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ADM- Road Eye: Advanced Traffic Sign Detection

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Abstract: - In recent years, a plethora of systems have emerged for recognizing traffic signs. This paper offers a comprehensive overview of the latest and most effective approaches in detecting and categorizing traffic signs. The primary goal of detection techniques is to pinpoint the precise areas containing traffic signs, which are classified into three main categories: color-based, shape-based, and learning-based methods of Alex net, Desnse net, and Mobil net (ADM) models. Moreover, methods of classification are divided into two groups; those relying on manually crafted features such as HOG, LBP, SIFT, SURF, BRISK, and those leveraging deep learning. The paper summarizes various detection and classification methods, along with the datasets utilized, for quick reference. Additionally, it provides suggestions for future research directions and recommendations to enhance traffic sign recognition performance..

Keywords: ADM, Image processing, Object detection, Traffic sign detection, Traffic sign classification, Vehicle safety.

I. INTRODUCTION

The United Nations has projected a staggering increase of approximately 50% in road fatalities from 2010 to 2020, leading to an estimated 1.9 million deaths. To address this alarming trend, the United Nations initiated the "Decade of Action for Road Safety" in 2011. Driver Assistance Systems have emerged as a potential solution to mitigate accidents by automating tasks such as lane departure warning systems and traffic sign recognition. In recent years, there has been a growing emphasis on the detection and interpretation of traffic signs, now considered a critical aspect of intelligent vehicles. Driver distractions such as fatigue or focusing on navigation may cause drivers to overlook important information on traffic signs, particularly in adverse weather conditions. Consequently, enhancing driving safety and improving automatic detection and road sign recognition systems have become imperative to reduce the number of road fatalities. However, despite their evident benefits, these advancements encounter various challenges unrelated to technology. Factors such as changes in lighting, scale, weather conditions, obstructions, and rotations pose significant hurdles that could potentially diminish the performance of traffic sign recognition systems.

The primary challenge in traffic sign recognition systems lies in achieving high accuracy when processing large volumes of video data, rather than merely detecting or recognizing a traffic sign accurately in a static image. To illustrate the issue of incorrect alarms, a traffic sign detection system was implemented on a smartphone, capturing 30 frames per second, resulting in 108,000 frames in a 1-hour video. Assuming a sign is detected every 4 minutes, with each sign lasting for 2 seconds relative to the car's speed, the system would discover a total of 15 signs within the hour. Each sign would appear in 60 frames, leaving 107,100 frames without any signs. Considering a false positive accuracy rate of 1%, the system would generate 17 false alarms per minute (or 1,071 in 1 hour). Additionally, within 4 minutes, there would be 1 true positive and 68 false alarms. This high rate of false alarms may lead many users to eventually disable the application. Traffic sign recognition systems typically comprise three main stages: localization, detection, and classification.

If incorrect alerts occur during the detection phase, the effectiveness of the classification phase is compromised, as the classifier is typically not trained to handle false alarms. Road signs are classified based on various distinguishing characteristics they possess, primarily categorized into five groups based on their shapes and colors: warning signs (red triangle), prohibition signs (red circle), reservation signs (blue rectangle), mandatory signs (blue circle), and

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temporary signs (yellow triangle). The objective of this document is to summarize current and effective techniques for identifying and categorizing traffic signs. It outlines various methods for detecting traffic signs, categorized into color-based, shape-based, and learning-based approaches, including deep learning methods. The focus is on traffic sign classification methods, initially discussing learning methods utilizing manually created features, followed by deep learning methods. Additionally, this paper presents various publicly accessible datasets for traffic sign detection and classification to facilitate achieving its objective.

II. RELATED WORKS

De La *et al.* [1] the authors emphasize that traffic signs will maintain their crucial role for autonomous vehicles, as they are inherently designed for easy recognition by human drivers due to their distinct colors and shapes, which stand out from natural environments. The algorithm proposed in this paper leverages these features and comprises two main components. Firstly, for detection, the algorithm utilizes color thresholding to segment the image and employs shape analysis techniques to detect the signs within the segmented regions. Secondly, for classification, a neural network is employed to categorize the detected signs. The paper also demonstrates some results obtained from natural scenes. Furthermore, the algorithm's applicability extends beyond traffic signs, as it can also detect other types of marks that instruct a mobile robot to perform specific tasks at designated locations.

Fleyeh *et al.* [2] introduce a novel color detection and segmentation algorithm tailored for road signs, with a focus on mitigating the impact of shadows and highlights to enhance color segmentation accuracy. The algorithm operates on images captured by a digital camera installed in a vehicle. Initially, RGB images are converted into the HSV color space, facilitating better handling of color variations. Subsequently, the shadow-highlight invariant method is employed to isolate and extract the colors associated with road signs even under challenging lighting conditions. The effectiveness of this method is rigorously tested on a substantial dataset comprising hundreds of outdoor images captured in varying light conditions, including scenarios with shadows and highlights. Results demonstrate the algorithm's robustness, achieving an impressive segmentation accuracy rate of over 95%, thereby highlighting its efficacy in real-world applications.

Lim *et al.* [3] outlines a multi-stage recognition technique for traffic signs, beginning with their detection via a color segmentation method within road scenes. Once detected, the signs are forwarded to the recognition system for classification. The proposed recognition method consists of three distinct stages:

(i) color Histogram Classification: Traffic signs are initially classified based on their color histograms.

(ii)Shape Classification: Following color classification, signs undergo shape classification to further refine identification.

(iii) RBF Neural Classification: The final stage utilizes Radial Basis Function Neural Networks (RBFNN) for precise classification.

Due to the distinct color and shape attributes of traffic signs, they can be categorized into smaller subclasses, facilitating easier recognition through RBFNN. Before inputting signs into the RBFNN, features are extracted using Principal Component Analysis (PCA) to reduce the dimensionality of the original images. Subsequently, Fisher’s Linear Discriminant (FLD) is applied to further refine the most discriminant features. The performance of the proposed hybrid system is thoroughly evaluated and compared against a purely neural classifier. Experimental results showcase the superiority of the proposed method, as it achieves a higher recognition rate, underscoring its effectiveness in traffic sign recognition applications.

Broggi *et al.* [4] presents a comprehensive road sign detection and classification system comprising a three-step algorithm: color segmentation, shape recognition, and neural network classification. The ultimate objective is to detect and classify nearly all road signs found on Italian roads. Color segmentation is chosen for its potential for real-time execution, as it is generally faster than shape-based segmentation. To optimize computational efficiency, only the RGB color space, directly provided by the camera, or color spaces attainable through linear transformations, are utilized. Shape detection employs two distinct methods: one based on pattern matching using simple models, and the other relying on edge detection and geometrical cues. The complete set of considered road signs is categorized based on their shape and color attributes. Subsequently, a neural network is constructed and trained for each set of road signs.

Zaklouta *et al.* [5] underscores the critical role of traffic signs within Driver Assistance Systems (DAS), emphasizing their function in providing safety information to drivers in a clear and easily comprehensible manner. Triangular signs, in particular, serve to warn drivers of impending hazards such as sharp curves or wild animals. In this paper, an efficient algorithm is presented for the detection and recognition of warning signs. The algorithm leverages a Histogram of Oriented Gradients (HOG) technique to detect approximately 95% of triangular warning signs. Additionally, a Blackhat filter is applied to mitigate a significant portion of false alarms. Further refinement is achieved through an approximate nearest neighbor search using a KD-tree, which eliminates 100% of the remaining false detections while also distinguishing between different types of signs. One notable advantage of employing HOG features is the ability to detect both static (red frame) and dynamic (illuminated) warning signs using a single detector, thereby necessitating only one image scan. This approach streamlines the detection process and enhances the algorithm's efficiency in identifying various warning signs on the road.

Itti *et al.* [6] introduce a visual attention system inspired by the behavior and neuronal architecture of the early primate visual system. This system amalgamates multiscale image features to construct a unified topographical saliency map. Subsequently, a dynamic neural network is employed to prioritize attended locations in descending order of saliency. By swiftly identifying conspicuous locations through a computationally efficient process, the system effectively breaks down the complex problem of scene understanding. This approach enables detailed analysis of selected locations, facilitating efficient comprehension of the scene.

Maldonado *et al.* [7] an automatic road-sign detection and recognition system leveraging Support Vector Machines (SVMs). Within both automatic traffic-sign maintenance and visual driver assistance systems, detection and recognition of road signs are crucial functionalities. The system is designed to detect and recognize circular, rectangular, triangular, and octagonal signs, covering all prevalent shapes of Spanish traffic signs. Road signs play a pivotal role in providing drivers with vital information, aiding them in navigating safely and efficiently by guiding, warning, and regulating their actions. The proposed recognition system harnesses the generalization properties of SVMs and comprises three stages:

1. Segmentation: The system segments images based on pixel color, utilizing colors such as red, blue, yellow, white, or combinations thereof.

2. Traffic-sign detection: Shape classification is performed using linear SVMs to detect signs.

3. Content recognition: Recognition of sign content is accomplished using Gaussian-kernel SVMs.

The segmentation stage, based on colors like red, blue, yellow, white, or combinations thereof, enables the detection of all traffic signs, with some signs detectable via multiple colors. Experimental results demonstrate a high success rate and minimal false positives in the final recognition stage. These results indicate the algorithm's robustness against translation, rotation, scale variations, and even partial occlusions in many scenarios.

Gómez-Moreno *et al.* [8] conducts a quantitative comparison of various segmentation methods, including novel approaches, that have proven effective in traffic sign recognition. These methods fall into categories such as color-space thresholding, edge detection, and chromatic/achromatic decomposition. Additionally, the author evaluates the support vector machine (SVM) segmentation method and explores speed enhancement using a lookup table (LUT). The primary criterion for assessing these segmentation methods is their overall performance throughout the entire recognition process, which encompasses the segmentation, detection, and recognition stages. To evaluate these methods, the author applies the complete recognition system to a set of images containing at least one traffic sign while varying the segmentation method. This approach allows for the observation of performance modifications resulting from the segmentation technique employed. The findings indicate that the most effective methods are those normalized with respect to illumination, such as RGB or Ohta Normalized, while there is no significant improvement observed with the use of Hue Saturation Intensity (HSI)-like spaces. Furthermore, employing an LUT with a reduction in the less-significant bits enhances speed without compromising quality. Although SVMs used in color segmentation yield promising results, further enhancements are necessary when applied to achromatic colors.

Liu *et al.* [9] present a robust Traffic Sign Detection (TSD) framework designed to swiftly detect multiclass traffic signs in high-resolution images while maintaining a high detection rate. This framework introduces three key contributions:

1. Novel Features: The framework introduces two novel features named multiblock normalization local binary pattern (MN-LBP) and tilted MN-LBP (TMN-LBP). These features effectively capture the characteristics of multiclass traffic signs, enabling accurate detection.

2. Split-Flow Cascade (SFC) Tree Structure: A tree structure known as split-flow cascade is introduced, leveraging shared features among multiclass traffic signs to construct a coarse-to-fine TSD detector. This hierarchical approach enhances detection efficiency.

3. Common-Finder AdaBoost (CF. AdaBoost) Algorithm: The CF. AdaBoost algorithm is designed to identify common features across different training sets, facilitating the development of an efficient Split-Flow Cascade tree (SFC-tree) for multiclass TSD.

Through experiments conducted on a dataset comprising high-resolution images, the proposed framework demonstrates the capability to detect multiclass traffic signs with high accuracy in real-time.

Benallal *et al.* [10] highlight that their research project aims to develop a computer vision system integrated into a vehicle capable of identifying and locating road signs. However, they acknowledge several constraints that limit the feasible solutions. These constraints include the necessity for a real-time system, a preference for a single-camera approach to simplify hardware, and the requirement for efficient performance on low-cost hardware. To address these challenges, the authors initially adopt a color segmentation strategy for road sign recognition. They conduct a comprehensive study of the behaviour of RGB components of various road signs across different lighting conditions, from sunrise to sunset. Their analysis reveals that a simple comparison of the RGB components taken pairwise is adequate for real-time segmentation of road signs. By leveraging this colour segmentation strategy, the authors aim to develop a robust and efficient road sign detection system that meets the real-time processing requirements and hardware constraints of in-vehicle applications.

III. MATERIALS AND METHODS

A. Detection Techniques

The elaboration of the color-based segmentation methods discussed:

i. RGB Space Method

- De La Escalera et al. utilize the RGB color space due to the nonlinearity of HSI (Hue, Saturation, Intensity) formulas.
- They employ the relationship between the RGB components within this space to discern areas of interest in the image.
- Thresholding techniques are commonly employed in this method. For instance, Ruta et al. apply filtering for each pixel using the following equations:
  - ($f_R(X) = \max(0, \min(x_R - x_G, x_R - x_B) / S)$) …………(1)
  -
  - ($f_B(X) = \max(0, \min(x_B - x_R, x_B - x_G) / S)$) …………(2)

  - ($f_Y(X) = \max(0, \min(x_R - x_B, x_G - x_B) / S)$) …………(3)
- This approach generates three maps (red, blue, and yellow) for each RGB image, where the dominant color exhibits high intensity while weaker signals have lower intensities.

ii. R'G'B' Space Method

- King et al. prefer the R'G'B' color space for its efficiency in traffic sign detection.
- Initially, they normalize the RGB channels by intensity (I).

- Subsequently, four new images are constructed using specific equations to enhance the intensity of the dominant color.
- Thresholding is applied to binarize the resulting images (R, G, B, Y), followed by morphological operations to remove unwanted pixels.
- This approach has shown a high detection rate of up to 93.63% for traffic sign panels.

Additionally, a filtering mechanism is proposed by King et al. to eliminate undesirable pixels, aimed at reducing execution time while maintaining detection accuracy.

These methods leverage color-based segmentation to effectively identify areas of interest, particularly traffic signs, in images. Each approach offers its own advantages in terms of accuracy, efficiency, and computational complexity.

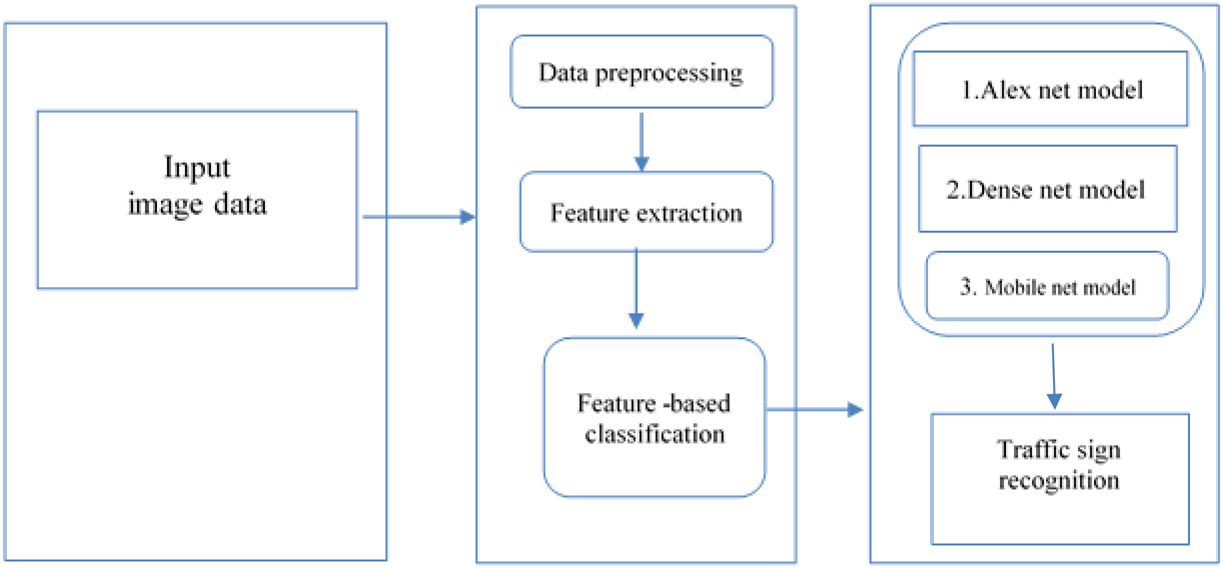

Figure 1. Proposed Road Sign Detection Architecture

B. Methods that are based on the shape of an object

In the context of shape-based methods for object detection, the reliance on color segmentation is minimized due to its susceptibility to various factors such as distance, weather conditions, time of day, and sign reflection. Instead, these methods focus on identifying object indications by analyzing the edges of the image using structural or comprehensive techniques.

Shape-based methods offer advantages over color-based approaches as they can handle grayscale images and analyze their gradients. While they are generally more reliable, they can be computationally expensive due to the processing required for edge detection. However, they are capable of handling grayscale images, which is essential for scenarios where color data may not be sufficient.

In countries like Japan, certain highway code signs come in pairs with different shapes, but they may appear identical when converted to grayscale. To differentiate them, a significant amount of color data is required. Some authors opt to utilize color information to identify the area of interest and then apply shape techniques to detect the position of signs and recognize their geometric shapes.

C. Learning-based methods

Previous approaches face common challenges such as variations in lighting, obstacles, changes in size, rotation, and movement. However, machine learning offers a potential solution, albeit requiring a substantial annotated dataset. Viola and Jones employ a series of detectors with increasing complexity, utilizing classifiers based on

Haar wavelets and AdaBoost algorithm. The Viola-Jones detector is applied to identify triangular traffic signs, achieving high accuracy [11] rates (90%-96%) with approximately 1000 images during training. Drawbacks include the need for extensive training data and false positive rates.

Bario et al. propose an attentional cascade consisting of a cascade of classifiers, with each entry representing the region of interest detected by the previous classifier. The Adaboost algorithm is utilized for classifier learning. The authors also introduce a Forest-ECOC classification strategy to handle multiclass problems. Results show detection rates ranging from 60% to 75% with low false positive rates per image. Treatment rate remains unspecified due to offline operation, with no discussion on rectangular panels or color information utilization.

Priscariu et al. describe the use of Adaboost classifier with Viola and Jones detector, followed by SVM operating on normalized RGB channels. The system effectively deals with motion blur using 3D region-based tracking.

Chen et al. investigate the combined use of Adaboost and support vector regression (SVR) for traffic sign identification. Assessment on three datasets reveals recall rate of 80.85% and precision rate of 94.52%, with detection time ranging from 0.05 to 0.5 seconds and 16 minutes for training.

A genetic algorithm-based approach is applied for traffic sign detection, handling variations in size, rotation, weather conditions, and partial obstructions. While not designed for real-time processing, the method effectively addresses various challenges, though panel shape identification takes approximately 2 seconds per image.

D.Publicly Available Detection Datasets

i. German Traffic Sign Detection Benchmark (GTSDB) Dataset

- The GTSDB dataset focuses on single-image traffic sign detection, comprising 900 images of size 1360 × 800 pixels. These images are split into 600 training images and 300 evaluation images, categorized into three classes: mandatory, warning, and prohibitory.
- It features an online evaluation system enabling immediate analysis and ranking of submitted results.

ii. Belgium Traffic Sign Dataset (BTSD):

- BTSD includes over 10,000 annotations and images categorized into mandatory, warning, and prohibitory classes.
- It offers four video sequences captured in Belgium, suitable for tracking experiments.

iii. Laboratory for Intelligent and Safe Automobiles (LISA) Dataset

- The LISA dataset comprises videos and annotated frames, containing 7855 images with 47 categories of traffic signs.
- Approximately 6610 images are annotated, with varying sizes from 640 × 480 to 1024 × 522 pixels.

iv. Swedish Traffic Signs Dataset (STSD)

- STSD consists of over 20,000 images captured along more than 350 km of Swedish highways and city roads.
- Every fifth frame from the sequence is manually annotated, and the dataset can be utilized for tracking applications.

v. Data Set of Italian Traffic Signs (DITS)

- DITS is a recent dataset derived from 43,289 images extracted from 14 hours of videos captured in Italy, encompassing both day and night scenes.
- The detection dataset contains 1416 training images and 471 test images, along with text files containing annotations.
- It defines three shape-based super-classes: Prohibitive, Indication, and Warning.

E. Classification Methods

In this section, recent and efficient methods for traffic sign classification are highlighted. Firstly, methods utilizing hand-crafted features such as HOG, LBP, SIFT, and BRISK are discussed. Secondly, deep learning methods that have surpassed human performance are cited.

Learning Methods Based on Hand-Crafted Features

- Fatin Zaklouta and Her Team
  - The authors analyzed the effectiveness of various sizes of Histogram of Oriented Gradients (HOG) descriptors and Distance Transforms, utilizing K-d trees and random forests.
  - Random forests were found to be more resilient to changes in the background compared to K-d trees.
  - Random forests achieved an accuracy rate of 97.2% with HOG descriptors and 81.8% with Distance Transform, while K-d trees reached 92.9% and 67%, respectively.

- Ellahyani and His Colleagues
  - HOG characteristics were computed in the HSI color model and merged with the LSS traits. Random forest was preferred as a classifier.
  - The GTSDB achieved a recognition rate of 97.43%, while the entire system achieved a recognition rate of 94.21% at a speed of 8-10 frames per second.
- Evaluation of Humans and Machine Learning Methods:
  - The authors presented the outcomes of a linear classifier trained using Linear Discriminant Analysis (LDA).
  - Different feature representations, including HOG1, HOG2, and HOG3, were evaluated. HOG2 achieved the highest accuracy level of 95.68%, followed by HOG1 with 93.18% and HOG3 with 92.34%.
- Hierarchical Approach to Traffic Sign Recognition:
  - Due to uneven distribution of samples among traffic sign categories, a hierarchical approach was suggested.
  - The initial level employs the Adaboost classifier and Aggregate Channel Features (ACF) to categorize signs based on geometric shape into three groups.
  - In the next level, a random forest classifier is used to recognize traffic signs based on HOG, LBP, and HSV features.
  - Accuracy rates achieved with the GTSRB and STSD datasets were 95.97% and 97.94%, respectively.

F. Deep learning methods

The conventional manual features have limited capabilities in capturing information and are closely linked to expert knowledge, therefore they are not effective in distinguishing patterns within a large dataset. In order to resolve this issue and improve the accuracy of recognition, it is essential to utilize deep features. Pierre Sermanet and Yann Le Cun employed Convolutional Networks (ConvNets) to train on 32x32 color images from the GTSRB dataset, aiming to extract invariant features of traffic signs. They achieved an accuracy of 98.97%, surpassing human performance (98.81%).

Furthermore, they enhanced their networks' capabilities and breadth by disregarding color data, resulting in an unprecedented achievement of 99.17%. The researchers achieved the most favourable outcome when color information was excluded. Hence, they speculated that normalized color channels might contain more valuable data compared to raw color. However, they acknowledged that this approach is still distant from being applicable in real-time situations.

The training of fully connected layers in convolutional neural network (CNN) utilizes back-propagation. However, the sensitivity of back-propagation and excessive training of fully connected layers can negatively affect the overall performance and generalization ability of the CNN. Typically, writers employ CNN as a tool to extract features and make classifications. It is indeed effective, yielding impressive outcomes when dealing with a large and intricate network and extensive dataset.

Alternatively, the authors suggest a different method in which CNN functions as a generator of deep features. This implies that only the initial eight layers are retained and the fully connected layers are removed. The Extreme learning machine (ELM) is utilized as a classifier because of its ability to generalize well and it takes input from CNN. The suggested technique requires approximately 5 to 6 hours for training, without the use of a GPU. It attains a recognition rate of 99.40% without the application of any data augmentation or preprocessing techniques. However, it is not able to handle motion blur effectively.

Qian and colleagues additionally employ CNN as a tool to extract features, while utilizing a multilayer perceptron (MLP) as a classifier. In contrast to the conventional ConvNet, the authors utilize the position rather than the maximum values in the max pooling layer. The process of max pooling positions (MPPs) involves encoding each maximum value position into a 4-bit binary value. These binary values are then combined to form the MPPs feature. The use of MPPs significantly improves the accuracy to 98.86% on GTSRB.

Xie and colleagues note that the majority of incorrectly classified signs, specifically 80%, share identical characteristics such as color, shape, and pictogram. To address this issue, they suggest using a two-step sequential CNN. The initial CNN is trained using the class label, while the subsequent stage is trained separately on broader categories based on the shape and pictogram. The proposed method achieves a 97.94% accuracy on GTSRB dataset, resulting in a reduction of misclassified instances from 430 to 202 by employing the cascaded CNN. There is no mention of the time it takes for execution.

A recent Convolutional Neural Network (ConvNet) model has been suggested to decrease the parameter count by 27%, 22%, and 3%, respectively, in comparison to the ConvNets already utilized. Additionally, the researchers have introduced a compact version of ConvNet that reduces the parameter count by 52% compared to the previously proposed ConvNet.

In order to enhance the precision of classification, they also suggested a novel approach to build an optimal Convolutional Neural Network (ConvNet) by selecting the best number of ConvNets that achieve the highest accuracy possible, while minimizing the number of arithmetic operations. This resulted in accuracy rates of 88% and 73% with fewer arithmetic operations. Their suggested approach achieved an accuracy of 99.23% using two compact ConvNets and 99.61% using only five ConvNets on the GTSRB dataset. In contrast, there is a precision of 99.46% when utilizing a group of 25 ConvNets, and a precision of 99.65% when employing 20 ConvNets.

To assess how effective the new ConvNet model suggested and its capacity to handle larger amounts of data, the researchers conducted a test. They utilized the ConvNet that had already been trained on the GTSRB dataset to detect traffic signs in the BTSC dataset. The accuracy achieved for this task was 92.12%.

A basic deep neural network architecture was implemented to identify circular traffic signs, resulting in a successful recognition rate of 97.5% on GTSRB dataset. Two additional CNN designs are suggested. The single-scale architecture involves two sets of convolutional layers and two local fully connected layers, which are then followed by a softmax classifier. In the context of a multiscale architecture, the result of the initial convolutional layer serves as input for both the second convolutional layer and the first fully connected layer. The two designs are assessed using both the GTSRB dataset and their unique dataset known as DITS, which contains Italian traffic signs. The single scale architecture achieved an accuracy rate of 97.2% on the GTSRB dataset and 93.1%.

G. Publicly available classification datasets

The datasets used for traffic sign recognition provide crucial resources for developing and evaluating algorithms in this domain. Among these datasets is the German Traffic Sign Recognition Benchmark (GTSRB), which contains over 50,000 images categorized into 43 classes, with each class comprising a minimum of 9 traffic signs. With image sizes ranging from 15 × 15 to 222 × 193 pixels, GTSRB offers three precomputed characteristics, including various versions of HOG features, Haar-like features, and hue histograms, making it accessible even to individuals without extensive knowledge in image processing. Additionally, the Belgium Traffic Sign Classification (BTSC) dataset, a subset of BTSD, presents specific regions of interest with over 4000 training images and 2000 testing images, distributed across 62 different classes. Another notable dataset is the revised MASTIF dataset, which focuses on selected regions of interest within the MASTIF dataset, offering 4028 training images and 1644 testing images divided into 30 categories. Lastly, the Data Set of Italian Traffic Signs (DITS) includes 8048 training images and 1206 testing images, covering 58 categories of signs with varying sizes. These datasets collectively provide a rich and diverse set of traffic sign images for algorithm development and evaluation in the field of traffic sign recognition.

IV. RESULTS AND DISCUSSIONS

A. Results

Figure. 2. Sign Boards used for Experiments

Figure. 3. Sign Boards used for Experiments

Table 1. Results for the different methods

SL NO	METHOD	ACCURAC
1	ALEXNET	93%
2	DENSNET	96.2%
3	MOBILENET	98.7%

Alex Net: Achieved an accuracy of 93%. This means that when Alex Net was applied to the road sign detection task, it correctly classified 93% of the road signs.

Dense Net: Achieved an accuracy of 96.2%. Dense Net performed better than Alex Net, correctly classifying 96.2% of the road signs.

Mobile Net: Achieved an accuracy of 98.7%. Mobile Net outperformed both Alex Net and Dense Net, achieving the highest accuracy of 98.7%. This means that Mobile Net had the highest success rate in correctly identifying road signs in the given dataset.

B. Future research directions

The current advanced state of traffic sign recognition systems faces several challenges, including the absence of reliable information and a comprehensive dataset that encompasses signs from various regions, including those not compliant with The Vienna Convention on road signs and signals, and recorded in diverse situations. Existing datasets have reached their limits and suffer from an uneven distribution of samples across traffic sign classes, impacting classification accuracy. To address these issues, researchers advocate for the development of a new, intricate dataset with a balanced sample distribution and high-resolution images. High resolution is particularly crucial for identifying signs at a distance, considering the speed of travel and the time it takes to pass a sign. Moreover, enhancing the tracking module's capabilities is essential to monitor signs effectively, ensuring timely detection within a one-second timeframe, given a camera capturing 30 frames per second.

Traffic sign recognition systems typically comprise detection and classification stages, with classification performance heavily reliant on detection results. Therefore, optimizing detection is paramount, with emphasis on reducing false alarms. Precision in classification also warrants attention, necessitating exploration of additional distinctive characteristics for accurate depiction of various traffic sign categories. While deep features have shown promise in this regard, there is a lack of research on their adaptability to new datasets, presenting a potential avenue for future investigation. Overall, future research efforts should focus on refining both detection and classification stages to achieve higher precision and adaptability across diverse datasets and real-world scenarios.

V. CONCLUSION

This paper summarizes recent advancements in traffic sign detection and categorization, categorizing detection methods into color-based, shape-based, and learning-based approaches. These methods have shown detection rates ranging from 90% to 100% on existing datasets, albeit with varying effectiveness. Achieving high classification accuracy relies on utilizing distinctive characteristics and robust classification models. Learning methods employing manually crafted features have demonstrated satisfactory results, while deep learning techniques such as Convolutional Neural Networks (CNNs) have surpassed 99% accuracy. However, despite these achievements, the current datasets have limitations, necessitating the development of a more comprehensive universal dataset. Although detection and classification methods have shown high accuracy, they have yet to achieve real-time performance, crucial for real-world Advanced Driver Assistance Systems (ADAS) applications. The posed question raises several key points: Can these recent methods maintain their performance in real-world scenarios or with different datasets? Can they achieve real-time execution on smartphone devices, similar to CPU and GPU environments? Lastly, the development of a universal traffic sign recognition system remains an open field of research, highlighting the need for further advancements in this area.

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