Summer Training Project

On

TRAFFIC SIGN RECOGNITION

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INTRODUCTION TO PROJECT

To recognise traffic signs using CNN taken from the dataset of Belgium Traffic Signs which consist of :-

- Training datasize: 4575 images belonging to 62 classes
- Validation datasize: 1277 images belonging to 62 classes
- Testing datasize: 1243 images belonging to 62 classes

This model comprises of 2 convolution, 2 pooling and 2 dense layers which are fed to a non-linear activation function "Softmax" to classify these images

LITERATURE REVIEW

WHAT IS TRAFFIC SIGN RECOGNITION?

- Traffic-sign recognition (TSR) is a technology by which a vehicle is able to recognize the traffic signs put on the road e.g. "speed limit" or "children" or "turn ahead". This is part of the features collectively called ADAS.

- The technology is being developed by a variety of automotive suppliers. It uses image processing techniques to detect the traffic signs.

- The detection methods can be generally divided into color based, shape based and learning based methods.

- Traffic sign recognition has direct real-world applications such as driver assistance and safety, urban scene understanding, automated driving, or even sign monitoring for maintenance.

- It is a relatively constrained problem in the sense that signs are unique, rigid and intended to be clearly visible for drivers, and have little variability in appearance.

HISTORY OF TRAFFIC SIGN RECOGNITION:-

- The Vienna Convention on Road Signs and Signals is a treaty signed in 1968 which has been able to standardize traffic signs across different countries. About 52 countries have signed this treaty, which includes 31 countries from Europe.
- The convention has broadly classified the road signs into seven categories designated with letters A to H. This standardization has been the main drive for helping the development of traffic-sign recognition systems that can be used globally.
- Traffic-sign recognition first appeared, in the

form of speed limit sign recognition, in 2008 for the 2009 Vauxhall Insignia. Later in 2009 they appeared on the new BMW 7 Series, and the following year on the Mercedes-Benz S-Class. At that time, these systems only detected the round speed limit signs found all across Europe.

- Second-generation systems can also detect overtaking restrictions. It was introduced in 2008 in the Opel Insignia, later followed by the Opel Astra and the Saab 9-5.

METHODOLOGY, PROBLEM FORMULATION AND POSSIBLE SOLUTION

After importing the python libraries that are needed for our project.

Then the following procedure is followed:-

Load data:- We have the training data having 4575 images, Validation data having 1277 image and

Testing data having 1243 images which are belonging to 62 classes.

We use keras flow_from_directory() to load data.

Analyze data:- We have our training, validation, test datasets of as directory iterator.

Training, Testing, Validation sets contains 143 tuples, each of size 2. The first element of a tuple having shape of (32,35,35,1) and second element of tuple having shape of (32,62).

Here 32 is the batch size of training, testing and validation dataset's images. (35,35,1) representes **grayscale** image of size 35x35. And 62 is the total no of classes.

Data preprocessing:- Now the images are greyscale images have pixel values that ranges from 0-255. We have converted the images of shape 35x35x1 into 35x35 which is fed into the network. Now our data is in int32 format so we convert it into float32 in order to rescale the pixel values in the range 0-1.

In the next step, we need to convert the class label into one hot encoding vector. In one-hot encoding, we convert the categorical data into a vector of numbers. The reason why we convert the categorical data in one hot encoding is that machine learning algorithms cannot work with categorical data directly. we generate one boolean column for each category or class. Only one of these columns could take on the value 1 for each sample. Hence, the term one-hot encoding.

Model:- We convert the image matrix to an array, rescale it between 0 and 1, reshape it so that it's of size 35x35, and feed this as an input to the network.

We use two convolution layers:

- The first layer have 16-3x3 filters.
- The first layer have 32-3x3 filters.

In addition, there are two max-pooling layers each of size 2 x 2.

Compile the model:- After the model is created, we compile it using the Adam optimizer, one of the most popular optimization algorithms.

Train the model:- We train the model with Keras fit_generator() function. The model trains for 50 epochs. The fit_generator() function will return a history object.

Finally our model is trained with an accuracy of 92-97% and the training loss are quite low.

Validation accuracy is also 90-95% which shows that the difference between their accuracy are quite low.

Evaluation of model:-

From the graphs plotted we can see that the validation loss and validation accuracy both are in sync with the training loss and training accuracy. Even though the validation loss and accuracy line are not linear, but it shows that your model is not overfitting: the validation loss is decreasing and not increasing, and there is not much gap between training and validation accuracy.

Therefore, we can say that your model's generalization capability became much better since the loss on both test set and validation set was only slightly more compared to the training loss.

RESULTS

Test accuracy:-

Our model’s test accuracy is 90-95%.

Predictions:-

We predicted the labels of given sample images from the testing data and compared with the actual labels.

By looking at a few images, we cannot be sure as to why our model is not able to classify the some images correctly, but it seems like a variety of the similar patterns present on multiple classes affect the performance of the classifier although CNN is a robust architecture.

CONCLUSION

By applying ConvNets to the task, traffic sign classification becomes much easier and gives better accuracy of about 90-95%.

Using this recognition system, an application for the driver safety purpose is built.

The application will keep the driver updated about the traffic signs for better driving assistance and safety.

In future the driver assistance system can be used in cars to work according to the traffic signs and the recognition system can be used in self driving cars to learn and understand the traffic signs.