Traffic Sign Recognition and Classification using Deep Neural Networks

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Abstract

Deep Neural Networks such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have been applied in various applications, including machine vision and computer vision. One of the most notable emerging applications of deep neural networks is Advanced Driver Assistance System (ADAS). In ADAS model, the deep neural networks have outperformed the manual human performance in terms of traffic sign recognition and classification. to the problem of traffic sign recognition, with promising results. This study has proposed a novel Convolutional Neural Network (CNN) architecture for recognizing and classifying traffic signs. The German Traffic Sign Recognition Benchmark dataset is used for experimental analysis. The outcome shows that the proposed model performs comparatively better. The results also indicate that the implemented CNN model with Adam optimizer and RankMax activation performs well for recognizing and classifying traffic sign images.

Keywords: Traffic sign recognition, Convolutional Neural Networks, Optimization, Advanced Driver Assistance System (ADAS).

1. Introduction

In this digital era, the volume of data generated is increasing unprecedentedly, resulting in the development of new technologies. One of the potential technologies to develop intelligent and autonomous models is Neural Networks (NN). This technique has created interesting and new possibilities in almost every domain, by playing a predominant role in

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computer vision applications, as these require large data processing in real time [1]. In NN, the Convolution Neural Networks (CNN) is emerging as a potential solution, as these networks ease the model training process and produce accurate results. Recently, CNNs were successfully integrated in the following applications: unmanned aerial vehicle recognition [2], medical image classification [3], facial emotion recognition [4], vehicle number plate and vehicle classification [5], handwritten character recognition [6], etc.

Traffic sign recognition is the most pressing concern nowadays. Generally, different traffic signs are designed in different shapes and colour in order to make the people understand the traffic rules, road directions, and the approaching road conditions while traveling. The main objective for developing a traffic sing recognition and classification systems is to reduce the increasing number of road accidents. Usually, a traffic sign recognition system will be developed in two stages: one stage to recognize and localize the traffic signs and another stage to classify the traffic signs detected. Here, the neural network architectures like CNN, RNN can be integrated in the traffic sign classification stage. The existing systems can detect the traffic signs but in case of worst scenarios like blurred vision, obstacles and lighting conditions, the system fails to detect [7].

A general illustration of Traffic Sign Recognition is shown in Figure 1. Here, the traffic signs are present in the top, left and right sides.

Figure 1. General Illustration of Traffic Sign Recognition

The article is organized as follows: Section 2 discusses about the existing research works in traffic sign recognition and classification. Section 3 discusses about the workflow of the CNN architecture and the proposed modified CNN model for traffic sign recognition and classification. Section 4 depicts the comparative experimental analysis and finally the section V concludes the proposed research work.

2. Literature Review

Generally, the traffic sign recognition and classification are done in different ways. One way is using the conventional manual classification methods and another emerging way is automating the entire detection and learning process by using the emerging machine learning and deep learning technique [8]. To be more particular, all the existing traffic signs have a proper standardized colour code and shape. This helps to easily detect the traffic signs. Colour based segmentation and thresholding are the commonly used colour-based traffic sign detection methods in the recent past [9]. These techniques are used to convert RGB to HIS or YCbCr in order to reduce the environmental sensitivity caused by the RGB colour space. The major challenge faced by this traditional method is lighting variations and colour fading due to the outdoor environment. To overcome these challenges, researchers have moved further to developing shape-based traffic sign recognition methods [10], the most popularly known method is Hough Transform. This method also has a disadvantage of consuming high computational time in the process of object detection; hence it fails in real-time implementation [11]. To improve the process of object detection particularly in the field of traffic sign recognition, the sliding window method is implemented by using HOG and viola jones-based approach. Since traffic signs are found in all the sides of the road, the aforementioned methods will become more complex and time consuming. To reduce the complexity, further a particular region-based object detection method has been developed. This reduces the search area and as a result the traffic sign detection model will become more cost efficient [12].

Recently, researchers are more focused on traffic sign classification rather than detection, this can be achieved by implementing Machine Learning (ML) classifiers like Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbour. Recently, the deep neural networks models are highly preferred, the models such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs) and Ensemble Learning. A recent research work [13] has developed a traffic sign detection and classification method by including colour invariants and Histogram of Gradients (HOG) technique.

The utilization of neural networks reduces the search space and also classifies the traffic signs. While using neural networks, we need to first pre-process and normalize the data in order to enhance the classification and detection performance of the classifier. Most of the existing research works are focused on classifying the traffic signs in a hierarchical manner [14]. This research work proposed a novel approach for traffic sign recognition and classification, which utilizes CNN with ADAM optimization and RankMax activation [15] for recognizing and classifying the traffic signs from the publicly available German Traffic Sign Recognition Benchmark dataset. The experimental results also show the efficiency of the proposed model and its improved accuracy.

3. Proposed Traffic Sign Recognition Model

The workflow of the proposed model is through three different stages:

- Data Pre-Processing
- Recognition
- Deep CNN based Classification

The detailed illustration of the workflow is given in Figures 2 and 3

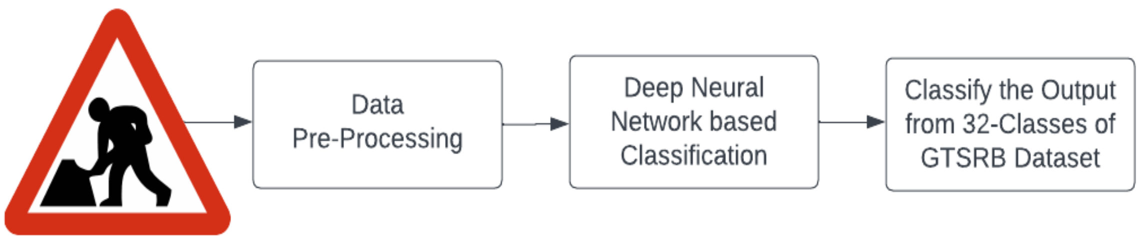

Figure 2. Basic Workflow of the Proposed Model

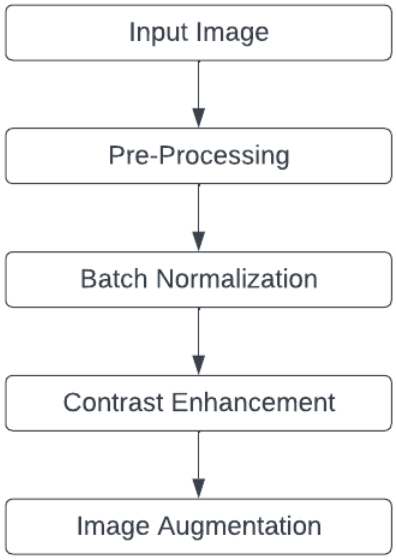

Figure 3. Image Data Pre-Processing and Enhancement Process

3.1 Data Collection

This research work has utilized the German Traffic Sign Recognition Benchmark (GTSRB) dataset, 2011 [16]. Here, we have considered totally 38202 training images and 12540 testing images. All the images are in different size, colour, contrast and brightness. Totally, the dataset has 43 image classes, where each class represent the traffic signs type and data.

3.2 Data Pre-Processing

Here, the pre-processing step involves the greyscale conversion and this step is followed by filtering the dataset to consider only images larger than 32 X 32 pixels for further image processing step. This step has been done, to improve the performance of the network even for medium sized images as most of the existing methods are focused on processing only the larger images. Here, the dataset is further divided into 80: 20 ratios for the training and testing datasets. Then, the data labels are created.

3.3 Normalization

Here, the batch normalization method is used to train the neural network to work faster and also to make the network to work more stable by normalizing the input layers by using the re-scaling and re-centering process. This process helps to accurately normalize the data for each batch [17].

3.4 Contrast Enhancement

Recently, many algorithms have been developed to enable contrast enhancement in image processing tasks, here, this study uses Adaptive histogram equalization technique [18] to improve the image contrast and its effectiveness.

3.5 Image Augmentation

In order to augment the final contrast enhanced images, this study uses the thinning operation to remove the selected pixels from the foreground image area [19].

3.6 Proposed Deep CNN Architecture

Figure 4 shows the architecture of the proposed deep neural network for classifying the traffic signs from German Traffic Sign Recognition Benchmark (GTSRB) dataset. In the proposed CNN architecture, neurons are arranged in a 3-dimensional space, with the third element referring to the total number of filters. The proposed neural network includes three convolutional layers followed by maxpooling and fully connected layers. Furthermore, a dropout layer is used after every fully connected layer.

Here, the augmented image with a basic image size of 32 X 32 as input, which is further classified into any one of the 32 classes of the dataset. Convolutional layers generate a convolved feature map by computing the filter weights and input to which it is connected. The network uses filters with a size 5 X 5 to obtain the final output. The pooling layers is used to perform downsampling. In order to solve the multi-label classification problems, the RankMax activation function is used to allocate a parameter to individual training instance. The output volume will be calculated after each and every layer by using the following formula:

$$\frac{I_S-F_S+2X}{M_S}+1 \tag{1}$$

I_S – Size of the input

F_S – Size of the filter

X – Used zero padding volume

M_s – Stride value in maxpooling layer

After performing the convolution and pooling, the flattened single vector output will be obtained. Further, the final fully connected layer computes the score of 32 classes present in German Traffic Sign Recognition Benchmark (GTSRB).

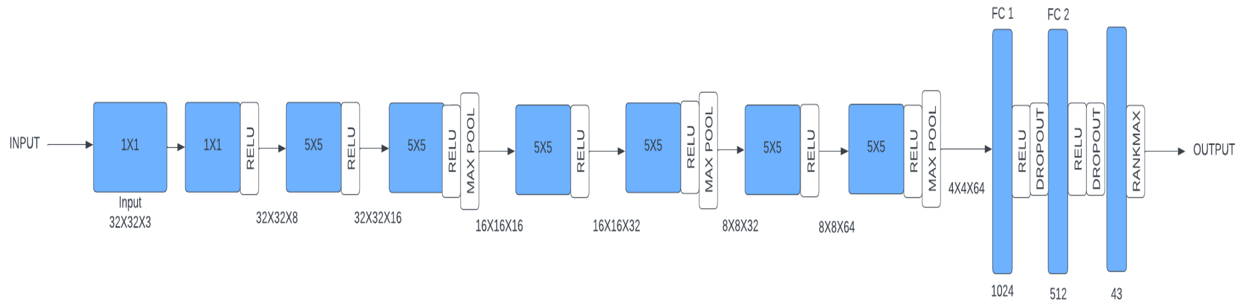

Figure 4. Architecture of the Proposed CNN for Traffic Sign Recognition

4. Experimental Results

4.1 Experimental Setup

The proposed model is implemented with Keras and TensorFlow. The experiment is carried out in $Core\ (TM)\ Intel\ (R)\ i5\text{-}\ 7500\ CPU\ @\ 3.40\ GHz$. The proposed CNN is implemented with German Traffic Sign Recognition Benchmark (GTSRB) dataset. Further, ReLU activation function is integrated with each neural layer.

4.2 Accuracy Analysis with and without Dropout Layer

This study has compared the testing and training accuracy with and without using the dropout layer. The average results are tabulated in Table I and II and the resultant graphical plot is given in Figures 5 and 6. From Table I it is highly evident that the proposed model faces the overfitting issue as the testing accuracy is lower than the training accuracy. To overcome the overfitting challenge, this study preferred using dropout combined with batch normalization and maxpooling layers. Finally, from Table II it is evident that the proposed model equipped with dropout and batch normalization has successfully overcome the overfitting challenge.

Table 1. Testing and Training Accuracy Without Dropout

Dataset	Trainable Images	Accuracy (Training)	Accuracy (Testing)	No. of Epochs
GTSRB	38202	98.52	93.19	10

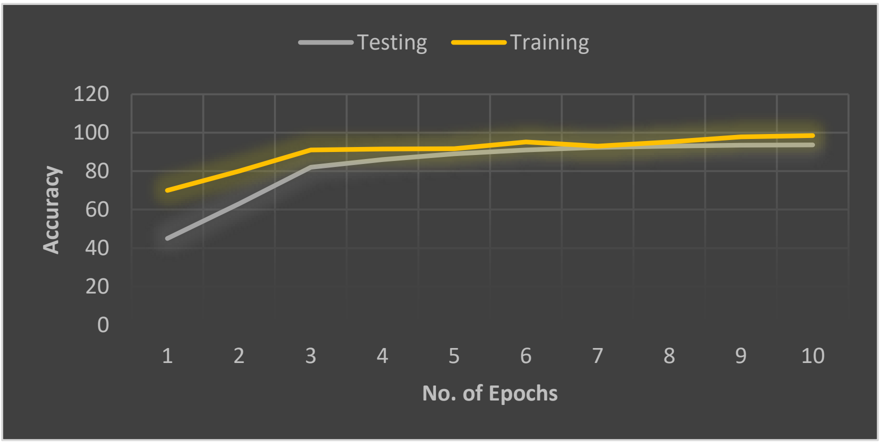

Figure 5. Accuracy Plot without using Dropout

Table 2. Testing And Training Accuracy with Dropout

Dataset	Trainable Images	Accuracy (Training)	Accuracy (Testing)	No. of Epochs
GTSRB	38202	97.02	98.25	10

Figure 6. Accuracy Plot with Dropout

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4.3 Accuracy Analysis with Different Optimizers

Next, this study focused on the implementation of optimization techniques to train the proposed model with dropout. This study has compared the implementation of optimization techniques like SGD, RMSProp and Adam optimizers and found that the Adam optimizer has resulted in a better accuracy with 0.3 dropout value. SGD updated weights incrementally after every epoch. ON the other hand, RMSProp has added all the values together to calculate the weight sum.

The Adam optimizer uses the following equation to update the weights

$$X = X - \alpha J_{dx} \quad (2)$$

$$J_{dx} = \beta J_{dx}(1 - \beta)dx \quad (3)$$

Where,

α = Learning Rate

β = Hyperparameter (Constant value = 0.9)

Table 3. Accuracy Results of Using Different Optimization Methods

Dataset	**Accuracy (Training)**	**Accuracy (Testing)**	**No. of Epochs**	**Optimization Method**	**Level of Dropout**
GTSRB	84.59	89.16	10	SGD	0.2
GTSRB	91.18	94.69	10	RMSProp	0.2
GTSRB	98.25	97.82	10	Adam	0.2
GTSRB	87.22	91.27	10	SGD	0.3
GTSRB	92.25	95.43	10	RMSProp	0.3
GTSRB	98.12	98.51	10	Adam	0.3

4.4 Accuracy Analysis with Different Activation Functions

Totally, three different activation functions are considered in this research study to improve the results. The testing and training accuracy obtained using Rankmax activation has outperformed the results produced by sigmoid and softmax function. Rankmax performs well and poses higher adaptivity as it adapts to individual training samples. This feature helps to easily predict and determine the targeted class. Table IV shows the comparative performance of all the activation functions.

Table 4. Accuracy Results of Using Different Activation Functions

Dataset	Accuracy (Training)	Accuracy (Testing)	No. of Epochs	Activation Function	Level of Dropout
GTSRB	94.89	93.65	10	Sigmoid	0.3
GTSRB	96.83	97.34	10	SoftMax	0.3
GTSRB	97.12	97.92	10	RankMax	0.3

5. Conclusion

This study has proposed a novel deep neural network model for recognizing and classifying the traffic signs. Here, the experimentation has been done by using the publicly available German Traffic Sign Recognition Benchmark (GTSRB) dataset and the proposed architecture with dropout, Adam optimizer and RankMax activation has resulted in a better accuracy. The dropout layer has reduced the overfitting challenge by performing the model averaging operations. Further, the RankMax activation function is used in the output layer to calculate the probability and increase the adaptivity of the network. For network training, this study has preferred using Adam optimizer after performing a detailed comparative analysis on the performance of different optimizers. In future, this study can be extended to implement quantum neural networks for enhancing the predictive results.

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