Traffic signal classification

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Abstract

In today's world of rapid advancements in technology and the increasing adoption of autonomous vehicles, it is important to follow traffic rules to avoid traffic jams and accidents. For this reason, it is essential that these vehicles have functionalities to read and comprehend the traffic signs. This led to the idea of creating a smart system that can read and understand the traffic signals using supervised learning, in particular classification to learn models and predict the traffic signs using the Scikit-learn library. Using a dataset from the German Traffic Sign Recognition Benchmark, this project involves extensive image preprocessing techniques such as normalization, resizing, and conversion to consistent formats and Feature extraction was performed using Img2Vec tool. The classifiers explored include Decision Tree, Random Forest, Gaussian Naïve Bayes, Multi-layer Perceptron, and Support Vector Classifier. All these models are evaluated using stratified k-fold cross-validation that helps in making sure that their training sets have representation near the distribution of the classes of the population, thereby ensuring that the models do not overfit. The performance analysis used accuracy, precision, recall, and F1 score. The best performance was achieved for the Support Vector Classifier, which obtained accuracy of over 98%, proving such an algorithm to be robust in a high-dimensional data environment. On the other side, the obtained results proved that when working with quite complex classification tasks, ensemble methods and neural networks are way much more effective than the classical decision trees. This research not only enhances the capabilities of autonomous driving systems but also contributes to safer driving environments by improving traffic sign recognition.

Introduction

According to the Insurance Information Institute (III), failure to obey traffic signs, signals, or an officer account for 8% of the driving behaviors reported for drivers and motorcycle operators involved in fatal crashes in the United States [1]. Not only in The U.S. but in places of Europe 14.76% of the accidents occur due to the ignorance of the traffic signs [2]. These statistics show a very critical concern in the area of traffic management and safety.

With the rapid advancement of technology in these developing countries, there is an increase in the preference for autonomous vehicles. A report by Ericsson Consumer Lab highlights that over 47% of people from these rapid technology developing countries prefer self-driving cars, which is indicating a significant interest in the adoption of autonomous vehicle technology [3]. So, it is very important that these self-driving vehicles detect and follow proper traffic signs and signals to avoid roadblocks and accidents.

For classification and recognition of traffic signs in transportation management systems, computer vision, image processing technology and machine learning are serving as critical tools. The accurate categorization of traffic signals is crucial for effective traffic management. The major challenge is the implementation of a system that will carry out the classification accurately using these tools, which will be very useful in solving numbers of problems like the reduction in traffic jams, minimization of accidents, and making the movement of traffic run smoother in urban areas.

The main objective of our project is to develop a system that uses image processing and machine learning techniques to improve the accuracy of traffic sign classification. Our approach involves extracting features from different traffic sign images to train the effective classification model. Additionally, we have performed methods like improved cross validation and other methods to overcome the problem of imbalance in the dataset. Also, we are exploring various machine learning algorithms to train on these features and select the best performing model. The results for the approach are based on accuracy, precision and recall.

Related Work

There are numerous methodologies and techniques used in the area of traffic sign classification to ensure signs are identified correctly for traffic management systems to operate efficiently and accurately. Various deep learning models have provided impressive results when it comes to image classification. One such model is CNN. Convolution Neural

Networks (CNNs) are widely used for traffic sign classification. By taking advantage of the fact that CNNs automatically learn hierarchical representations from raw pixel data, eliminating the need for manual feature extraction. Adrian et al, used Keras and Deep Learning for the traffic sign classification. The images are resized and normalized to have pixel sizes between 0 to 1. The first layer, which is the convolutional layer, creates feature maps by applying filters to the input image. Next an activation function is applied which is mostly ReLU (Rectified Linear Unit) which makes the model non-linear and then the pooling layer reduces the dimensionality. After several iterations through the convolutional and pooling layers a one-dimensional vector is passed through the fully connected layers. This process obtained nearly 95% accuracy.[4]

The alternative models for the traffic sign classification are using neural networks and hierarchical classification techniques. Sylwia Kuros and Tomasz Kryjak, used Quantum Neural Networks. Here, the images are encoded into quantum states by the process called amplitude encoding and then quantum operations are performed on the states followed by a classical convolutional layer and activation function. The obtained final quantum state is used for the classification. This process obtained nearly 94% accuracy.[5]

Idoia Ruiz and Joan Serrat, used hierarchical novelty detection. Here, the model hierarchical taxonomy to find the closest superclass of a novel object. The top-down and flatten methods are the two approaches used. This process obtained nearly an accuracy of 80%.[6]

Other methods which are used for traffic sign classification are the traditional Machine Learning methods like KNN, SVM, Naive Bayes Classifier, etc. These methods show impressive results than the Deep Learning methods.

Data

Image datasets are typically used for training and evaluating the models. This can help in classifying the traffic signs images. As mentioned, we are using images as our data, which is a visual data type. The dataset used in this project was obtained from the German Traffic Sign Recognition Benchmark [7]. The dataset consists of approximately 34000 images, in which each one of them represents a traffic sign belonging to one of 42 classes. The dataset includes a wide-ranging variety, such as speed limits with a series of warnings, besides regulatory signs, encompassing all classes defined by international standards of the road. The dataset images underwent a couple of preprocessing steps. These were to make the dataset appear uniform so that models would perform their operations in machine learning equally. This included normalizing the images to resize them to a standardized output dimension of (32, 32, 3), representing a width of 32 pixels, a height of 32 pixels, and 3 color channels (RGB). Additionally, these images were changed into a standard format (.png) suitable for processing. The Fig.1. shows example images from the dataset. This Dataset includes traffic image signs in different environmental conditions, lighting conditions, which the model needs to handle effectively.

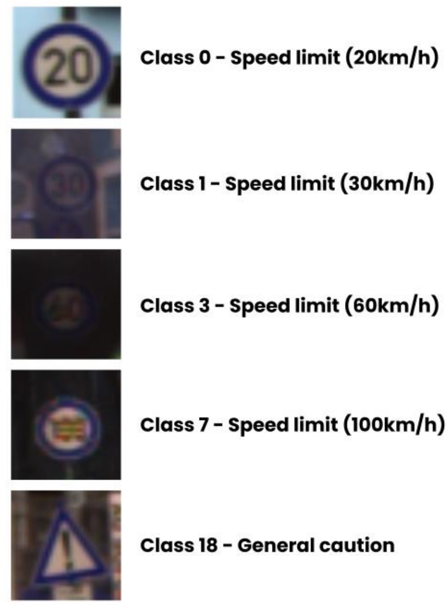

Fig.1. Example images from different classes in the Dataset

The dataset contains a different number of images in each of its categories. As shown in Fig.2, the dataset is irregularly distributed among the 42 classes of traffic signs. The x-axis of the bar graph represents the categories that are unique to each type of traffic sign. The y-axis represents the number of training images available for each category. This imbalance in the dataset, with most images belonging to Class 1 and the least to Class 42, will affect the model performance whereby it will overfit the majority class. It will perform well on the majority class prediction and poorly on the minority class, and hence, this leads to poor generalization of new data.

To address these imbalances and increase the robustness of the model, we use advanced Cross-Validation strategies along with feature scaling, ensemble techniques, and model diversity. We would like to attempt, using these approaches, to bring down the effect of class imbalance and improve generalization performance across all classes.

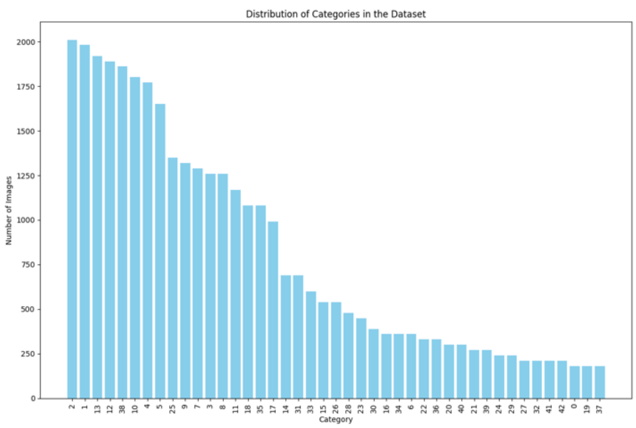

Fig.2. Distribution of Class in the dataset

Methods

Our approach to developing an automated traffic sign recognition system involves constructing and evaluating multiple machine learning models. We aim to identify the model that demonstrates the highest efficacy in classifying a diverse range of traffic signs. The process encompasses feature extraction, model training, and extensive validation using k fold cross-validation. Fig.3. Illustrates the flow diagram for the overall process.

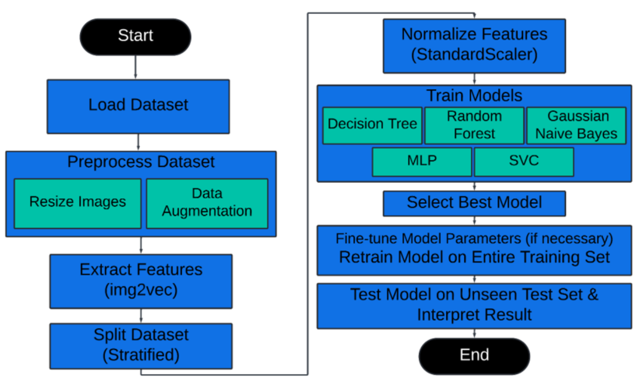

Fig.3. Overview of the methodology

Feature Extraction

After preprocessing, the process of feature extraction was accomplished using the Img2Vec tool. This method involves transformation of the raw images into a format that can be easily handled by the machine learning models. The Img2Vec tool applies deep learning techniques to process essential information from traffic signs into compact feature vectors. This is extremely important because it allows the training of the following models to focus on the most informative parts of the data in order to improve the overall performance of the models. Fig.4. Shows feature extraction visualization for a sample traffic sign input image. The input was an image of a traffic sign sent to the Img2Vec tool, and then it continued to be processed. The output is represented by a feature vector with 512 numerical values. The vector obtained is effectively compressed into a form that machine learning algorithms can more easily process. The vector manages to grasp unique patterns and properties of the traffic sign, which are the reasons why classifier models can properly classify and distinguish the sign properly according to features extracted.

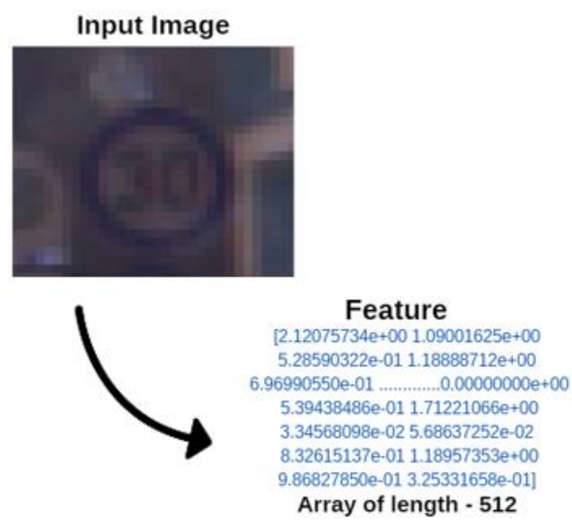

Fig.4. Feature vector of a sample traffic sign image

Model Development and Validation:

The classifiers evaluated include Decision Tree, Random Forest, Gaussian Naïve Bayes, Multi-layer Perceptron, and Support Vector Classifier.

1. Decision Tree

The Decision Tree Classifier serves as a fundamental model in our analysis. It gives us a clear and straightforward mechanism of decision-making through the creation of a model in the form of a tree with decisions and probable outcomes. However, it is prone to overfit, more especially with imbalanced datasets. To address this, stratified k-fold cross-validation was applied, such that in each fold the general class distribution will be mirrored and then the features were standardized using Standard Scaler in order to have a consistent input that helps in generalizing the model towards better performance on unseen data.

2. Random Forest

The Random Forest Classifier is an extension of the decision tree, in that it builds an ensemble of trees in order to make better classification and the ability to avoid overfitting. Such a model is good because it handles variance and bias through multiple trees. We are going to further ensure its effectiveness through stratified k-fold cross-validation to maintain an equal class distribution across each training fold. Also, the features were standardized using Standard Scaler in order to have a consistent input.

3. Gaussian Naïve Bayes

Gaussian Naïve Bayes is a simple and efficient model that operates under the assumption of independence between all of the features. It works quite perfectly with a large dataset and performs well with the inherent class imbalance by adjusting class priors. As a means of evaluating the model, we used stratified k-fold cross-validation besides the standardizing of features using Standard Scaler in order to have consistent input, a very crucial factor for the model is maintaining the integrity and the distribution of the dataset while training.

4. Multi-Layer Perceptron

The Multi-Layer Perceptron Classifier is a type of neural network that can capture complex patterns within data that are not linearly separable. This gives the technique its strength in terms of flexibility and depth of learning capabilities tailored through hyperparameter optimization. The robustness of the model to imbalanced data was further enhanced by performing a stratified k-fold cross-validation process and features were standardized using Standard Scaler to ensure consistent input, which ensures that each subset of data is representative of the whole.

5. Support Vector Machine

The Support Vector Machine Classifier has better performance in high-dimensional spaces. This model is adaptive and, by proper tuning of its hyperparameters, it could be appropriate for an imbalanced dataset. Stratified k-fold cross-validation to ensure comprehensive testing and validation and features were standardized using Standard Scaler to ensure consistent input, which has proven effective in achieving high accuracy and reliability.

After all these models have been trained, the performance of each of the models has been quantitatively assessed using some specific evaluation metrics, including accuracy, precision, recall, and the F1 score. The metric-based evaluation identifies the most effective approach in machine learning for traffic sign recognition to be used for the final system, ensuring that its ability would be realized in performing reliably under varied conditions.

Model Evaluation and Results

In the comparative analysis of machine learning classifiers for recognition of traffic signals, we have chosen a set of evaluation metrics that allow us to have an opinion on how good each of the models perform. We chose accuracy because it directly describes the overall correctness of the model. Precision is important in understanding the proportion of true positives against all positive predictions, a factor that is essential in applications where the consequence of a false positive is significant. Recall was applied to test the model's capability of recognition of all relevant instances, and in cases where a true positive should not be missed, that may prove disastrous. The F1 score, as a weighted average of the precision and recall of the two, was used to get a single measure that can give a balance between the two in cases where both precision and recall are equally important.

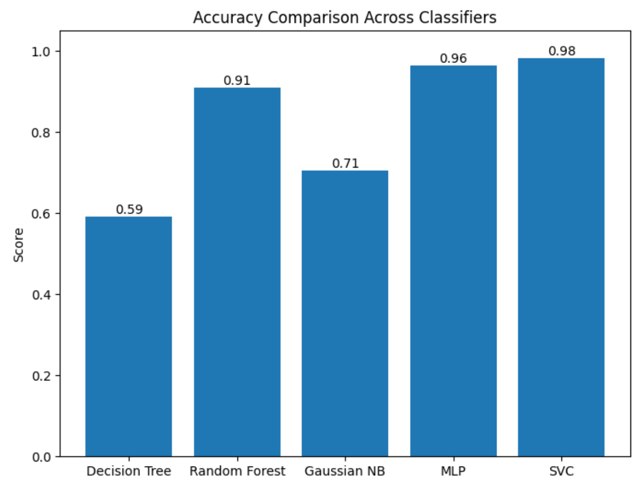

Fig.5. Accuracy Comparison across Classifiers

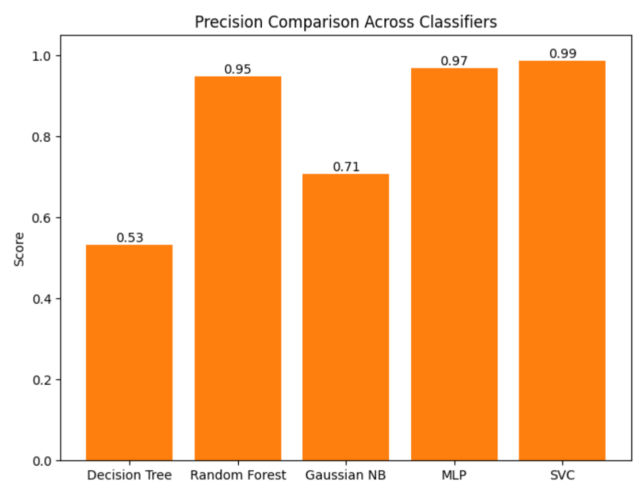

Fig.6. Precision Comparison across Classifiers

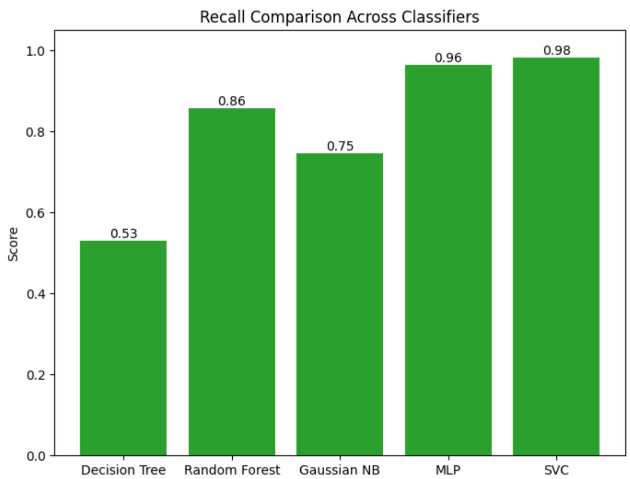

Fig.7. Recall Comparison across Classifiers

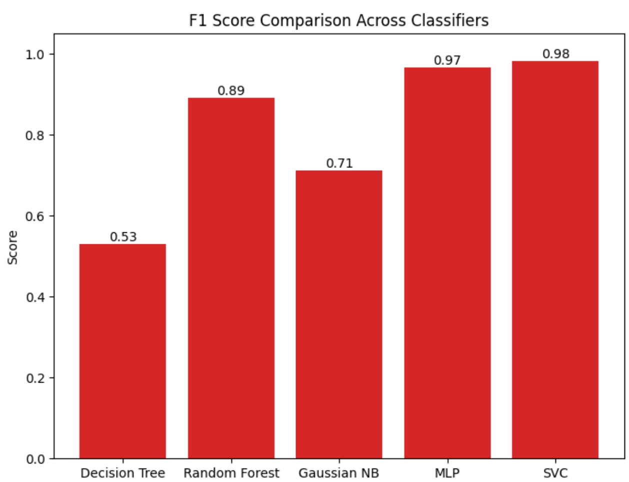

Fig.8. F1 Score Comparison across Classifiers

The Decision Tree Classifier demonstrated a relatively lower performance with an accuracy of 59%, reflecting its susceptibility to overfitting in the context of an imbalanced dataset. The precision and recall both stood at 53%, along with an F1 score of 53%, indicating a potential mismatch between the classifier's structure and the complex patterns within the traffic sign images.

The Random Forest Classifier, an ensemble of decision trees, showed marked improvements with an accuracy of 91%. Its precision at 95% and recall at 86% suggest a better grasp on the data's variance, reducing overfitting significantly. The F1 score of 89% confirms the Random Forest's enhanced ability to manage the balance between recall and precision effectively, making it a strong candidate for traffic sign classification.

With the Gaussian Naive Bayes classifier, we observed moderate success, achieving 71% accuracy. The precision and recall were both at 71% and 75%, respectively, with an F1 score mirroring the precision. The assumption of independence between features is a limitation for this classifier, given the complexity and interdependence of visual features in traffic sign imagery.

Our Multi-Layer Perceptron Classifier performed exceptionally well, with an accuracy of 96% and a comparable F1 score of 97%. The high precision of 97% and recall of 96% suggest that the MLP's tailored architecture effectively captures the underlying complexities in the dataset, providing robust performance for classifying traffic signs.

The Support Vector Classifier achieved the highest scores among all models tested, with an accuracy of 98%, precision of 99%, and recall of 98%. The F1 score at 98% corroborates its exceptional performance. The SVC's adaptability and efficiency in managing high-dimensional, imbalanced datasets make it ideal for our application in traffic sign recognition. Based on the comprehensive evaluation, SVC is our classifier of choice for deploying a system aimed at enhancing the functionality of autonomous vehicles. Fig.9. Shows sample traffic sign images with their corresponding classification outputs, showcasing the system's ability to accurately identify and categorize various traffic signs.

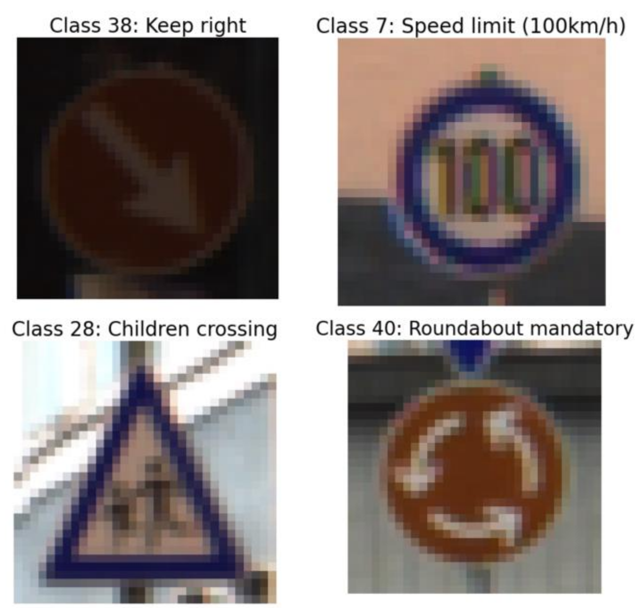

Fig.9. Sample outputs of the Traffic Sign Classifier build using SVC

Conclusion

This study successfully developed a system applying image processing and machine learning techniques for the classification of traffic signs. The developed system encompasses those methodologies applied in preprocessing steps, such as normalization and resizing of images, up to the stage of feature extraction through the Img2Vec tool in preparation for the final stage of machine-learning classification. Different classifiers discussed in the study include a Decision Tree, Random Forest, Gaussian Naïve Bayes, Multilayer Perceptron, and Support Vector Classifier. The classifiers are evaluated for their performance by accuracy, precision, recall, and F1 score measures.

The results obtained from the experiments reveal that while simple models like the Decision Tree, may be prone to overfitting, mostly in cases of imbalanced datasets, more sophisticated models like the Support Vector Classifier having an accuracy rate of above 98%, can handle high-dimensional spaces and robustly manage complex classification tasks. High-dimensional data are known to be better by ensemble methods and neural networks than just basic decision trees, thereby further emphasizing that complex models work. This finding indicates a strong potential for the application of such algorithms in autonomous driving systems to enhance road safety and traffic efficiency.

However, the limitation of this system is that it requires a well-balanced and diverse dataset. Such imbalance in the existing dataset may lead to overfitting, which has been prevented using stratified k-fold cross-validation and other techniques. Nevertheless, an even higher rate of progress can still be made if the data set can be augmented with different conditions of images of traffic signs and if the models are further fine-tuned for better precision in the class of new unseen data.

Future work would be focused towards enlarging the dataset, exploration of the application of convolutional neural networks that can capture better spatial hierarchies in visual data, and integration of the system in a real-time recognition tool for autonomous vehicles. Continuous improvement in the system's capability to accurately classify a wide array of traffic signs in diverse environmental conditions remains a priority.

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