IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⪾ Peer-reviewed / Refereed journal ⪾ Vol. 11, Issue 10, October 2023

DOI: 10.17148/IJIREEICE.2023.111005

Neural Network based Traffic sign Survey

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Abstract: Traffic sign classification is one of the most important aspect to be considered in our day to day life. Traditionally, traffic signs have been categorized using standard computer vision methods, but it also takes lot of time to manually process important features of the image. To solve This problem, many people are using deep learning techniques.

In this paper we have proposed a method for Traffic sign classification.

Keywords: Advanced Driver Assistance, traffic sign classification, deep learning, convolution neural networks.

I. INTRODUCTION

Traffic sign classification plays a very important role in advanced driver assistance system. It also plays a vital role in automated driving system. Several times driver has to face many challenges especially on the road which is unknown to him and trying to focus on the road while driving, often some of the road signs are missed out by the driver which are not properly visible or the signs which are occluded, and this act proves to be dangerous for humans in terms of safety. To avoid such problems there must be some appropriate way which will inform the driver.

Several challenges such as occlusion, lightning condition, illumination changes, false detection, image distortion, complex traffic scenes do not make way for successful recognition of traffic signs. Traffic Sign classification, Detection and Recognition application not only ensures road safety, but also assists the driver in the driving process.

And lot of times another problem faced by the driver isto not understand what exactly the meaning of the given traffic sign is even if he come across the traffic sign on his way. Due to the advancement in the driver assistance system, no longer the driver will face the problem of what the traffic sign says.

Our paper talks about classifying the traffic sign on the road in two steps: classification and recognition of the sign. There are several ways to classify a sign like in [1], where the author used a modified version of the CNN model like inpaper [2], where the CNN model is used to classify the traffic sign. However, this method uses a Region of Interest (ROI) based approach using the shape and color of the traffic signs. Then after ROI this system is then passed through the recognition step.

In paper [11], they used support vector machine for recognizing. Our paper uses softmax as a top 5 predictor to analyze the probabilities to recognize the traffic sign. The authors in this paper have obtained a higher accuracy of prediction by using the CNN model. They have obtained an accuracy of 97.31% for classification using CNN model.

And an accuracy of 99.37% for classification of the traffic sign.

The work is organized in the following sections:

1. Section I represent the introduction of Traffic Sign Classification.
2. Section II represents the related work.
3. Section III addresses the details about the benchmarkdataset.
4. Section IV gives the detailed information related tothe proposed system.
5. Section V shows the performance and results of theproposed system.
6. Section VI Conclusion and Future-scope.

II. RELATED WORK

Several methods are published for traffic sign recognition that is, Broggi et al. [3] for classifying different traffic signs they used several neural networks. From the detection step they used the shape and color information to select the appropriate neural network.
F. Moutarde et al. [4], proposed the speed limit detectionand recognition and tracking. The classifier used has been trained

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using 4,000 samples with 23 classes, where the samples per class are in between the range of 30 to 600. Theclassification accuracy using this method is 94%.

For the shape-based methods, Hough Transform [5] A. Ruta et al., [5] M. A. Garcia-Garrido et al., is commonly used for traffic sign classification. Sliding window with a region classifier [3] I. M. Creusen et al., is used.

In [10] H. S. Malvar, proposed a classification on the German traffic sign dataset and acquired the accuracy of 95.5% by using the support vector machines. The dataset comprised of ∼43,000 traffic sign samples which were having 43 sign classes.

In [12], they have first extracted three features which aredense SIFT (Scale invariant feature transform) features, HOG (Histogram of oriented gradients) features and LBP (Local binary pattern) features, then those features were encoded using locality-constraint linear coding (LLC). Generally, good features are very difficult to design.

With the use of the Convolution Neural Network (CNN) it is no more needed to extract the hand-crafted features. The convolution neural network (CNN) automatically does this job on its own.

For geometrical variations of traffic signs, they used the data augmentation method for enlarging the dataset [6]– [7].

III. DATASET

There were several datasets for processing of the proposed system. The dataset I used for this purpose is German Traffic Sign Benchmark dataset (GTSRB). The dataset consists of 43000 images. The number of images was increased to 53000. Then the dataset is further split into Training and Testing. Among which number of training images are 39000 and the number of images used for testing were 12000.

The dataset includes several complex traffic signs suchas uneven lightning conditions, traffic signs occluded by trees or some other objects in the surrounding, uneven tilts in the traffic signs, similarity in colors of the background and the traffic sign, also the actual scene maps. By using all these complex signs, we verify the ability of our proposed algorithm on this dataset.

Figure1: Sample images of dataset.

The figure 1 shows the sample images of the German traffic sign Benchmark Dataset (GTSRB). The dataset comprised of 43 classes. For example, stop, turn right, speedlimit, etc.

IV. PROPOSED METHOD

In this proposed system we used 2 different trained CNNarchitectures. The CNN models used are VGG-16, MKNet CNN. One of the CNN model from the above-mentioned model used 6 layers.

The proposed system consists of the following steps:

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A. Data Augmentation

The Data Augmentation is the way of increasing the amount of data from the existing data. To improve the performance of the deep learning neural networks we have to increase the amount of data available. The Data Augmentation step generates the more data for only those classes which are having less representations.

After the data augmentation step in the proposed system the number of images were increased from 43,000 to near about 70,000.

The steps included in Data augmentation are as follows:

- Translation - The images were translated by 0.2units.
- Scaling - The images are scaled by the factor of2.
- Rotation - The images are rotated by the angleof 15º

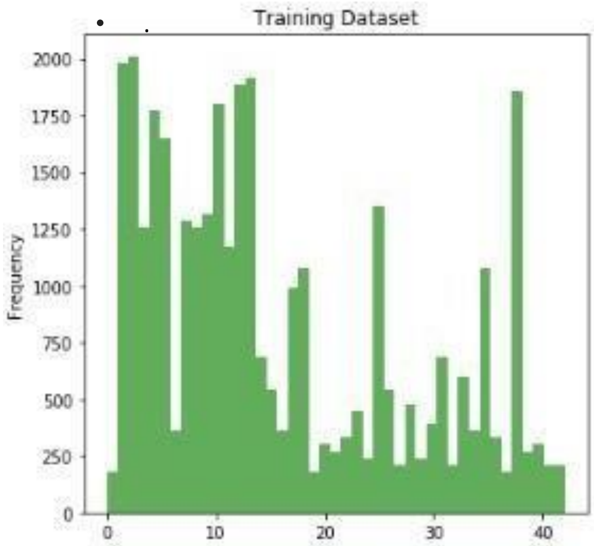

Figure2: Before Data Augmentation

Figure3: After Data Augmentation

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B. Preprocessing

Preprocessing consists of following steps:

- RGB to Gray - It reduces the training time. And the color increases the complexity of the model. With the help of gray scale images, we can talk about the brightness, contrast, edges, and so on of an image.
- Normalization - Normalization is a process that changes the range of pixel intensity value. It enhances the images which is

Figure 4: Before Preprocessing

Figure 5: After Preprocessing

C. System overview

The proposed system is shown in the Figure 6. The stageof our proposed system is the acquisition of the input image from the dataset followed by data augmentation and image preprocessing. Once the images are pre-processed then this output data is given as an input to the proposed CNN architecture.

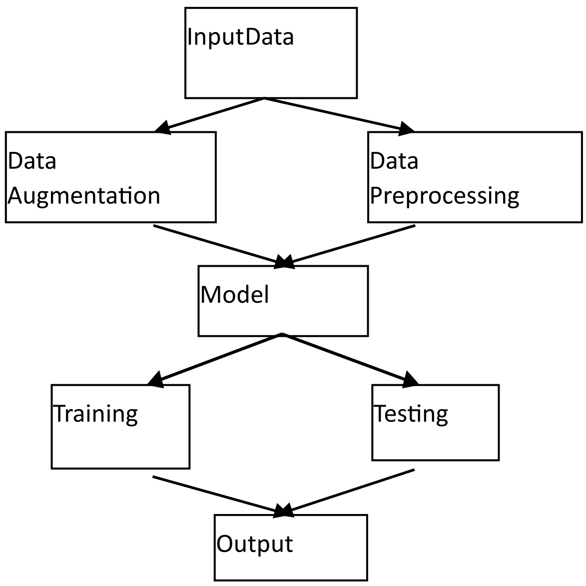

Figure 6: System overview.

D. Network Architecture

The CNN is the uncommon sort of multi-layer neural network. It extracts the features by combining the layers of the neural network. The layers that are combined are convolution layer, pooling layer, and activation layer.

Every CNN architecture is trained with back propagation, and therefore it gives the leading performance on different benchmark datasets. CNN models lead to powerful description ability. But it is still unclear that how it learns the features inside the network.

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The preprocessed images are given to CNN architecture. The images are given to this stage is for classification. The network consists of two convolution layers followed by activation layer, max pooling layer and dense layer. To avoid over-fitting dropout is used. Sigmoid activation function is used for convolution layer and fully connected layer. Corresponding to each category softmax layer has layer has 43 categories.

Based on the previous work the hyper-parameter and structure of the network were initialized, we trained the proposed CNN using ADAM as solver type, with a batch size of 32 images. The weight decay strategy ranging from 0.0001 to 0.01. The learning rate used is 0.001.
The network structure is similar to one of the CNN models. Where the size of the input image is 32*32 pixels and the images used were converted to gray scale. And the last fully connected layer has 43 neurons. The hyper parameters used, leads to increase the accuracy of the system.

TABLE I.
SELECTION OF CNN PRAMETERS

Layer	Type	Feature map and Size(output)	kernel
1	Input	32*32*1 Grayscale image	
2	Convolution C1 5*5	32*32*16	1*1
3	Activation (ReLU)		
4	Max Pooling M1	16*16*16	2*2
5	Convolution C2 3*3	14*14*80	1*1
6	Activation (ReLU)		
7	Max Pooling M2	14*14*80	1*1
8	Convolution C3	12*12*12	1*1
9	Activation (ReLU)		
10	Max Pooling M3	6*6*30	2*2
11	FC	750	
12	Dropout		
13	FC	350	
14	Dropout		
15	FC	43	

Additionally, for comparing the performance of the proposed system we have used the pre-trained model of VGG-16. The image size used for VGG-16 is 224*224 so we have converted the image size to the dimensions. The VGG-16 Architecture is shown in the Figure 7.

V. RESULTS AND PERFORMANCE

For improving the accuracy, we used 2 CNN models. It is demonstrated in the Table II. The following table is the comparison of all the 2 CNN models. As seen in Table II., there is an increase in the accuracy of the Traffic Sign classification. The classification rate for the used dataset is increased by 3.12%.

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Table II.Results

Dataset	Model	Accuracy
GTSRB	VGG-16	97.31
GTSRB	MKNet CNN	99.37

VI. CONCLUSION AND FUTURE SCOPE

We presented Convolution Neural Network architecture on the GTSRB traffic sign dataset. We have achieved 99.37% accuracy with the use of image dimensions 32*32.

And the top 5 prediction score 94.86%. For achieving the ideal Advanced Driver Assistance System or completely driverless system this model helps us to go a step closer. And still there are lot many things that can be improved. The overall performance could also be improved and customized with the help of more datasets and from different countries.

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