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Review on Indian traffic sign detection and recognition using deep learning

Gopal Krishna1, Devendra Kumar Meda2
1ME Scholar, Department of Electronics and Communication, Jabalpur Engineering College, Jabalpur, M.P., India
2Assistant Professor, Department of Electronics and Communication, Jabalpur Engineering College, Jabalpur, M.P., India

ABSTRACT
Traffic sign detection and recognition (TSDR) plays a crucial role in intelligent transportation systems (ITS), advanced driver assistance systems (ADAS), and autonomous driving technologies. In the context of India, the development of robust traffic sign recognition systems is particularly challenging due to diverse road conditions, variations in sign design, occlusions, weather conditions, faded or damaged signs, and complex backgrounds. With the rapid advancement of artificial intelligence, deep learning techniques have emerged as powerful tools for automatically detecting and classifying traffic signs with high accuracy. This review paper presents a comprehensive analysis of recent research on Indian traffic sign detection and recognition using deep learning approaches. The study examines various deep learning architectures such as Convolutional Neural Networks (CNN), You Only Look Once (YOLO), Region-Based Convolutional Neural Networks (R-CNN), Faster R-CNN, and Single Shot MultiBox Detector (SSD) that have been applied for traffic sign detection and classification. It also reviews publicly available datasets and Indian-specific traffic sign datasets used for training and evaluation. The paper highlights the advantages of deep learning models in handling complex visual features, real-time detection requirements, and large-scale image datasets compared with traditional machine learning approaches. Furthermore, this review identifies key challenges associated with Indian traffic environments, including inconsistent sign visibility, illumination variations, and limited annotated datasets. The comparative analysis of existing methodologies is presented in terms of accuracy, computational efficiency, and real-time implementation capability. Finally, the paper discusses potential future research directions, including the integration of edge computing, transfer learning, and lightweight deep learning models for efficient deployment in intelligent transportation systems. This review aims to provide researchers and practitioners with a clear understanding of current developments, challenges, and emerging opportunities in Indian traffic sign detection and recognition using deep learning techniques.
Keywords: Indian traffic sign detection, deep learning-based recognition, convolutional neural networks (CNN), intelligent transportation systems (ITS), computer vision in road safety

I. INTRODUCTION

This research presents an improved version of Mask R-CNN (RMR-CNN) aimed at traffic sign detection and recognition specifically designed for Indian roads. Although considerable research has been carried out worldwide on traffic sign detection (TSD) and recognition (TSR), the majority of datasets and models derive from foreign roads, restricting their use in India. The absence of a substantial, standardized dataset for Indian traffic signs has posed a challenge in creating precise systems for Indian road conditions. This study fills that void by developing a tailored dataset of manually collected Indian traffic signs, classified according to types and real-world variations such as scaling, orientation, and lighting. The RMR-CNN model improves upon the standard Mask R-CNN by incorporating various pre-processing techniques, including shape detection, region of interest (ROI) selection, and adjustments to colour probabilities. These enhancements are designed to boost accuracy in detecting and identifying traffic signs across the varied conditions typical of Indian roads. The model was evaluated against other deep learning models, such as Fast R-CNN and Mask RCNN, for both traffic sign detection and recognition tasks.

II. LITERATURE REVIEW

Rajesh Kannan Megalingam et al.[1]Traffic signs play a crucial role in managing traffic on the road, disciplining the drivers, thereby preventing injury, property damage, and fatalities. Traffic sign management with automatic detection and recognition is very much part of any Intelligent Transportation System (ITS). In this era of self-driving vehicles, calls for automatic detection and recognition of traffic signs cannot be overstated. This paper presents a deep-learning-based autonomous scheme for cognizance of traffic signs in India. The automatic traffic sign detection and recognition was conceived on a Convolutional Neural Network (CNN)- Refined Mask R-CNN (RM R-CNN)-based end-to-end learning. The proffered concept was appraised via an innovative dataset comprised of 6480 images that constituted 7056 instances of Indian traffic signs grouped into 87 categories. We present several refinements to the Mask R-CNN model both in architecture and data augmentation. We have considered highly challenging Indian traffic sign categories which are not yet reported in previous works. The dataset for training and testing of the proposed model is obtained by capturing images in real-time on Indian roads. The evaluation results indicate lower than 3% error. Furthermore, RM R-CNN's performance was compared with the conventional deep neural network architectures such as Fast R-CNN and Mask R-CNN. Our proposed model achieved precision of 97.08% which is higher than precision obtained by Mask R-CNN and Faster R-CNN models.

Ghazanfar Latifet al.[2] Car manufacturers around the globe are in a race to design and build driverless cars. The concept of driverless is also being applied to any moving vehicle such as wheelchairs, golf cars, tourism carts in recreational parks, etc. To achieve this ambition, vehicles must be able to drive safely on streets stay within required lanes, sense moving objects,

sense obstacles, and be able to read traffic signs that are permanent and even temporary signs. It will be a completely integrated system of the Internet of Things (IoT), Global Positioning System (GPS), Machine Learning (ML)/Deep Learning (DL), and Smart Technologies. A lot of work has been done on traffic sign recognition in the English language, but little has been done for Arabic traffic sign recognition. The concepts used for traffic sign recognition can also be applied to indoor signage, smart cities, supermarket labels, and others. In this paper, we propose two optimized Residual Network (ResNet) models (ResNet V1 and ResNet V2) for automatic traffic sign recognition using the Arabic Traffic Signs (ArTS) dataset. Additionally, the authors developed a new dataset specifically for Arabic Traffic Sign recognition consisting of 2,718 images taken from random places in the Eastern province of Saudi Arabia. The optimized proposed ResNet V1 model achieved the highest training and validation accuracies of 99.18% and 96.14%, respectively. It should be noted here that the authors accounted for both overfitting and underfitting in the proposed models. It is also important to note that the results achieved using the proposed models outperform similar methods proposed in the extant literature for the same dataset or similar-size dataset.
ASSEMLALI Hamzaet al.[3] In recent years, the advancement of deep learning technologies has significantly impacted various domains and the field of transportation is no exception. As the demand for robust and accurate traffic sign classification systems continues to rise, this study presents an in-depth exploration and comparison of various techniques employed in the field. Focusing on state-of-the-art methodologies, we assess the effectiveness and performance of multiple classification approaches for traffic sign recognition. The review presents an extensive survey of the literature, encompassing traditional computer vision methods, machine learning algorithms, and the latest advancements in deep learning. The comparative analysis aims to identify the strengths and limitations of each technique, considering factors such as computational efficiency and accuracy. Additionally, the paper implements four models—CNN, ResNet50, VGG19, and EfficientNetB7—for traffic sign classification on the GTSRB dataset, the accuracy results are reported as 99.25%, 99.28%, 98.95%, and 98.24% respectively.
H. S. Gowri Yaaminiet al.[4] Accurate and precise detection of lanes and traffic signs is predominant for the safety and efficiency of autonomous vehicles and these two significant tasks should be addressed to handle Indian traffic conditions. There are several state-of-art You Only Live Once (YOLO) models trained on benchmark datasets which fails to cater the challenges of Indian roads. To address these issues, the models need to be trained with a wide variety of Indian data samples for the autonomous vehicles to perform better in India. YOLOv8 algorithm has its challenges but gives better precision results and YOLOv8 nano variant is widely used as it is computationally less complex comparatively. Through rigorous evaluations of diverseness in the datasets, the proposed YOLOv8n transfer learning models exhibits remarkable performance with a mean Average Precision (mAP) of 90.6 % and inference speed

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of 117 frames per second (fps) for lane detection whereas, a notable mAP of 81.3 % for traffic sign detection model with a processing speed of 56 fps.

Hui Chenet al.[5] This review discusses the progress made in the traffic-sign detection and recognition methods and algorithms over the last decade with analyzing the strengths and drawbacks of each algorithm. The recent development of traffic sign recognition on the roads highlights the necessity for precise detection of road's traffic signs in various driving scenarios. In addition, the connections between the detection algorithms before and after the advent of deep learning are revealed. The Traffic sign recognition has been developed to identify various shapes, sizes, orientations, and appearances of signs in diverse conditions. Researchers have proposed numerous algorithms to address these challenges. The traffic recognition methods have been categorized in this paper into three main techniques, namely, conventional, deep learning, and hybrid based methods. The algorithms are compared with each others via regression, segmentation, and hybrid techniques, specifically SSD, YOLO, Faster R-CNN, Pixel Aggregation Network, and Mask R-CNN. The results demonstrate that the hybrid based detection algorithms outperform others in true-positive rates, false-positive rates, the number of test images, accuracy, and processing time. Such outcomes illustrate the potential of hybrid methods in the creation of accurate and effective TSD systems, thereby paving the way for further research in this field.

ReshmaDnyandev VartakKoliet al.[6] This study aims to compare traffic sign (TS) and obstacle detection for autonomous vehicles using different methods. The review will be performed based on the various methods, and the analysis will be done based on the metrics and datasets.In this study, different papers were analyzed about the issues of obstacle detection (OD) and sign detection. This survey reviewed the information from different journals, along with their advantages and disadvantages and challenges. The review lays the groundwork for future researchers to gain a deeper understanding of autonomous vehicles and is obliged to accurately identify various TS.The review of different approaches based on deep learning (DL), machine learning (ML) and other hybrid models that are utilized in the modern era. Datasets in the review are described clearly, and cited references are detailed in the tabulation. For dataset and model analysis, the information search process utilized datasets, performance measures and achievements based on reviewed papers in this survey.Various techniques, search procedures, used databases and achievement metrics are surveyed and characterized below for traffic signal detection and obstacle avoidance.

Md. Ariful Islamet al.[7] Traffic sign detection and classification have significant impacts in the field of automated driving system, traffic management, driver assistance system, to detect traffic rules violations etc. In this paper, we have presented the Bangladesh road traffic sign benchmark dataset, which consists of 10259 real-world traffic sign images captured from various locations in Bangladesh and 10259 annotated images. A Total of 31 distinct traffic sign images were collected including Crossroad, Emergency Stopping, Sharp left turn. For image

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annotation, a sophisticated tool, Roboflow, has been utilized and data augmentation techniques have been applied to enhance the diversity of the images. The dataset is useful for training and testing of any deep convolutional neural networks (CNNs) models for traffic sign recognition. The dataset is publicly accessible via the following link: https://zenodo.org/records/14969122
Swastik Saxenaet al.[8] Traffic sign detection and recognition in an unconstrained environment is a challenging task for autonomous vehicle operations. The small traffic signs in the captured image make this problem harder. Furthermore, detecting and recognizing these signs accurately in real-time is crucial. This work proposes a modified YOLOv4-based deep learning model that uses CSPDarknet53 as the backbone. We have applied data preprocessing and image enhancement strategies for better model generalization. For this purpose, a nighttime image enhancement method is used to illuminate night images. In our work, prior to the YOLOv4 model, anchor boxes are calculated using the K-Means clustering algorithm, which uses Generalized Intersection over Union (GIoU) as the distance instead of Intersection over Union (IoU). Our modified architecture uses an improved PANet with grouped convolutional layers in the detection neck and an additional feature scale for detecting smaller traffic signs. The proposed model has been experimented on the Mapillary Traffic Sign Dataset (MTSD) and the Tsinghua-Tencent 100K dataset (TT-100K). MTSD consists of global traffic signs from different countries, and TT-100K consists of traffic signs from China. We have also tested the performance of the proposed model on our own dataset, consisting of Indian traffic sign images. The proposed model is compared with existing state-of-the-art models. We have achieved an accuracy of 94.80% and 80.71% on the TT-100K dataset and MTSD dataset, respectively, which outperforms existing methods. We have also performed the cross-data experiment on the German Traffic Sign Detection Benchmark (GTSDB) and Indian Traffic Signs Dataset (ITSD) using the model trained on MTSD. We have achieved 91.74% and 63.64% accuracy on GTSDB and ITSD datasets, respectively.
Maciej Olszewskiet al.[9] Detection and recognition of traffic signs are two analytic processes in vehicular systems that contribute to increasing driver safety, warning, and preventing collisions by improving drivers' focus and awareness. They are also crucial for developing self-driving vehicles that can sense the environment through a camera eye and understand the road restrictions. Convolutional Neural Networks (CNNs) play an essential role in both processes by finding the traffic sign objects on acquired images or video frames and recognizing their meaning. However, CNN architectures running on vehicles need minimization, ensuring satisfactory performance and efficient operation with decreased computational resources. In this paper, we investigate two CNN architectures for traffic sign detection and two architectures for traffic sign recognition. Our experiments confirm that light models for both processes can successfully perform the achieved tasks, reaching effectiveness close to the complex models reported in the scientific literature.

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Yanqiong Zhanget al.[10] Sign language, a visual-gestural language used by the deaf and hard-of-hearing community, plays a crucial role in facilitating communication and promoting inclusivity. Sign language recognition (SLR), the process of automatically recognizing and interpreting sign language gestures, has gained significant attention in recent years due to its potential to bridge the communication gap between the hearing impaired and the hearing world. The emergence and continuous development of deep learning techniques have provided inspiration and momentum for advancing SLR. This paper presents a comprehensive and up-to-date analysis of the advancements, challenges, and opportunities in deep learning-based sign language recognition, focusing on the past five years of research. We explore various aspects of SLR, including sign data acquisition technologies, sign language datasets, evaluation methods, and different types of neural networks. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have shown promising results in fingerspelling and isolated sign recognition. However, the continuous nature of sign language poses challenges, leading to the exploration of advanced neural network models such as the Transformer model for continuous sign language recognition (CSLR). Despite significant advancements, several challenges remain in the field of SLR. These challenges include expanding sign language datasets, achieving user independence in recognition systems, exploring different input modalities, effectively fusing features, modeling co-articulation, and improving semantic and syntactic understanding. Additionally, developing lightweight network architectures for mobile applications is crucial for practical implementation. By addressing these challenges, we can further advance the field of deep learning for sign language recognition and improve communication for the hearing-impaired community.

Mohammed Al-Mahbashi et al.[11] Reliable detection of traffic signs and lights (TSLs) at long range and under varying illumination is essential for improving the perception and safety of autonomous driving systems (ADS). Traditional object detection models often exhibit significant performance degradation in real-world environments characterized by high dynamic range and complex lighting conditions. To overcome these limitations, this research presents FED-YOLOv10s, an improved and lightweight object detection framework based on You Only look Once v10 (YOLOv10). The proposed model integrates a C2f-Faster block derived from FasterNet to reduce parameters and floating-point operations, an Efficient Multiscale Attention (EMA) mechanism to improve TSL-invariant feature extraction, and a deformable Convolution Networks v4 (DCNv4) module to enhance multiscale spatial adaptability. Experimental findings demonstrate that the proposed architecture achieves an optimal balance between computational efficiency and detection accuracy, attaining an F1-score of 91.8%, and mAP@0.5 of 95.1%, while reducing parameters to 8.13 million. Comparative analyses across multiple traffic sign detection benchmarks demonstrate that FED-YOLOv10s outperforms state-of-the-art models in precision, recall, and mAP. These results highlight FED-YOLOv10s as a robust, efficient, and deployable solution for intelligent traffic perception in ADS.

Priyanka Choudharyet al.[12] Intelligent vehicle safety relies on the Traffic Sign Detection and Recognition (TSDR) system. The real-world varying light affects the visibility of traffic signs and emphasizes the necessity of a robust TSDR. Existing solutions face challenges in effectively balancing accuracy and inference time for such challenges. The proposed work introduces an adaptive framework integrating preprocessing and enhancement modules with the existing detection network. The preprocessing module employs a Fuzzy Inference System (FIS) to evaluate the illumination channel and calculate the image's exposure quality. Low-light images are directed to enhancement depending on the exposure quality, while good-light images are passed to the detection network directly. The enhancement module improves image brightness while preserving color details through illumination adjustment using the proposed Adjustment Factor Prediction Convolutional Neural Network (AFPCNN). Finally, YOLOv8 is used for TSDR from the image. The results entail accuracy comparisons of simulated low-light images using three publicly available datasets: the German Traffic Sign Detection Benchmark (GTSDB), the Tsinghua-Tencent 100K (TT100K), and the Mapillary Traffic Sign Dataset (MTSD). The proposed enhancement module improves Recall and mean Average Precision on randomly dark images by 10–18 % and 5–9 % across the benchmark datasets. Furthermore, the proposed framework enhances the detection accuracy by 1–2 % by adaptively selecting only low-light images for enhancement instead of enhancing all images from varying light conditions.

Mohammed S. Assiri et al.[13] Hand gestures (HG) are the key communication technique for hearing-impaired people, which poses a problem for millions of individuals globally after communicating with those who don't have hearing impairments. The importance of technology in improving accessibility and thus raising the standard of living for persons with hearing impairments is globally acclaimed. Machine learning (ML) is a section of artificial intelligence (AI) that concentrates on developing a method that depends on data. The major problem of HG recognition is that the machine does not identify the human language straightforwardly, and human–machine interaction is required of media for communication, which is determined by machines and, in addition to humans, to assist hearing-impaired individuals and ageing people. Thus, HG recognition as a communication media is necessary to provide instructions to the computer. This paper proposes the Swin Transformer-Driven Framework for Gesture Recognition by Integrating Deep Learning with the Secretary Bird Optimization (STFGR-IDLSBO) methodology. The main intention of the STFGR-IDLSBO methodology is to develop an efficient and robust system for gesture recognition to assist hearing-impaired persons. Initially, the proposed STFGR-IDLSBO method utilizes adaptive bilateral filtering (ABF) in the image pre-processing stage to reduce noise while preserving the edges of the gestures in the captured images. Furthermore, the swin transformer (ST) is a feature extractor that effectively captures multiscale representations and spatial hierarchies from gesture images. The hybrid model integrates the convolutional neural network and bi-directional long short-term memory (CNN-BiLSTM) technique, which is employed for the gesture classification process. Finally, the secretary bird optimizer algorithm (SBOA) is utilized for the optimum hyperparameter tuning of the CNN-BiLSTM classifier. To ensure the enhanced performance of the STFGR-IDLSBO methodology, a wide range simulation investigation is performed under the Traffic Police Gesture dataset. The performance validation of the STFGR-IDLSBO technique portrayed a superior accuracy value of 99.25% over existing methods.

Kundan Meshramet al.[14] The detection and timely repair of potholes are crucial for maintaining road safety and minimizing vehicle damage. However, existing methods often suffer from limitations such as reliance on single-modal data, poor generalization across diverse environments, and suboptimal resource management. To address these challenges, we propose a comprehensive framework for enhanced pothole detection and repair optimization using advanced deep learning techniques. Our approach integrates four key methodologies: Multimodal Enhanced Pothole Detection with Person-Level Data (M-E-Pot holeNet), Hybrid Machine Learning-Deep Learning for Classification (Hybrid-Pot holeNet), Deep Reinforcement Learning for Pot hole Detection and Repair Optimization (DRL-Pot holeOpt), and Transfer Learning for Pothole Detection in Diverse Environments (TL-Pot holeAdaptNet). M-E-Pot holeNet employs a Self-Supervised Multimodal Transformer (SSMT) to fuse camera, accelerometer, and crowdsourced smartphone data, achieving robust detection with a 97 % accuracy and under 2 % false positive rate. Hybrid-Pot holeNetcombines Graph Attention Networks (GAT) and XGBoost, modeling spatial road features to classify potholes with 95 % accuracy and an F1-Score of 0.92. DRL-Pot holeOpt uses Soft Actor-Critic (SAC) with Bayesian Optimization to efficiently schedule repair tasks, reducing repair costs by up to 20 % and crew travel time by 15–25 %. Finally, TL-Pot holeAdaptNet leverages Domain-Adversarial Neural Networks (DANN) to ensure cross-domain adaptability, with 90 % accuracy in new environments and a 40–50 % reduction in domain discrepancy. This multi-faceted approach addresses the limitations of previous work by providing scalable, real-time, and resource-optimized solutions for pothole detection and maintenance, offering significant improvements in accuracy, cost efficiency, and adaptability.

Hamza Assemlaliet al.[15] In recent years, advancements in autonomous driving technologies have shown significant potential to improve road safety, although their current impact remains a subject of ongoing research and debate. At the core of this improvement is obstacle detection, a crucial element for ensuring the effective functioning and security of these systems. Despite substantial progress, challenges remain in the detection and classification of dynamic road obstacles, which pose greater risks than fixed ones; both drivers and the obstacles in question can suffer fatal consequences because of collisions with dynamic obstacles. This highlights the urgent need for systems that can alert drivers in advance, thereby preventing accidents. The

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current paper presents a deep learning-driven approach to detect and classify dynamic obstacles, including pedestrians, vehicles, and animals. By integrating data from various datasets, we developed and adapted CNN architecture for this task, enhancing the reliability and safety of autonomous driving systems. This approach demonstrated significant improvements under various conditions. We have gotten a classification accuracy of 99.5% and a detection precision of 97.1%. The results indicate that our architecture offers a better ability to identify and classify road obstacles, thus contributing to the advancement of autonomous driving technologies.

III. THE PROCESS OF RECOGNIZING AND CLASSIFYING

The process of recognizing and classifying various types of traffic signs via the use of various machine learning strategies is referred to as traffic sign classification. This can be accomplished by teaching a computer algorithm to recognize different types of traffic signs based on the visual characteristics of the signs themselves by providing the algorithm with a large dataset of labeled images of traffic signs and allowing the algorithm to learn from its mistakes [1]. In most cases, there are numerous stages involved in the categorization process. Initially, the picture that will be analyzed is subjected to preprocessing, which enhances the characteristics of the image and makes it appropriate for analysis. After this step, a feature extractor is used to the picture in order to pull out important characteristics such as color, shape, and texture. These attributes are then fed into a machine learning model, such as a convolutional neural network (CNN), which has been trained on a large dataset consisting of labeled traffic signs. The goal of this model is to be able to recognize traffic signs. The input attributes are analyzed by the model, and the result is a probability distribution across the various classes of traffic signs. This distribution provides an indication of which sign class the input picture most likely corresponds to [2].

Fig.1. Indian Traffic Sign

IV. TRAFFIC SIGN DETECTION METHODS

Traffic sign detection and recognition system majorly uses 3 types of methods based on these feature vectors identification of traffic sign is computed uniquely, the methods are namely as follows:

- Color-based method
- Shape-based method
- Other methods

V. EXISTING SYSTEM

In the area of traffic sign detection and recognition, a considerable amount of work has been put forward.As two global characteristics of traffic signs, several authors concentrated on the color and shape attributes of image for detection. These features can be used to detect and trace a moving object in a series of frames. This approach is helpful when the target to be identified is a special color that is distinct from the background color. To detect an object with a certain shape, object borders, corners, and contours may be used. However authors only focused on the detection and recognition measures, ignoring the voice feature, which is an essential driver warning system. In addition, hyper parameter tuning has received less attention. As a result, the proposed system would concentrate on different parameters of the CNN algorithm in order to improve accuracy without requiring additional computing resources

VI. RELATED WORK

This section provides a review of previous research on the detection of traffic signs in various regions of the world. Lue et al. (2018) [1] proposed a 3-stage information-driven framework for identifying image-oriented and text-oriented signs, using a camera mounted on a vehicle. The three stages include return-on-investment (ROI) extraction, refinement-description of ROI, and post-processing. However, their proposal had a significant drawback in the extensive post-processing stage. Mammeri et al. (2013) [2] addressed issues with the TSDR structure, a crucial component of ADAS, but their system only operated within a limited frequency range and had difficulty recognizing traffic signs with a lowerresolution camera, as well as camera vibrations and movements. Lee and Kim (2018) [3] developed a remarkable CNN traffic-sign identification system that simultaneously computes the precise location and boundary of traffic signs. While the accuracy was excellent, Lee's group was limited by highresolution photos. Hu et al. (2016) [4] focused on three classes of objects: traffic signs, cars, and cycles. Their proposal detected all the three classes, by a single learning-based detection framework. In their model, the traffic sign detector needed the least amount of time as they used a smaller number of subdetectors. When additional features were added for detection of other objects, the runtimes for the detection noticeably increased. Greenhaigh J and Mirmhdi (2015) [5] used the scene structure to pinpoint search regions within the image that have a higher probability of containing a traffic sign. Maximally stable extremal regions (MSERs) and hue, saturation, and value colour thresholding are used to locate a large number of candidates, which are then reduced by applying constraints based on temporal and structural information. Individual lines are scanned first as Maximally stable extremal regions and then they are grouped into to line. However, the false up-sides resulted in significant losses due to frustrated primary data, and the processing rate decreased from 14 frames per second to 6 frames per second.

VII. CHALLENGES

While there is the potential for a great many advantages to be gained from traffic sign categorization, there are a number of obstacles that need to be solved in order to produce accurate and trustworthy results:

- Variety in lighting circumstances The appearance of traffic signs may change depending on the lighting conditions, such as whether they are being seen in direct sunshine, in the shade, or in low-light settings. Because of this, it could be challenging for the algorithm to effectively recognize and categorize indicators.
- Obscurations and clutter: It is possible for other things, such as trees or other cars, to partly hide traffic signs. Moreover, traffic signs may be accompanied by debris. Because of this, the algorithm may have a more difficult time recognizing and categorizing the sign.
- Variety in look The appearance of traffic signs may change for a number of reasons, including normal wear and tear, acts of vandalism, and variations in design that exist across nations or areas. Because of this, it could be challenging for the algorithm to appropriately categorize the sign.
- Insufficient training data: In order to train a machine learning algorithm for the classification of traffic signs, it is necessary to have a big collection of pictures of traffic signs that have been tagged. Nevertheless, such databases could be lacking in size or variety, which is especially problematic for identifying unusual or infrequent indications.
- Performance in real time: The algorithm used for traffic sign categorization has to be able to function in real time for certain applications, such as autonomous cars and driver assistance systems, in order to deliver information that is both fast and accurate. Because of this, the algorithm has to be improved so that it can handle data as quickly and effectively as possible. In order to find solutions to these problems, it is necessary to pay close attention to the development and implementation of the algorithm for traffic sign classification, as well as the collection and curation of highquality training data. It is necessary to do ongoing research in computer vision and machine learning in order to build traffic sign categorization algorithms that are more reliable and accurate.

VIII. CONCLUSION

We presented a literature review on traffic sign identification using machine learning techniques, as well as a comparative study and analysis of these techniques in this paper. CNN performs well for recognition and with the aid of hyper parameter tuning, accuracy or recognition rate can be improved. As a result, in the proposed scheme to design a warning traffic sign detection system for drivers, we used CNN for traffic sign recognition. The images will be taken with a camera mounted on the car during the image acquisition stage and the recognition process will be done using the CNN algorithm after preprocessing. The machine issues a voice alert when a traffic sign is identified. This model can be used in circumstances requiring precise navigation.

This review highlights the significant progress achieved in Indian traffic sign detection and recognition through the application of deep learning techniques. Modern deep learning models such as CNN, YOLO, Faster R-CNN, and SSD have demonstrated improved accuracy and efficiency compared with traditional machine learning methods, particularly in complex traffic environments. These approaches enable automatic feature extraction and robust classification, which are essential for real-time intelligent transportation systems.

However, the Indian traffic environment presents unique challenges, including variations in sign appearance, poor visibility, weather conditions, occlusions, and limited availability of well-annotated datasets. Addressing these issues requires the development of more robust and lightweight deep learning models capable of operating efficiently in real-world conditions.

Future research should focus on creating larger Indian traffic sign datasets, improving model generalization, and integrating advanced techniques such as transfer learning, edge computing, and hybrid deep learning frameworks. Such developments will support the effective implementation of traffic sign recognition systems in advanced driver assistance systems and smart transportation infrastructure across India.

IX. FUTURE SCOPE

In the future, we hope to investigate other architecture and compression strategies to create a virtually optimal network for each module, addressing all of the CCs in the CURE-TSD dataset in terms of performance and inference speed.

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