DFR-TSD: A Deep Learning Based Framework for Robust Traffic Sign Detection under Challenging Weather Conditions

Veldhandi Srivardhan[1], Indira baddam[2]

[1]Student, CBIT.

[2]Associate professor, CBIT

Abstract: Robust traffic sign detection and recognition (TSDR) is of paramount importance for the successful realization of autonomous vehicle technology. The importance of this task has led to a vast amount of research efforts and many promising methods have been proposed in the existing literature. However, the SOTA (SOTA) methods have been evaluated on clean and challenge-free datasets and overlooked the performance deterioration associated with different challenging conditions (CCs) that obscure the traffic images captured in the wild. In this paper, we look at the TSDR problem under CCs and focus on the performance degradation associated with them. To overcome this, we propose a Convolutional Neural Network (CNN) based TSDR framework with prior enhancement. Our modular approach consists of a CNN-based challenge classifier, Enhance-Net, an encoder-decoder CNN architecture for image enhancement, and two separate CNN architectures for sign-detection and classification. We propose a novel training pipeline for Enhance-Net that focuses on the enhancement of the traffic sign regions (instead of the whole image) in the challenging images subject to their accurate detection. We used CURE-TSD dataset consisting of traffic videos captured under different CCs to evaluate the efficacy of our approach. We experimentally show that our method obtains an overall precision and recall of 91.1% and 70.71% that is 7.58% and 35.90% improvement in precision and recall, respectively, compared to the current benchmark. Furthermore, we compare our approach with SOTA object detection networks, FasterRCNN and R-FCN, and show that our approach outperforms them by a large margin.

Index Terms: *Traffic sign detection, traffic sign recognition, convolutional neural network*

1. INTRODUCTION

Traffic sign detection and recognition play a crucial part in driver assistance systems and autonomous vehicle technology. One of the major prerequisites of safe and widespread implementation of this technology is a TSDR algorithm that is not only accurate but also robust and reliable in a variety of real-world scenarios. However, in addition to the large variation among the traffic signs to detect, the traffic images that are captured in the wild are not ideal and often obscured by different adverse weather conditions and motion artifacts that substantially increase the difficulty level of this task. Being a challenging research problem, several studies have been carried out on TSDR. A detailed overview of these studies can be found. The whole task of TSDR can be subdivided into two independent tasks: Traffic Sign Detection (TSD) and Traffic Sign Recognition (TSR). Traditional research methodologies of TSD mostly rely on manual feature extraction of various attributes such as geometrical shapes, edge detection, and color information. Color-based approach mostly comprises of threshold-based segmentation of traffic sign region in a particular color space such as Hue-SaturationIntensity (HSI), Hue-Chroma-Luminance (HCL) and others. However, one major drawback of these colorbased approaches is that these are highly susceptible to the change in illumination that can frequently occur in realworld scenarios. To overcome this challenge, shape-based approaches have been extensively used in the existing literature that comprise of Canny-Edge detection, HistogramOriented Gradients (HOG), Haar-Wavelet features and Fast Fourier Transform (FFT). However, size and scale variation, disorientation and occlusions of traffic sign regions due to the motion artifacts during real-time video feed hinder the practical application of these approaches. On the other hand, the methodologies for TSR utilize color and/or shapebased features to train classifiers such as Random Forest and Support Vector Machine (SVM). However, there is no comprehensive method to identify the best features set and the best classifier for TSR.

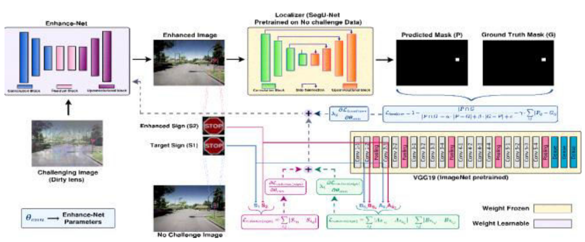


Fig 1 Example Figure

Recent advancement of deep learning (DL) in different computer vision tasks such as image recognition [11], image segmentation [12] and object detection problems [13] has led to a large scale adoption of these algorithms for TSDR [14], [15], [16]. Lee et al. have used a custom designed CNN to simultaneously detect and estimate the boundary of the traffic sign regions [17]. Compared to the objects that frequently appear in the existing object detection datasets, traffic sign regions are very small and thus have a very small region of interest (ROI) to background ratio. To address this challenge, Yuan et al. have proposed a CNN-based multi-resolution feature fusion architecture [18]. They have also proposed a vertical spatial sequence attention (VSSA) module to gain more context information for better detection performance. A major advantage of DL-based methods is that they are completely data-driven that does not require any manual feature engineering. In order to facilitate the development and evaluation of these algorithms, a number of datasets have been introduced such as GTSDB [19], LISA [20], BelgiumTS [21] and TT100K [21]. However, neither these methods nor these datasets have considered sufficient types and levels of CCs that arXiv:2006.02578v1 [eess.IV] 3 Jun 2020 2 can frequently arise during the capture of the traffic image [6].

2. LITERATURE SURVEY

Vision-Based Traffic Sign Detection and Analysis for Intelligent Driver Assistance Systems: Perspectives and Survey:

In this paper, we provide a survey of the traffic sign detection literature, detailing detection systems for traffic sign recognition (TSR) for driver assistance.

We separately describe the contributions of recent works to the various stages inherent in traffic sign detection: segmentation, feature extraction, and final sign detection. While TSR is a well-established research area, we highlight open research issues in the literature, including a dearth of use of publicly available image databases and the over-representation of European traffic signs. Furthermore, we discuss future directions of TSR research, including the integration of context and localization. We also introduce a new public database containing U.S. traffic signs.

A review on automatic detection and recognition of traffic sign:

Evidently, Intelligent Transport System (ITS) has progressed tremendously all its way. The core of ITS are detection and recognition of traffic sign, which are designated to fulfill safety and comfort needs of driver. This paper provides a critical review on three major steps in Automatic Traffic Sign Detection and Recognition(ATSDR) system i.e., segmentation, detection and recognition in the context of vision based driver assistance system. In addition, it focuses on different experimental setups of image acquisition system. Further, discussion on possible future research challenges is made to make ATSDR more efficient, which inturn produce a wide range of opportunities for the researchers to carry out the detailed analysis of ATSDR and to incorporate the future aspects in their research.

Robust traffic sign shape recognition using geometric matching:

A novel approach for recognising various traffic sign shapes in outdoor environments is presented. To reduce the influence of digital noise and extract the shape of each individual traffic sign, the external boundaries of traffic signs segmented based on colour information are simplified and decomposed through discrete curve evolution whose stop stage is determined by an arc similarity measure in tangent space. The recognition of a closed candidate shape is achieved through the direct matching with templates. An optimal enclosure is generated to minimise the geometric differences between the retrieved unclosed candidate shape and templates. The experimental results justify that the proposed algorithm is translation, rotation and scaling invariant, and gives reliable shape recognition in complex traffic scenes where clustering and partial occlusion normally occur.

Image segmentation and shape analysis for road-sign detection:

In recent years, extensive study has been performed to recognize road signs. Many methods have been developed over these years for road sign detection. Signs are used to represent some special circumstantial information of environment. Road signs provides important information for warning, guiding people to make their movements easier, safer and more convenient. This paper presents two different methods for road sign detection and recognition which has based on color and shape. The first method is Gielis curve fitting. In this method algorithm is applied to different shapes like circular, triangular, octagonal. Fitting contour points into a Gielis curve takes a lot of time, which naturally cannot be acceptable in a real-time system. Hence, further investigation and improvement is required to decrease the processing time. It gives 85% accuracy for road sign recognition. The second method is based on Neural network. The Neural network stages were performed to recognize the traffic sign patterns. The first step is to reduce the number of MLP inputs by preprocessing the traffic sign image, and the second step is to search for the best network architecture by selecting a suitable error criterion for training with LMA. Using neural network, road sign classification gives 90% accuracy for different type of signs (circular, triangular, octagonal).

Color exploitation in hog-based traffic sign detection:

We study traffic sign detection on a challenging large-scale real-world dataset of panoramic images. The core processing is based on the Histogram of Oriented Gradients (HOG) algorithm which is extended by incorporating color information in the feature vector. The choice of the color space has a large influence on the performance, where we have found that the CIELab and YCbCr color spaces give the best results. The use of color significantly improves the detection performance. We compare the performance of a specific and HOG algorithm, and show that HOG outperforms the specific algorithm by up to tens of percents in most cases. In addition, we propose a new iterative SVM training paradigm to deal with the large variation in background appearance. This reduces memory consumption and increases utilization of background information.

3. METHODOLOGY

Traditional research methodologies of TSD mostly rely on manual feature extraction of various attributes such as geometrical shapes, edge detection, and color information. Color-based approach mostly comprises of threshold-based segmentation of traffic sign region in a particular color space such as Hue-SaturationIntensity (HSI), Hue-Chroma-Luminance (HCL) and others. However, one major drawback of these colorbased approaches is that these are highly susceptible to the change in illumination that can frequently occur in realworld scenarios.

Drawbacks

1. Manual feature extraction.
2. Highly susceptible to the change in illumination that can frequently occur in realworld scenarios.

In this paper, we look at the TSDR problem under CCs and focus on the performance degradation associated with them. To overcome this, we propose a Convolutional Neural Network (CNN) based TSDR framework with prior enhancement. Our modular approach consists of a CNN-based challenge classifier, Enhance-Net, an encoder-decoder CNN architecture for image enhancement, and two separate CNN architectures for sign-detection and classification. We propose a novel training pipeline for Enhance-Net that focuses on the enhancement of the traffic sign regions (instead of the whole image) in the challenging images subject to their accurate detection. We used CURE-TSD dataset consisting of traffic videos captured under different CCs to evaluate the efficacy of our approach.

Benefits

1. Improved performance.
2. Our approach outperforms them by a large margin.

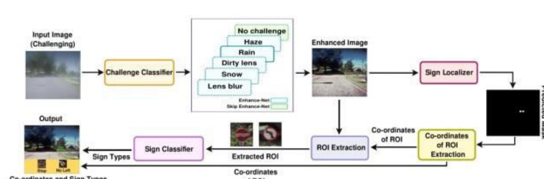


Fig 2 Proposed Architecture

Modules

To implement this project we have designed following modules

- Generate & Load Traffic Sign CNN Model: using this module we will generate and load Traffic sign CNN model
- Upload Test Image & Clear: using this module we will upload test image and then apply CNN model to clear weather affected images
- Detect Sign from Clear Image: now clear image will be input to CNN sign detection model to detect sign
- Propose CNN Training Graph: using this module we will plot CNN training accuracy and loss graph.

4. IMPLEMENTATION

Many algorithms are available to detect traffic signs but all those algorithms are trained on clear images and expect clear images only for detection but some time due to weather condition quality of the image will be degrade and existing algorithm may not able to detect signs from such weather affected images. To overcome from above problem author of this paper has introduced CNN algorithm which consists of two parts. First part will remove weather affected part from the image and clear it and second part will detect traffic signs.

Propose algorithm is based on Deep learning CNN algorithm to detect traffic signs robustly hence called as DFR-TSD. Propose algorithm get trained on 'CURE-TSD' dataset and able to get accuracy up to 99%.

CNN:

A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. When it comes to Machine Learning, Artificial Neural Networks perform really well. Neural Networks are used in various datasets like images, audio, and text. Different types of Neural Networks are used for different purposes, for example for predicting the sequence of words we use Recurrent Neural Networks more precisely an LSTM, similarly for image classification we use Convolution Neural networks. In this blog, we are going to build a basic building block for CNN.

In a regular Neural Network there are three types of layers:

Input Layers: It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image).

Hidden Layer: The input from the Input layer is then feed into the hidden layer. There can be many hidden layers depending upon our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.

Output Layer: The output from the hidden layer is then fed into a logistic function like sigmoid or softmax which converts the output of each class into the probability score of each class.

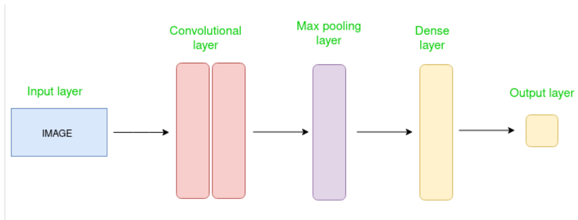
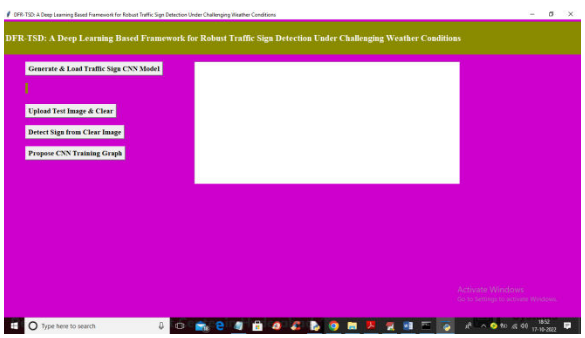


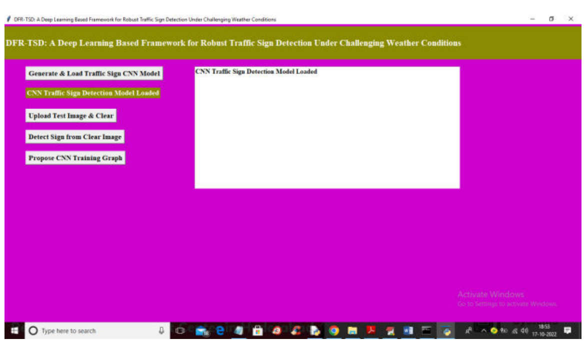
Fig 3 CNN Architecture

5. RESULTS AND DISCUSSIONS

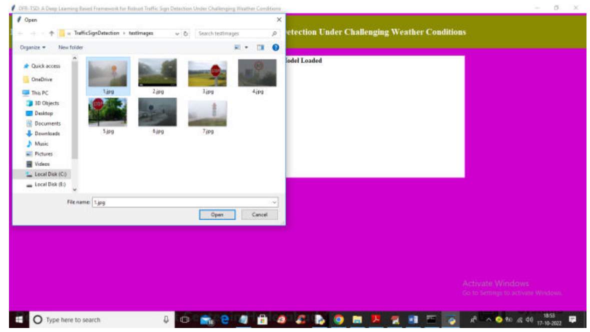
To run project double click on 'run.bat' file to get below screen



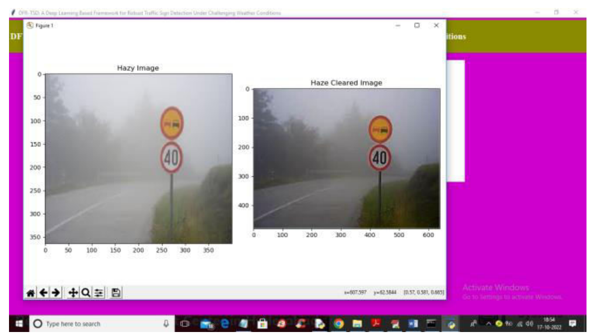
In above screen click on 'Generate & Load Traffic Sign CNN Model' button to generate and load CNN model and get below screen



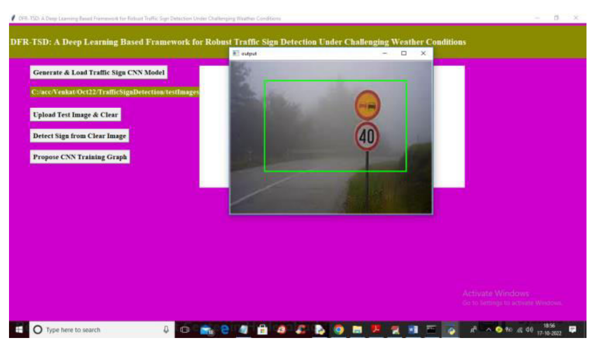
In above screen CNN Model loaded and now click on 'Upload Test Image & Clear' button to upload weather affected test image and then clean it



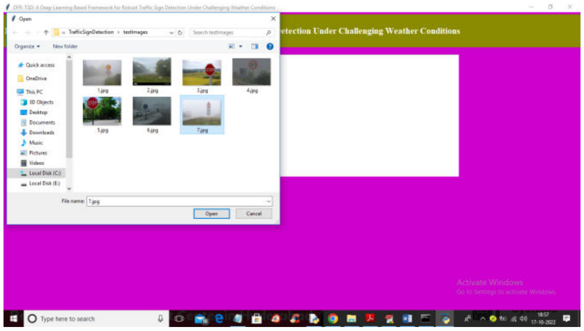
In above screen selecting and uploading '1.jpg' file and then click on 'Open' button to load and clean image and get below output



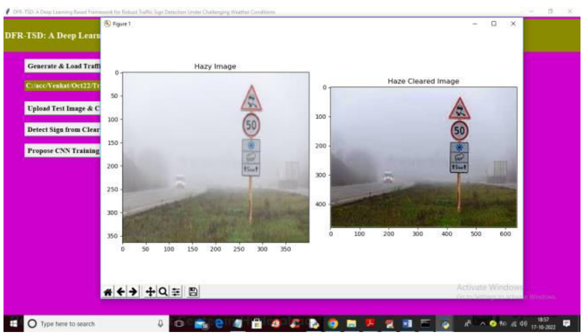
In above screen first image is the weather affected image (which can be from cloudy haze, rain, or bad light or bad camera lens) and second is the clean image and you can see the difference between both images and now click on 'Detect Sign from Clear Image' button to get below output



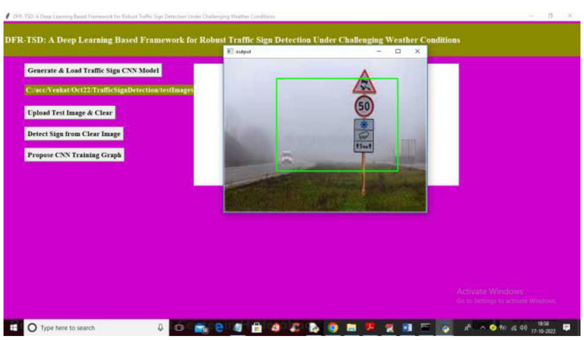
In above screen CNN model detected traffic sign and put bounding box around it and now test other image



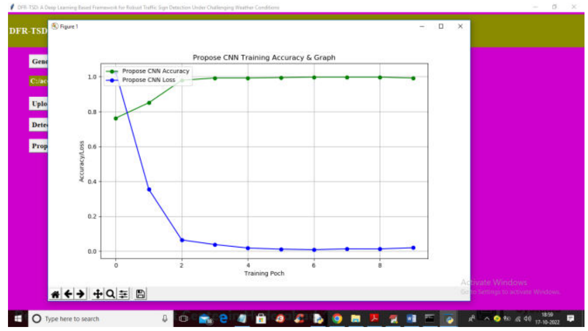
In above screen selecting and uploading 7.jpg and then click on 'Open' button to get below output



In above screen first image is the weather affected image and second one is the clean image and now click on 'Detect Sign from Clear Image' button to get detection output



In above screen traffic sign detected and similarly you can upload and test other images and now click on 'Propose CNN Training Graph' button to get below output



In above graph x-axis represents 'Training Epoch' and y-axis represents 'Accuracy and loss values' and green line represents accuracy and blue line represents loss. In above graph we can see with each increasing epoch accuracy got increase and loss got decrease.

6. CONCLUSION

In this paper, we have presented a deep CNN-based modular and a robust framework for TSDR under various CCs. We have highlighted the performance degradation of the existing TSDR algorithms due to the presence of different CCs and proposed a deep CNN-based approach that effectively alleviates the problem. A VGG16 architecture-based challenge classifier, that successfully detects and classifies the challenge, directs the image to the appropriate Enhance-Net which recovers the features that are useful for the successful detection of the traffic sign regions. Unlike the existing whole image enhancement-based methods, the Enhance-Nets are trained by our proposed novel loss function and training pipeline that incorporate traffic sign region focused MAE in both pixel and feature domain with the sign detection loss as a constraint. This effectively ensures the enhancement of the sign regions subject to their accurate detection. We have also experimentally showed that traffic sign regions are more important for enhancement, in order to obtain higher detection performance. Finally, we evaluate the efficacy of the modular structure of our approach by comparing its performance with two different end-to-end trained deep CNN-based object detection networks where our approach outperforms both of them. Due to our modular approach, each module of our framework can be designed independently. This opens up a vast research scope in this field. As future work, we wish to explore and design the optimum architecture for each module so that all of the CCs present in the CURE-TSD dataset are best addressed.

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