Traffic Sign Detection using Deep Learning Image Segmentation and CNN

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Abstract – *Now a day autonomous vehicle is evolving so need for efficient and accurate real time detection of traffic sign is needed. In this paper we propose real time detection system using CNN. We use efficient preprocessing to help detection faster and accurate. In this method, an automatic segmentation used to segment traffic sign area and a convolution neural network is devoted to extract traffic sign image features automatically, and the extracted convolution feature map is sent into a Region Proposal Network (RPN) for foreground objects filtration and regression of bounding boxes. After that, we use the classification network to perform specific classification tasks and further compute the bounding box regression. The experiments perform on the Indian Traffic Sign Detection and the and robustness to different light, block, and motion.*

Key Words: Traffic sign, segmentation, CLACHE, ResNet-18, deep learning, CNN

1.INTRODUCTION

The intelligent detection and identification of traffic signs has become a basic function for intelligent network-linked automotive systems and is also a direction for the development of intelligent traffic. However, due to the complexity of driving environments, the detection and recognition of traffic signs are often affected by various factors including: passing vehicles, buildings, and roadside vegetation. The driver nor the vehicle vision system can accurately determine the meaning of traffic signs and as such cannot make the correct judgment on the next driving operation. For this reason, researchers have put forward methods that hope to identify traffic signs in real time.

The first step in identifying a traffic sign is the ability to detect the location of a traffic sign from the image, and the second is to identify the meaning of the sign. At present, there are two common methods for detecting traffic signs. One separates the traffic sign according to its color and shape characteristics. For example, the literature [1] uses a Gaussian model to segment the image, obtaining the position of the traffic sign, and extracts the histogram of oriented gradient (HOG) features, and then finally uses support vector machines (SVM) to classify the signs. The literature [2] uses a random sample consensus (RANSAC) matching traffic sign template to distinguish the traffic sign position through the detection of Harris corners. The other method uses neural networks to learn to accurately identify traffic signs. The literature [3] constructs a hyper-pixel map model based on the color and boundary features of the scene graph and through a priori position, thresholds segmenting the regions of interest (ROI) of the traffic sign and using the convolutions of Caffeine's neural network training to identify traffic signs. The literature [4-5] uses the deep convolutional neural networks to extract the image features and identify the traffic signs through the support vector machine (SVM). With the continuous development of neural network algorithms, deep learning methods based on neural networks have become better at image recognition problems. Based on the ideas of deep learning and transfer learning, this paper uses the method of Faster Region-based Convolutional Neural Network (Faster R-CNN) algorithm [6] and the pre-trained deep neural network model, Alex Net [7], to carry detect traffic signs in the graphed image. After testing theories, a model capable of detecting traffic signs was obtained, and its validity verified by testing images of the test set.

The generated neural networks are mainly applied for image classification, but automatic segmentation (AutoSegNet) proposed by Zhimin Xu and Si Zuo in 2020[8]. The search architectures are constructed by stacking the down sampling layer, the bridge layer, and the up-sampling layer, which are explored by a recurrent neural network. Compared with other related methods for image segmentation, their method has a small search space but can explore most of the state-of-the-art supervised image segmentation models. They perform verification on two datasets, and the results show that AutoSegNet achieves superior segmentation results with clear and continuous segmented edges, as well as better image details.

2. PROPOSED SYSYEM

We take Indian traffic sign for our project. In order to help the detection, we first pre process the image. Deep learning based automatic segmentation used for segmenting traffic sign and background. Segmented traffic sign area given to CNN for recognition for final result. Fig 1 shows the block diagram of the proposed system.

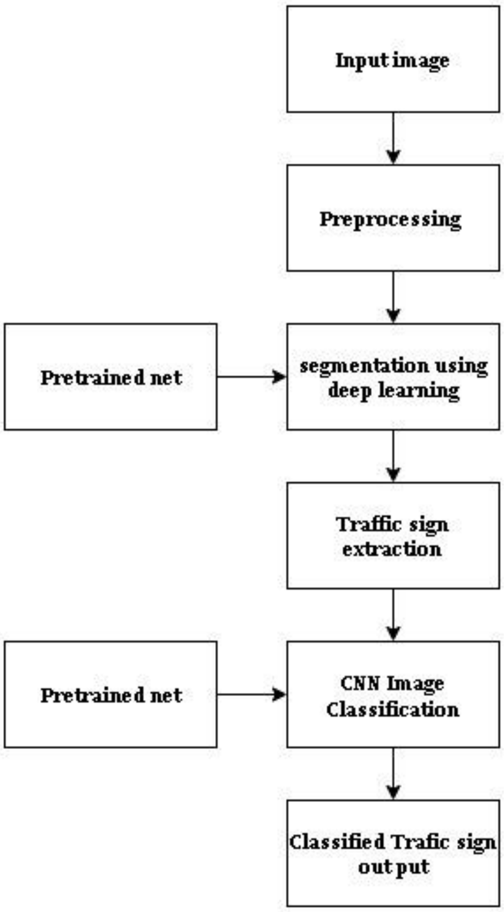

Fig -1: Proposed system block diagram

2.1 Input image

We use 960x720 pixel RGB image for training and detection of traffic sign. Data base created using different sources online and offline and images are taken by different cameras. Fig 2 show one of the tested input image.

Fig -2: Input image

2.2 Preprocessing

In preprocessing we convert RGB image to LAB first. Later apply CLAHE to luminance plane for image enhancement. Then convert back to RGB image.

Fig -3: Original (left) and Contrast Enhanced (right) Image

2.3 Automatic segmentation

Define We use deep learning technique used to segment image in to two back ground and sign area. We have two part in automatic segmentation first one is training and segmentation. We use Residual Networks (ResNet)-18. ResNet-18 is a convolutional neural network that is 18 layers deep. As we design increasingly deeper networks it becomes imperative to understand how adding layers can increase the complexity and expressiveness of the network. Even more important is the ability to design networks where adding layers makes networks strictly more expressive rather than just different.

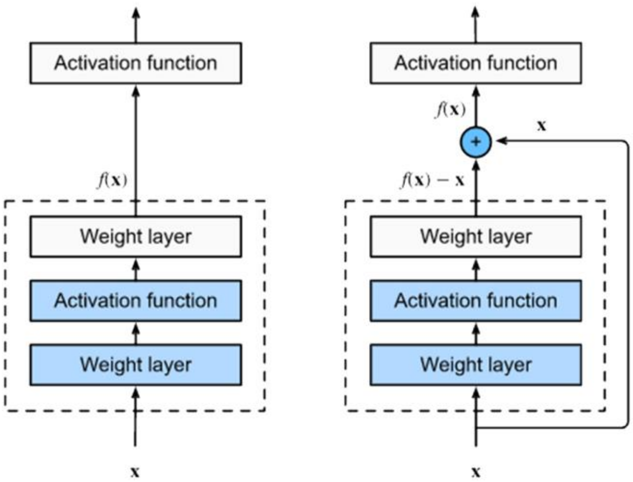

Fig -4: A regular block (left) and a residual block (right)

Fig 4 shows the regular and residual block of Resnet. input x and desired underlying mapping we want to obtain by learning is f(x), to be used as the input to the activation function on the top. On the left of Fig.4, the portion within the dotted-line box must directly learn the mapping f(x). On the right, the portion within the dotted-line box needs to learn the residual mapping f(x)−x, which is how the residual block derives its name. If the identity mapping f(x)=x is the desired underlying mapping, the residual mapping is easier to learn. The right figure in Fig. 4 illustrates the residual block of ResNet, where the solid line carrying the layer input x to the addition operator is called a residual connection with residual blocks, inputs can forward propagate faster through the residual connections across layers.

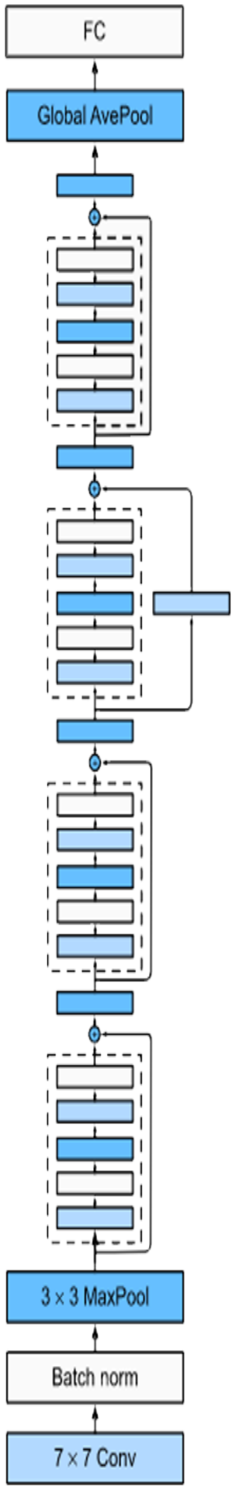

Fig -5: ResNet-18 architecture

Fig. 5 shows the ResNet-18 architecture. There are 4 convolutional layers in each module. Together with the first 7×7 convolutional layer and the final fully-connected layer, there are 18 layers in total. Therefore, this model is commonly known as ResNet-18.

2.3.1 Training

We use multiple images and its label mask for training.

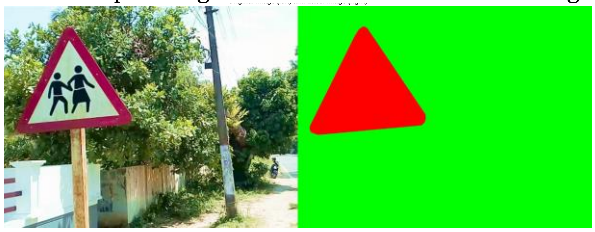

Fig -6: Original Image (left) and Label Image (right)

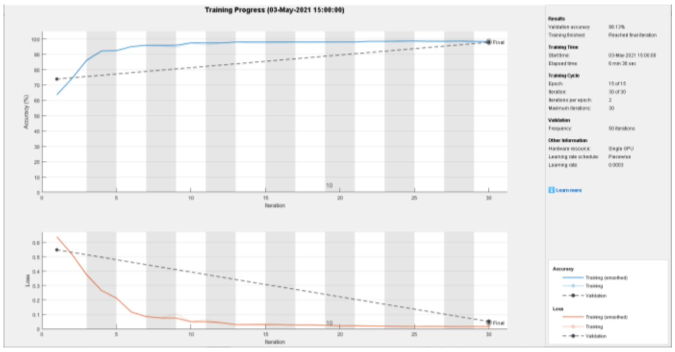

Fig -7: Training progress graph

Fig.6 shows the image and its label mask. In label green color represents background and red represents traffic sign. Fig 7 shows the training graph. Training ends with validation accuracy of 98.13%.

2.3.2 Segmentation

Input image is given to the trained ResNet and it gives segmented output, that is background and sign region.

Fig -8: Segmented output

Fig.8 shows the segmented output, here red region indicates sign and green region indicates background.

2.4 Traffic sign extraction

Fig -9: extracted traffic sign

Segmented traffic sign area extracted using area-based filtering, to avoid unvented small regions detected in automatic segmentation. Fig. 9 shows the extracted sign.

2.5 CNN

The extracted traffic sign is given to the trained CNN for the recognition of traffic sign. Here we use 5 different traffic signs to detect. The training graph is shown in fig. 10. CNN has 10 layers.

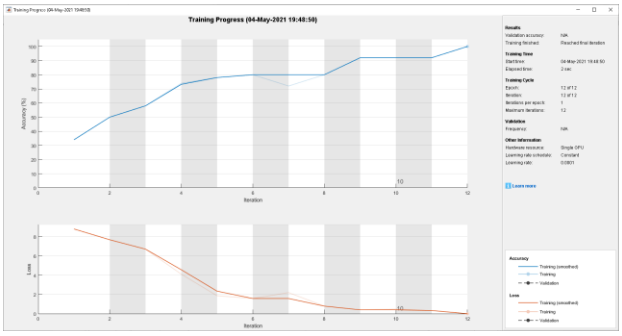

Fig -10: CNN training

3. RESULT

We use Matlab 2020a for implementing our proposed work. Recognized traffic sign in Matlab, fig.2 image as input is shown in fig.11

```
ss =

    'THE CLASS IS   : 3.000000 '

WORK
>>
```

Fig -11: Matlab command window output

We take the Men at Work sign as input and its original class is 3 and detect is also same.

4. CONCLUSIONS

In this work we propose an automatic segmentation for traffic sign, which helps the detection easer. Convolutional neural network helps faster and accurate detection of traffic sign. Our work helps in automated vehicles in feature. In this paper we mainly focus on automatic segmentation using deep learning. We got good result using training with 25 number of images. Further increasing the number of testing images result accuracy increases.

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