Traffic Sign Classification for Road Safety using CNN

Haree Krishna P P
Computer Science and Engineering
Amrita Vishwa Vidyapeetham
Chennai, Tamil nadu
hareepp2002@gmail.com

Sindhu Ravindran*
Assistant Professor
Computer Science and Engineering
Amrita Vishwa Vidyapeetham
Chennai, Tamil Nadu
r_sindhu@ch.amrita.edu*
*Corresponding author

Vikneswaran Vijean
Senior Lecturer
Electronic Engineering & Technology
Universiti Malaysia Perlis
Perlis, Malaysia
vikneswaran@unimap.edu.my

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***Abstract*— In today's life, Traffic sign identification is a significant domain of environment awareness system. This traffic sign identification is becoming a top priority for modern transportation systems as it is highly essential to maintain the road safety nowadays. While detecting the traffic signs using various target detection techniques, many real-time problems are being faced like easy omission, undesirable light, inaccurate positioning for traffic signs (during detection), disorientation, motion blur, color fade, occlusion, rain, and snow. In view of these problems that the traffic signs cannot be recognized well, many novel target detection technologies are emerging, which in-turn solves these problems. This article introduces a reliable traffic sign categorization system, with the help of OpenCV for image enhancement and a five-layered Convolution Neural Network. The significance of sophisticated traffic sign identification for preventing accidents and promoting road safety is emphasized by this research that classifies traffic signs. The proposed CNN model has proved to achieve a remarkable classification accuracy and flexibility in response to changes in sign and environment, as demonstrated by the outcomes of the experiments. The strength of the proposed model has been tested on the German Traffic Sign Dataset and the experimental results have unfolded the fact that this model has recognized German traffic signs, with a better classification accuracy of 97.3%.**

Keywords: Convolutional Neural Network, OpenCV, Cross Cultural Adaptation, Image enhancement, Classification.

I. INTRODUCTION

Indian roads have traffic signs for safety reasons. The signs are positioned at precise intervals from the needed action so that the driver can react in a timely manner. As such, traffic signs are a tool of traffic control that demands the utmost attention, respect, and appropriate response from the driver in cases where the driver's failure to do so results in accidents. As the amount of vehicle traffic increases and demands more effective traffic management and infrastructure development, road safety has become a top priority in our fast-paced culture. It depends on the appropriate interpretation and recognition of traffic signs, which serve as a crucial informational channel between drivers and traffic authorities. Road safety might be significantly increased by the convergence of modern technologies like deep learning and computer vision.

To aid in route planning, enforce traffic laws, and inform motorists quickly about potential hazards, intelligent transportation systems rely on traffic sign recognition. The main problem in this sector is making the recognition models adjust to the different geography and hence traffic sign standards of these areas. Different countries use different sets of traffics signs, which differ in terms of shape, color, placement context and symbols. These regional variations pose a challenge to the recognition systems since what may work for one set of signs may not work for others. Hence we need to be able to adapt traffic sign recognition models from one dataset to another whenever we are dealing with datasets of different countries or regions. Convolutional Neural Networks (CNNs) were used as a method approach in this research for traffic sign classification. The standard is known as German Traffic Sign Dataset that has different signs from Germany's roads. This has been done through image augmentation and preprocessing using OpenCV. As such, the suggested model uses three convolutional layers and five-layer CNN architecture with two hidden layers for classification for feature extraction purposes.

Nevertheless, due to the increasing number of autonomous vehicles on the roads, modern traffic control systems rely primarily on the recognition of road signs by both humans and self-driving cars in order to enforce traffic regulations. But problems exist as it is difficult to maintain trusty and precise road sign recognition systems in various practical situations with environmental factors. An attempt is made in this paper to develop and evaluate a road sign recognition system that uses German road signs data in order to tackle these issues. Some of the techniques that were implemented in this proposed system included OpenCV for image enhancement and proprietary 5-layer Convolutional Neural Network (CNN) architecture, composed of 3 convolutional layers, and 2 hidden layers for classification. The main objective of the study was to increase the accuracy of traffic signs reading as well as improve such reading's robustness under challenging daily life conditions while also assessing its performance on a benchmark dataset. This article is aimed at giving an insight on how well the technique works, its applicability to road safety and computer vision/intelligent transportation issues.

II. Related Works

Yi Yan et al. found in a study that adaptive picture enhancement and lightweight attention block named Feature Difference (FD) can greatly assist in recognizing traffic signs even under challenging lighting conditions [1]. In 2021, Xinghao Yang et al., also, introduced the Targeted Attention Attack (TAA) strategy which increased success rates and reduced perturbation loss for real-world traffic sign recognition systems making them less vulnerable to adversarial attacks [2]. Therefore, these findings give us some useful ways of dealing with problems of traffic signs identification.

For an efficient approach to the detection of Traffic Signs, Xu Yuan et al. applied an improved framework named YOLOv5S-A2 that was faster and more accurate than any other previous methods [3]. Shouhui He et al. performed better in their work [4] where they offered a new method based on visual inspection to compensate for CNNs' insufficiency during finding Road Signs. In another astonishing research report, Domen Tabernik and his colleagues used mask R-CNN on DFG Traffic Signs Dataset which consists of 200 classes including challenging ones that have not been seen before[5]. Kan Xie et al. presented a privacy-preserving federated learning approach by using Spike Neural Networks (SNNs) as a solution for efficient and safe Traffic Sign Recognition in the internet of vehicles (IoV)[6].

According to Haiyan Guan et al., their two step strategy aimed at creating a way of identifying traffic signs and recognizing them to be used in a digital picture and LiDAR point cloud [7]. In 2020 Gámez Serna et al. formulated an inclusive traffic sign identification model that has both text-based and symbol-based signs which performed at par with state of the art techniques [8]. Weidong Min et al. proposed a new traffic sign recognition (TSR) technique in 2022 by combining the position of structural traffic signs with semantic scene knowledge [9].

Jing Yu et al. used a fusion model that combines the YOLO-V3 and VGG19 networks to identify and recognize traffic signs quickly and precisely achieves an accuracy of more than 90% on a public dataset [10]. In 2021, the Automotive Repository of Traffic Signs (ARTS) dataset is used by Fayha Almutairy et al. and advocates for deep neural networks in Traffic Sign Recognition [11]. YOLOv4-Tiny based improved light-weight traffic sign recognition algorithm is proposed by Lanmei Wang et al. to enhance detection accuracy and positioning accuracy. The algorithm demonstrates improved performance while maintaining processing speed [12]. In order to regularize the long-tail distribution and solve the long-tail problem in traffic sign recognition, Jiangong Wang et al. developed a unique generative adversarial network for picture formation. This greatly increased identification accuracy [13].

In 2020, a two-stage CNN-based solution for recognizing small traffic signs in complex traffic scenarios was proposed by Lijing Wei et al. It combines feature maps effectively and enhances local feature recognition, outperforming existing methods [14]. Uday Kamal et al. proposed a method that treats traffic sign detection as an image segmentation problem and introduces the SegU-Net, a network combining SegNet and U-Net architectures. It demonstrates robust performance and generalizability on various datasets, making it suitable for efficient traffic sign detection in autonomous vehicle scenarios [15]. In recent times, many deep learning based research works there have been carried out by various researchers in this genre [16], [17].

Similar to the reviewed work, the proposed approach aims to solve all the problems in traffic sign classification by using a 5 layered modified CNN model. Traditional CNNs often have a more shallow architecture, typically consisting of a sequence of convolutional layers followed by pooling layers and eventually fully connected layers [18], [19]. There can be less convolutional layers in them. With three convolutional layers and a deeper architecture, the five-layered modified CNN can extract more complex and abstract information from the input pictures.

III. Dataset

Optimizing traffic sign classification for improved road safety is the main goal of this research. German Traffic Sign Recognition Benchmark, or GTSRB dataset is used for this research on traffic sign recognition which is a benchmark for traffic signs and researchers frequently use for the traffic sign classification . It contains a variety of signs that are commonly seen on German roadways which offers an example of real traffic sign scenarios, . It includes traffic signs of warning, regulatory, and instructional signs, that are included in the collection to exhibit the diversity observed in the actual world. Form, colour, and text vary depending on the type of sign. The study tested and trained the CNN model for traffic sign identification applications through the use of GTSRB dataset which has more than fifty thousand images.

Figure 1. Sample images of Dataset

Table 1. Dataset Information

Dataset Split	Number of Images
Training	35,000 images
Validation	4,000 images
Testing	12,000 images

The accuracy of German traffic sign recognition algorithms is being closely evaluated by experts with a reliance on GTSRB dataset that has 39,000 pictures for training and 12,000 images for testing purposes. This dataset is so crucial in that it represents the unique German traffic sign standards which may differ from others. Consequently, continuous use of GTSRB allows researchers to test and measure their algorithms to give best possible results based on real-world German road traffic. Importantly this data set enhances road safety as well as facilitating successful implementation of traffic sign recognition systems in Germany through giving insights into cross-cultural adaptation and an accurate interpretation of German traffic signs.

IV. Models and Methods

A. *Traffic Sign Classification Model*

The traffic sign classification model uses Convolutional Neural Network (CNN) architecture in order to classify the traffic sign images effectively.

Layers:

- Input Layer: To maintain uniformity every image in the collection is usually reduced to a particular dimension
- Convolutional Layers: These are the first three layers in the architecture and are responsible for feature extraction.
- Pooling Layers: After each convolutional layer, a pooling layer is included to downsample the feature maps.
- Fully Connected Layers: For classification, two completely connected hidden layers are added after feature extraction and downsampling.
- Output Layer: The softmax activation function is used in the final output layer for multi-class classification.

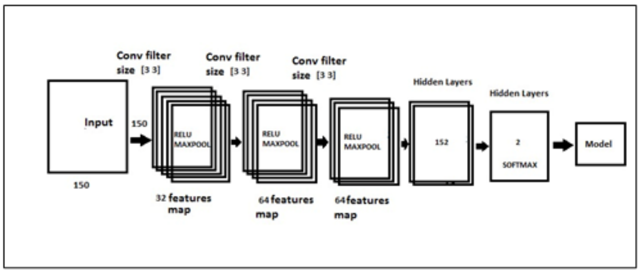

Figure 2. CNN Architecture

V. Methodology

A. *Data Collection and Preparation:*

As such, the German Traffic Sign Recognition Benchmark (GTSRB) collection is large and diverse as it contains over 50 000 images and 43 different traffic sign classes. There is a separate dataset for traffic signs that can be collected or obtained to test how well the algorithm performs on different types of roads. The data must be prepared for training – OpenCV does scaling, normalization, and data augmentation..

B. *Convolutional Neural Network Model :*

For traffic signs classification, Convolutional Neural Network (CNN) is chosen. Three convolutional layers along with two hidden fully connected layers constitute model's architecture for classification. Consequently, Convolutional layers are used to extract spatial features/patterns from input images while fully-connected ones enable the model to make fine-grained predictions. For instance, Pooling layers help in downsampling feature maps whereas ReLU and other activation functions help to introduce non-linearity.

C. *Model Training:*

The CNN model is trained by dividing the GTSRB dataset into training and validation sets. For best results, hyper parameters like learning rate, batch size, and optimizer are modified. The model's loss is minimized during training by using the backpropagation technique, and overfitting is prevented by checking on the validation set's accuracy.

D. *Model Testing and Evaluation:*

We evaluate the model's performance using the German Traffic Sign Testing Dataset. German traffic signal recognition is evaluated by measuring the model's accuracy. Testing is then conducted utilizing the various traffic signs to assess how well the model adapts to a wide range of norms and traffic signs. The model's cross-cultural recognition capabilities are evaluated using the performance metrics.

E. *Cross-Cultural Adaptation:*

The study's primary focus is on the model's capacity to adapt to regional differences in traffic signs. Importantly for real-world use, the testing results with the traffic sign dataset provide insight into how well the model generalizes to a different collection of signs.

F. Scope and Limitations:

This study illustrates advancements in CNN-based traffic sign recognition (TSR), with a focus on cross-cultural adaption to the German traffic sign dataset and other traffic signs. The project aims to promote cross-cultural adaptation of TSR systems, and facilitate practical applications in autonomous vehicles, traffic management, and road safety. Limitations include potential data variability, generalization constraints of the model, training data quality, susceptibility to environmental factors, resource requirements, and considerations for adversarial attacks and real-world integration. These factors may have an impact on the model's performance and applicability in different conditions and regions.

VI. EXPERIMENTAL RESULTS

We split the German Traffic Sign Dataset into training and validation sets in order to train the CNN model during the first experiment phase. The model was trained using a given number of epochs and a predetermined learning rate. During training, the model showed rising performance; throughout the course of the epochs, the loss decreased and the training accuracy increased gradually. The validation accuracy also showed encouraging trends, suggesting that the model was learning the skills needed to identify German signs.

In order to assess the ability of the model to recognize German traffic signs, we tested it using German Traffic Sign Testing Dataset. The results are as follows:

Accuracy: When tested on the German Traffic Sign Testing Dataset, the model gave an accuracy rate of 97.3%. By Class Performance: The model worked differently for different traffic sign classes such that some signs indicated where it had a strength while others showed where it failed because of cultural differences while others demonstrated better recognition accuracy

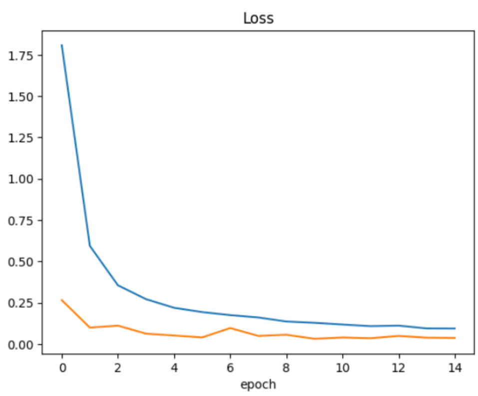

Figure 3. Loss Curve

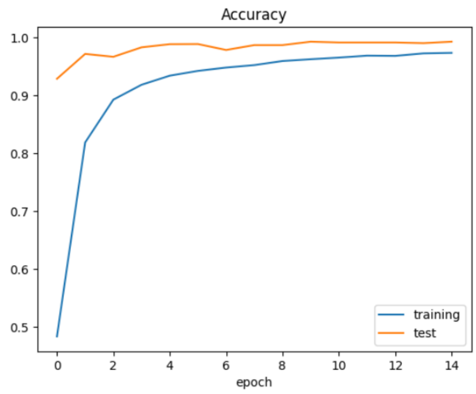

Figure 4. Training-Testing Accuracy

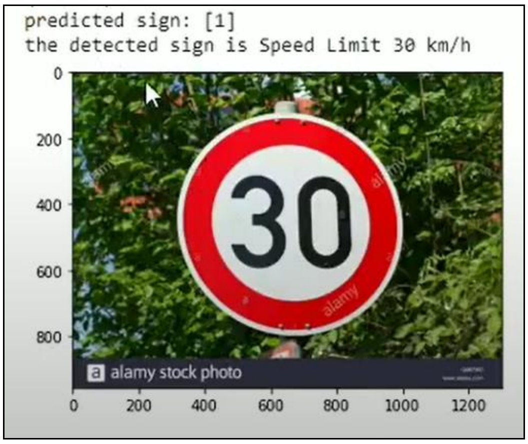

Figure 5. Outcomes of Classification Results

VII. CONCLUSION

This study aims at increasing cross-cultural adaptation with regard to German Traffic Sign Dataset by using Convolutional Neural Networks (CNNs) for Traffic Sign Recognition (TSR). The findings showed that 97.3% accuracy was achieved during recognition of road signs in Germany. Research' findings show that the suggested CNN model possesses a great performance in terms of classification accuracy as well as adaptability to changes in sign and environment. This work is important because it demonstrates how deep learning models can be trained to generalize and adapt to different traffic sign datasets. It sets the stage for the creation of reliable, cross-cultural traffic sign recognition systems that work effectively in different kinds of traffic situations. It also discusses how these models can be applied to real-world scenarios where there are diverse traffic sign standards resulting in better road safety and improved traffic control that goes beyond their initial training set.

VIII. FUTURE WORKS

Future traffic sign identification research is probably going to focus on improving the system's capacity to recognize a wider variety of traffic signs from other nations and languages. Throughout its evolution, the resilience and efficiency of the model will be continuously improved. In order to encourage safer driving conditions, a focus will be on putting in place real-time alert systems for prompt driver support as well as enhancing interaction with smart city projects and transportation authorities. Moreover, the creation and execution of an all-encompassing and internationally flexible traffic sign identification system will depend on the extension of security and privacy protocols, user input, and regulatory standard compliance.

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