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TRAFFIC SIGNS RECOGNITION AND CLASSIFICATION USING CNN ALGORITHM

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Abstract: *The self-driving cars are cars in which the passenger can fully depend on the car for traveling. But to achieve level 5 autonomous, it is necessary for vehicles to understand and follow all traffic rules. In the world of Artificial Intelligence and advancement in technologies, many researchers and big companies like Tesla, Uber, Google, Mercedes-Benz, Toyota, Ford, Audi, etc. are working on autonomous vehicles and self-driving cars. So, for achieving accuracy in this technology, the vehicles should be able to interpret traffic signs and make decisions accordingly. There are several different types of traffic signs like speed limits, no entry, traffic signals, turn left or right, children crossing, no passing of heavy vehicles, etc. Traffic signs classification is the process of identifying which class a traffic sign belongs to. So, in this project we have built a deep neural network model that can classify traffic signs present in the image into different categories. With this model, we are able to read and understand traffic signs which are a very important task for all autonomous vehicles.*

Keywords: *Traffic signals, self-driving cars, Traffic signs recognition, convolutional neural networks.*

I. INTRODUCTION

It is necessary for self-driving cars to understand and follow all traffic rules so the passenger can fully depend on the car for traveling. So many researchers and big companies like Tesla, Uber, Google, Mercedes-Benz, Toyota, Ford, Audi, etc. are working on autonomous vehicles and

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self-driving cars to improve the algorithm which can classify a traffic sign to its class without any error. Vehicles with driver support have many drawbacks such as accidents due violating traffic rules, unable to recognize traffic signs in certain weather conditions and etc. These all can be solved using self-driving cars which recognizes traffic signs with greater accuracy [1].

Road sign recognition has become a major challenging field in academics as well as in industry. The major application of this systems can be mostly used in the upcoming Artificial Intelligence (AI) world to understand environment and also being one of the most important parts in Advance Driver Assistance Systems (ADAS).If confusion occurs in recognizing warning signs, then it may be dangerous. However, because of different environmental situations, there are few cases where the road signs will get completely perverted, making their appearance challenging for humans and machines. The difficulties found with the Road sign collection could be eliminated by the utilization of different artificially generated data without must burden on the classifier to recognize. Our paper discusses recognition of sign in two major ways which are classification and extraction. There are many ways in recognizing a signal. The paper [2] uses a modified Hough Transform to determine the coordinates of the road sign, or like in paper, where Circular Hough Transform is used to determine the circular prohibitor sign. Methods used in paper and use the information about the shape of the road sign in the detection step, based on the Histogram features and Support Vector Machine classifiers. Using these papers as a reference, the appearance of the sign remains constant in each example. And only the view reference is changed with each sign. The fact is that the pattern of sign is always the same, the only change is the view that a recognition camera or the driver sees and also the environment which makes difficult to recognize, this contribute the different variations in recognition, this can be achieved by updating different conditions of traffic signs in the training set. Our method doesn't require real time data because we used training data set which consists of the photographs that are very similar to the real-world data. The objective of using this data set is to increase our detecting precision as more as possible which should be greater than 90% close to actual observation. So, whenever a sign is scanned it may not be same as the real-world sign but our method uses CNN to

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recognize any similarities between them and classifies as the same sign [3].

II. LITERATURE SURVEY

Street security and traffic management is current issue over the globe. Regular events of fatal accidents bringing about the loss of lives and different assets. There can be various incitements prompting these disasters like poor street upkeep, neglectful driving, mental condition of driver, casual attitude of pedestrians. Another major reason prompting to this may be the poor law implementation and improvised upkeep of street traffic signs. Blocked or then again decayed signs may delude the driver. The present method emphasis on Convolution Neural Network which helps to recognize traffic signs without above stated issues. In this present deep neural network model, we have resized the images using different layers to predict the image and classify accurately.

The method described by Shustanov, P. Yakimov [5] used for Road Sign Detection and Recognition is image processing technique which consist of a group of (CNN) for the recognition called as ensemble. The recognition rate for the CNN is very high, which makes it more desirable for various computer-based vision tasks. The method used for the execution of CNN is TensorFlow. The members of this paper achieved more than 99 percent of accuracy for circular signs on using German data sets.

SING COLOR SEGMENTATION.[2] Wali etal [6] describes how they have used to implement a novel method for sign recognition. They used advanced ARK-2121 technology which is small computer which they installed this tech on the car. The major techniques in the recognition step of the sign were SVM and HOG. They achieved an accuracy of 91% in detection and about 98% average on the classification process.

R. Qian etal [7] describes the analysis and design process of “German Traffic Sign Recognition Benchmark” dataset. The outputs of this project showed that algorithms of machine learning showed very well in recognition of traffic signs. The participants got a very good percentage of 98.98 recognition rate which is as high as human perfection on these datasets.

In [8] addresses the algorithms for detecting and tracking traffic signs. The method for localization, which is a modification of the generalized Hough transform, has been developed considering the constraints on the time for processing a

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single frame. The algorithm shows effective results and functions well with the pre-processed images. Tracking using the value of the vehicle current speed has improved the performance of the system, as the search area in the adjacent frames can be significantly reduced. In addition, the presence of a sign in the sequence of adjacent frames in predicted areas significantly increases the confidence of correct recognition. Classification, which is the final step, ensures that the entire procedure has been executed successfully.

In papers [9], the authors proposed effective implementations of the image pre-processing and traffic signs localization algorithms, which performed in real time. Using a modified Generalized Hough Transform (GHT) algorithm, the solution allowed to determine the exact coordinates of a traffic sign in the acquired image. Thus, in the classification stage, the simple template matching algorithm was used. Combined with precise localization stage, this algorithm showed the final results of 97.3% accuracy of traffic sign recognition.

III. EXISTING SYSTEM

A vehicle manually driven by a person for travelling. With, the existing system, there can be various incitements prompting these disasters like poor street upkeep, neglectful driving, mental condition of driver, casual attitude of pedestrians. Another major reason prompting to this may be the poor law implementation and improvised upkeep of street traffic signs Blocked or then again decayed signs may delude the driver.

Issues

The major problem with the vehicles is drivers are failing to recognize the traffic sign accurately and sometimes may violate the traffic rules. With this, accidents may take place and also may cause trouble to others traveling on road.

IV. PROPOSED SYSTEM

In this project, we will build a deep neural network model that can classify traffic signs present in the image into different categories. With this model, we are able to read and understand traffic signs which are a very important task for all autonomous vehicles. With this, in self-driving cars passengers can fully depend on the car for traveling.

SYSTEM ARCHITECTURE

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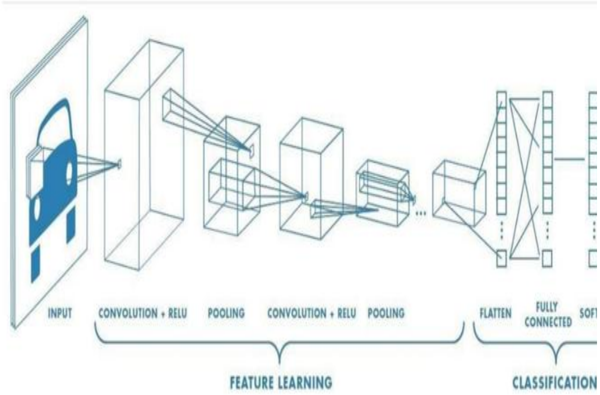

Fig.1 System architecture

Using a fully connected neural network to make an image classification requires a large number of layers and neurons in the network, which increases the number of parameters leading the network to over-fitting (memorizing the training data only). The input image may also lose its pixels correlation properties since all neurons (carrying pixels values) are connected to each other. Convolutional neural networks have emerged to solve these problems through their kernel filters to extract main features of the input image and then inject them into a fully connected network to define the class. The chosen architecture in our application is convolutional neural network. It contains 6 layers of convolution and simplification functions made by 3x3 kernel filters, Batch Normalization and a max pooling filter of 3x3 to reduce at last the input image of 32x32. The name "convolutional neural network" indicates that the network employs a mathematical operation called convolution. Convolution is a specialized kind of linear operation.

A CNN typically has three layers: a convolutional layer, pooling layer, and fully connected layer.

Convolution Layer

The convolution layer is the core building block of CNN. It carries the main portion of the network's computational load. The main objective of convolution is to extract features such as edges, colors, corners from the input. As we go deeper inside the network, the network starts identifying more complex features such as shapes, digits, face parts as well. At the end of the convolution process, we have a featured matrix which has lesser parameters(dimensions) than the actual image as well as more clear features than the actual one.

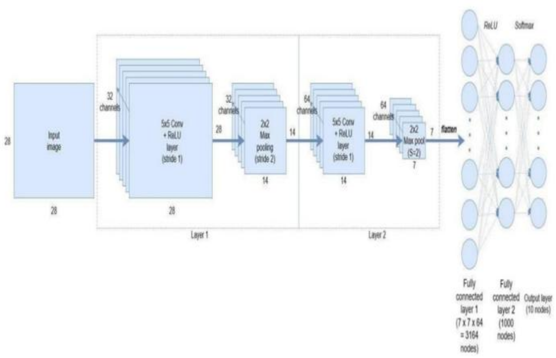

Fig.2 Convolutional layer

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Apply the ReLu (Rectified Linear Unit)

Without applying this function the image classification will be treated as a linear problem while it is actually a non-linear one

Pooling Layer

Pooling layers are used to reduce the spatial size of representation generated by previous kernels after convolution. In this layer, we try to extract the dominant features from a restricted amount of neighbourhood. There are two types of pooling techniques: AVERAGE-pooling and MAX-pooling. So, after pooling layer, we have a matrix containing main features of the image and this matrix has even lesser dimensions. These layers are used to extract dominant features that are positional and rotational invariant. It is common practice to include a pooling layer in between two convolutional layers. The most common pooling layer is the max pooling layer but both the methods reduce the dimensionality and computation efforts

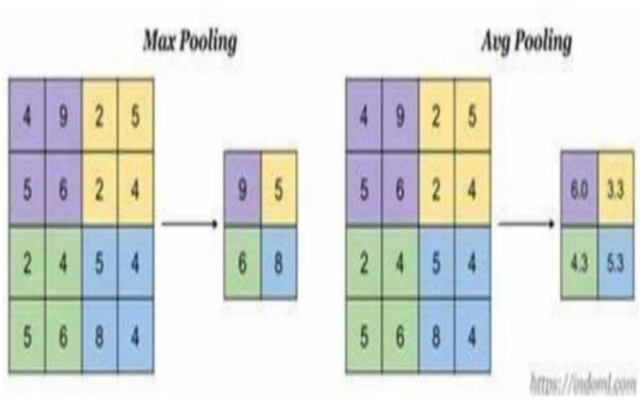

Fig.3 Pooling Layer

Fully Connected Layer

After the pooling layer, we find the fully connected layers (FCN) that are used to make final predictions. An FCN layer obtains resources in a vector form from a previous resource extraction layer, multiplies a weight matrix, and generates a new resource vector whose computation pattern is a dense matrix vector multiplication. After this point, the network obtained the feature map of the input value, which will proceed with a regular feed forward back propagation neural network.

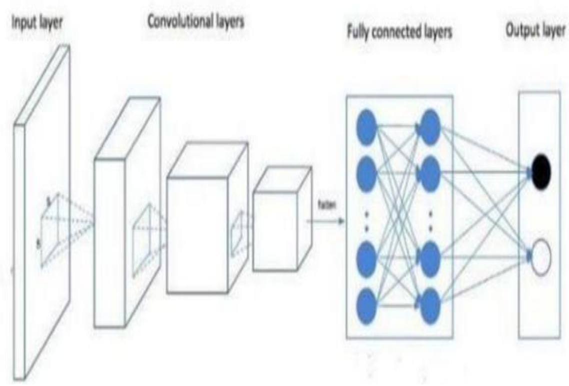

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Fig.4 Fully connected Layer

IMPLEMENTATION

Data Collection

The dataset for this project is downloaded from the site name Kaggle. The dataset contains more than 50,000 images of different traffic signs. It is further classified into 43 different classes. The dataset is quite varying, some of the classes have many images while some classes have few images.

Data preparation and model construction

• To make are model predict accurate result we first perform some operations on out dataset to make it understandable by our model. There are Some steps to follow.

a) Importing the required libraries and our dataset

b) Handling the missing dataset and reducing the noise present in the dataset.

c) Training our dataset and making a model so that we get an accurate result.

Model Training

After building the model architecture, we the train the model using model.fit().The model trained in such a way that the image captured by the vehicle is resized and also undergoes resolution if the image captured is blur or in dim light areas.

Model Testing and Evaluation

Our dataset contains a Test folder and in attest.csv file, we have the details related to image path and their respective class labels. We extract the image path and labels using pandas. Then to predict the model, we have to resize our images to 30*30 pixels and make Numpy array containing all image data. Compare the Image captured by the vehicle with the dataset. We imported the accuracy score and observed how our model predicted the actual labels. We achieved a 95% accuracy in this model.

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V. RESULTS

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Fig.5 Children crossing the road traffic sign

Fig.6 No vehicle passing over weight3.5 tons traffic sign

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Fig.7 Turn left ahead

Fig.8 Bumpty road traffic sign

VI. CONCLUSION

In this Python project with source code, we have successfully classified the traffic signs classifier with 99% accuracy in and also visualized how our accuracy and loss changes with time, which is pretty good from a simple CNN model. We are able to classify images which are small in size, blurry images, big in size and etc with the help of optimizer. In the future, we believe higher accuracy can be achieved by applying further techniques and also by adopting more modern architectures which works in any weather conditions.

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