Highly sensitive Deep Learning Model for Road Traffic Sign Identification

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Abstract

Computer vision and artificial intelligence plays major role in avoiding road accidents and large death numbers due to attention lack of driver. Recognition of traffic signs may help drivers to get alert. In this project recognition of traffic signs such as ‘Go’, ‘Straight’, ‘Speed Limit’, ‘stop’, ‘No passing’, etc. are used. We used a deep learning method known CNN with the help of LeNet architecture for the traffic sign classification and identification. Google Colaboratorywhich offers cloud based Jupyter Notebook environment that allows us to use supporting packages like NumPy, TensorFlow, keras, GPU etc. We have optedabove design to absorb thefeatures of the dataset such as contour based or liveliness-basedqualities by considering features such asscalability, rotation, luminous changes.By feeding GTSRB dataset to it Accuracy of the designed model is achieved to 98.50 %.

Keywords: Computer Vision (CV), Deep learning, Road Safety, LeNet-CNN model, trafficsign recognition,Accuracy, Automatic driving vehicle.

I. Introduction

The past some years rising in number of vehicles for that traffic flow congestion and traffic data has been blow up. Individual traveler and intelligent transformation in that traffic flow is useful for drivers.Traffic flowprediction using different advanced technology we can collect the data features from the road at different practical scenarios such as road's physical data such as traffic movements, multi object classification and road features such as potholes, danger curves, speed limits, and more.

Basically, convolutional neural networks are preferred for most the art of the state deep neural network algorithmsin maximum image dependent tasks. Convolution records the spatial data features of the image by applying the kernel function in convolution layer. A CNN model is designed by input, unknown, output layers. The unknown or hidden layer again contains convolutional, fully connected, pooling, normalization layers.to teach and evaluate the model.

We used a sophisticated dataset known as German Traffic Sign Recognition Benchmark (GTSRB)to classify recognizes the detected traffic signs from traffic scenes. We verified the achievement of the total model on GTSRB.

Regarding the remaining paper, in Section II, the old research and contribution is surveyed. In Section III, dataset used in the study is presented. In Section IV,our image processing is depicted. In Section V, model design process is shown. In Section V, result analysis is done.

II.Literature Survey

A.The written review of the literature presents an argument that explains the model used for modeling recognition of traffic sign.Traffic sign recognition using BoVW (Bag of visual words) is used in existing studies. Intelligent transportation work such as MLS (Mobile Laser Scanning) is also based on recognition of traffic sign which is studied by Yang Yu etAl in 2016. Classifier such as SVM (Support vector machine) is used for recognition of traffic sign by given model BoVW by the author Gao etAl. in 2016. For keypoint extraction from each image, SIFT (Scale Invariant Feature Transformation) is used.

B.The written review of literature presents an argument that explains the model describes multiclass CNN used for Traffic sign detection as noted by Hengliang Luo, Yi Yang, Bei Tong, Fuchao Wu, Bin Fan (Nov-2017). this paper presents the deep learning technique used for Traffic sign detection. they used the dataset is German Traffic Sign Recognition Benchmark (GTSRB)-2017 and German Traffic Sign Detection-2017. After, training and testing the model with the dataset the model acquired an accuracy of 87.30%.

C.The written review of the literature presents an argument that explains the model used for Traffic Sign Recognition using Deep learning for Autonomous Driverless Vehicles. As described by Vigneswaran, Seenivasaga Ayyalu R, Jayanthi Sree S (Apr-2021), They used the algorithm that extended work on the classical LeNet-5 CNN model. The proposed method makes use of Gabor based kernel followed by a normal convolutional kernel after the pooling layer. The optimization technique used now is the Adams method. The proposed method gives accuracy up to nearly 99%.

D.The proposed review of literature presents an argument that explains the model used for highly compact Deep CNN Architecture for Real-time Embedded traffic sign classification by Alexander Wong, Mohammad Javad Shafiee, and Michael St. Jules (Oct-2018).They introduced Micronet, a highly compact deep CNN network for real-time embedded traffic sign recognition designed based on microarchitecture design principles such as spectral microarchitecture augmentation, parameter precision optimization, etc. The resulting micronut possesses a model size of just ~1MB and ~510,000 parameters while still achieving a human performance level of accuracy of 98.9%.

III. The Dataset

In the view of accurate training, validationand testing the described method, primarily we used GTSRB Dataset.it is a multi-class, single-image classification related dataset. It has more than 50000 images contained 43 classescategorized into 39,209 training images and 12630 testing images. theimages have varying light conditions and rich backgrounds.

These images are reshaped to 30*30*3. Pixels range 15x15 and 250x250, indicates the variation in image size. Pixels 40X40 is considered as average size of an image first 40 represents number of rows and second 40 value, number of columns. In dataset will be splited as 20% images used for training and 80% images used for testing.

Fig. 3.1 Sample Traffic signs from dataset

In above figure, we displayed some sample images of traffic sign which are available in input dataset. The dataset includes Stop, turn left, speed limit, go slow, left turn, right turn, dangerous curve, no entry etc.

IV. Image data preprocessing

The 43 subfolders (0 to 42) available in our “train”named folder. Each child folder represents unique class. our defined OS module will help us in the iteration of every image with their respective classes and labels and store each image with its corresponding labels into lists. By using NumPy array, the data is fed to the model, so convert this list into array.

We should shuffle our dataset in random way to bring down model variance and over fitting. Shuffling will help in training almost all data points therefore training will be better and gives desired outcomes.

There is a necessity to categorize our input data into training, validation and test subsets to reduce network from over fitting.One hot encoding changes the categorical data into numeric data by splitting a single column into multiple columns.

In GTSRB dataset, there is unequal imagesin the 43 classes. So, we make use of data augmentation technique which will increase the data unnaturally with some minor geometric conversions (like noise addition,translation,rotation,flipping) from existing data to achieve the diversity on the train dataset.

For the described model, we are choosing 20 epochs to get better accuracy compared to other epoch values. Basically, an epoch will train the CNN model with the whole training data in one cycle.

s.no	No of epochs	Accuracy of the model	Time taken
1	5	97.71	15 mins
2	10	98.45	20 mins
3	15	99.20	30 mins
4	20	98.50	40 mins
5	30	98.47	50 mins

Table 4.1: No of Epochs to Accuracy

From the above table, we can conclude that by varying the epoch number, the processing time of model is more.so we can train our model to 20 epochs is better

V. Methodology

An inspired concept called Convolutional Neural Network (CNN) which is a type of Artificial Neural Network (ANN) which is mostly applied to solve the problems like object or image classification and recognition.The basic CNN is classified in three primary divisions:

1. Input image characteristics will be selected by selecting limited features of input image.
2. The image pooling layer basically designed to lower the input image measurements without losing the crucial characteristics.
3. The dense layer known fully connected layer takes the outcomes obtained from convolution layer and prediction can be done at the last layer.

Gradient descent method is used for initialization of neural network and hence recognition as well as classification results are very good using CNN, compare to the state of art techniques. Stride and padding are the main two task in convolution process.

Particular features are extracted from available features using CNN model. Sequential modelling can be done using keras libraries from python. Output of one neuron will be passed to input of other neuron using hidden layers. Layers information is displayed in below figure.

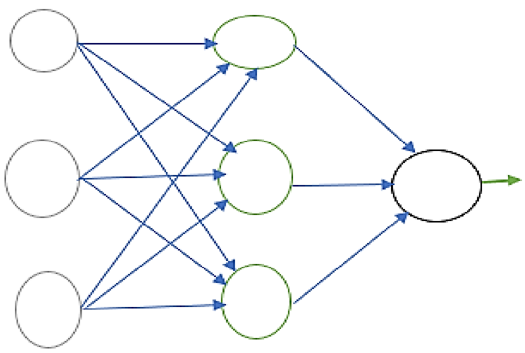


Fig. 5.1 CNN ArchitectureA) Input Layer B) Hidden Layer C) Output Layer

LeNet architecture fed with image input shape with 30*30*3. First convolutional layer has a depth of 32 and filter size of (5,5), again the same parameters are used in 2^{nd} layer of the CNN. Nonlinear alteration can be provided with very high mutability using convolutional layer with higher benefits.

The primary benefit of using second convolutional layer is that it has high mutability in giving non-linear alterations without ruining information. After that Max pooling operation eliminates information of the signal, the dropout layer which will disguise that reduces the activity of some neurons towards the forthcoming layer and neglects unmodified all others.

Batch normalization is also a layer in the architecture which brings each layer of the network has to learn more self-reliantly.

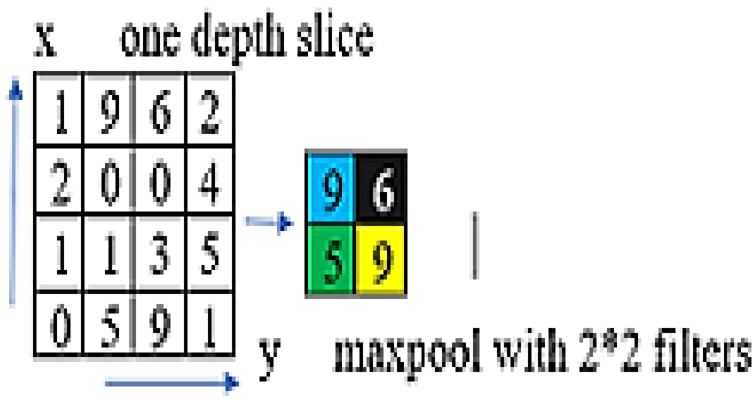
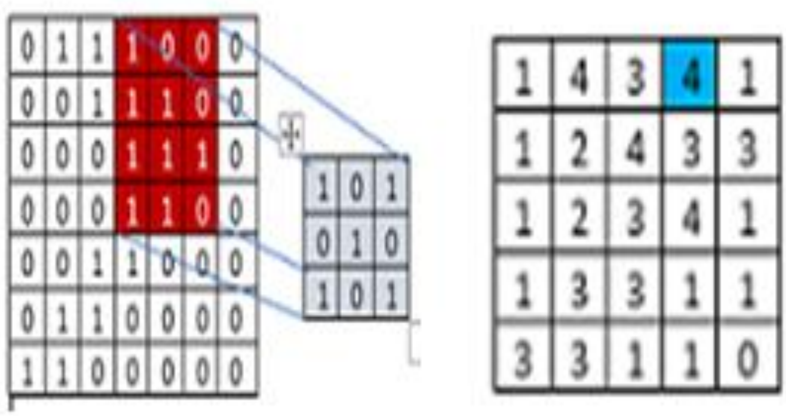


Fig 5.2: maxpooling

Dot product is calculated between kernel and input pixels using convolution orbit over input image. This process will help in finding unique features of image so that classification can be done easily.



IK=I*K

Fig5.3: convolution flow of data

Traffic sign classification and recognition is extremely invert to linear conversion need to be put on source data.so assembling multiple convolutions by using Rectified Linear Units (ReLu) will do it convenient to learn.

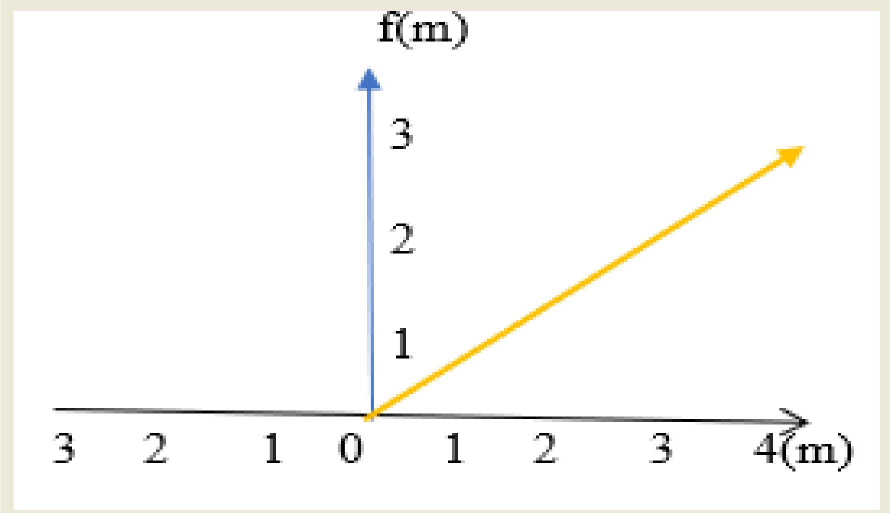


Fig 5.4: f(m) =maximum (0, m)

The succeeding LeNetcontains 3rd and 4thconvolution layers with depth of 64 and kernel size of (3, 3) and ReLU works as activation function, combined with maximum pooling layer. After the fourconvolutions, applied a dropout, which will do regularization in which weights are assigned with a likelihood.therandom weights will be “dropped” sonow the model from overfitting is decreased.

Input features are in 2D format and flattening helps us to convert into 1D vector which are then given input to fully connected layer. These all layers are connected to each other like ReLU layer and dropout layer, used for removing the overfitting, fully connected layer is used after that which represents the classes types.The apply‘SoftMax’ function being closing activation function in the network because itstandardizes the input vector to a span that generallygenerates aprobabilistic perception.

For the accurate result the following are steps:

Step1). It is important understanding of Google Colaboratory anddownloading the data of GTSRBfrom Kaggle.

Step 2). Unzip the dataset and upload it into a google drive then assign its path to root of the operating system.

Step 3). Get the information about the python and import necessary libraries and dataset for the image data processing and manipulations.

Step 4) For the scaling of data use normalization method for the range 0 to 1. If the data is less so it is difficult to complete the statistics.

Step 5) Split that data into 70% and 30% for testing and training purpose respectively.

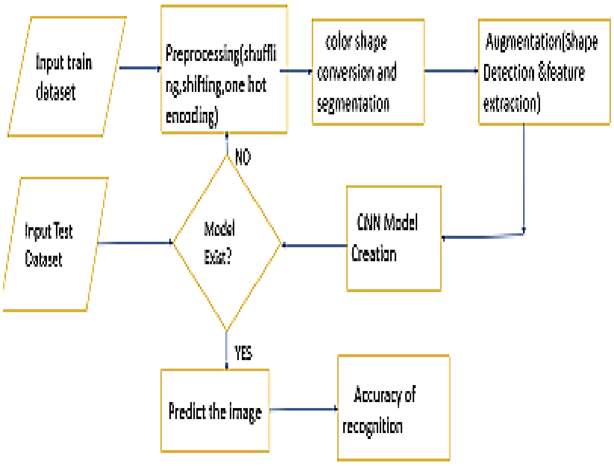


Fig 5.5. Flowchart of traffic sign

classification and recognition

Step 6) we preprocess the dataset like shuffling, shifting, one hot encoding using various inbuilt libraries.

Step 7) performs color, shape conversion and segmentation for extracting crucial features of the image.

Step 8). Data Augmentation (rotation, zooming, width and height shifts, flipping) is done for Shape Detection and feature extraction.

Step 9). Design CNNand choose appropriate architecture, filters, activation functions, no of epochs etc. accordingly.

Step10). Input the Test Dataset to the designed model and, predict the image and calculate accuracy in percentage.

VI.Result Analysis

Proposed model uses CNN model for prediction of road traffic signs and its is observed that LeNet performs very well in digit, image based classifications.

```
lr = 0.001
epochs =20

opt = Adam(lr=lr, decay=lr / (epochs * 0.5))
model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
```

Fig.6.1 Model designed with different epochs and performance analysis calculation.

So Here 20 epochs are considered for prediction of accuracy and loss of the designed model.

```
Test Data accuracy:  98.50356294536817
```

Fig 6.2 test data accuracy

Accuracy obtained by proposed model is 98.503562 which is practically an accurate model.

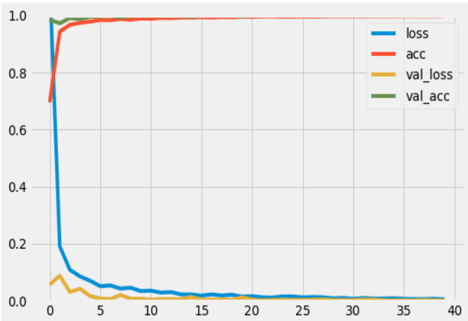


Fig.6.3Loss and Accuracy Graphs w.r.t epochs

VII. Conclusion

Fig 7.1 actual image and predicted image

The foremost profit ofconvolutional neural networkis itauto detects features sort of human supervisions. Image may have different variations such as angle change or may be image is near or far, algorithm identifies its label. Time required for recognition of traffic sign is very less (0.4 seconds). The prediction accuracy is obtained as 98.5027 which is a very high accuracy.

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