the existing literature related to traffic sign recognition, computer vision, and deep learning methods. Section III explains the proposed methodology, including dataset preparation, preprocessing techniques, CNN architecture, model training, and classification process. Section IV presents the experimental analysis and evaluates the system using performance metrics such as Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and training performance. Finally, Section V concludes the study and outlines possible directions for future research aimed at further improving traffic sign recognition systems.

II. RELATED WORK

A. *Traditional Traffic Sign Recognition Methods*

Traditional traffic sign recognition systems mainly relied on image processing techniques such as color thresholding, shape detection, and template matching. These methods detected traffic signs based on predefined colors, geometric shapes, and stored templates. Although they were effective under controlled conditions, their performance was significantly affected by changes in illumination, weather conditions, image noise, occlusions, and complex backgrounds, resulting in lower recognition accuracy in real-world scenarios.

B. *Deep Learning-Based Traffic Sign Recognition*

Recent advancements in Deep Learning have greatly improved the performance of traffic sign recognition systems. Models such as Convolutional Neural Networks (CNN), ResNet, YOLO, and EfficientNet automatically learn discriminative visual features from traffic sign images without requiring handcrafted feature extraction. These approaches provide higher classification accuracy, improved robustness, and better generalization under challenging road conditions. Motivated by these advantages, the proposed work employs a CNN-based Traffic Sign Detection and Recognition System for accurate traffic sign classification.

C. *Dataset Description (GTSRB)*

The proposed system is trained and evaluated using the German Traffic Sign Recognition Benchmark (GTSRB) dataset, one of the most widely used benchmark datasets for traffic sign recognition research. The dataset contains more than 50,000 labeled traffic sign images belonging to 43 different traffic sign classes, including speed limits, warning signs, prohibition signs, mandatory signs, and other regulatory signs. The images vary in size, illumination, viewing angle, and environmental conditions, making the dataset suitable for training robust deep learning models. The diversity and quality of the GTSRB dataset enable the CNN model to learn meaningful visual features and achieve high recognition accuracy across different traffic sign categories.

D. *Limitations of Existing Methods*

Although significant progress has been made in traffic sign recognition using traditional image processing and deep learning techniques, several limitations still exist. Traditional approaches based on color thresholding, shape detection, and template matching rely heavily on handcrafted features and predefined rules, making them sensitive to illumination changes, weather conditions, image noise, occlusions, and faded traffic signs. Machine learning methods such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest improve classification accuracy but still require manual feature extraction and feature selection, limiting their ability to learn complex visual patterns. Recent deep learning models such as ResNet, YOLO, and EfficientNet achieve high recognition accuracy; however, many of these models require large computational resources, longer training times, and high-end hardware for deployment. Some existing systems also focus mainly on traffic sign detection without providing a simple and user-friendly interface for real-time traffic sign classification.

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E. Proposed Approach and Its Advantages

To overcome these limitations, the proposed work presents a Traffic Sign Detection and Recognition System using Convolutional Neural Networks (CNN). Unlike traditional methods, the proposed CNN model automatically learns discriminative visual features directly from traffic sign images, eliminating the need for handcrafted feature extraction. The system is trained using the German Traffic Sign Recognition Benchmark (GTSRB) dataset containing 43 traffic sign classes, enabling accurate recognition of various traffic signs under different environmental conditions. Image preprocessing techniques such as resizing, normalization, noise reduction, and image enhancement improve the quality of input images before classification. Furthermore, a Streamlit-based graphical user interface allows users to upload traffic sign images or capture images through a webcam and receive real-time prediction results along with confidence scores. The proposed framework provides higher recognition accuracy, improved robustness, faster prediction, and a practical solution suitable for Intelligent Transportation Systems (ITS), Advanced Driver Assistance Systems (ADAS), and autonomous vehicle applications.

III. METHODOLOGY

The proposed Traffic Sign Detection and Recognition System is a deep learning-based framework designed to accurately detect and classify traffic signs from input images. The system integrates image preprocessing, computer vision techniques, Convolutional Neural Networks (CNN), and real-time prediction to recognize traffic signs belonging to multiple categories. The framework is trained using the German Traffic Sign Recognition Benchmark (GTSRB) dataset containing 43 traffic sign classes. The proposed system consists of six major phases: image acquisition and preprocessing, traffic sign detection, CNN-based feature extraction, model loading and classification, prediction display, and performance evaluation. The overall workflow of the proposed system is illustrated in Figure 1.

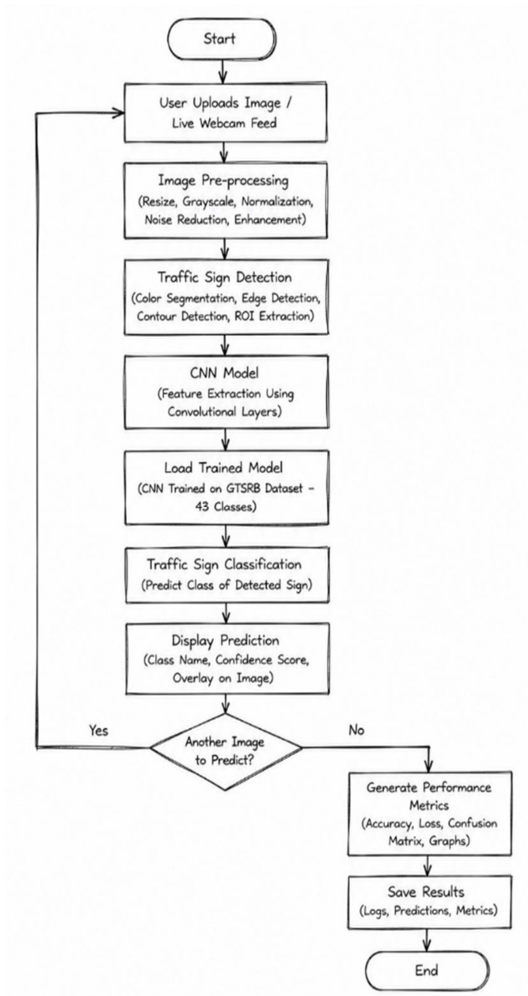

Fig 1 : Workflow Architecture

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IV. LIST OF PHASES

1) PHASE 1: Image Acquisition and Preprocessing

The proposed system begins by accepting an input image either through image upload or a live webcam feed. Users can upload traffic sign images in standard formats such as JPG, JPEG, or PNG, or capture real-time images using a webcam. Since the input images may vary in size, lighting conditions, orientation, and image quality, preprocessing is required before classification.

Initially, the uploaded image is resized to a fixed resolution suitable for the CNN model. Image normalization is then performed to standardize pixel intensity values and improve model convergence during prediction. Noise reduction techniques are applied to remove unwanted image distortions, while image enhancement improves the visibility of important traffic sign features. If required, grayscale conversion is performed to simplify image representation during preprocessing.

These preprocessing operations reduce the effects of illumination changes, background noise, and image inconsistencies while preserving essential visual characteristics such as color, shape, and boundary information. The processed image serves as the input for the traffic sign detection stage.

2) PHASE 2: Traffic Sign Detection

After preprocessing, the system detects the traffic sign within the input image using computer vision techniques. Initially, color segmentation is used to identify traffic sign regions based on their distinctive colors such as red, blue, and white. Edge detection is then applied to identify object boundaries and highlight the outline of potential traffic signs.

Next, contour detection identifies closed object boundaries corresponding to candidate traffic signs. Based on the detected contours, the system extracts the Region of Interest (ROI) containing the traffic sign while removing unnecessary background information.

The extracted ROI ensures that only the relevant traffic sign is forwarded to the CNN model, thereby improving classification accuracy and reducing computational complexity.

3) PHASE 3: CNN-Based Feature Extraction

The extracted traffic sign image is provided as input to the Convolutional Neural Network (CNN) for automatic feature extraction. Unlike traditional image processing techniques that rely on manually designed features, CNN automatically learns important visual characteristics directly from training images.

The convolutional layers identify low-level and high-level features such as edges, corners, textures, colors, and shapes. Activation functions such as ReLU (Rectified Linear Unit) introduce non-linearity, allowing the model to learn complex image representations. Max Pooling layers reduce feature dimensions while preserving the most important information.

The learned feature maps are flattened and passed through fully connected layers, enabling the network to generate a comprehensive representation of the traffic sign. This automatic feature extraction significantly improves recognition accuracy compared to conventional handcrafted methods.

4) PHASE 4: Traffic Sign Classification

Once feature extraction is completed, the system loads the pre-trained CNN model developed using the German Traffic Sign Recognition Benchmark (GTSRB) dataset. The trained model has learned visual patterns from 43 different traffic sign classes, including speed limits, warning signs, prohibition signs, mandatory signs, and other regulatory signs.

The CNN processes the extracted features and computes the probability for each traffic sign category. The class with the highest probability is selected as the final prediction. This classification process enables the system to accurately recognize previously unseen traffic sign images.

The trained model provides reliable predictions by utilizing deep learning-based feature learning and classification techniques.

5) PHASE 5: Prediction Display

After classification, the predicted traffic sign is presented through the user interface developed using Streamlit. The system displays the predicted traffic sign label together with its corresponding confidence score, indicating the certainty of the prediction.

The prediction result is overlaid on the uploaded image, allowing users to easily visualize the detected traffic sign. If the user wishes to classify another traffic sign image, the workflow repeats from the image acquisition stage. This interactive interface enables efficient real-time traffic sign recognition using both uploaded images and live webcam input.

6) PHASE 6: Performance Evaluation Metrics

The performance of the proposed Traffic Sign Detection and Recognition System is evaluated using standard classification metrics. The CNN model is assessed based on Training Accuracy, Validation Accuracy, Training Loss, and Validation Loss during the training process to monitor learning performance.

After training, the model is further evaluated using Accuracy, Precision, Recall, and F1-Score to measure classification effectiveness. A Confusion Matrix is generated to analyze class-wise prediction performance and identify any misclassified traffic signs. In addition, prediction confidence scores, latency, and graphical performance analyses are used to evaluate the efficiency of the proposed system.

These evaluation metrics provide a comprehensive assessment of the model's classification capability, robustness, and overall suitability for intelligent traffic sign recognition applications.

A. CNN Classification Evaluation Metrics

The performance of the proposed Traffic Sign Detection and Recognition System is evaluated using commonly used classification metrics such as Accuracy, Precision, Recall, and F1-Score. These metrics measure the effectiveness of the Convolutional Neural Network (CNN) in correctly classifying traffic sign images while evaluating the balance between correct predictions, false positives, and false negatives.

1) Accuracy

Accuracy measures the overall performance of the CNN model by calculating the proportion of correctly classified traffic sign images among all tested samples. A higher accuracy indicates better classification performance.

$$\text{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

2) Precision

Precision evaluates the correctness of the positive predictions made by the CNN model. It represents the percentage of predicted traffic sign classes that are actually correct. High precision indicates fewer false positive predictions.

$$\text{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

3) Recall

Recall measures the ability of the CNN model to correctly identify all actual traffic sign classes. It indicates how effectively the model detects positive samples while minimizing false negatives.

$$\text{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

4) F1-Score

The F1-Score combines Precision and Recall into a single performance metric. It provides a balanced evaluation of the CNN model, particularly when the dataset contains class imbalance.

$$\boldsymbol{F1} = \frac{\mathbf{2} \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

B. CNN Training Performance Metrics

In addition to the classification metrics, the proposed CNN model is evaluated using Training Accuracy, Validation Accuracy, Training Loss, and Validation Loss during the training process. These metrics help monitor the learning behavior of the model and ensure that it generalizes well to unseen traffic sign images.

1) *Training Accuracy:* Training Accuracy represents the percentage of correctly classified traffic sign images in the training dataset during each training epoch. It indicates how effectively the CNN learns the features present in the training data. A steadily increasing training accuracy reflects successful model learning.

2) Validation Accuracy: Validation Accuracy measures the model's classification performance on unseen validation data after each training epoch. It evaluates the generalization capability of the CNN model and helps detect overfitting or underfitting.
3) Training Loss: Training Loss represents the error between the predicted output and the actual traffic sign class during the training process. As training progresses, the loss value should gradually decrease, indicating that the CNN model is learning meaningful image features.
4) Validation Loss: Validation Loss measures the prediction error on the validation dataset. A low validation loss indicates that the model performs well on unseen traffic sign images. Comparing training loss and validation loss helps evaluate the stability and robustness of the trained CNN model.

V. RESULTS AND ANALYSIS

The proposed Traffic Sign Detection and Recognition System was evaluated using the German Traffic Sign Recognition Benchmark (GTSRB) dataset containing 43 traffic sign classes. The Convolutional Neural Network (CNN) model was trained over 10 epochs, and its performance was assessed using standard classification metrics, including Accuracy, Training Loss, Validation Loss, Confusion Matrix, and Confidence Score Distribution. The experimental results demonstrate that the proposed model effectively learns discriminative traffic sign features and achieves reliable classification performance.

A. Training Accuracy Analysis

The training and validation accuracy curves demonstrate the learning capability of the CNN model throughout the training process. During the initial epochs, both training and validation accuracy increase rapidly, indicating that the model successfully learns meaningful visual features from the traffic sign images. As the number of training epochs increases, the accuracy gradually stabilizes, showing consistent learning behavior without significant fluctuations.

After 10 epochs, the CNN model achieves a training accuracy of 97.12% and a validation accuracy of 94.35%. The small difference between the two curves indicates good generalization capability and suggests that the model does not suffer from significant overfitting. The continuous improvement in accuracy confirms that the CNN effectively captures the shape, color, and structural characteristics of traffic signs.

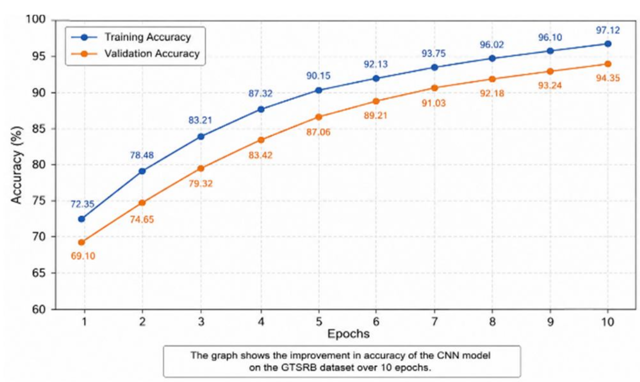

Fig 1: Training Accuracy and Validation Accuracy Graph

B. Training Loss Analysis

The training and validation loss curves illustrate the optimization performance of the CNN model during training. Initially, both loss values are relatively high because the model begins with randomly initialized weights. As training progresses, the loss decreases steadily, indicating continuous improvement in prediction accuracy.

The training loss decreases from 1.85 to 0.15, while the validation loss decreases from 1.98 to 0.19 after 10 epochs. The gradual reduction of both curves demonstrates stable convergence of the learning process. Since the validation loss follows a similar trend as the training loss, the model successfully learns generalized features without experiencing severe overfitting or underfitting

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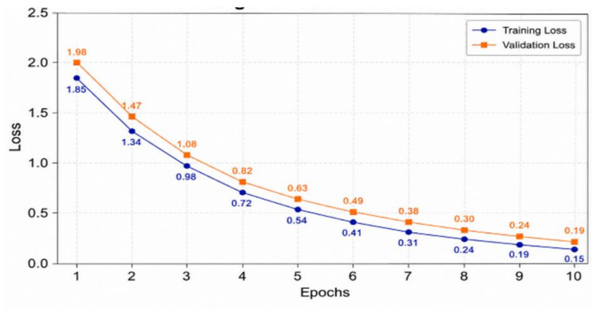

Fig 2 : Training Loss and Validation Loss Graph

C. Confusion Matrix Analysis

The confusion matrix provides a detailed evaluation of the classification performance for different traffic sign categories. Most predictions are concentrated along the main diagonal, indicating that the majority of traffic signs are classified correctly.

Minor misclassifications occur among visually similar traffic signs, such as different speed limit categories, which share similar shapes and colors. However, the overall number of incorrect predictions remains very low compared to the correctly classified samples. The confusion matrix demonstrates that the proposed CNN model effectively distinguishes between different traffic sign classes and achieves high classification accuracy across multiple categories.

D. Confidence Score Distribution Analysis

The confidence score distribution illustrates the prediction certainty of the CNN model. Most predictions exhibit confidence values between 0.88 and 1.00, with an average confidence score of approximately 0.92. This indicates that the model produces highly confident predictions for the majority of traffic sign images.

Only a small number of predictions fall below the average confidence level, primarily for traffic signs that contain visual similarities or challenging image conditions. Overall, the confidence distribution confirms the reliability and robustness of the proposed traffic sign recognition system.

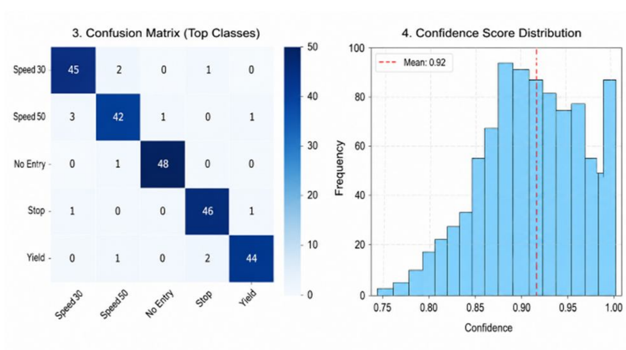

Fig 3 : Confusion Matrix and Confidence Score Distribution

E. Overall Performance Analysis

The experimental results demonstrate that the proposed CNN-based Traffic Sign Detection and Recognition System performs effectively on the GTSRB dataset. The model achieves high training and validation accuracy while maintaining low training and validation loss, indicating efficient learning and strong generalization capability. The confusion matrix shows accurate classification across multiple traffic sign categories with only a few misclassifications, while the confidence score distribution confirms that most predictions are made with high certainty.

Overall, the proposed framework provides an accurate, reliable, and efficient solution for automatic traffic sign recognition. The achieved performance demonstrates the suitability of the system for real-world applications such as Intelligent Transportation Systems (ITS), Advanced Driver Assistance Systems (ADAS), and autonomous vehicle technologies.

VI. CONCLUSION

This study presented a Traffic Sign Detection and Recognition System using a Convolutional Neural Network (CNN) to provide an intelligent and efficient solution for automatic traffic sign recognition. By combining image preprocessing, computer vision techniques, and deep learning-based feature extraction, the proposed framework accurately detects and classifies traffic signs from uploaded images or live webcam input. The system utilizes the German Traffic Sign Recognition Benchmark (GTSRB) dataset containing 43 traffic sign classes, enabling the model to learn diverse traffic sign patterns and improve recognition performance.

The experimental evaluation demonstrates the effectiveness of the proposed framework at different stages of the recognition process. During image preprocessing, techniques such as resizing, normalization, noise reduction, and image enhancement improved the quality of input images and enhanced feature extraction. The CNN model achieved a training accuracy of 97.12% and a validation accuracy of 94.35%, while the training and validation loss decreased steadily throughout the training process, indicating stable model convergence and good generalization. The confusion matrix further confirmed that the model correctly classified the majority of traffic sign categories, with only a few misclassifications occurring among visually similar traffic signs. Additionally, the confidence score distribution showed that most predictions were made with high confidence, demonstrating the reliability of the proposed recognition system.

By integrating computer vision with deep learning, the proposed framework provides a significant improvement over traditional traffic sign recognition methods that rely on handcrafted features. The developed Streamlit-based user interface enables users to upload traffic sign images or capture images through a webcam and obtain real-time prediction results along with confidence scores, making the system practical and user-friendly.

Overall, the proposed CNN-based Traffic Sign Detection and Recognition System demonstrates high accuracy, robustness, and computational efficiency. The promising experimental results indicate that the framework can effectively support Intelligent Transportation Systems (ITS), Advanced Driver Assistance Systems (ADAS), and future autonomous vehicle technologies by providing accurate and reliable traffic sign recognition under diverse road conditions.

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