IPASJ International Journal of Computer Science (IIJCS)
Web Site: http://www.ipasj.org/IIJCS/IIJCS.htm
A Publisher for Research Motivation .... Email:editoriijcs@ipasj.org
Volume 9, Issue 7, July 2021 ISSN 2321-5992

Traffic Sign Detection and Recognition using Neural Architecture Search

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ABSTRACT

Traffic sign detection and recognition plays an important role in Autonomous vehicles. There are various recent researches are held to support this task. Recent advances in deep neural networks simplify the risk of traditional detection and recognition methods. In this paper, we look at traffic sign detection as an image segmentation problem and a deep neural network based approach is proposed to solve it. For this we introduce a new network by constructing a automatic segmentation using SegNet with the help of Neural architecture search(NAS). NAS is a tool for automatically constructing a deep neural network.

Keywords: Deep neural network, Neural architecture search

1. INTRODUCTION

Automatic traffic sign detection and recognition (ATSDR) is a fascinating problem in computer vision, and it's especially relevant in the context of self-driving vehicles. To enhance road safety, it is used in advanced driver assistance systems and autonomous vehicles. Because of the variety of traffic signs and challenging environment, ATSDR is a difficult problem to solve in real time. Furthermore, the addition of motion distortions to a live traffic video feed makes identification and recognition much more challenging. The topic has been studied for a long time, and numerous techniques to handle it have been offered, with a full overview available in [1] and [2]. These methods, in general, divide the task into two parts: traffic sign detection (TSD) and traffic sign recognition (TSR), and treat each independently. The detection stage identifies regions in a image that may include traffic signs, and the recognition step categories these identified regions into certain sign kinds or backgrounds. The colour and shape information of traffic signals are used in traditional TSD techniques to detect them. The majority of color-based segmentation methods rely on thresholding the input image in a certain colour space. In this case, approaches that work in the Hue-Saturation-Intensity (HSI) colour space have been widely employed [3]–[7] because they yield superior segmentation performance than methods that work in the RGB colour space [8], [9]. This is because, in comparison to other colour spaces, the HSI space captures intensity information better in variable lighting situations and better replicates human vision. Gao et al. [10], [11] used Hue-Chroma-Luminance (HCL) colour space to examine colour temperature fluctuations, whereas Khan et al. [12] used Lab colour space to deal with colour and intensity variations independently. YCbCr [13] and YUV [14] colour spaces have also been found to yield superior outcomes by some authors. TSD has also made use of shape detecting algorithms.Because of the size and scale variations, disorientation, and occlusion of traffic signs in road scenes, consistently detecting forms from images is difficult. When the image is packed with items of similar shape, this becomes even more challenging. While different properties have been presented for shape identification, edges appear to be the most relevant. Canny edge detection [15] is a prominent method for performing this task that has been employed by several researchers [16]–[19]. In addition, the Histogram of Oriented Gradients (HOG), which is commonly used to detect persons at images, has been shown to be effective in detecting traffic signs [13], [20]–[22]. According to several authors,Haar-Wavelet-like features perform well [23]–[25].Apart from them, distance to bounding box (DtB) [26], [27] are important considerations.as well as the Fast Fourier Transform (FFT) [28].As shape feature descriptors, the results are substantial. However, there are several exceptions.There is no complete method for determining the optimal feature as these findings have been published on a variety of datasets

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Volume 9, Issue 7, July 2021
ISSN 2321-5992

Neural Architecture Search is used to segment images (NAS).Given a learning dataset, Neural Architecture Search (NAS) seeks to find the optimum neural network architecture. It is currently being used for image classification and language modelling with great success. NAS is made up of two parts: a controller that generates the neural network's architectural parameters and a validation neural network that validates the given architecture parameters by building, training, and testing the network. Reinforcement learning is used to optimize the controller and validation network. The trained network's accuracy will be provided back to the controller as a reward, guiding it to continue to optimize. A procedure like this will repeat for a set number of epochs or end when a given parameter reaches a certain value.

In this paper we are taking 7 different type of traffic signs-Give way, Stop, School, No Parking, Work, Go slow and Turn Left. The dataset is segmented automatically by NAS Network and recognized by CNN.

2. METHODOLOGY

This paper propose a CNN based model to detect and recognize traffic signs from images. The model consists of two parts, Detection and Classification. The first part is Detection which is achieved by NAS Segmentation .It is a CNN that isolates probable regions of traffic sign from the image and the second part is classifier,it is a network that classifies the localized regions (Fig.1)

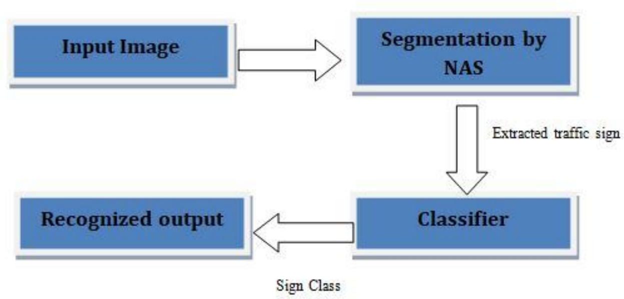

Figure 1 Proposed Method

- Collected Images and trained Neural Architecture Search model which returns a pixel-wise segmentation using downsampling and hybrid dilated layer. Upsampling layer generate original image as output.
- Extracted proposed sign regions from the input image, which correspond to islands of high probability in the output mask.
- These extracted sign regions are used to train our classifier, which detects if the proposed region is a part of one of the 7 types of traffic signs that need to detect.

2.1 Detection

Detection is achieved by NAS Segmentation. AutoSegNet, an Automated Fully Convolutional Neural Network architecture inspired by SegNet, is used to implement NAS segmentation. The network is made up of two stages: a downsampling encoder and an upsampling decoder, which are linked together using a residual learning technique. The suggested method's main principle is that by exploring the downsampling layer, bridge layer, and upsampling layer using a recurrent neural network (RNN) controller, the AutoSegNet can find the optimum neural network design for traffic sign segmentation from learning data. The downsampling layer convert the input image (fig 2) into pixel wise segmentation and gives red and green portions. The red portion gives required traffic sign and green portion is removed by skip connections of layers. Hybrid dilated layer produce convolution operation at a time and gives the segmentation traffic sign outputs (fig 3) with the help of upsampling layer. These outputs are used for training the Classifier CNN.

Figure 2 Dataset

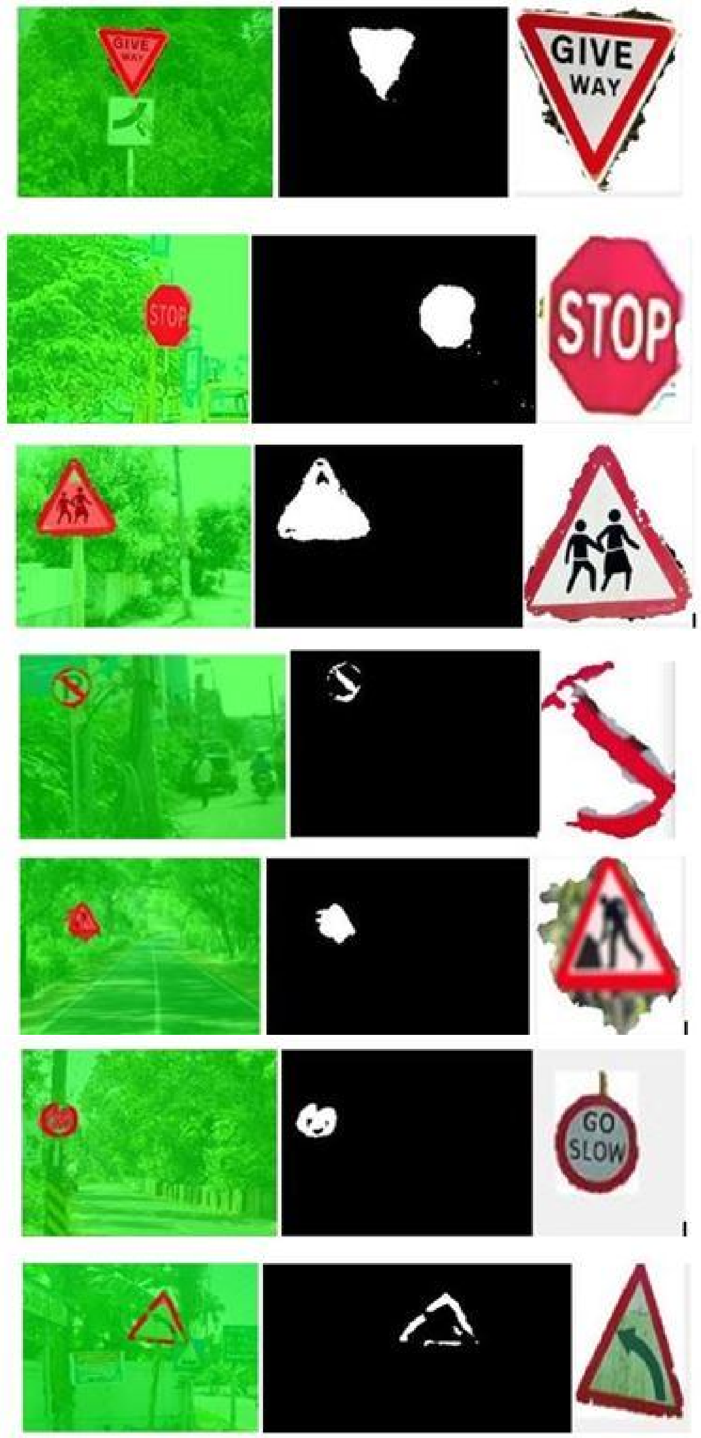

Figure 3. Segmentation output

2.2 Recognition

The segmented traffic signs are used for training and testing of CNN. Convolution neural network (CNN) are common method for solving pattern recognition difficulties. A neural network is a mathematical model that is similar to biological neural networks in that it is made up of neural units that are connected to each other via artificial neurons. In most cases, neurons are arranged in layers, with connections formed exclusively between neurons from adjacent layers. The input low-level feature vector is placed in the first layer and changed to the high-level feature vector as it moves from layer to

layer. The number of classifying classes is equal to the number of output layer neurons. As a result, the output vector is a vector of probabilities indicating the likelihood that the input vector belongs to the corresponding classes .Fig 4 shows recognized traffic sign classes.

Figure 4. Recognized output

2.3 Experimental Setup

In this section, discussing the training procedures in detail along with a description of our traffic sign dataset. The networks are trained separately because of our separate CNN. All of the network training and implementation tests were carried out in hardware settings that comprised of Processor Intel(R) Core(TM) i3-7020U CPU,2.30GHz,2300 Mhz,2 Core(s) and the necessary codes are written in MATLAB.Traffic sign dataset consist of 6000 images of 7 different traffic signs .From that 80% of dataset is used for training and 20% data is used for validation and testing.

2.3.1 Training of segmentation NAS

The input images are given in to the NAS network.The best segmentation accuracy is obtained at 0.003 learning rate. The accuracy curve shows 98.13 % accuracy after 30 iterations. The loss is also minimum and tends to zero after 15 epochs and 30 iteration.

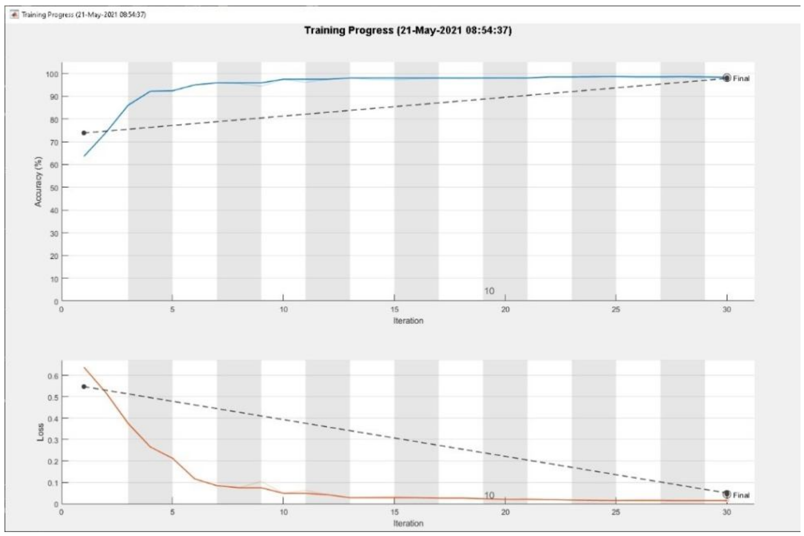

Figure 5 (a) Accuracy Curve (b) Loss Curve of segmentation NAS Network

2.3.2 Training of Recognition CNN

We are training the CNN with segmentation output obtained by segmentation NAS network and CNN learns different features of each classes. For training we are using CNN with 2 convolution blocks.Each with 20 filters of 5x5 filtersize, a ReLU activation layer, max-pooling layer and fully connected layer for 7 classes,softmax layer and classification layer.So total it has 9 hidden layers.Fig.6 shows as epoch and iteration is increased the accuracy is also increased to 99.6% and loss is getting to zero as iteration reaches to 20.

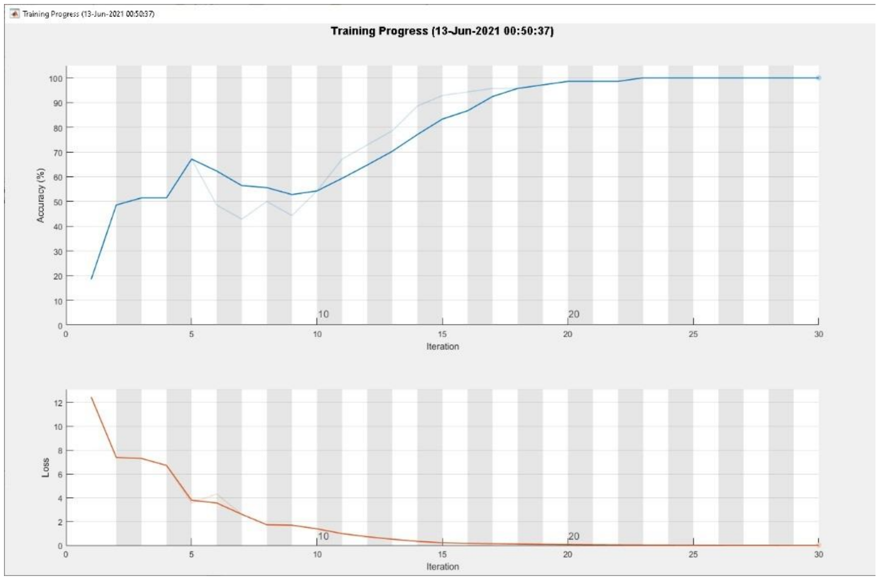

Figure 6. (a)Accuracy Curve (b) Loss Curve of Recognition CNN

2.3.3 Result

Test result of different class of traffic signs are shown in the Fig.7.The confusion matrix is used to describe the performance of a classification model on traffic sign dataset. Matrix shows 92.5 % accuracy for this model. Each sign shows accuracy of 86.1%, 90.5% 100% ,87.8% ,100%, 78.6%,100% respectively for 7 classes.

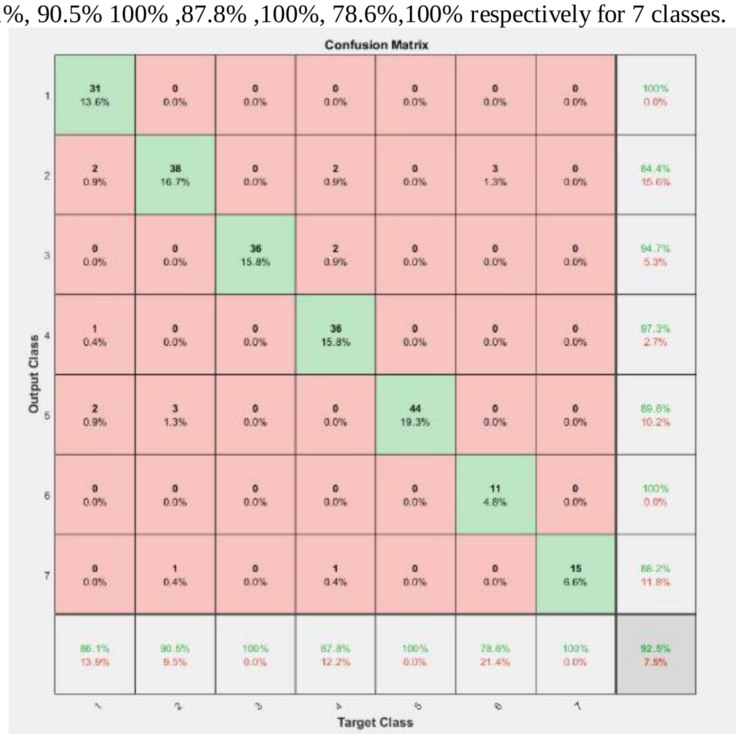

Figure 7. Confusion Matrix

3. CONCLUSION

An automatic traffic sign detection and recognition system based on a modular convolutional neural network architecture is provided in this paper. The automated NAS network is a segmentation architecture that has been proposed to detect the traffic signs from the input images.The overall accuracy of the system is 92.5% and Table-1 shows accuracy of different class of traffic signs.

Table 1.Accuracy of signs

Traffic Sign	Accuracy
Give Way	86.1%
Stop	90.5%
School	100%
No Parking	87.8%
Work	100%
Go Slow	78.6%
Turn Left	100%

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