



Traffic Sign Detection and Recognition using Deep Learning

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Abstract Detecting and recognizing traffic signs automatically is vital for efficiently managing traffic-sign inventory with minimal human intervention. While existing methods in the computer vision field excel at recognizing signs pertinent to advanced driver-assistance and autonomous systems, they cover only a fraction of the total traffic sign categories, leaving a significant portion unaddressed. This gap poses a challenge for automating traffic-sign inventory management, which requires handling a broader range of signs. In our study, we tackle this challenge by employing a convolutional neural network (CNN) approach, specifically the mask R-CNN, to handle the entire detection and recognition process in a seamless manner. We propose several enhancements to improve the detection performance, which we evaluate on a dataset comprising 200 different traffic sign categories, including those not previously explored. These findings indicate the feasibility of deploying our approach in real-world applications for traffic-sign inventory management.

Keywords: Data preprocessing, Traffic sign detection, Traffic sign recognition and Transmission.

1. Introduction

Traffic sign recognition is a complex task that's crucial for road safety, requiring expertise in computer vision and machine learning. As road networks become more complex, efficient recognition systems are increasingly vital. This technology improves transportation safety, especially with AI and ADAS. Despite its benefits, visibility challenges and environmental factors can hinder recognition, particularly with warning signs. Despite these obstacles, advancements in computer vision and machine learning are essential for improving recognition accuracy and overall road safety. To maintain traffic flow efficiency and safety, proper inventory management of traffic signs is a crucial responsibility. This work is typically done by hand. In order to ensure consistency with the current database, traffic signs are manually localized and recognized offline by a human operator after being photographed with a vehicle-mounted camera. But when it comes to thousands of kilometres of roads, this kind of human labour can take a very long time. Detecting broken or absent traffic signs more quickly would increase safety and drastically cut down on the amount of manual labour required if this duty were automated. Automatic detection of traffic signs is a vital step in automating this work in place of manual localization and recognition. Traffic sign detection and recognition have been covered by earlier benchmarks.

2. Literature Survey

Through the help of image processing techniques [1] specifically, the use of a CNN ensemble for recognition Shustanov and Yakimov developed a reliable method for road sign detection and recognition. This TensorFlow-powered ensemble method has a remarkable recognition rate, which makes it a tempting choice for a variety of computer vision problems. Using German datasets, their approach produced an amazing accuracy for circular signs That surpassed 99% [3].

Wali et al. presented an alternative technique for sign identification that makes use of the cutting-edge ARK-2121 technology [2] that is installed in automobiles. SVM and HOG algorithms were merged in the recognition step, yielding an average classification accuracy of almost 98% and a 91% detection accuracy [8].

The "German Traffic Sign Recognition Benchmark" [3] dataset analysis and design procedure are described by R. Qian and colleagues [5]. The project's results demonstrated how successfully machine learning algorithms recognized traffic signs. On these datasets, the participants achieved an excellent identification rate of 98.98%, which is equal to human perfection.

3. Design



3.1. System Architecture

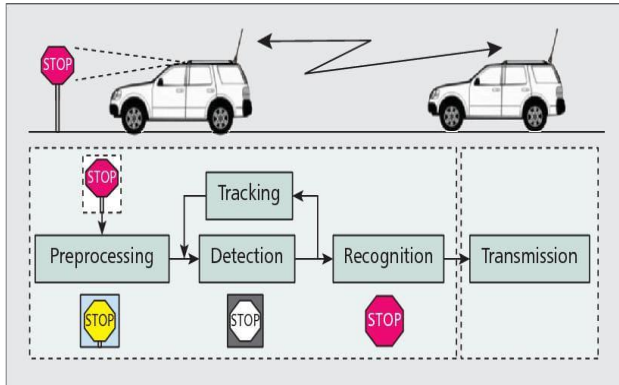


Figure.1 Overview of entire work flow

3.2. Module Description

3.2.1. Segmentation

Segmentation involves dividing a visual image into distinct subsets of pixels known as Image Objects, thereby simplifying the image and facilitating easier analysis [4]. Thresholding, on the other hand, entails converting a grayscale input image into a binary image by applying an optimal threshold.

3.2.2. Data Preprocessing Module

In certain scenarios, it can be beneficial to streamline images by removing redundant details, such as converting colourful images to grayscale [7]. This is because colour isn't always essential for discerning objects within an image; grayscale can often suffice for identifying important features [6]. Colour images inherently contain more data and complexity due to their representation in three channels, whereas grayscale simplifies this by reducing the number of pixels to be processed. For tasks like recognizing traffic signs, grayscale values are often adequate for accurate identification, making the process more efficient [8].

3.2.3. Traffic Sign Recognition Module

Deep Learning, a subset of Machine Learning, encompasses Convolutional Neural Networks (CNNs). These algorithms emulate the information storage mechanisms of the human brain but on a more compact scale. Image classification involves extracting features from images to discern patterns within a dataset [3]. CNNs are particularly adept at this task due to their strong feature extraction capabilities. Within CNNs, filters play a pivotal role. Filters, which come in various shapes and sizes, facilitate localized communication between neurons, capitalizing on the spatial arrangement of image elements. Convolution, the process of element-wise multiplication between two matrices, forms the foundation of CNNs. This

involves sliding a filter over an image matrix to compute the dot product, resulting in an "Activation Map" or "Feature Map". The output layer comprises multiple convolutional layers responsible for feature extraction. Hyperparameter optimization is crucial for optimizing CNN performance[8]. It identifies the hyperparameters that yield optimal performance on a validation set. These parameters, including the learning rate and the number of units in a dense layer, must be set prior to the learning process. Our system prioritizes hyperparameters such as dropout rate, learning rate, kernel size, and optimizer.

3.2.4. Traffic Sign Detection Module

In this module, we've tackled the challenge of identifying and categorizing numerous traffic signs, primarily aimed at streamlining traffic sign inventory management. Given the multitude of categories coupled with subtle differences between them but considerable variations within each category, we've put forth a detection and recognition method employing the Mask RCNN detector. Our system offers an effective deep learning solution capable of learning and distinguishing among a wide array of categories, ensuring swift and accurate detection [8].

4. Results

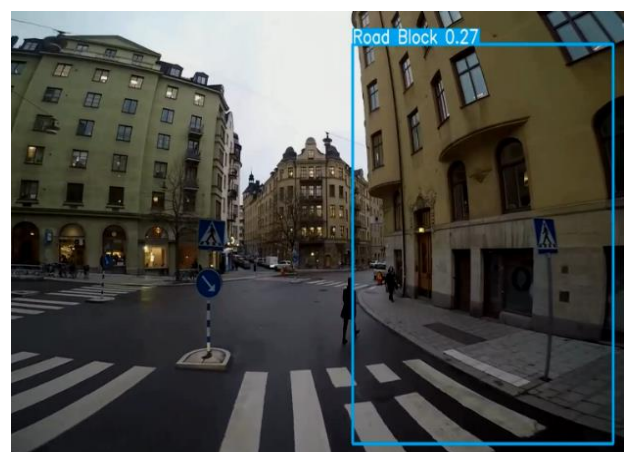
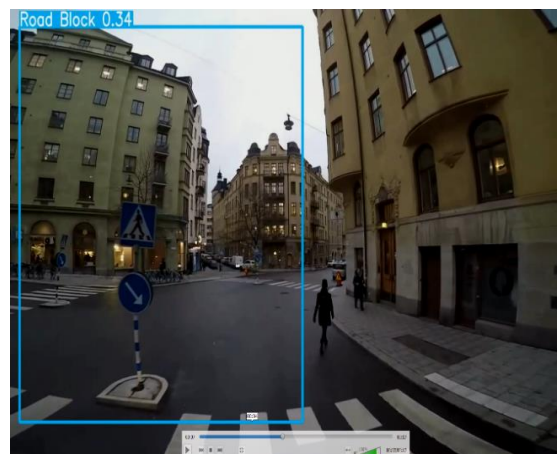


Figure.2 Image Analysis

5. Conclusion and Future scope

In conclusion This paper relies on both colour and shape to detect signs, favouring CNN algorithms for their high efficiency. However, challenges arise when signs have reflections affecting their colour or when signs are incomplete, impacting shape recognition and leading to detection errors. Detection at night poses another challenge; while infrared cameras can accurately detect signs, non-infrared webcams may struggle, increasing the risk of accidents. Incorporating a text-to-speech module in the model alleviates driver burden, allowing them to focus entirely on driving rather than monitoring signs, thus reducing accidents during both day and night. Despite using a low GPU system, achieving 100% efficiency for distant signs remains unattainable. However, the inclusion of a text-to-speech module paves the way for integration into advanced Driver Assistance Systems. This project's hardware requirements are minimal compared to other models, reducing costs and avoiding hardware-related issues. Our system is always looking for signs, which means it will eventually find signs even if there are no signs nearby, the output flows continuously. As a result, there are false detections either unneeded or unnecessary. Raising the threshold value could help with this. to identify signs. It is also possible to enhance and personalize the overall performance using the assistance from additional international datasets

References

- [1]. P. Yakimov Shustanov, "CNN Design for Real-Time Traffic Sign Recognition," Third International Conference "Information Technology and Nanotechnology," ITNT2017, Samara, Russia, April 25–27, 2017.
- [2]. Hussain, A., Wali, S. B., Hannan, M. A., & Samad, S. A. (2015). A Colour Segmentation, Shape Matching, and Support Vector Machine Based Automatic Traffic Sign Detection and Recognition System. 2015, 1–11; doi:10.1155/2015/250461. Mathematical Problems in Engineering
- [3]. R Nivedha , P Saalim , T Naveen , S Noorshavalli , Y Uday Kiran, "Customer Profiling Method for Hi-Tech Trading Apps" ,International Journal of Computational Science and Engineering Research, vol. 1, no. 3, p. 6, July. 2024, doi: <https://doi.org/10.63328/IJCSE-R-V1R1IP2>
- [4]. Park, E., Jang, C., Kim, H., and Kim, H. (2016). Using CNN and MSERs, data biased traffic sign recognition was achieved. ICEIC 2016, Da Nang, Vietnam, pp. 14. International Conference on Electronics, Information, and Communications.10.1109/ELINFOCOM.2016.7562938 can be found at this link.
- [5]. Hatolkar, Y., Patil, S., and Agarwal, P. (2018). A Survey on Road Traffic Sign Recognition System utilizing Convolution Neural Network. Yu, Y., Gu, J., Huang, Z., & Liu, H. (2017). An effective approach utilizing an extreme learning machine for traffic sign recognition. 47(4) IEEE Transactions on Cybernetics, 920-933.
- [6]. Tian, L., Xiao, L., Hu, Y., Li, C. (2012). recognition of salient traffic signs using a sparse representation of visual experience. 2012, Xiamen, China: International Conference on Computer Vision in

Remote Sensing, pp. 273-278. 10.1109/CVRS.2012.6421274 can be found at this link.

- [7]. Yu Z, Xin L, Shi W, and others (2017) A hardware accelerator for traffic sign detection that runs on FPGA. Very Large-scale Integration Systems, IEEE Transactions4:1362–1372.
- [8] Sonderman T, Rosario G, and Zhu X. (2018) Traffic signal recognition using deep transfer learning(C) IEEE International Conference on Integration and Reuse of Information, 2018.
- [8]. S Muni Ratnam , D Ragulamma , P Tejaswani , G Swathi , K Vijayalakshmi, "Identification of Knee Osteoarthritis Disease using Convolutional Neural Networks" , International Journal of Computational Science and Engineering Research, vol. 1, no. 4, p. 73, Nov. 2025, doi: 10.63328/ijcser-v1r4p14

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