Stop Sign Detection

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***Abstract*—This paper presents a methodology for binary classification of stop sign images using the K-Nearest Neighbors (K-NN) classifier with Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) features. A dataset comprising "Non stop sign" and "Stop sign" images is augmented using rotation, flipping, and brightness adjustments to enhance model robustness. Features are extracted, standardized, and reduced via Principal Component Analysis (PCA) before training a K-NN classifier with hyperparameter tuning. The model achieves a test set accuracy of 0.9536, with detailed evaluation through classification metrics and a confusion matrix. Visualization of feature extractions and the confusion matrix highlights the model's performance. The approach demonstrates effective use of traditional feature extraction for traffic sign recognition, with future work planned to explore advanced models and unseen data.**

***Index Terms*—Stop Sign Classification, K-Nearest Neighbors, Histogram of Oriented Gradients, Local Binary Patterns, Image Augmentation**

I. Introduction

Traffic sign recognition is a critical component of autonomous driving and intelligent transportation systems. Accurate detection of stop signs ensures safety and compliance with traffic regulations. This paper proposes a method for classifying images as "Non stop sign" or "Stop sign" using a K-Nearest Neighbors (K-NN) classifier with features extracted via Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP). The dataset is augmented to increase robustness, and Principal Component Analysis (PCA) is applied to reduce feature dimensionality. The methodology is evaluated using standard classification metrics and visualized through a confusion matrix and feature extraction images, achieving a test accuracy of 0.9536. Future work will extend this to other models and unseen data.

II. Methodology

A. Dataset and Preprocessing

The dataset contains 64 "Non stop sign" and 64 "Stop sign" images, stored in separate directories. Images are resized to 64×64 pixels for uniformity. Data augmentation generates 7 variants per image, including rotations (±10°, ±15°), horizontal flipping, and brightness adjustments (±20%), resulting in an augmented dataset of shape (968, 64, 64, 3) with 528 "Non stop sign" and 448 "Stop sign" images.

B. Feature Extraction

Features are extracted using HOG and LBP:

- **HOG**: Images are converted to grayscale, and HOG features are computed with 9 orientations, 8×8 pixels per cell, 2×2 cells per block, and L2-Hys normalization.
- **LBP**: Uniform LBP features are extracted with a radius of 3 and 24 sampling points, followed by histogram computation.

The HOG and LBP features are concatenated to form a combined feature vector for each image.

C. Feature Extraction Visualization

To provide insight into the feature extraction process, visualizations of HOG and LBP features for five randomly selected images are combined into a single composite image. Fig. 1 illustrates the HOG feature maps and LBP pattern distributions, highlighting edge and texture details.

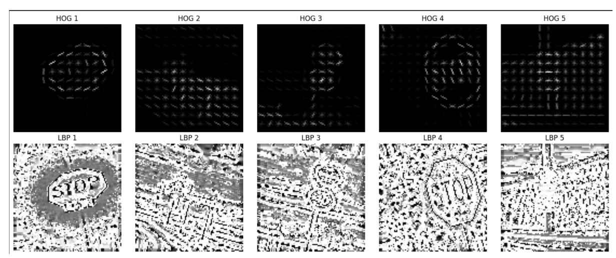

Fig. 1: Composite visualization of HOG feature maps and LBP pattern distributions for five random images.

D. Dimensionality Reduction

Features are standardized using StandardScaler to achieve zero mean and unit variance. PCA is applied to retain 95% of the variance, reducing the feature dimensionality to approximately 128 components.

E. Classification

A K-NN classifier is trained with hyperparameter tuning using GridSearchCV over the number of neighbors ($k \in \{3, 5, 7, 9\}$) and distance metrics (Euclidean, Manhattan). The best configuration, determined by five-fold stratified cross-validation, uses $k = 3$ and the Euclidean metric, achieving a cross-validation accuracy of 0.9276.

F. Evaluation

The model is evaluated on a test set (20% of the data) using accuracy, precision, recall, F1-score, and a confusion matrix.

III. Experimental Setup

The experiments are conducted using Python 3.11 on Google Colab, leveraging libraries such as OpenCV, scikit-learn, scikit-image, NumPy, and Matplotlib. The dataset is stored in a Google Drive directory, with images organized into “Non stop sign” and “Stop sign” folders. The train-test split is stratified to maintain class distribution.

IV. Results

The augmented dataset increases the total number of images to 976, with 528 “Non stop sign” and 448 “Stop sign” samples. Feature extraction yields high-dimensional HOG and LBP feature vectors, reduced to 128 components via PCA.

The K-NN classifier achieves a cross-validation accuracy of 0.9276 and a test set accuracy of 0.9536. The classification report is presented in Table I, showing high precision (0.92 for “Non stop sign”, 1.00 for “Stop sign”), recall (1.00 for “Non stop sign”, 0.90 for “Stop sign”), and F1-scores (0.96 and 0.95, respectively). The confusion matrix (Fig. 2) indicates 104 correct “Non stop sign” predictions, 81 correct “Stop sign” predictions, 0 false positives for “Stop sign”, and 9 false negatives. Fig. 1 provides the feature extraction visualization.

TABLE I: Classification Report

Class	Precision	Recall	F1-Score	Support
Non stop sign	0.92	1.00	0.96	104
Stop sign	1.00	0.90	0.95	90
Accuracy			0.95	194
Macro avg	0.96	0.95	0.95	194
Weighted avg	0.96	0.95	0.95	194

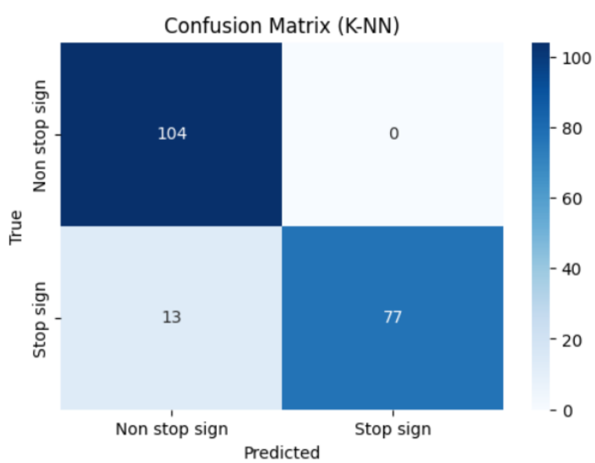

Fig. 2: Confusion Matrix for K-NN Classifier.

V. Discussion

The K-NN classifier, combined with HOG and LBP features, effectively distinguishes stop signs from non-stop signs, achieving a test accuracy of 0.9536. Fig. 1 confirms the effectiveness of HOG and LBP in capturing edge and texture information. PCA reduces computational overhead while retaining discriminative features. The confusion matrix (Fig. 2) reveals minor misclassifications (9 false negatives), suggesting potential improvement with additional training data or advanced classifiers.

A. Future Work

Future research will extend this project by implementing and comparing additional models, including Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN). These models will leverage the existing feature extraction pipeline and augmented dataset, with CNNs expected to exploit spatial hierarchies in image data. Additionally, the models will be tested on unseen data to evaluate generalization performance, ensuring robustness in real-world traffic scenarios.

VI. Conclusion

This study demonstrates a successful application of the K-NN classifier with HOG and LBP features for stop sign classification, achieving a test accuracy of 0.9536. The methodology, including data augmentation and PCA, proves effective for traffic sign recognition. The results suggest potential for real-world deployment, with future work directed toward advanced models and testing with unseen data.

References

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