International Journal of Recent Engineering Research and Development (IJRERD)
ISSN: 2455-8761
www.ijrerd.com || Volume 09 – Issue 03 || May - Jun 2024 || PP. 190-194

Fast Traffic Sign Detection using Deep Learning for Automotive Application

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Abstract: This research introduces a novel approach for real-time traffic sign detection using the YOLOv5 algorithm within the context of autonomous vehicle control. With the increasing demand for intelligent transportation systems, the rapid and accurate detection of traffic signs is essential for ensuring safe and efficient autonomous navigation. The proposed system leverages the YOLOv5 deep learning architecture for its efficiency in object detection tasks, particularly in scenarios requiring low latency and high accuracy. A curated dataset encompassing diverse traffic signs and signals from various environmental conditions is employed for training and validation purposes. The methodology involves initial pre-processing of camera images to extract pertinent features related to traffic signs, followed by training the YOLOv5 architecture to recognize and classify different types of signs (such as speed limits, stop signs, yield signs, etc.). Evaluation metrics including precision, recall, and F1-score validate the model's performance, ensuring robust detection capabilities. The system is designed for real-time inference, enabling prompt and accurate decision-making for autonomous vehicles. Results demonstrate promising outcomes in terms of both detection accuracy and computational efficiency, affirming its potential to enhance safety and autonomy in dynamic traffic environments.

Keyword: YOLOv5 algorithm, Deep learning, Traffic signals, CNN.

1. Introduction

The evolution of autonomous vehicles has driven the quest for intelligent systems capable of comprehending and responding to complex traffic environments. Central to this pursuit is the swift and accurate detection of traffic signs and signals, which serves as a fundamental pillar for safe and efficient autonomous navigation. Conventional approaches to traffic sign and signal detection have faced challenges in meeting the stringent requirements of real-time processing and precise recognition in diverse environmental conditions. However, the emergence of deep learning techniques, particularly the YOLOv5 algorithm, has sparked immense interest due to its prowess in object detection tasks. This research endeavors to leverage the capabilities of YOLOv5 to develop a high-speed and robust system for traffic sign detection in the context of automotive applications. The primary objective is to design an intelligent system that enables vehicles to rapidly interpret and react to traffic signs and signals, facilitating enhanced safety and efficiency in autonomous driving scenarios. The significance of this work lies in its potential to address critical challenges faced by autonomous vehicles, including the need for quick decision-making in dynamic traffic environments. By harnessing the power of deep learning and real-time processing, the proposed system aims to elevate the performance standards of traffic sign and signal detection, contributing to the broader landscape of intelligent transportation systems. The subsequent sections of this paper will delve into the methodology employed, the dataset utilized for training and validation, the architecture and workings of YOLOv5, the evaluation metrics for assessing detection performance, and the implications of this research on advancing the capabilities of autonomous vehicles in real-world traffic scenarios.In this study embarks on a path toward optimizing traffic sign detection, fostering safer and more efficient autonomous driving experiences through the integration of cutting-edge deep learning techniques within automotive applications.

2. Literature Survey

Lucas Tabelini, et.al:(2020), Deep Traffic Sign Detection and Recognition is described as Deep learning has been successfully applied to several problems related to autonomous driving, often relying on large databases of real target-domain images for proper training. The acquisition of such real-world data is not always possible in the self-driving context, and sometimes their annotation is not feasible. Moreover, in many tasks, there is an intrinsic data imbalance that most learning-based methods struggle to cope with. Particularly, traffic sign detection is a challenging problem in which these three issues are seen altogether. To address these challenges, we propose a novel database generation method that requires only (i) arbitrary natural images, i.e., requires no real image from the target-domain, and (ii) templates of the traffic signs. The method does not aim at overcoming the training with real data, but to be a compatible alternative when the real data is not available. The effortlessly generated database is shown to be effective for the training of a deep detector on traffic signs from multiple countries. On large data sets, training with a fully synthetic data set almost matches the performance of training with a real one. When compared to training with a smaller data set of real images, training with synthetic images increased the accuracy by 12.25%. The proposed method also improves the performance of the detector when target-domain data are available

Muhammad Atif, et.al:(2021),Towards Enhancing Traffic Sign Recognition through Sliding Windows is described as Automatic Traffic Sign Detection and Recognition (TSDR) provides drivers with critical information on traffic signs, and it constitutes an enabling condition for autonomous driving. Misclassifying even a single sign may constitute a severe hazard, which negatively impacts the environment, infrastructures, and human lives. Therefore, a reliable TSDR mechanism is essential to attain a safe circulation of road vehicles. Traffic Sign Recognition (TSR) techniques that use Machine Learning (ML) algorithms have been proposed, but no agreement on a preferred ML algorithm nor perfect classification capabilities were always achieved by any existing solutions. Consequently, our study employs ML-based classifiers to build a TSR system that analyzes a sliding window of frames sampled by sensors on a vehicle. Such TSR processes the most recent frame and past frames sampled by sensors through (i) Long Short-Term Memory (LSTM) networks and (ii) Stacking Meta-Learners, which allow for efficiently combining base-learning classification episodes into a unified and improved meta-level classification. Experimental results by using publicly available datasets show that Stacking Meta-Learners dramatically reduce misclassifications of signs and achieved perfect classification on all three considered datasets. This shows the potential of our novel approach based on sliding windows to be used as an efficient solution for TSR.

Abhishek Balasubramaniam, et.al:(2022), Object Detection in Autonomous Vehicles is described as Object detection is a computer vision task that has become an integral part of many consumer applications today such as surveillance and security systems, mobile text recognition, and diagnosing diseases from MRI/CT scans. Object detection is also one of the critical components to support autonomous driving. Autonomous vehicles rely on the perception of their surroundings to ensure safe and robust driving performance. This perception system uses object detection algorithms to accurately determine objects such as pedestrians, vehicles, traffic signs, and barriers in the vehicle's vicinity. Deep learning-based object detectors play a vital role in finding and localizing these objects in real-time. This article discusses the state-of-the-art in object detectors and open challenges for their integration into autonomous vehicles. We discussed the landscape of various object detectors being considered and deployed in emerging AVs, the challenges involved in using these object detectors in AVs, and how the object detectors can be optimized for lower computational complexity and faster inference during real-time perception. We also presented a multitude of open challenges and opportunities to advance the state-of-the-art with object detection for AVs. As AVs are clearly the transportation industry's future, research to overcome these challenges will be crucial to creating a safe and reliable transportation model.

3. Proposed system

A cutting-edge system for fast traffic sign detection in automotive applications has been developed utilizing the YOLO (You Only Look Once) algorithm, a powerful deep learning technique. This system swiftly identifies traffic signs using a camera feed and processes the information in real-time. Upon detection, it triggers alerts to the driver through an LCD display and a buzzer, ensuring immediate awareness of the traffic conditions. Additionally, this innovative setup is designed to integrate with vehicle control systems, enabling automatic adjustments based on detected traffic signs. For instance, it can regulate vehicle speed or initiate specific actions in response to the recognized signs, thereby enhancing road safety and driving efficiency. Its advantages isYOLO's ability to process images rapidly enables quick detection of traffic signs, ensuring timely responses to changing road conditions and the system's integration with vehicle control systems enables automatic adjustments based on detected signs, potentially enhancing driving efficiency and safety. For instance, it can prompt speed adjustments or suggest lane changes in response to detected signs.

4. System Architecture

Training Phase:

1. **Input Image:**Start with a training image from your dataset.
2. **Preprocessing:**Apply preprocessing steps such as normalization (scaling pixel values to a range, e.g., [0, 1]), data augmentation (e.g., rotation, flipping), and possibly resizing to ensure consistency in input dimensions.

3. **Convolution Layer:**Use a convolutional layer to convolve the input image with learnable filters (kernels). This layer extracts local features from the image through sliding windows of filters.
4. **Rectified Linear Unit (ReLU) Layer:** Apply the ReLU activation function element-wise to introduce non-linearity, allowing the network to learn complex patterns in the data.
5. **Max Pooling Layer:**Perform max pooling to downsample the feature maps obtained from the convolutional layer. Max pooling helps in reducing the spatial dimensions while retaining important features.
6. **Feature Extraction (Result):**After passing through convolution, ReLU, and pooling layers, you obtain a set of feature maps that represent learned features from the input image.
7. **Classification (CNN):**Use the extracted features as input to a fully connected neural network (typically after flattening or global pooling the feature maps). This network performs classification tasks, where it learns to map the extracted features to specific classes (e.g., traffic sign types).

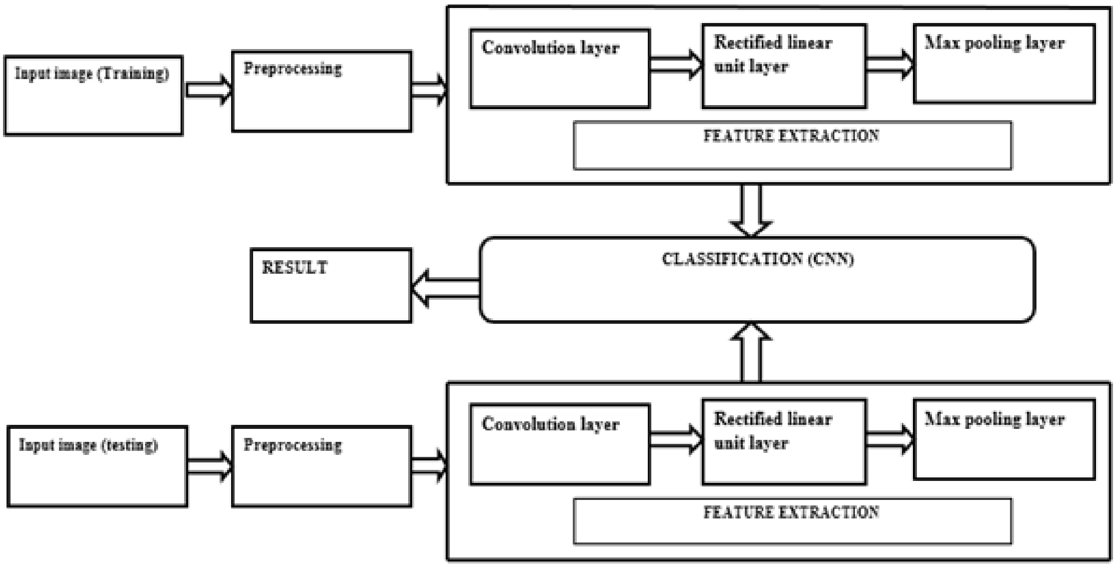

Figure 1: System Architecture

Testing Phase:

1. **Input Image:**Take a new image from the test dataset or real-world scenario.
2. **Preprocessing:** Apply the same preprocessing steps as used during training (e.g., normalization, resizing) to ensure consistency and fairness in comparison.
3. **Convolution Layer:**Feed the preprocessed image through the same convolutional layer used during training. The learned filters will extract relevant features from the new input image.
4. **Rectified Linear Unit (ReLU) Layer:** Apply ReLU activation function to the convolutional layer's output to introduce non-linearity.
5. **Max Pooling Layer:**Perform max pooling to down sample the feature maps obtained from the convolutional layer.
6. **Feature Extraction (Framework):**Obtain feature maps as a result of convolution, ReLU activation, and max pooling layers. These feature maps represent learned features from the test image.
7. **Classification (CNN):**Utilize the feature maps as input to the same or a separately trained fully connected neural network for classification purposes. The network maps the extracted features to predict the class of the traffic sign present in the test image.

5. Implementation

To implement a robust traffic sign detection system using deep learning, we first collect and preprocess a comprehensive dataset of annotated traffic sign images. This dataset is crucial for training our convolutional neural network (CNN), where we employ architectures optimized for object detection such as YOLO or SSD. During training, each input image undergoes standard preprocessing steps including normalization and data augmentation to enhance model generalization. The CNN architecture consists of convolutional layers for feature extraction, rectified linear units (ReLU) for introducing non-linearity, and max-pooling layers for spatial down sampling. Post feature extraction, a classification layer interprets the extracted features to identify specific traffic sign types. Fine-tuning with transfer learning from pre-trained models like those on COCO dataset further enhances performance. For deployment in automotive settings, optimizing the model for real-time processing on hardware such as GPUs is crucial, ensuring the system can handle varying environmental conditions and provide accurate, timely detection of traffic signs.

6. Results

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

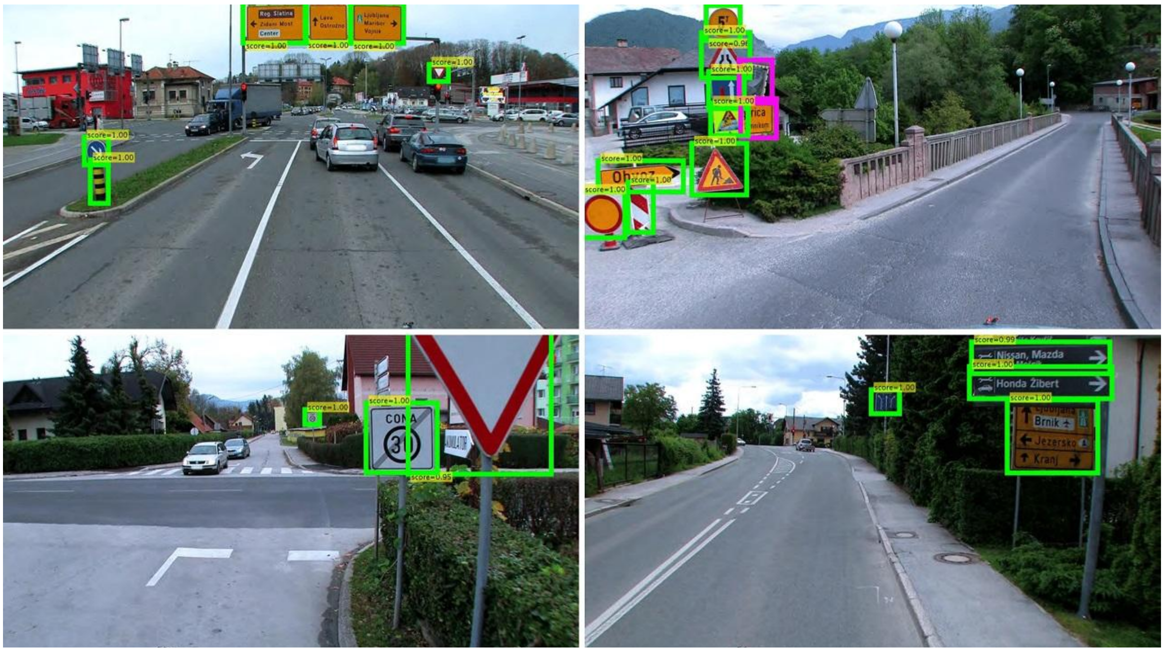

Figure 2: Traffic Sign Detect

Machine learning algorithms are mathematical model mapping methods used to learn or uncover underlying patterns embedded in the data. Machine learning comprises a group of computational algorithms that can perform pattern recognition, classification, and prediction on data by learning from existing data.

7. Conclusion

In this project, smart cars can detect and recognize traffic signs by the proposed YOLO algorithm. This is done by using a trained algorithm, the real-time data is processed to capture from a different environment. The performance of the model examines great when compared to other models. This algorithm has good efficiency so the recognition rate and average time interval are significantly improved. Smart cars can detect and recognize traffic signs by the proposed algorithm. Initially, spatial threshold segmentation is employed by the HSV color space, and traffic signs are effectively detected to support the features. Secondly, the classical machine learning model is extended to improve the recognition rate. Finally, the detection, recognition, and classification of traffic signs are conducted to support the deep learning. In machine learning Model, more layers were used to check for the accuracy is improved. This is done by using a trained algorithm, the real-time data is processed to capture from a different environment. The performance of the model examines great when compared to other models. This algorithm has good efficiency so the recognition rate and average time interval are significantly improved. In the future, the performance and further optimization of the algorithm will be error-free. It will be useful in driving the safety of autonomous vehicles.

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