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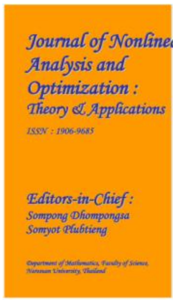

TRAFFIC SIGNS DETECTION

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ABSTRACT: Traffic sign recognition stands as a critical research area crucial for the advancement of autonomous vehicle technology. With the increasing demand for automated driving systems, there arises a pressing need for efficient handling of input data. Unlike traditional methods that may involve complex transformations or sophisticated image processing techniques, autonomous systems demand real-time analysis to make split-second decisions. This necessity becomes even more pronounced in urban environments characterized by a multitude of factors such as numerous traffic signs, advertisements, parked vehicles, pedestrians, and other moving or background objects, all of which contribute to the complexity of recognition tasks.

1. INTRODUCTION

Autonomous Vehicle Driving Systems (AVDS) play a critical role in recognizing potential hazards, understanding driving constraints, and assessing opportunities for safe navigation. To bolster the capabilities of AVDS in the Indian context, an original dataset comprising Indian traffic signs was meticulously curated using advanced deep learning techniques. In assessing the performance of the RMR-CNN model, a state-of-the-art approach in traffic sign detection and recognition, conventional models based on deep neural networks were employed. Among these, Convolutional Neural Networks (CNNs) have emerged as a cornerstone technology, achieving significant milestones in image analysis. Leveraging the power of CNNs and other deep neural network frameworks, such as Fast Region-Based Convolutional Neural Networks, paved the way for robust detection and recognition of traffic signs in varied environmental conditions.

The overarching objective of this research endeavor was to identify proactive measures aimed at mitigating traffic accidents. By harnessing the capabilities of advanced deep learning techniques and meticulously curated datasets, the study aimed to empower AVDS with enhanced capabilities for real-time detection, recognition, and interpretation of Indian traffic signs.

2. REVIEW OF LITERATURE

" The German traffic sign recognition benchmark a multi-class classification competition,". This paper proposes the design and analysis of the "German Traffic Sign Recognition Benchmark" dataset and competition. The results from the competition indicate that cutting-edge machine learning algorithms exhibit exceptional performance in the intricate task of traffic sign recognition. Participants achieved an impressive accuracy rate of up to 98.98%, a level comparable to human performance on the dataset.

Addressing the imperative of real-time traffic sign recognition, the paper "Towards Real-Time Traffic Sign Detection and Classification" introduces a dual-module framework. In the detection module, the input color image undergoes transformation into probability maps via a color probability model. Subsequently, road sign proposals are generated by identifying maximally stable extremal regions on

these maps. These proposals are then subjected to further refinement and classification using an SVM classifier equipped with color Histogram of Oriented Gradients (HOG) features. In the classification module, a Convolutional Neural Network (CNN) is deployed to categorize the detected traffic signs into their respective subclasses within each super class.
In the study "Traffic Indication Symbols Recognition with Shaped Context" by Kii Li and Weyao Lan from Xiamen University, China, a distinct methodology is proposed for traffic sign detection. Initially, the HIS color model is employed in conjunction with circle detection to identify potential traffic sign regions. Subsequently, morphological operations and edge tracing are applied to delineate the contours of these regions, followed by the application of the Hough circle transform to pinpoint the target region. Noise removal and edge detection are then performed to obtain a clear silhouette boundary of the traffic indication symbol, and shape context analysis is employed based on the contour of the object.

3. RELATED WORK

S Safety Enhancement: Traffic signs as vital visual cues for drivers, providing information about speed limits, road conditions, hazards, and regulatory instructions. Accurate detection of traffic signs can help drivers make informed decisions, reduce the risk of accidents, and improve overall road safety.
Autonomous Driving: With the rapid advancements in vehicle technology, there is a growing demand for robust and reliable systems capable of accurately detecting and interpreting traffic signs in real-time. CNN-based approaches offer the potential to develop sophisticated autonomous driving systems that can navigate complex traffic environments safely and efficiently.
Dataset Availability: The availability of large annotated datasets, such as the German Traffic Sign Recognition Benchmark (GTSRB) dataset, has facilitated the development and evaluation of CNN-based models for traffic sign detection. These datasets provide researchers with valuable resources for training, validation, and benchmarking their algorithms.
Efficiency and Real-time Performance: Efficient detection of traffic signs is essential for real-time applications such as autonomous driving and ADAS. CNN-based methods can leverage parallel processing and optimization techniques to achieve fast inference speeds while maintaining high detection accuracy, enabling timely responses to changing traffic conditions.

4. PRINCIPAL COMPONENT ANALYSIS (PCA)

Three essential pre-processing steps precede the application of the Mask R-CNN algorithm for sign detection and recognition: feature extraction, region of interest (ROI) selection, and color analysis.
***Shape Detection**:* The initial preprocessing step in our system involves detecting shapes in live video capture images. Upon detection, both color and grayscale images are obtained. Initially, the camera's color image data is converted to grayscale. Subsequently, we apply contour detection techniques from OpenCV to identify the contours of objects in the image. Using the obtained contour values, we calculate the area of each contour.
Based on the area of the contours, we determine the shape of the traffic sign using threshold parameters specified by the user. These detected traffic sign images are then passed to the Region of Interest (ROI) module for further processing.
This approach allows us to accurately identify and isolate traffic signs from the background in live video capture, laying the foundation for subsequent processing and analysis.
Region Of Interest (ROI): To achieve this, our model employs three algorithms tailored to detecting specific shapes: the Hough Circle package for circular ROIs, and Counter and Edge detection algorithms for triangles and squares, respectively. Each algorithm is designed to identify the corresponding shape within the image and mark it as an ROI using a distinct colour. By segmenting the image into regions of interest, our model ensures that only relevant areas are analysed, thereby optimizing computational resources and reducing processing time.
Furthermore, we utilize colour probability analysis to quantify the presence of RGB pixel values within the identified ROIs. This analysis allows us to assess the likelihood of a region containing a traffic sign based on its color characteristics. By leveraging this information, our model can prioritize regions with higher probabilities of containing traffic signs, thereby enhancing the efficiency and accuracy of the detection process.
Color Probability: Using this dataset, the number of pixels corresponding to red, black, and white

colors is calculated in real-time by analyzing the range of RGB values from the image dataset. For each pixel in the image, a counter is incremented for red, black, and white colors based on the determined range. The range of RGB pixel counts is computed from the dataset while the image is positioned both towards and away from the sunlight to ensure robustness across different lighting scenarios. Following the color probability analysis, the processed image is then forwarded to the model for further processing and traffic sign detection and recognition. This meticulous preprocessing step ensures that the model receives input data that has been optimized for accurate and reliable performance under varying lighting conditions.

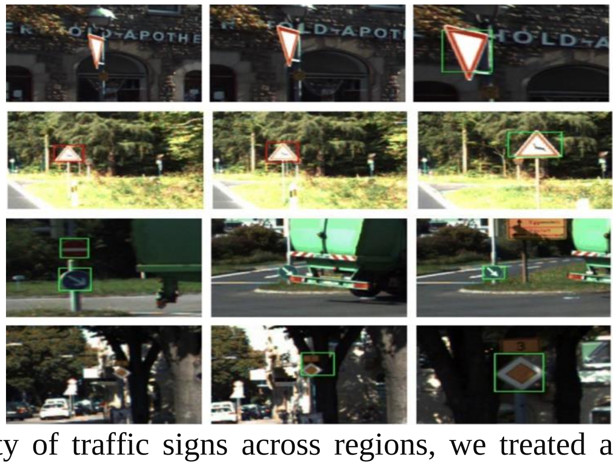
In our system, we developed a Convolutional Neural Network (CNN) model with filters of various dimensions, including 3x3, 5x5, 9x9, and up to 31x31. We conducted experiments to determine the optimal filter size for accuracy in traffic sign recognition. For training and validation, we utilized the German Traffic Sign Recognition Benchmark (GTSRB) dataset, consisting of 50,000 images across 43 classes. Additionally, we incorporated an Indian dataset for testing purposes using Transfer Learning techniques. The datasets were split into training, validation, and test sets.

The images and their respective labels were organized and processed into numpy arrays. Our CNN architecture featured a single convolutional layer equipped with 32 filters, activated by the Rectified Linear Unit (ReLU) function. Subsequently, a down sampling layer employing 2x2 maximum pooling was applied. Following this, a hidden affine layer comprising 500 neurons was incorporated, followed by an output layer containing 43 neurons, each representing a distinct class of traffic signs. Throughout the training process, we utilized the mean Average Precision (mAP) metric to assess the accuracy of our model iteratively. in class number. Data related to images was stored in x-train , x-test , x-validation and corresponding id in each class is stored in y-train , y-test , y-validation.

After splitting the data, we built models using various filters, resulting in nine models with differing accuracies. Among these, the model with 3x3 filters demonstrated the highest accuracy.

In our analysis, we observed that traffic signs exhibit distinct color patterns compared to their surroundings. To leverage this, we introduced statistical image analysis to identify common traffic sign colors. This analysis aided in colour normalization, ensuring robust recognition across different weather conditions and environments.

For input image processing, we used a web camera optimized for human vision. Colour segmentation was performed using YUV420 encoding, with subsequent resampling and transformation into the CIELAB colour space for filtering. This filtering isolated colours specific to traffic signs, enhancing recognition accuracy.

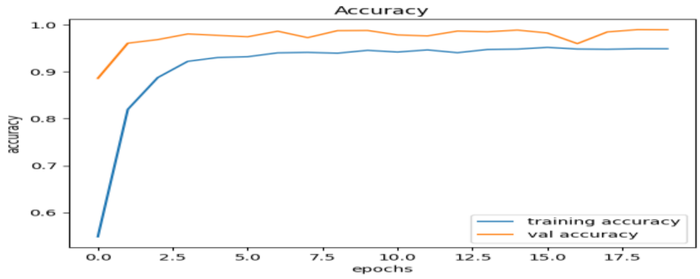


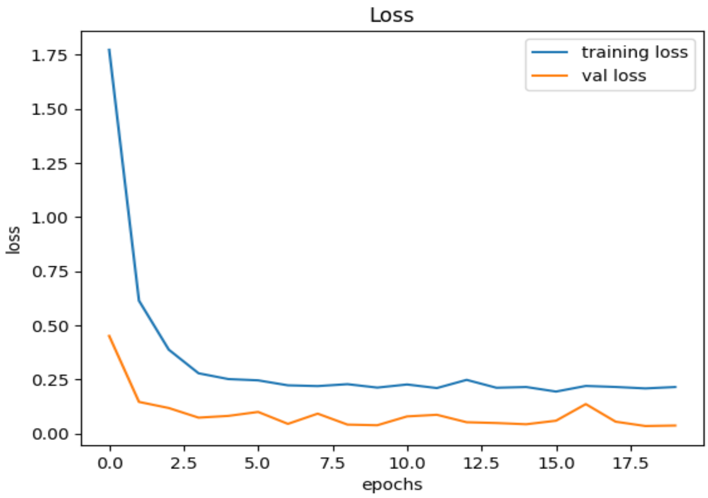
Recognizing the variability of traffic signs across regions, we treated a wide range of colours as potential traffic sign colours to ensure inclusivity. Additionally, we addressed variations in sign appearance by employing robust ROI selection algorithms and Haar-like features for fragment-based recognition.

In conclusion, our system employs a CNN model optimized for traffic sign recognition, leveraging color analysis and region-based approaches to achieve accurate and robust performance across diverse environments and sign variations.

5. EXPERIMENTAL RESULTS

After executing the outlined methodology, we derived multiple models by experimenting with filters of various dimensions, each yielding differing levels of accuracy.





Once we determined the most accurate . we proceeded to the detection phase using the Framework. The input size of the network was set to specific spatial dimensions—82x82, 94x94, and 106x106. Prior to feeding the images into the network, they were resized to these dimensions by the framework, without maintaining aspect ratio.
For detection purposes, we utilized the trained model to classify the detected images. Additionally, we employed a CSV file containing the names of 43 different classes of sign from the dataset. This allowed us to label the traffic sign images are based on the predictions made by the model.

6. CONCLUSION

Utilizing a Convolutional Neural Network (CNN) with varying filters significantly enhanced our traffic sign classification system, resulting in the selection of the most accurate model with an impressive 87% accuracy. this model using the German Traffic Sign Recognition Benchmark (GTSRB) dataset and validated its performance with the Indian Dataset. The detection model effectively identifies traffic signs within the environment and accurately classifies them into their respective categories. Leveraging Transfer Learning, we fine-tuned the model specifically for Indian Traffic Signs, ensuring adaptability across diverse scenarios.
By employing Transfer Learning and robust CNN architecture, our system exhibits resilience against lighting changes, occlusions, and object deformations, making it invaluable for Driver Support Systems. Through extensive experimentation, we achieved a classification accuracy of 95%, demonstrating the system's robustness and efficacy.

7. FUTURE SCOPE

An emerging avenue for future exploration involves the real-time traffic sign recognition system that utilizes onboard vehicle cameras to capture live video footage. This system would be capable of promptly detecting and identifying traffic signs .Real-time, providing timely alerts or instructions to the driver to facilitate safe navigation. Further research could focuses on optimizing the system processing speed .It ensures rapid response time.
Enabling drivers to take appropriate actions promptly.
Moreover, there is potential for the development of artificial intelligence (AI) algorithms capable of autonomously verifying reports, images, and videos without the need for human intervention. By leveraging advanced, these AI systems could streamline and expedite the verification process, thereby enhancing efficiency and accuracy. Additionally, research efforts may explore integrating AI-powered

verification systems into various domains, including journalism, social media, and online content moderation, to facilitate smoother and faster information validation processes.

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