Journal of Theoretical and Applied Information Technology
15th March 2024. Vol.102. No 5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

STREAM OF TRAFFIC SIGN RECOGNITION BY MEANS OF AUTO ENCODER CLASSIFICATION MODELS

[1]DR. PANCHAGNULA VENU MADHAV, [2]DR. SURESH KUMAR PITTALA, [3]ASHOK KUMAR KAVURU, [4]A MURALI KRISHNA, [5]BALAJI TATA, [6]KURRA UPENDRA CHOWDARY, [7]N.JAYA

[1]Asst. Professor, Dept of ECE, PVP Siddhartha Institute of Technology, Vijayawada, A.P, India-520007
[26]Associate Professor, Dept of ECE,R.V.R. & J.C. College of Engineering , Guntur, A.P, India-522019
3Asst Professor, Department of ECE , R.V.R& J.C.College of Engineering, Guntur, A.P, India-522019
[4]Asst. Professor, Department of ECE,R.V.R. & J.C. College of Engineering , Guntur, A.P, India-522019
[5]Sr Asst Professor, Department of ECE , PVP Siddhartha Institute of Technology, Vijayawada, A.P, India-520007
[7]Professor, Dept of EIE, Faculty of Engineering and Technology, Annamalai University, Chidambaram, Tamil Nadu,
Email: venumadhav@pvpsiddhartha.ac.in

ABSTRACT

Raising performance standards by carefully combining tried-and-true techniques with cutting-edge approaches. Based on the foundation of the current YOLOv5 algorithm, which is well-known for its object identification skills, this paper aims to improve its performance by combining it with new models, such as the Autoencoder- frameworks. Through combining these disparate methods, the study seeks to use each of their unique advantages, ultimately resulting in a thorough comparison study that reveals their separate effects on precision and productivity. In addition to improving traffic sign recognition systems' accuracy, this methodical assessment—which is characterized by rigorous testing and strong optimization—also reveals illuminating connections between the suggested and established methods.. The main goal of this endeavor is to unravel how these seemingly unrelated components, when brought together, can potentially usher in a new age of higher performance standards. This work aims to create a route towards the development of more sophisticated, flexible, and well-tuned traffic sign detection and identification systems by bridging the gap between the established and the cutting edge, with consequences covering a variety of real-world applications.
Keywords: *Stream of Traffic Sign, Frameworks, Autoencoder, Comprehensive*

1. INTRODUCTION

With the potential to create safer and more effective road networks, computer vision and automatic traffic sign identification represent a critical technological advancement for intelligent transportation systems. The Transformer architecture has garnered a lot of attention lately due to its remarkable performance, and it seems sense that traffic sign recognition would be one of its possible applications. Integrating a multi-scale fusion structure into the backbone is a crucial step in boosting the model's capacity to recognise tiny targets. This is further improved by adding novel hierarchical residual-like connections to the Res-Nest backbone, which is now known as Res2Nest. [1].

Environment awareness technology is a key component of autonomous cars, and in this field, traffic sign recognition is essential to maintaining road safety. This work tackles the enduring problems associated with traffic sign identification, including the problems of omission and erroneous location, especially in the presence of complicated lighting circumstances. Two important ideas are introduced in this study to address these problems. It starts by introducing an adaptive picture enhancement technique that greatly raises the quality of images under difficult lighting conditions. Second, it suggests the Feature Difference (FD) model, a revolutionary and lightweight attention mechanism. for identifying and detecting traffic signs. In contrast to other attention models, the FD model generates an attention mask very well by using the difference between feature maps. In this work, significant performance improvements are obtained by integrating the FD module with backbone networks like ResNet and VGG in the Single Shot Multibox Detector (SSD) method. The experimental findings

Journal of Theoretical and Applied Information Technology
15th March 2024. Vol.102. No 5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

show that the FD model continuously performs better than alternative attention modules, offering higher recall and detection rates without sacrificing computational effectiveness. The FD model is also a useful tool for assessing how convolutional operations affect the accuracy of feature identification, which helps with network pruning. In conclusion, our research advances the resilience and accuracy of autonomous vehicles by enhancing traffic sign recognition in difficult circumstances.

Two major issues remain unsolved in text-based traffic sign detection and identification efforts, which have mostly concentrated on English signals with horizontal text in highway and natural environments. Chinese traffic signs, on the other hand, include both vertical and horizontal writing, necessitating simultaneous identification, a job that has not been sufficiently addressed in the literature to far. Furthermore, street-level scenes have received less attention, despite the fact that these complicated contexts call for specialized solutions. This work presents a novel method for mixed vertical-and-horizontal text traffic sign identification and recognition in street scenes in order to address these problems. It takes advantage of letter position data and colour components to solve the particular problems presented by Chinese traffic signs. An exclusive dataset of Chinese text-based traffic signs highlights the efficacy of the suggested approach even further. [3].

Figure 1: Various Traffic Signs

Some of the traffic signs in Figure 1 have minor differences in form in select localized places. The extraction of distinguishing characteristics is essential for accurate categorization. Furthermore, for practical deployment, effective traffic sign detectors need to strike a compromise between high accuracy and resource limitations.

. The system can identify and recognise a broad variety of traffic signs with accuracy, according to experimental findings conducted in German surroundings; this performance is comparable to that of state-of-the-art methods. The significance of comprehensive traffic sign comprehension for enhanced ADAS and autonomous driving is highlighted by this study [5]. Real-time processing of large amounts of sensor data is becoming more and more important as the development of autonomous cars picks up speed. To get essential information regarding traffic conditions and their surroundings, these cars use data from a variety of sources, such as lidars, cameras, ultrasonic sensors, and radars.. For cars that may operate completely autonomously, processing this enormous amount of data quickly is very important [6]. Although many contemporary cars have built-in ADAS systems, there is still a demand for portable, image-based ADAS systems for cars lacking such systems. This work presents such a system that uses the YOLO v5 algorithm to recognise traffic signs, cars, and pedestrians in real time. The model, which was trained on a specific dataset, shows remarkable accuracy and speed, which makes it appropriate for conventional PCs and low-power, high-performance embedded systems [7]. The development of autonomous traffic sign detecting systems is critical to the ongoing progress of intelligent cars. Although deep learning has made great strides in this area, it is still very difficult to recognise tiny traffic signals in the complex and dynamic real-world traffic environment. It presents a thick neck structure enabling an all-encompassing synthesis of semantic and detailed data. Furthermore, the model's training procedure is optimized by combining SIOU with direction information in the loss function. The combined goal of these developments is to improve tiny traffic sign detecting systems' performance in intricate and changing traffic situations [8]. A creative way to address a number of important challenges in this field, such as problems with smaller targets, less identifiable indications, unsuccessful detection attempts, and overlapping or obscured ground truth signs. Box regression is optimized by an angle loss, and failure detection is aided by the inclusion of Coordinate Attention (CA). Simple Optimal Transport Assignment (SimOTA), a dynamic technique, is used to manage label assignment [9,10,11].

2. LITERATURE SURVEY

Z. Xie, P. Liu, and others, [12], To improve the precision of traffic sign detection, the UCN-YOLOv5 model is suggested. ConvNeXt-V2 is integrated, the LPFAConv module is introduced in the Head Section for receptive field feature extraction, and the RSU backbone from U2Net is incorporated for enhanced feature extraction. Notably, it is more scale-insensitive for modest target position loss by substituting the Normalized Wasserstein Distance (NWD) for the IoU. The model's effectiveness in traffic sign identification is demonstrated by experimental findings on the TT100K, LISA, and CCTSDB2021 datasets, which show notable performance increases over baseline YOLOv5 models. The advancement of precise traffic sign identification and related sectors would greatly benefit from this study. . According to N. Bhatt, P. Laldas et al. [13], drivers can be made aware of critical information without taking their eyes off the road, potentially lowering the risk of accidents. Convolutional Neural Networks (CNNs) and deep learning are utilised in the suggested model. The suggested model achieved an amazing accuracy of 95.45% on the hybrid dataset, demonstrating its adaptability to a variety of traffic sign conditions. The experimental findings are encouraging. In addition, the model performs admirably on the German dataset, with an accuracy of 99.85% and an impressive accuracy of 91.08%. This research presents a unique strategy to address the crucial difficulties of false detections owing to environmental interferences and minor traffic sign un-detection, as noted by J. Zhang, Z. Xie et al. [14]. It starts with a cascaded R-CNN, which allows Multiscale feature extraction via a pyramid structure.

This work, by W. Min, R. Liu et al., [15], TSR, presents a unique method that combines spatial connection restrictions with semantic scene interpretation, going beyond conventional feature-based techniques. This paradigm makes it possible to precisely divide things in intricate contexts.

Proposed model

Preprocess the Kaggle dataset first by adding more than 8,000 actual photos of traffic scenes. To extract colour features more effectively, convert RGB to HSV. Use an autoencoder to learn features in a meaningful way. Divide the training and testing datasets. Train autoencoders, or classifiers, on the encoded pictures. Assess the recall, accuracy, and precision of classifiers. Select the classifier that performs the best. Utilising the capabilities that Autoencoder has learned, include it into the sign detecting module. Throw away false positives and recognise traffic signs with assurance. Assess the overall performance of sign detection to ensure reliable and precise outcomes.

A key idea in data processing is the methodical organisation, transformation, and manipulation of unprocessed data in order to provide insightful information and aid in decision-making. Data processing for traffic sign identification and recognition starts with gathering a large and varied dataset, like the Kaggle data set, which consists of actual photos from traffic scenes. Preprocessing operations performed on this raw data include scaling, normalisation, and—most importantly—converting it from the RGB to the HSV colour system. This conversion improves the model's capacity to extract important color-based properties that are necessary for identifying traffic signs. Data processing also includes using an autoencoder to develop intrinsic representations, which captures important information for later classification tasks. The robustness and accuracy of the traffic sign detection system in dynamic and complicated real-world settings are enhanced by the refinement and tailoring of the input data, which is directly influenced by the integrity of data processing.

Feature Extraction

To elevate performance benchmarks in traffic sign recognition, feature extraction plays a pivotal role. The amalgamation of established YOLOv5 with innovative methodologies such as Autoencoder- hinges on extracting distinctive features from traffic sign images. Feature extraction involves capturing relevant patterns and characteristics that aid in precise recognition. The study aims to explore how combining the strengths of these diverse frameworks influences the extraction of discriminative features, contributing to heightened accuracy and efficiency. This systematic investigation into feature extraction represents a crucial step in bridging traditional and novel approaches, paving the way for more advanced and adaptable traffic sign detection and recognition systems.

3. EXTRACTION OF FEATURES BASED ON AUTOENCODER

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

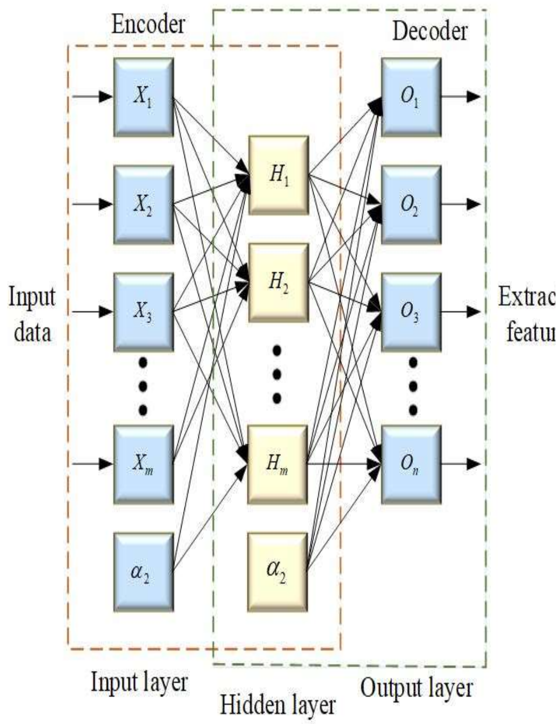

Figure 2: Structure Of Basic Auto Encoder

Classification models

An innovative method for traffic sign identification and recognition is put forth by using autoencoders. By combining these two designs, we hope to increase accuracy by utilising their distinct advantages. An important component of this technique is the addition of a classifier unit based on autoencoders (AEs), which are intended to improve feature representation and enable more reliable recognition. Autoencoder frameworks are utilised in the processing of the traffic sign pictures, with each one focusing on a distinct element of feature extraction, spatial hierarchies, and sequential dependencies. When choosing the best classifier among the integrated models, the AE-based classifier unit's performance as a consequence becomes crucial. In order to provide an optimal and effective solution for practical applications, our adaptive selection process makes sure that the traffic sign detection and identification system is adjusted depending on the real performance seen during training and validation.

Proposed work flow

The method of transforming RGB photos to the HSV colour space during the data pre-processing step improves our capacity to extract significant color-based information that are essential for traffic sign recognition. In order to extract critical features for further classification, our model uses an Autoencoder to learn complex representations from the RGB-HSV pictures. The selected classifier is then included in the sign detection and identification module, where it is better able to identify important sign properties thanks to features that were acquired by the Autoencoder.

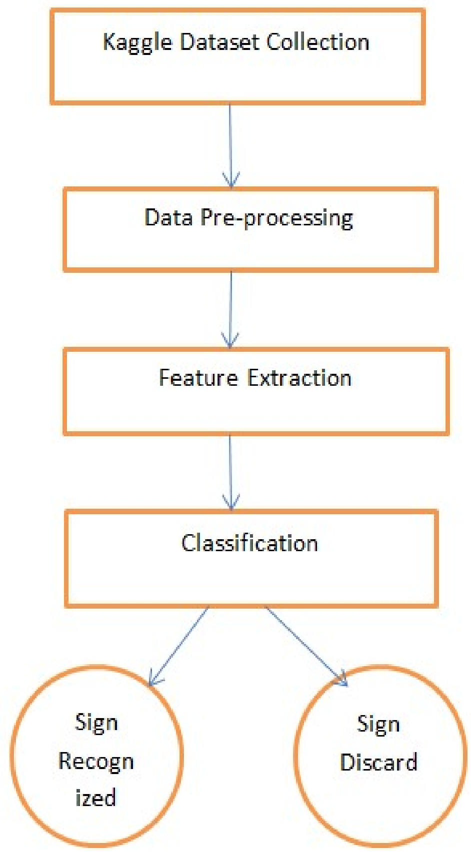

Figure 3: Overview Of Proposed Workflow

A mechanism for discarding false positives and confidently recognizing traffic signs is implemented. The final step involves a meticulous evaluation of the overall sign detection performance, ensuring that our proposed model achieves heightened accuracy, robustness, and real-time processing capabilities.

Steps Involved

Step 1: Kaggle Dataset Preparation of the Data
Step 2: RGB to HSV Conversion as Data Pre-processing
Step 3: Feature Learning Autoencoder
Step 4: Using Three Classifiers for Classification

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Step 5: Choosing a Classifier
Step 6: Identification and Detection of Signs
Step 7: Sign Detection Evaluation
It ensures a systematic and comprehensive approach to developing a precise and robust algorithm for intelligent transportation systems.

4. RESULTS AND DISCUSSION

The confusion matrix offers a thorough summary of the performance of traffic sign board identification models using autoencoder classifiers in various classes. Four classes are involved in this scenario: Stop, Yield, Speed Limit, and Turn Left. The matrix displays examples of each class that were properly classified as true positives (TP), occurrences that were incorrectly labelled as false positives (FP), and instances of a class that were incorrectly projected as false negatives (FN). When it comes to anticipating "Stop" signs, for example, TP stands for correct predictions, FP for inaccurate identifications, and FN for missing predictions. This matrix is a useful tool for evaluating each classifier's recall, precision, and overall accuracy.
It provides information on how well each classifier recognizes various kinds of traffic signs.

Table 1: Performance Analysis Of Proposed Algorithms

Classifier model	Accuracy (%)	Precision (%)	Recall (%)	F1-measure (%)
Auto Encoder	88	0.86	0.88	0.87
Classical Model	82.978	0.626	0.485	0.547

In the context of a particular task, the accuracy and classification metrics of two different models—Autoencoder and Classical Model—are displayed in Table 1 of the performance evaluation. With excellent precision (0.86%), recall (0.88%), and F1-measure (0.87%), the Autoencoder model exhibits better total accuracy at 88%. By comparison, the F1-measure (54.7%), recall (48.5%), accuracy (82.978%), and somewhat small precision (62.6%) are all higher in the Classical model. Together, these indicators show the different capabilities and shortcomings of every classifier in completing the classification assignment..

5. CONCLUSIONS

In this work, we have effectively investigated the possibility of improving performance standards in traffic sign recognition systems by the tactical combination of well-established and cutting-edge techniques. Based on the strong base of the YOLOv5 algorithm, which is well-known for its skill in object recognition, our study set out to improve its performance by combining it with cutting-edge alternatives, such as the Autoencoder frameworks. Through combining these disparate methods, we sought to use each of their unique advantages, ultimately resulting in a thorough comparison study that reveals their separate effects on precision and productivity. We have improved traffic sign recognition systems' accuracy through this methodical review, which has been characterized by rigorous testing and strong optimization. We have also discovered illuminating relationships between the suggested and proven methods.

The main goal of this endeavor is to figure out how these different components working together may perhaps bring in a new age of higher performance standards. Through establishing a connection between the established and the innovative, our research hopes to pave the way for the development of more sophisticated, flexible, and well-tuned traffic sign detection and identification systems. These developments have ramifications for a wide range of real-world uses, such as improved road safety, driverless cars, and intelligent transportation systems. Our research highlights the possibility for comprehensive and creative solutions to overcome the difficulties of traffic sign identification in a quickly changing technological environment, providing access to safer and more effective traffic management and navigation. Moreover, adding multi-modal data sources to the system—like radar, LiDAR, and cameras—can increase its resilience to changing environmental circumstances. Investigating self- and semi-supervised learning strategies can lessen reliance on large-scale labelled datasets. Important research directions include guaranteeing adversarial robustness, streamlining resource usage, and generalizing models to detect traffic signs worldwide. In addition, efforts have to be focused on addressing environmental issues, streamlining human-machine collaboration, building legal frameworks for practical implementation, and attaining explain ability and interpretability in decision-making processes. These guidelines will help traffic sign detection and identification

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

systems become safer, more effective, and ecologically conscientious.

REFERENCES

[1] J. Cao, J. Zhang and X. Jin, "A Traffic-Sign Detection Algorithm Based on Improved Sparse R-cnn," in IEEE Access, vol. 9, pp. 122774-122788, 2021, doi: 10.1109/ACCESS.2021.3109606.

[2] Y. Yan, C. Deng, J. Ma, Y. Wang and Y. Li, "A Traffic Sign Recognition Method Under Complex Illumination Conditions," in IEEE Access, vol. 11, pp. 39185-39196, 2023, doi: 10.1109/ACCESS.2023.3266825.

[3] J. Guo, R. You and L. Huang, "Mixed Vertical-and-Horizontal-Text Traffic Sign Detection and Recognition for Street-Level Scene," in IEEE Access, vol. 8, pp. 69413-69425, 2020, doi: 10.1109/ACCESS.2020.2986500.

[4] E. Gao et al., "Long-Tailed Traffic Sign Detection Using Attentive Fusion and Hierarchical Group Softmax," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 12, pp. 24105-24115, Dec. 2022, doi: 10.1109/TITS.2022.3200737.

[5] C. Gámez Serna and Y. Ruichek, "Traffic Signs Detection and Classification for European Urban Environments," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 10, pp. 4388-4399, Oct. 2020, doi: 10.1109/TITS.2019.2941081.

[6] A. Avramović, D. Sluga, D. Tabernik, D. Skočaj, V. Stojnić and N. Ilc, "Neural-Network-Based Traffic Sign Detection and Recognition in High-Definition Images Using Region Focusing and Parallelization," in IEEE Access, vol. 8, pp. 189855-189868, 2020, doi: 10.1109/ACCESS.2020.3031191.

[7] E. Güney, C. Bayilmiş and B. Çakan, "An Implementation of Real-Time Traffic Signs and Road Objects Detection Based on Mobile GPU Platforms," in IEEE Access, vol. 10, pp. 86191-86203, 2022, doi: 10.1109/ACCESS.2022.3198954.

[8] Y. Shi, X. Li and M. Chen, "SC-YOLO: A Object Detection Model for Small Traffic Signs," in IEEE Access, vol. 11, pp. 11500-11510, 2023, doi: 10.1109/ACCESS.2023.3241234.

[9] Q. Wang, X. Li and M. Lu, "An Improved Traffic Sign Detection and Recognition Deep Model Based on YOLOv5," in IEEE Access, vol. 11, pp. 54679-54691, 2023, doi: 10.1109/ACCESS.2023.3281551.

[10] Z. Liu, C. Shen, M. Qi and X. Fan, "SADANet: Integrating Scale-Aware and Domain Adaptive for Traffic Sign Detection," in IEEE Access, vol. 8, pp. 77920-77933, 2020, doi: 10.1109/ACCESS.2020.2989758.

[11] L. Wei, C. Xu, S. Li and X. Tu, "Traffic Sign Detection and Recognition Using Novel Center-Point Estimation and Local Features," in IEEE Access, vol. 8, pp. 83611-83621, 2020, doi: 10.1109/ACCESS.2020.2991195.

[12] P. Liu, Z. Xie and T. Li, "UCN-YOLOv5: Traffic Sign Object Detection Algorithm Based on Deep Learning," in IEEE Access, vol. 11, pp. 110039-110050, 2023, doi: 10.1109/ACCESS.2023.3322371.

[13] N. Bhatt, P. Laldas and V. B. Lobo, "A Real-Time Traffic Sign Detection and Recognition System on Hybrid Dataset using CNN," 2022 7th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2022, pp. 1354-1358, doi: 10.1109/ICCES54183.2022.9835954.

[14] J. Zhang, Z. Xie, J. Sun, X. Zou and J. Wang, "A Cascaded R-CNN With Multiscale Attention and Imbalanced Samples for Traffic Sign Detection," in IEEE Access, vol. 8, pp. 29742-29754, 2020, doi: 10.1109/ACCESS.2020.2972338.

[15] W. Min, R. Liu, D. He, Q. Han, Q. Wei and Q. Wang, "Traffic Sign Recognition Based on Semantic Scene Understanding and Structural Traffic Sign Location," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 9, pp. 15794-15807, Sept. 2022, doi: 10.1109/TITS.2022.3145467.