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A Study on Traffic Sign Detection and Recognition Systems Using Machine Learning

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Abstract
In recent times, Advanced Driver Assistance Systems (ADAS) and Autonomous Driving Systems (ADS) have become the major research areas in the automobile sector. Further, Traffic Sign Recognition (TSR) plays a significant role in ADAS and ADS. Therefore, TSR can be classified in two stages: Detection and Recognition through classification. In the traffic system, detecting traffic signs is tricky because of the signs' shapes, sizes, and complexity of the scenes in which they appear. Moreover, the vision parameters also play a vital role. Certainly, we have seen significant developments in machine learning (ML) and deep learning (DL) methodologies in recent years. Eventually, it has become the mainstream method that helps to detect and classify signs and has achieved phenomenal results. In this paper, we have reviewed and evaluated several ML-based methods for TSR with their performance.

***Keywords**: Machine learning, Deep Learning, Neural Network, Traffic Sign Detection*

Introduction

The electronics and software have been widely used in the Traffic Sign Detection and Recognition system for various uses. These systems are mainly concentrated on Light Detection and Ranging (LiDAR) and cameras that are managed by the essential sensing mechanism. Most of the software has been comprised of pattern recognition and computer vision algorithms to procure better outcomes. The main primary process of the system is to detect and locate the traffic sign with the provided scenes, and this information is utilized as an input in order to track and classify [1]. Therefore, the accuracy of the entire process significantly influences the performance evaluation of ADS and ADAS.

Moreover, there are several methods have been developed and executed in order to perform the TSR. One of the primary and early methods of traffic sign recognition is utilizing the shape and color of the signs to predict the environment [1] [2]. Hence, these systems are entirely based on color and shape, focusing on notifying the human driver regarding the presence and nature of traffic signs. Table 1 and Table 2 explain the traffic signs' color meaning, and shapes denoted in the traffic system [2].

Table 1 - Standard Road Sign Backgrounds and their Meaning

Colour	Meaning	
Red	Prohibition and warning	
Blue	Directive	
Green	Guidance and Milage	
Orange	Construction and maintenance	
Brown	Recreation	
Yellow	Warning	
White	Auxiliary	

Table 2 - Standard Road Sign shapes and their Meaning

Shape	Meaning
Circle	Prohibition
Equilateral triangle pointing up	Warning
Equilateral triangle pointing down	Yield
Octagon	Stop
Diamond	Construction and maintenance
Rectangle	Regulation and guidance

There are several techniques have been developed and proposed in the existing system to detect colors from traffic signs. Further, five significant categories have been classified and summarized in Table 3. It is considered that color plays an essential role in the traffic system and provides distinct features that help the drivers to capture the situation and assist the researchers in designing an effective traffic sign detection system.

Table 3 - Summary of colour-based traffic sign recognition

Category	Paper	Year	Method
RGB Based Thresholding	[3]	2019	Adaptive Color Thresholding Segmentation
	[4]	2020	Variable Thresholding
	[5]	2020	Global Optimum Thresholding
Hue and Saturation Thresholding	[6]	2020	Histogram Equalization-based HSV space
	[7]	2021	CNN-based HSV - Hue, Saturation Value
Thresholding other spaces	[8]	2022	Ohta Thresholding
	[9]	2021	Ohta Thresholding
	[10]	2019	Lab Thresholding
Chromatic/Achromatic Decomposition	[13]	2020	Empirical Mode Decomposition - EMD
	[14]	2019	RGB, HSV, achromatic segment
Pixel Classification	[11]	2020	Convolutional Neural Network (CNN)
	[12]	2021	Traffic Sign - TS-Yolo-based CNN

It is significant to use appropriate traffic signs in the detection process; therefore, the Shape-based characteristics are utilized to identify it. There are four different categories: Shape Detection, Shape Matching & Analysis, Fourier Transformation, and Key-points Detection, that has been summarized in Table 4. Moreover, the methods have the ability to detect the shape contours, including triangles, circles, rectangles, and octagons.

Table 4 - Summary of shape-based traffic sign detection systems

Category	Paper	Year	Method
Shape Detection	[15]	2019	Triangle, Rectangle, and Other shapes
	[16]	2020	Different Shapes
	[17]	2020	Different shapes
Shape Analysis and Matching	[18]	2019	Rectangular, Octagonal, Inverted Triangular, and Triangular Circular
	[19]	2019	Rectangle, Triangle, Octagon, and Circular
Fourier Transformation	[20]	2020	Circle, Diagonal Bar, Horizontal Bar, and Vertical Bar
	[21]	2019	Different Shapes
Key-points Detection	[22]	2021	Circle, Triangle, and Rectangle
	[23]	2020	Curves and Lines
	[24]	2020	Ellipses, Octagons, Rectangle, and Triangles

Furthermore, apart from the color or shape-based methods, there are a few different techniques like Maximally stable Extremal Regions MSERs can be utilized to recognize both color and shape. Further, these methods are utilized in high contrast regions like uniform grey tones with shapes. It is also used to extract the colored regions within traffic signs and detect text-based traffic signs in the traffic system.

Different ML-based techniques such as SVM, CNN, and AdaBoost have been utilized in the traffic detection system; however, techniques like the CNN model cannot be trained in the experimentation for different dimension images. Sometimes, it is difficult to solve real-time issues. Moreover, the major drawback of traffic sign visual recognition is that it is difficult to analyze certain conditions such as blurring, noise, orientation, and scale changes.

The main contribution of this paper is to study the different ML-based techniques for traffic sign detection and recognition systems with the appropriate comparative analysis and studies of the existing techniques in this paper. Moreover, the different methods of TSD and TSR have been elaborated in this study with comparison tables that concentrate on different ML techniques. The current study will provide a proper perception of different ML-based techniques to help the researchers find an effective solution in the traffic detection system.

Overview of Machine Learning Based Methods

Machine learning (ML) or Deep Learning (DL) techniques have become popular in recent years, and these techniques have been actively deployed to address traffic sign detection and recognition. Therefore, the traffic sign detection-based ML techniques include AdaBoost, Support Vector Machines (SVM), and Neural Networks. The different existing techniques used in the transport system have been summarized in Table 5.

Table 5 - Overview of Machine Learning (ML) Methods utilized in the Transport System

Category	Paper	Year	Features	Training method and detection structure
AdaBoost based methods	[25]	2019	Cascade	Synthetic Aperture Radar (SAR)
	[26]	2019	Harri-like rectangular	Millimeter-wave radar
	[27]	2019	Structure Haar	Classifier
	[28]	2020	Temporal and Network traffic	Decision Tree, SMO - Sequential minimal optimization, PNN - Probabilistic Neural Network
	[29]	2020	Network Traffic	AIDS - Anomaly-based Intrusion Detection System
	[30]	2020	Network Traffic	Multiple training, Boosting
	[31]	2021	Integration of traditional artificial and Morphological Features	Multiple U-nets, end-to-end model
	[32]	2021	Haar-like	Adaboost classification
	[33]	2020	Object recognition features	Cascade Classifier
SVM based methods	[34]	2019	Signal	SVM-based classification
	[35]	2019	Point-based	SVM-based Point Cloud-Classification
	[36]	2019	LBP, HOG	SVM-based traffic-density
	[37]	2020	Hand-crafted illumination	SVM-based classifier
	[38]	2020	Twelve-fold	SVM-based pattern-recognition
	[39]	2019	Discrete and continuous Features	TRedSVM - Collaborative Classification Method-based on SVM
	[40]	2020	HSG, NRULBP descriptors	Heuristic SVM
	[41]	2022	Traffic Data	SVM-based Real-time-identification Technique
	[42]	2021	Correlated Features	SVM-based intrusion-detection
	[43]	2021	Raw traffic data	Kernel-SVM
CNN based methods	[44]	2020	Faster R-CNN	
	[45]	2019	Pyramidal Convolutional Networks	
	[46]	2020	YOLOv3	
	[47]	2020	YOLOv4	
	[48]	2020	Dense-RefineDet - Deep-learning-based, Object-detection framework	
	[49]	2019	CNN-based object detector	
	[50]	2019	DeepCNN	
	[51]	2019	Ensemble CNN	

AdaBoost Methods

AdaBoost - Viola and Jones proposed adaptive Boosting [31], and it is considered an efficient algorithm utilized for object detection issues, including face detection. Moreover, this method uses Haar-like features depicted in Figure 1 with the integral images. The AdaBoost algorithm and cascading classifier are used to create a rapid and accurate object detection system. Therefore, these techniques can be effectively used for traffic sign detection.

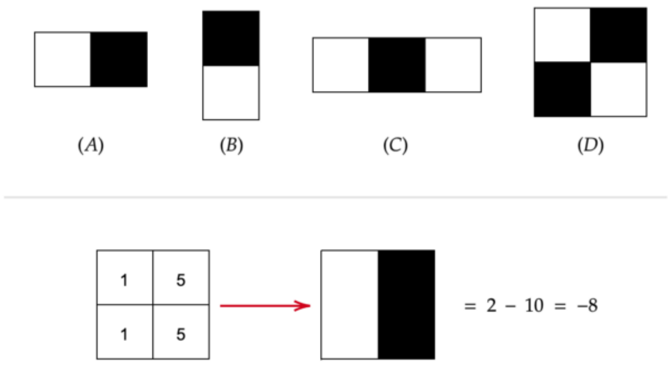

Figure 1 - Haar-like Features

SVM Methods

SVM - Support Vector Machines [34] [37] is considered as a type of supervised ML algorithms that can be utilized for solving most of the classification and regression challenges. Therefore, these techniques has been utilized with the hyperplane decision boundary that are normally determined between classes of features. An illustration is represented in Figure 2.

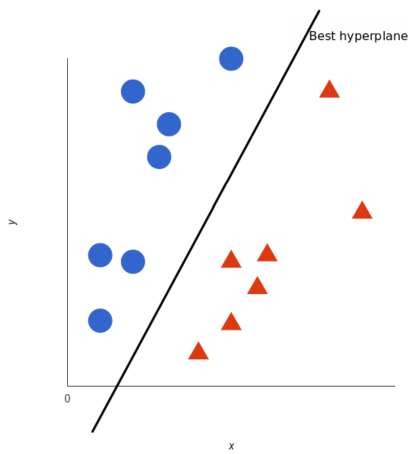

Figure 2 - SVM determining the best hyperplane that separates two classes of features

According to existing techniques, traffic sign detection has been mainly classified into three stages: The first stage defines the colour segmentation that can be achieved utilizing thresholding techniques with the HSI - Hue, Saturation, and Intensity colour space. The second stage defines the shape classification that is achieved utilizing the application of SVM techniques. Finally, the third stage defines the pattern recognition achieved using non-linear SVM techniques.

CNN Based Methods

The main use of CNN - Convolutional Neural Networks has been used for TSD - Traffic sign detection issues stated in [50] and [51]. Moreover, the SVM and AdaBoost-based methods use manually fabricated methods to achieve efficient results. Certainly, the CNN features are determined through the use of NN - Neural Networks. Further, NN has been used in a breakthrough for crafting a solution to traffic sign detection and recognition problems. The CNN is considered a DL algorithm that can take an input image and assign weights to various distinguishable objects in the specific image in order to differentiate one from the other. The schematic representation of the CNN is depicted in Figure 3.

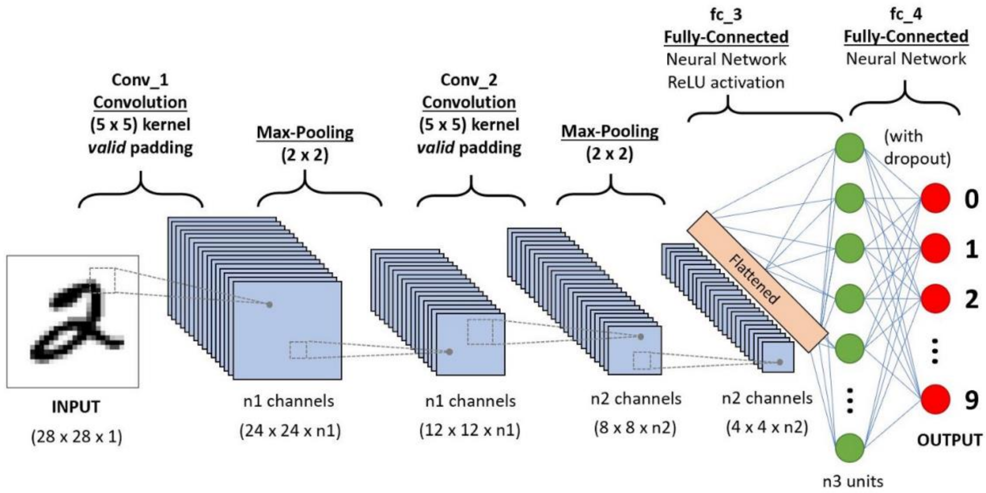

Figure 3 - Convolutional Neural Network Layers

The input image will be taken as pixel values in the matrix format with the appropriate dimensions in the CNN layers, including width, height, and depth. Therefore, the convolutional layer computes the output of neurons connected to the local regions of the input. The parameters are composed of kernels - a set of learnable filters that are convolved across the input image to produce the activation map. As a result, the network learns that the filters can get triggered with certain features which pop up on the input image. Moreover, the Rectified Linear Unit (ReLU) layer will normally perform an element-wise activation function, and it can be defined as [53]:

$$F(x) = \max(0, x)$$

The pooling layer has been generated with the maximum activation in a given region. The output layer is considered a fully connected layer. It is commonly utilized with softmax activation to evaluate the output probability distribution over the number of output classes to achieve the required output classification. In order to use CNN in TSD - Traffic Sign Detection and TSR - Traffic Sign Recognition, the appropriate object detection techniques should be utilized to train the CNN that helps in traffic signs detection and recognition with the standard datasets.

Object Detection Techniques

In this section, the different approaches to object detection have been discussed with a comparison of the existing methods. In recent years, various advances have been made in ML and pattern recognition using CNNs. Therefore, apart from the regular CNN techniques, several advancements have been made to improve the outcome's performance. Moreover, various techniques, including R-CNN, Fast R-CNN, and YOLO, have emerged with the recent development in a faster and more compact way.

Furthermore, the R-CNN model generates features in a specific targeted region using CNN techniques. According to the algorithms utilized in the existing system, the selective search is employed to extract 2000 regions from the entire input image, and these regions have been referred to as region proposals. Hence, the sunsets of these regions are identified in the image and are employed for object classification in the regions. It is significant to note that instead of classifying a large number of regions, it has been used 2000 regions [54].

The existing CNN-based techniques are utilized in different scenarios, and in recent research, the upgraded version - Fast-RCNN has been utilized to enhance the performance of the network. Instead of feeding the region to the CNN, the input image is fed to the CNN in order to generate a convolutional feature map, and the feature map has been used in the region to identify and warp into squares. Further, utilizing a Region of Interest (RoI) pooling layer, feature maps are reshaped into fixed sizes so that they can act as an input into a fully connected layer. In most research, the Softmax layer is used to classify certain explored regions to produce the boundary box's offset values.

In [55], the Faster-RCNN has been utilized to eliminate the selective search and enable the network to learn the region proposals. Therefore, the image has been provided as an input to a convolutional network that provides a convolutional feature map similar to Fast R-CNN. However, a separate network has been utilized to identify the region proposal rather than using a selective search algorithm on the feature map. Then, an RoI pooling layer has been used in the predicted region proposals to reshape, and it helps in the classification of images that exist in the proposed region in order to predict the offset values for the bounding boxes.

Moreover, the You-Only-Look-Once (YOLO) has been used to look at a different section of the images rather than looking at the complete image to obtain a high probability of containing the object in concern. A single CNN has been used to predict multiple bounding boxes with the class probabilities [56]. Table 6 provides the Comparison of YOLO techniques with the existing techniques.

Table 6 - Comparison of YOLO with other CNN techniques

Fast RCNN	R-CNN	YOLO
Classification-based	Classification-based	Regression-based
Utilizes single-deep convent	Utilizes 2000 conv-Nets for every region	Utilizes single CN for entire image
Utilizes selective search method	Utilizes selective search method	-
Requires 49secs to test a single image	Requires 2.3secs to test a single image	Requires less than 2secs to test a single image
Faster compared to RCNN	Slow execution and cannot be implemented in the real-time	Can be executed in real-time environment
Utilizes Softmax for classification	Utilizes SVM for classification	Utilizes Regression for Classification
Generates Bounding Box Regression Head and CH - classification head	Generates Bounding Boxes	Generates Bounding Box and contextual prediction concurrently
Able to find small objects	Able to find small objects	Facing struggle to find small objects that appear in groups

Standard Datasets

The dataset contains a collection of data, and every ML and DL techniques need an appropriate dataset to train the data and procure an efficient outcome. Certainly, it is difficult to compare the TSR methods utilized in different countries to identify the traffic sign due to variations in the datasets [1]. However, the data of TSR algorithms available publicly has been summarized in Table 7.

Table 7 - List of Publicly available datasets for TSD and TSR Studies

Dataset	Public Dataset Details					
	Purpose	Classes	Total Images	Total Signs	Image Size	Country
GTSDB	Detection	43	900	1,213	1,360 x 800	Germany
GTSRB	Recognition	43	50,000+	50,000+	15 x 15 to 250 x 250	Germany
BTSD	Detection	62	4,627	4,627	1,628 x 1,236	Belgium
BTSC	Recognition	62	7,125	7,125	26 x 26 to 527 x 674	Belgium
TT100k	Detection/Recognition	45	30,000	30,000	2,048 x 2,048	China
LISA	Detection/Recognition	49	6,610	6,610	640 x 480 to 1,924 x 522	United States
STS	Detection/Recognition	7	3,488	3,488	1,280 x 960	Sweden
RUG	Detection/Recognition	3	60	60	360 x 270	Netherland
Stereopolis	Detection/Recognition	10	251	251	960 x 1,080	France
FTSD	Detection/Recognition	N/A	N/A	N/A	640 x 480	Sweden
MASTIF	Detection/Recognition	N/A	13,036	13,036	720 x 576	Croatia
ETSD	Recognition	164	82,476	82,476	6 x 6 to 780 x 780	Europe

Analysis of Machine Learning Based TSD and TSR

The different methods, including AdaBoost, SVM, and CNN-based, are reviewed. The comparison results on the public dataset GTSDB, BTSD, TT100k, and LISA have been listed in Table 8 with the methods utilized in the existing system with Prohibitive, Danger, Mandatory, and Time that evaluates the Area Under Curve(AUC), Average Precision (AP), recall, and accuracy. Moreover, the test sets of the small, medium, and large size signs have been depicted with the references as “Small,” “Med,” and “Large.”

Table 8 - Comparison on TSD methods against the publicly available Datasets.

Dataset	Methods	Prohibitive (AUC)	Danger (AUC)	Mandatory (AUC)	Time(s)
GTSDB	HOG+LDA	70.33%	35.94%	12.01%	NA
	Hough-Like	26.09%	30.41%	12.86%	NA
	Viola-Jones	90.81%	46.26%	44.87%	NA
	HOG+LDA+SVM	100%	99.91%	100%	3.533
	ChnFtrs	100%	100%	96.98%	NA
	HOG+SVM	99.98%	96.46%	95.76%	3.032
	SVM+Shape	100.00%	98.85%	92.00%	0.4 - 1.0
	SVM+CNN	NA	99.78%	99.62%	12.0 - 32.0
	SFC-tree	100%	99.20%	98.57%	0.192(3.19 GHz CPU)

	CNN	99.89%	99.93%	99.16%	0.162(Titan X GPU)
BTSD	ChnFtrs	94.44%	97.40%	97.96%	1.0 - 3.0 (Intel Core i7 870 CPU, GTX 470 GPU)
	AdaBoost+SVR	93.45%	99.88%	97.78%	0.05 - 0.5 (Intel Core i7 4770 CPU)
	Faster-RCNN	43.93% (Small) 97.8% (medium) 98.31% (large)			0.165 (Tesla K20 GPU)
TT100K	Fast - RCNN	Recall 56% Accuracy 50%			NA
	Faster-RCNN	AP% 31.22%(Sm) 77.17%(med) 94.05%(lar)			0.165 (Tesla K20 GPU)
	Multi-class Network	Recall 91% Accuracy 88%			NA
LISA	ICF	87.32% (diamond)	96.03%(stop)	91.09%(No Turn)	NA
	ACF	98.98% (diamond)	96.11%(stop)	96.17%(No Turn)	NA

Conclusion

We presented a study on traffic sign recognition and identification that utilizes various Machine Learning techniques with the appropriate comparative analysis and studies of the existing techniques in this paper. Moreover, the different methods of TSD and TSR have been elaborated in this study with comparison tables that concentrate on different ML techniques. Further, the color and shape-based methods have been identified and explained thoroughly; however, they may not be appropriate for complex scenarios. Furthermore, it is noted that most of the development of ML-based techniques has been processed on publicly available datasets. Nevertheless, these techniques should be improvised to check their contemporary applications, including self-driving cars. It is important to find an efficient solution using an ML-based method to develop a state-of-the-art result even while handling the complex scenes, vague signs, and HD images. Eventually, it is necessary to check whether the applied techniques are well recognized and improved based on certain parameters, such as accuracy in the traffic detection system. This study will provide proper insights into different ML-based techniques that will help the researchers find an efficient and appropriate solution for the traffic detection system in the future.

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