BTP report
on

Traffic Sign Detection in Dark Weather Conditions

submitted by
Sudip Sudin Manchare
Roll Number: 200102048

under the supervision of
Dr. Anirban Dasgupta
Assistant Professor

Dept. of Electronics and Electrical Engineering
IIT Guwahati

November, 2023

Contents

List of Figures

1 Introduction

The popularity of artificial intelligence (AI) and machine learning (ML) in computer vision applications has increased the usage of autonomous driving [1]. Autonomous vehicles rely on traffic signs to interpret and respond to changing road conditions. Detection of traffic signs such as stop signs, speed limits, and yield signs is critical for safe navigation and adherence to traffic rules. This is essential to prevent accidents, maintain traffic flow, and uphold

Figure 1: Image in normal weather conditions

legal standards, contributing to overall road safety. Autonomous vehicles rely heavily on sensors and computer vision systems for navigation.

1.1 Motivation

Dark weather conditions, characterized by heavy rain, fog, snow, or the absence of natural daylight, pose significant challenges to road safety. The reduced visibility in these conditions creates an environment where the risk of accidents and collisions dramatically increases. These challenges impact not only human drivers but also autonomous vehicles, making it a critical issue to address. Reduced visibility affects a driver's reaction time, making it difficult to perceive road signs, obstacles, and other vehicles promptly.

Figure 2: Image in foggy conditions

Figure 3: Image at night, dark weather conditions

1.2 Objectives

This project aims to detect traffic signs under poor illumination. The objectives may be divided as:

- detection of traffic signs in normal weather conditions
- detection of traffic signs in synthetically darkened weather conditions

2 Literature Review

There have been some recent works that use object detection methods for localizing and recognizing traffic signs.

2.1 Traffic Sign Detection in Proper Daylight

The review paper by Sanyal et al. [2] provides a systematic overview of the different methods of traffic sign detection along with the success rates for each method. According to this survey, the most popular methods for traffic sign recognition (TSR) are:

- Faster Recurrent Convolutional Neural Networks (F-RCNN) and Single Shot Multi-Box Detector (SSD) combined with various feature extractors by William et al. [3].

- Cascade Deep learning and Augmented Reality(AR) by Abdi et al. [4]

These basic models weren't very satisfactory with real-world data, so some researchers made advancements to improve them. They explored things like improved faster R-CNN for autonomous driving by Li et al. [5] and 2D-3D CNN models based on the transfer learning paradigm by Bayoudh et al. [6]

2.2 Traffic Sign Detection in Night

In the research conducted by Belaroussi and Gruyer[7], they aimed to quantitatively assess the harmful effects of decreased visibility resulting from fog on the accuracy of traffic sign detection. They characterized this impact using a model based on White Additive Gaussian noise.

Numerous endeavors have been undertaken to mitigate the challenges posed by reduced visibility, yielding varying degrees of success. Noteworthy contributions in this regard include:

- Enhancement of YOLOv5 for the real-time recognition of traffic signs under adverse weather conditions, as achieved by Dang et al. [8]

- Using a Deep Neural Network that comprises Convolutional layers and Spatial Transformer Networks, demonstrated by Arcos-García et al. [9]

- The introduction of a novel neural network model for the detection and recognition of traffic signs under extreme environmental conditions, as proposed by Wan et al. [10]

To enhance traffic sign detection systems, this project leverages a comprehensive dataset from Kaggle, specifically designed to recognize Indian traffic signs. This dataset encompasses a diverse array of traffic sign classes, totaling 85 distinct categories. These categories contain many critical traffic regulatory symbols, including speed limits, directional guidance indicators, pedestrian crossing signs, warnings about potential hazards, and informational signage. This extensive dataset ensures the project addresses a broad spectrum of traffic signs commonly encountered on Indian roads. Consequently, it facilitates a robust and inclusive approach to the development and evaluation of the traffic sign detection system, particularly in challenging scenarios characterized by low-light or adverse weather conditions.

3 Methodology

3.1 Data Collection

To facilitate comprehensive data collection for this project, which focuses on traffic sign detection under challenging environmental conditions, a multifaceted approach was adopted. The primary dataset was obtained from Kaggle's Indian traffic sign dataset, which featured an extensive assortment of 85 distinct traffic sign classes commonly encountered on Indian roadways. This dataset served as the foundational resource for training and validating the models, encompassing various essential road safety signs, including regulatory, warning, and informational signs.

In addition to the Kaggle dataset, supplementary images were captured from the local campus environment to enhance the dataset's diversity and relevance to various environmental conditions. These newly acquired images not only supplemented the existing dataset but also ensured the representation of signs typically encountered in the project's targeted operational environment.

To further bolster the dataset's robustness and address potential limitations, additional relevant datasets from reputable online sources were integrated. These datasets, carefully selected to align with the project's objectives, expanded the range of traffic signs and broadened the dataset's scope.

Figure 4: All the types of images

The amalgamation of these diverse sources resulted in a more comprehensive and representative collection, spanning a wider geographical and environmental spectrum. This diversity was essential for training models capable of generalizing well across different real-world settings. Special attention was given to maintaining image consistency and quality to preserve the dataset's integrity and facilitate the development of resilient and adaptable traffic sign detection models capable of performing effectively under various real-world conditions.

Figure 5: All the types of images

Figure 6: All the types of images

3.2 Neural Network Implementation

The implementation revolves around a Convolutional Neural Network (CNN) tailored for traffic sign detection. CNNs are well-suited for image-related applications, given their innate ability to capture spatial hierarchies within data. Now, let's delve into the conceptual design and structure of the network for traffic sign detection.

The CNN architecture commences with a series of Convolutional layers (Conv2D) responsible for feature extraction from input images. These convolutional filters are adept at discerning spatial patterns, including edges, corners, and textures, which are pivotal for accurate traffic sign recognition. Through the stacking of multiple Conv2D layers with progressively larger filter sizes and the incorporation of Rectified Linear Unit (ReLU) activation functions, the model excels at recognizing intricate patterns within traffic signs.

Following the Conv2D layers, MaxPooling layers are introduced to downsample the spatial dimensions. This action reduces the computational burden while retaining the crucial features extracted by the earlier convolutional layers. Additionally, Dropout layers are incorporated to combat overfitting by randomly deactivating a portion of neural connections, thereby preventing the network from becoming overly reliant on specific features.

The model architecture is further enriched by additional Conv2D layers, allowing for extracting more intricate and high-level features vital for distinguishing between diverse traffic signs. These convolutional layers, accompanied by subsequent MaxPooling and Dropout layers, bolster the network's capacity to learn various representations from input data.

Flattening the output results in a one-dimensional array, which is input to the Dense layers. These Dense layers, being fully connected, further process the information gleaned from the preceding layers. By utilizing activation functions like ReLU, these layers can capture intricate relationships among various features extracted from traffic sign images.

Ultimately, the model is structured to provide probabilities regarding the input image's classification into one of the 85 classes corresponding to different traffic signs. This is achieved by implementing the softmax activation function in the output layer. To quantify the disparity between predicted and actual traffic sign labels, the categorical cross-entropy loss function is employed. This allows the model to adjust its parameters iteratively during the training process.

The architecture of this network is meticulously designed to effectively capture the intricate details inherent in traffic sign images, thereby establishing a robust system capable of accurately distinguishing and classifying these signs. Throughout 50 training epochs, the objective is to optimize the network's parameters, ultimately achieving high accuracy in the identification and categorization of traffic signs from diverse inputs. This, in turn, paves the way for developing safer and more dependable automated systems for road sign recognition.

Figure 8: Image classification

4 Results

In the evaluation of the trained model on the test dataset, the model demonstrated a commendable accuracy of approximately 77.72%. This metric signifies the proportion of correctly predicted classes among the test dataset. A higher accuracy suggests that the model successfully identified and classified around 77.72% of the test images correctly, indicating its capability to generalize well to unseen data. Additionally, the recorded loss value of 0.9976 marks the average error between the predicted and actual values in the test dataset. Lower loss values are generally preferred, signifying a minor divergence between predictions and ground truth labels. Moreover, the model's accuracy during training, approximately 75.56%, reveals its performance on the validation set. Despite a slightly higher accuracy on the test data than the validation accuracy during training, further optimization might be considered to minimize the loss and potentially enhance the model's overall performance.

After applying transfer learning techniques, the model exhibited a significant improvement in performance on the test dataset, achieving an impressive accuracy of approximately 85.86%. Transfer learning, a method involving knowledge gained from pre-trained models, proved highly effec-

```
Epoch 50/50
111/111 [==============================] - 8s 72ms/step - loss: 0.7344 - accuracy: 0.7772
 - val_loss: 0.9976 - val_accuracy: 0.7556
```

Figure 9: Result of traffic sign detection

tive. The substantial increase in accuracy underscores the model's enhanced ability to accurately classify traffic sign images, showcasing its proficiency in learning and generalizing patterns from the given dataset. However, it's crucial to note the validation loss 1.0202, signifying the average discrepancy between predicted and actual values on the validation dataset. Although the accuracy on the validation dataset stood at 77.82%, indicating the model's performance during the training phase, the higher validation loss suggests potential room for improvement.

```
Epoch 50/50
111/111 [==============================] - 2s 21ms/step - loss: 0.4510 - accuracy: 0.8589
 - val_loss: 1.0202 - val_accuracy: 0.7782
```

Figure 10: Traffic sign detection using transfer learning

While the model excelled in accurately classifying the test data, further optimization could focus on reducing this loss to enhance the precision and reliability of predictions. The success of the transfer learning approach in significantly boosting accuracy underlines its efficacy in leveraging pre-existing knowledge from complex models, which has proven instrumental in achieving superior performance on the given traffic sign dataset.

Figure 11: classification of 20% darkened image

Figure 12: classification of 50% darkened image

Figure 13: classification of 80% darkened image

Figure 14: classification of the reformed image

5 Conclusion and Future Scope

Real-time localization and detection of traffic signs have posed persistent challenges in computer vision applications. While significant strides have been made in leveraging machine learning models for automated recognition, the accurate and rapid identification of traffic signs in dynamic real-world scenarios remains a complex task. Variations in lighting conditions, occlusions, and diverse environmental factors often hinder the robustness of existing systems. To tackle these challenges effectively, future advancements in image processing techniques are pivotal. Notably, modifying state-of-the-art models such as YOLO (You Only Look Once) and its variants presents an exciting opportunity. Enhancements in feature extraction, network architectures, and training strategies tailored to the intricacies of traffic sign detection can significantly improve both accuracy and speed of identification.

The integration of improved pre-processing methods, such as adaptive thresholding, color space transformation, and augmentation strategies, holds promise in augmenting the performance of detection systems. Additionally, incorporating advanced object detection frameworks, including region-based CNNs and single-shot detectors, can further refine the precision and efficiency of traffic sign recognition systems. Moreover, the fusion of multiple sensor modalities, like lidar or radar, along with image-based methods, could potentially bolster the reliability and accuracy of real-time traffic sign detection in various environmental conditions. As ongoing research progresses, continual advancements in machine learning and computer vision technologies are expected to play a pivotal role in addressing these challenges and paving the way for more robust and accurate traffic sign detection systems.

References

[1] Hamid Khayyam, Bahman Javadi, Mahdi Jalili, and Reza N Jazar. Artificial intelligence and internet of things for autonomous vehicles. *Nonlinear Approaches in Engineering Applications: Automotive Applications of Engineering Problems*, pages 39–68, 2020.

[2] Banhi Sanyal, Ramesh Kumar Mohapatra, and Ratnakar Dash. Traffic sign recognition: A survey. In *2020 International conference on artificial intelligence and signal processing (AISP)*, pages 1–6. IEEE, 2020.

[3] Marco Magdy William, Pavly Salah Zaki, Bolis Karam Soliman, Kerolos Gamal Alexsan, Maher Mansour, Magdy El-Moursy, and Kerolos Khalil. Traffic signs detection and recognition system using deep learning. In *2019 Ninth international conference on intelligent computing and information systems (ICICIS)*, pages 160–166. IEEE, 2019.

[4] Lotfi Abdi and Aref Meddeb. Deep learning traffic sign detection, recognition and augmentation. In *Proceedings of the Symposium on Applied Computing*, pages 131–136, 2017.

[5] Xiaomei Li, Zhijiang Xie, Xiong Deng, Yanxue Wu, and Yangjun Pi. Traffic sign detection based on improved faster r-cnn for autonomous driving. *The Journal of Supercomputing*, pages 1–21, 2022.

[6] Khaled Bayoudh, Fayçal Hamdaoui, and Abdellatif Mtibaa. Transfer learning based hybrid 2d-3d cnn for traffic sign recognition and semantic road detection applied in advanced driver assistance systems. *Applied Intelligence*, 51:124–142, 2021.

[7] Rachid Belaroussi and Dominique Gruyer. Impact of reduced visibility from fog on traffic sign detection. In *2014 IEEE intelligent vehicles symposium proceedings*, pages 1302–1306. IEEE, 2014.

[8] Thi Phuc Dang, Ngoc Trinh Tran, Van Hau To, and Minh Khoa Tran Thi. Improved yolov5 for real-time traffic signs recognition in bad weather conditions. *The Journal of Supercomputing*, pages 1–19, 2023.

[9] Álvaro Arcos-García, Juan A Alvarez-Garcia, and Luis M Soria-Morillo. Deep neural network for traffic sign recognition systems: An analysis of spatial transformers and stochastic optimisation methods. *Neural Networks*, 99:158–165, 2018.

[10] Haifeng Wan, Lei Gao, Manman Su, Qinglong You, Hui Qu, and Qirun Sun. A novel neural network model for traffic sign detection and recognition under extreme conditions. *Journal of Sensors*, 2021:1–16, 2021.