Real Time Traffic Sign Classification Using Deep Learning

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Abstract. Traffic sign recognition is a critical component in the improvement of ITS and also the creation of self-driven and partly self-driven motor vehicles and ADAS. Automated traffic sign classification is the process of real-time interpretation of traffic sign displayed so that drivers and vehicles can be informed of the right decision to make. This not only helps in the direction but also plays a great role in enhancing road safety by contributing to the reduction of traffic accident rates. The real-time traffic sign classification technique that is proposed here involves the use of Convolutional Neural Networks (CNNs); a deep learning architecture. CNNs are rather appropriate for image recognition because they contain some mechanisms that allow them to detect some objects in images automatically, including edges, shapes, or patterns. Thus, the high accuracy and robustness of this approach are reached due to training the model on the large and diverse dataset and system's ability to recognize a large number of traffic signs in different conditions, for example, in different lighting, weather, or in the presence of cluttered roads. This model's training dataset consists of more than 35,000 images which include 43 classes of traffic signs. The use of a big number of samples from each class enhances the ability of the model to generalize on various traffic signs, enhancing the model's performance in real conditions. Due to real-time processing capacity, this technique allows the vehicle to observe the environment continuously, identify traffic signs that are relevant and inform the driver or the autonomous system.

Keywords Realtime, intelligent transportation systems, ADAS, CNN.

1 Introduction

Traffic sign prediction is an project meant for the development of end to end technology that will be used to detect traffic signs from images in real time. This technology is important to most advanced driver assistance systems (ADAS) and fully autonomous cars since it allows cars to recognize traffic signs on their own. The system is modelled to be able to identify not just a single traffic sign but also multiple signs in a single image that can include various road signs that may cover speed limits, stop sign, do not pass zone etc. Because the technology teaches the system to detect as many signs as possible, it is crucial in improving the safety and intelligence of driving while also playing an important role in self-driving capabilities.

For the construction of the traffic sign prediction system, we use a vast and diverse set of images containing thousands of traffic signs in real-world conditions. This dataset ranges from simple basic traffic signs which represent different road regulations and signs to the complex ones which represent different road conditions and places. It includes traffic signs photographed at different lights, from different perspectives, and in different settings such as city, roads, and highways, and rural roads. The variety of

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data in the dataset is important to obtain high accuracy and successful work of the system in real-life conditions, where traffic signs can have different appearance due to the current weather, time, and geographic location.

Preprocessing of the data is important in the creation of this system. It includes a process of formatting the raw images to feed them into the machine learning model to enhance the data order. Some of the data pre-processing techniques include; resizing of images, normalization of pixel values and putting the data in proper form for training. In addition, the use of image augmentation increases the randomness of the training data which increases the versatility of the system. For example, in some cases, specific images will be 'brightened' to give a different lighting effect, or 'tilted' slightly to match up with the effect given by a different camera position, or 'noisy' to simulate a lower quality image. These transformations help the system to learn traffic signs in different conditions, which will be useful when the system is used in real world settings.

The performance of predicting traffic sign is evaluated in real-time testing; the trained model predicts traffic signs from video streams. There is a use of webcam or other camera to capture traffic signs as it appears on the screen, and the model has to predict in real time. The efficiency of the system is assessed by regularly verifying the correctness of its prognosis. The real time aspect of the system is important because it shows that the model is able to classify traffic signs in real time, thus giving the vehicle's control system or the driver up to date information. The system should be able to identify signs as they exist in the road environment and respond by producing a signal to the driver or other action such as changing speed or direction.

The most significant issue in this project will be to decide how much data is enough for making the right predictions. The effectiveness of the system depends on the kind and amount of training data available. Limited training data set results in high risk of poor model performance particularly on unseen traffic sign or conditions. Through understanding the data necessary for the system to perform at its best, we are in a position to feed the system with a variety of data so that it can perform in the best way possible in other scenarios. It is indispensable for the effective traffic sign recognition system formation which is able to function in various conditions and can be implemented in actual self-driving car projects.

2 Related works

ZHANG et al. [1] implemented applied in Yolov3 environment for improving more superior systems such as the advanced driver-assistance systems and self-driving vehicles. This paper discusses the issues that were associated with the conventional detection techniques and introduces the reader to the idea of deep learning and more so the CNNs. The new design integrated three-scale spatial pyramid pooling to enhance the feature description and has another path for the precise localization of the small objects. The sample data show that the method is effective even in conditions of high competition. For the research, both national and provincial funds are used.

Wang et al [2] presents two new lightweight convolutional neural networks for traffic sign classification, designed specifically for environments with low computational resources and high accuracy. A teacher network uses high density and knowledge transfer to enhance the training of a less complex student network. The parameters of

the student model are reduced to five convolutional layers, which contribute to high recognition accuracy. Additional, channel pruning is used to strip off unimportant channel, which enhances the network more. These models offer nearly comparable levels of accuracy to large models while at the same time requiring fewer resources which makes them suitable for deployment on mobile platforms.

Zhu et al. [3] focuses on the traffic sign recognition through deep learning approaches, YOLOv5 and SSD models are analyzed. To perform their experiments the researchers extended the dataset to 2182 images divided into eight traffic sign classes. The average precision per category of YOLOv5 was 97.70% for the mAP@0.5 metric compared to SSD's 90.14%. Also, YOLOv5 doubled the detection speed in comparison with YOLOv4 and was about 30 FPS, while SSD was only 3.49 FPS, which makes it suitable for real-time usage. The work further highlights the benefits that deep learning brings to enhancing traffic sign recognition systems

Wang et al. [4] presents an enhanced YOLOv5 architecture designed for the identification of traffic signs in real time at various scales. To improve the detection accuracy of objects with different physical dimensions, it uses an AF-PFN, an AAM, and a FEM. In order to improve the dataset and the model, the approach also includes an autonomous data augmentation mechanism. Extensive testing using the TT100K dataset is conducted based on the created models, demonstrating the system's excellent accuracy and real-time capacity. Mobile gadgets in intelligent transportation systems can use this optimized network

Zhang et al. [5] presents a Cascaded R-CNN with imbalanced sample management and multiscale attention to improve traffic sign detection, particularly for smaller ones. In complex situations, this paper proposes a multiscale feature extraction method using attention models that can increase detection rates. Additionally, it can boost the density of hard negative samples in training and solve the issue of false positives with comparable objects. Overall, the suggested approach demonstrates comparatively excellent accuracy and recall rates in our experimental research on the GTSDB, CCTSDB, and Lisa datasets.

Haque et al. [6] presents "deep Thin", a new, lean CNN architecture specifically designed for traffic sign recognition, which is energy-frugal and that can be trained without the need for GPUs. It minimizes the computational cost per layer but can retain a considerable accuracy by employing a limited number of feature maps. It is for this reason, Deep Thin has been shown to attain near state of the art performance on the GTSRB and BTSC datasets using many orders of magnitude fewer parameters than other methods. Furthermore the architecture is capable of transfer learning, thus allowing for outstanding fits to a broad range of datasets containing traffic signs with just a little degree of fine-tuning.

Mehta et.al [7] concerns itself with the classification of vehicles using machine learning models for the analysis of data. That is why it discusses various strategies for identifying images and subsequently, classifying the vehicles into certain categories based on deep learning methods. The effectiveness of different architectures is assessed in the study with a view of achieving higher level of accuracy and faster classification. The obtained results reveal that there are significant improvements in the classification

capability using deep learning over conventional approaches. The paper also points out the idea of improving the model to make it more efficient in practical use.

Sawalka et.al [8] concentrates on traffic signs detection in real environment with the help of advanced technologies like CNNs in order to increase vehicles safety. It underlines significance of the identification of traffic signs and recognition of speed for the vehicles in real mode for self-driving cars. The proposed system identifies and classifies traffic signs by the color and the shape of the signs using Support Vector Machines (SVM) classifiers. The focus of the study is the application of this technology in automobiles to address and minimize human factors that endanger lives on the road.

3 Methodology

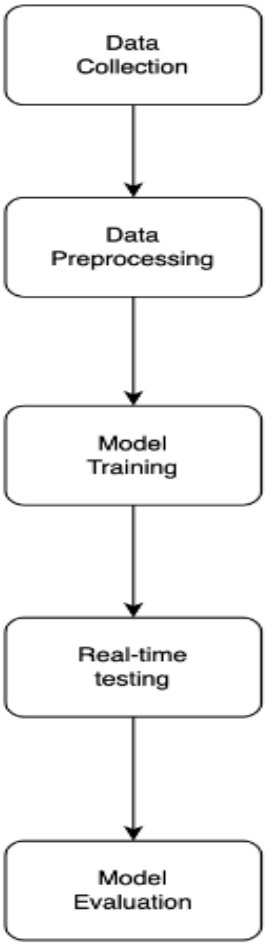

Fig. 1. Flow chart of the proposed system.

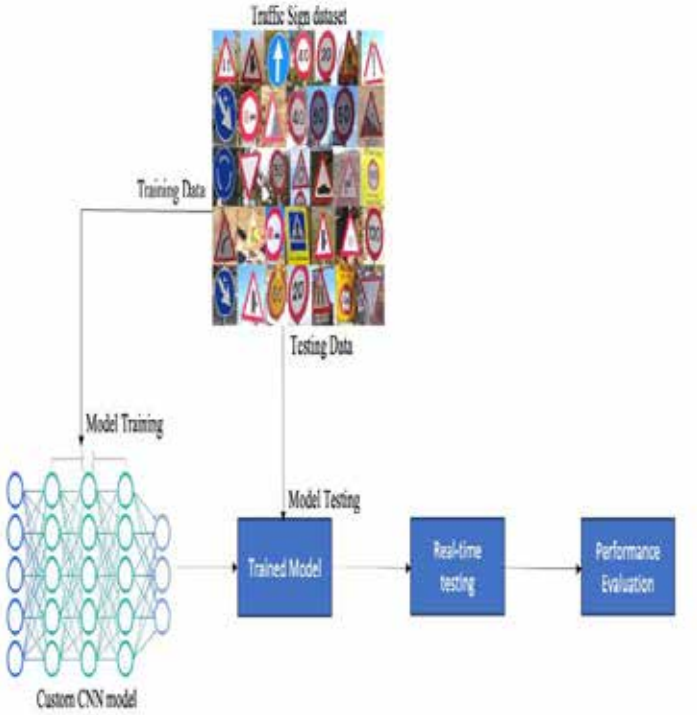

Fig. 2. Model Architecture.

This is the methodology and Model Architecture of our project on building a real time traffic sign classification based on the flow given in the fig 1 and fig 2.

3.1 Data Collection

Initially, a complete dataset of images was collected for various classes of traffic signs, including speed limits, stop signs, no passing zones, and more. The dataset hosts over 35,000 images belonging to 43 different classes proper distribution according to the real-world traffic signs. The distribution of classes over the database is shown in fig 1

3.2 Data Preprocessing

The data is collected we can then resize all the images to have the same pixel size for improved results. After that we apply rotation, zooming and shifting techniques for enhancing the generalizing capability of the model built is further performed. Which one will help to train the model better.

3.3 Model Training

The data is then trained with the custom CNN model over several epochs. The dataset further splits into trained, validation, testing dataset for the model.

3.4 Real-time testing

To enhance the performance evaluation, the model built is tested in actual real world environment and the traffic signs are recorded from the webcam. Then the system utilizes the feed to look out for the type of sign and this comes with features which illustrate the possibility of its prediction.

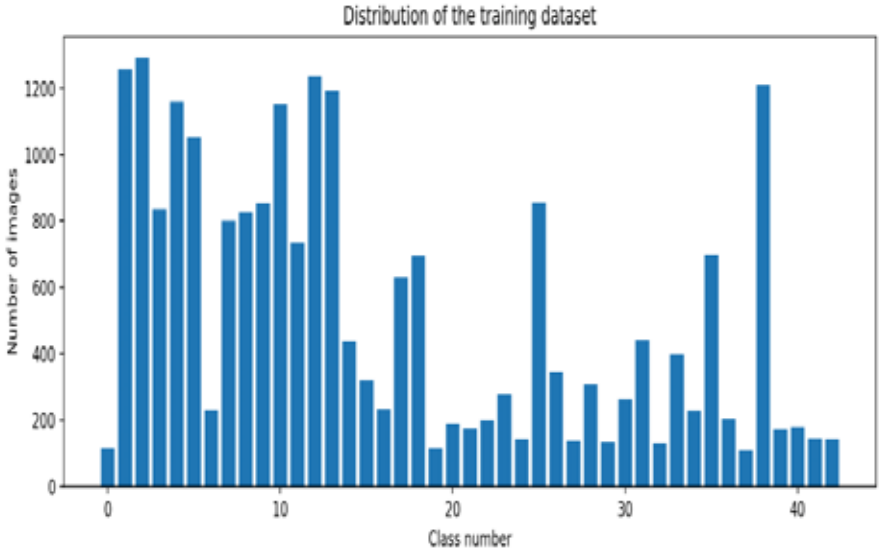

Fig. 3. Distribution of classes over dataset.

3.5 Model Evaluation

The accuracy of the model and the loss for both creating and validating the model are considered. The classification report is created for the model to gain the complete results of the model. The performances of the model are measured with Accuracy, Precision, Recall and F1-score.

4 Results And Analysis

For this project, we trained a CNN model which has been slightly altered to be used on the traffic sign recognition dataset. CNNs are also appropriate for image classification because they can identify features from raw pixel data, hierarchy, edges, textures, and shapes that are important in recognizing traffic signs. Changes to the CNN were introduced specifically to improve generalization and reduce overfitting of the model so that it may be more effective at distinguishing between traffic signs regardless of different conditions or angles.

The measures adopted in assessing the model are useful in evaluating the criteria used in the assessment. The model achieved an F1-score of 0.97 which signify that the model provided a good level of both the precision and the recall. The value is 0.99 which means the model has high accuracy most of the times which is desirable in the

application of the model. A value of 0.98 means that when the model has predicted a traffic sign, it would be accurate most of the time and hence reduce on the false positive. The value of 0.97 was recalled to show the ability of the model in avoiding false negatives on traffic signs and hence the model can easily recognize most of the signs. These aspects show that the recognition and classification of traffic signs by the model is quite impressive.

In addition, the performance of the model training and validation during each of the ten epochs of the model training is shown in Fig. 3. In the case of the model, training and validation accuracy increase steeply at the beginning of the first epochs up to about the validation accuracy of 0.95. This rapid learning process shows that the given model has a decent capacity of learning and the model has the possibility of generalizing to the validation set.

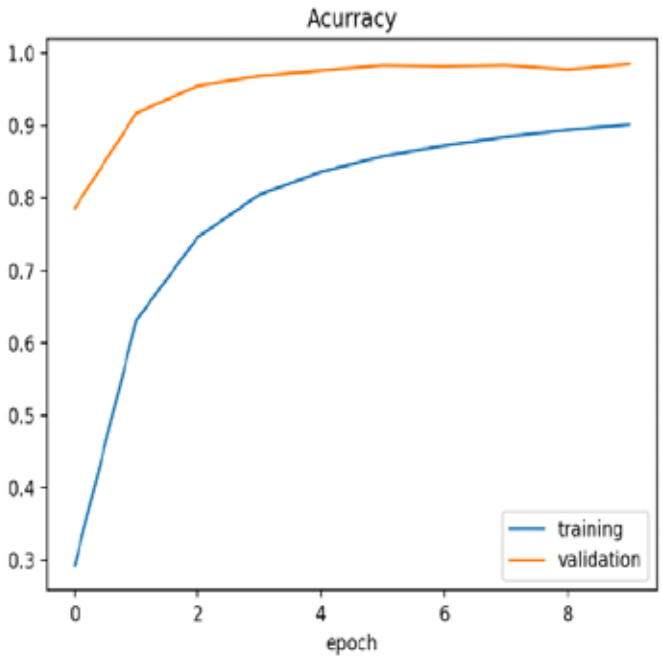

Fig. 4. Plot for Training Vs Validation Accuracy.

However, it is notable that the validation accuracy in the graph of Fig 4 does not change significantly after the first few epochs. When a model focuses too much on the training data so much that it can predict the results on the training data itself then it is said to have been overfitting. In this particular case, the validation accuracy does not fluctuate a lot, thus the model is not memorizing the training data. This makes the model capable of recognizing traffic signs even in unseen conditions in real world thus reducing the chances of the model to misrecognize traffic signs. Additionally, the graph in Fig 5 also depicts the training and validation loss values across the ten epochs.

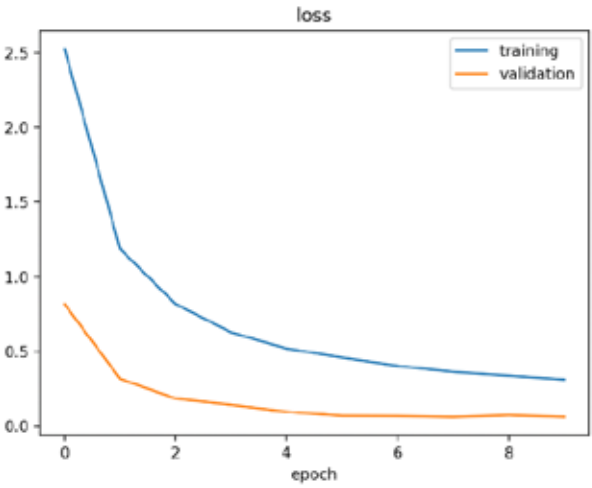

Fig. 5. Plot for Training Vs and Loss.

4.1 Real Time testing

To take the trained model to a level higher than that of testing, we have incorporated the model into a live real time evaluation system using Pickle for model serialization and OpenCV for real time image processing. Pickles are used to store a model after it has been trained and tested in the case of future use. This gives a benefit of being able to load the model back in to memory for use in real time applications without having to retrain the model each time. This approach makes it easier to deploy the model which can be integrated with other systems such as driver assistance or self-driving cars.

Fig. 6. Real-Time Traffic Sign Recognition Using AI-Based Object Detection.

Fig. 7. AI-Powered Traffic Sign Detection: Children Crossing Alert.

The model is detecting the sign correctly for a blurred image of speed limit 60 km/h as shown in fig 6 and fig 7.

5 Conclusion And Future Work

In this real time traffic sign classification project, a CNN was used as a model to classify images of traffic signs that are captured through a webcam feed. The dataset was set of traffic sign images which can further deal with the light conditions, weather conditions and occasional occlusions in practical scenarios. Furthermore, the framework could be improved through the integration of the temporal data from successive frames as well as the utilization of superior architectural designs such as Vision Transformers, thus improving predictive accuracy and response rates. Additional tweaking to fit for edge devices may also make it possible to deploy it on portable and embedded systems, allowing for its real-world usage in practical on-road situations. which was labelled and preprocessed to improve the consistency of the model. Augmentation techniques like rotation and zoom were used in order to make the model stronger. In real-time testing, each frame of the webcam is analyzed and labeled, and the sign recognized together with the degree of certainty is shown on the screen. Thus, high accuracy of the model shows its applicability for the autonomous driving and the advanced driver-assistance systems (ADAS). As a future work, there could be an addition of more data sets.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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