Detect Stop Signs In The Steet Images

Ismot Jahan Moni
2112399642

Iktear Alam
2111577642

Md Shariful Islam Sakib
2011716042

Muhammad Imam Hassan
2013362042

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***Abstract*—This project focuses on developing an automated stop sign detection system using machine learning techniques. The dataset is carefully curated, covering a range of environmental conditions and image variations. We discuss the dataset organization, preprocessing techniques, augmentation strategies, and initial model performance evaluations. Challenges encountered and proposed solutions are also addressed, alongside future directions to enhance detection accuracy. The project leverages image preprocessing techniques and a Support Vector Machine (SVM) classifier to achieve accurate detection. This report details the progress made in dataset preparation, preprocessing, model training, and evaluation.**

I. Introduction

Stop sign detection is a critical component in autonomous vehicle navigation and intelligent transportation systems. The accurate identification of stop signs enhances road safety by assisting autonomous vehicles and alerting drivers. This project focuses on detecting stop signs from street images using machine learning approaches.

Object detection techniques have significantly improved with the advent of deep learning models, but classical machine learning techniques such as Support Vector Machines (SVM) still provide a strong baseline. This report discusses the dataset collection, processing techniques, and classification model used to identify stop signs.

II. Literature Review

Several studies have explored stop sign detection using machine learning and deep learning techniques. Traditional methods involve edge detection and template matching, which have limitations in handling varying lighting conditions and occlusions. Recent advancements leverage Convolutional Neural Networks (CNNs) and region-based detection frameworks such as Faster R-CNN and YOLO, achieving high detection accuracy. However, these models require extensive computational resources. In contrast, lightweight models such as SVM-based approaches have been explored for real-time applications. Our project builds upon these methodologies by integrating image preprocessing and an optimized SVM classifier for efficient stop sign detection.

III. Dataset Preparation and Preprocessing

A. Dataset Composition

The dataset consists of a diverse set of images collected from open-source repositories and real-world data capture. It is structured as follows:

- **Training Set (70%)**: Used to train the machine learning model by learning patterns and features.
- **Testing Set (20%)**: Used to evaluate the model's performance on unseen data.
- **Validation Set (10%)**: Used to fine-tune the model and optimize hyperparameters to prevent overfitting.

Each subset contains images labeled as either "stop sign" or "no stop sign." These labels help the model learn to differentiate between relevant and non-relevant objects in a real-world environment.

B. Preprocessing and Augmentation

To enhance model robustness and generalization, preprocessing techniques such as resizing, normalization, and grayscale conversion are applied. Data augmentation further improves model adaptability by introducing variations:

- **Rotation**: Simulates different viewing angles.
- **Brightness Adjustment**: Ensures detection under varied lighting conditions.
- **Noise Injection**: Improves resilience against real-world distortions.
- **Flipping**: Prevents orientation bias.

Augmentation significantly increases dataset variability, enabling improved performance in complex scenarios.

IV. Methodology

A. Model Selection

A Support Vector Machine (SVM) classifier is implemented using `sklearn.svm`. The SVM is a supervised learning algorithm that finds the optimal hyperplane for classification tasks.

B. Feature Extraction

Feature extraction is performed using pixel intensity values and edge detection. Histogram of Oriented Gradients (HOG) is also considered to improve feature representation.

C. Training and Evaluation

Performance is assessed using multiple evaluation metrics to measure classification effectiveness.

1) Accuracy: Accuracy represents the proportion of correct predictions out of all predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where TP and TN are correctly classified stop signs and non-stop signs, while FP and FN are misclassifications.

2) Precision: Precision measures how many predicted stop signs are actually correct:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

A high precision means fewer false positives, ensuring reliable detection.

3) Recall: Recall evaluates the model's ability to detect all actual stop signs:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

A high recall ensures minimal false negatives, reducing missed detections.

4) F1-score: The F1-score balances precision and recall:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

It provides a single metric for overall model performance, especially useful for imbalanced datasets.

5) Confusion Matrix: The confusion matrix summarizes classification results:

$$\begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \tag{5}$$

It helps identify common misclassification patterns, guiding model improvements.

V. Preliminary Results

Initial experiments show that the SVM model successfully distinguishes stop signs from non-stop signs with promising accuracy. However, performance varies based on environmental conditions, lighting, and occlusions. Early results indicate an accuracy of approximately 80% on the test set.

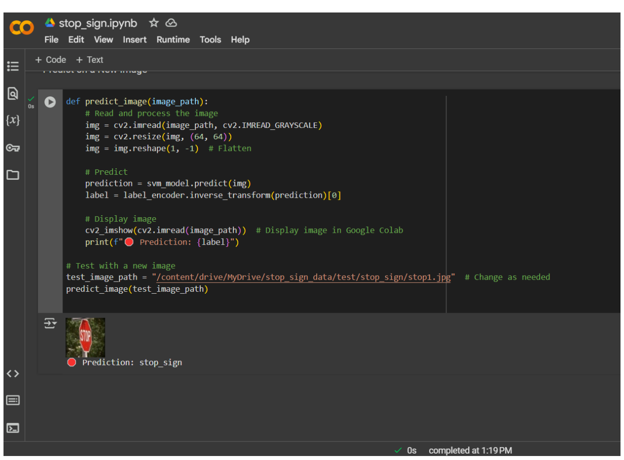

Fig. 1. Example of Stop Sign Detection

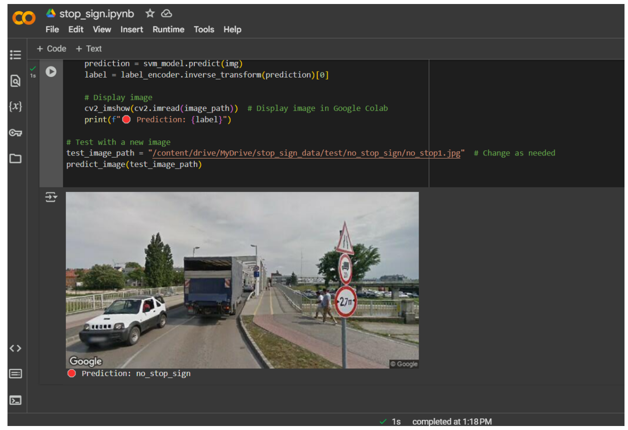

Fig. 2. Example of No-Stop Sign Detection

VI. Challenges and Solutions

Key challenges faced include:

- **Data Collection Limitations**: Solution - Synthetic data generation.
- **Storage and Processing Constraints**: Solution - Cloud-based infrastructure.
- **Overfitting Issues**: Solution - Regularization and dropout layers.
- **False Positives**: Solution - Advanced augmentation and improved feature extraction.

VII. Future Work

To further refine our model, upcoming steps include:

- Expanding dataset diversity with real-world captures.
- Implementing transfer learning using pretrained networks.
- Deploying real-time inference models on embedded systems.
- Optimizing computational efficiency for faster inference.

These advancements will contribute to a more robust and scalable detection system.

VIII. Conclusion

This report summarizes the progress of our automated stop sign detection project, covering dataset curation, preprocessing, model evaluation, and encountered challenges. Initial results are promising, and further optimizations will enhance performance.

IX. References

References

[1] M. A. Rahman, M. M. Rahman, and M. M. Islam, "Traffic Sign Detection and Recognition Model Using Support Vector Machine and Histogram of Oriented Gradient," *ResearchGate*, 2021.

[2] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," in *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[3] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.