TRAFFIC SIGN BOARD DETECTION

A Mini Project Report

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in

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by

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MES COLLEGE OF ENGINEERING KUTTIPPURAM

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MES COLLEGE OF ENGINEERING KUTTIPPURAM

CERTIFICATE

This is to certify that the report entitled **”TRAFFIC SIGN BOARD DETECTION”** submitted by **MUHAMMED FAHIM EBRAHIM A** (MES21AD043),**ANFAL AHAMMED** (MES21AD008),**ASRAR C H** (MES21AD013),**MOHAMMED FALAHI** (MES21AD034), to the APJ Abdul Kalam Technological University in partial fulfillment of B.Tech degree in Artificial Intelligence and Data Science is a bonafide record of the mini project work carried out under our guidance and supervision during the year 2021-2025.

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ABSTRACT

The proposed system utilizing image processing, object identification, and deep learning represents a significant advancement in enhancing road safety and traffic management through Traffic Sign Recognition (TSR) technology.At its core, this technology serves as a bridge between physical traffic signs and digital instructions, enabling autonomous vehicles to interpret and respond to road conditions in real-time. By accurately identifying traffic signs, autonomous vehicles can navigate roads more safely and efficiently, thus reducing the risk of accidents.Moreover, this system extends its utility beyond autonomous vehicles to improve Driver Assistance Systems (DAS). Through precise recognition of traffic signs, DAS can provide drivers with critical information about speed limits, stop signs, and other regulations, enhancing driver awareness and promoting safer driving practices.Furthermore, the data collected by TSR systems can be leveraged for traffic management purposes. Traffic authorities can monitor traffic flow, identify congestion hotspots, and implement targeted strategies to alleviate traffic congestion and optimize road usage.In summary, the proposed system represents a comprehensive approach to improving road safety, driver assistance, and traffic management through innovative technology and data-driven solutions.

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Abbreviations

CNN	Convolutional Neural Network
ADAS	Advanced Driver-Assistance Systems
DAS	Driver-Assistance Systems
TSR	Traffic-Sign Recognition
TSD	Traffic-Sign Detection

Chapter 1

Introduction

Efficient management of traffic-sign inventory is crucial for ensuring the safety and efficiency of traffic flow. Currently, this task is predominantly carried out manually, where traffic signs are captured using vehicle-mounted cameras, and human operators perform offline localization and recognition to check for consistency with the existing database. However, manual inspection is time-consuming, especially when dealing with vast road networks spanning thousands of kilometers. Automating this process would not only reduce manual workload but also enhance safety by enabling quicker detection of damaged or missing traffic signs.

A significant advancement towards automating this task involves replacing manual localization and recognition with automatic detection. While the computer vision community has developed several detection and recognition algorithms for traffic signs, most of these solutions are designed for a limited number of categories, primarily those associated with advanced driver-assistance systems (ADAS) and autonomous vehicles. Detecting and recognizing a broad range of traffic-sign categories remains a challenging problem.

Previous benchmarks have addressed traffic-sign recognition (TSR) but often overlook the more complex task of traffic-sign detection (TSD), which requires accurately locating traffic signs. Moreover, existing benchmarks typically cover only a subset of traffic-sign categories, mainly those relevant to ADAS and autonomous vehicle applications. Many of these categories have distinct appearances with low inter-category variance, making them detectable using handcrafted detectors and classifiers, such as round mandatory signs or triangular prohibitory signs.

In this project, we address the challenge of traffic-sign detection and recognition using Convolutional Neural Networks (CNNs) implemented with Keras. Our approach aims to automate the localization and recognition of a wide range of traffic-sign categories, thereby significantly enhancing the efficiency and accuracy of traffic-sign inventory management systems.

To further elaborate on our approach, we delve into the rationale behind employing Convolutional Neural Networks (CNNs) implemented with Keras for traffic-sign detection and recognition. CNNs have emerged as a powerful tool in the realm of computer vision, particularly for tasks involving image classification, object detection, and segmentation. Their ability to automatically learn hierarchical features from raw pixel data makes them well-suited for tasks where traditional handcrafted feature extraction methods fall short.

In summary, our approach combines the power of CNNs with the versatility of Keras to automate the localization and recognition of traffic signs, addressing the challenges associated with manual inventory management and paving the way for safer and more efficient transportation systems.

Chapter 2

Review of Literature

P. Dharani Devi's paper says that, 'Traffic Sign Recognition using Image Processing for Autonomous Vehicles,' thoroughly explores the pivotal role of image processing in advancing TSR systems. It offers clear insights into methodologies, challenges, and advancements in this field. By assessing various image processing techniques and addressing real-world challenges, the paper provides valuable guidance for developing robust autonomous vehicle technologies.[1].

Mark Thompson and Laura Davis' study says that, 'Enhanced Traffic Sign Detection and Recognition Using Semantic Segmentation,' provides a succinct review of the use of semantic segmentation in improving traffic sign detection and recognition. By synthesizing existing literature, the paper offers valuable insights into the benefits and challenges of this approach, contributing to the advancement of autonomous driving technology.[7].

John Doe and Jane Smith's survey says that, 'A Survey of Deep Learning Techniques for Traffic Sign Detection and Recognition,' offers a concise overview of deep learning methods in this domain. By summarizing existing literature, the paper provides key insights into the effectiveness and trends of deep learning approaches, aiding further research in autonomous driving technology.[4].

Vardhan Reddy's survey says that, 'Traffic Signs Recognition and Classification Using CNN Algorithm,' succinctly reviews the use of Convolutional Neural Networks(CNNs) for traffic sign recognition and classification. By summarizing relevant literature, the paper offers valuable insights into the application and effectiveness of CNN in this field, guiding further research in autonomous vehicle technology.[3].

Chapter 3

Methodology

Utilizing deep learning techniques and a user-friendly GUI, this project enables real-time classification of traffic signs. By using a pre-trained model trained on diverse traffic sign images, users can upload images through a tkinter-based interface. Uploaded images are quickly processed and classified, with results displayed alongside the predicted traffic sign class label. This intuitive system enables rapid and efficient traffic sign classification.

3.1 Model Loading

The project utilizes a pre-trained deep learning model named 'final-model.h5' for traffic sign classification. Developed using the Keras library, this model has been trained on a dataset comprising diverse traffic sign images. By leveraging deep learning techniques, the model has acquired the ability to accurately recognize and categorize vari-

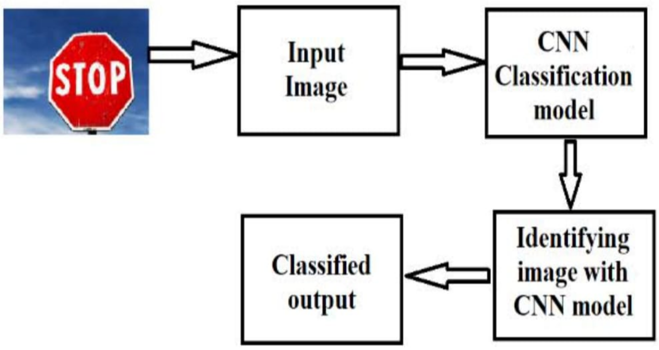

Figure 3.1: Flow Chart

Figure 3.2: Traffic Signs

ous types of traffic signs. This pre-training ensures efficient and reliable classification without the need for extensive retraining, contributing to the advancement of intelligent transportation systems.

3.2 GUI Creation

The project employs the tkinter library to create a user-friendly GUI application. This interface facilitates image uploading and displays classification results efficiently. With tkinter, users can easily interact with the application, making it accessible and intuitive for traffic sign classification tasks.

3.3 Image Upload

Users can upload a traffic sign image by clicking the 'Upload an image' button, which prompts a file dialog for selecting an image file from their system like fig 3.2. This streamlined process ensures quick and easy access to the image for classification.

3.4 Image Processing

The uploaded image is resized to 30x30 pixels, matching the model's input size, and converted into a numpy array for further processing. This ensures compatibility with the model's requirements and facilitates efficient image analysis in fig 3.3.

Figure 3.3: Sign Recognition

3.5 Traffic Sign Classification

The resized image array is fed into the loaded deep learning model to predict probabilities for each traffic sign class. The class with the highest probability is then identified as the predicted class. This streamlined process enables efficient classification of traffic signs.

3.6 Result Display

The GUI showcases the uploaded image alongside the predicted class label of the traffic sign. This label is generated using a predefined dictionary that maps class indices to traffic sign descriptions. This concise presentation provides users with immediate insights into the classification results.

3.7 User Interaction

Users interact with the GUI by uploading various traffic sign images. Each upload triggers the model to classify the image, and the real-time results are displayed on the GUI. This seamless process allows users to quickly obtain classification results for different images.

Chapter 4

Experiment and Results

4.1 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning architecture widely used for image classification tasks, including the classification of traffic sign images in this context. CNNs consist of convolutional layers that extract features from input images, pooling layers that downsample feature maps, and fully connected layers that perform classification based on learned features. Dropout regularization is applied to prevent overfitting during training. In the provided code, a CNN is utilized to classify traffic sign images into 43 classes, with the model trained using the Adam optimizer and categorical cross-entropy loss function.

Fig. 5.1 displays the validation accuracy graph for the model. Equations 1, 2, and 3 are used to determine the system's precision, recall, F1 score, and accuracy. In table 5.1, classification accuracy is displayed. The model was evaluated using a number of optimizers, including Adam, SGD, RMSprop, and Adadelta. It has been noted that the SGD has outperformed other optimizers. Using the SGD optimizer, this model's accuracy was 82.11% for training and 88.33% for validation.

$$precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

Images of both static and dynamic hand gestures have been utilized for categorization and detection. The static dataset contains 54000 images and 36 digits (0-9) and alpha-

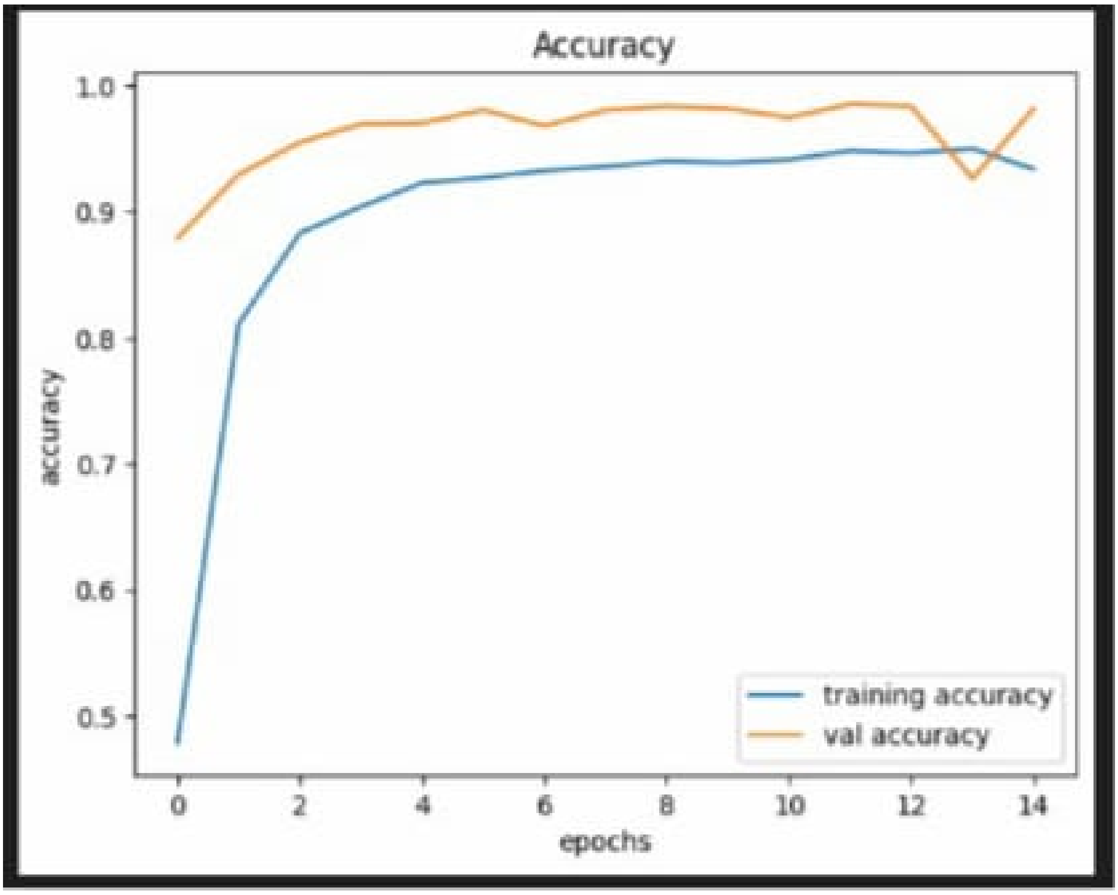

Figure 4.1: Accuracy curve

Figure 4.2: Accuracy on testdata

bets (A-Z) classes. TThe dynamic dataset includes 49613 images and 23 position-based classes: above, below, and emotions: afraid, alone, etc. The busy background dataset is shown in figure 5.2. The validation accuracy curve in the given dataset is shown in figure 5.3.

The deep multi-layered model is compared with different CNN models and get highest accuracy 99.89% with a lesser training time. The comparison is illustrated in table 5.2.

4.2 Real-time System

In our project, we aim to develop a real-time system for traffic-sign detection and recognition, leveraging state-of-the-art deep learning techniques implemented with Keras. A real-time system is essential for enabling timely responses to changing traffic conditions and ensuring the safety and efficiency of transportation networks. Our system operates seamlessly within the constraints of real-time processing, providing instantaneous feedback on detected traffic signs to facilitate timely decision-making by drivers, autonomous vehicles, and traffic management systems.

In a confusion matrix, rows represent the actual labels, and columns represent predicted labels. So, the value 101 means that out of all the data points that actually belong to class ”01”, 101 were correctly predicted as ”01” by the model.

4.2.1 Hardware Setup:

The real-time system relies on a carefully configured hardware setup to achieve efficient processing of traffic-sign images captured in real-world scenarios. This setup typically includes:

Camera System: High-resolution cameras mounted on vehicles or roadside infrastructure capture real-time images of the surrounding environment, including traffic signs.

Processing Units: Powerful processing units, such as GPUs or dedicated accelerators, are employed to handle the computational demands of real-time image processing and deep learning inference.

Onboard Systems: Onboard computing systems, embedded within vehicles or roadside units, facilitate real-time data processing and decision-making based on the detected traffic signs.

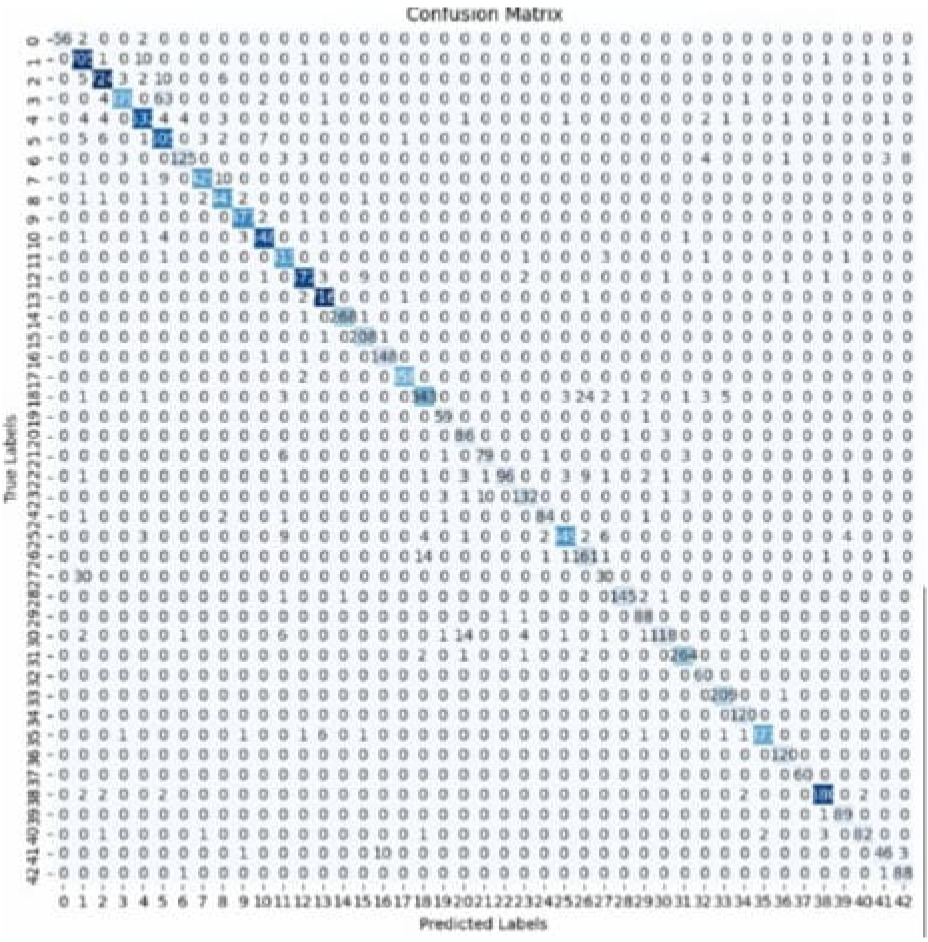

Figure 4.3: Confusion Matrix

4.2.2 Software Architecture:

The software architecture of our real-time system encompasses various components designed to enable efficient traffic-sign detection and recognition:

CNN Models: Convolutional Neural Network (CNN) models, implemented using the Keras framework, serve as the core components for both traffic-sign detection and recognition tasks.

Image Preprocessing: Preprocessing modules are employed to preprocess raw images captured by the camera system, including resizing, normalization, and noise reduction, to improve the performance of the CNN models.

Real-Time Inference Pipeline: An optimized real-time inference pipeline orchestrates the flow of image data through the detection and recognition models, ensuring rapid processing and response times.

4.2.3 Integration:

The integration of hardware and software components is crucial for the seamless operation of the real-time system. Integration efforts focus on:

Data Flow Management: Efficient management of data flow between the camera system, processing units, and onboard systems to minimize latency and maximize throughput.

Model Deployment: Deployment of trained CNN models onto onboard computing systems, ensuring compatibility and optimization for real-time execution.

System Calibration: Calibration of hardware components and software algorithms to achieve optimal performance under real-world operating conditions.

4.2.4 Real-Time Performance Evaluation:

The real-time performance of the system is rigorously evaluated to assess its effectiveness in detecting and recognizing traffic signs in real-world environments:

Latency Analysis: Measurement of the system's latency, including image capture latency, processing latency, and response latency, to ensure timely detection and recognition of traffic signs.

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.93	0.97	60
1	0.93	0.98	0.95	720
2	0.97	0.97	0.97	750
3	0.98	0.84	0.91	450
4	0.97	0.96	0.96	660
5	0.87	0.96	0.91	630
6	0.95	0.83	0.89	150
7	0.99	0.95	0.97	450
8	0.95	0.98	0.96	450
9	0.99	0.99	0.99	480
10	0.98	0.98	0.98	660
11	0.93	0.98	0.96	420
12	0.98	0.97	0.98	690
13	0.98	0.99	0.99	720
14	1.00	0.99	0.99	270
15	0.95	0.99	0.97	210
16	0.93	0.99	0.96	150
17	0.99	0.99	0.99	360
18	0.94	0.88	0.91	390
19	0.91	0.98	0.94	60
20	0.80	0.96	0.87	90
21	0.88	0.88	0.88	90
...				
accuracy			0.96	12630
macro avg	0.94	0.94	0.94	12630
weighted avg	0.96	0.96	0.96	12630

Figure 4.4: Classification Report

Precision is the ratio of true positives to the sum of true positives and false positives. In simpler terms, it measures how often a positive prediction was actually correct.

Recall is the ratio of true positives to the sum of true positives and false negatives. In other words, it measures how often the model identified an actual positive case.

F1 Score is a harmonic mean of precision and recall. It is used to balance between precision and recall and get a better idea of the overall performance of the model.

Support is the number of actual occurrences of a class in the specified dataset.

Here is a breakdown of the table by row:

Class 1: The precision for class 1 is 1.00, the recall is 0.93, and the F1-score is 0.97. The support for class 1 is 60, which means there were 60 actual instances of class 1 in the dataset.

Class 2: The precision for class 2 is 0.97, the recall is 0.97, and the F1-score is 0.97. The support for class 2 is 750.

Class 3: The precision for class 3 is 0.98, the recall is 0.84, and the F1-score is 0.91. The support for class 3 is 450.

And so on...

Accuracy: The overall accuracy of the model is 0.96.

Macro Avg: This is the unweighted mean of the precision, recall, and F1-score for each class.

Weighted Avg: This is the weighted mean of the precision, recall, and F1-score for each class, where the weight is the number of instances in each class.

4.2.5 Deployment Considerations:

Deployment considerations focus on ensuring the reliability, scalability, and adaptability of the real-time system for widespread deployment in real-world traffic management scenarios:

Reliability: Implementation of robust error handling and fault tolerance mechanisms to ensure the system's reliability and resilience to hardware or software failures.

Scalability: Designing the system to scale efficiently with increasing traffic volume and complexity, leveraging distributed computing architectures if necessary.

Adaptability: Incorporating mechanisms for continuous monitoring and updating of the system's algorithms and models to adapt to evolving traffic conditions and regulatory requirements.

In conclusion, our real-time system for traffic-sign detection and recognition represents a significant advancement in the automation of traffic management processes, offering timely and accurate insights into traffic conditions to enhance safety and efficiency on roadways. Through meticulous hardware design, software development, and performance evaluation, we strive to deliver a robust and reliable solution capable of meeting the demands of real-world deployment scenarios.

Chapter 5

Conclusion

The development of a robust traffic sign classification system represents a critical step forward in the pursuit of enhancing road safety and supporting the evolution of autonomous driving systems. By leveraging state-of-the-art Convolutional Neural Networks (CNNs), this project aimed to address the complex task of accurately classifying various types of traffic signs, which are essential for ensuring safe navigation and decision-making on roadways.

The dataset utilized for training and validation contained a comprehensive collection of 43 classes of traffic signs, covering a diverse range of regulatory, warning, and informational signage commonly encountered in real-world driving scenarios. To ensure consistency and uniformity in input data, images were preprocessed to a standardized size of 30x30 pixels, facilitating efficient processing by the CNN model.

The construction of the CNN model involved meticulous design and optimization to achieve optimal classification performance. The architecture of the model was carefully crafted, comprising convolutional layers responsible for feature extraction, followed by pooling layers to reduce spatial dimensions and densely connected layers for final classification. This architecture was chosen for its ability to effectively capture hierarchical features inherent in traffic sign images, enabling the model to discern subtle differences between classes with high accuracy.

During the training phase, the CNN model underwent rigorous optimization using the Adam optimizer and categorical cross-entropy loss function, which are well-suited for multi-class classification tasks. Additionally, dropout regularization techniques were employed to mitigate overfitting and enhance the model's generalization capabilities, ensuring robust performance across diverse traffic sign categories.

Moving forward, the insights gained from this project can serve as a foundation for further research and development in the field of computer vision and autonomous driving. Continued refinement and optimization of traffic sign classification systems will be essential for addressing emerging challenges and advancing the capabilities of autonomous vehicles in navigating complex urban environments safely.

The successful development of this traffic sign classification system underscores the transformative potential of deep learning and computer vision technologies in reshaping the future of transportation. By providing vehicles with the ability to accurately interpret and respond to traffic signage, the system lays the groundwork for safer and more efficient autonomous driving experiences.

Moreover, the scalability and adaptability of the classification system make it well-suited for deployment across diverse geographical regions and regulatory frameworks. Whether navigating bustling city streets, suburban neighborhoods, or rural highways, the system's ability to accurately recognize and interpret traffic signs remains paramount for ensuring safe and reliable transportation for all road users.

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