VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"Jnana Sangama", Belagavi, Karnataka, INDIA

A Mini Project Report
on

"Traffic Sign Recognition Model"

Submitted in partial fulfillment of the requirement for the Deep Learning Laboratory with Mini Project (20CSEL76) of VII Semester

Bachelor of Engineeringin
Computer Science and Engineering

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2023 – 2024

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CERTIFICATE

This is to certify that the VII Semester Mini Project in Deep Learning Laboratory entitled **Traffic Sign Recognition Model using CNN** carried out by **Sindhu B** (1GA20CS179), **Prathamesh R P** (1GA20CS182), is submitted in partial fulfillment for the award of the Bachelor of Engineeringin Computer Science and Engineering during the year 2023 2024. The Mini Project report has been approved as it satisfies the academic requirements concerning the mini project work prescribed for the said degree.

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DECLARATION

We, S I N D H U B bearing USN 1GA20CS179, PRATHAMESH R P bearing USN 1GA20CS182 students of seventh Semester B.E, Department of Computer Science and Engineering, Global Academy of Technology, Rajarajeshwari Nagar Bengaluru, declare that the Mini Project entitled "Traffic Sign Recognition model" has been carried out by usand submitted in partial fulfillment of the course requirements for the award of degree in Bachelorof Engineering in Computer Science and Engineering from Visvesvaraya Technological University, Belagavi during the academic year 2023-2024.

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Place:

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Date:19-02-

2024

ABSTRACT

The Traffic Sign Recognition (TSR) model is an essential and fascinating application of artificial intelligence in the domain of intelligent transportation systems. This project aims to develop a TSR model using advanced computer vision techniques and deep learning algorithms to accurately detect and classify traffic signs. By leveraging a vast dataset of annotated traffic sign images, a Convolutional Neural Network (CNN) architecture will be employed to achieve high accuracy in sign recognition. The model will be optimized to handle diverse challenges faced in real-life scenarios, such as varying weather conditions, occlusions, and lighting variations.

The significance of this project lies in its potential to revolutionize road safety and traffic management. By providing instantaneous and reliable traffic sign recognition, the TSR model will enhance drivers' situational awareness and promote adherence to traffic regulations, thus reducing the risk of accidents and traffic violations. Additionally, this project offers an excellent opportunity for college students to delve into cutting-edge technologies such as computer vision and deep learning, and gain valuable experience in model development, dataset preparation, and optimization techniques. Through this endeavor, students can acquire practical skills in AI-based applications while contributing to the broader goal of creating safer and smarter transportation systems for the future

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GLOSSARY

SRS	Software Requirement Specification
DFD	Data Flow Diagram
DL	Deep Learning

CHAPTER 1

INTRODUCTION

1.1 Definitions:

- Background: The initial part of the report provides the context and historical perspective on the need for an efficient Traffic Sign Recognition (TSR) system. It outlines the increasing importance of automated systems in enhancing road safety and traffic management.

- Motivation: This section explains the driving force behind the project, highlighting the need to address challenges in current traffic sign recognition methods. The motivation emphasizes the potential impact of a robust TSR model on reducing accidents and improving overall traffic flow.

- Objectives: The introduction clearly states the project's goals and what it aims to achieve. This could include the intention to design and implement a deep learning CNN-based model for real-time traffic sign classification, emphasizing accuracy and adaptability to various scenarios.

1.2 Report outline:

This project report on a Traffic Sign Recognition model is aimed at efficiently identifying different traffic signs in various scenarios using a deep learning Convolutional Neural Network (CNN). The introduction covers the background, motivation, and objectives, while the literature review explores existing models and challenges. The methodology section details data collection, preprocessing, and the design of the CNN, with insights into the training process. Implementation discusses the tools and hardware used. Experimental results highlight performance metrics and comparisons with other models. various scenarios evaluate the model's adaptability in diverse traffic conditions. Challenges and solutions are addressed, concluding with a summary, contributions, and future work. Acknowledgments express gratitude to dataset providers and collaborators. References cite relevant academic sources.

CHAPTER 2

REVIEW OF LITERATURE

2.1 System Study:

The system study involves an in-depth exploration of existing literature related to traffic sign recognition. The review focuses on methodologies employed in modern autonomous vehicles to interpret and respond to traffic signs. Noteworthy contributions include the introduction of Convolutional Neural Networks (CNNs) for traffic sign recognition by Sermanet and LeCun [1]. The German Traffic Sign Recognition Benchmark dataset, presented by Stallkamp et al. [2], serves as a crucial benchmark for evaluating recognition models. Additionally, approaches such as combining Histograms of Oriented Gradients (HOG) with Support Vector Machines (SVM) [3] and the application of deep neural networks [4] have been investigated. The review also highlights efforts to address challenges in real-world scenarios, including partial occlusion, as seen in the work by Li et al. [5].

2.2 Motivation:

The motivation behind this project stems from the critical role traffic sign recognition plays in the functionality of modern autonomous vehicles. Recognizing the need for improved accuracy and efficiency in interpreting and responding to traffic signs, the project draws inspiration from pioneering works in the field. The motivation is grounded in the potential positive impact on road safety and traffic management that an advanced traffic sign recognition model can bring.

2.3 Problem Statement:

The existing landscape of traffic sign recognition models faces challenges such as accuracy limitations and efficiency concerns, especially in real-world scenarios with varying conditions. This project aims to address these challenges by leveraging advancements in deep learning and building upon proven methodologies from the literature survey. The specific problem statement revolves around the need for a robust, real-time traffic sign recognition model that can accurately classify signs in diverse environments, including scenarios with partial occlusion and challenging lighting conditions.

2.4 Objectives:

The primary objective of this project is to design and implement a Traffic Sign Recognition model. Leveraging insights from the literature survey, the model aims to surpass current accuracy levels, particularly in real-world conditions. The project also seeks to contribute to the existing body of knowledge by exploring and refining the application of deep learning techniques for traffic sign recognition.

2.5 Scope of the Project:

The scope of this project extends to the development of a deep learning-based Traffic Sign Recognition model with a focus on real-time performance and adaptability to diverse scenarios. It encompasses the utilization of CNNs and other relevant techniques identified in the literature survey. The project's scope also includes the evaluation of the model's performance using benchmark datasets and comparisons with existing methodologies. The developed model is intended to have practical applications in enhancing the capabilities of autonomous vehicles for improved road safety and efficiency.

CHAPTER 3

SYSTEM REQUIREMENT SPECIFICATION

3.1 Functional Requirements

The functional requirements for the project outline the essential capabilities and features that the system must possess to meet its objectives:

1. Model Training: The system should train classification models on augmented datasets, ensuring robustness and accuracy in skin lesion classification.
2. Integration: Augmented images should be seamlessly integrated into the classification pipeline for model training and evaluation.
3. Performance Evaluation: The system must evaluate the performance of classification models using metrics such as accuracy, precision, and recall to assess their effectiveness in Traffic Sign Recognition into there respective classses.

3.2 Non-Functional Requirements

Non-functional requirements define the quality attributes and constraints that the system must adhere to:

1. Accuracy: The classification models implemented in the Traffic Sign Recognition system must achieve a high degree of accuracy in identifying and interpreting various traffic signs. This is crucial for ensuring reliable and precise responses to diverse traffic scenarios, contributing to overall road safety.

2. Real-time Performance: The system should exhibit efficient processing and classification of traffic sign images, minimizing latency to facilitate timely responses. Real-time performance is essential to ensure that the model can quickly and accurately recognize traffic signs in dynamic and rapidly

changing traffic conditions.

2. Scalability: The system architecture must support scalability to accommodate larger datasets and future enhancements. This ensures flexibility and adaptability over time, allowing the Traffic Sign Recognition model to handle an increasing number of diverse traffic signs and scenarios. Scalability is crucial for the system's long-term viability and relevance in evolving traffic management needs.

3.3 Hardware Requirements

The hardware requirements for the project are as follows:

- System : Intel i3 or above
- Hard Disk : 120 GB or above
- Monitor : 15’’ LED or above
- Input Devices : Keyboard, Mouse
- Ram : 8 GB or above

3.4 Software Requirements

The software requirements encompass libraries and frameworks essential for the project's functionality:

- Operating system : Windows 10 or above.
- Coding Language : PYTHON 3.6 or above
- Tools : Jupyter notebook and PyCharm

CHAPTER 4

SYSTEM DESIGN

4.1 DESGIN OVERVIEW:

The design of our Convolutional Neural Network (CNN) model for traffic sign recognition is geared towards making roads safer by accurately classifying various traffic signs. To start, we organize the data by converting class labels into a format suitable for multiclass classification. Our model architecture, created using the Keras Sequential API, involves multiple layers that perform crucial tasks like feature extraction, downsampling, and classification.

For feature extraction, Conv2D layers with ReLU activation are employed to let the model learn important features from input images. We use MaxPool2D layers to downsample feature maps and retain vital information. Dropout layers are added to prevent overfitting during training. The Flatten layer reshapes the 2D feature maps into a 1D vector for further processing.

Moving to classification, the Fully Connected module utilizes a Dense layer with ReLU activation to learn high-level representations from the flattened features. Another Dropout layer is included for regularization. The Output Layer, using softmax activation, outputs probabilities for each of the 43 traffic sign classes, enabling multiclass classification. During training, we compile the model with suitable optimizers and loss functions, employing backpropagation with stochastic gradient descent.

For evaluation, we use testing data to assess the model's accuracy and generalization, ensuring its effectiveness in real-world traffic sign recognition tasks. The dataset we work with, exemplified by the German Traffic Sign Recognition Benchmark (GTSRB) dataset on Kaggle, contains 32,648 photos. Notably, this dataset is unbalanced, focusing on 43 different traffic sign classes. In our analysis, we categorize and discuss findings, comparing the outcomes with other algorithms to better understand and optimize our model's performance.

4.2 SYSTEM ARCHITECTURE:

Our traffic sign recognition model's system architecture is designed to efficiently classify diverse traffic signs and contribute to enhanced road safety and traffic management. The architecture is organized into two main modules: Convolutional Feature Extraction and Fully Connected Classification.

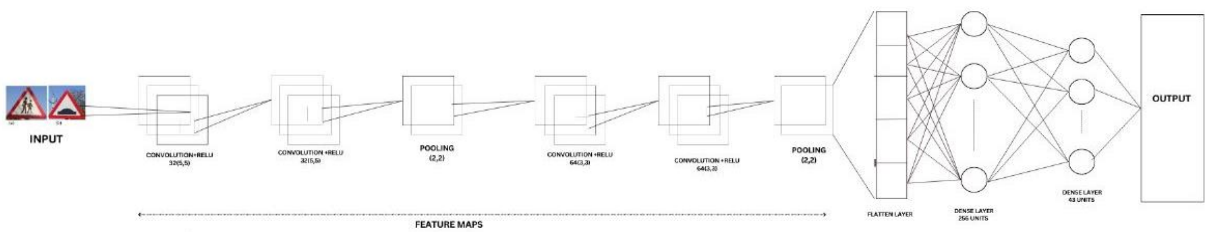

Fig 1.CNN Architecture for the proposed model

1. Convolutional Feature Extraction:

This module begins the process by utilizing Conv2D layers with ReLU activation to extract essential features from input traffic sign images. These convolutional layers enable the model to recognize intricate patterns and characteristics. To downsample the feature maps while retaining crucial information, MaxPool2D layers are incorporated. Dropout layers are strategically placed to prevent overfitting by deactivating certain neurons during training. Finally, a Flatten layer reshapes the 2D feature maps into a 1D vector, preparing them for further processing.

2. Fully Connected Classification:

The flattened features are then fed into the Fully Connected Classification module. This section of the architecture includes a Dense layer with ReLU activation, facilitating the learning of high-level representations. Another Dropout layer is introduced for regularization purposes, ensuring the model generalizes well to new data. The Output Layer employs softmax activation, producing probabilities for each of the 43 traffic sign classes, enabling effective multiclass classification.

Training and Evaluation:

During the training phase, the model is compiled with suitable optimizers and loss functions. Backpropagation, powered by stochastic gradient descent, refines the model's parameters. Subsequently, the model's performance is evaluated using dedicated testing data, assessing its accuracy and ability to generalize to real-world traffic sign recognition scenarios.

Data Considerations:

The system is trained and tested using the German Traffic Sign Recognition Benchmark (GTSRB) dataset, accessible on Kaggle, which contains 32,648 photos. Notably, the dataset is unbalanced, focusing on 43 different traffic sign classes. This architectural design aims to address the challenges posed by an unbalanced dataset and is geared towards achieving high accuracy and reliability in traffic sign classification tasks.

4.3 DATASETS:

Our traffic sign recognition model is trained and evaluated using the German Traffic Sign Recognition Benchmark (GTSRB) dataset, available on Kaggle. This dataset consists of 32,648 photos capturing 43 different traffic sign classes. It serves as a comprehensive and widely used benchmark for assessing the performance of traffic sign recognition models. However, it's important to note that the GTSRB dataset is unbalanced, requiring careful consideration during model training to ensure effective learning across all classes.

The complete range of dataset can be seen in the below Figure 1:

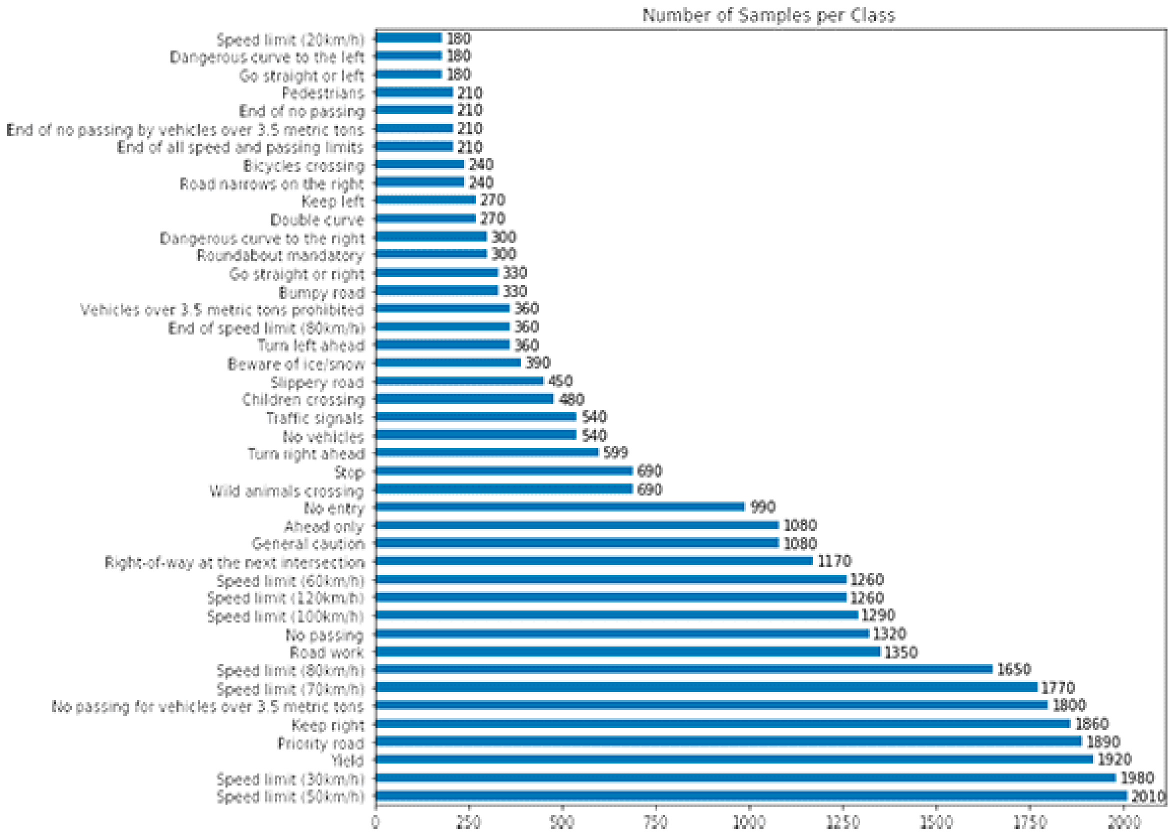

Fig.2. Total Distribution of images in the dataset

A training set and a testing set have been created from the dataset. The allocation of the photos is done in an 80:20 ratio, with roughly 80% going to the training set and the remaining 20% going to the testing set.

This division enables the estimation of the model's generalization capabilities by evaluating the performance of models trained on the training set on unobserved data from the testing set.

The pie chart representation of each dataset elements are shown below in the Figure 2:

Fig.3. Percentage distribution of the images for two different sets

4.4 Methods and Algorithms:

The model employs a Convolutional Neural Network (CNN) architecture for traffic sign recognition. The design leverages the Keras Sequential API and is divided into two main modules: Convolutional Feature Extraction and Fully Connected Classification.

1. Convolutional Feature Extraction:

- Utilizes Conv2D layers with ReLU activation for feature extraction from input traffic sign images.

- Incorporates MaxPool2D layers to downsample feature maps while retaining important information.

- Introduces Dropout layers to prevent overfitting during training.

- Applies a Flatten layer to reshape 2D feature maps into a 1D vector.

2. Fully Connected Classification:

- Uses a Dense layer with ReLU activation for learning high-level representations from the flattened features.

- Includes an additional Dropout layer for regularization.

- Employs an Output Layer with softmax activation, producing probabilities for each of the 43 traffic sign classes for multiclass classification.

3. Training and Evaluation:

The model is trained using stochastic gradient descent and compiled with appropriate optimizers and loss functions. Backpropagation refines the model's parameters during training. Subsequently, the model's performance is evaluated using testing data from the GTSRB dataset to ensure accurate classification and assess its ability to generalize to real-world traffic sign recognition scenarios.

CHAPTER 5

Implementation

5.1 Objective 1:

Objective 1 focuses on achieving a high degree of accuracy in classifying different traffic signs. The implementation involves the design and development of the Convolutional Neural Network (CNN) architecture, leveraging the Keras Sequential API. Data preparation includes converting class labels into one-hot encoding for multiclass classification. The Convolutional Feature Extraction module extracts important features from traffic sign images, while the Fully Connected Classification module learns high-level representations for effective multiclass classification.

5.2 Objective 2:

Objective 2 centers on ensuring real-time performance, allowing the system to efficiently process and classify traffic sign images with minimal latency. The implementation addresses this by optimizing the model architecture and incorporating features like MaxPool2D layers for downsampling and Dropout layers for preventing overfitting. The usage of softmax activation in the Output Layer facilitates quick and accurate multiclass classification.

5.3 Experiments:

Experiments involve training the model using the German Traffic Sign Recognition Benchmark (GTSRB) dataset. During training, the model is compiled with suitable optimizers and loss functions. Backpropagation with stochastic gradient descent refines the model's parameters. The experiments aim to validate the effectiveness of the model in meeting the defined objectives and requirements.

5.4 Results and Discussions:

The findings of the comparative evaluation of five alternative optimizers for headgear detection using a CNN are shown in Table 1. Adam, RMSprop, Adadelta, and Adagrad are the optimizers that are taken into account are included in the table.

The accuracy for the optimizer Adam is 92.85% with dropout regularisation . Adadelta With an accuracy of 76.34% with dropout , RMSprop performs the With an accuracy of 88.54%, Adadelta has the lowest accuracy with dropout of 76.34. Adagrad obtains an accuracy of 76.34 percent.

According to these findings, Adam outperforms the other investigated optimizers, obtaining excellent accuracy in both situations. While Adagrad and Adadelta display relatively lower accuracy.

OPTIMIZERS	ACCURACY	LOSS	VAL_ACCURACY	VAL_LOSS
ADAM	0.9285	0.2651	0.9777	0.0858
ADAGRAD	0.7419	0.9483	0.9087	0.4975
ADADELTA	0.7634	0.8674	0.9175	0.4382
RMS PROP	0.8854	0.8957	0.9226	0.3706

TABLE 1.EXPERIMENTAL RESULTS FOR OPTIMIZERS

5.4.1 Evaluation Metrics:

The evaluation metrics focus on assessing the model's performance. Metrics include:

- Accuracy: Measures the overall correctness of the model in classifying traffic signs.

- Precision, Recall, and F1-score: Provide insights into the model's ability to correctly identify and classify each traffic sign class.

- Confusion Matrix: Offers a detailed breakdown of the model's predictions and actual classifications, aiding in identifying areas of improvement.

Results and discussions analyze the model's performance against these metrics, highlighting strengths, areas for improvement, and the model's adaptability in diverse traffic scenarios. The objective is to validate the model's accuracy, real-time performance, and effectiveness in traffic sign recognition, ensuring its practical applicability for road safety and traffic management.

CHAPTER 6

CONCLUSION

In conclusion, traffic sign recognition models have witnessed substantial progress and innovation over the years, fueled by advancements in computer vision and deep learning. The surveyed research papers have demonstrated the efficacy of various approaches, ranging from traditional methods like HOG-SVM to state-of-the-art deep neural networks, in accurately detecting and classifying traffic signs. The utilization of large-scale benchmark datasets, such as the German Traffic Sign Recognition Benchmark, has facilitated fair comparisons and benchmarking of different models, driving the field's growth.

The integration of deep learning techniques, especially Convolutional Neural Networks (CNNs), has proven to be a game-changer in traffic sign recognition. CNN-based models excel at feature extraction and hierarchical learning, enabling them to capture intricate patterns present in traffic sign images, even under challenging real-world conditions. Moreover, some studies have explored hybrid approaches that combine the strengths of different methods, achieving further improvements in recognition accuracy and robustness.

As autonomous vehicles become increasingly prevalent, the accurate and efficient recognition of traffic signs remains a critical factor for ensuring safe and reliable autonomous driving systems. The findings from these research papers provide valuable insights and guidelines for designing effective traffic sign recognition models that can seamlessly integrate with autonomous vehicles. Future research may focus on enhancing models' interpretability, reducing computational complexity, and addressing domain adaptation challenges to generalize well across different road environments and signage variations. Ultimately, with continued research and development, traffic sign recognition models will play an integral role in advancing the safety and efficiency of autonomous driving systems on roads worldwide.

BIOBLOGRAPY

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