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CNN based Traffic Sign Classification using Adam Optimizer

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Abstract—**An automatic detection and classification of traffic signs is an important task in Advanced Driver Assistance System (ADAS).Convolutional Neural Network (CNN) has surpassed the human performance and shown the great success in detection and classification of traffic signs. The paper proposes an approach based on the deep convolutional network for classifying traffic signs. The Belgium traffic sign dataset (BTSD) is used for evaluation and experiment results shows that the proposed method can achieve competitive results compared with state of the art approaches. Different activations and optimizers are used to evaluate the performance of proposed architecture and it is observed that Adam (Adaptive Moment Estimation) optimizer and softmax activation performs well.**

Keywords- Adam optimizer, Belgium traffic sign dataset (BTSD), Convolutional Neural Network (CNN), Dropout, Traffic Sign Classification.

I. INTRODUCTION

Traffic sign detection is considered to be one of the most important part in the advance driver assistance system as it is necessary to detect traffic signs before they can be identified.traffic signs are designed with definite shape and color to provide the valuable information like traffic rules,route directions and different road conditions to drivers for safe driving.The main objective of designing the advance driver assistance system is to reduce the number of road accidents and wrong decisions. Designing smart vehicles for detecting traffic signs from the environment is one of the hot topics in today's traffic sign detection systems. Traffic sign detection and recognition system is mainly divided into two stages. First stage is the localization of traffic signs and second stage is the classification of detected traffic signs. Classification of traffic signs can be accomplished by using neural networks.

Traffic sign detection system reminds and warns the driver about upcoming traffic signs coming in a way. These systems have the ability to detect traffic signs even in worst case scenarios, but still sometimes it is difficult to detect traffic signs in challenging conditions .Some of the most common problems that may be encountered while classifying and detecting traffic signs are color fading, partial occlusion by surrounding obstacles, variation in lighting and weather conditions, shadowing, reflections from the sign boards during day hours and motion blurring. The detection and recognition of traffic signs has a variety of important application which includes advanced driver assisting systems, road surveying, autonomous driving, building and maintaining maps of signs, mobile mapping systems, vehicle navigations system, surveillance and self-govern robot navigation systems.

The rest of the paper is organized as follows. Section 2 reviews previous works on traffic sign classification and detection. The details of proposed system and proposed network architecture are described in Section 3.Section 4 shows the experiment results and Section 5 concludes the paper.

II. RELATED WORK

In general, traffic sign detection and classification methods are divided into two types. First is traditional or conventional methods and second is end to end learning or deep learning based methods. Most of the research works conducted on traffic sign classification and detection are based on these methods.

As traffic signs have definite shape and color ,color based methods and shape based methods are widely used for the detection and of the traffic signs. Color thresholding [1],color invariants [2],color segmentation [3] are the most common color based methods of detection. These methods convert the RGB color space [3] to other color space like, HIS[4], YCbCr [5] because RGB color space is very sensitive to environment. Drawbacks of these methods are Color fading and variation in lighting conditions. To overcome the problems of color based method, shape based methods like Hough transform [6] and EDCircle [1] are used widely. But these methods are very slow and takes more computational time for detection. So these methods can't applied for the practical use.

To improve the results sliding window based method [7] was proposed which uses HOG [8] and Viola-Jones [9] for traffic sign detection. These methods are complex and very time consuming. By knowing the fact that traffic signs are located in the two sides of roadways researchers have found out the new approach based on region proposal [10,11,12].Region based object proposal methods are widely used as compared to sliding window based methods as it reduces the search area.

Most of the traffic sign detection method uses different classifiers like neural networks [13],support vector machines

[14],convolutional neural network [15,16], random forests [13] and nearest neighbor [17] to classify the traffic signs from the environment. Out of these classifiers convolutional neural network is widely used for image classification problem.

In [2], a method based on color invariants and pyramid histogram of oriented gradients is used for traffic sign detection.

Approach based on the fully convolution network guided traffic sign proposals followed by the deep Convolutional Neural Network (CNN) has been used in [10] which reduces the search area classifies the traffic sign proposals.

In the study by Dan Ciresan,Ueli Meier,Jonathan Masci,Jurgen Schmidhuber [18], various Deep Neural Networks (DNNs) trained on differently preprocessed data were combined into Multi Column Deep Neural Network (MCDNN) for boosting the performance of the classification and Detection.

Most of the research work focuses on the CNN [15,19,20] for classifying traffic signs as they have the ability of learning features in a hierarchical way.

This work proposes an approach for traffic sign detection which uses the CNN for classifying the traffic signs from the publicly available Belgium traffic sign dataset (BTSD) [21].Experiment results based on this network architecture shows that CNN works efficiently and gives better accuracy.

III. PROPOSED METHOD

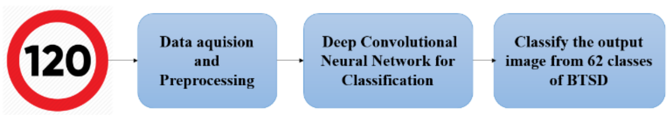

Figure 1 Pipeline of the proposed method

Fig.1 shows the the pipeline for the proposed method which includes three stages :data acquisition, preprocessing and classification..

A. Data Acquisition::

Traffic sign images in the BTSD database are extracted from the video sequences. The database does not take account of the disturbance of motion blur,fogy or rainy weather.

B. Convolutional Neural Network:

A convolutional neural network is a kind of feed forward neural network widely used for the image based classification object detection and object recognition.The basic principle behind the working of CNN is the idea of using convolution, which produces the filtered feature maps stacked over each other. Fig. 2 shows the key operations involved in CNN which includes convolution, non-linearity spatial pooling and convolved feature maps generated by this operation.

A CNN is made up of different Layers as shown in the Fig.3.Each layer has a simple application of transforming an input 3D volume to an output 3D volume that may or may not have trainable parameter.

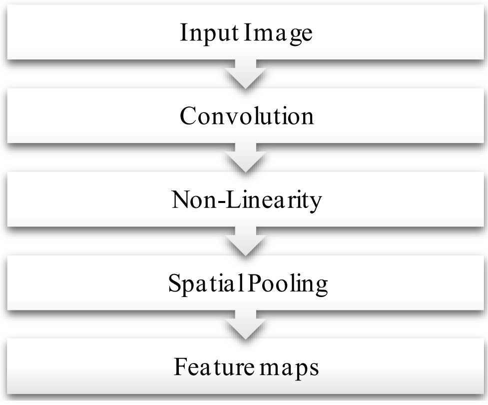

Figure 2 Key operations in CNN

C. CNN Architecture :

Fig.3 shows the architecture of CNN which this paper has proposed for classifying traffic signs from the Belgium traffic sign dataset (BTSD). In Convolutional neural network neurons are arranged in 3 dimensions width, height and depth where depth refers to the total number of filters. The network consists of three convolution layers each followed by the maxpooling layers and two fully connected layers. The dropout layer has been used in between two fully connected layers.The proposed network takes the color image of size 64 × 64 as an input and classifies it into RGB image as an input and classify it into one of the 62 classes from the dataset.

Convolutional layer gives convolved feature map as an output after applying the dot product between the weights of the filter and a small region of input to which they all are connected to. The network uses 32 filters with a size 3×3, so the output volume of a first convolution layer is given by [62×62×32]. After that pooling layer is used which is basically used to perform downsampling operation.Output volume of this layer has a size of [31×31×32] as it uses maxpooling with a stride 2 and filter size 2×2. Likewise the output volume of each layer can be calculated. In Convolutional neural network, the size of the output volume for each layer can be calculated using following formula:

$$\frac{W - F + 2P}{S} + 1 \qquad (1)$$

Where W is the size of input ,F is the size of filter ,S is the value of stride used in maxpooling layer,P is the amount of zero padding used on the border. After performing convolution and pooling operation, the output of maxpooling layer is flatten into a single vector as shown in Fig.3.Then fully connected layer is used to compute the scores for 62 classes as there are 62 classes present in the Belgium traffic sign dataset (BTSD).

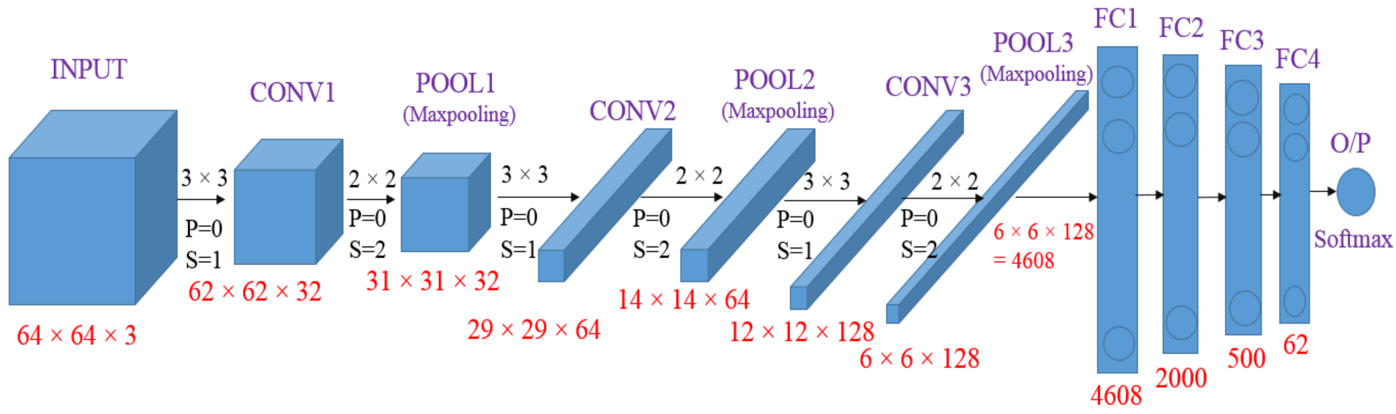

Figure 3 Proposed network architecture of convolutional neural network

IV. Experiment Results

A. Dataset:

In this paper Belgium traffic sign dataset (BTSD) [21] is used as a database which has been adopted widely in most of the research work for classifying and detecting traffic signs. The dataset set contains 4575 training images and the 2520 test images.Traffic sign images of these database extracted from the environment does not take account of the disturbance occurred due to motion blur and rainy weather. As shown in the Fig.4 the traffic signs of Belgium traffic sign database are divided into five categories,i.e.,Prohibitive signs with red color and circular shape, Mandetory signs with blue color and circular shape, Danger signs with red color and triangular shape,Derestriction signs and rest of the traffic signs fall under the category of unique signs.

Figure 4 Different classes of Belgium traffic sign dataset (BTSD)

B. Experimental setup:

Proposed system is implemented with Keras library and using Tensorflow as backend engine. The experiments are conducted on Intel (R) Core (TM) i5–7500 CPU @ 3.40 GHz with 8GB RAM , 64-bit operating system. Implementation of CNN (Convolutional Neural Network) was performed on Belgium traffic sign dataset (BTSD) [21] dataset. Adam (Adaptive Moment Estimation) optimizer [25] is used to train the network.Relu activation function is used for each neuron of CNN. Loss function used is sparse categorical cross entropy.

C. Results on Belgium traffic sign Dataset (BTSD):

The proposed architecture is applied on Belgium traffic sign dataset (BTSD). This paper emphasizes on the solution to traffic sign classification and detection. This work shows an effective implementation of classification with the network architecture that performs well. Table I Shows the layer wise details of proposed network architecture like output volume of the each layer and no of parameters to be handled by each layer.

TABLE I SPECIFICATIONS OF CNN

Layer (Type)	**Output shape**	**Parameters**
Conv_1	62,62,32	896
Max Pooling_1	31,31,32	0
Conv_2	29,29,64	18496
Max pooling_2	14,14,64	0
Conv2D_3	12,12,128	73856
Max pooling_3	6,6,128	0
Flatten	4608	0
Dense _1	2000	9218000
Drop out_1	2000	0
Dense _2	500	1000500
Drop out_2	500	0
Dense_3	62	31062

Total parameters to be handled by the proposed network is 13,89,543.ReLu activation function has been used in between the hidden layers of the network.ReLu does not activate all neurons at the same time which is considered to be the major advantage of using it as an activation function compared to other activation function.

TABLE II RESULTS ON BTSD BEFORE DROPOUT

Dataset	Total Trainable Parameters	Training Accuracy	Testing Accuracy	Epochs
BTSD	10342810	98.26	92.18	10

As can be seen from the Table II, training accuracy is higher than testing accuracy. This issue is called overfitting. There are lots of ways to improve the network performance.In case of overfitting: dropout [22], batch normalization [23], size of datasets, maxpooling, relu layer (non linearity) are the widely used methods. Table III shows the results on BTSD after applying the dropout as a regularization.Dropout randomly drops some of the neurons.

TABLE III RESULTS ON BTSD AFTER APPLYING DROPOUT

Dataset	Total Trainable Parameters	Training Accuracy	Testing Accuracy	Epochs
BTSD	10342810	96.61	97.06	10

TABLE IV DIFFERENT OPTIMIZERS USED IN PROPOSED ARCHITECTURE

Dataset	Training Accuracy	Testing Accuracy	Epochs	Optimizer	Dropout
BTSD	82.95	87.26	10	SGD	0.2
BTSD	97.40	96.31	10	Adam	0.2
BTSD	85.73	90.40	10	SGD	0.3
BTSD	96.61	97.06	10	Adam	0.3

Table IV shows the different optimizers used to train the network with dropout values.Adam optimizer with 0.3 dropout value shows the better result compared to SGD (Stochastic Gradient Descent) optimizer as it adaptively learn weights. In SGD ,weights are updated incrementally after each epoch (means passing over the whole training dataset).Adam uses following equation to update weights.

$$w = w - \alpha J_{dw} \quad (2)$$

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

Where α is learning rate and β is hyper parameter and its recommended value is 0.9.

TABLE V DIFFERENT ACTIVATION USED IN PROPOSED ARCHITECTURE

Dataset	Training Accuracy	Testing Accuracy	Epochs	Activation	Dropout
BTSD	95.08	94.68	10	Sigmoid	0.3
BTSD	96.61	97.06	10	Softmax	0.3

Table V shows the different activation applied on the network and furthermore dropout has been used to improve the results.Training and testing accuracy using softmax activation shows the better result compared to sigmoid.The main advantage of using softmax as an activation compared to other activation is it computes the probability of each and every class.And output in terms of probability is more helpful in predicting and determining the target class.

Fig.5 shows the result of training and testing accuracy plotted against number of epochs without using dropout. And results of training and testing accuracy with dropout is shown in Fig.6.In a same way result of training and testing loss plotted against epochs are shown in Fig.7 and Fig.8.

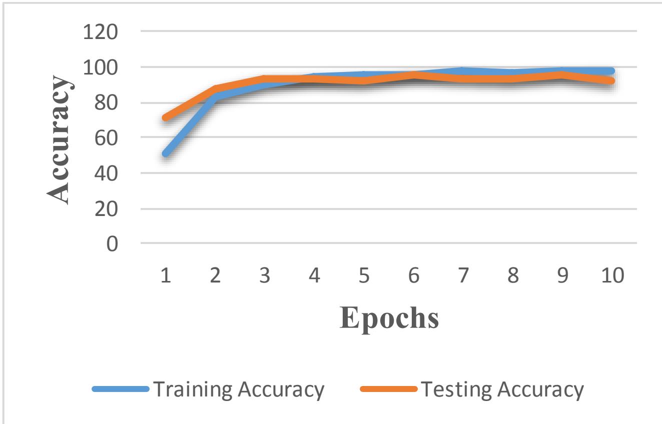

Figure 5 Training and testing accuracy without dropout

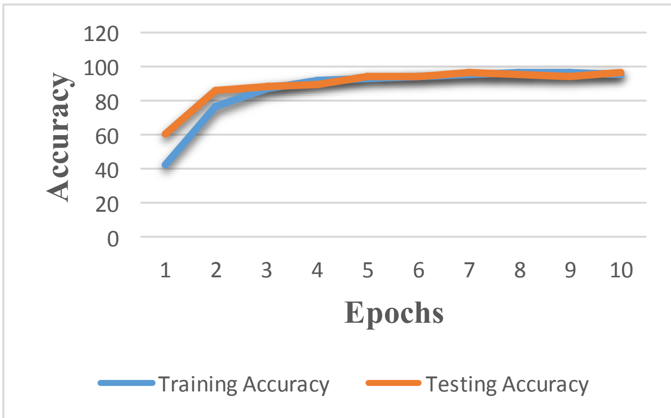

Figure 6 Training and testing accuracy with dropout

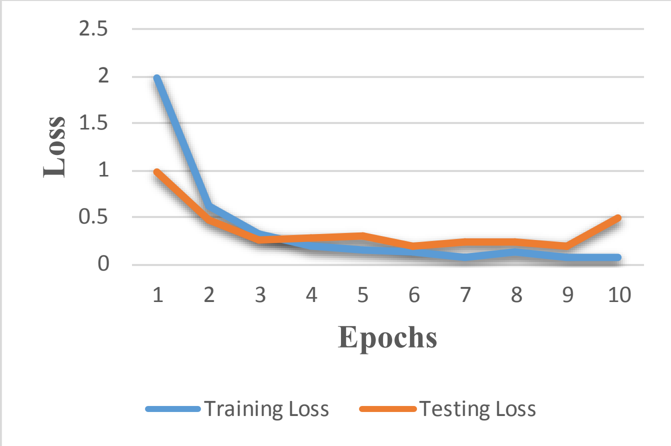

Figure 7 Training and testing loss without dropout

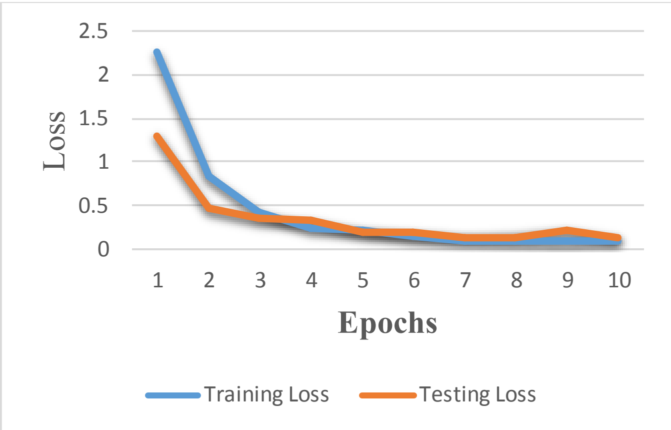

Figure 8 Training and testing loss with dropout

CONCLUSION

In this paper, an approach based on the Convolutional Neural Network (CNN) for classifying traffic signs is proposed. Evaluation was carried out on the publicly available Belgium traffic sign dataset (BTSD) and the architecture showed the better accuracy. Furthermore, it uses dropout to overcome the problem of overfitting as it randomly drops some of the units from neural network and it is also considered to be the most efficient way of model averaging. The proposed network architecture uses softmax as an activation in an output layer because it calculates a probability of every possible class.For training the network Adam optimizer is used and it is observed that it adapts faster compared to other optimizers like SGD.

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