Traffic Sign Recognition System based on Belief Functions Theory

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Abstract: Advanced Driver Assistance Systems (ADAS) have a strong interest in road safety. This type of assistance can be very useful for collision warning systems, blind spot detection and track maintenance assistance. Traffic Sign Recognition system is one of the most important ADAS technologies based on artificial intelligence methodologies where we obtain efficient solutions that can alert and assist the driver and, in specific cases, accelerate, slow down or stop the vehicle. In this work, we will improve the effectiveness and the efficiency of machine learning classifiers on traffic signs recognition process in order to satisfy ADAS reliability and safety standards. Hence, we will use MLP, SVM, Random Forest (RF) and KNN classifiers on our traffic sign dataset first, each classifier apart then, by fusing them using the Dempster-Shafer (DS) theory of belief functions. Experimental results confirm that by combining machine learning classifiers we obtain a significant improvement of accuracy rate compared to using classifiers independently.

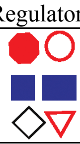
1 INTRODUCTION

Recent technological advancements are expected to steer growth in favour of the global autonomous car industry through 2025. With the emergence of advanced technology, automakers are expected to invest heavily in autonomous and electronic vehicle technology. For instance, “Waymo” began as the Google Self-Driving Car (Google car) Project in 2009 and has been testing its vehicles since early 2017 until now (Waymo Safety Report, 2017).

The continuing evolution of automobile technology aims to deliver even greater safety benefits and automated driving systems that can one day handle the whole task of driving when we don’t want to or can’t do it ourselves. In this context, Traffic Signs Recognition (TSR) System is considered one of the most important Advanced Driver Assistance Systems (ADAS) technologies. It can assist drivers or be part of automatic driving systems in real time in order to facilitate the driving process and optimize the level of safety and comfort on the road.

In fact, in the driving environment, traffic sign types and patterns are incoherent in various countries. Hence, the TSR system uses the combined feature of shape and colour to identify and recognize traffic signs into many categories such as warning, regulatory and informative signs. Table 1 shows the different types of signs used in European roads.

Table 1: European traffic sign categories definition (main categories and shapes).

Danger/Warning	Regulatory	Informative
		

TSR system uses various methods that first detect and extract the candidates’ regions of the traffic sign (ROIs) and then classify them according to predefined classes.

Several methodologies have already been applied to image recognition and have given good results. However, they still suffer from such problems like losing some details of the image when extraction image features and the ineffectiveness of the used classifier. In fact, the loss of information is due to

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many forms of external noise like fading and blurring effect, affected visibility, multiple appearances of the sign, chaotic background, viewing angle problem, damaged and partially obscured sign, etc. Hence, we find ourselves in a situation of indecision where even the use of machine learning algorithms for the classification of traffic sign images does not solve the problem of uncertainty.

Therefore, in order to overcome this limitation, we propose, in this paper, the use of Dempster-Shafer (DS) theory of belief functions (Dempster, 1967), (Shafer, 1976) to make decisions on detected signs with uncertainty (Yager and Liu., 2008). In order to classify ROI images, the DS rules of classifiers fusion will be used by combining the outcomes provided from MLP, RF, KNN and SVM classifiers.

This paper will be structured as follows: section 2 will present the machine learning algorithms and the DS theory applied to traffic sign images. Section 3 will describe our proposed contribution to classify detected traffic signs. Section 4 will show experimental results and discussion. In the conclusion, we will propose some perspectives to extend this work.

2 MACHINE LEARNING AND DS-THEORY

A lot of works were proposed to deal with image classification through different machine learning methods and belief functions, especially the Dempster-Shafer (DS) theory which is based on rule combination and fusion of classifiers.

2.1 Machine Learning

A machine learning classifier is a system able to predict the class of a phenomenon being observed.

The use of a classifier depends on the application and the nature of available data set. In (Ksantini, Ben Hassena and Delmotte, 2017) authors present a comparison between ML classifiers according to 5 criteria: Speed of classification, accuracy, tolerance to noise and Robustness.

There are a variety of applications areas in which ML classifiers can be applied like road safety. In this field of application, several ML classifiers provide good accuracy rates like:

- Multiple Layer Perceptions classifier (MLP) is a single-layer neural network organized in a cascade and subdivided in an input layer, one or more hidden layers and an output layer. (Genevieve, Taif and Wasfy,2019)
- K-nearest neighbour classifier (KNN) is based on a distance function that calculates similarity between the object to classify and its neighbours. (Karthiga, Mansoor and Kowsalya, 2016)
- Support Vector Machine classifier (SVM) is based on the statistical learning theory. Thus, the goal of this method is a binary classification of data. (Anusha and Renuka, 2019)
- Random Forest classifier (RF) is an ensemble of classification trees, where each tree contributes with a single vote for the assignment of the most frequent class to the input data. (Ellahyani, El Ansari and El Jaafari, 2016)

In (Wahyono and Kang-Hyun, 2014), authors employed SVM, RF, KNN and MLP for three types of traffic sign recognition (warning, prohibition and mandatory) from the German Traffic Sign Dataset. Achieved accuracy was 78.7%, 76.3%, 76.3% and 70% for KNN, SVM, RF and MLP classifiers, respectively.

Authors in (Gomes, Rebouças and Neto, 2016) presented obtained accuracy rates of several classifiers for the recognition of the segmented speed limit digits for embedded applications. Obtained results were 87.12%, 97.04%, 98.51% for MLP, SVM and KNN classifiers respectively.

We notice that machine learning algorithms were used to classify different types of traffic sign images with proportional accuracy rates that can be improved by using the strengths of one method to complete the weakness of another algorithm. In the next part we introduce belief functions theory which has been applied to pattern recognition and specially to supervised classification.

2.2 DS Theory

In the previous part, we have presented the classification algorithms which can deal only with certain and complete information. So, in this part we will treat the case of uncertain data by using belief functions theory.

The Dempster-Shafer (DS) theory of belief functions was introduced by Arthur P. Dempster in the context of statistical inference in 1968, and was later developed by Glenn Shafer in 1976 as a theory of evidence. This theory represents the formalism for making decisions with uncertainty. It has been applied to supervised and unsupervised classification (Thierry, 2019).

In (Xu, Krzyzak and Suen, 1992) and (Liu, Pan, Dezert, Han, and He, 2018), the outputs of classifiers have been expressed by the formalism of belief functions and have been combined with the Dempster's rule in the case of classifier fusion.

In (Xu, Davoine, Zha and Denœux, 2016) (Minary, Pichon, Mercier, Lefevre and Droit, 2017), the used approach was the conversion of the decisions obtained from classifiers such as the conversion of the SVM into belief functions.

The basics of DS theory are:

- Mass function m: represents an element of evidence X with value in Ω and m (A) quantifies the belief allocated to the proposition. It is defined by:

$$m:\ 2^{\Omega} \rightarrow [0,1] \text{ with } \sum_{A \subseteq \Omega} m(A) = 1 \quad (1)$$

- Correction of the information: the mass function m and the belief degree in the reliability of the source μ. The new mass function of the weakness operation is:

$$^{\mu}m\,(A) = \mu * m(A)\,;\ \forall A \neq \Omega \quad (2)$$

- Information fusion: the mass function m1 obtained from the source S1 and the mass function m2 obtained from the source S2. The new mass function after the use of Dempster' rule is defined by:

$$(m1 \oplus m2)(C) = \sum_{A,B:\,C=A\cap B} m1(A) * m2(B) \quad (3)$$

- Decision making: we need a pignistic transformation which represents the probability distribution obtained from the fusion result. This transformation is defined by:

$$Betp(\omega) = \sum_{\{A\subseteq\Omega\ ,\ \omega\in A\}} \frac{m(A)}{(1-m(\varnothing))|A|} \quad (4)$$

The decision will be made by choosing the element x with the greatest probability from pignistic transformation:

$$Rp(x) = \underset{x\in\Omega}{\arg\max}\ Betp(\omega)(x) \quad (5)$$

3 PROPOSED METHODOLOGY

Our methodology is based on 3 parts:

- Data processing
- Traffic sign classification using machine learning classifiers (MLP, SVM, Random Forest and KNN)
- Traffic sign classification using DS theory of belief functions for classifiers fusion.

3.1 Data Processing

Given the diversity of road sign pictograms for each country and due to the lack of a French traffic sign dataset Benchmark, we are led to build a dataset mixing road signs images from the German Traffic Sign Dataset and images generated from image processing codes.

We have built a dataset containing 26560 images divided into 15 classes (8 speed limit classes and 7 Mandatory traffic signs classes) shown in figure 1. In fact, the number of samples per class varies from one class to another. The top class (Speed limit 30km/h) has over 3500 examples while the least represented class (Go straight or left) has fewer than 500 examples. This unbalanced dataset depends from the training process.

Our dataset will be gradually incremented in order to reach all the road signs pictograms.

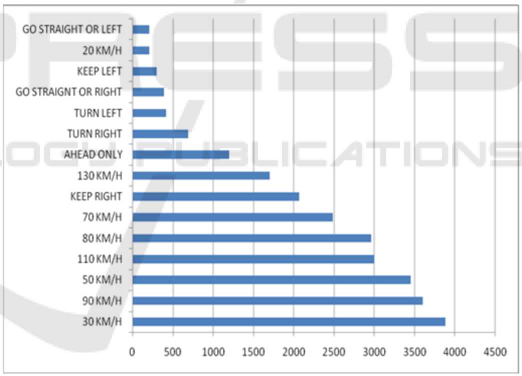

Figure 1: Distribution of traffic sign images.

According to traffic sign image classification; we used histogram of oriented gradient (HOG) feature descriptor in order to extract features from the image. The main reasons to use it are that it is accurate and fast and we can easily run the program on a CPU. In fact, gradients (x and y derivatives) of an image are useful because the magnitude of gradients is large around edges and it is known that edges and corners pack in a lot more information about object shape than flat regions so the gradient intensities of an image can reveal some useful local information that can lead to recognition of the image (Reinaldo, Manurung, Simbolon and Christnatalis, 2019).

After that, machine learning algorithms and DS theory are applied to determine the best accuracy rate for traffic sign classification.

3.2 Traffic Signs Classification using Machine Learning Algorithms

In order to train and test MLP, SVM, RF and KNN classifiers, we first calculate HOG descriptor for every image in the dataset. Then, we split data into a training set (90%) and a testing set (10%). Finally, we save the trained model obtained in order to validate it on other traffic sign images detected from a real time camera.

Experimental results shown in Figure 2, 3, 4 and 5 are presented in the form of confusion matrix which is a table with 4 different combinations of predicted and actual values (TP, TN, FP and FN):

- True Positives (TP): The number of positive instances that were classified as positive.
- True Negatives (TN): The number of negative instances that were classified as negative.
- False Positives (FP): The number of negative instances that were classified as positive.
- False Negatives (FN): The number of positive instances that were classified as negative.

These combinations are extremely useful for measuring Precision, Recall and Accuracy rate:

- Precision, often referred to as positive predictive value, is the ratio of correctly classified positive instances to the total number of instances classified as positive:

$$\text{Precision} = \frac{\text{True positive}}{\text{True Positive} + \text{False Positive}} \quad (6)$$

- Recall, also called sensitivity or true positive rate, is the ratio of correctly classified positive instances to the total number of positive instances:

$$\text{Recall} = \frac{\text{True positive}}{\text{True Positive} + \text{False Negative}} \quad (7)$$

- F1 combines precision and recall as single value:

$$\text{F1} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

We note that all results are obtained with a PC having the hardware configuration: Intel® Core (TM) i5-7200 CPU, 64 bits; RAM: 8GB.

We notice from the previous confusion matrix that the accuracy rate is important: MLP 86%, SVM: 83%, Random Forest: 83% and KNN: 81%. Despite these results, the traffic sign recognition system must

Accuracy: 86.03 %

	precision	recall	f1-score	support
Speed (20km/h)	1.00	0.82	0.90	11
Speed (30km/h)	0.83	0.87	0.85	384
Speed (50km/h)	0.93	0.83	0.88	368
Speed (70km/h)	0.94	0.89	0.91	246
Speed (80km/h)	0.93	0.81	0.86	330
Keep left	1.00	0.95	0.98	22
Turn right	1.00	0.99	0.99	72
Turn left	1.00	1.00	1.00	30
Ahead only	1.00	1.00	1.00	134
Go straight or right	1.00	0.97	0.99	37
Go straight or left	1.00	1.00	1.00	19
Keep right	1.00	1.00	1.00	224
Speed (90km/h)	0.72	0.78	0.75	343
Speed (110km/h)	0.68	0.93	0.79	276
Speed (130km/h)	0.79	0.58	0.67	160
accuracy			0.86	2656
macro avg	0.92	0.89	0.90	2656
weighted avg	0.87	0.86	0.86	2656

Figure 2: MLP Confusion matrix.

Accuracy: 82.91 %

	precision	recall	f1-score	support
Speed (20km/h)	1.00	0.91	0.95	11
Speed (30km/h)	0.84	0.75	0.79	384
Speed (50km/h)	0.85	0.81	0.83	368
Speed (70km/h)	0.93	0.86	0.89	246
Speed (80km/h)	0.90	0.75	0.82	330
Keep left	1.00	1.00	1.00	22
Turn right	1.00	0.99	0.99	72
Turn left	1.00	1.00	1.00	30
Ahead only	1.00	1.00	1.00	134
Go straight or right	0.97	1.00	0.99	37
Go straight or left	1.00	1.00	1.00	19
Keep right	1.00	1.00	1.00	224
Speed (90km/h)	0.60	0.84	0.70	343
Speed (110km/h)	0.75	0.81	0.78	276
Speed (130km/h)	0.77	0.61	0.68	160
accuracy			0.83	2656
macro avg	0.91	0.89	0.89	2656
weighted avg	0.84	0.83	0.83	2656

Figure 3: SVM Confusion matrix.

Accuracy: 82.83 %

	precision	recall	f1-score	support
Speed (20km/h)	1.00	0.55	0.71	11
Speed (30km/h)	0.92	0.75	0.83	384
Speed (50km/h)	0.90	0.82	0.86	368
Speed (70km/h)	0.94	0.84	0.89	246
Speed (80km/h)	0.97	0.74	0.84	330
Keep left	0.96	1.00	0.98	22
Turn right	1.00	0.99	0.99	72
Turn left	1.00	1.00	1.00	30
Ahead only	1.00	0.99	1.00	134
Go straight or right	1.00	1.00	1.00	37
Go straight or left	1.00	1.00	1.00	19
Keep right	0.99	1.00	0.99	224
Speed (90km/h)	0.55	0.88	0.68	343
Speed (110km/h)	0.68	0.85	0.75	276
Speed (130km/h)	0.82	0.51	0.63	160
accuracy			0.83	2656
macro avg	0.92	0.86	0.88	2656
weighted avg	0.86	0.83	0.83	2656

Figure 4: RF Confusion matrix.

Accuracy: 81.36 %

	precision	recall	f1-score	support
Speed (20km/h)	0.82	0.82	0.82	11
Speed (30km/h)	0.83	0.80	0.81	384
Speed (50km/h)	0.78	0.83	0.81	368
Speed (70km/h)	0.97	0.86	0.91	246
Speed (80km/h)	0.75	0.81	0.78	330
Keep left	1.00	1.00	1.00	22
Turn right	1.00	0.99	0.99	72
Turn left	1.00	1.00	1.00	30
Ahead only	1.00	1.00	1.00	134
Go straight or right	1.00	1.00	1.00	37
Go straight or left	1.00	1.00	1.00	19
Keep right	1.00	1.00	1.00	224
Speed (90km/h)	0.68	0.68	0.68	343
Speed (110km/h)	0.78	0.67	0.72	276
Speed (130km/h)	0.56	0.67	0.61	160
accuracy			0.81	2656
macro avg	0.88	0.87	0.88	2656
weighted avg	0.82	0.81	0.82	2656

Figure 5: KNN Confusion matrix.

have the minimum of possible errors in order to ensure road safety requirements.

Therefore, we choose to use DS theory in order to improve further the accuracy rate of TSR system.

3.3 DS Theory

Given the mass function for every classifier of the DS theory (m1, m2, m3 and m4) for respectively MLP, SVM, RF and KNN classifiers, we have got 11 types of combination (data fusion) between classifiers based on the mass's combination DS rule:

- $m1 \oplus m2$
- $m1 \oplus m3$
- $m1 \oplus m4$
- $m2 \oplus m3$
- $m2 \oplus m4$
- $m3 \oplus m4$
- $m1 \oplus m2 \oplus m3$
- $m1 \oplus m2 \oplus m4$
- $m1 \oplus m3 \oplus m4$
- $m2 \oplus m3 \oplus m4$
- $m1 \oplus m2 \oplus m3 \oplus m4$

The pignistic transformation of the obtained masses helps us to make a decision about the obtained algorithms after fusion.

4 EXPERIMENTAL RESULTS AND DISCUSSION

Before using information fusion, each classifier has a degree of weakness. Table 2 represents the error rate of the classifiers MLP, SVM, RF and KNN on validation data set.

Table 2: Degrees of weakness of MLP, SVM, RF and KNN.

Classifier	MLP	SVM	RF	KNN
Weakness Degree	13.97	17.09	17.17	18.64

In our experiments, we have used the Dempster-Shafer theory in fusion of two, three and four machine learning classifier outputs in order to decrease the weakness degrees. Hence, by using (2), the new mass functions were then combined by Dempster-Shafer rule (3) associating 2, 3 and 4 classifiers.

The decision was made by the pignistic risk (4) and (5) that shows the performance of belief functions in terms of error rate in test set. Obtained results are summarized in Table 3, 4 and 5.

Table 3: Degrees of Accuracy and Weakness after combining two classifiers.

Combined Classifiers	Accuracy Rate	Degrees of weakness of fusion
MLP and KNN	97.37 %	2.63 %
MLP and RF	97.56 %	2.44 %
MLP and SVM	97.53 %	2.47 %
KNN and SVM	97.41 %	2.59 %
KNN and RF	97.44 %	2.56 %
SVM and RF	97.54 %	2.46 %

Table 4: Degrees of Accuracy and Weakness after combining three classifiers.

Combined Classifiers	Accuracy Rate	Degrees of weakness of fusion
MLP and SVM and KNN	99.32 %	0.68 %
MLP and SVM and RF	99.34 %	0.66 %
MLP and KNN and RF	99.33%	0.67 %
SVM and KNN and RF	99.33%	0.67%

Table 5: Degrees of Accuracy and weakness after combining four classifiers.

Combined Classifiers	Accuracy Rate	Degrees of weakness of fusion
MLP and SVM and KNN and RF	99.85 %	0.15

As a conclusion, the results obtained from the different confusion matrix of different classifiers have shown that the accuracy of these algorithms is excellent for predicting obligation traffic signs (keep right, ahead only, turn right, turn left, keep left, go straight or left) and good for some speed limit signs (20 km/h, 70 km/h and 80km/h) but some problems have appeared for identifying the other speed limit traffic signs correctly.

In addition to that, we have shown that the information fusion has the lowest error rate in comparing with other classifiers. So, the accuracy obtained using Dempster-Shafer theory in traffic sign classification is better than that obtained using machine learning classifiers independently.

5 CONCLUSION AND PERSPECTIVES

Driving assistance systems can help drivers and automatic driving systems to avoid the occurrence of a dangerous situation that could lead to an accident, free the driver from a number of tasks that could reduce their vigilance and assist him in his perception of the environment. Therefore, safety and reliability validation of Advanced Driver Assistance Systems (ADAS) is strongly recommended.

In this paper, we have proposed a methodology based on Machine Learning algorithms and belief functions theory to improve the performance of TSR systems. We carried out a combinatorial study of several classifier outputs in order to find the best combination leading to this improvement. For this, we have classified data into 15 sets based on pictograms. Then, firstly, we have used machine learning algorithms (MLP, SVM, RF and KNN) to classify detected signs. Secondly, we have applied DS theory by combining 2, 3 and 4 of the previous classifiers. This methodology has given us better results than using the different classifiers each one apart.

As perspectives, we will extend our traffic sign dataset by other classes in order to obtain a full French traffic sign dataset then we would apply Dempster-Shafer theory on deep learning algorithms and compare obtained results with this work.

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