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Traffic Sign Recognition Using Convolutional Neural Network

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ABSTRACT: This work offers a new data-driven method for recognizing different types of traffic signs in image sequences acquired by a camera, including both symbol-based and text-based signs. This system is divided into three stages: extraction of traffic sign regions of interest (ROIs), refinement and classification of ROIs, and post-processing. The most stable extremely areas on grey and adjusted RGB channels are used to derive traffic sign ROIs from each frame. The proposed multi-task convolutional neural network, which is trained with a vast amount of data, including synthetic traffic signs and images tagged from street views, then refines and assigns them to their precise classes. Finally, the post processing combines the data from all frames to make a judgement on recognition. The proposed system's usefulness has been demonstrated by experimental data.

KEYWORDS: CNN, Machine Learning, pre-processing, Classification autonomous driving, traffic sign, deep learning, detection.

I. INTRODUCTION

In recent years, the deep learning has been applied to the field of traffic sign detection and recognition methods and has proved to yield excellent performance. The CNN Method is a deep learning technique capable of receiving an input image, prioritizing unique elements within it, and discriminating between them [8]. When compared to other classification algorithms, the amount of pre-processing required is significantly less. Filters are hand-engineered in primitive methods by individuals with sufficient experience. Automated Driving and Driver Assistance Systems both rely significantly on traffic sign recognition [1]. Due to the significant visual changes in traffic sign images caused by partial occlusion, shifting viewpoints, illuminations, and weather conditions, this operation is challenging for a computer to perform. Traffic sign recognition consists of two stages: detection and categorization [15]. The objective of detection is to locate and size existing traffic signs within an image, whereas the objective of classification is to assign a class label to each identified traffic sign. The implementation of efficient object recognition algorithms was made possible by a recent advance in the field of machine learning, which relies on deep learning techniques. This method has also been used to identify and recognize traffic signs with success. Convolutional In recent years, the deep learning has been applied to the field of traffic sign detection and recognition which neural networks (CNNs) are the state-of-the-art methods for object detection and recognition, and they achieve significant results in the tasks of traffic sign detection (TSD) and traffic sign recognition (TSR) [1]-[4]. There are online databases of traffic signs that have been compiled and annotated by various research groups in order to provide a benchmark that can be used for both detection and recognition tasks. German Traffic Sign Recognition Benchmark [3][11] with 43 classes for recognition only; European dataset [10] with 62 classes for both detection and recognition; the extended MASTIF database [13] with 31 classes; and the Tsinghua-Tencent 100K dataset [4] with 45 classes are some of the most commonly used. These databases, on the other hand, normally have a restricted number of different traffic signs. As a result, evaluating and comparing different detection and recognition systems is difficult.

II. RELATED WORK

In this section we will get an overview of the past work done in the field of TSR and TSD. The increasing number of automobiles on the road necessitates the deployment of automated driver aid technology. These systems are also crucial parts of self-driving cars. A traffic sign recognition system is an automated technology that gives self-driving automobiles with context awareness. In [1], the utility of CNN-based object detection approaches, such as Faster R-CNN, in Traffic Sign Recognition systems has been demonstrated, with human-level accuracy and real-time performance. Despite their cutting-edge real-time detection speeds, single stage detection systems such as YOLO and SSD are not recommended for traffic sign identification due to their low accuracy and difficulty with small object recognition. RetinaNet has shown encouraging results in terms of the accuracy and speed required to address object detection tasks. To address the issues of low accuracy and small item detection, it employs Focal Loss and a Feature Pyramid Network (FPN). A performance comparison against a Faster R-CNN-based sign and a YOLOv3-based detector, as well as a RetinaNet-based traffic sign recognition system for self-driving cars, is included in this work. The CNN-based traffic sign class recognizer is used in conjunction with the RetinaNet-based traffic sign detection network. The German Traffic Sign Recognition Benchmark (GTSRB) is used to assess classifier performance, whilst the German Traffic Sign Detection Benchmark (GTSDB) is used to train and test networks.

The authors in [7], addressed the two issues at that moment. To begin with, Chinese traffic signs include both horizontal and vertical text, unlike English traffic signs, which only have horizontal writing. To the best of my knowledge, no research has been done on the simultaneous recognition of horizontal and vertical text in Chinese text-based traffic signs. Second, the majority of available approaches are geared toward rural and highway environments, with only a few focusing on street settings and presented a combined vertical-and-horizontal-text traffic sign identification and recognition algorithm for street level scenes to address these issues. First, in the very complicated street scenes, an effective mixture of different red, green, and blue components is employed to differentiate the traffic signs from various things of similar hue. Second, unlike English letters, many Chinese characters have interconnected strokes, which can cause a character to be misread as two or more characters. The Chinese text lines on text-based traffic signs are usually both horizontal and vertical, unlike the English text lines, which are solely horizontal. The text lines are formed using the location and structural information of the characters in our proposed method. A collection of Chinese text-based traffic signs has been compiled. The proposed strategy appears to be effective based on the results of the experiments.

In the paper [8], the YOLOv3 framework was used to develop a traffic sign detection and recognition algorithm. For network training, the public traffic dataset TT100K and the Taiwan road scene image dataset are employed. In the performance evaluation, multiple input image resolutions and ROI for network training and testing were compared thoroughly. In tests, the proposed method was able to produce a map with a 92.99 percent accuracy using the 21 most typical traffic signs on the road.

In [11], TensorFlow's Object Detection API was utilized in this research to detect and recognize assistance-intent traffic signage in Turkey. For traffic signs, a dataset suitable for TensorFlow's Object Detection API was created using images taken in a variety of traffic and weather circumstances. A web-based data tagging tool was created to assist in the preparation of this dataset. This dataset was trained using the proper deep learning model, and the results were generated using the test data. Despite the scarcity of training data, the results for the test image are satisfactory.

III. METHODOLOGY

SYSTEM ARCHITECTURE: -

In this system we are taking input as an image. As we know that we are performing image processing operation on system, so that we are using four modules of image processing like preprocessing, segmentation, feature extraction and classification where we use our CNN algorithm [3][14]. so first we have passed input as an image then in preprocessing RGB conversion to gray followed by Binary conversion is done. After that in the segmentation part the image is divided into the small pixels then in the extraction part system extract the geometry-based feature of traffic sign. then in classification where we use our CNN algorithm to classify and predict [8]. We pass this geometry-based features of

traffic sign to the classification phase for classification and prediction, then on that basis it detects the traffic sign and then convert it into the voice alert[4]-[7]. The modules used in the project are:

- **Pre-Processing:** The machine will process the input. The data-set will be trained by the pre-processing in data set which will remove the noisy parts of the input. After which you can resize the data-set.
- **Segmentation:** It entails segmenting a visual input to make image analysis easier. We can split the image up into segments in which we can do further processing if we want to remove or identify something from the rest of the image, such as detecting an object from a context. This is referred to as segmentation. Segments are made up of sets of pixels, or "super-pixels," that represent objects or parts of objects.
- **Feature Extraction and Classification:** Points, edges, and artifacts are all examples of image structures that can be used as functions. Feature extraction is the method of reducing the number of features in a dataset by reusing previously used ones (and then discarding the original features). The original set of features should then be capable of summarizing the vast majority of the data contained in the new reduced set of features [9]. Feature extraction starts with measured data and generates derived values (features) that are intended to be insightful and non-redundant, thus promoting learning and generalization processes and, in some cases, resulting in more precise human interpretations. The extraction of features and the reduction of measurements are inextricably related. CNNs are used for image detection and recognition due to their high precision. In a classification convolutional neural network, each set of neurons analyzes a specific region or "feature" of the image in a three-dimensional structure. A CNN's neurons are divided into groups that each concentrate on a different aspect of the picture. The algorithm examines smaller sections of the images. The end result is a probabilistic vector predicting the likelihood of each feature in the image belonging to a class or category.

ALGORITHM USED: -

Convolutional Neural Network:

CNN is a supervised learning network. It is a machine learning technique that takes an input image and gives significance (learnable weights and biases) to different aspects/objects while also distinguishing them. There are three layers of CNN: **1) Convolutional Layer:** The feature extraction is performed via a convolution layer, which is a core component of the CNN design. Convolution is made up of a mix of linear and nonlinear procedures.

2) Pooling Layer: A pooling layer down samples the feature maps, introducing translation invariance to minor shifts and distortions and reducing the number of learnable parameters by reducing their in-plane dimensionality. It is worth noticing that none of the pooling layers have learnable parameters, despite the fact that filter size, stride, and padding are hyperparameters in pooling operations, similar to convolution operations.

3) Fully Connected Layer: The final convolution or pooling layer's output feature maps are converted to a one-dimensional array of numbers and connected to one or more fully connected layers, also called as dense layers, in which each input is coupled to each output by a learnable weight.

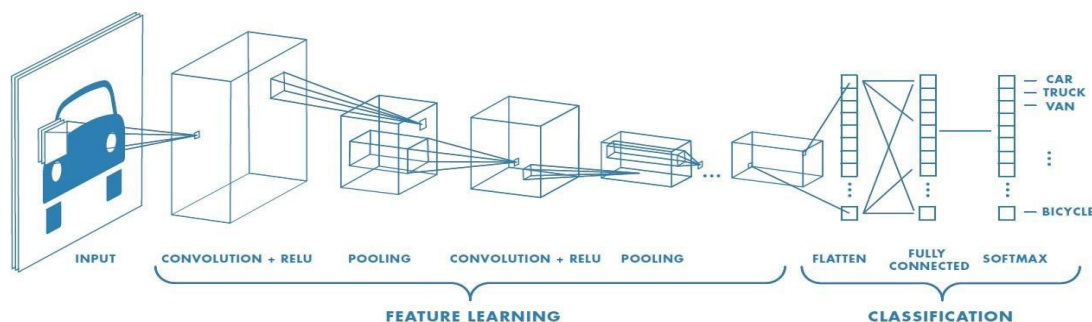


Fig 1. Basic Architecture of CNN (Saha, Dec2018)

IV. EXPERIMENTAL RESULTS

Using this approach, we have tested few categories of images from German traffic sign Recognition benchmark dataset (GTSRB). The system has achieved a good accuracy rate. We have developed a Graphical user interface which gets redirected to a front-end camera through which the tested images can be clearly recognized and are classified into their corresponding categories. The outputs of the work described are attached below.

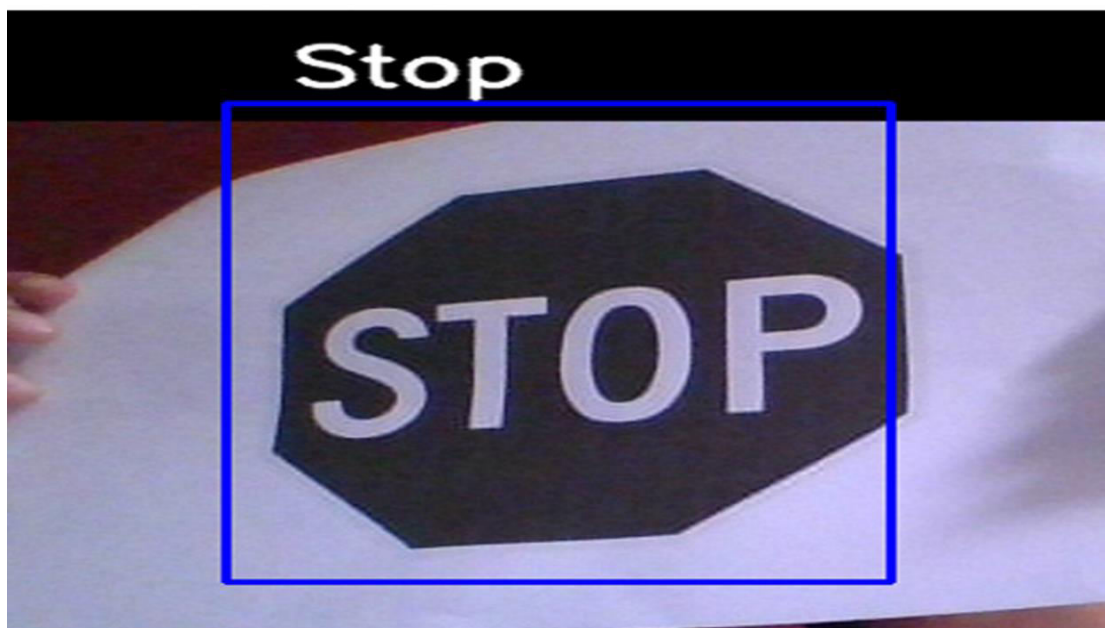


Fig 2. STOP sign recognized

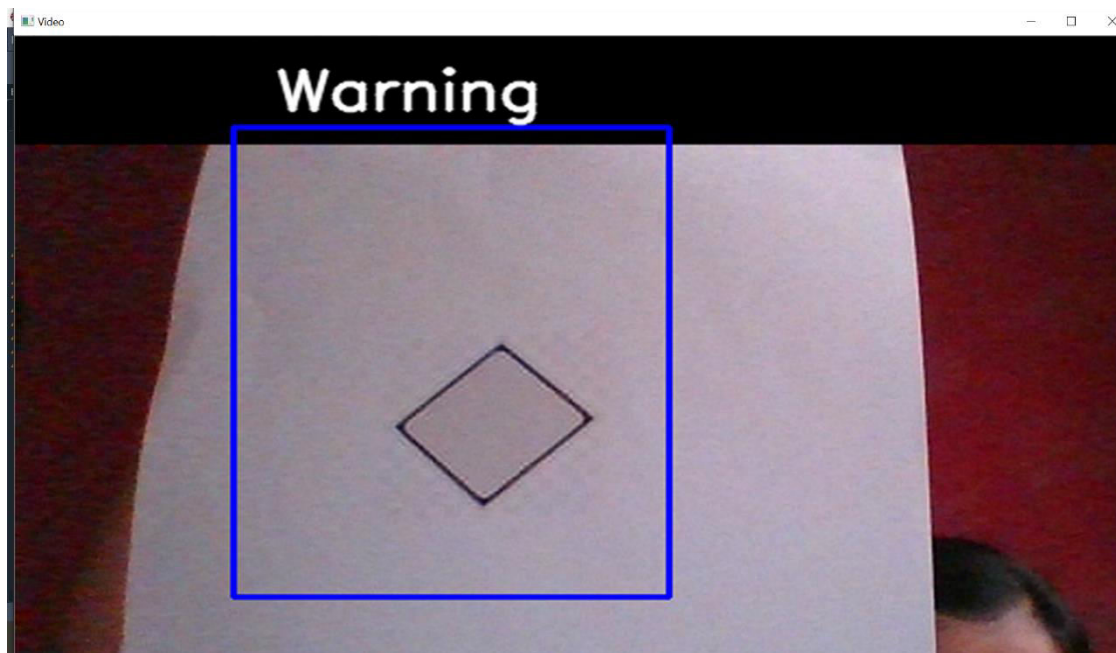


Fig 3. Warning sign



Fig 4. Keep Right Sign



Fig 5. NONE (no-image)

V. CONCLUSION

The purpose of this study is to create a system that can recognize the traffic signs quickly. The photos were acquired and supplied to the system for preprocessing utilizing RGB to Grey color segmentation during the picture acquisition stage. The CNN method, which we utilized in the classification section, is used in the recognition step. In terms of accuracy, on the supplied dataset German traffic sign recognition benchmark (GTSRB), the proposed CNN architecture has achieved an accuracy of 98%. The suggested CNN classification module pre-processes the image and filters the backdrop before recognizing the relevant classes and categories of traffic signs. We also conclude that as the number of epochs increases, the model's accuracy improves. In future work, to increase the reliability of the system for its real-time implementation, we can use high-power GPU's and powerful deep-learning based object detectors acquired with high-resolution camera's.

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