

An Efficient Machine Learning Technique based on Support Vector for Traffic Sign Classification

Md Shahab Akhter¹, Sneha Deokate²

¹M.Tech Scholar, ²Assistant Professor, Department of Computer Science and Engineering, School of Research and Technology, People's University Bhopal, India

Abstract-- Traffic sign classification is a crucial task in the develop-ment of intelligent transportation systems and autonomous vehicles. In this paper, we propose an efficient machine learning technique based on Support Vector Machine (SVM) for accurately and swiftly classifying traffic signs. SVM's ability to handle high-dimensional data and nonlinear decision boundaries makes it well-suited for this application. Moreover, its capacity to avoid overfitting ensures robust generalization to unseen data, making it suitable for real-world scenarios.

Index Terms- Traffic sign, SVM, ML, DL, AI, Classification.

I. INTRODUCTION

The Traffic sign classification is a critical component of modern intelligent transportation systems and plays a pivotal role in ensuring road safety and efficiency. With the rapid advancements in computer vision and machine learning, automated traffic sign recognition has gained significant attention as an essential technology for autonomous vehicles, driver assistance systems, and traffic management applications. The ability to accurately and swiftly identify traffic signs from images captured by cameras mounted on vehicles empowers these systems to make informed decisions, adhere to traffic regulations, and respond effectively to dynamic road conditions.

The complexity of traffic sign classification arises from the vast diversity of signs found on roads worldwide. Traffic signs vary in shape, color, size, and content, indicating a wide range of instructions, warnings, and regulatory information. Accurately classifying these signs is a challenging task due to the variability in illumination, weather conditions, occlusions, and other environmental factors that can affect the quality of the images.

To address these challenges, researchers have explored various machine learning techniques, including Support Vector Machine (SVM), which has emerged as a powerful approach for traffic sign classification. SVM is a supervised learning algorithm known for its effectiveness in handling high-dimensional data and nonlinear decision boundaries. By leveraging the concept of finding optimal hyperplanes to separate different classes, SVM can create efficient classifiers with strong generalization capabilities. One of the key advantages of SVMs in traffic sign classification is their ability to handle the high dimensionality of image data. Traffic sign images typically contain a large number of pixels, resulting in a highdimensional feature space. SVMs' ability to perform well even in high-dimensional spaces makes them well-suited for this task, where each pixel's position and color contribute to the sign's overall appearance and meaning.

Furthermore, SVMs' ability to avoid overfitting is of utmost importance in real-world traffic sign recognition scenarios. The capability to generalize to previously unseen signs or images is crucial for safe and reliable operations on roads with changing traffic conditions. SVM's structural risk minimization principle ensures that the model does not overfit to the training data, making it robust and dependable in practical applications.

Another significant advantage of SVMs is their computational efficiency, especially in comparison to some other complex machine learning algorithms. This efficiency makes SVMs particularly suitable for on-board implementations in vehicles with limited computational resources. Real-time traffic sign recognition is essential for enabling timely responses and ensuring a seamless integration of autonomous vehicles into existing traffic environments.

While SVMs offer many advantages for traffic sign classification, continuous research and development seek to improve their performance even further. Feature engineering, a crucial step in traffic sign classification, involves extracting meaningful and discriminative features from the image data. The selection of appropriate kernel functions and tuning of hyperparameters are essential aspects that can significantly impact the classification accuracy of SVMs.

Recent advancements have also explored hybrid approaches, combining SVMs with deep learning techniques like convolutional neural networks (CNNs). These hybrid models aim to leverage the strengths of both SVMs and CNNs to achieve state-of-the-art performance on traffic sign recognition tasks. Such developments promise to push the boundaries of accuracy and efficiency in traffic sign classification.



II. METHODOLOGY

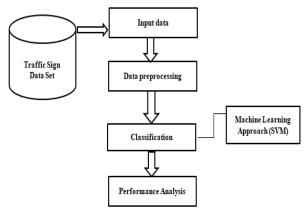


Figure 1: Flow Chart

Figure 1 is presenting the work flow chart. Support Vector Machines (SVMs) are powerful machine learning algorithms that can be applied to traffic sign classification tasks. SVMs are widely used for binary and multi-class classification problems, including traffic sign recognition. Here's an overview of how SVM techniques can be employed for traffic sign classification:

- Data Preparation: Collect a labeled dataset of traffic sign images, covering different types of signs with variations in lighting conditions, perspectives, and weather conditions. Preprocess the images by resizing them to a consistent size and converting them to a suitable format for SVM training.
- Feature Extraction: Extract meaningful features from the traffic sign images to represent them numerically. Common techniques for feature extraction include Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), or Local Binary Patterns (LBP). These features capture the distinctive characteristics of traffic signs and provide valuable information for SVM classification.
- Data Split: Divide the dataset into training, validation, and test sets. The training set is used to train the SVM model, the validation set aids in tuning hyperparameters, and the test set is used to evaluate the model's performance on unseen data.
- Model Training: Train an SVM model using the extracted features and the corresponding labels of the traffic sign images. SVMs aim to find an optimal hyperplane that separates different classes of signs in a high-dimensional feature space. During training, the SVM learns the decision boundary that maximizes the margin between different classes while minimizing classification errors.

- Hyperparameter Tuning: Fine-tune the SVM model by optimizing its hyperparameters. Parameters such as the kernel type (e.g., linear, polynomial, or radial basis function), regularization parameter (C), and kernel-specific parameters need to be determined. This tuning is typically done using cross-validation techniques to find the combination that yields the best performance.
- Model Evaluation: Evaluate the performance of the trained SVM model using the validation set. Metrics such as accuracy, precision, recall, and F1-score can be calculated to measure the model's classification performance. Adjust the hyperparameters or consider alternative feature extraction methods if the model's performance is not satisfactory.
- Testing and Deployment: Assess the performance of the SVM model on the test set to evaluate its realworld accuracy. Once satisfied with the model's performance, it can be deployed for traffic sign classification tasks. This may involve integrating the model into software applications, embedded systems, or utilizing it in real-time traffic management systems.

III. SIMULATION RESULTS

The simulation is performed using spyder 3.7 python software.

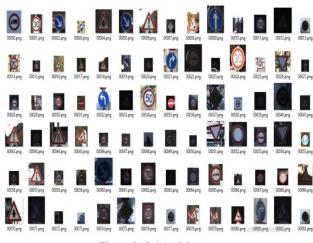


Figure 2: Original dataset

The figure 2 is showing the dataset, which is taken from the kaggle machine learning website.



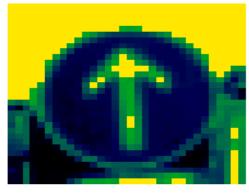


Figure 3: Prediction-1

Figure 3 is showing the prediction running process in the python spyder environment.

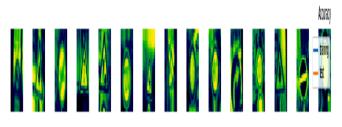


Figure 4: Prediction during testing and training

Figure is 4 is showing prediction during testing and training of traffic sign classification.

Table 1:
Result Comparison

Sr. No.	Parameter	Existing Work	Proposed Work
1	Method Name	SIFT	SVM
2	Accuracy	96.04%	97.67%
3	Classificatio n error	3.96%	2.33%

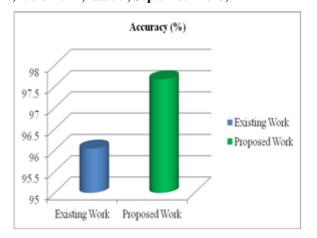


Figure 5: Result graph-Accuracy

IV. CONCLUSION

The Support Vector Machine (SVM) technique has proven to be a powerful and effective method for traffic sign classification. Through its ability to create optimal decision boundaries and handle high-dimensional data, SVMs have demonstrated remarkable accuracy and robustness in the task of recognizing and categorizing traffic signs from images. This paper presents an efficient machine learning technique based on support vector for traffic sign classification. The accuracy attained by the SVM was 97.67%, whereas the accuracy achieved by the existing method was 96.04%.

REFERENCES

- K. Lin and Z. Wang, "Traffic Sign Classification by Using Learning Methods: Deep Learning and SIFT Based Learning Algorithm," 2022 14th International Conference on Computer Research and Development (ICCRD), Shenzhen, China, 2022, pp. 239-243, doi: 10.1109/ICCRD54409.2022.9730126.
- [2] M. C. Pupezescu and V. Pupezescu, "Novel automatic traffic sign classification system using a semi-supervised approach," 2022 23rd International Carpathian Control Conference (ICCC), Sinaia, Romania, 2022, pp. 177-180, doi: 10.1109/ICCC54292.2022.9805952.
- [3] J. G. Park and K. -J. Kim, "A method for feature extraction of traffic sign detection and the system for real world scene," 2022 IEEE International Conference on Emerging Signal Processing Applications, Las Vegas, NV, USA, 2022, pp. 13-16, doi: 10.1109/ESPA.2012.6152433.



- [4] A. S. Utane and S. W. Mohod, "Traffic Sign Recognition Using Hybrid Deep Ensemble Learning for Advanced Driving Assistance Systems," 2022 2nd International Conference on Emerging Smart Technologies and Applications (eSmarTA), Ibb, Yemen, 2022, pp. 1-5, doi: 10.1109/eSmarTA56775.2022.9935142.
- [5] A. Kherraki, M. Maqbool and R. E. Ouazzani, "Robust Traffic Signs Classification using Deep Convolutional Neural Network," 2022 International Conference on Intelligent Systems and Computer Vision (ISCV), Fez, Morocco, 2022, pp. 1-6, doi: 10.1109/ISCV54655.2022.9806122.
- [6] M. Vashisht and B. Kumar, "Robust Classification of Traffic Signs using MRMR Feature Reduction Technique," 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), Faridabad, India, 2022, pp. 558-561, doi: 10.1109/COM-IT-CON54601.2022.9850672.
- [7] I. B. Sani, I. S. Zakari, M. M. Idrissa and D. Abdourahimoun, "Machine Learning based Classification of Traffic Signs Images from a Robot-car," 2022 IEEE Multi-conference on Natural and Engineering Sciences for Sahel's Sustainable Development (MNE3SD), Ouagadougou, Burkina Faso, 2022, pp. 1-6, doi: 10.1109/MNE3SD53781.2022.9723100.

- [8] I. Nasri, A. Messaoudi, K. Kassmi, M. Karrouchi and H. Snoussi, "Adaptive Fine-tuning for Deep Transfer Learning Based Traffic Signs Classification," 2021 4th International Symposium on Advanced Electrical and Communication Technologies (ISAECT), Alkhobar, Saudi Arabia, 2021, pp. 1-5, doi: 10.1109/ISAECT53699.2021.9668592.
- [9] L. Kovács and G. Kertész, "Hungarian Traffic Sign Detection and Classification using Semi-Supervised Learning," 2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania, 2021, pp. 000437-000442, doi: 10.1109/SACI51354.2021.9465555.
- [10] H. Fu and H. Wang, "Traffic Sign Classification Based on Prototypes," 2021 16th International Conference on Intelligent Systems and Knowledge Engineering (ISKE), Chengdu, China, 2021, pp. 7-10, doi: 10.1109/ISKE54062.2021.9755432.
- [11] E. Sarku, J. Steele, T. Ruffin, B. Gokaraju and A. Karimodini, "Reducing Data Costs- Transfer Learning Based Traffic Sign Classification Approach," SoutheastCon 2021, Atlanta, GA, USA, 2021, pp. 1-5, doi: 10.1109/SoutheastCon45413.2021.9401900.
- [12] Y. Swapna, M. S. Reddy, J. V. Sai, N. S. S. Krishna and M. V. Teja, "Deep Learning Based Road Traffic Sign Detection and Recognition," 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2021, pp. 1-4, doi: 10.1109/ICIRCA51532.2021.9545080.