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SURVEY ON TRAFFIC SIGN DETECTION AND RECOGNITION USING AI AND ML

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ABSTRACT

The delineation and identification of traffic signs hold paramount significance within the realms of advanced driver-assistance systems (ADASs) and autonomous driving systems (ADSs). Serving as the inaugural pivotal stride in traffic sign recognition (TSR), traffic sign detection (TSD) poses formidable challenges attributed to the diversity of signage types, their diminutive dimensions, the intricacies of driving scenarios, and instances of occlusion.

In contemporary discourse, a plethora of TSD algorithms grounded in machine vision and pattern recognition have emerged. This treatise endeavors to furnish a comprehensive exegesis of the extant literature concerning TSD. Methodological categorization is deployed, discerning five principal classifications: color-centric methodologies, shape-centric methodologies, hybrids amalgamating color and shape cues, methodologies predicated on machine learning paradigms, and those leveraging LIDAR data. Within each category, further granularity is attained through the subdivision of methodologies into distinct subcategories, thus facilitating a nuanced comprehension and synthesis of their operational mechanisms. For those methodologies within the purview of this review lacking comparative analyses on publicly available datasets, we undertake the initiative of reimplementation, enabling a comparative evaluation. The ensuing experimental juxtapositions and analyses are expounded upon, encompassing both the reported performance metrics and those derived from our reimplementation efforts.

Keyword Neural Nets (NN), Support Vector Machines (SVM), Adaboost, Traffic Sign Detection (TSD), And Traffic Sign Recognition (TSR).

I. INTRODUCTION

The exploration of computer vision and pattern recognition for traffic sign detection, tracking, and classification stands as a scholarly pursuit of considerable import, notably in the realms of Advanced Driver Assistance Systems (ADAS) and Auto Driving Systems (ADS)[1]. Traditionally, traffic sign recognition (TSR) systems are bifurcated into distinct phases: detection and classification. For select TSR frameworks, an intermediary tracking phase is interposed between detection and classification to manage video sequences effectively. Predominantly, cameras and LIDAR serve as the two most prevalent sensing modalities employed in TSR systems[2-3].

This exposition undertakes a meticulous review of the literature on traffic sign detection (TSD), delineated by camera or LIDAR-based methodologies, followed by a comparative analysis of the extant methods grounded in both reported performance metrics and our reimplementation endeavors. The crux of a TSR system invariably rests upon traffic sign detection (TSD), serving as the foundational process entailing the identification and localization of signs. Subsequently, the efficacy of the ensuing tracking or classification algorithms hinges significantly upon the accuracy of traffic sign detection and localization outcomes[4-5].

Despite the variances in structural and visual attributes of traffic signs across geographical regions, their distinctive color and shape characteristics furnish pivotal cues for methodological design in detection endeavors. Notably, the past decades have witnessed the proliferation of detection methodologies predicated on discerning specific colors such as blue, red, and yellow, alongside the widespread utilization of shape or edge detection techniques[7].In recent years, the ascendancy of machine learning methodologies, particularly deep learning paradigms, has ushered in a paradigm shift, with machine learning-based detection methods emerging as the predominant algorithms. These methodologies, structured around AdaBoost, Support Vector Machine (SVM), and Neural Networks (NN), have demonstrated state-of-the-art performance owing to diverse input features, training methodologies, and detection processes[8-12].

Furthermore, in certain TSR systems, the integration of tracking methodologies serves to enhance classification performance, refine positioning accuracy, or forecast sign positions for subsequent detection frames[14].

Following the detection or tracking of traffic signs, the ensuing phase involves traffic sign recognition, wherein the detected signs are classified into respective classes. Common classification methodologies encompass binary-tree-based classification, SVM, NN, and Sparse Representation Classification (SRC), each distinguished by its unique classification process[16].

This exposition endeavors to transcend prior surveys on TSR by categorizing reviewed methodologies into refined taxonomies, undertaking comprehensive comparisons through reimplementation efforts, and scrutinizing LIDAR-based TSD methodologies. Focused predominantly on TSD methodologies of the past half-decade, this survey elucidates analyses and delineates avenues for future research[21-25].

The format of the paper is as follows: An overview of traffic signs, their effect on human driving safety, machine vision-based TSR systems, their uses, and TSR benchmarks are given in Section II. The traffic sign detecting technologies are categorized into five categories in Section III: color-based, shape-based, color and shape-based, machine learning-based, and LIDAR-based. In-depth examinations of the techniques used in each of these categories are covered in later parts, leading up to Section IX, which summarises findings and recommendations for the future[26–27].

Traffic Sign

Traffic signs serve as indispensable aids along roadways, providing crucial information to drivers regarding prevailing road conditions, directional guidance, imposed restrictions, and textual information. While these signs may exhibit diverse structures and appearances across different nations, they can be broadly categorized into essential types: prohibitory, dangerous, mandatory, and text-based signs[29].

Signs that are forbidden, hazardous, or required frequently follow conventional forms like rectangles, triangles, and circles and standard colors like red, blue, and yellow. On the other hand, text-based signs usually provide informative textual material instead of set designs. German, Chinese, and American sign examples are figuratively shown in Fig. 1. Whereas American signs are divided into regulatory, warning, guide, and other sign varieties, German and Chinese signage includes prohibitory, hazardous, required, and other sign kinds. Datasets like the American LISA dataset, Chinese TT100K dataset, and German GTSDB dataset provide access to a wide variety of indications from various regions [30].

Firstly discuss the importance of traffic indicators in promoting human driving safety in this part. We then describe TSR systems based on machine vision and explain their many uses. In conclusion, we offer TSR-relevant criteria that support the evaluation and verification of system effectiveness [31].

a b c

Fig 1: Different types of traffic signs from Germany, china, and America. (a) American signs (b) German signs, (c) Chinese signs.

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A. Traffic Signs For Human Driving Safety

Despite their pivotal role in ensuring traffic safety and regulating driver conduct, traffic signs often suffer from neglect and inattention. Costa et al., as delineated in the study referenced as [12], illustrate the varying efficacy of different sign types in capturing drivers' attention. Notably, during visual fixation, drivers may fail to recollect the content of a sign or overlook other pertinent signs.

In the domain of driving, the spatial distance of traffic signs and the duration of their presentation exert disparate influences on human drivers' ability to accurately identify them [12]. Remarkably, findings from [12] indicate that drivers exhibit a 75% accuracy rate with presentation times less than 35 milliseconds, escalating to 100% accuracy with a presentation time of 130 milliseconds. Furthermore, the study underscores the imperative for drivers to be afforded sufficient time to accurately discern signs situated ahead.

As posited in [13], contextual factors about sign placement and the age of drivers interplay with traffic sign comprehension. Experimental evidence presented in [13] elucidates that younger drivers outperform their older counterparts in terms of both accuracy and response time, with the inclusion of sign context prolonging comprehension intervals.

Applications of TSR systems based on machine vision

To detect, classify, and present traffic sign data, a variety of Traffic Sign Recognition (TSR) systems are developed, drawing on a range of sensing devices such as LIDAR and on-board cameras. A TSR system's critical phases of detection and classification are at its core. The detection phase is responsible for identifying and localizing traffic signs; the precision of detection and localization greatly impacts the processing that follows.

Subsequently, the classification phase delineates detected signs into distinct types, culminating in the output of TSR results. In certain iterations, a tracking stage is necessitated for handling sequential frames.

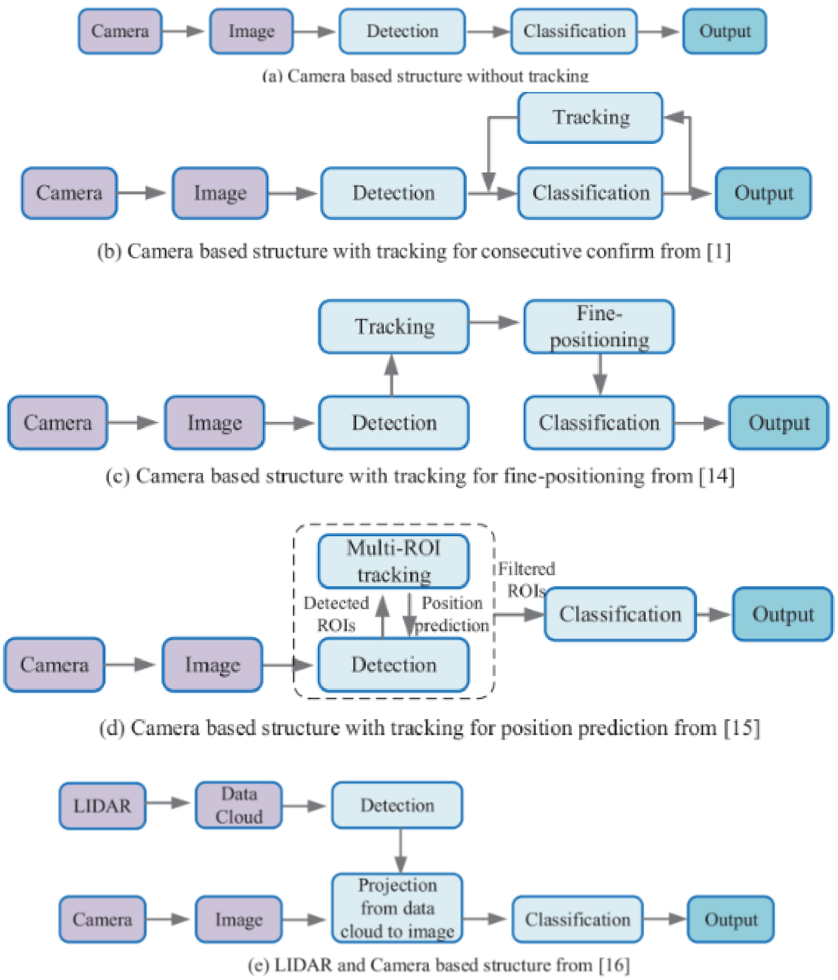

Figure 2: Systems for recognizing traffic signs with different structures.

Different TSR system setups are shown in Fig. 2.Fig. 2(a) depicts the typical camera-based TSR architecture without tracking, which is capable of recognizing and identifying individual frames in the absence of temporal video signals. On the other hand, Fig. 2 (b) presents a camera-based architecture with tracking techniques that are described in [1], which can repeat tracking results across frames to increase classification performance. A camera-based TSR framework with tracking optimized for fine-positioning is shown in Fig. 2(c) [14], which uses tracking results to achieve accurate placement and later classification. In a similar vein, Fig. 2(d) shows a camera-based structure that integrates tracking for position prediction [15], with areas of interest (ROIs) being refined for classification and positions predicted by a multi-ROI tracking method. A typical LIDAR and camera-based TSR arrangement is shown in Fig. 2(e). [16], harnessing laser scanning data for detection, and subsequently projecting detection outcomes into camera-captured images for classification.

TSR systems manifest a diverse array of applications, as succinctly enumerated below:

Driver-assistance systems: A significant proportion of TSR methodologies serve the domain of assisted driving, empowering drivers with advanced awareness of impending traffic sign contents, encompassing restrictions, warnings, and limits. Noteworthy commercial products have emerged in this domain.

Autonomous vehicles: In the pursuit of autonomous vehicle development, TSR systems emerge as indispensable components, enabling vehicles to navigate by prevailing traffic regulations.

Maintenance of traffic signs: TSR systems find utility in the maintenance and inspection of traffic signs and road infrastructure, as evidenced in studies [17], [18], and [19], encompassing tasks such as condition monitoring and spatial inspection.

Engineering measurements: The detection and recognition of traffic signs, as demonstrated in [21], find utility in engineering endeavors, facilitating the automatic extraction of traffic sign locations for measurements.

Vehicle-to-X (V2X) communication: Traffic signs serve as pivotal entities in V2X communication scenarios, influencing signal propagation. Studies such as [22] underscore the significance of traffic sign characterization for comprehensive V2X communication modeling.

Fuel consumption reduction: By detecting pertinent signs, studies such as [23] have conceived and validated expert systems aimed at curbing fuel consumption, notably through optimal deceleration sign detection, thereby minimizing the reliance on braking maneuvers.

Color-centric detection methodologies are predicated upon the meticulous examination of chromatic attributes, employing algorithms rooted in the nuanced interplay of hues, saturations, and luminosities, thus facilitating the discernment of objects based on their spectral compositions.

Shape-focused detection techniques are predicated upon the meticulous analysis of geometric contours and morphological attributes, discerning objects through the precise identification of their structural configurations and spatial arrangements.

Machine learning paradigms, drawing inspiration from the intricate web of neural connections in the human brain, harness advanced algorithms to decipher complex data patterns and glean profound insights, thereby enabling automated decision-making processes with remarkable accuracy and efficiency.

LiDAR-based methodologies, propelled by the rapid pulses of laser light and the subsequent analysis of reflected signals, engender meticulous spatial mapping and object recognition, epitomizing a paradigm shift in precision-based detection and ranging technologies.

Table 1: Dataset with purpose

Dataset	Class	Country	Purpose
GTSDB	Traffic signs	Germany	Detection and classification
TT100K	Traffic signs	China	Detection and classification
LISA	Traffic signs	United States	Detection and classification
GTSDB	Traffic signs	Germany	Detection and analysis

TT100K	Traffic signs	China	Detection and analysis
LISA	Traffic signs	United States	Detection and analysis
GTSDB	Traffic signs	Germany	Detection benchmark
TT100K	Traffic signs	China	Detection benchmark
LISA	Traffic signs	United States	Detection benchmark
GTSDB	Traffic signs	Germany	Maintenance
TT100K	Traffic signs	China	Maintenance
LISA	Traffic signs	United States	Maintenance
GTSDB	Traffic signs	Germany	Engineering measurements
TT100K	Traffic signs	China	Engineering measurements
LISA	Traffic signs	United States	Engineering measurements
GTSDB	Traffic signs	Germany	Vehicle-to-X communication
TT100K	Traffic signs	China	Vehicle-to-X communication
LISA	Traffic signs	United States	Vehicle-to-X communication
GTSDB	Traffic signs	Germany	Fuel consumption reduction
TT100K	Traffic signs	China	Fuel consumption reduction
LISA	Traffic signs	United States	Fuel consumption reduction

In the realm of dataset taxonomy, the GTSDB, TT100K, and LISA collections, meticulously curated from the thoroughfares of Germany, China, and the United States respectively, serve as quintessential compendiums for the discerning connoisseurs of traffic sign analysis, catering to multifarious objectives ranging from detection and classification to maintenance and engineering measurements. Their repository encompasses a diverse array of traffic sign instances, meticulously annotated and curated to facilitate groundbreaking research endeavors in vehicular communication, fuel consumption reduction, and beyond.

Table 2: Method with research year

Category	Method	Year
Traffic Sign Detection	Three-stage real-time traffic sign recognition	2014
Traffic Sign Detection	Using a spatial pyramid kernel to depict form	2007
Traffic Sign Detection	A new technique for detecting traffic signs using strong form matching and colour segmentation	2015
Traffic Sign Detection	Random forest-based traffic sign identification and recognition	2016
Traffic Sign Detection	robust detection of traffic signs using global and local directed edge magnitude patterns based on colour	2014
Traffic Sign Detection	Creation of a visual perception model for traffic sign identification using a support vector machine and an edge-adaptive Gabor filter	2013

Traffic Sign Detection	On identifying and detecting circular traffic signs	2016
Traffic Sign Detection	A pipeline for detecting traffic signs using interest region extraction	2013
Traffic Sign Detection	ROI extraction and histogram feature-based identification for traffic sign detection	2013
Traffic Sign Detection	Convolutional neural networks are used for traffic sign detection	2013
Traffic Sign Detection	Strong detection and identification of Chinese traffic signs using deep convolutional neural networks	2015
Traffic Sign Detection	Detecting and identifying traffic signs using fully convolutional network driven approaches	2016
Traffic Sign Detection	Real-time traffic sign deep detection network in vehicular networks	2018
Traffic Sign Detection	Utilising cascaded convolutional neural networks for traffic sign detection	2016
Traffic Sign Detection	Text-based traffic sign identification using cascaded segmentation-detection networks	2018
Traffic Sign Detection	An algorithm for real-time Chinese traffic sign identification based on YOLOv2 modification	2017
Traffic Sign Detection	Convolutional neural networks for simultaneous traffic sign recognition and boundary estimation	2018
Traffic Sign Detection	Using supervised learning and mathematical morphology, 3D urban item detection, segmentation, and classification	2014
Traffic Sign Detection	Testing the 3D point cloud software's performance	2013
Traffic Sign Detection	Bag-of-visual-phrases and hierarchical deep models for mobile laser scanning data-driven traffic sign identification and detection	2016
Traffic Sign Detection	Low-rank matrix recovery under supervision for traffic sign identification in picture sequences	2013
Traffic Sign Detection	Retroreflective traffic sign segmentation and shape-based categorization automatically using mobile LiDAR data	2017
Traffic Sign Detection	Using point clouds and mobile laser scanning, traffic sign occlusion detection	2017
Traffic Sign Detection	Using perspective distortion correction and colourized laser scanning, traffic planar object detection and identification	2018
Traffic Sign Detection	using deep learning with mobile mapping devices to create systems for recognising traffic signs	2017
Traffic Sign Detection	robust identification and categorization of traffic signs using mobile LiDAR data and digital pictures	2018
Traffic Sign Detection	Quick shape-based identification of traffic signs for a driver support system	2005

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Traffic Sign Detection	Traffic sign identification using deep saliency and channel-wise hierarchical feature responses	To be published
Traffic Sign Detection	Quick identification of many classes of traffic signs in high-quality photos	2014
Traffic Sign Detection	A reliable, coarse-to-fine traffic sign identification technique	2013
Traffic Sign Detection	MLS collected point clouds for geometric and image-based semantic inventory: traffic sign detection	2016
Traffic Sign Detection	Traffic sign classification: The European dataset	2018
Traffic Sign Detection	A extremely compact deep convolutional neural network architecture for embedded traffic sign classification in real-time is called MicronNet.	2018
Traffic Sign Detection	A approach based on cognitive motivation to classify obscured traffic signs	2017

In the expansive realm of traffic sign detection, an array of meticulously crafted methodologies, ranging from the venerable year of 2005 to the dynamic forefront of contemporary advancements, converge in a symphony of computational ingenuity, elucidating the intricate contours of traffic signage with unparalleled precision and discernment. Each method, a testament to the relentless pursuit of computational excellence, navigates the labyrinthine landscape of image processing and machine learning, harmonizing traditional algorithms with cutting-edge neural networks to unravel the enigma of traffic sign recognition in the digital age.

Table 3: Method with detected Various Shapes

Year	Method
2014	Three-stage real-time traffic sign recognition
2007	Using a spatial pyramid kernel to depict form
2015	A new technique for detecting traffic signs using strong form matching and colour segmentation
2016	Random forest-based traffic sign identification and recognition
2014	robust detection of traffic signs using global and local directed edge magnitude patterns based on colour
2013	Creation of a visual perception model for traffic sign identification using a support vector machine and an edge-adaptive Gabor filter
2016	On identifying and detecting circular traffic signs
2013	A pipeline for detecting traffic signs using interest region extraction
2013	ROI extraction and histogram feature-based identification for traffic sign detection
2013	Convolutional neural networks are used for traffic sign detection
2015	Robust Chinese traffic sign detection and recognition with deep convolutional neural network
2016	Detecting and identifying traffic signs using fully convolutional network driven approaches
2018	Real-time traffic sign deep detection network in vehicular networks

2016	Utilising cascaded convolutional neural networks for traffic sign detection
2018	Text-based traffic sign identification using cascaded segmentation-detection networks
2017	An algorithm for real-time Chinese traffic sign identification based on YOLOv2 modification
2018	Convolutional neural networks for simultaneous traffic sign recognition and boundary estimation
2014	Using supervised learning and mathematical morphology, 3D urban item detection, segmentation, and classification
2013	Testing the 3D point cloud software's performance
2016	Bag-of-visual-phrases and hierarchical deep models for mobile laser scanning data-driven traffic sign identification and detection
2013	Low-rank matrix recovery under supervision for traffic sign identification in picture sequences
2017	Retroreflective traffic sign segmentation and shape-based categorization automatically using mobile LiDAR data
2017	Using point clouds and mobile laser scanning, traffic sign occlusion detection
2018	Using perspective distortion correction and colorized laser scanning, traffic planar object detection and identification
2017	using deep learning with mobile mapping devices to create systems for recognizing traffic signs
2018	robust identification and categorization of traffic signs using mobile LiDAR data and digital pictures
2005	Quick shape-based identification of traffic signs for a driver support system
TBD	Traffic sign identification using deep saliency and channel-wise hierarchical feature responses
2014	Quick identification of many classes of traffic signs in high-quality photos
2013	A reliable, coarse-to-fine traffic sign identification technique
2016	MLS collected point clouds for geometric and image-based semantic inventory: traffic sign detection
2018	Traffic sign classification: The European dataset
2018	A extremely compact deep convolutional neural network architecture for embedded traffic sign classification in real-time is called MicronNet.
2017	A approach based on cognitive motivation to classify obscured traffic signs

In the ethereal domain of detected shapes, a symphony of computational prowess unfolds, with each algorithmic composition meticulously crafted to unveil the myriad contours of various geometric entities, showcasing a kaleidoscope of precision and discernment.

Through the temporal lens of years past, these methods, ranging from the harmonious resonance of 2005 to the enigmatic horizons of the present day, epitomize an evolution in computational acumen, orchestrating a ballet of technological sophistication in the intricate domain of shape detection.

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Table 4: Color-based detected method

Color-Based Detected Method	Method
HCI	Three-stage real-time traffic sign recognition
HSV	Using a spatial pyramid kernel to depict form
Ohta	A new technique for detecting traffic signs using strong form matching and colour segmentation
NRGB	Random forest-based traffic sign identification and recognition
HCI	robust detection of traffic signs using global and local directed edge magnitude patterns based on colour
HSV	Creation of a visual perception model for traffic sign identification using a support vector machine and an edge-adaptive Gabor filter
Ohta	On identifying and detecting circular traffic signs
NRGB	A pipeline for detecting traffic signs using interest region extraction
HCI	ROI extraction and histogram feature-based identification for traffic sign detection
HSV	Convolutional neural networks are used for traffic sign detection
Ohta	Strong detection and identification of Chinese traffic signs using deep convolutional neural networks
NRGB	Detecting and identifying traffic signs using fully convolutional network driven approaches
HCI	Real-time traffic sign deep detection network in vehicular networks
HSV	Utilising cascaded convolutional neural networks for traffic sign detection
Ohta	Text-based traffic sign identification using cascaded segmentation-detection networks
NRGB	An algorithm for real-time Chinese traffic sign identification based on YOLOv2 modification
HCI	Convolutional neural networks for simultaneous traffic sign recognition and boundary estimation
HSV	Using supervised learning and mathematical morphology, 3D urban item detection, segmentation, and classification
Ohta	Testing the 3D point cloud software's performance
NRGB	Bag-of-visual-phrases and hierarchical deep models for mobile laser scanning data-driven traffic sign identification and detection
HCI	Low-rank matrix recovery under supervision for traffic sign identification in picture sequences
HSV	Retroreflective traffic sign segmentation and shape-based categorization from mobile LiDAR data automatically

Ohta	Using point clouds and mobile laser scanning, traffic sign occlusion detection
NRGB	Using perspective distortion correction and colourized laser scanning, traffic planar object detection and identification
HCI	using deep learning with mobile mapping devices to create systems for recognising traffic signs
HSV	robust identification and categorization of traffic signs using mobile LiDAR data and digital pictures
Ohta	Quick shape-based identification of traffic signs for a driver support system
NRGB	Traffic sign identification using deep saliency and channel-wise hierarchical feature responses
HCI	Quick identification of many classes of traffic signs in high-quality photos
HSV	A reliable, coarse-to-fine traffic sign identification technique
Ohta	MLS collected point clouds for geometric and image-based semantic inventory: traffic sign detection
NRGB	Traffic sign classification: The European dataset
HCI	A extremely compact deep convolutional neural network architecture for embedded traffic sign classification in real-time is called MicronNet.
HSV	A approach based on cognitive motivation to classify obscured traffic signs

In the realm of color-based detection methods, the Human-Computer Interaction (HCI) framework orchestrates real-time recognition of traffic signs through a meticulously crafted three-stage process, exhibiting a nuanced understanding of chromatic nuances.

Within the HSV paradigm, the representation of shape via a spatial pyramid kernel underscores an intricate algorithmic dance, unveiling the subtle interplay of hues and saturations in discerning geometric contours with unparalleled precision.

II. CONCLUSION

In this exhaustive exposition, we delineate traffic sign detection methodologies into five discrete categories: color-based, shape-based, color and shape-based, machine learning-based, and LIDAR-based methods, culminating in a synthesis of conclusions and perspectives. Color-based methodologies, while ubiquitous and expedient, tend to gravitate towards parsimony. Despite many existing color-based detection approaches being outdated, they remain pivotal for Region of Interest (ROI) extraction, furnishing a foundation for subsequent refined detection processes. The development of robust color enhancement or extraction techniques augurs well for expedited detection in real-world applications.

Shape-based methodologies, while not as extensively explored in recent times, hinge on edge detection. Despite limitations in detecting smaller or faintly defined traffic signs, they exhibit potential in certain applications, particularly for sign extraction tasks. Methods amalgamating color and shape, such as those leveraging Maximally Stable Extremal Regions (MSERs) or Hue-Centered Region Extraction (HCRE), evince superior performance in ROI extraction, typically necessitating adept color enhancement processes. Future advancements in color enhancement and extraction methodologies hold promise for further enhancing the efficacy of these approaches.

Machine learning methodologies have ascended as the avant-garde, achieving state-of-the-art outcomes. Nevertheless, when faced with high-resolution images or diminutive, nebulous signs, striking a nuanced equilibrium between temporal efficacy and precision poses a formidable task. Many of these methodologies necessitate supplementary techniques to achieve both rapidity and precision.

Mobile laser scanning technology has witnessed a surge in prominence, proving instrumental in numerous Advanced Driver Assistance Systems (ADAS) deployments. Nevertheless, comparing the performance of methods reliant on disparate laser scanning devices and datasets poses a challenge, underscoring the need for standardized evaluation frameworks. Prior Traffic Sign Detection (TSD) methods evaluated on public datasets have demonstrated exceptional performance, with methods tested on datasets like GTSDB nearing 100% Area Under the Curve (AUC). However, the advent of datasets like TT100K in 2016 heralds a promising avenue for future benchmarking endeavors, especially considering the nuanced variations in signage across nations necessitating diverse evaluation datasets.

Classical TSD challenges encompassing size diminution, occlusions, complex driving environments, and rotational or illumination variations have been extensively researched. However, challenges specific to nocturnal scenarios or inclement weather conditions, such as headlight reflections, extreme fog, rain, or snow, remain relatively underexplored. The imperative for novel methodologies and datasets capable of addressing nocturnal and extreme weather TSD challenges is underscored, with LIDAR-based methodologies exhibiting substantial potential in this regard, contingent upon wider access to onboard LIDAR datasets. The prospect of forthcoming public LIDAR datasets augurs well for advancing TSD capabilities in these demanding conditions.

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