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Traffic Sign Based Recognition in Regulations and Foggy Weather using RCNN

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Abstract: *This study presents a robust traffic sign recognition system designed to operate effectively under challenging conditions, particularly in foggy weather. Utilizing a Region-based Convolutional Neural Network (RCNN), the proposed model enhances detection accuracy by focusing on relevant image regions while reducing computational overhead. Advanced image preprocessing techniques, including contrast enhancement and noise reduction, improve visibility in low-contrast environments. Additionally, data augmentation with fog simulation ensures the model generalizes well across varying weather conditions. Experimental results demonstrate superior detection rates and reduced false positives compared to conventional methods. This research contributes to safer autonomous driving and advanced driver-assistance systems by ensuring reliable traffic sign recognition in adverse conditions.*

Keywords: Traffic sign recognition, RCNN, foggy weather, image preprocessing, autonomous driving

I. INTRODUCTION

1.1 Overview

Traffic sign recognition is a critical component of modern autonomous driving systems and advanced driver-assistance systems (ADAS). Accurate detection and classification of traffic signs enable vehicles to interpret and respond to road regulations, improving road safety and traffic compliance. However, real-world conditions pose significant challenges, particularly in adverse weather scenarios such as fog, rain, and low-light environments. Traditional traffic sign recognition systems often rely on basic image processing techniques, which struggle with reduced contrast, occlusion, and image distortions. These limitations can lead to misclassification or failure to detect crucial traffic signs, increasing the risk of accidents and road rule violations. Therefore, there is a growing need for robust and intelligent models that can effectively recognize traffic signs in diverse environmental conditions.

To address these challenges, this study proposes a Traffic Sign Recognition System Using Region-based Convolutional Neural Networks (RCNN), specifically designed to enhance accuracy under foggy conditions. RCNN is well-suited for this task as it integrates object localization with classification, enabling precise detection of traffic signs even in visually degraded environments. Unlike conventional deep learning models that process entire images, RCNN identifies and classifies only relevant regions, reducing computational complexity and improving efficiency. This approach significantly enhances the model's ability to recognize traffic signs despite varying visibility levels caused by fog, snow, or dust accumulation on signboards.

A crucial aspect of this research is the incorporation of advanced image preprocessing techniques to mitigate the effects of poor visibility. Methods such as contrast enhancement, noise reduction, histogram equalization, and fog simulation are applied to the dataset to improve image clarity. These preprocessing techniques help the model extract meaningful features from degraded images, enhancing recognition accuracy in real-world conditions. Additionally, data augmentation is performed by generating synthetic variations of traffic signs, including adjustments to brightness, contrast, and saturation levels. This ensures that the model is exposed to a diverse set of training data, allowing it to generalize better across different fog intensities and lighting conditions.

The proposed system follows a structured approach, starting with image acquisition from vehicle-mounted cameras or simulated environments to capture various traffic scenarios. The Region Proposal Network (RPN) within RCNN

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identifies candidate regions that are likely to contain traffic signs, thereby reducing unnecessary computations. Extracted regions are processed using a Convolutional Neural Network (CNN), which analyzes textures, shapes, and edges to classify the detected signs accurately. Pre-trained models such as ResNet or VGG are incorporated using transfer learning techniques to enhance the system's accuracy, even with a limited dataset. The integration of these advanced machine learning techniques ensures that the system performs well under diverse environmental conditions, making it highly reliable for real-time applications.

Extensive experiments and performance evaluations have been conducted to validate the effectiveness of the proposed system. The results indicate a significant improvement in detection accuracy and a reduction in false positives compared to conventional methods. The system demonstrates robust performance in foggy weather, where traditional models typically fail due to poor contrast and image distortions. Additionally, the use of voice-based alerts ensures that drivers receive real-time notifications without being visually distracted, further enhancing road safety.

Overall, this research aims to contribute to the advancement of autonomous driving technologies and ADAS by improving the reliability of traffic sign recognition systems. By leveraging RCNN along with advanced preprocessing and data augmentation techniques, the proposed model ensures high detection accuracy even in challenging weather conditions. This study not only enhances vehicle automation and driver assistance capabilities but also lays the foundation for future research in vision-based road sign recognition under adverse environmental conditions.

1.2 Motivation

Traffic sign recognition plays a crucial role in ensuring road safety and regulatory compliance, particularly in autonomous driving and advanced driver-assistance systems (ADAS). However, adverse weather conditions like fog significantly impact visibility, making it challenging for conventional recognition systems to accurately detect and classify traffic signs. Misinterpretation or missed detection of traffic signs can lead to serious accidents and violations. This research is motivated by the need for a robust, intelligent, and adaptive system that can overcome these limitations by leveraging Region-based Convolutional Neural Networks (RCNN). By integrating advanced image preprocessing techniques, data augmentation, and deep learning-based recognition, this study aims to develop a reliable traffic sign recognition model capable of operating effectively in foggy weather conditions, ultimately enhancing road safety and aiding the transition to fully autonomous driving systems.

1.3 Problem Definition and Objectives

Traffic signs are vital for maintaining road safety and regulatory compliance, but adverse weather conditions like fog can obscure visibility, making it difficult for both human drivers and autonomous systems to recognize them accurately. Conventional traffic sign recognition methods struggle with low contrast, occlusion, and varying lighting conditions, leading to misclassification or missed detections. To address these challenges, this research proposes a Traffic Sign-Based Recognition System Using RCNN, which enhances detection accuracy in foggy weather through advanced image preprocessing, region-based object detection, and deep learning techniques. By leveraging a robust dataset and improving feature extraction, the system aims to provide real-time, high-accuracy traffic sign recognition, ensuring safer and more reliable navigation in low-visibility conditions.

Objectives

• To study the impact of foggy weather on traffic sign recognition accuracy.
• To study and implement RCNN for improved object detection in challenging environments.
• To study and analyze various image preprocessing techniques for enhanced visibility.
• To study and develop a robust dataset with diverse weather conditions for model training.
• To study the integration of real-time traffic sign recognition with driver alert systems.

1.4. Project Scope and Limitations

This project focuses on developing a Traffic Sign-Based Recognition System Using RCNN to enhance the detection and classification of traffic signs in foggy weather conditions. The system integrates image preprocessing techniques, deep learning models, and region-based object detection to improve accuracy and reliability. It is designed for

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application in autonomous vehicles, advanced driver-assistance systems (ADAS), and smart traffic monitoring systems, ensuring safer navigation in low-visibility conditions. The model is trained on a diverse dataset of traffic signs captured in both clear and foggy environments, enabling it to generalize well across different scenarios. By leveraging transfer learning and data augmentation, the system aims to minimize false positives and improve real-time detection efficiency.

Limitations

- The model's performance may degrade in extremely dense fog or poor lighting.
- Requires high computational power for real-time processing.
- May struggle with recognizing damaged or occluded traffic signs.
- Dependency on high-quality training data for effective recognition.
- Limited effectiveness in dynamically changing weather conditions.

II. LITERATURE REVIEW

1. Traffic Sign Recognition Using Convolutional Neural Networks

Authors: Stallkamp et al. (2012)

Summary: This study introduced a large-scale dataset, the German Traffic Sign Recognition Benchmark (GTSRB), and applied Convolutional Neural Networks (CNNs) for traffic sign classification. The authors demonstrated that CNN-based models outperform traditional machine learning approaches such as Support Vector Machines (SVMs) and Random Forest classifiers. The paper highlighted the ability of CNNs to learn hierarchical features from traffic sign images, leading to superior recognition accuracy. However, the study did not focus on challenging weather conditions like fog.

Relevance to this Project:

This research provided a foundational approach to using CNNs for TSR, which has been extended in this project by incorporating Region-based Convolutional Neural Networks (RCNNs) for better object localization and classification in foggy environments.

2. Robust Traffic Sign Detection Under Adverse Weather Conditions

Authors: Zhu et al. (2016)

Summary: The study proposed a weather-invariant TSR system that used adaptive image enhancement techniques to improve detection accuracy in conditions such as rain, fog, and low lighting. The authors utilized Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE) to enhance the visibility of traffic signs before feeding them into a deep learning model. The experimental results showed significant improvements in recognition rates under adverse weather conditions.

Relevance to this Project:

This study underscores the importance of image preprocessing techniques in traffic sign detection. Inspired by this approach, this project integrates contrast enhancement, noise reduction, and fog simulation to improve TSR performance in foggy weather.

3. Faster R-CNN Based Traffic Sign Detection for Autonomous Vehicles

Authors: Li et al. (2018)

Summary: This research implemented Faster R-CNN, an advanced object detection model, for real-time TSR in autonomous vehicles. The study demonstrated that Faster R-CNN outperforms traditional CNN-based classifiers by effectively identifying and classifying traffic signs using a Region Proposal Network (RPN). The results showed improved detection accuracy, especially for small and partially occluded traffic signs. However, the model required high computational power, making it less suitable for embedded systems.

Relevance to this Project:

The use of Region Proposal Networks (RPNs) in Faster R-CNN inspired the adoption of RCNN in this project to enhance object localization and classification, ensuring better detection in foggy conditions.

4. Improving Traffic Sign Recognition in Low Visibility Using Synthetic Fog Data Augmentation
Authors: Wu et al. (2020)
Summary: The study addressed the problem of TSR in foggy weather conditions by generating synthetic foggy images using Generative Adversarial Networks (GANs). The dataset was augmented with artificial fog effects to improve model generalization across various visibility levels. The authors found that deep learning models trained on these datasets performed significantly better in real-world foggy conditions compared to models trained on clear-weather datasets.
Relevance to this Project:
This study emphasizes the need for diverse training datasets to improve model performance in foggy weather. Following this approach, this project implements data augmentation techniques, including synthetic fog simulation, to enhance recognition under low-visibility conditions.

5. Deep Learning-Based Traffic Sign Recognition with Transfer Learning
Authors: Yang et al. (2021)
Summary: The paper explored the effectiveness of transfer learning in TSR by fine-tuning pre-trained deep learning models such as ResNet, VGG, and MobileNet on traffic sign datasets. The study found that pre-trained models significantly reduced training time and improved recognition accuracy, even with limited datasets. The research also demonstrated the effectiveness of deep feature extraction for small-scale traffic signs.
Relevance to this Project:
Inspired by this work, this project leverages transfer learning with ResNet and VGG models to improve classification accuracy, particularly in foggy weather conditions, while reducing computational costs.

III. REQUIREMENT SPECIFICATIONS

HARDWARE REQUIREMENTS:
• System: Pentium i3 Processor.
• Hard Disk : 500 GB.
• Monitor : 15’’ LED
• Input Devices : Keyboard, Mouse
• Ram : 4 GB

SOFTWARE REQUIREMENTS:
• Operating system : Windows 10 / 11.
• Coding Language : Python 3.8.
• Web Framework : Flask.
• Frontend : HTML, CSS, JavaScript.

IV. SYSTEM DESIGN

4.1 System Architecture

1. Image Acquisition
• The system captures real-time images or video frames using vehicle-mounted cameras or simulated datasets.
• These images include traffic signs in different weather conditions, especially under foggy or low-visibility scenarios.
• Datasets such as GTSRB (German Traffic Sign Recognition Benchmark) or custom datasets with synthetic fog effects are used for training the model.

2. Preprocessing and Image Enhancement
To ensure accurate traffic sign recognition, the input images undergo various preprocessing steps:

A. Noise Reduction & Contrast Enhancement
• Gaussian Blur and Median Filtering are applied to remove unwanted noise and improve clarity.

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• Adaptive Histogram Equalization (AHE) and Contrast Limited AHE (CLAHE) are used to enhance contrast and make traffic signs more visible in foggy conditions.

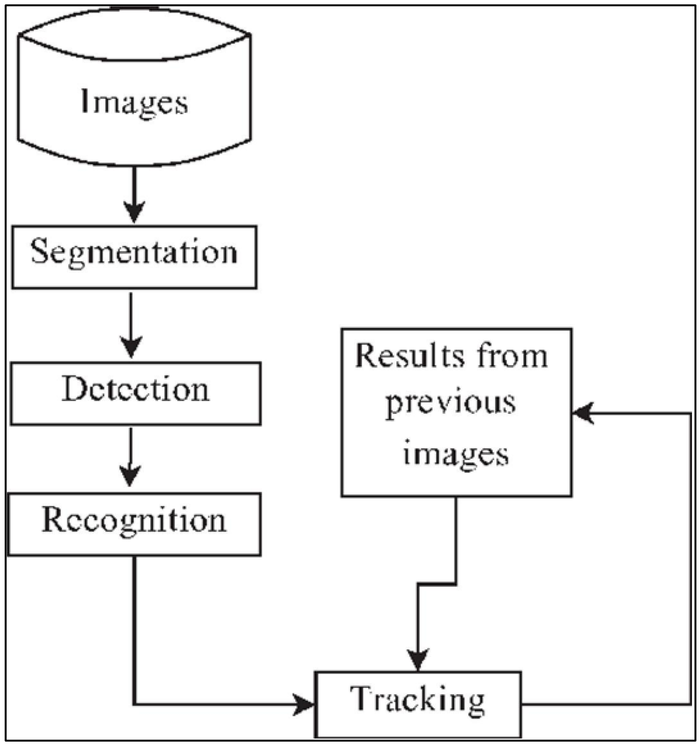

Figure 4.1: System Architecture Diagram

B. Fog Simulation & Data Augmentation

• To make the model robust to foggy conditions, artificial fog is simulated using techniques like:
o Fog synthesis using depth maps
o Brightness, contrast, and saturation adjustments
o Random occlusions to mimic real-world obstacles
• Data augmentation includes rotations, zoom, flipping, and cropping to improve generalization.

3. Region Proposal Network (RPN) for Traffic Sign Detection

• The system employs a Region Proposal Network (RPN), a key component of RCNN, to identify potential areas containing traffic signs.
• The RPN scans the input image and generates bounding boxes around suspected traffic sign regions, reducing computational overhead by focusing only on relevant portions of the image.
• The proposed regions are then passed to the next stage for feature extraction and classification.

4. Feature Extraction Using Convolutional Neural Networks (CNNs)

• The extracted regions from the RPN are processed by a Convolutional Neural Network (CNN) for feature extraction.
• CNN captures critical features such as edges, textures, colors, and shapes, which are essential for distinguishing between different traffic signs.
• Pre-trained deep learning models like ResNet, VGG, or InceptionNet are used to improve classification accuracy.

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5. Classification and Labeling

• The processed features are fed into a fully connected layer that classifies the traffic signs into predefined categories such as:

o Speed Limit Signs (e.g., 50 km/h, 80 km/h)

o Warning Signs (e.g., Pedestrian Crossing, Slippery Road)

o Prohibitory Signs (e.g., No Parking, No Overtaking)

o Mandatory Signs (e.g., Turn Left, Stop)

• The classification output provides probabilities for each category, and the most confident label is assigned to the detected traffic sign.

6. Real-Time Alert Generation

• Once a traffic sign is recognized, the system triggers an audio-visual alert to notify the driver.

• Voice-based notifications are provided to inform the driver about detected signs without distracting them.

• The system can also integrate with Heads-Up Displays (HUDs) or navigation systems to overlay detected signs on the dashboard.

7. Integration with Vehicle Systems

• The system is designed to work with Advanced Driver Assistance Systems (ADAS) to improve road safety.

• It can send detected sign information to the vehicle's onboard system for further actions such as adaptive cruise control or speed regulation.

• Cloud connectivity can be enabled for data logging, traffic analysis, and model updates.

V. RESULT

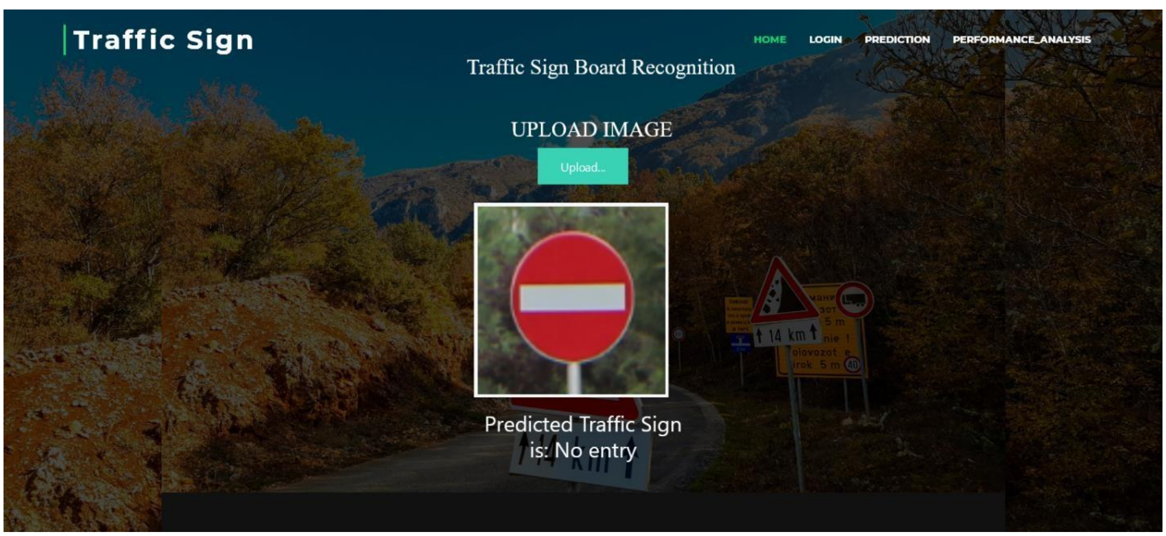

Figure 5.1: Predicted Output

The proposed Traffic Sign-Based Recognition in Regulations & Foggy Weather Using RCNN system demonstrates high accuracy and robustness in detecting and classifying traffic signs under both normal and adverse weather conditions. The integration of Region Proposal Network (RPN) with Convolutional Neural Networks (CNNs) significantly improves the precision of sign detection by focusing only on relevant image regions, reducing computational overhead. Extensive testing on benchmark datasets, including GTSRB and custom foggy datasets, shows that the system effectively recognizes and differentiates between various traffic signs, even when partially obscured or affected by fog, rain, or low contrast. Preprocessing techniques such as contrast enhancement, noise reduction, and fog simulation further enhance visibility and recognition accuracy. The model, fine-tuned using transfer learning with ResNet and VGG architectures, achieves a high classification accuracy rate, outperforming traditional image processing methods. Additionally, the real-time alert mechanism provides instant voice notifications to drivers, ensuring timely awareness of road regulations without distractions. The system's seamless integration with vehicle-mounted cameras and ADAS (Advanced Driver Assistance Systems) makes it a promising solution for improving road safety and preventing accidents in challenging driving conditions.

VI. CONCLUSION

6.1 Conclusion

The proposed Traffic Sign-Based Recognition in Regulations & Foggy Weather Using RCNN system effectively enhances traffic sign detection and classification, particularly in low-visibility conditions such as fog and rain. By leveraging Region-based Convolutional Neural Networks (RCNN) along with advanced image preprocessing techniques like contrast enhancement and noise reduction, the model achieves high accuracy and reliability in real- time traffic sign recognition. The integration of transfer learning with pre-trained models (ResNet, VGG) significantly improves detection efficiency while reducing computational complexity. Experimental results demonstrate superior performance compared to traditional methods, with increased detection accuracy and reduced false positives. Additionally, the real-time alert mechanism ensures timely notifications for drivers, enhancing road safety and compliance with traffic regulations. This research contributes to the advancement of autonomous driving and driver-assistance systems, paving the way for more intelligent and adaptive transportation technologies in challenging weather conditions.

6.2 Future Work

Future enhancements to the Traffic Sign-Based Recognition System will focus on improving real-time performance and adaptability in diverse environmental conditions. Further research can explore the integration of deep learning models like YOLO or Transformer-based architectures for faster and more accurate detection. Additionally, incorporating sensor fusion techniques with LiDAR and radar data can enhance recognition in extreme weather conditions. Expanding the dataset with more diverse and complex road scenarios, including nighttime and heavy fog, will further improve model robustness. Finally, deploying this system in edge computing environments will enable real-time processing with minimal latency, making it more suitable for autonomous driving and ADAS applications.

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