Automatic Traffic Sign Recognition System Using CNN

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ABSTRACT

In recent times, self-driving vehicles have been widely adopted across different countries as they are equipped to drastically reduce the number of road accidents and congestion on the road thereby improving the traffic efficiency. To detect, identify, and label the traffic signs on the road in order to help the Advanced Driver Assistance Systems (ADAS) in these autonomous vehicles with navigation details, a Traffic Sign Recognition (TSR) System using a deep convolutional neural network model, Mask RCNN (Mask Regional Convolutional Neural Network), is proposed in this paper that aims to help the autonomous vehicles comprehend the road ahead and safely navigate to the desired destination. This paper presents the detection and labelling of Indian and European Signs and also the results of the system working efficiently under various challenging visibility conditions. The results obtained show that the Mask RCNN model has recorded higher performance compared to all the other CNN models that have been previously used for traffic sign recognition.

KEYWORDS
Binary Mask, Challenging Visibility Conditions, Mask RCNN, RoI, Traffic Sign, Traffic Sign Recognition System

INTRODUCTION

The conceptualization of smart cities over the past few decades has resulted in urban areas transforming into high-tech digital societies and leveraging the technological advancements to come up with initiatives and innovative solutions thereby aiming to make the lives of every citizen easy in all possible facets. There has also been an alarming growth of population which has caused an enormous increase in the number of vehicles on the road resulting in traffic congestion and road casualties. It has been estimated that due to lack of sufficient traffic knowledge, human error in driving and also driving under unsafe road environments, millions of road accidents are recorded every year causing damage to the vehicle or the public property incurring economic losses to the country or even worse, fatal injuries. Today, with the fast pace growth of technology, the development of the Intelligent Transport System (ITS) to improve the commute efficiency is highly paramount and an indispensable need of the hour as mobility has become a major concern these days. These Intelligent Transport Systems use the “Autonomous Driving Technology” to enhance the transportation infrastructure and traffic safety for both the commuter and the pedestrians by reducing the number of accidents and also

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minimizing vehicle pollution emission. With the recent advancements in the automobile industry, the autonomous driving technology has transitioned from the realms of a fictional concept to a viable and commercial possibility over the past few years. These autonomous vehicles are equipped with a driving support function, “Advanced Driver Assistance System”, to safely sense the surroundings and navigate with nominal human intervention. The traffic signs on the side of the road provide the necessary warnings and navigation information required for commuting and these vehicles require the installation of automated systems that can well-recognize and analyze real-time traffic events and also identify and understand the well-placed ahead road signs while driving on the road to ensure safety to both the pedestrians and the commuters.

To facilitate this purpose, this paper intends to present an “Automatic Traffic Sign Recognition System” built using Mask RCNN that can recognize, label and categorize the traffic signs under ideal conditions but also under a wide range of challenging visibility conditions like rain, haze, shadow, overexposure etc. and be able to deliver accurate traffic sign identification to be more universally acceptable. Over the years, these Traffic Sign Recognition Systems have been either built around only text-based signs or to work for datasets comprising of only clear condition-free traffic data using CNN models like RCNN, Fast RCNN and Faster RCNN, but by implementing the proposed TSR system using Mask RCNN, an extension of the Faster RCNN model and a relatively new CNN model, on two datasets namely the CURE-TSD (Challenging Unreal and Real Environment for Traffic Sign Detection) dataset and the Indian Cautionary Traffic Sign Dataset, both comprising of real-time traffic data under various conditions. Using this system, the recognition and labelling of signs have been proved to be more precise and accurate than all the previously-used CNN models due to the pixel-level segmentation that happens only in the Mask RCNN model and not the other CNNs. This pixel-level instance segmentation model that generates and classifies the desired region proposals and also highlights them is found to be a more effective approach to build TSR systems for vehicles implying the autonomous technology as the Mask RCNN is capable of enhancing the detected RoIs with a binary mask which is in advance to the other CNN models where the mask predictions help determine the object classification. The proposed TSR system is expected to improve the quality of mobility in autonomous vehicles, enhance traffic surveillance and road safety as these are the integral aspects of an Intelligent Transport System.

BACKGROUND

With the advent of self-driving cars, there have been numerous approaches to identify traffic signs using machine learning techniques. To facilitate this work, numerous datasets are available from around the world. These datasets may consist of videos, images, or just traffic sign images. This field of research is very wide, with numerous approaches to consider. While applications may vary, the main idea that such a system should operate in real time is common to most research papers. The evolution of machine learning has brought this goal closer to reality with newer algorithms employed every year to achieve better accuracy and throughput rate.

Traffic signs can be classified on the basis of their category (Cautionary, Mandatory, Informative etc.) and they can further be classified on the basis of the particular type (Speed Limit, Stop etc.). The non-uniformity in traffic signs from country to country proves to be a major hurdle in comparing the results of such works. To compare similar works in this domain, it is important to understand the different approaches and algorithms commonly employed by researchers.

A generalized approach to achieve traffic sign recognition follows two main steps – Detection and Classification. One common method, particularly in some older research papers, is to use colour segmentation ((Miura et al., 2000); (Maldonado-Bascón et al., 2007); (Benallal et al., 2003); (Ruta et al., 2010)). This process is considered to be especially beneficial when attempting to work with simple, low-cost hardware to produce real time identification of road signs. Benallal et al. (2003) in their paper discuss using colour-based segmentation for the detection phase. Despite the variation in
colour throughout the day, they find that considering the difference in RGB components provide reliable results. According to them, colour segmentation is beneficial when considering images with small or low-resolution traffic signs. In another paper, Maldonado-Bascón et al. (2007) expand the colour-based segmentation to include yellow and white. They have identified that only few colours are commonly used with specific shapes for most traffic signs. After a pixel level colour-based segmentation, traffic sign shape is classified using another commonly utilized method, Linear SVMs. In this manner once detection is complete, content classification is performed using Gaussian- Kernel SVMs. While their system does not operate in real time, it does show high success rates even with partial occlusion.

Support Vector Machines (SVMs) as seen in the case above are supervised learning methods that are used for classification. With respect to traffic sign recognition, SVMs are widely used in combination with a number of other techniques such as Histogram of Oriented Gradients ((Zaklouta et al., 2012); Alefs et al., 2007); (Ellahyani et al., 2016); (Greenhalgh et al., 2012)). Zaklouta et al. (2012) in their paper, compare the performance of k-d trees, SVMs and random forests utilizing different sized HOG descriptors. Their proposed system, working with a German dataset, uses the previously mentioned techniques to perform classification and also uses Random forests or fisher’s criterion to select features of highest significance. Related to HOG are the Edge Oriented Histograms which differ in how orient gradients are calculated. Alefs et al. (2007) in their paper discuss a system for road sign detection based on EOH. The main aim of their paper is to detect traffic signs at the earliest possible time, and they have achieved up to 85% accuracy for objects with 12 pixels width. Apart from this, numerous other variations on colour and shape-based classification have been implemented with varying degrees of accuracy and time consumption ((Barnes et al., 2008); (Alam et al., 2020); (Garg et al., 2019); (Kamal et al., 2019); (Kuo et al., 2007); (Paulo et al., 2007); (Salti et al., 2015)).

More recently many object detection tasks are being handled by Neural Network based architectures. By using a series of different types of Neural networks or using them in combination with some other technique high accuracy rates are observed. Many different Neural network architectures have been used for Traffic Sign recognition tasks including but not limited to ANNs, DNNs and CNNs ((Supreeth et al., 2016); (Aghdam et al., 2016); (Zuo et al., 2017); (Vennelakanti et al., 2019); (Swaminathan et al., 2019); (Mehta et al., 2019); (Gavrilescu et al., 2018); (Islam et al., 2019); (Kale et al., 2015); (Roubil et al., 2019); (Wei et al., 2018); (William et al., 2019)). Among these, CNNs have progressed the most with variations such as RCNN, Fast RCNN and Faster RCNN being implemented for this purpose ((Garg et al., 2019); (Gavrilescu et al., 2018); (Roubil et al., 2019); (Wei et al., 2018); (William et al., 2019)). These newer methods have negated the need for manual feature extraction and automatically provides region proposals. Zuo et al. (2017) in their paper propose a system for traffic sign detection which makes use of Faster RCNN that, when compared to its predecessor Fast RCNN, has an increased model speed.

Most methods address the need for high accuracy rates, close to real time operability as well as robust functionality even with partially obscured or unclear input. While most datasets available online present clear images shot up close, for the purpose of training the system proposed in this paper, the CURE-TSD challenging video dataset was used. Temel et al. (2019) in their paper discuss and compare the performance of various benchmarking algorithms such as VGG, GoogleNet, ResNet and U-Net. They also compare the result for each class of challenging conditions.

The proposed system makes use of the more recently developed Mask RCNN, which has recently gained a lot of attention for other object detection applications. Mask RCNN is an extension of the previously discussed Faster RCNN and it provides an additional object mask in addition to the class label and coordinates for the bounding boxes. Serna et al. (2019) in their paper, propose a system that uses Mask RCNN for Traffic sign detection and classification and is trained using an extended version of the German Traffic Sign Detection Benchmark dataset. They however mention that the training set was limited.

To address this issue as well as to improve accuracy in traffic sign recognition under challenging conditions, the proposed modified system uses the Mask RCNN algorithm. It includes the Indian Cautionary Traffic Sign dataset along with the Belgian CURE-TSD dataset to train the system for
traffic signs from both countries under more challenging visibility conditions. In addition to this a filter routine which aims to improve the accuracy of the overall system is introduced. Compared to the system discussed above, the modified pipeline differs in the pre-processing stage as well as in the refinement and classification stages.

**METHODOLOGY**

The proposed system as illustrated in Figure 1 is implemented in a pipeline approach where the CURE-TSD video dataset and the Indian Cautionary Traffic Sign dataset serve as input. The video data is preprocessed and broken down into frames. The extracted video frames and image data are pre-annotated with the traffic sign labels and they move to the Traffic Sign RoI Detection module. Here, the input gets converted into a feature map by the Feature Pyramid Network (FPN) which is then scanned by the Region Proposal Network (RPN) to generate potential traffic sign object proposals. Next, RoI Pooling is performed to resize the feature map and then the RoI Classifier classifies the

![Figure 1. Overall architecture diagram of the proposed Traffic Sign Recognition System](image-url)
generated proposals and finally the detected traffic sign regions are enhanced with bounding boxes and softmasks using mask segmentation. This RoI enhanced input moves to the RoI Refinement module where the wrongly identified non-traffic sign RoIs are discarded. Finally, the refined RoIs enhanced input moves to the Traffic Sign Classification module where the Sign-Type Classifier identifies, labels and classifies the potential traffic signs into their corresponding classes. By the end of the pipeline, there will be a Traffic Sign Recognition System that can effectively detect and enhance real-time videos with labelled traffic signs under any visibility condition.

The entire implementation of the proposed TSR system is in the form of a pipeline where pipeline (A) that has the Traffic Sign RoI Detection and Refinement modules, can be exclusively trained to detect and generate bounding boxes and binary masks for all traffic sign objects under any visibility condition ensuring no traffic sign is missed during the first detection pass and pipeline (B) which has the Sign-Type Classifier, that aims at identifying, labelling and classifying only the detected signs can be further trained to label signs of other countries.

**VIDEO-PREPROCESSING**

Video-preprocessing is carried out for the CURE-TSD dataset. Here, Frame Extraction happens where all the video clips are iterated and each of them is split into individual frames. These frames are then grouped into training, validation and testing sets for each sign type along with the corresponding level of challenging condition.

**DATASET PREPARATION**

The traffic-images from the Indian Cautionary Traffic Sign dataset and the video frames extracted from the CURE-TSD dataset are manually annotated using the VGG Image Annotator tool where all the traffic sign objects are outlined and labelled. The corresponding parameters are stored in a JSON file for further processing down the pipeline. The manual annotation is performed as the chosen datasets don’t have pre-labelled traffic sign data.

**TRAFFIC SIGN ROI DETECTION**

The RoI Detection module as illustrated in Figure 2 is used to detect and generate bounding boxes and masks for the traffic sign objects. Here, the pre-annotated and labelled frames are used to train

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**Figure 2. Traffic Sign RoI Detection Module**
a pre-trained Mask RCNN model that has the initial weights to detect a set of pre-trained objects. The model library’s dataset class is overridden to load the new JSON annotations. The model is then trained on this new ‘traffic_sign’ class by excluding the last layer of pre-trained Mask RCNN’s weights to be able to generate a new weights file for the traffic sign class. In pipeline (A), this module is instantiated in the inference mode with its own server instance. Using the traffic sign weights file generated during the training phase, the module detects and generates a python dictionary that holds a list of the detected traffic sign RoI’s labels, their bounding box coordinates and mask values. Then, this dictionary is passed to the model’s data visualization routine that enhances the original frame bounding boxes (dotted lines), masks and labels for the detected traffic sign objects and in some cases for invalid traffic sign objects too.

**ROI REFINEMENT**

The candidate RoIs labelled in the previous module may hold objects wrongly identified as a traffic sign. The RoI Refinement module illustrated in Figure 3 discards the invalid non-traffic sign RoIs and retains only the valid ones for further processing. Here, frames enhanced with bounding boxes and masks for both valid and invalid traffic sign objects move to the refinement module. The class score values of the detected objects are extracted and based on the various test runs of the model instance, the “Detection_Min_Confidence” parameter is set to a threshold value of (>0.9). Only those RoIs whose corresponding class scores meet the set threshold will be considered as a valid traffic sign object and the RoIs falling below the threshold will be removed from the dictionary. Finally, the frames from this module hold only traffic sign RoIs and their bounding box coordinates are persisted in a data file to use them as a filter criterion in the subsequent stages of the processing pipeline.

**TRAFFIC SIGN CLASSIFICATION**

The input frame then moves to the Sign-Type Classifier implemented in pipeline (B) as illustrated in Figure 4 which identifies, labels and classifies the previously detected signs from the precedent pipeline. The Classification module is intentionally kept in a separate pipeline as it is more efficient to extensively train the detection/refinement modules to detect all the traffic signs under varying visibility challenges as a potential traffic sign object and the classification module can be specially trained to identify, label and classify the specific types of signs, Indian and European Traffic Signs. Similar to the RoI Detection module, the pre-annotated frames labelled with the specific type of traffic sign...
sign are used to train the classifier and generate a weights file for all the traffic signs considered. Using this, when the classifier is instantiated, it identifies and labels the traffic signs. To ensure that the classifier doesn’t label objects that have not been detected by the previous modules, a filtering routine is introduced.

ROI FILTERING AND CLASSIFICATION

The filtering routine takes the bounding box coordinates of the RoIs extracted in the Refinement phase and compares them against the coordinates of the RoIs identified by the Classifier, setting the required buffer parameters. Only those RoIs that were found to be lying within the regions of the previously detected RoIs were considered valid and the corresponding parameters of only those RoIs were pushed to the new dictionary object for display and classification purposes. Next, a classification routine is constructed to categorize the labelled signs into their corresponding traffic sign classes: Cautionary, Mandatory and Informative Signs.

RESULTS AND DISCUSSION

While testing the proposed system using video data, it is first broken down into frames and stored in a frames list. The potential signs are detected, invalid RoIs are refined and then, the detected signs are recognized and marked on the frame by enhancing them with masks and bounding boxes. Finally, after all the frames are processed, they are linked back together to give an MP4 file holding...
all the traffic signs labelled under any condition. The sequential working of the proposed system is illustrated in Figure 5 with a sample input as shown below:

This section contains an overview of the datasets used to train the system as well as the results obtained for the proposed method. It covers the metrics used to evaluate the systems performance as well as the calculated outputs. It also includes a comparison of the systems performance for different challenging visibility conditions. All training and testing for the proposed system was done using Google Colab notebooks. The free version of this service provided remote access to GPUs with limited disk space.

**Figure 5. Overview of the Proposed Traffic Sign Recognition System**

![Pipeline Diagram](image)

**DATASET DESCRIPTION**

The proposed system is intended to recognize traffic signs from Europe as well as some common Indian Traffic signs. It is expected to work with frames that have clear visibility as well as frames that pose challenges. In order to train the system to do so, two separate datasets were used – the CURE-TSD dataset as well as the Indian Cautionary Traffic Sign Dataset. While both these datasets come with some form of labelling, for the purpose of running Mask RCNN, annotation was carried out again. In general traffic signs fall into three main categories – Mandatory, Cautionary and Informative Signs.

A. CURE-TSD (Challenging Unreal and Real Environment for Traffic Sign Detection):
This is a large-scale video dataset, containing both Real videos with challenges synthesized over them as well as unreal computer-generated sequences as shown in Figure 6. The real-world video seems to be filmed in Belgium. With limited resources available, the system was trained with the Real video data alone. This European traffic sign dataset consists of 49 unique video sequences, each of 30 seconds length, along with 12 other versions with visibility challenges synthesized over them. These challenges include Decolourization, lens blur, dirty lens, haze, rain etc. Each of these challenges have 5 levels of increasing occlusion. This results in 2989 real video clips containing a number of different traffic signs. This data set, during frame extraction, was split into 300 frames each, allowing the system to be trained to recognize traffic signs at a variety of positions and distances.

B. Indian Cautionary Traffic Sign Dataset:

This dataset contains the real-time traffic images of Indian road signs that are categorised into 17 traffic sign classes like Pedestrian Crossing, Narrow Bridge, Guarded Railway Crossing etc. This, however, is an image only dataset that contains over 9900 images taken under both challenge-free and certain visibility conditions.

DETECTION PERFORMANCE

A common metric used to evaluate the performance of similar models is Average Precision. It is calculated by taking the area under the Precision-Recall curve. Precision and Recall values themselves provide a good insight into the performance of the system. For calculating these values, the Intersection over Union (IoU) or Jaccard index is taken as 0.5. It determines whether a prediction is true or not by taking the ratio of the predicted bounding boxes to the actual bounding boxes to the union of the same. This implies that only those traffic signs identified with an IoU value of at least 0.5 are considered True Positive (TP). Otherwise, it is considered as a False Positive (FP) identification.

Precision is considered to be the positive predictive value. It is the ratio of the total number of true positives to the total predicted positives (Equation 1). It gives insight into how many of the system’s positive predictions are actually accurate. Recall, on the other hand, measures the sensitivity of the system. It is the ratio of the total number of predicted true positives to the actual number of positives (Equation 2). It can be used to judge how many of the actual positive occurrences of an event the system is able to catch.
Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (1)

Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (2)

For the proposed system, average precision and recall values were calculated by calculating the mean values for a randomly selected validation set. The system achieves 68.23% precision and 64.63% Recall.

Using precision and recall, Mean Average Precision (mAP) can be calculated. It is obtained by calculating the Average Precision (AP) from the area under the curve for all classes and finding the mean value (equation 3). The mAP value represents the overall accuracy of the entire system. Using this method, the mAP score for the proposed system was calculated to be 75%.

\[ mAP = \frac{1}{n} \sum_{k=1}^{n} AP_k \quad (3) \]

\( AP_k \) = The\ AP\ of\ class\ \( k \)
\( n \) = Number\ of\ classes

Apart from the metrics to evaluate the entire system, comparison of the proposed systems performances for different challenge types has also been studied. Similar to the Temel et al. (2019) paper, the performance of different visibility challenges such as rain, overexposure etc. has been compared against the challenge free condition as well as against each other and displayed in Figure 7.

Figure 7. Detection results of a frame under different challenging conditions tested using the proposed system
For this paper, instead of performance degradation, class scores that represent the system’s confidence in its prediction have been considered. For each of the challenge classes, class scores of a randomly selected set of images have been calculated and average calculated.

According to results illustrated in Figure 8, the proposed system has an average class score of 0.938 for challenge free frames. It has the highest confidence value in predicting images with the dust challenging condition, and the least confidence in predicting with overexposed bright frames.

From the results calculated in Table 1, it is clear that the use of Mask RCNN to train a Traffic Sign Recognition System is viable. With access to better local GPUs that would allow more intensive training, this methodology could yield even higher accuracy rates. With the current capabilities, while the system does face some difficulty in identifying traffic signs under certain conditions such as over exposure and rain, when at a greater distance, it is capable of providing accurate classification rather close up.

**Figure 8. Average class score by Challenge-Type (Adapted from Temel et al. (2019))**

![Figure 8](image)

**Table 1. Results for the proposed system**

| Metric               | Result   |
|----------------------|----------|
| Precision            | 68.23%   |
| Recall               | 64.63%   |
| Mean Average Precision| 75%      |

**CONCLUSION**

The proposed system extracts the pre-recorded video footage from the camera mounted on the autonomous vehicle; and using Mask RCNN’s object detection model, it detects traffic sign objects by drawing boundaries around them and highlighting them with binary masks. Then, the detected RoIs are refined to retain only the valid traffic sign objects. Finally, using the refined RoIs, the potential traffic signs are labelled and classified providing autonomous vehicles the necessary navigation details. The system efficiently recognizes both Indian and European Signs under a wide range of tough visibility challenges with reliable levels of accuracy through demonstration proving
Mask RCNN to be a better choice among all the other CNN algorithms available for implementing a Traffic Sign Recognition System.

The proposed system can be further trained to work not just with symbol-based signs but also text-based signs, regional signs and sign boards that mark other road details like roads, streets etc. Further research with faster computers and memory-efficient GPUs would be needed to achieve more accurate real-time Traffic Sign Identification Systems. Also, to vastly expand the system’s applicability on a global scale, it can be trained to identify and label traffic signs throughout the world under clear as well as less-than-ideal conditions. Inclusion of physical alerts like flashlights or noise can also be introduced to alert the commuter based on the class of the identified traffic sign.

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