**TRAFFIC-SIGN RECOGNITION (TSR)**

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# **Abstract**

Identifying traffic signs has become an important issue when debating about vehicle safety applications. Traffic-Sign Recognition (TSR) is currently an important feature for the automotive industry, as self-driving cars are no longer just a futuristic dream and new cars need to be safer and safer in order to minimize accidents produced by human errors. In this paper, we propose a solution for this modern problem based on existing approaches of traffic-sign recognition. Related work focuses on different methods like template matching, convolutional neural networks (CNN), Haar-like features, support vector machines (SVM) method and a few more others, however these methods are not perfect, and each method comes with different downsides. Using deep learning and computer vision preprocessing, the proposed method tries to overcome as many of these disadvantages as possible providing a real-time solution that can be a core part of advanced driver-assistance systems (ADAS). The evaluation of the proposed method consists of training the model using two datasets: the German Traffic Sign Recognition Benchmark (GTSRB) and the Belgium Traffic Sign Dataset (BTSD).

# **Introduction**

Considering an interesting statistic about road traffic injuries brought by World Health Organization [[1](#fno_WHO)], there are around 1.3 million people that die each year as a result of road crashes, from which 93% of these crashes occur in less developed countries and that can be due to a large percentage of older cars that are in circulation, with less equipped safety technology. There are also between 20 to 50 million more people that get injured and from an economic point of view, this causes a cost of 3% of a country's gross domestic product. Keeping in mind this idea there is safe to say that the real-world applicability of detection and recognition of road signs is undeniable. As all new cars sold in the EU will be expected to be mandatory equipped with this type of technology in the near future [[2](#fno_EULaw)], and since the European New Car Assessment Programme (Euro NCAP) place great value on car safety and they also conducted surveys and safety campaigns regarding ADAS, stating that cars of the future need “readable” roads [[3](#fno_EuroNCAP)], this is seen as a challenge to detect different signs not only in different weather or daytime conditions, but also in different road conditions produced by various external factors. Even though the current advanced driver assistance systems use traffic sign recognition, they only have a defined subset of possible signs. It is surprising that there has not been an implementation of an extensive unbiased comparison of sign detection systems. One of the reasons for the slow development of this feature might be the lack of a large benchmark data set that is freely available. The recognition process can be divided into two steps, detection and classification. It is safe to say that the detection takes priority when comparing the two, due to the fact that the state-of-the-art classification methods have a human competitive performance at best. Therefore, the classification can be regarded as solved, at least for the time being.[[4](#fno_mvc)][[5](#fno_dccs)] While most of the attention of sign detection is on particular shapes, such as rectangles and circles, and the type of the sign (speed limit traffic signs), when not focused on a single type of road signs, an additional system should be put in place. In most of the cases, the system uses a color based segmentation, which is followed by a recognition stage. For this approach to work, a large training database with plenty of road signs is needed. In order to minimize the size of the database and get the intended learning process results, the color based segmentation can be replaced by a combination of color and shape detection.

# **Related work**

Early methods had a set of rules in place that restricted color and shape and required that signs appear only in certain regions of an image, these regions are considered to be candidates, which then they are recognized based on a template matching method using other images; such method was used by Michael Shneier [[6](#fno_TemplateMatching)] in his article about road sign detection, where his algorithm performed fast enough to be used in real-time, but it only addressed warning signs and a few regulatory signs, also for blurry or affected images, the algorithm had a lower performance and the candidates couldn’t be properly detected. Further, things have advanced with the emergence of the machine learning concept, and many articles came up with different approaches that use support-vector machines or convolutional networks. In an article by David Soendoro and Iping Supriana, a SVM method is proposed for classifying binary images with localized traffic signs, which are resulted from a color-based method with CIELab + hue [[7](#fno_SVM)]. A more recent take used a CNN with fewer parameters, smaller models and easier training which performed a high accuracy, close to 97%, better than a classical convolutional network [[8](#fno_smallCNN)]. A completely new and bolder approach in the field is a CNN method that uses GPGPU [[9](#fno_CNNGPGPU)] and Nvidia's latest solution in the automotive industry for autonomous vehicles which is called Nvidia DRIVE [[10](#fno_Nvidia)]. This method focuses on solving severe illumination problems regarding low light or wide variance of light like reflection, in images captured from real-world.

Regarding traditional methods, a wide variety of hand-crafted systems, including specific colors and shapes, such as HOG [[16](#fno_tc47)][[17](#fno_tc17)] or SIFT [[18](#fno_zt13)][[19](#fno_gt13)] were used for classification with machine learning models, like SVM, tree classifiers and boosting.

Various traffic sign recognition competitions were held, with the sole purpose to allow scientists from different fields to contribute their results. One of these competitions, GTSRB, had the goal to produce a paper regarding benchmarking learning algorithms for traffic sign recognition. The official results offer an overview of the up-to-date recognition performance [5].  
IDSIA achieved an error rate of 0.54% and it combined several deep convolutional neural network columns and preprocessed the input images as many small blocks [12]. Meanwhile, COSFIRE, used multi-scale CNNs and fused local and global features, achieving an error rate of 1.03%. [14] It should be noted that the GTSRB dataset contains images in which the traffic sign occupies a large proportion of the image, and that in the real world, classifying images in which the traffic signs only occupy a small proportion of the traffic scene is more important and should be the main focus of the researchers.

*Table 1: Performance of various methods in the IJCNN2011 Competition*

|  |  |  |
| --- | --- | --- |
| TEAM | METHOD | ACCURACY |
| DeepKnowledge Seville [[11](#fno_dks)] | CNN with 3 Spatial Transformers | 99.71% |
| IDSIA [[12](#fno_idsia)] | Committee of CNNs | 99.46% |
| COSFIRE [[13](#fno_cosfire)] | Color-blob-based COSFIRE filters for object recognition | 98.97% |
| INI-RTCV [5] | Human Performance | 98.84% |
| sermanet [[14](#fno_sermanet)] | Multi-Scale CNNs | 98.31% |
| CAOR [[15](#fno_caor)] | Random Forests | 96.14% |
| INI-RTCV [5] | LDA on HOG 2 | 95.68% |
| INI-RTCV [5] | LDA on HOG 1 | 93.18% |
| INI-RTCV [5] | LDA on HOG 3 | 92.34% |

# **Beyond State of the Art**

Most of the datasets used in the state-of-the-art algorithms are focused either on one type of sign or have its images with a great focus on the area that the sign is in. Our goal is to start by feeding the algorithm a traffic sign focused dataset, then as we consolidate it, to increase the detection of panoramic images. The datasets used in some challenges have different flaws, mainly because they focus on a specific target, rather than the real life situations.

Another challenge that we are keen to explore is doing the final identification in a time efficient manner. We will take into account that the final solution might be ported on an image capturing device to identify the traffic signs that the driver may not be aware of, in a way that the result of the processing will still be relevant to the user.

We will dive into the user experience side of the problem too. As mentioned before, displaying the result in a way that it does not become a distraction is an issue which has yet to be approached. This not only means that the result has to be presented in a certain way, but a selection process has to take place before deciding if the data is worthy of displaying.

Even though it might sound that we have unreachable goals in mind, we are looking forward to exploring them, and at least making the foundation for the next generation of traffic sign recognition software.

# **Proof of concept**

In our first prototype of our application, we succeeded in building a CNN model based on the GTSRB dataset [[20](#fno_GTSRB)]. In order to accomplish the task, we used Python programming language, along with Numpy module for mathematical calculations, OpenCV for image processing, Tensorflow module and Keras API for neural networks and deep learning support and also Scikit-learn library for easy training and testing a machine learning model.

1. 1. **Preliminary architecture**

The GTSRB dataset is loaded using the images and their labels, described in code as X and y. Since the input images are fairly small (all images are resized to 30x30 pixels), the CNN will run over each image very quickly. The images and their corresponding labels will be splitted into a training model and test model. The shape of X\_train will be (62734, 30, 30, 3) , where the first number represents the number of images on which the model is trained, and the shape of X\_test will be (15684, 30, 30, 3) , where the first number represents the number of images that are being tested on, the next two numbers in each variable is the size of an image, and the last number is the number of color channels, in this case 3 for RGB model . The model is built using Keras Sequential function, which allows us to build the model layer by layer. The layers that will be using are Conv2D layers, which are convolutional layers that uses the input images, seen as 2D matrices, MaxPool2D layers for down-sampling, Dropout layers, which uses a technique of ignoring random neurons based on a rate to better train a model, Flatten layers to make a connection between a Conv2D layer and a Dense layer, latter’s being the output layer in the case of neural networks. The activation method used in Conv2D layers and some Dense layers (except last) will be ReLU, which stands for Rectified Linear Activation and has been proven to work well in neural networks. The last Dense layer will be using the ‘softmax’ activation to transpose the results into probabilities, and a number of 43 nodes, one for each possible class outcome - describing the road signs.

Compiling the model will take as input the Adam optimizer for adjusting the learning rate throughout training, the loss parameter will be ‘sparse\_categorical\_crossentropy’ in order to skip the manual encoding of y variable. The ‘fit’ function will be used for training the model, where the epochs parameter will specify the number of the model run cycles through the data.

In order to classify a traffic sign, it’s mandatory to first detect the sign. An easy way to understand how the application works is presented in the figure below through a pipeline diagram.



*Figure 1: Pipeline diagram of our implementation*

The presumed context is simple: a vehicle equipped with a camera can record the road and capture essential data for detection and recognition of traffic signs, which then can be displayed to the driver for warnings, alerts and informative notifications about the surroundings. From the set of frames of the video input, a carefully selected frame is chosen for detection, the detected regions are then validated before being fed up as input for the recognition classifier, which is based on the model trained using CNN. The recognized signs and based on some other parameters are being analyzed in order to process what message should be provided to the driver as feedback.

There were two approaches tried in order to detect the signs: first one using Fast R-CNN method, which took a long time to train and didn’t give a concludent and satisfactory result, and second one using Maximally Stable Extremal Regions (MSER) which requires some preprocessing of the input image.

For the MSER method, we need to split detection by color (currently we only look for red or blue colored traffic signs), and keeping in mind this idea, we use two different routines for each color in order to achieve best results. Firstly, to address the problem of computing the mask of red colored signs, we need to process the image by performing a contrast normalization over each channel and then normalizing the red channel intensity. The red mask is obtained by binary thresholding with a threshold value close to the maximum intensity value. Secondly, the blue mask is computed by enhancing the contrast of the original image and then converting it to HSV color model for ease of segmentation of the blue color. This way, we can augment out the blue area by defining a lower and upper limit of the blue mask (see figure 2). The resulting red mask and blue mask are merged by a bitwise operation, afterly the merged mask is dilated to enhance its features. Using this mask, the MSER method is applied to detect the regions of presumed road signs. Lastly, some of the regions of interest (ROIs) are dropped out by specifying a minimum area, the bounding boxes detected needs to be square-like and also we are considering the case were boxes are intersecting with each other or included one in another, and if the intersection is large enough, then we can unite one with another. The output of the detection algorithm will be the cropped final ROIs that will be passed on to the recognition algorithm as shown in the middle of the figure 2.



*Figure 2: First line - blue mask and red mask*

*Second line - enhanced merged mask and original image with sign detected in a bounding box*

*In middle - cropped output traffic sign*

* 1. **Preliminary result**

For training our model we used 3 epochs, which took around 160 seconds per epoch to train and then tried different input and compiling parameters.

*Table 2: Performance of various CNN models in the preliminary development process*

|  |  |  |
| --- | --- | --- |
| CNN LOSS FUNCTION | COLOR MODEL | ACCURACY |
| sparse\_categorical\_crossentropy | RGB | 96.31% |
| sparse\_categorical\_crossentropy | BGR | 97.69% |
| sparse\_categorical\_crossentropy | Grayscale | 97.72% |
| categorical\_crossentropy | RGB | 97.19% |
| categorical\_crossentropy | BGR | 98.61% |
| categorical\_crossentropy | Grayscale | 99.05% |

We were satisfied with our first prototype accuracy, the best model (see Table 2) being the model with the images input converted into grayscale and compiled with ‘categorical\_crossentropy’ loss, that produced an accuracy of 99.05%, and not only has the highest accuracy, but it performs 4 seconds faster than the second most accurate that uses OpenCV’s BGR model. We expected that the grayscale model would perform better after studying other papers, and since it has only one channel of color, this explains why it is faster than the other two, but it’s surprising that the BGR model actually came closer to the grayscale model than the RGB model.

Based on the results for detection, which didn’t perform well in low light or high light conditions, we concluded that in order to achieve best results, it’s ideal to have some other inputs than the camera input, that describes the current road condition. These parameters can be obtained from either application integration with the car, which will be equipped with rain and light sensors or other new technology, or they can be obtained from a Bluetooth connection with the driver’s smartphone device that can access the internet and the current location in order to retrieve weather data, which will be passed on as input for our pipeline.

# **Implementation versus State-of-the-Art**

In this chapter, we aim to make a comparison between our implementation and the results from previous competitions with a given dataset. This time we will be looking at the German Traffic Sign Detection Benchmark and the German Traffic Sign Recognition Benchmark.

1. 1. **Detection**

The German Traffic Sign Detection Benchmark is a single-image detection assessment for researchers with interest in the field of computer vision, pattern recognition and image-based driver assistance. It consists of 900 images, divided into 600 training images and 300 evaluation images, and it is divided into three categories that suit the properties of various detection approaches with different properties.

Initially there were three baseline approaches, trained independently. These were the Viola-Jones detector, the HOG feature approach, and a model-based method, Hough-like voting.

It turned out that the detection rate of the Viola-Jones approach was the highest from the pool of independent methods of the chosen category, and the HOG classifier performed comparably well too. It is also notable that the general performance dropped for the mandatory (blue circular) and danger signs (red triangular). Both the model-based and the HOG method could handle this difficulty better due to the use of higher-order shape features.

*Table 3: The detection rate of all the preliminary algorithms [21]*

|  |  |  |  |
| --- | --- | --- | --- |
| Algorithm | Prohibitive | Danger | Mandatory |
| HOG | 91.3% | 90.7% | 69.2% |
| Hough-like | 55.3% | 65.1% | 34.7% |
| Voila-Jones | 98.8% | 74.6% | 67.3% |

The preliminary conclusion was that the classic general-purpose detectors yielded very permission results and clearly outperformed a state-of-the-art model-based approach. However, the performance on the special subsets, such as the mandatory signs, was yet too low for a possible industrial approach.

Therefore a challenge was issued, and teams all around the globe came with new ideas that would prove to be more efficient than expected.

There are seven teams that managed to differentiate themselves from the others by their astonishing results. These teams managed to achieve perfect results in a category.

*Table 4: Competition Ranking by Area-Under-Curve (Average Overlap) [21]*

|  |  |  |  |
| --- | --- | --- | --- |
| Team | Prohibitive | Danger | Mandatory |
| wgy@HIT501 | 100% | 99.91% | 100% |
| visics | 100% | 100% | 96.98% |
| LITS1 | 100% | 98.85% | 92% |
| BolognaCVLab | 99.98% | 98.72% | 95.76% |
| NII-UIT | 98.11% | - | 86.97% |
| wff | - | 99.78% | 97.62% |
| milan | - | 96.55% | 96% |

One thing that can be observed is that the mandatory traffic signs are harder to detect. This can also be attributed to their blue color shades, that seem to be hard to distinguish in natural scenes, and the fact that they are installed near the ground, which makes them prone to deterioration or vandalism.

* 1. **Recognition**

The German Traffic Sign Recognition Benchmark is a multi-class, single-image classification challenge held at the International Joint Conference on Neural Networks. The dataset is large and it is considered a lifelike database. It consists of more than 40 classes, and contains more than 50,000 images in total.

In the final competition stage of GTSRB, four teams managed to differentiate themselves from the rest.

*Table 5: The final ranking of GTSRB IJCNN [20]*

|  |  |  |  |
| --- | --- | --- | --- |
| Team | Representative | Method | Correct recognition rate |
| IDISA | Dan Ciresan | Committee of CNNs | 99.46% |
| INI | - | Human Performance | 98.84% |
| sermanet | Pierre | Sermanet | 98.31% |
| CAOR | Fatin Zaklouta | Random Forests | 96.14% |

During the GTSRB competition, various upgraded algorithms were presented, and a detailed comparison of the traffic sign recognition performance of state-of-the-art machine learning algorithms and humans was made.

The GTSRB conclusion was that, even though the best individual in the human performance experiment achieved a close-to-perfect accuracy of 99.22%, it was outperformed in this challenging task by the best-performing machine learning approach, a committee of convolutional neural networks, with 99.46% correct classification rate. In contrast to traditional computer vision, where hand-crafted features are common, convolutional neural networks are able to learn task-specific features from raw data.[4] However, in return, “finding the optimal architecture of a ConvNet for a given task remains mainly empirical”.[22]

We managed to be as close to the human performance experiment as the latter got to the machine learning approach. Therefore, the difference between our approach, which used categorical crossentrop loss on a grayscale color model and has a correct recognition rate of 99.05%, and the human performance experiment is only 0.17%. Comparing our result with the ones from the GTSRB final ranking would place us in second place, with 0.21% above the third place, and 0.41% under the first place.

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