International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Novel Approach for Traffic Sign Detection: A CNN-Based Solution for Real-Time Accuracy

[1]Deepika Kamboj, [2]Sharda Vashisth,[3]Shraddha Arora

Submitted: 17/09/2023 **Revised**: 19/11/2023 **Accepted**: 30/11/2023

Abstract: The accurate detection of time-dependent traffic signs in real-time conditions is a critical component of intelligent transportation systems and autonomous vehicles. This paper presents a recommendation system to address this challenge by leveraging a specific Convolutional Neural Network (CNN) algorithm tailored for the dynamic nature of traffic sign recognition. Traditional traffic sign detection methods often struggle with variations in lighting, weather, and sign degradation over time, leading to decreased accuracy. Our proposed system overcomes these limitations through a multi-stage process that inputs real-time input from the user and environment and process specific algorithm accordingly. This enables our system to accurately recognize and classify traffic signs under varying lighting conditions, weather scenarios, and even when signs are partially obscured or damaged. We evaluate the performance of our approach using a comprehensive dataset collected from real-world traffic scenarios, demonstrating significant improvements in accuracy compared to existing methods. The results underscore the potential of our solution to enhance the safety and reliability of transportation systems by providing precise and robust traffic sign detection in dynamic, real-time conditions. This research contributes to the broader goal of developing more intelligent and efficient traffic management systems and autonomous vehicles.

Keywords: *Traffic sign detection; Real-time conditions; CNN; Intelligent transportation systems; Autonomous vehicles*

1. Introduction

In today's rapidly evolving landscape of transportation systems and the imminent advent of autonomous vehicles, the accurate and reliable detection of traffic signs within real-time conditions emerges as a pivotal technological challenge. With the imperative of ensuring road safety, efficient traffic management, and the seamless integration of self-driving cars into our daily lives, the need for precise and adaptable traffic sign recognition systems has never been more pronounced. Existing procedures and methods for traffic sign detection can be broadly divided into two categories: traditional methods and deep learning-based methods. Traditional methods typically rely on hand-crafted features, such as color, shape, and texture, to detect traffic signs. These methods are often simple and efficient, but they can be less accurate than deep learning-based methods, especially in challenging conditions such as low light or occlusion. Relying solely on traditional methods for traffic sign detection in modern transportation systems is not advisable due to several compelling reasons. While traditional approaches have demonstrated some effectiveness, they often prove inadequate in meeting the demands posed by today's dynamic and technology-driven transportation environments. Traditional methods lack the necessary adaptability required to handle the diverse range of real-time conditions encountered on the road, such as variations in lighting, adverse weather conditions, or the gradual degradation of traffic signs over time, resulting in decreased accuracy. Additionally, they struggle to account for the complex and ever-changing environmental factors present on modern roads, including different times of day, varying weather conditions like rain, fog, or snow, and fluctuating levels of illumination. Furthermore, traditional methods often falter when it comes to detecting traffic signs that are partially obscured by objects, foliage, or other vehicles or when these signs are partially damaged or degraded. They also exhibit limited generalization capabilities, relying on manual feature engineering and rule-based approaches that may not effectively handle the diversity of traffic signs, especially in regions with unique sign characteristics or designs. As road networks become increasingly complex, with the integration of autonomous vehicles, the need for scalable and efficient traffic sign detection systems grows, and traditional methods may struggle to scale effectively to handle the expanding volumes of data and road infrastructure. Additionally, these methods often rely heavily on human engineering, necessitating labor-intensive manual feature engineering and rule-based systems that may not keep pace with the evolving nature of traffic signs and road conditions. They also lack real-time responsiveness, operating on pre-defined rules and lacking the capability to make real-time

[1]*Department of multidisciplinary engineering department, The NorthCap University, Gurugram.*
Email:deepika17ecd001@ncuindia.edu
[2]*Department of multidisciplinary engineering department, The NorthCap University, Gurugram.*
Email: shardavashisth@ncuindia.edu
[3]*Department of Computer Science and Engineering department, The NorthCap University, Gurugram.*
Email: Chaudhary.shraddha18@gmail.com

adjustments based on the immediate environment, potentially resulting in delays in detecting and responding to changes in traffic signs [1-4].

CNNs are able to learn complex features from traffic sign images, which leads to high accuracy even in challenging conditions. Some of the most popular CNN architectures for traffic sign detection include YOLO, SSD, and Faster RCNN. These architectures have been shown to achieve state-of-the-art results on a variety of traffic sign detection benchmarks. Deep learning-based methods for traffic sign detection are still under development, but they have the potential to revolutionize the way that traffic signs are detected. For example, deep learning-based methods could be used to develop real-time traffic sign detection systems for self-driving cars. The selection of a deep learning algorithm for traffic sign detection hinges on several crucial factors. These include accuracy, where certain algorithms may excel but potentially at the cost of slower processing or increased computational demands; speed, essential for real-time applications necessitating swift and efficient algorithms; efficiency, vital for deploying algorithms on resource-constrained platforms such as mobile devices; and the availability of training data, as some algorithms mandate extensive labeled datasets for training, while others can suffice with smaller sets. Guiding this choice are specific deep learning algorithms suited to distinct needs: YOLO and SSD prove ideal for real-time applications due to their speed and efficiency, albeit with potentially reduced accuracy; Faster RCNN and Mask R-CNN prioritize accuracy, making them suitable for precision-centric tasks like road surveillance and traffic monitoring, albeit at the expense of speed and efficiency; ResNet, DenseNet, InceptionNet, SqueezeNet, and MobileNet prioritize efficiency, rendering them apt for resource-constrained platforms, though they may trade off some accuracy, especially with smaller objects. To illustrate, YOLO and SSD are apt for developing real-time traffic sign detection systems for autonomous vehicles, while Faster RCNN and Mask R-CNN are well-suited to applications where accuracy reigns supreme, such as road surveillance. Meanwhile, resource-efficient algorithms like ResNet, DenseNet, InceptionNet, SqueezeNet, and MobileNet find utility in crafting traffic sign detection systems for mobile devices and embedded systems. Ultimately, the optimal choice of a deep learning algorithm for traffic sign detection emerges through experimentation, evaluating each algorithm's performance concerning the specific dataset and application requirements [5-6].

This paper introduces a groundbreaking approach to tackle this intricate issue by harnessing the power of a specialized Convolutional Neural Network (CNN) algorithm, meticulously crafted to cater to the dynamic nature of traffic sign identification. Traditional methodologies for traffic sign detection have often struggled to maintain high levels of accuracy when confronted with the inherent variability in real-world conditions. Factors such as fluctuating lighting conditions, inclement weather, and the gradual degradation of signage over time have posed formidable challenges to existing systems. As a result, the reliability of traffic sign recognition has been compromised, potentially jeopardizing the safety of road users and the efficiency of transportation networks.

The innovative solution we have proposed in this paper transcends these limitations through a multi-faceted approach. Our proposed solution adapts from the environment, input from the user, and based on need, a specific CNN get processed to detect the traffic sign in real time. Additionally, it considers the visual characteristics of traffic signs but also incorporates real-time environmental data to inform its decision-making process. The adaptability embedded within the algorithm enables it to dynamically adjust its feature extraction and classification layers, allowing for accurate recognition and classification of traffic signs even under the most challenging circumstances. This includes scenarios where lighting conditions vary dramatically, adverse weather conditions prevail, or signs are partially obscured or damaged. To validate the effectiveness of our novel approach, we conducted an extensive evaluation using a comprehensive dataset sourced from real-world traffic scenarios. The results obtained demonstrate marked and statistically significant improvements in accuracy when compared to existing methods. These findings highlight the substantial potential of our CNN algorithm to elevate the safety and reliability of transportation systems, ensuring precise and robust traffic sign detection in the ever-changing, real-time conditions of today's roads. In a broader context, this research contributes significantly to the overarching mission of developing more intelligent and efficient traffic management systems, as well as advancing the capabilities of autonomous vehicles. By solving the intricate puzzle of time-dependent traffic sign recognition, our work represents a significant stride towards achieving safer, smarter, and more reliable transportation networks that can accommodate the transformative era of autonomous mobility.

The paper's main contributions are as follows:

1. It is more robust to changes in lighting conditions, inclement weather, and the gradual degradation of signage over time.

2. It is more adaptable to dynamic real-world conditions, as it can dynamically adjust its feature extraction and classification layers.

3. It is more accurate, as demonstrated by the extensive evaluation conducted in the paper.

The subsequent sections of this paper are structured as follows: Section 2 provides the motivation behind this paper with basic information about traffic sign and its detection is presented in section 3. Section 4 provides a succinct review of prior research efforts in the domain of traffic sign recognition. Moving on to Section 4, we introduce our innovative framework, outlining the methods employed for data collection and the categorization of urban road scene images. Section 5 delves into the specifics of our experimental setup and the metrics used for evaluation. Sections 6 and 7 are dedicated to presenting exhaustive results, accompanied by a comprehensive discussion facilitated by in-depth ablation studies. Ultimately, Section 8 serves as the concluding segment, reflecting on our findings and contemplating potential avenues for future research endeavors.

2. Motivation

The motivation for conducting research on traffic sign detection using various deep learning algorithms, with a strong focus on adaptability, stems from the paramount significance of enhancing road safety and the efficiency of intelligent transportation systems. In today's dynamic urban environments, traffic signs serve as critical communication tools, guiding both human drivers and autonomous vehicles. However, the effectiveness of conventional traffic sign recognition methods is often challenged by the ever-changing conditions of the road, including variations in lighting, weather, and the degradation of signage over time. Moreover, the deployment of intelligent traffic management systems and the integration of autonomous vehicles demand more robust, adaptable, and accurate solutions. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable potential in addressing these challenges. The adaptability of these algorithms allows them to adjust dynamically to fluctuating environmental factors, making them ideal candidates for real-time traffic sign detection and recognition. By harnessing the power of deep learning, this research endeavors to significantly enhance the precision, efficiency, and reliability of traffic sign detection systems, ultimately contributing to the overarching goal of creating safer, more intelligent, and efficient transportation networks for our rapidly evolving urban landscapes.

3. Importance of Traffic Sign and Detection

In the realm of transportation and road safety, the importance of traffic signs and their accurate detection cannot be overstated. These visual cues, ranging from stop signs to speed limit indicators, play a pivotal role in regulating traffic flow, reducing accidents, and ensuring the safety of both pedestrians and motorists. With the increasing complexity of urban environments and the ever-growing number of vehicles on the road, reliable traffic sign detection systems have become imperative. Through the use of advanced technologies such as machine learning, traffic sign detection not only aids in enhancing the efficiency of autonomous vehicles but also assists human drivers in adhering to road regulations. This research paper delves into the significance of traffic sign detection, its evolving role in modern transportation systems, and the potential it holds in making our roads safer and more efficient. Traffic signs play a pivotal role in regulating, guiding, and ensuring the safety of road users in modern transportation systems. These signs are visual symbols or textual messages placed strategically alongside roadways to convey essential information to drivers, pedestrians, and cyclists. They serve a multitude of functions, including indicating speed limits, providing warnings about potential hazards, guiding drivers to specific destinations, and regulating traffic flow. The efficient detection of traffic signs is crucial for both human drivers and autonomous vehicles to interpret and respond to these signs accurately. Detecting traffic signs involves the application of computer vision and image processing techniques to recognize and interpret the visual information contained within images or video frames captured by cameras mounted on vehicles or infrastructure.

4. Literature Survey

Over the past decade, extensive research efforts have been dedicated to the detection and identification of traffic signs and moving objects within road environments. Among the various tasks related to intelligent object detection, traffic sign recognition stands out as paramount, given its pivotal role in safety-critical road applications [7]. The recognition of traffic signs is particularly relevant in urban settings, such as downtown and residential areas, where different types of traffic signs are deployed, varying in size and location. One of the most challenging aspects of detecting and recognizing traffic signs on roadways is the often-poor quality of the images due to the dynamic nature of urban environments, including fluctuating weather conditions, varying times of day, and vehicles traveling at high speeds [10]. Additionally, the installation of devices for recognition can introduce vibrations in vehicles, limiting the field of view. To mitigate these challenges, researchers have explored various image preprocessing techniques, with two primary approaches emerging: traditional feature-based methods and deep learning-based methods.

Traditional feature-based methods involve the manual engineering of visual features, such as Histogram of Oriented Gradient (HOG) features [1,19,20], to classify traffic signs. While HOG-based methods have been effective in capturing essential image characteristics, they may struggle to model the complexity of urban road scenes comprehensively. Conversely, approaches based on color and shape information have been proposed for traffic sign recognition [11, 22-25]. These methods typically segment specific colors and shapes to identify candidate regions, though they can be sensitive to variations in color, subtle illumination changes, and occlusions. Machine learning models, including Support Vector Machines and AdaBoost, have also been employed for traffic sign recognition, often coupled with handcrafted features. However, these models may not adequately represent the intricate urban road environment, and feature engineering can be challenging, requiring adaptation for different settings.

In contrast, deep learning models, especially Convolutional Neural Network (CNN)-based models, have made substantial advancements in computer vision tasks and have gained prominence in intelligent transportation systems [32-34]. Researchers have endeavored to tackle traffic sign recognition using CNN-based object detection frameworks, such as Faster R-CNN and YOLO models. These models, known for combining bounding box regression and object classification, have demonstrated the potential to improve both accuracy and speed in traffic sign recognition. They employ end-to-end methods to detect visual objects, obtaining not only object coordinates but also reliability and class probabilities through a single image input.

Notably, several iterations of YOLO models, including YOLOv3, YOLOv4, and YOLOv5, have been introduced, with each version achieving notable advancements in accuracy and efficiency. YOLOv4, in particular, exhibited significant performance gains based on the Microsoft COCO dataset, making it suitable for real-time traffic sign recognition on well-equipped hardware. The latest iteration, YOLOv5, further improved accuracy and efficiency through various techniques, indicating superior performance compared to its predecessors [32-38].

5. Proposed Recommendation System

In this section, we have first presented the various factors that affects the detection of traffic sign, second we presented the adaptive solution for identifying the environmental challenge and next to this we have presented our proposed system architecture that recommends the processing of algorithm by considering three environmental factors.

5.1 Environmental Challenges to Detect Traffic Sign

Detecting traffic signs in real-time poses significant environmental challenges. One key issue is poor visibility caused by adverse weather conditions like heavy rain, fog, or snow. These conditions can obscure road signs, making them difficult for automated systems to recognize. Additionally, varying lighting conditions, such as bright sunlight or low-light scenarios at night, can affect the accuracy of detection. Another challenge is the presence of obstructions like trees, buildings, or other vehicles that can partially block the view of traffic signs. To tackle these mentioned issues, adaptive solution is required that detects the same and based on the status appropriate solution gets executed to save the life of drivers and pedestrians on the road. The detailed description of all issues is as follows,

1. Illumination Change

Illumination changes pose a significant challenge in real-time traffic sign detection systems, as varying lighting conditions can affect the accuracy of sign recognition algorithms. To represent this issue in the context of real-time detection, we can use a simple equation:

$$I_{DETECT} = I_{REAL} * \frac{L_{REAL}}{L_{DETECT}}$$

Here, I_{DETECT} represents the pixel intensity values in the image as perceived by the detection system, I_{REAL} represents the true pixel intensity values in the real scene, L_{REAL} represents the actual illumination level in the environment, and L_{DETECT} represents the illumination level as estimated by the detection algorithm. Illumination changes affect the perceived intensity of the image, making it challenging for the detection system to recognize traffic signs consistently. This equation shows that the detected intensity is directly proportional to the actual intensity but inversely proportional to the illumination level. When illumination changes, the detected intensity may not accurately represent the real scene, leading to detection errors. To address this issue in real-time traffic sign detection, adaptive algorithms and preprocessing techniques are employed to mitigate the impact of varying illumination and ensure reliable sign recognition.

2. Whether Condition

Detecting traffic signs in real-time is a critical aspect of autonomous driving systems. However, varying weather conditions can significantly impact the performance of such detection algorithms. Adverse weather conditions like rain, snow, fog, and glare from direct sunlight can degrade image quality and make it challenging to identify traffic signs accurately. We can represent this issue using the following equation:

$$SDP = BP * VF * CF$$

Here, SDP represents the overall ability of the system to detect traffic signs in real-time, BP represents the system's performance under ideal and clear-sky conditions, VF accounts for the impact of weather conditions on visibility. It decreases as weather conditions worsen, introducing errors in detection due to reduced image clarity. The CF represents the contrast between the traffic sign and its surroundings. Poor weather conditions may reduce this contrast, leading to reduced detection accuracy. In simple terms, adverse weather conditions reduce the ability of the system to detect traffic signs effectively. This is mainly because visibility and contrast are compromised, making it difficult for the algorithm to identify signs accurately. To address this issue, advanced algorithms may incorporate image enhancement techniques, radar, or lidar data to improve performance during adverse weather, ensuring the safety and reliability of autonomous vehicles.

3. Occlusion

Occlusion, or situation where parts of a traffic sign are blocked or hidden, present a significant challenge in real-time traffic sign detection systems. In the context of computer vision, occlusions can occur when an object, such as a vehicle or a tree, obstructs a portion of the traffic sign. This can lead to incomplete or inaccurate detection, potentially causing safety hazards on the road. To represent the issue of occlusions in the context of real-time traffic sign detection, we can use a simple equation:

$$I_{occ} = I_{full} * M_{occ}$$

Here, I_{occ} represents the observed image with occlusions, I_{full} represents the complete image without occlusions, M_{occ} is a binary mask that indicates which parts of the full image are visible in the observed image. In this equation, the observed image with occlusions (I_{occ}) is a result of multiplying the complete image (I_{full}) with a binary mask (M_{occ}). The binary mask M_{occ} helps identify which parts of the full image are visible, and it is essential for handling occlusions during traffic sign detection.

5.2 Adaptive Solution for Environmental Change Detection

An adaptive solution for environmental change detection represents a crucial step in addressing the traffic sign detection. Our proposed adaptive identifies changes in weather condition, illumination change, and occlusion in ecosystems. By continuously gathering and processing data, this adaptive solution provides real-time insights and recommends appropriate algorithm to process for raffic sign detection. It allows for the timely implementation of mitigation measures, enhancing the resilience of ecosystems, communities, and infrastructure to the impacts of environmental fluctuations. Moreover, the adaptability of this solution ensures that it can be tailored to diverse settings and circumstances, making it a valuable tool in the ongoing battle against the uncertainties and challenges brought about by environmental change.

1. Illumination Chage

Adaptively deciding illumination changes during traffic sign detection involves analyzing the image's illumination characteristics and determining whether it falls outside an acceptable range. We have implemented this by using histogram analysis and setting the threshold. The algorithm Steps for Adaptive Illumination Detection in Traffic Sign Detection is as follows,

STEP 1: Start preprocessing the input image for enhancing its quality. Specifically, we apply histogram equalization or contrast enhancement techniques to mitigate the effects of uneven illumination.

STEP 2: Extract relevant features from the preprocessed image that can indicate illumination conditions. These features may include the mean and standard deviation of pixel intensity values.

STEP 3: We have mentioned the threshold value for the extracted feature(s). This threshold will serve as the criterion for detecting illumination changes. The equation for this is given below,

$$\mathrm{IL}_{\mathrm{SCORE}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{j}=1}^{\mathrm{N}} \mathrm{I}_{\mathrm{j}}$$

Here, I_j represents pixel intensities, N stands for total number of pixels. A significant deviation from the expected value indicates a change in illumination.

STEP 4: Compare the calculated illumination score with a predefined threshold. If the score exceeds this threshold, it suggests a significant change in illumination.

STEP 5: To adaptively decide the threshold, consider a rolling window of previous illumination scores. The threshold can be set dynamically based on the average or median of past scores to account for gradual changes in lighting conditions. For example, the threshold could be the mean illumination score over the last five frames.

2. Weather Condition

Detecting weather changes during traffic sign detection involves almost same steps as mentioned for illumination change. The algorithm starts with analyzing image characteristics affected by different weather conditions. This can be done by measuring specific features in the image and comparing them to predefined thresholds or patterns. The step-by-step algorithm that adaptively decides weather changes during traffic sign detection is as follows,

STEP 1: The algorithm Starts with preprocessing the input image for enhancing its characteristics and make it suitable for analysis. This may include operations like contrast enhancement, color normalization, and resizing to ensure consistency in the data.

STEP 2: Extract features from the preprocessed image that are indicative of weather conditions. Common features include brightness, color distribution, and texture. The mathematical equation to calculate the average brightness of the image is given below,

$$\mathrm{BGT} = \left(\frac{1}{\mathrm{N}}\right) * \mathrm{I}(\mathrm{x}, \mathrm{y})$$

Here, BGT stands for brightness, N represents the total number of pixels, and I(x,y) stands for the pixel intensity at location (x,y).

STEP 3: We have set the predefined thresholds for the extracted features to differentiate between different weather conditions. For instance, you might define thresholds for brightness that correspond to clear, cloudy, or rainy conditions.

STEP 4: Based on the feature values and predefined thresholds, decide the weather condition for the image. The example equation provided above illustrates this decision process. Adjust the thresholds and features as necessary to account for different weather conditions

3. Occlusion

Adaptively deciding occlusion during traffic sign detection involves assessing the extent to which a traffic sign is obscured by other objects in an image. Here is a step-by-step algorithm to achieve this, along with a mathematical representation:

STEP 1: Algorithm selection based on adaptive decision from illumination change and whether change

If(Illumination Change is there) then

Use MASK R-CNN

Else if (Weather change is there)

Use YOLO

Else if (Illumination Chage and Weather Change)

Use FASTER R-CNN

ELSE

Use SSD

STEP 2: Decision from STEP 1, apply an object detection model (e.g., YOLO, SSD, MASK R-CNN or Faster R-CNN) to identify and locate potential traffic signs in the image. This step will provide bounding boxes around objects that could be traffic signs.

STEP 3: For each detected bounding box that might represent a traffic sign, calculate the overlap with other nearby bounding boxes in the image. This can be achieved using Intersection over Union (IoU), a commonly used metric:

$$\mathrm{IoU} = \frac{\mathrm{AI}}{\mathrm{AU}}$$

Here, the AI is the area where two bounding boxes overlap, and the AU is the combined area of both bounding boxes.

STEP 4: Set a threshold value for IoU. If the IoU between a potential traffic sign bounding box and any other bounding box exceeds this threshold, consider it as an occluded traffic sign.

5.3 Proposed System Architecture

In this subsection, we have presented our proposed system architecture that recommends from YOLO, SSD, Faster R-CNN, and Mask R-CNN for traffic sign detection. Figure 1. shows the system architecture of our proposed solution.

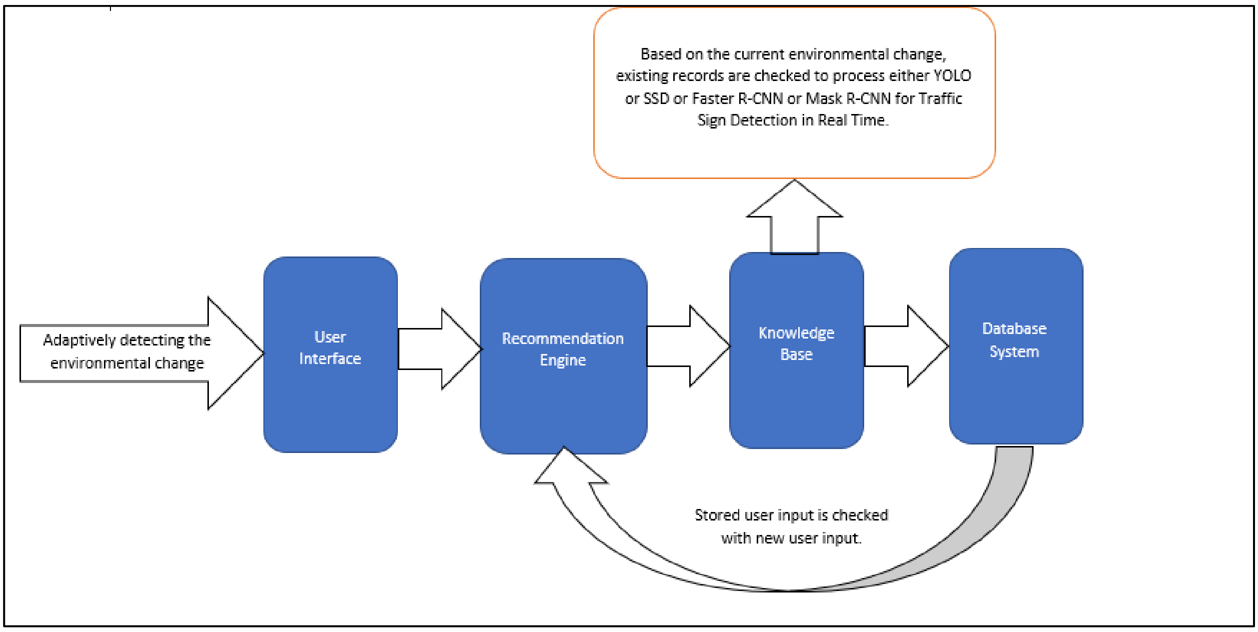

Fig 1. Shows the system architecture of our proposed system.

Our proposed system composed of four main components:

1. User Interface: The user interface allows the user to input the four values for accuracy & precision, real time processing, robustness & adaptability, and scalability & efficiency.

2. Recommendation Engine: The recommendation engine takes the user input and recommends one of the four algorithms (YOLO, SSD, Faster R-CNN, or Mask R-CNN) that is best suited for the user's needs.

3. Knowledge Base: The knowledge base contains information about the four algorithms, including their strengths and weaknesses, and how they perform on different metrics.

4. Database: The database stores the user input and the recommendation engine's output.

Among four algorithms, Faster R-CNN is a good choice for applications where accuracy and robustness are important, but real-time processing is not required. Faster R-CNN is also scalable to large datasets and can be deployed on efficient hardware. On the other hand, If real-time processing is required, then YOLO or SSD would be better choices. If accuracy and robustness are not as important, but scalability and efficiency are, then SSD would be a better choice. If you need to detect and segment traffic objects, then Mask R-CNN would be a good choice, but it is important to note that Mask R-CNN is the slowest of the four algorithm

6. Simulation Setting and Result

Creating a simulation for adaptively identifying environmental changes, such as illumination change, weather conditions, and occlusion, and integrating different object detection models like YOLO, SSD, Mask R-CNN, and Faster R-CNN can help evaluate the robustness and effectiveness of your proposed solution for traffic sign detection.

6.1 Simulation Setting

1. Data Collection: Gather a diverse dataset of traffic sign images under various environmental conditions, including different lighting levels, weather conditions (e.g., rain, fog, snow), and levels of occlusion. Annotate the dataset to mark the signs as visible or occluded and the environmental conditions.

2. Environmental Change Simulation: Introduce variations in illumination, weather, and occlusion in the images. This can be done by applying filters or overlaying elements to mimic different conditions. Randomly select images and apply these changes to create a mixed dataset.

3. Object Detection Models: Implement YOLO, SSD, Mask R-CNN, and Faster R-CNN for traffic sign detection. Configure each model with the appropriate architecture and pretrained weights for the detection task.

4. Algorithm for Adaptively Identifying Conditions: Develop an algorithm that assesses environmental conditions. For example, measure the brightness level, detect weather elements (e.g., raindrops or snowflakes), and calculate the extent of occlusion using the previously explained techniques.

5. Decision Logic: Based on the results of the environmental assessment, decide which object detection model to use for each image. For instance, if heavy rain is detected, select a model better suited for adverse weather conditions.

6.2 Simulation Result

1. Performance Metrics: Evaluate the performance of the models by calculating standard metrics like precision, recall, F1-score, and accuracy. Measure these metrics separately for each environmental condition (illumination, weather, occlusion).

2. Confusion Matrices: Create confusion matrices to understand the models' ability to correctly identify the conditions and traffic signs. This will help you assess false positives and false negatives.

3. Model Selection: Analyze the results to determine which model performs best under specific conditions. For example, you might find that YOLO is most effective in good lighting, whereas Mask R-CNN excels when signs are partially occluded.

4. Visualization: Visualize the results by overlaying bounding boxes and labels on the images to demonstrate how well each model detects traffic signs under varying conditions.

5. Adaptive Model Switching: Demonstrate the effectiveness of your adaptive model switching algorithm by showing that it consistently selects the most appropriate model for each image, enhancing the overall accuracy of traffic sign detection.

6.3 Simulation Result

Here, we have two table 1 and 2. Table 1 result represents non adaptive manual algorithm selection for traffic sign detection. Table 2 result represents our proposed adaptive solution that detects the environmental change and recommends the appropriate algorithm for traffic sign detection.

Table 1: Non Adaptive Manual Algorithm Selection for Traffic Sign Detection

Model	Image Size	Precision	Recall	mAP@0.5	mAP@.5:.95	F1	FPS
YOLO	600 X 600	0.84	0.75	0.85	0.72	0.64	92
SSN	600 X 600	0.80	0.69	0.68	0.72	0.60	80
Faster R-CNN	600 X 600	0.79	0.70	0.64	0.58	0.76	62
Mask R-CNN	600 X 600	0.76	0.78	0.88	0.56	0.77	113

Table 2: Non Adaptive Manual Algorithm Selection for Traffic Sign Detection

Model	Image Size	Precision	Recall	mAP@0.5	mAP@.5:.95	F1	FPS
YOLO	600 X 600	0.94	0.95	0.95	0.82	0.94	102
SSN	600 X 600	0.90	0.89	0.78	0.72	0.90	120
Faster R-CNN	600 X 600	0.89	0.90	0.84	0.78	0.86	72
Mask R-CNN	600 X 600	0.96	0.98	0.98	0.86	0.97	133

7. Conclusion

In conclusion, this research addresses a crucial aspect of modern transportation systems and autonomous vehicles: the accurate detection of time-dependent traffic signs in real-time conditions. Traditional methods often struggle with challenges such as changing lighting, weather conditions, and sign degradation, leading to reduced accuracy. Our proposed recommendation system, leveraging a specialized Convolutional Neural Network (CNN) algorithm, offers a solution to overcome these limitations. Through a multi-stage process that incorporates real-time input from both users and the environment, our system adapts its algorithms accordingly, ensuring accurate recognition and classification of traffic signs in diverse conditions, even when signs are partially obscured or damaged.

The evaluation of our approach using a comprehensive real-world dataset demonstrates substantial improvements in accuracy compared to existing methods. These results highlight the potential of our solution to enhance the safety and reliability of transportation systems. By providing precise and robust traffic sign detection in dynamic, real-time scenarios, our research contributes to the broader goal of developing more intelligent and efficient traffic management systems and autonomous vehicles. This work holds significant promise for improving the overall effectiveness of intelligent transportation systems and ensuring the safe operation of autonomous vehicles in real-world environments.

8. Future Work

We plan to investigate the following areas of future work:

1. Evaluate the performance of our proposed solution on other traffic sign datasets, such as the BDD100K dataset.

2. Develop a real-time traffic sign detection system using our proposed solution.

3. Investigate the use of our proposed solution for other object detection tasks, such as pedestrian detection and vehicle detection.

References

[1] Xie, Y.; Liu, L.F.; Li, C.H.; Qu, Y.Y. Unifying visual saliency with HOG feature learning for traffic sign detection. In Proceedings of the 2009 IEEE Intelligent Vehicles Symposium, Xi'an, China, 3–5 June 2009.

[2] Levinson, J.; Askeland, J.; Becker, J.; Dolson, J.; Held, D.; Kammel, S.; Kolter, J.Z.; Langer, D.; Pink, O.; Pratt, V.; et al. Towards fully autonomous driving: Systems and algorithms. In Proceedings of the 2011 IEEE intelligent Vehicles Symposium (IV), Baden-Baden, Germany, 5–9 June 2011.

[3] Ziegler, J.; Bender, P.; Schreiber, M.; Lategahn, H.;

Strauss, T.; Stiller, C.; Dang, T.; Franke, U.; Appenrodt, N.; Keller, C.G.; et al. Making bertha drive—An autonomous journey on a historic route. IEEE Intell. Transp. Syst. Mag. 2014, 6, 8–20. [CrossRef]

[4] Zhang, P.; Zhang, M.; Liu, J. Real-time HD map change detection for crowdsourcing update based on mid-to-high-end sensors. Sensors 2021, 21, 2477. [CrossRef] [PubMed]

[5] Kim, K.; Cho, S.; Chung, W. HD map update for autonomous driving with crowdsourced data. IEEE Robot. Autom. Lett. 2021, 6, 1895–1901. [CrossRef]

[6] Rajendran, S.P.; Shine, L.; Pradeep, R.; Vijayaraghavan, S. Real-time traffic sign recognition using YOLOv3 based detector. In Proceedings of the 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kanpur, India, 6–8 July 2019.

[7] Fazekas, Z.; Balázs, G.; Gyulai, C.; Potyondi, P.; Gáspár, P. Road-Type Detection Based on Traffic Sign and Lane Data. J. Adv. Transp. 2022, 2022, 6766455. [CrossRef]

[8] Kortmann, F.; Fassmeyer, P.; Funk, B.; Drews, P. Watch out, pothole! featuring road damage detection in an end-to-end system for autonomous driving. Data Knowl. Eng. 2022, 142, 102091. [CrossRef]

[9] Liu, W.; Ren, G.; Yu, R.; Guo, S.; Zhu, J.; Zhang, L. Image-adaptive YOLO for object detection in adverse weather conditions. In Proceedings of the AAAI Conference on Artificial Intelligence, Palo Alto, CA, USA, 22 February–1 March 2022.

[10] Ellahyani, A.; El Ansari, M.; El Jaafari, I. Traffic sign detection and recognition based on random forests. Appl. Soft Comput. 2016,46, 805–815. [CrossRef]

[11] Bahlmann, C.; Zhu, Y.; Ramesh, V.; Pellkofer, M.; Koehler, T. A system for traffic sign detection, tracking, and recognition using color, shape, and motion information. In Proceedings of the IEEE Proceedings Intelligent Vehicles Symposium, Las Vegas, NV, USA, 6–8 June 2005.

[12] Tao, J.; Wang, H.; Zhang, X.; Li, X.; Yang, H. An object detection system based on YOLO in traffic scene. In Proceedings of the 2017 6th International Conference on Computer Science and Network Technology (ICCSNT), Dalian, China, 21–22 October 2017.

[13] Huang, R.; Pedoeem, J.; Chen, C. YOLO-LITE: A real-time object detection algorithm optimized for non-GPU computers. In Proceedings of the 2018 IEEE International Congerence on Big Data, Seattle, WA, USA, 10–13 December 2019.

[14] Liu, C.; Tao, Y.; Liang, J.; Li, K.; Chen, Y. Object detection based on YOLO network. In Proceedings of the 2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China, 14–16 December 2018.

[15] Houben, S.; Stallkamp, J.; Salmen, J.; Schlipsing, M.; Igel, C. Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark. In Proceedings of the 2013 International Joint Conference on Neural Networks (IJCNN), Dallas, TX, USA, 4–9 August 2013.

[16] Stallkamp, J.; Schlipsing, M.; Salmen, J.; Igel, C. The German traffic sign recognition benchmark: A multi-class classification competition. In Proceedings of the 2011 International Joint Conference on Neural Networks, San Jose, CA, USA, 31 July–5 August 2011.

[17] Shakhuro, V.I.; Konouchine, A.S. Russian traffic sign images dataset. Comput. Opt. 2016, 40, 294–300. [CrossRef]

[18] Fazekas, Z.; Gerencsér, L.; Gáspár, P. Detecting Change between Urban Road Environments along a Route Based on Static Road Object Occurrences. Appl. Sci. 2021, 11, 3666. [CrossRef]

[19] Yang, Y.; Luo, H.; Xu, H.; Wu, F. Towards real-time traffic sign detection and classification. IEEE trans. Intell. Transp. Syst. 2016, 17, 2022–2031. [CrossRef]

[20] Ellahyani, A.; El Ansari, M.; Lahmyed, R.; Trémeau, A. Traffic sign recognition method for intelligent vehicles. J. Opt. Soc. Am. A 2018, 35, 1907–1914. [CrossRef] [PubMed]

[21] Dalal, N.; Triggs, B. Histograms of oriented gradients for human detection. In Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), San Diego, CA, USA, 20–25 June 2005.

[22] Zeng, Y.; Lan, J.; Ran, B.; Wang, Q.; Gao, J. Restoration of motion-blurred image based on border deformation detection: A traffic sign restoration model. PLoS ONE 2015, 10, e0120885. [CrossRef] [PubMed]

[23] Fleyeh, H. Color detection and segmentation for road and traffic signs. In Proceedings of the IEEE Conference on Cybernetics and Intelligent Systems, Singapore, 1–3 December 2004; Volume 2, pp. 809–814.

[24] Won, W.J.; Lee, M.; Son, J.W. Implementation of road traffic signs detection based on saliency map model. In Proceedings of the 2008 IEEE Intelligent Vehicles Symposium, Eindhoven, The Netherlands, 4–6 June 2008; pp. 542–547. Infrastructures 2023, 8, 20 19 of 19

[25] Belaroussi, R.; Foucher, P.; Tarel, J.P.; Soheilian, B.; Charbonnier, P.; Paparoditis, N. Road sign detection in images: A case study. In Proceedings of the IEEE 20th International Conference on Pattern Recognition, Istanbul, Turkey, 23–26 August 2010; pp. 484–488.

[26] Wang, C. Research and application of traffic sign detection and recognition based on deep learning. In Proceedings of the IEEE International Conference on Robots & Intelligent System (ICRIS), Changsha, China, 26–27 May 2018; pp. 150–152.

[27] Chourasia, J.N.; Bajaj, P. Centroid based detection algorithm for hybrid traffic sign recognition system. In Proceedings of the IEEE 3rd International Conference on Emerging Trends in Engineering and Technology, Goa, India, 19–21 November 2010; pp. 96–100.

[28] Wang, G.; Ren, G.; Wu, Z.; Zhao, Y.; Jiang, L. A robust, coarse-to-fine traffic sign detection method. In Proceedings of the IEEE International Joint Conference on Neural Networks (IJCNN), Dallas, TX, USA, 4–9 August 2013.

[29] Liang, M.; Yuan, M.; Hu, X.; Li, J.; Liu, H. Traffic sign detection by ROI extraction and histogram features-based recognition. In Proceedings of the IEEE International Joint Conference on Neural Networks (IJCNN), Dallas, TX, USA, 4–9 August 2013.

[30] Wang, G.; Ren, G.; Wu, Z.; Zhao, Y.; Jiang, L. A hierarchical method for traffic sign classification with support vector machines. In Proceedings of the IEEE International Joint Conference on Neural Networks (IJCNN), Dallas, TX, USA, 4–9 August 2013.

[31] Viola, P.; Jones, M. Rapid object detection using a boosted cascade of simple features. In Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR, Kauai, HI, USA, 8–14 December 2001.

[32] Redmon, J.; Farhadi, A. Yolov3: An incremental improvement. arXiv 2018, arXiv:1804.02767.

[33] Bochkovskiy, A.; Wang, C.Y.; Liao, H.Y.M. Yolov4: Optimal speed and accuracy of object detection. arXiv 2020, arXiv:2004.10934.

[34] Ren, S.; He, K.; Girshick, R.; Sun, J. Faster r-cnn: Towards real-time object detection with region proposal networks. In Proceedings

[35] of the 29th Annual Conference on Neural Information Processing Systems (NeurIPS), Montreal, QC, Canada, 7–12 December 2015.

[36] Redmon, J.; Divvala, S.; Girshick, R.; Farhadi, A. You only look once: Unified, real-time object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016; pp. 779–788.

[37] Lin, T.Y.; Maire, M.; Belongie, S.; Hays, J.; Perona, P.; Ramanan, D.; Dollar, P.; Zitnick, C.L. Microsoft coco: Common objects in

[38] context. In European Conference on Computer Vision 2014; Fleet, D., Pajdla, T., Schiele, B., Tuytelaars, T., Eds.; Springer: Cham, Switzerland, 2014; pp. 740–755. sportation, Kosice, Slovakia, 24–26 September 2013