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TRAFFIC SIGN DETECTION UNDER FOGGY ENVIRONMENT USING MACHINE LEARNING

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Abstract: In order to improve road safety and traffic management, traffic sign detection is an essential part of contemporary intelligent transportation systems. The approaches, developments, and methods for traffic sign detection are thoroughly reviewed and analyzed in this work. We examine different methodologies used in this field for computer vision and machine learning and talk about their advantages and disadvantages. We also provide a thorough analysis of the difficulties associated with datasets, practical applications, and new developments in traffic sign recognition. In order to create safer and more effective road networks, researchers, engineers, and policymakers can benefit greatly from this study's synthesis of the body of existing knowledge.

***Index Terms* - Traffic Sign Detection , Machine Learning , Road Safety, CNN , Dataset Challenges.**

I. INTRODUCTION

Autonomous vehicles must recognize traffic signs in order to protect people both inside and outside of them. People and things are transported by a multitude of components that make up the transportation environment. For everyone's safety in our immediate community, knowing the facts about traffic signs is essential[1]. TSD has also made use of shape-detection techniques. Consistently identifying shapes from images is a problem due to variations in size and scale, disorientation, and occlusion of traffic signs in road scenes. It also becomes problematic when the image is cluttered with objects of similar shapes.

Although a number of features have been suggested for shape-detection, edges seem to be the most crucial one[2]. A basic driver assistance system centered on frame-by-frame observation of motion frames may be established, and alarm signals can then be generated in accordance with that observation using a technique that combines a video camera and an active machine with the vehicle. The driver would therefore be able to make the choice with ease[3]. Analysis of road signs is one of the key components of an automated driving assistance system. The foundation of every updated transportation system is the quality real-time observation of road signs. In this research, we suggested a system that uses supervised classification methods to recognize traffic signs[4].

For the majority of image-related tasks, convolutional neural networks are typically employed with the most advanced deep learning neural network algorithms.Convolution uses the kernel function in the convolution layer to extract the image's spatial information. Input, output, and hidden layers make up a CNN. Convolutional, pooling, fully connected, and normalization layers make up the remaining hidden layers. CNNs have significant limitations and drawbacks, but they function incredibly well for image-related tasks. CNN is unable to accurately depict the relative orientation and spatial [5].

Artificial neural networks' limitations have been greatly reduced by ongoing advancements in computer hardware, ushering in a golden age for machine learning research and development. One class of machine learning techniques is deep learning. It is far more efficient to use this neural network model than the traditional TSR algorithms to extract the useful features from the road image. This could lead to improvements in the algorithms' robustness and generalization[6]. The field of autonomous vehicles saw a significant advancement in 1987 with the development of traffic sign recognition (TSR), which dates back to the early 1980s. It primarily targets speed limit signs and uses traditional image segmentation and template matching algorithms.

The average time for the recognition process is 0.50 seconds. The systems weren't operating in real time, the images weren't very large, and they couldn't be integrated into practical applications because of the hardware that wasn't yet developed[7].Improving contrast and image quality is the main goal of haze reduction. A basic picture enhancing technique is Multi-Scale Retinex (MSR). MSR [2, 3] bases its core thesis on the concept that an object's color is determined by its capacity to reflect light, independent of the light source's absolute intensity[8].

II. Related Work

This research suggested a UV correlation model among sight distance, haze grade, and traffic sign detection performance in order to investigate the link between driving sight distance and traffic sign detection performance in haze environments. First, an experimental data set is created by synthesizing the German traffic sign data set (GTSDB) into three levels: light, hazy, and dense. Following dehazing using the Guided Filter Dehazing Algorithm, traffic signs are detected using the Faster R-CNN model. With a detection accuracy of up to 95.11%, the model demonstrates its remarkable generalization and flexibility. Second, haze determines the weight by using the driving sight distance as the U layer and the Faster RCNN model's detection result as the V layer, establishing the UV correlation.

2.1 “A Practical Approach of Recognizing and Detecting Traffic Signs using Deep Neural Network Model”

As a result of many technological developments and growing usage of artificial intelligence in our daily routines, the number of autonomous and self-driving vehicles has expanded dramatically. To be effective and efficient, autonomous cars must be able to recognize and interpret a variety of traffic signs and take appropriate responses. A technology known as Traffic Sign Recognition can be used to determine a large number of different traffic signs. Traffic Sign Recognition is a technique that enables self-driving or autonomous vehicles to recognize traffic signs on the road. We must classify the images into their appropriate categories or groupings once they have been recognized. We accomplish this by creating a Convolutional Neural Network model.

2.2 “Automatic Traffic Sign Detection and Recognition Using SegU-Net and a Modified Tversky Loss Function with L1- Constraint ”

Traffic-sign detection is a central part of au- tonomous vehicle technology. Recent advances in deep learning algorithms have motivated researchers to use Neural Networks to perform this task. However, most of these methods are limited in terms of the depth of architecture that is used, the amount of data they are trained on or the size of signs they can detect in practical road scenarios. In this paper, we look at traffic- sign detection as an image-segmentation problem and propose a deep Convolutional Neural Network (CNN)- based approach to address it. To this end, we propose a new network, the SegU- Net, which we form by merging state- of-the-art segmentation architectures – SegNet [1] and U- Net [2] – to detect traffic- signs from video sequences. We use a separate network, inspired by the VGG16 architecture, to classify the detected signs. We train the SegU-Net on the challenge-free (i.e., not degraded by environmental conditions and processing) sequences of the CURE-TSD dataset which contains over 1.7 million images of traffic-scenes.

This segmentation-approach formed the core part of our submission for the IEEE Video and Image Processing (VIP) Cup 2017, where it achieved a winning precision and recall of 73% and 61% on the challenge-free images of the dataset. Here, we improve upon our previous work by focusing on detecting the large number of small signs that are present in the dataset. In order to do this, we use the Tversky Loss function constrained by an L1 term, instead of the simple Intersection over Union (IoU), for training our network. The Tversky loss allows us to boost recall by properly weighing the contribution of the areas of small signs during training while the constraint term prevents the network from compromising precision in doing so. The resultof these changes are an improved precision and recall of 86.8%and 86.5%, respectively, on the challenge-free CURE-TSD images, which is the current state-of-the-art on this part of the dataset.

2.3 “Traffic Sign Recognition System (TSRS): SVM and Convolutional Neural Network”
TSRS (Traffic Sign Recognition System) may plays a significant role in self driving car, artificial driver assistances, traffic surveillance as well as traffic safety. Traffic sign recognition is necessary to overcome the traffic related difficulties. The traffic sign recognition system has two parts- localization and recognition. In localization part, where traffic sign region is located and identified by creating a rectangular area. After that, in recognition part the rectangular box provided the result for which traffic sign is located in that particular region. In this paper, we describe an approach towards traffic signs recognition system. Here, we worked on 12 selected sign to traffic sign detection and recognition purpose. In this intention, we used Support Vector Machine (SVM) and Convolutional Neural Metwork (CNN) individually to detect and recignize the traffic signs.
We obtained 98.33% accuracy for SVM with 80:20 train and test data ratio. On the other hand, the test result was 96.40% accurate for CNN.

2.4 “Identifying Traffic Signs In A Hazy Environment Using A Vehicle's Viewing Distance”
Identifying traffic signs in hazy environments is crucial for road safety, but it can be challenging due to reduced visibility. This research proposes a method to improve traffic sign recognition by investigating the relationship between sight distance, haze grade, and traffic sign detection performance. To test their approach, we used the German traffic sign database The data showed that detection accuracy decreased as haze levels increased, with accuracy levels of A (more than 96%), B (88%-95%), and C (85%-93%) achieved at different sight distance thresholds in different haze conditions.

2.5 “Traffic sign recognition based on deep learning”
Intelligent Transportation System (ITS), including unmanned vehicles, has been gradu- ally matured despite on road. How to eliminate the interference due to various environ- mental factors, carry out accurate and efficient traffic sign detection and recognition, is a key technical problem. However, traditional visual object recognition mainly relies on visual feature extraction, e.g., color and edge, which has limitations. Convolutional neural network (CNN) was designed for visual object recognition based on deep learning, which has successfully overcome the shortcomings of conventional object recognition. In this paper, we implement an experiment to evaluate the performance of the latest version of YOLOv5 based on our dataset for Traffic Sign Recognition (TSR), which unfolds how the model for visual object recognition in deep learning is suitable for TSR through a comprehensive comparison with SSD (i.e., single shot multibox detector) as the objective of this paper. The experiments in this project utilize our own dataset. Pertaining to the experimental results, YOLOv5 achieves 97.70% in terms of mAP@0.5 for all classes, SSD obtains 90.14% mAP in the same term.
Meanwhile, regarding recognition speed, YOLOv5 also outperforms SSD.

2.6 “The Improved Framework for Traffic Sign Recognition Using Guided Image Filtering”
In the lighting conditions such as hazing, raining, and weak lighting condition, the accuracy of traffic sign recognition is not very high due to missed detection or incorrect positioning. In this article, we propose a traffic sign recognition (TSR) algorithm based on Faster R-CNNand YOLOv5. The road signs were detected from the driver’s point of view and the view was assisted by satellite images. First, we conduct image preprocessing byusing guided image filtering for the input image to remove noises. Second, the processed image is input into the proposed networks for model training and testing. Three datasets are employed to verify the effectiveness of the proposed method finally. The outcomes of the traffic sign recogni- tion are promising.

2.7 “The Recognition Of Traffic Speed Limit Sign In Hazy Weather”
Hazy weather affects drivers’ sightline seriously and causes a high potential safety hazard. This paper proposes a novel approach for recognizing the speed limit sign in hazy weather. It consists of three major modules: haze removal, speed limit sign location, and sign recognition. In haze removal, this paper proposes to dehaze image with the dark channel prior. The speed limit sign is located by Histogram of Oriented Gradient (HOG) feature extraction and Support Vector Machine (SVM) classification and is recognized by the seven layers Convolutional Neural Networks (CNN). Experimental results show that the

proposed method has better performance than the state-of-art dehazing methods and the processing time is also reduced.
The recognition rate of the speed limit signs is 98.51% that is better than the human performance, and the classifier can recognize the speed limit sign with rotation, shift, scale and other distortions.

2.8 “Traffic Sign Detection And Recognition Based On Convolutional Neural Networks”
Traffic sign detection and recognition topic are one of the most popular topics of computer vision and image processing in recent years, as they play an important role in autonomous driving and traffic safety. This paper proposes a system that will detect and classify different types of traffic signs from images. This paper differs from other papers as it uses signs that are globally recognized and isn’t limited to very few signs like many other papers. The number of signs used in this paper for classification is 28, which are used all around the globe. Two separate neural networks have been used for detection and recognition purpose; one classifies the sign and other the shape. Image augmentation has been used to create the training and validation dataset. 40,000 images have been used to train the first classifier with 28000 positive images (images that contain the traffic signs) and 12000 negative images(images that do not contain any traffic signs) and 3600 images were used to train the second classifier with 2400 positive images and 1200 negative images.
The images are processed to find the region of interest, which is then fed to two CNN classifiers for classification.

2.9 “Traffic Sign Detection under Challenging Conditions: A Deeper Look Into Performance Variations and Spectral Characteristics”
Traffic signs are critical for maintaining the safety and efficiency of our roads. Therefore, we need to carefully assess the capabilities and limitations of automated traffic sign detection systems. Existing traffic sign datasets are limited in terms of type and severity of challenging conditions. Metadata corresponding to these conditions are unavailable and it is not possible to investigate the effect of a single factor because of simultaneous changes in numerous conditions. To overcome the shortcomings in existing datasets, we introduced the CURE-TSD- Real dataset, which is based on simulated challenging conditions that correspond to adversaries that can occur in real-world environments and systems. We test the performance of two benchmark algorithms and show that severe conditions can result in an average performance degradation of 29% in precision and 68% in recall.
We investigate the effect of challenging conditions through spectral analysis and show that challenging conditions can lead to distinct magnitude spectrum characteristics. More- over, we show that mean magnitude spectrum of changes in video sequences under challenging conditions can be an indicator of detection performance.

2.10 “Traffic-Sign Detection and Classification Under Challenging Conditions: A Deep Neural Network Based Approach”
Traffic sign detection and classification is of paramount importance for the future of autonomous vehicle technology. Many promising methods have been proposed in the literature to perform this task. However, almost all of them work well only with clear and noise-free images, and, do not provide satisfactory results in the presence of chal- lenging image-capture conditions (such as noise, variation of illumination, motion artifacts, etc.) In this paper, we propose a Convolutional Neural Network (CNN)-based approach for detecting and classifying traffic signs which is robust against such challenging environmental conditions. In the proposed model, our approach is to consecutively (i) detect the type of challenge present in the image, (ii) selectively preprocess the image to enhance the sign-features (iii) localize traffic sign proposals from the preprocessed image using a network specifically trained for the detected challenge-type, and, finally,
(iv) classify the sign proppsals extracted from the image. These tasks are carried out by implementing CNNs of varying architecture and depth.
The challenge-detector and classifier are implemented by using a VGG-16-type architecture, whereas the localizer is similar to the U-Net architecture. The proposed model has been evaluated on the Traffic-Sign Recognition Dataset provided for the IEEE VIP Cup 2017. Experiments demonstrate that, it is robust enough to attain satisfactory detection and classification accuracy even in the presence of the given challenges, with an overall precision and recall of 62% and 42% respectivley.

2.11 "Traffic Sign Detection Based on Driving Sight Distance in Haze Environment"

To explore the relationship between traffic sign detection performance and driving sight distance in haze environment, this paper proposed a UV correlation model among sight distance, haze grade and traffic sign detection performance. First, the German traffic sign data set (GTSDB) is synthesized into experimental data setaccording to three levels of light haze, haze and dense haze. The Faster R-CNN model is utilized to detect the traffic signs after dehazing by Guided Filter Dehazing Algorithm. The detection accuracy is as high as 95.11%, which shows that the model has strong generalization ability and adaptability. Second, the weight is determined by haze, taking the driving sight distance as U layer and the detection result of Faster RCNN model as V layer, establishing the UV correlation model. Finally, KM algorithm is used to solve the correlation model, and the best matching result between UV layers is gained.

The experimental results show the haze level significantly affects the driving sight distance, and then affects the detection accuracy of traffic signs. When the driving Sight distance threshold is 300 meters, 100 meters and 50 meters in light haze, haze and dense haze, the KM algorithm obtains the detection accuracy levels of A (higher than 93%), B (88%-93%) and C (85%-88%), respectively.

III. Conclusion

Conclusively, the creation of a traffic sign detecting system is an essential undertaking that has great promise for improving road safety, transportation effectiveness, and the development of autonomous cars. We may comprehend the scope and needs of such a system more fully by carefully examining viability and taking into account a number of important variables.By helping drivers, autonomous cars, and advanced driver assistance systems (ADAS) recognize and react to different kinds of traffic signs, traffic sign recognition systems have the potential to greatly increase road safety. In order to decrease accidents and problems involving traffic, they also help to improve adherence to traffic laws.

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