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Classification and Prediction of Traffic Sign Recognition using Deep Learning Algorithm

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ABSTRACT

Traffic Sign Recognition plays a key role in improving traffic safety by providing drivers with important information about speed limits and potential hazards on the road. Road sign detection, classification, and image segmentation are the three stages of a real-time road sign recognition and classification system that it offers. Color enhancement technique is used to extract red areas in the image. In this work, convolutional neural networks are used to detect, classify and recognize traffic signs. TSR is a challenging task due to various constraints such as visual environment, physical impairment, and partial occlusions. In order to overcome these drawbacks, CNNs are frequently employed to identify and extract features from traffic signs. This research work is used prevent of possible collisions and enhances the driving experience.

Keywords: Traffic Sign Recognition (TSR), Classification, Road sign recognition, Image segmentation, Color enhancement technique, convolutional Neural Network(CNN).

INTRODUCTION

Traffic Sign Recognition is a safety technology system that identifies traffic signs and transmits the information shown on the sign to the driver through the infotainment screen, head-up display, or instrument cluster. Most TSR systems can identify speed limit, stop and "no entry" signs. Instantly helps drivers or automated driving systems effectively detect and recognize road signs of the main types of road signs: Regulatory signs, Warning signs, Guidance signs, Information signs, Construction and maintenance signs. The lack of road signs can be caused by a number of things, including changes in concentration, exhaustion, and inadequate sleep.

Recognizing traffic signs is important since it alert drivers of any signs they may have missed recently because they were distracted or inattentive. Enhancing safety, traffic sign recognition enables drivers to maintain focus in complex traffic scenarios and facilitates adherence to speed limits. The classification of traffic signs has a substantial influence on overall road safety, traffic flow efficiency, urban planning, and environmental considerations. With the continuous evolution of technology, there is the potential to enhance road safety and efficiency for all users as advancements are made.

Traffic sign classification plays a vital role in road safety. It ensures that drivers obey important rules such as stopping at red lights or slowing down near schools, reducing the risk of accidents. In addition, it helps traffic management by coordinating traffic lights and suggesting alternative routes during road works. Planners are using this technology to design more efficient roads and signs, making transportation smoother for everyone. People with special needs also benefit because the system can provide information through sounds or touch signals. In addition, it offers valuable data for research and policy-making, leading to better road regulations and plans. Last but not least, it is environmentally friendly, as it helps reduce fuel consumption and harmful emissions by maintaining efficient operations.

LITERATUREREVIEW

Akatska and Imai [1] attempted to make an early traffic sign recognition system. A system capable of automatic recognition of traffic sign could be used as assistance for drivers, alerting them about the presence of some specific sign (e.g. a one-way street) or some risky situation (e.g. driving at a higher speed than the maximum speed allowed). It also can be used to provide the autonomous unmanned some specific designed signs. Generally, the procedure of a traffic sign recognition system can be roughly divided of two stages namely detection and classification.

Shustanov, P. Yakimov [2] used for Road Sign Detection and Recognition is image processing technique which consist of a group of (CNN) for the recognition called as ensemble. The recognition rate for the CNN is very high, which makes it more desirable for various computer-based vision tasks. The method used for the execution of CNN is TensorFlow. The members of this paper achieved more than 99 percent of accuracy for circular signs on using German data sets

Walietal [3] describes how they have used to implement a novel method for sign recognition. They used advanced ARK-2121 technology which is small computer which they installed this tech on the car. The major techniques in the recognition step of the sign were SVM and HOG. They achieved an accuracy of 91% in detection and about 98% average on the classification process

R.Qianetal [4] describes the analysis and design process of "German Traffic Sign Recognition Benchmark" dataset. The outputs of this project showed that algorithms of machine learning showed very well in recognition of traffic signs. The participants got a very good percentage of 98.98 recognition rate which is as high as human perfection on these datasets.

Mammeri et al. [5] addressed the challenges and undesirable factors of the TSDR system, an essential component of ADAS. However, the system put forth by Mammeri's team worked over only a limited frequency range; besides, the recognition of traffic signs with a low-resolution camera, camera vibrations and oscillations posed tricky challenges for moving vehicles.

Chen and Lu [6] suggested a traffic sign detection technique, using Adaptive Boosting (Adaboost) and Support Vector Recognition (SVR). A TSR method, using high contrast region extraction and extended sparse representation, which uses color enhancement technique and voting of neighboring features, was presented in Liu et al. Color of other objects, which are in traffic signs, get enhanced, imposing a delay in TSR is the downside of their model.

Zhangka et al. [7] counted all the colour information of the sign images and set the thresholds for red, yellow and blue based on the statistical information, i.e. using global colour features for sign image detection.

Huang Zhiyong et al.[8] use the feature that RGB corresponds to a certain range of three-component difference values to obtain empirical thresholds after repeated experiments, and then segment the signs for detection, and this method does not require any multiplication operation

DATASET DESCRIPTION

Images from the German Traffic Sign Recognition Benchmark (GTSRB) dataset are frequently used to train a convolutional neural network (CNN) algorithm for the detection and classification of German traffic signs. This dataset contains a comprehensive collection of 43 different classes of traffic signs, from speed limits to entrance signs. The data is organized into two primary folders: Training and Testing, each containing several subfolders, one for each traffic sign class. The CNN algorithm uses image recognition and classification techniques to analyze these road sign images and identify their corresponding class labels.

Table 1.Path and Description of Traffic signs image Database

Folders	**Description**
Training	Found 216 images belonging to 43 classes includes Road work, Turn right ahead, Stop
Testing	Found43imagesbelongingto43classesincludesRoad work, Turn right ahead, Stop

The Sample Dataset is downloaded from the kaggle dataset repository which is shown in figure 1.

Fig 1: Sample Dataset

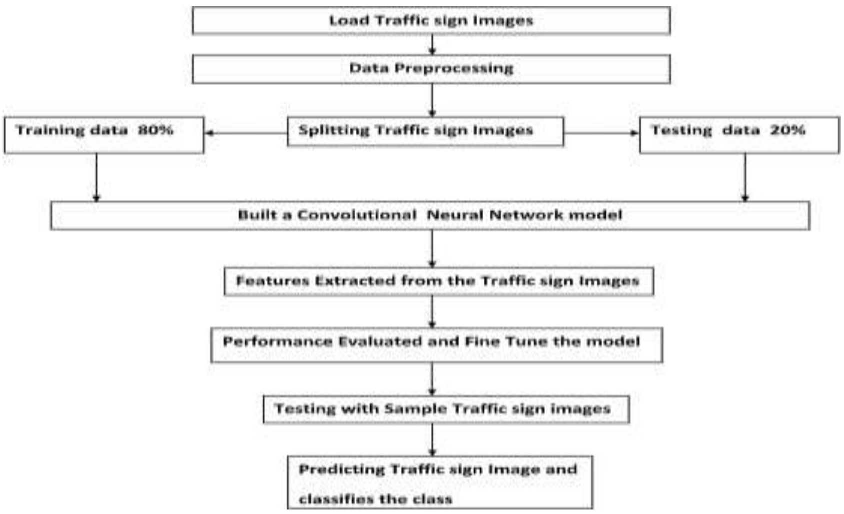
DATA PREPROCESSING

The dataset has been preprocessed with contrast enhancement and the sample dataset after preprocessing is shown in figure 2.

Fig2. Preprocessing of Sample Dataset

METHODOLOGY

The proposed methodology is shown in figure 3.



aFig.3.Methodology of the Research work

CNN Methodology:

During the training phase, the CNN model learns to distinguish and recognize the unique features that characterizeeachofthe43 classes of traffic signs. This is important for accurate classification. The CNN model is trained using the training dataset, and through repeated optimization, it improves its internal parameters and representations. From distinctive images, our algorithm learns to extract relevant information including shape, color, and pattern. Once the training model is completed, testing data comes into play. It has visuals separate from the training material. This test dataset is used to evaluate the performance of the CNN model. The effectiveness of the model is evaluated based on its ability to correctly detect and classify different German road signs into their respective classes. In total, the GTSRB dataset includes 43 different road sign classes with a collection of 258 images across these classes. The goal of the CNN model is to successfully categorize each image into one of these classes, thereby demonstrating its ability to recognize a wide variety of road signs, contributing to the advancement of road sign recognition systems and road safety.

This is a thorough process that explains how to detect and classify traffic signs using convolutional neural networks (CNN):

Import packages: The necessary packages, including Tensor Flow, Keras, and Numpy, are imported to build the CNN model.

Load road sign images: The road sign images are loaded into the system and the corresponding labels for each image are also loaded.

Data Preprocessing: In this step, images are contrast-enhanced by converting the original to gray scale and rescaling the pixel values from the original range [0, 255] to the new range [0, 1].

Splitting road sign images: The road sign images are divided into two sets: training images (80%) and test images (20%). This distribution helps to train a model on a subset of the data and verify its accuracy on another subset.

Building a Convolutional Neural Network Model: In this step, a CNN model is built, which includes convolutional layers, pooling layers, and dense layers. The model is trained on Training images using back propagation and its performance is monitored.

Feature Extraction: The CNN model is then used to automatically learn features frompre-processed road sign images such as edges and textures, shapes and patterns, symbols and text, and from these road sign images that distinguish one type of class from another.

Performance evaluation and model fine-tuning: Model accuracy and error rate are calculated using images of test road signs. If the model performance is not satisfactory, fine-tuning is done by adjusting the hyper parameters and optimizing the model architecture.

Testing with a sample road sign image: The trained CNN model is tested with a sample road sign image to verify its performance in road sign recognition.

Traffic Image Prediction: After the model has been trained and tested, it is ready to predict thetraffic sign image class. When a road sign image is input, the CNN model predicts which road sign class the image belongs to and converts it to voice.

EXPEIMENTAL RESULTS

Convolutional and pooling layers make up the first few levels of the model architecture, which are then followed by entirely connected layers. The input image is categorized into one of the 43 classes in the final layer using softmax activation. Categorical cross-entropy loss and the Adam optimizer are used to train the model.

The Image Data Generator function from Keras is used to create the training and testing data. The training and testing data are pre-processed by color enhancement and rescaled to 1/255.

The model is trained for 230 epochs, and the training and testing accuracy and loss are plotted for each epoch. The accuracy and loss curves show that the model is performing well on the training and testing data, and there is no over fitting or under fitting.

The final model achieves an overall training accuracy of 0.9878 and a testing accuracy of 0.9799. The training loss is 0.0569, and the testing loss is 0.0972. These results indicate that the model is performing well on the given dataset and can accurately classify traffic sign images into their respectivecategories.

Additionally, sample imagers from each of the 43 categories of traffic signs are used to evaluate the model. All of the traffic signs are appropriately classified by the model.

5.1. EVALUATION METRICS

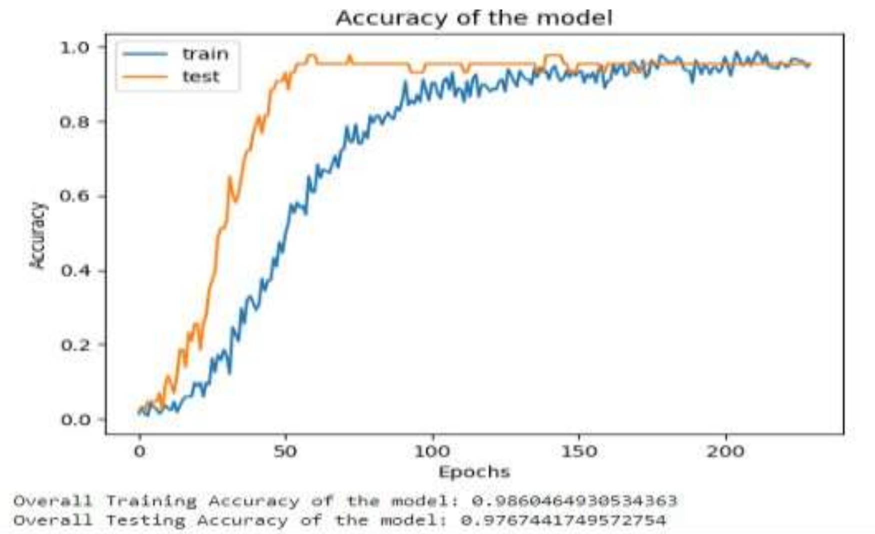
In order to evaluate the performance of a CNN for Traffic sign detection and Classification, metrics can be used:

Accuracy:

This is the most common evaluation metric used to measure the overall performance of a classification model. It is defined as the ratio of the number of correctly classified samples to the total number of samples. However, accuracy can be misleading when the classes are imbalanced or the misclassification of certain classes is more important than others.

A CNN model can be trained and tested to perform better and provide results with the highest degree of accuracy. A model can start with a lower degree of accuracy and eventually reach the highest accuracy. The model can be trained using different criteria depending on the data provided, and the selection of new results is categorized into the appropriate traffic sign recognition class. The plotting of training and testing accuracy is shown in figure 4.

Fig.4. Comparing Training and Testing Accuracy of the model



A CNN model can be trained and tested to perform better and provide results with minimal loss. The model can start with a higher degree of loss and eventually reach a minimum loss. The plotting of training and testing loss is shown in figure 5.

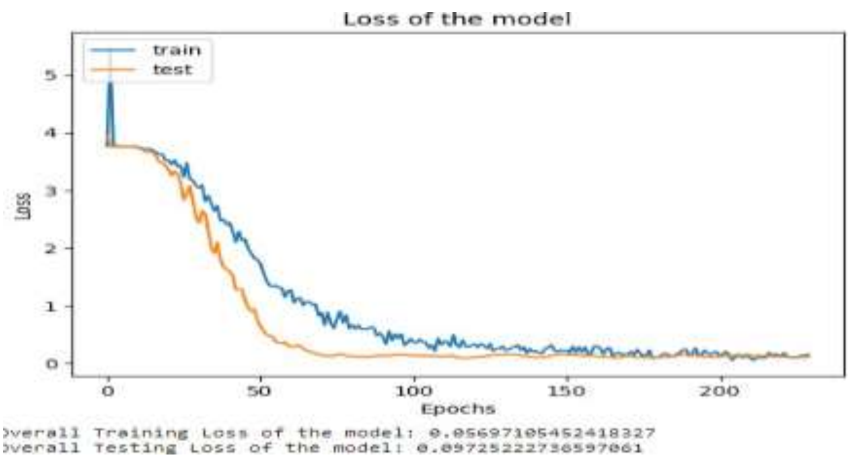


Fig.5. Comparing Training and Testing Loss of the model

The use of deep learning models in road sign recognition is a transformative advance in road safety and transportation technology. Using trained deep learning models, the system can accurately predict the type of traffic sign present in an input image, often captured by vehicle-mounted cameras. This technology is essential to increase driver awareness and road safety. When an input image is loaded, it is pre-processed and run through a deep-learning model to determine a predicted class label that corresponds to a particular traffic sign. This real-time information empowers drivers by providing critical data such as speed limits, road condition warnings and directions, ensuring they can make informed decisions on the road.

CONCLUSION

The application of deep learning algorithms, especially convolutional neural networks (CNN), has proven to be a highly effective tool in the field of traffic sign recognition. These algorithms have proven their ability to accurately detect and classify traffic signs, thereby increasing the safety and efficiency of traffic systems. By harnessing the power of CNN-based models, we have made significant progress in automating road sign recognition, reducing the risk of accidents and improving overall road safety. As technology continues to advance, we can expect even greater improvements in traffic sign recognition, ultimately leading to safer and more efficient roadways. The future of traffic sign recognition using deep learning is exciting, with the potential to significantly enhance road safety, traffic management, and the efficiency of transportation systems. Continued research, development, and collaboration between the automotive industry, technology companies, and regulatory bodies will be essential to realize these advancements. In the future, they can take real-time video footage to recognize the traffic signs and also they can use the Indian dataset.

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