Silly Signs Classifier, HUE, HAARland and pHOGgers

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Motivation

Accurate traffic sign recognition is crucial for road safety. Our research project aims to improve this recognition by exploring the potential of SVM and Random Forest algorithms with the GTSRB dataset. By leveraging machine learning techniques and feature extraction methods like HUE, HAAR-Like, and HOG, we seek to overcome challenges such as variations in lighting conditions and occlusions. Our goal is to enhance the overall reliability and effectiveness of traffic sign recognition systems, contributing to safer and more efficient roads.

Class label

Dataset and Features

The German Traffic Sign Recognition Benchmark dataset is widely employed for evaluating and benchmarking traffic sign recognition algorithms. It was developed by the Institute of Neural Information Processing at the University of Ulm and comprises over 50,000 labeled images of traffic signs obtained from real-world scenarios.
This dataset exhibits high diversity, encompassing 43 distinct classes representing various traffic signs such as speed limits, right of way, and no entry and others.
The classes are distributed approximately uniformly, ensuring a balanced number of samples per class. Each data point in the dataset consists of a color image depicting a traffic sign along with its corresponding label. The images possess varying dimensions, typically around 32 pixels in height and width. Notably, the dataset solely contains the images themselves without any supplementary columns or features beyond their inherent content. [1]

From this dataset, we extracted three types of features: HOG, Haar-like, and HUE features. These features are widely employed for effective image classification purposes.

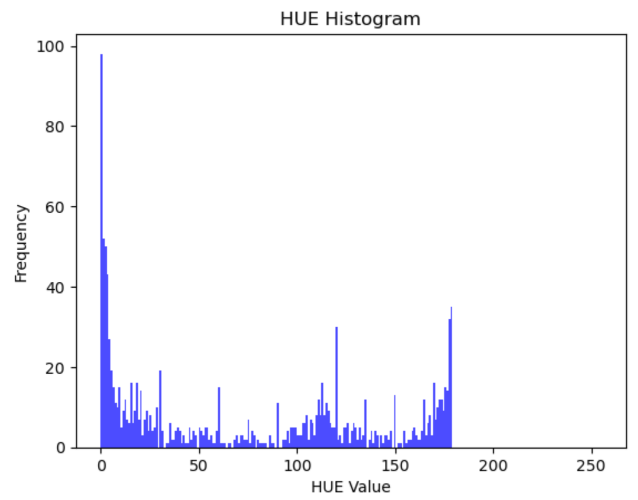
- HOG features encode the local gradient information in an image, capturing the distribution of edge orientations, thereby representing object contours and shapes.
- Haar-like features are simple and computationally efficient, making them suitable for real-time tasks. They are computed by comparing the intensity of adjacent rectangular regions, enabling the detection of basic shapes and patterns.
- HUE features capture the dominant color and color distribution in an image, providing valuable information about object appearance.

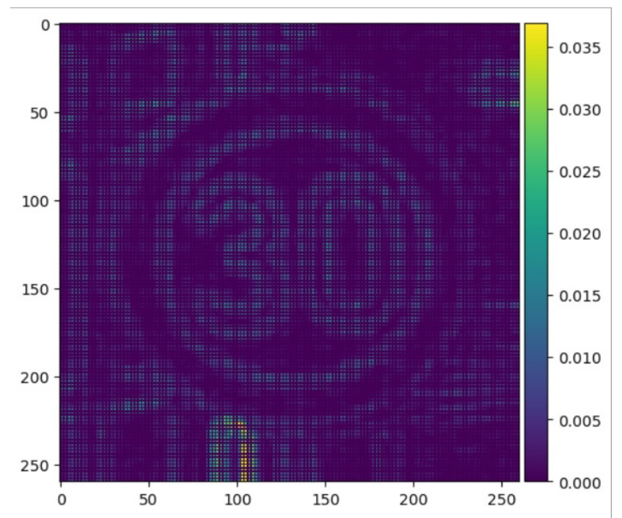
Methods

In our study, we utilized two models, namely Random Forest and Support Vector Machines (SVM). The Random Forest model employs an ensemble learning technique by constructing multiple decision trees during the training process and combining their predictions to achieve precise classifications.

In contrast, Support Vector Machines (SVM) aim to identify an optimal hyperplane that maximizes the separation between different classes in the feature space. In our research, we utilized the radial basis function (RBF) kernel and employed automatic gamma selection.

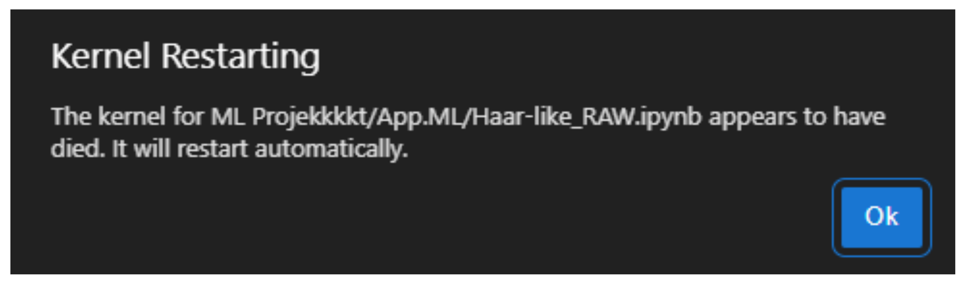
Both the Random Forest and Support Vector Machines (SVM) models were trained and evaluated using the GTSRB dataset. For feature extraction, we employed the Histogram of Oriented Gradients (HOG) method. To ensure consistent scaling, we applied the StandardScaler to normalize the feature for both methods. The performance of the models was assessed using the accuracy_score metric.

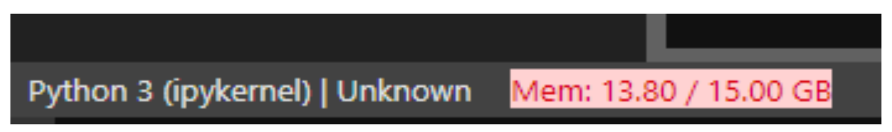




Exemplary Results

- The results of the SVM and Random Forest for the HOG features were pretty high and relative similar to each other
- The results of the SVM and Random Forest for the HUE-Features are compared to HOG Features not accurate and the difference between the models are high. It's interesting that the SVM has a much lower accuracy as the Random Forest
- Extracting the Haar-like Features seems to be requiring a lot of resources. During the extraction we get above our maximum of 15GB of memory and causing the kernel to crash





Evaluation and Discussion

To evaluate our model, we calculated various performance metrics for each individual class, including accuracy, precision, recall, and F1-score. Additionally, we also determined the overall accuracy, which considers the performance across all classes collectively.

- Accuracy measures the overall correctness of predictions across all classes.
- Precision quantifies the proportion of correctly predicted instances for a specific class out of all instances predicted as that class, emphasizing the model's ability to avoid false positives.
- Recall quantifies the proportion of correctly predicted instances for a specific class out of all actual instances of that class, indicating the model's ability to avoid false negatives.
- The F1-score combines precision and recall into a single metric that offers a balanced measure of performance for each class.

Feature	SVM	Random Forest
HOG	98%	94.5%
HUE	57.9%	74.7%
HAAR-LIKE	FAILURE	FAILURE

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Class: 38
Precision: 0.9951807228915662
Recall: 0.9880382775119617
F1-Score: 0.9915966386554621
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Conclusions

Given the existence of previous findings referencing a CNN model with a 99% accuracy, we initially anticipated significantly inferior outcomes with SVM and Random Forest models. However, we were pleasantly surprised by the nearly perfect accuracy achieved. As anticipated, the results obtained from the Random Forest model were inferior to those from the Support Vector Machine.
For forthcoming endeavors, it would be advantageous to expand the database to encompass European street signs, rather than being restricted to German street signs. Additionally, the inclusion of bicycle traffic signs in the dataset is also feasible.

References:
[1] https://sid.erda.dk/public/archives/daaeac0d7ce1152aea9b61d9f1e19370/published-archive.html
[2] Aurelien Geron, Praxiseinstieg Machine Learning, O'Really, 2019
[3] https://www.youtube.com/watch?v=thcB1NcorV8