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NEURAL NETWORKS BASED TRAFFIC SIGN DETECTION USING CNN

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Abstract:-

Automatic detection and recognition of traffic signs plays a crucial role in management of the traffic-sign inventory. It provides accurate and timely way to manage traffic-sign inventory with a minimal human effort. In the computer vision community the recognition and detection of traffic signs is a well-researched problem. A vast majority of existing approaches perform well on traffic signs needed for advanced drivers assistance and autonomous systems. However, this represents a relatively small number of all traffic signs (around 50 categories out of several hundred) and performance on the remaining set of traffic signs, which are required to eliminate the manual labour in traffic-sign inventory management, remains an open question. In this paper, we address the issue of detecting and recognizing a large number of traffic-sign categories suitable for automating traffic-sign inventory management. We adopt a convolutional neural network (CNN) approach, the Mask R-CNN, to address the full pipeline of detection and recognition with automatic end-to-end learning. We propose several improvements that are evaluated on the detection of traffic signs and result in an improved overall performance. This approach is applied to detection of 200 traffic-sign categories represented in our novel dataset. Results are reported on highly challenging traffic sign categories that have not yet been considered in previous works. We provide comprehensive analysis of the deep learning method for the detection of traffic signs with large intra-category appearance variation and show below 3% error rates with the proposed approach, which is sufficient for deployment in practical applications of traffic-sign inventory management.

Keywords:- Deep learning, Traffic-sign detection and recognition, Traffic-sign dataset, Mask R-CNN, Traffic-sign inventory management...

1. INTRODUCTION:

Machine learning algorithms have gained importance nowadays. Spam filtering, speech understanding, face recognition, road sign detection are only a few examples where machine learning is deployed. In traffic zones, Traffic Sign Recognition and classification can be used to automatically identify traffic signs. This is done automatically by the system as the traffic sign is detected and the sign name is displayed. So, even if any sign is missed by the driver or has any lapse in concentration, it will be detected. This helps to accordingly warn the drivers and forbid certain actions like over speeding. It also disburdens the driver and hence, increases his/her comfort. Thus, ensuring and keeping a check on the traffic signs and accordingly following them. Traffic signs, indeed, provide us a multitude of information and guide us accordingly so that we can move safely. Traffic Sign Classification is very useful in Automatic Driver Assistance Systems. A convolutional neural network is a class of deep learning

networks, used to examine and check visual imagery. It is used to train the image classification and recognition model because of its high accuracy and precision.

Traffic symbols are the hushed presides on the road. Survive it a person steering the ship or a bystander, having noise data concerning road refuge is basic for each and every one prior to striking the streets. Traffic signs give data about the street conditions ahead, give guidelines to be followed by the significant meeting point or intersection, warning or lead drivers, and warranty for suitable functioning of avenue travel. Creature unconscious of lane symbols is similar to leaving in front even though one probable risk. It preserves prompt loss tax and material goods. An individual should be identifiable (traverse an unruffled or oral test) with the traffic symbols and metaphors prior to securing a lashing authorize in India. Traffic sign characterization is a cycle of unsurprisingly deceiving traffic symbols beside the lane, as well as rapidity boundary symbols, carefulness symbols, consolidate symbols, and so into view. Having the option to naturally perceive traffic symbols accredit us to

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manufactures more brilliant vehicles". Self-driving vehicles need traffic sign acknowledgment so as to appropriately parse and comprehend the street. Essentially, "driver alert" frameworks inside vehicles need to comprehend the street around them to help and ensure drivers. Traffic sign acknowledgment is only one of the issues that PC vision and profound learning can understand. The traffic signs are situated as an afterthought or head of the street. They give headings on how ought to carry on out and about, so the traffic can continue securely and easily. Everybody must realize the traffic signs! Street Safety symbols are consists of 3 Types:

1. Required symbols: 40 traffic symbols are wield to pledge at no cost enlargement of traffic and build the lane patrons aware of explicit acts and guidelines, limitations, forbiddances. Contravention of these street security symbols are a crime, consisting to regulation.

2. Anticipatory symbols: This 35 traffic symbols formulate the lane patron's conscious of risky situation away from home and concerning heretofore. The operators, appropriately, obtain important tricks to compact among the situation.

3. profitable symbols: This 13 traffic symbols deal among lane patrons regarding objections, separation, optional procedures, and perceptible places similar to food connections, public latrines, near via clinics, etc. The Road security Week is event celebrated in India from Jan 11th, 2020 to Jan 17th, 2020.

2 RELATED WORKS:

In today's world, identification of traffic signs has become an important aspect of our lives. Looking at the increasing traffic, to ensure safety of all and for automatic driving in the future, traffic sign classification is utmost necessary. Considerable research has been done around recognition of traffic and road signs. In 1987, the first research on the topic "Traffic Sign Recognition" was done by Akatsuka and Imai , where they tried to build a fundamental system that could recognize traffic signs and alert the drivers and ensure his/her safety. But this was used to provide the automatic recognition for only some specific traffic signs. Traffic sign recognition initially

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appeared in the form of only speed limit recognition in 2008. These symbols could only detect the circular speed limit signs. On the other hand, later, systems were designed that performed detection on overtaking signs. This technology was available in the Volkswagen Phaeton and in the 2012 in Volvo S80, V70 and many more. But the

major drawback of these systems was that they could not detect the city limit signs as they were mostly in the form of direction signs. But nowadays, such systems are expected to be present in the future cars to help drivers while driving.

In [1], the authors used the colour processing system to reduce the effect of brightness and shadow on the images. This was the very first research done on this topic by the authors, Akatsuka and Imai. In [2], the authors have done a survey on traffic sign detection and recognition, where HOG (Histogram of Oriented Gradients) is used for classification purpose. In [3], a complete study of different traffic sign recognition algorithms has been done, where the highest accuracy (99.46%) was obtained by MCDNN (Multicolumn Deep Neural Network). In [4], the authors have developed a model where they are converting the images to grey scale first and then filter those images using simplified Gabor wavelets. The Gabor filters are used to extract features. These wavelets are important as they help to minimize the product of its standard deviation in both the time and frequency mapping. The authors extracted the regions of interest for recognition purpose and classified the signs using “Support Vector Machine” (SVM).

In [5], the authors have extracted the regions of interest in the detection stage and further examined the shapes of such regions. Here, in the classification system, they took the regions of interest and classified them into different classes.

In [6], the authors have created a module which consists of numerous convolutions. They combined the 1*3 kernel and 3*1 kernel and finally linked it with the 1*1 kernel to attain the 3*3 kernel. This was used to extract more features and thus reduce the

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number of parameters. In [7], the author has reviewed the traffic sign detection methods and divided them into 3 types of methods: color, shape and learning based methods. In [8], the author used the number of peaks algorithm to detect and recognize circular shaped traffic signs.

In [9], the authors have tried creating a classification model using the Enhanced LeNet-5 architecture, which consists of two consecutive convolution layers (before the layer) to extract high level features from the image. Also, they have used the data augmentation technique to make the dataset stable. In [10], the authors have used the technique of colour segmentation and the RGB based detection which is used to identify the traffic signs on the road. The optimizer used was "Stochastic Gradient Descent" with Nesterov Momentum. The text to speech system was implemented to alert the driver about the traffic sign. Also, they utilized the GPU (graphical processing unit) system, as part of hardware. In [11], the authors have tried generating a dataset for the Arabic Road signs and thus develop a CNN model for Arabic sign recognition .

3 PROPOSED SYSTEM

In the proposed system, Traffic sign detection and recognition is achieved by CNN algorithm. Before classification input pre-processing is done in order to remove noise, reduce the complexity and improve the precision of the implemented algorithm. Since we can't write a special algorithm for each condition under which an image is taken, we tend to transform images into a format that can be solved by a general algorithm. At the end voice alert message will be given to driver.

Image Pre-processing:

1. Gray Scale Conversion: To save space or reduce computing complexity, we can find it helpful to remove redundant details from images in some situations. .Converting colorful images to grayscale images, for example. This is because color isn't always used to identify and perceive an image in several objects.

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Grayscale may be sufficient for identifying such artefacts [1][3]. Color images can add needless complexity and take up more memory space because they hold more detail than black and white images color images are represented in three channels, which means that converting it to grayscale reduces the number of pixels that need to be processed. For traffic signs gray values are sufficient for recognition

2. Threshold and Segmentation: Segmentation is the method of partitioning a visual image into different subgroups (of pixels) called Image Objects, which reduces the image's complexity and makes image analysis easier. Threshold is the method of using an optimal threshold to transform a grayscale input image to a bi-level image [4].

Traffic sign recognition:

Deep Learning is a subdomain of Machine Learning that includes Convolutional Neural Networks. Deep Learning algorithms store information in the same manner as the human brain does, but on a much smaller scale .Image classification entails extracting features from an image in order to identify trends in a dataset. We are using CNN for traffic sign recognition as it is very good at feature extraction [1][2].In CNN, we use filters. Filters come in a variety of shapes and sizes, depending on their intended use. Filters allow us to take advantage of a specific image's spatial localization by imposing a local communication pattern between neurons. Convolution is the process of multiplying two variables pointwise to create a new feature. Our image pixels matrix is one function and our filter is another. The dot product of the two matrices is obtained by sliding the filter over the image. Matrix called "Activation Map" or "Feature Map". The output layer is made up of several convolutional layers that extract features from the image. CNN can be optimized with the help of hyper parameter optimization. It finds hyper parameters of a given machine learning algorithm that deliver the best performance as measured on a validation set. Hyper parameters must be set before the learning process can begin [1]. The learning rate and the number of units in a dense layer are provided by it. In our system will consider dropout rate, learning rate, kernel size and optimizer hyper parameter.

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Convolutional Neural Network Architecture

1. Convolution Layer

This layer is major building block in convolution process. It performs convolution operation to identify various features from given image[1]. It basically scans entire pixel grid and perform dot product. Filter or kernel is nothing but a feature from multiple features which we want to identify from input image. For example in case of edge detection we may have separate filter for curves, blur, sharpen image etc. As we go deeper in the network ,more complex features can be identifies

2. Pooling Layer This layer is used for down sampling of the features. It reduces dimensionality of large image but still retains important features. It helps to reduce amount of computation and weights. One can choose Max pooling or Average pooling depending on requirement. Max pooling takes maximum value from feature map while average takes average of all pixels.

3. Activation Function This layer introduce non linear properties to network. It helps in making decision about which information should be processed further and which not. Weighted sum of input becomes input signal to activation function to give one output signal This step is crucial because without activation function output signal would be simple linear function which has limited complex learning capabilities. Types of activation function includes Sigmoid function, Tan H, ReLU, Identity, Binary Step function. Sigmoid function is mostly used in backpropagation its range is 0 to 1 while TanH range is -1 to 0,Optimization is easy in this function. Range for ReLU is 0 to infinity, it's a most popular activation function .

4. Flattening Layer The output of the pooling layer is in the form of a 3D feature map, and we need to transfer data to the fully connected layer in the form of a 1D feature map. As a result, this layer transforms a 3*3 matrix to a one-dimensional list.

5. Fully connected Layer Actual classification happens in this layer. It takes end result of convolution or polling layer by flattened layer and reaches a classification decision. Here every input is connected to every output by weights .It combines the features into more attributes that better predicts the classes

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4 DATASET AUGMENTATION

For the raw data in our dataset, a few images were captured in landscape view. Firstly, we made use of the software called JPEG Autorotate to rotate the images to portrait direction. After that, due to ultrahigh definition images with too long training time, we resized the image whilst keeping the same aspect ratio between width and height. Thus, we normalized all images in our dataset to be 1128 × 2016 and 1536 × 2048. The image annotation for model training in YOLOv5 requires the label information. In this paper, we utilized a labelling tool, namely Labellmg. Especially, we need to convert the format which suits to YOLO because the default format was designed for PascalVOC. Each label comprises of five parameters: Index of classification, center point coordinates (x, y), width w, w≥x≥1, and height h, h≥y≥1. Once all labelling work is accomplished, we group all images in our dataset into training test and test dataset with the proportion 8:2. We put images and corresponding annotation files into our folders, respectively

Class	Sample	Num.	Class	Sample	Num.
No U-turn		271	Road bump		329
Road works		294	Watch for children crossing		176
Crosswalk ahead		313	Give way		317
Stop		286	No entry		196

Figure 1 : Dataset summarisation

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5. EXPERIMENTS AND RESULTS

Traffic sign classification is the process of automatically recognizing traffic signs (like speed limit, yield, and caution signs, etc.) and accordingly classifies them as to which class they belong to. The project has two main functionalities: Prediction on the newly generated dataset (fig. 6) and live web cam traffic sign detection. In this model Forty Three modules of pictures in the dataset. This is an image so conv2D was used two times 2D Convolution layer following this down sample an image the one MaxPooling2D layer. This is completed multiple times for the successful extraction of highlights, which is trailed by the dense layers. Activation function rectified linear unit was used. Flatten function used for converting our data into single dimensional array format. A dropout probability value is 0.5 for the hidden layers. One Dense layer used to feed the all production from the prior layer. Compilation using loss is “categorical_crosentropy” and the optimizer is adam.

Building the reproduction design, first train the model using the model.fit() function which takes the training set, validation set, batch size (32,64)and no of epochs.34799 used for training, 12630 used for testing. Once training the copy for 15 epochs the accuracy was stable. To save in the file name into “traffic_recognition.h5” file. Training data set of our model got 97.8% accuracy.

German Traffic Sign Recognition Benchmark as our data set, Convolutional neural network used obtaining 97.8% accuracy.CNN useful to run neural network directly on the images and more efficient and accurate than many other neural networks. The most troublesome aspect of the venture was to tweak CNN model boundaries. It was some of the time lumbering as I didn't know in which course I ought to go. In any case, this is the specialty of Machine Learning. I explored comparative ventures and attempted to bring a few thoughts into my model. The fascinating part was additionally information enlargement with picture pivot and changing splendor which was likewise prompted by numerous individuals doing this venture.

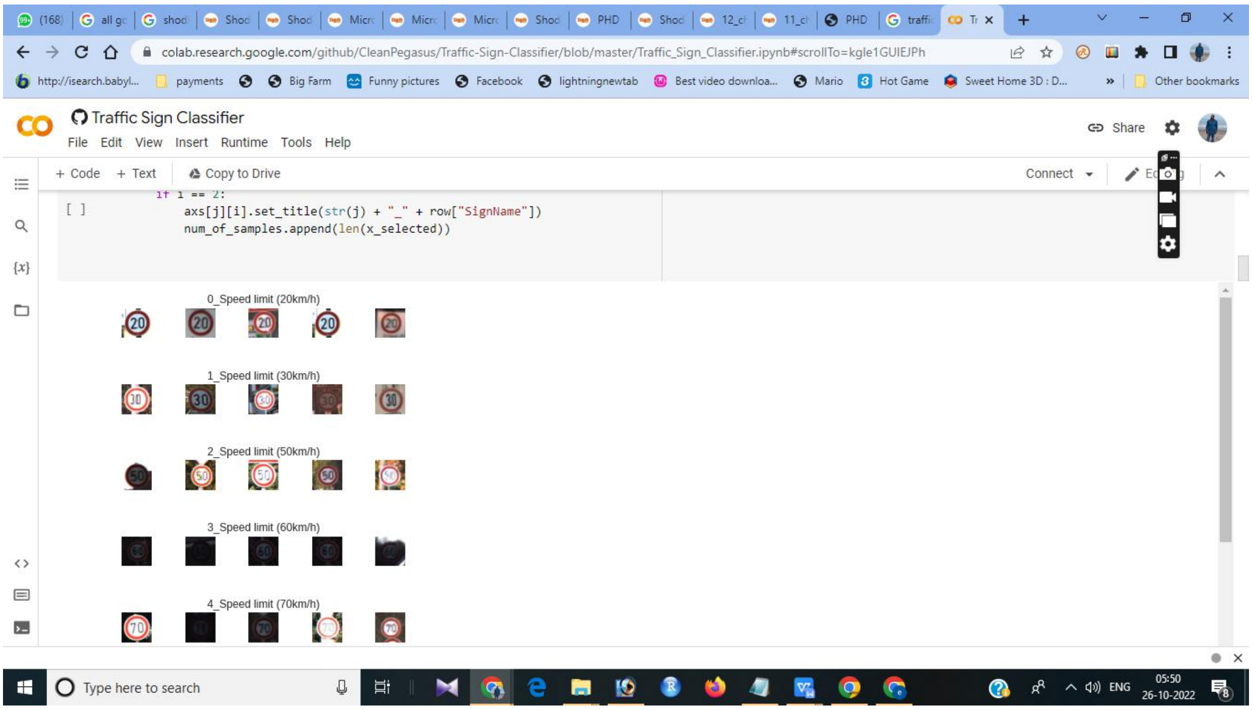

Figure 2 : Data set visualization

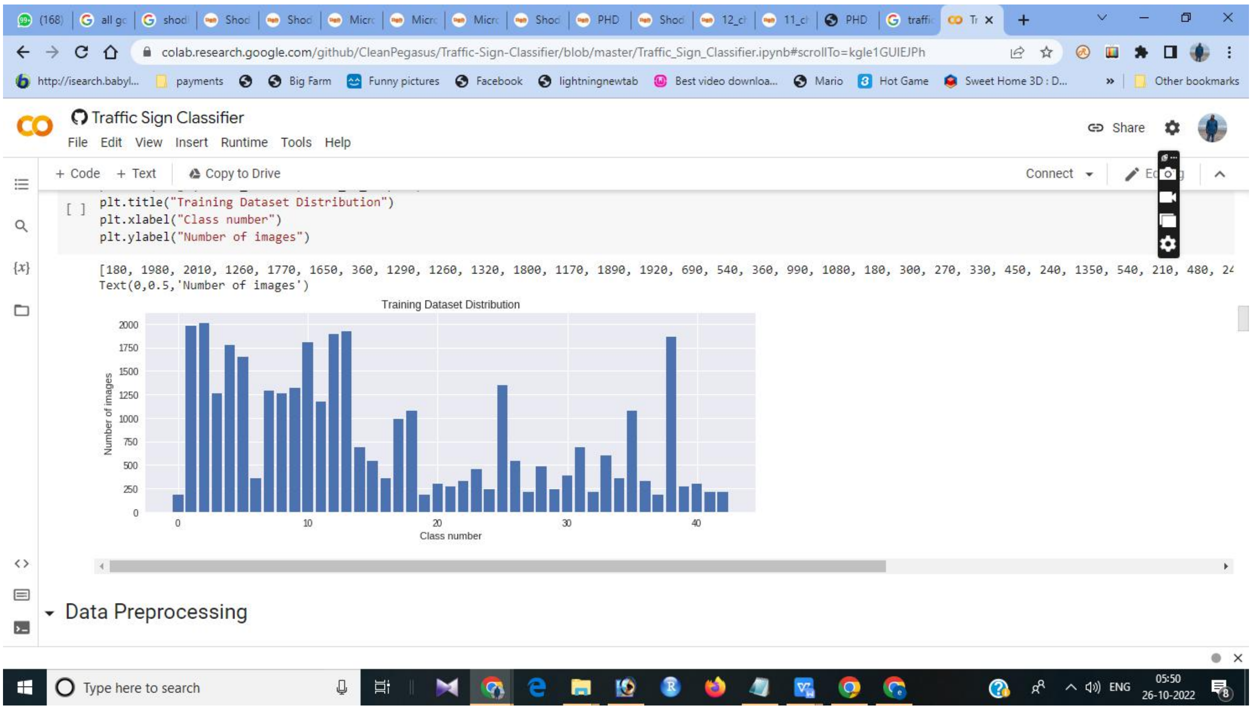

Figure 3 : Training Dataset Distribution

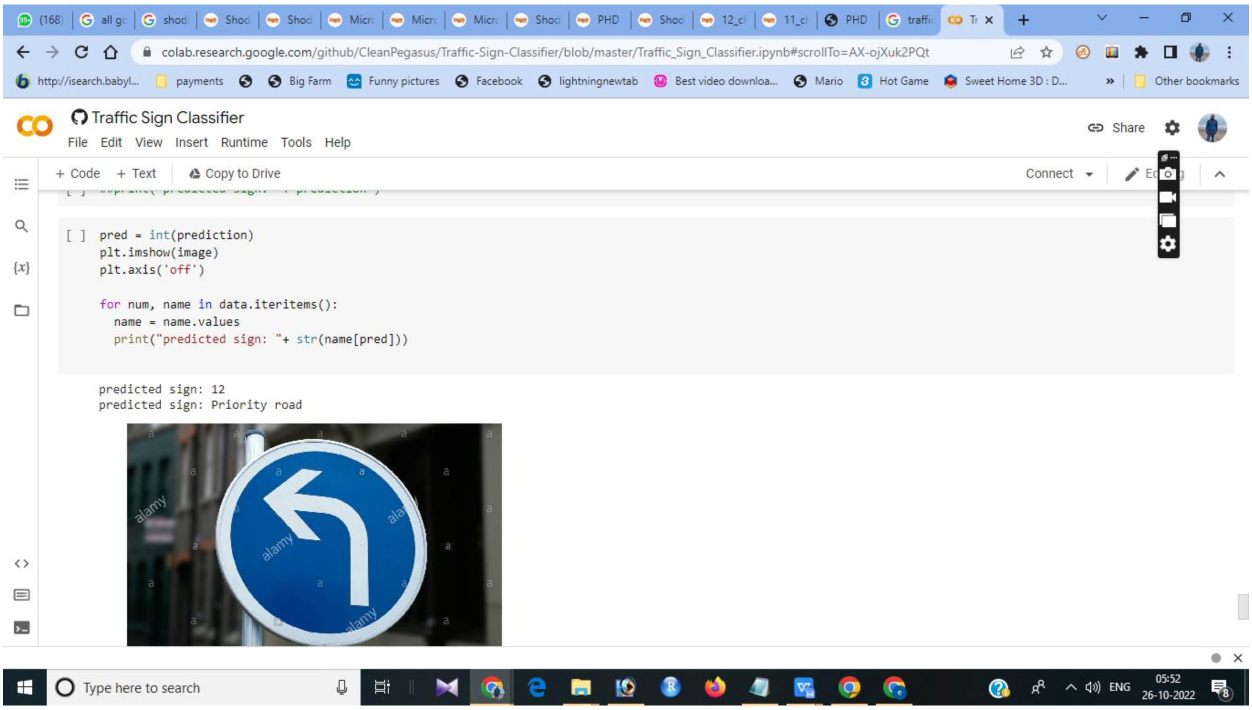

Figure 4 : Word representation of the data

6 CONCLUSION:

The rising number advanced bots operating on social platforms like Twitter and Facebook, the need for better low-cost methods to detect bots is evident. We have proposed an Faster RCN and Resnet algorithm that lets us utilize both tweet content and metadata to identify bots on the Twitter level. Our algorithm can attain an extremely high level of accuracy, exceeding 97percent .The proposed algorithm performs an undetermined set of learning actions that update the accuracy value. Faster RCNN can be used to identify the features of the tweets and the relation between the tweets. The proposed algorithm can achieve the benefits from incrementally learning. Twitter datasets are utilized to test the effectiveness for our method. The test results demonstrate that our algorithm is able to improve in accuracy when compared to other algorithms.

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