Recognition of Sri Lankan Traffic Signs using Machine Learning Techniques

A. Priscilah Nivetha[1] and M.S. Suhail Razeeth[2]

[1]*Department of Information Technology, Trincomalee Campus, Eastern University, Sri Lanka*
[2]*Department of Information and Communication Technology, South Eastern University, Sri Lanka*

[1]nivethaa@esn.ac.lk, [2]razeethsuhail@seu.ac.lk

Abstract

The recognition of traffic signs is a crucial component of driver assistance systems that have been extensively researched worldwide. However, it remains a challenging issue due to the increasing number of vehicles, road signs, and the lack of awareness among drivers and other road users. A Traffic Sign Recognition (TSR) system is an advanced autonomous technology designed to assist drivers by accurately identifying and interpreting traffic signs. This system plays a crucial role in enhancing driver awareness and ensuring appropriate responses to various traffic conditions. The precise recognition of traffic signs is essential for maintaining road safety and improving the overall driving experience. This study focuses on the recognition of Sri Lankan traffic signs and examines the combination of classifiers with a specific feature extractor. A dataset of 300 images of road signs was utilized for this study by capturing the images. The Scale-Invariant Feature Transform (SIFT) was used as a feature descriptor in this process. The classifiers employed were Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN). Different combinations of SVM and k-NN were applied to the dataset, and the study achieved 100% accuracy with various combinations of k-NN. The study found that the combination of SIFT and SVM is the most effective method for the proposed recognition of traffic signs.

Keywords: Sri Lankan Traffic signs, Traffic signs recognition, SIFT, SVM, k-NN, machine learning

I. INTRODUCTION

With the rise in traffic density and the push towards autonomous vehicles, accurately identifying and responding to traffic signs is essential for ensuring road safety and compliance with traffic laws. Human drivers can easily miss or misinterpret signs due to distractions or poor visibility, leading to accidents and traffic violations. Traffic sign recognition systems address these issues by providing real-time, reliable detection and interpretation of road signs, aiding drivers in making safer decisions and enabling autonomous vehicles to navigate more effectively. This technology is vital for reducing accidents, enhancing driver assistance systems, and paving the way for fully autonomous driving solutions.

Traffic sign recognition is a crucial technology in modern transportation systems, playing a vital role in enhancing road safety and enabling autonomous driving. By using advanced image processing and machine learning algorithms, traffic sign recognition systems can accurately identify and interpret various road signs. This technology helps drivers make informed decisions in real-time and assists autonomous vehicles in navigating complex road environments. As the development of intelligent transportation systems continues, traffic sign recognition stands out as a key component in reducing accidents and improving the overall efficiency of road networks. Traffic sign recognition using machine learning involves training algorithms to automatically detect and classify traffic signs from images. Machine learning (ML) is an umbrella term that refers to a broad range of algorithms that perform intelligent predictions based on a dataset (Nichols, et al., 2019). The traffic sign datasets are often large, perhaps consisting of millions of unique data points.

Machine learning models are powerful tools that enable systems to learn from data and make predictions or decisions without being explicitly programmed. These models analyze patterns and relationships within large datasets, allowing them to identify trends, classify information, and make informed predictions. In traffic sign recognition machine learning models are used to process and interpret visual data, identifying and categorizing various traffic signs with high accuracy.

In this study, systematic experiments were conducted to evaluate the performance of classification using SIFT feature representation combined with k-Nearest Neighbor (k-NN) and Support Vector Machines (SVM). The evaluation was performed on a newly created dataset of Sri Lankan traffic signs, focusing on six randomly selected sign types.

The rest of the paper is organized as follows. The literature is reviewed in Section II. The experimental methods are presented in Section III. The results of the experiment and the discussion are presented in Section IV and lastly, the conclusion and future works of the paper are presented in Section V.

II. LITERATURE REVIEW

In this section a summarization of some studies related to road sign recognition is presented.

There are varieties of models and algorithms available for road sign detection. (Nikam & Dhaigude, 2017), proposed a novel system for automatic road sign detection and recognition. The system segments input images in YCbCr color space and detects road signs using shape filtering. Recognition of the road sign symbols is achieved through Principal Component Analysis (PCA). The study also discussed many roads sign detection and recognition techniques. MESR, HSV, SVM, OCR, HIS, and HOG. The system is designed to be both efficient and robust in detecting and recognizing road sign symbols. It is obvious from the study that machine learning and deep learning techniques are used for road sign detection algorithms.

Table 01: Comparability Study with Different Datasets and Models

Study	Model	Dataset	Accuracy
SVM Based Method			
(Mahesh, 2018)	SIFT and SVM	No Details are provided	90%
(Møgelmose, et al., 2012)	SVM, KNN, Random Forest, and Naïve Bayes	Real-time Indonesian Traffic Signs	86%
(Ali, et al., 2023)	SVM and HOG	GTSDB, GTSRB, Linköping University, Real-Time Taiwanese Traffic Signs	94.9%
(Rahmad, et al., 2018)	SVM and KNN	Real-time Indonesian Traffic Signs	82.01%
Other Methods			
(Ardianto, et al., 2017)	CNN	GTSDB, GTSRB	96%
(Sugiharto & Harjoko, 2016)	CNN	Real-Time Russian Traffic Signs	87%
(Chakraborty & Deb, 2015)	SVM, CNN	Own collection of 12 signs of Sri Lankan traffic signs	SVM – 98.33 % CNN – 96.40%
(Roxas, et al., 2018)	CNN	GTSRB	95%
(Wang, 2018)	SVM and SIFT	Sri Lankan Traffic sign Dataset	87%
(Filatov, et al., 2017)	SVM, KNN, MPC, DT, AdaBoost	Sri Lankan Traffic sign Dataset	90%
(Kiridana, et al., 2022)	CNN, SVM	Google Street View	98.5%
Our Method			
*	SVM, KNN, and SIFT	300 images of Sri Lankan traffic signs	**100%**

(Adam & Ioannidis, 2014) presented a comprehensive methodology for road sign detection and recognition, addressing various challenges. It emphasized the effectiveness of using HOG descriptors to represent Regions of Interest (ROIs) and employed HIS color space for thresholding in the detection stage. For recognition, a Histogram of Oriented Gradients (HOG) is used, with Support Vector Machines (SVMs) handling classification. The system also included a successful step for separating overlapping signs and demonstrated high competence, showing robustness to changes in illumination, scale, and partial occlusions. The study shows 94.34% of accuracy the road sign signal.

In (HU, et al., 2010) they proposed a Traffic Sign Recognition (TSR) method that effectively addresses challenges such as weather conditions, shooting angle, and distance variation. Experiments were conducted on training image sets classified by these factors. The method utilizes the SIFT technique to extract sign features, forms a codebook using K-means clustering, and classifies the signs with an SVM based on feature distribution. The results demonstrate that our method is robust to variations in weather, distance, and shooting angle, achieving a high accuracy rate of 93% with a low computation time of 0.098 seconds per image.

III. METHODOLOGY

Here, we discuss the compositional parts, and the process engaged with building and fostering our model. The proposed work is based on the Bag of Features approach. The bag of features approach includes the following phases: feature extraction, codebook creation, histogram representation and learning and classification. The main idea is to generate histograms of images for the classification process. MATLAB R2021a and Windows 10 with 8GB RAM were used for all the implementations. Figure 01 illustrates the steps involved in the implementation process.

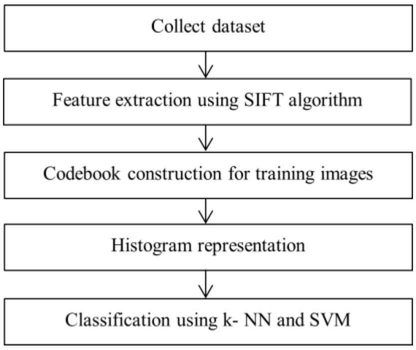


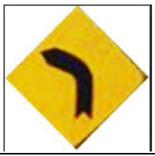
Figure 01: Methodology

Dataset

The dataset for this study comprises 300 images of Sri Lankan traffic signs: two informational signs and four warning signs. The dataset was captured from mobile with a good lighting condition. Initially, the road signs were cropped and normalized to a size of 200×200 pixels from the original image. The Images in each class were divided into two parts 70% for the training dataset and 30% for the testing dataset.

Figure 02: Class images of the dataset

Table 02: Road Sign Dataset

Sign	Train	Test
	35 Images	15 Images
	35 Images	15 Images
	35 Images	15 Images
	35 Images	15 Images
	35 Images	15 Images
	35 Images	15 Images

Feature extraction using the SIFT algorithm

SIFT was employed to extract features from the images. SIFT transforms data images into scale-invariant coordinates relative to local features. This process involves extracting features from the image, representing them as distinct patches, and then converting these patches into a collection of 128-dimensional vectors.

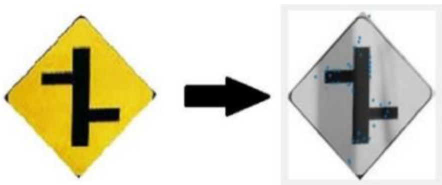


Figure 03: SIFT feature extraction
Codebook construction for training images.

Codebook construction involves generating visual words or codewords through clustering techniques applied to the original feature space. The K-means algorithm was used for clustering on the training dataset. It is because of the simplicity, efficiency, scalability and speed of the algorithm. Generally, K-means clustering algorithms are straightforward to understand, works very fast, handle large amount of data, therefore this study is utilized k-means cluster as a one of the algorithms over SVM to train the dataset and check the validity. Besides, K-means clustering partitions a set of N features into k clusters, with each feature assigned to the nearest cluster based on the mean of the cluster's members. The centers of these clusters are then used to create codewords, which together form the codebook.

Histogram Representation

The images were represented by histograms using the constructed codebook. Separate histograms were generated for both the training and testing images.

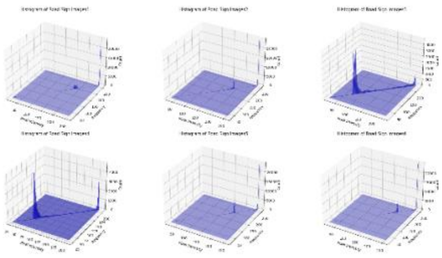


Figure 04: Histogram of road sign images

Classification using k- NN and SVM

The k-Nearest Neighbor (k-NN) approach was used for classification. It calculates pairwise Euclidean distances between key point representations of a test image and all labelled training images in the dataset. The Euclidean norm distance was employed to measure the distance between key points, with k values set to 1, 3, 5, 7, and 9.

Support Vector Machine (SVM) was used as an additional classifier. For multiclass classification, a linear SVM was trained using the one-versus-all (OVA) approach. The OVA rule separates each class from the others and assigns the test image to the class with the highest classifier response. The SVM^{light} package was utilized for the experiments.The accuracy rate for each classification was calculated, and this data was used to analyze the performance of the classifiers.

IV.RESULTS AND DISCUSSION

In this section, the outcomes of the execution of the methods referenced in the above-proposed works will be specified.

Table 03 presents the classification rates for different k values in the k-NN algorithm (k = 1, 3, 5, 7, and 9). All results shown in Table 01 were obtained without dimensionality reduction of the features extracted by the Bag of Features (BoF) method. This approach was chosen to preserve the full feature set and ensure that no potentially important information was lost during the dimensionality reduction process.

Table 03: Classification using different k values

K values	**Accuracy**
k=1	100.00%
k=3	97.78%
k=5	97.78%
k=7	96.67%
k=9	94.44%

Figure 05 illustrates the changes in classification rates when using the combination of SIFT and SVMs with parameter tuning. The graph depicts the impact of varying C values between 2^{-14} and 2^{10} on classification performance. The C value is the regularization parameter to avoid overfitting values. Normally high C value provides overfitting and low C value provides underfitting, the value between 2^{-14} and 2^{10} provide optimal performance to provide best classification performance without overfitting and underfitting.

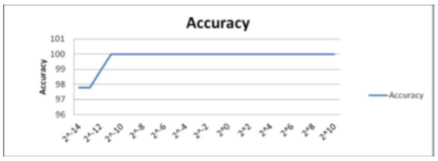


Figure 05: Graph of classification accuracy rates for SIFT + SVM with parameter tuning of C values ranging from 2^{-14} to 2^{10}

According to Table 03, as the number of nearest neighbors k in the k-NN algorithm increases, the accuracy rate decreases. Parameter k determines how many neighboring examples are considered when making a classification. Although considering more neighbors can generally improve classification accuracy, an increase in k may lead to a decline in accuracy if it introduces noise or less

relevant information into the decision-making process.
In Figure 05, which illustrates the combination of SIFT and SVM, the accuracy remains stable until a notable increase is observed when the parameter C is set from 2^{-12} to 2^{-10}. The parameter C in SVM controls the cost of classification errors. A larger C value focuses on minimizing classification errors by finding a more precise margin, while a smaller C emphasizes maximizing the margin, potentially leading to some classification errors. As C increases, the model becomes better at classifying points accurately, leading to higher accuracy rates. At certain points, the accuracy reaches 100% and remains consistent. Therefore, combining SIFT with an SVM classifier, particularly with optimal C values, yields the highest accuracy in our proposed method.

Table 01 above shows the comparative studies of SVM, CNN with different datasets. Different Dataset with different SVM, and other techniques shows different accuracies for relevant countries. For the Sri Lankan dataset k-NN with SIFT feature extraction technique is better suite, and it provides highest accuracy. Besides, In the available road sign dataset of Sri Lanka, this study got more accuracy with k-NN and SIFT.

On the other hand, if the other studies are changing parameters of the model and consider feature engineering techniques it also provides higher accuracy without any suspects.

V. CONCLUSION

Traffic sign recognition is a critical aspect of driver assistance systems and has been extensively studied globally. Intelligent autonomous systems for traffic sign recognition are essential for helping drivers understand and respond accurately to road signs. This study focuses on the recognition of Sri Lankan traffic signs, utilizing machine learning techniques to enhance the system's effectiveness. Specifically, Scale-Invariant Feature Transform (SIFT) is used as the feature descriptor, with Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) classifiers employed for the recognition process. The results indicated that combining SIFT with SVM is the most effective method for traffic sign recognition, offering significant improvements in classification accuracy and efficiency.

In the future, this study can be enhanced by extending the recognition to include a broader range of Sri Lankan traffic signs and enabling real-time detection, as the current approach is limited to still images. Additionally, expanding the dataset to include more diverse examples would improve the model's robustness. Further research could also involve comparing the proposed model with other existing models to evaluate its relative performance and effectiveness.

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