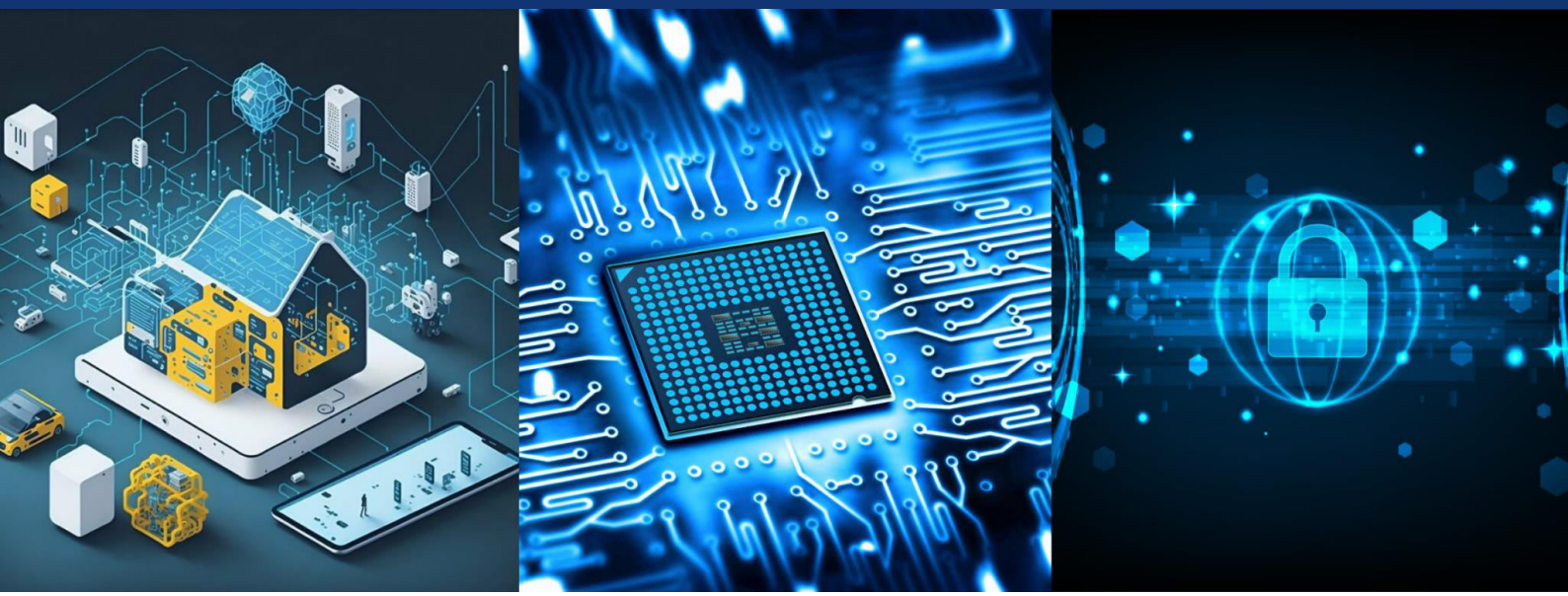
IJIRCCE

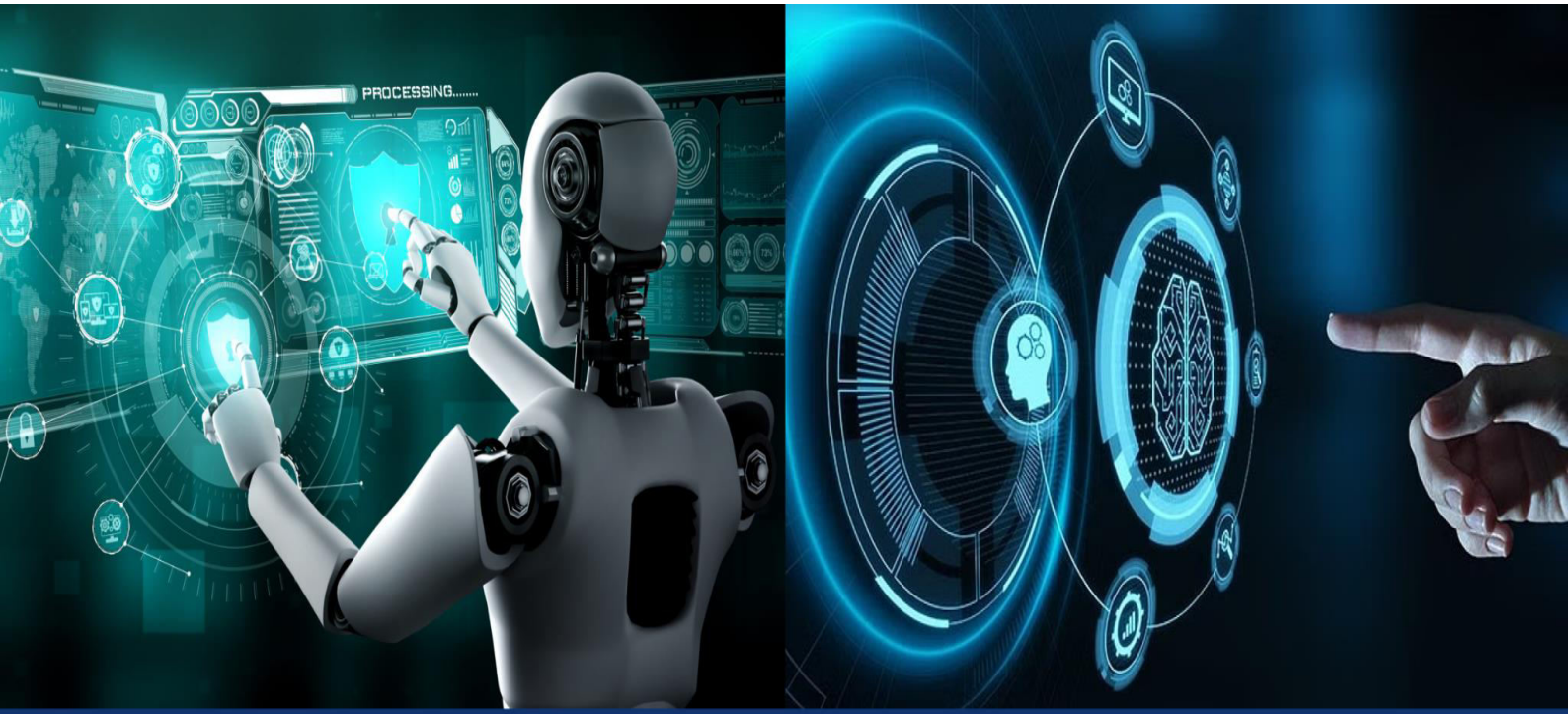
ISSN(O): 2320-9801

ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 9.927

Volume 14, Issue 11, November 2026

© 2026 IJIRCCE | Volume 14, Issue 11, November 2026 DOI: 10.15680/IJIRCCE.2026.1411010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Traffic Sign Detection and Recognition using Deep Learning

Prof. Faiz Rangari, Aaryan Sonawane, Vibhor Chavhan, Shailendra Singh

Department of Electronics and Computer Science, Vidyalankar Institute of Technology, Mumbai, Maharashtra, India

ABSTRACT: This paper reviews "Indian traffic sign detection and recognition using deep learning," which proposes a Refined Mask R-CNN (RMR-CNN) for Indian traffic-sign detection and recognition. The study addresses the domain gap between models trained on foreign traffic-sign benchmarks and signs observed on Indian roads. The authors report a custom dataset of 6,480 images, 7,056 sign instances, and 87 categories, and describe preprocessing, region-of-interest selection, model refinements, and data augmentation. The paper reports 97.08% precision and 96.75% recall for RMR-CNN in its model comparison. This review examines the problem, literature context, methodology, reported results, merits, and limitations. A separate section summarizes results from our own GTSDB detector and GTSRB classifier prototype; these results are explicitly distinguished from the reviewed paper and are not directly comparable because the datasets and evaluation protocols differ. The review identifies local sign coverage, unknown-class rejection, and independent testing on Indian road images as important directions for further work.

KEYWORDS: Traffic Sign Recognition; YOLO; Convolutional Neural Network; GTSDB; GTSRB.

I. INTRODUCTION

Traffic-sign detection and recognition are important applications of computer vision in Intelligent Transportation Systems (ITS) and Advanced Driver Assistance Systems (ADAS). Traffic signs communicate essential information regarding speed limits, road regulations, warnings, restrictions and directions. Accurate identification of these signs can help drivers understand road conditions and make appropriate driving decisions.

Traditional traffic-sign recognition systems generally use manually designed image features, colour segmentation and geometric shape analysis. Although these methods can perform effectively under controlled conditions, their performance may decrease when signs appear at different distances, orientations and illumination levels. Faded signs, partial occlusion, motion blur and complex backgrounds further increase the difficulty of recognition.

Deep-learning techniques have significantly improved image analysis by automatically learning visual features from training data. Convolutional Neural Networks (CNNs) are commonly used for image classification, whereas object-detection models such as You Only Look Once (YOLO) identify and locate objects within complete images. These approaches provide a foundation for developing automated traffic-sign recognition systems.

Traffic-sign recognition consists of two major tasks: detection and classification. Detection identifies the location of a traffic sign within a road-scene image, generally by generating a bounding box around the sign. Classification determines the category of the detected sign. A combined system can process complete road images containing one or more signs without requiring manual cropping.

However, a classification model alone cannot identify the location of signs in a complete road scene, while an object detector may not provide the detailed category information required by the user. Therefore, this project combines a YOLO-based detector with a CNN classifier to perform these two tasks sequentially.

The proposed system uses the German Traffic Sign Detection Benchmark (GTSDB) for training and evaluating the detection model and the German Traffic Sign Recognition Benchmark (GTSRB) for training and evaluating the classification model. The recognized class is connected to a Python-based knowledge base that provides the corresponding traffic-sign name, meaning and suggested driver action.

© 2026 IJIRCCE | Volume 14, Issue 11, November 2026 DOI: 10.15680/IJIRCCE.2026.1411010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The main objectives of this work are:

1. To develop a YOLO-based model for detecting traffic signs in complete road-scene images.
2. To classify detected traffic signs into the 43 supported GTSRB categories using a CNN.
3. To integrate a knowledge base for displaying the meaning and recommended action associated with each recognized sign.
4. To implement confidence-based decision thresholds for identifying uncertain predictions.
5. To evaluate the detection and classification components using appropriate benchmark datasets.
6. To examine the limitations of the system when tested with Indian traffic-sign images.

II. LITERATURE SURVEY

Research in traffic-sign detection and recognition has developed from conventional image-processing techniques to deep-learning-based classification and object-detection architectures. Different datasets and model architectures have been introduced to improve recognition accuracy and detection performance under real-world conditions.

Houben et al. [2] introduced the German Traffic Sign Detection Benchmark (GTSDB), which provides real-world road-scene images for evaluating traffic-sign detection. The benchmark includes traffic signs appearing at different positions and scales against complex backgrounds. It established an evaluation framework for comparing detection methods and highlighted the distinction between locating signs in complete images and classifying individual sign regions.

Stallkamp et al. [3] presented the German Traffic Sign Recognition Benchmark (GTSRB), which contains more than 50,000 images distributed across 43 traffic-sign categories. The dataset became an important benchmark for evaluating traffic-sign classification algorithms. Their study demonstrated the challenges caused by variations in illumination, weather conditions, visibility and sign appearance.

Sermanet and LeCun [4] investigated traffic-sign recognition using multi-scale Convolutional Neural Networks. Their approach used features obtained at multiple stages of a convolutional network to improve recognition. The study demonstrated the effectiveness of CNN-based methods in learning relevant visual features directly from traffic-sign images.

Cireşan et al. [5] proposed a Multi-Column Deep Neural Network (MCDNN) for traffic-sign classification. The approach combined predictions from multiple neural networks trained with differently preprocessed images. The authors reported a recognition rate of 99.46% in the final phase of the German traffic-sign recognition benchmark, demonstrating the potential of deep neural networks for high-accuracy classification.

Zhu et al. [6] introduced the Tsinghua-Tencent 100K (TT100K) traffic-sign benchmark for detection and classification in real-world environments. The dataset contains 100,000 street-view images and approximately 30,000 traffic-sign instances. The study emphasized the difficulty of detecting small traffic signs under variations in illumination, weather and background conditions.

Neuhold et al. [7] introduced the Mapillary Vistas dataset for semantic understanding of street scenes. It contains diverse high-resolution road images collected under different environmental conditions and using different imaging devices. Although it is not exclusively designed for traffic-sign recognition, it provides valuable context for developing computer-vision systems capable of understanding complex road environments.

Redmon et al. [8] proposed You Only Look Once (YOLO), a single-stage object-detection architecture that predicts bounding boxes and class probabilities directly from an entire image. Unlike region-based detection approaches, YOLO performs detection through a unified network, making the architecture suitable for applications requiring efficient object localization.

He et al. [9] introduced Mask R-CNN, which extends Faster R-CNN by adding an instance-segmentation branch to predict object masks along with bounding boxes. Ren et al. [10] introduced Faster R-CNN, which uses a Region Proposal Network to generate candidate object regions. These region-based approaches provide effective object-localization techniques but may involve greater computational requirements depending on the implementation.

© 2026 IJIRCCE | Volume 14, Issue 11, November 2026 DOI: 10.15680/IJIRCCE.2026.1411010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Megalingam et al. [1] proposed a Refined Mask R-CNN (RMR-CNN) approach specifically for Indian traffic-sign detection and recognition. Their study introduced a custom dataset containing 6,480 images, 7,056 traffic-sign instances and 87 categories. They reported 97.08% precision and 96.75% recall for the proposed RMR-CNN model. This research highlights the importance of developing traffic-sign recognition systems suitable for local road environments.

The reviewed literature indicates that detection and classification are complementary tasks. Although benchmark datasets demonstrate the effectiveness of deep-learning techniques, variations in traffic-sign designs across countries remain an important challenge. This motivates the development and evaluation of a modular detection and recognition system and further testing on Indian road images.

III. PROPOSED ALGORITHM

A. Design Considerations:

- Initial battery energy (IBE) is 50Jules for each node.
- Nodes are able to calculate its residual battery energy (RBE).
- Keeping track of previously used paths.
- Considered all possible paths at beginning.
- Receiving energy is not considered.
- The time when no path is available to transmit the packet is considered as the network lifetime.

B. Description of the Proposed Algorithm:

Aim of the proposed algorithm is to maximize the network life by minimizing the total transmission energy using energy efficient routes to transmit the packet. The proposed algorithm is consists of three main steps.

Step 1: Calculating Transmission Energy:

The transmission energy (TE_{node}) of each node relative to its distance with another node is calculated by using eq.(1) [8].

$$TE_{node} \alpha d^n$$
$$TE_{node} = k\, d^n \qquad \text{eq. (1)}$$

where k is constant and n is path loss factor which is generally between (2-4) [8].

Step 2: Selection Criteria:

Node should have more residual battery energy (RBE) than the required transmission energy (TE_{node}) to transmit the packet to the next node in the route. All the nodes in the route will be checked with this condition even if one node of a route is not satisfying this condition then that route will not be considered as a feasible solution. All the other routes having all the nodes with sufficient amount of energy are considered as the feasible solution. And those nodes having equal RBE than (TE_{node}) are made to go into sleep mode. This selecting criterion helped to prolong the network life by avoiding the link breakage. We tried to avoid the repeated use of the path. But at one stage we have to compromise with energy efficiency when we have a route with less energy consumption but it is already being used and a rout with maximum consumption of energy which is not used. So till this point we avoided repeated use of the paths and tried to increase the network life. Transmission energy of a node to node in a rout is calculated according to the distance and the total transmission energy (TTE_R) for that rout is calculated using eq. (2).

$$TTE_R = \sum_{i=1}^{m} TE \qquad \text{eq. (2)}$$

where m is the number of hops in the route, $TE = TE_{node}$ is the transmission energy between the nodes. The route having minimum total transmission energy i.e. min (TTE_R) will be selected as energy efficient route.

Step 3: Calculating Residual Battery Energy (RBE):

After transmitting the packet, residual battery energy for each node of the route is calculated using eq. (3) with parameters initial battery energy (IBE) and TE_{node}.

© 2026 IJIRCCE | Volume 14, Issue 11, November 2026 DOI: 10.15680/IJIRCCE.2026.1411010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

$$RBE = IBE - TE_{node} \quad \text{eq. (3)}$$

IV. METHODOLOGY

A. Proposed System Architecture

The proposed system follows a two-stage deep-learning approach consisting of traffic-sign detection and traffic-sign classification. The first stage uses a YOLO-based object-detection model to identify traffic signs in complete road-scene images. The second stage uses a CNN classifier to recognize each detected sign and assign it to one of the 43 predefined GTSRB categories.

After classification, a Python-based knowledge base retrieves the corresponding sign name, description and suggested driver action. A confidence-based decision mechanism is also considered to identify uncertain predictions.

The overall workflow consists of the following stages:

1. Input image acquisition.
2. Image preprocessing.
3. Traffic-sign detection using YOLO.
4. Bounding-box extraction and region cropping.
5. Image resizing and normalization.
6. Traffic-sign classification using CNN.
7. Confidence evaluation.
8. Knowledge-base lookup.
9. Display of the recognition result and corresponding information.



Fig.1. Proposed architecture of the traffic-sign detection and recognition system

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

B. Dataset Preparation

Two publicly available datasets are used to develop and evaluate the detection and classification components: the German Traffic Sign Detection Benchmark (GTSDB) and the German Traffic Sign Recognition Benchmark (GTSRB).

1. German Traffic Sign Detection Benchmark (GTSDB):

GTSDB is used to train and evaluate the YOLO-based detection model. It contains complete road-scene images in which traffic signs appear at different locations and scales. The associated annotations provide the location of traffic signs, enabling the detection model to learn bounding boxes around the target objects.

For this project, the detector is configured as a single-class object detector, where the target class represents a traffic sign. This allows the model to identify sign locations without distinguishing between individual traffic-sign categories.

2. German Traffic Sign Recognition Benchmark (GTSRB):

GTSRB is used to train and evaluate the CNN classification model. It contains traffic-sign images belonging to 43 different categories. Each image is associated with a corresponding class label, allowing the CNN to learn the visual characteristics of different traffic signs.

Before training, images and annotations are prepared according to the input requirements of the respective models. Detection annotations are converted into the format required by the YOLO implementation. Classification images are resized and associated with their corresponding class labels. Consistent preprocessing is applied during training and inference.

C. Traffic-Sign Detection Using YOLO

The detection stage uses the You Only Look Once (YOLO) object-detection framework to locate traffic signs in complete road-scene images.

Unlike image-classification models, which assign a label to an entire image, YOLO predicts bounding boxes and confidence scores for objects present within the input image.

In the proposed implementation, the detector is configured as a single-class detector. Its target class represents a traffic sign. The identification of individual traffic-sign categories is performed separately by the CNN classifier.

During inference, a road-scene image is passed to the trained YOLO model. The detector generates bounding boxes and associated confidence scores. Predictions below the selected detection confidence threshold are discarded, while accepted bounding boxes are used for extracting individual traffic-sign regions.

A detection confidence threshold of 0.25 is used in the current prototype. This threshold determines which predicted bounding boxes are accepted for further processing.

D. Region Extraction and Image Preprocessing

After detection, each accepted bounding box is used to crop the corresponding traffic sign from the original road-scene image. This operation isolates the sign from the surrounding environment and allows the classification model to focus on its visual features.

The extracted image region is resized to the input dimensions expected by the CNN. Pixel values are normalized according to the preprocessing procedure used during classifier training.

These operations provide a consistent input representation for the classification model. The quality of the extracted region is important because an inaccurate bounding box may exclude important portions of a sign or include unnecessary background information.

Therefore, the output of the detection stage directly influences the performance of the classification stage.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

E. Traffic-Sign Classification Using CNN

A Convolutional Neural Network is used to classify each extracted traffic-sign image into one of the 43 GTSRB categories.

During training, the CNN learns visual features such as edges, shapes, colours, symbols and patterns that distinguish different traffic signs. Convolutional layers extract spatial features from the input images, while activation and pooling operations help the network learn increasingly representative features.

The extracted features are then passed to classification layers that generate scores for the 43 traffic-sign categories. The class with the highest output score is selected as the initial prediction.

For every detected sign, the classifier generates a predicted class and an associated confidence score. In the current prototype, a classification confidence threshold of 0.70 is considered. Predictions below this threshold can be treated as uncertain rather than being accepted unconditionally.

F. Knowledge-Base-Based Sign Interpretation

After classification, the predicted class identifier is passed to a Python-based knowledge base.

The knowledge base contains predefined mappings between the supported traffic-sign class identifiers and their corresponding sign names, meanings and suggested driver actions.

For example, when the classifier predicts a speed-limit sign, the knowledge base retrieves the corresponding speed limit and the associated driving instruction.

The retrieved information is displayed along with the detected sign to make the system output more meaningful and understandable to the user.

The knowledge base uses predefined mappings rather than an additional neural network. Therefore, the interpretation stage depends on the correctness of the CNN prediction and the corresponding stored information.

G. Confidence-Based Decision Mechanism

The proposed system uses confidence thresholds to identify potentially unreliable detections and classifications.

The YOLO detector uses a confidence threshold of 0.25. The CNN classification confidence threshold is considered at 0.70.

In addition to the highest classification score, the difference between the highest and second-highest class scores may be used to identify ambiguous predictions. A margin threshold of 0.20 is explored for this purpose.
When the highest classification score is below the selected threshold, or when the difference between the top two class scores is too small, the prediction can be flagged as uncertain.

These thresholds are configurable and require validation on representative data. They are intended to improve decision reliability but cannot guarantee that every accepted prediction is correct.

H. End-to-End Processing Workflow

The complete system operates through the following sequence:

1. **Input acquisition:** Receive a road-scene image containing one or more traffic signs.
2. **Traffic-sign detection:** Apply the trained YOLO model to predict bounding boxes and detection confidence scores.
3. **Detection filtering:** Retain bounding boxes satisfying the selected confidence threshold.
4. **Region extraction:** Crop each detected traffic sign from the original image.
5. **Image preprocessing:** Resize and normalize the extracted image region.
6. **Traffic-sign classification:** Pass the extracted region through the CNN to predict one of the 43 supported classes.
7. **Confidence evaluation:** Evaluate the classification confidence and identify uncertain predictions.
8. **Knowledge-base lookup:** Retrieve the corresponding sign name, meaning and recommended driver action.

© 2026 IJIRCCE | Volume 14, Issue 11, November 2026 DOI: 10.15680/IJIRCCE.2026.1411010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

9. **Output generation:** Display the detected sign, predicted category, confidence information and associated description.

This modular workflow allows the detection, classification and interpretation components to be evaluated separately. It also helps identify whether an error originates from a missed detection, an inaccurate crop, a classification mistake or an incorrect knowledge-base mapping.

V. RESULTS AND DISSCUSSION

A. Traffic-Sign Classification Results

The CNN classification model was evaluated using the official test set of the German Traffic Sign Recognition Benchmark (GTSRB), containing 12,630 images across 43 traffic-sign classes.

The trained CNN achieved a classification accuracy of **97.34%** on this test set. This result demonstrates the ability of the model to distinguish between the traffic-sign categories represented in GTSRB.

Classification accuracy is important for the second stage of the proposed system, in which the detected traffic-sign regions are cropped and passed to the CNN for recognition.

However, standalone classification accuracy does not represent the performance of the complete system because it does not account for missed detections or inaccurate bounding boxes generated by the YOLO detector.

A confusion matrix and class-wise accuracy analysis can provide additional information about categories that are frequently misclassified.

B. Traffic-Sign Detection Results

The YOLO-based detection model was evaluated on a validation split of 102 GTSDB road-scene images.
The recorded detection metrics are presented in Table I.

TABLE I: YOLO-BASED TRAFFIC-SIGN DETECTION RESULTS

Evaluation Metric	Result
Precision	96.9%
Recall	88.1%
mAP@0.50	95.4%
mAP@0.50:0.95	74.4%
Validation images	102

Precision represents the proportion of predicted detections that correspond to valid traffic signs, whereas recall represents the proportion of ground-truth traffic signs successfully detected.

The precision of 96.9% indicates that most accepted detections correspond to valid signs. However, the recall of 88.1% indicates that some traffic signs were missed by the detector.

The mAP@0.50 metric evaluates detection performance at an intersection-over-union threshold of 0.50. The mAP@0.50:0.95 metric evaluates performance across multiple overlap thresholds, providing a more demanding assessment of bounding-box localization.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The difference between these two values indicates that localization accuracy at stricter overlap requirements remains an area for improvement.

Since the validation split contains only 102 images, these results should be interpreted within the context of the evaluated dataset and should not be considered proof of performance in all real-world environments.

C. End-to-End System Performance

The complete system combines YOLO-based traffic-sign detection, CNN-based classification and a Python-based knowledge base.

The reported evaluation recorded **98.08% classification accuracy among matched detections** and **86.93% end-to-end sign-level accuracy**.

These measurements represent different aspects of the system. Classification accuracy among matched detections evaluates the recognition stage when a predicted detection can be associated with a ground-truth traffic sign. End-to-end sign-level accuracy also reflects failures in earlier stages, including missed detections and unsuitable bounding boxes.

The difference between these measurements highlights the importance of evaluating the complete detection-and-recognition pipeline rather than relying exclusively on standalone CNN accuracy.

Following classification, the knowledge base retrieves the corresponding traffic-sign name, meaning and suggested driver action using the predicted class identifier. Since this stage relies on predefined mappings, the displayed interpretation depends on the correctness of the classifier prediction and stored information.

D. Qualitative Testing on Indian Traffic Signs

Preliminary testing was conducted using four local photographs containing Indian traffic signs.

Under the YOLO detection confidence threshold of 0.25, two of the four images did not produce a detection. For the available detected regions, the CNN returned top-class confidence scores ranging approximately from 0.28 to 0.67.

These observations indicate that the current prototype may have difficulty detecting or confidently recognizing certain Indian traffic signs.

Potential reasons include differences between the German training datasets and Indian traffic-sign designs, variations in image quality, illumination, viewing angles and surrounding backgrounds.

The four-image test is qualitative and is too small to establish a reliable estimate of recognition accuracy on Indian roads. Therefore, these observations should be treated as preliminary evidence of generalization limitations rather than as a formal performance benchmark.

© 2026 IJIRCCE | Volume 14, Issue 11, November 2026 DOI: 10.15680/IJIRCCE.2026.1411010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

```
SIGN 1
------------------------------------------------------------
Sign Name       : Speed Limit 80 km/h
GTSRB Class     : 5
YOLO Confidence : 0.660
CNN Confidence  : 1.000
Meaning         : Maximum permitted speed is 80 km/h.
Driver Action   : Keep speed at or below 80 km/h.

SIGN 2
------------------------------------------------------------
Sign Name       : Speed Limit 80 km/h
GTSRB Class     : 5
YOLO Confidence : 0.614
CNN Confidence  : 0.612
Meaning         : Maximum permitted speed is 80 km/h.
Driver Action   : Keep speed at or below 80 km/h.
```



Fig.2. Traffic-sign detection results on GTSDB road-scene images



© 2026 IJIRCCE | Volume 14, Issue 11, November 2026 DOI: 10.15680/IJIRCCE.2026.1411010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

```
IMAGE 2/10: 00057.ppm
Original size: (1360, 800)
YOLO detections: 1

SIGN 1
------------------------------------------------------------
Sign Name       : Speed Limit 30 km/h
GTSRB Class     : 1
YOLO Confidence : 0.862
CNN Confidence  : 1.000
Meaning         : Maximum permitted speed is 30 km/h.
Driver Action   : Keep speed at or below 30 km/h.
```

Fig.3. Traffic-sign classification output with the predicted class and corresponding sign information.

```
IMAGE 1/4: 20261001_195154.jpg
Original size: (6752, 12000)
YOLO detections: 0

No traffic sign detected above the YOLO threshold.
Try a clearer image or review the detection threshold.
```



Fig.4. Examples of failed traffic-sign detection in local Indian road images.

E. Limitations and Discussion

The results demonstrate the feasibility of combining a YOLO detector, a CNN classifier and a rule-based knowledge base into a modular traffic-sign recognition system.

Separating detection and classification allows each component to be evaluated independently. The knowledge base further converts the predicted class identifiers into understandable traffic-sign information.

However, several limitations remain:

1. Dataset limitations: The detection and classification models are trained using German traffic-sign datasets, which do not fully represent the diversity of Indian traffic signs.
2. Detection limitations: The relatively small validation split and missed detections indicate the need for more extensive testing.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

3. Classification limitations: The CNN is restricted to 43 predefined categories and may not correctly recognize unsupported or unfamiliar traffic signs.
4. Error propagation: An inaccurate bounding box or an incorrectly cropped region may affect the final classification result.
5. Confidence limitations: Confidence thresholds can identify uncertain predictions, but they do not guarantee that a high-confidence prediction is correct.

Future evaluation should include a larger dataset of Indian traffic signs, different environmental conditions and a clearly documented end-to-end evaluation procedure.

VI. CONCLUSION AND FUTURE WORK

This paper presents a two-stage deep-learning approach for traffic-sign detection and recognition by combining a YOLO-based object detector with a CNN classifier.

The YOLO model identifies traffic-sign locations in complete road-scene images, while the CNN classifies the extracted regions into one of the 43 categories supported by the GTSRB dataset. A Python-based knowledge base maps the predicted class identifiers to their corresponding sign names, meanings and recommended driver actions.

The CNN achieved 97.34% classification accuracy on the official GTSRB test set. The YOLO detector recorded 96.9% precision, 88.1% recall and 95.4% mAP@0.50 on the 102-image GTSDB validation split. Preliminary testing on four Indian road photographs revealed limitations in detecting and recognizing local traffic signs.

The results demonstrate the feasibility of integrating object detection, image classification and knowledge-based interpretation into a traffic-sign assistance system. However, further improvements are required to support diverse traffic-sign categories and real-world road environments.

Future work will focus on incorporating Indian-specific traffic-sign datasets, improving detection under different lighting and viewing conditions, expanding the classification vocabulary, and introducing an explicit unknown-sign rejection mechanism. The system may also be extended into a mobile application that accepts camera input or uploaded images and displays the corresponding traffic-sign information.

REFERENCES

[1] R. K. Megalingam, K. Thanigundala, S. R. Musani, H. Nidamanuru, and L. Gadde, “Indian traffic sign detection and recognition using deep learning,” International Journal of Transportation Science and Technology, vol. 12, no. 3, pp. 683–699, 2023, doi: 10.1016/j.ijtst.2022.06.002.

[2] S. Houben, J. Stallkamp, J. Salmen, M. Schlipsing, and C. Igel, “Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark,” in Proceedings of the International Joint Conference on Neural Networks (IJCNN), 2013, pp. 715–722, doi: 10.1109/IJCNN.2013.6706807.

[3] J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel, “Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition,” Neural Networks, vol. 32, pp. 323–332, 2012, doi: 10.1016/j.neunet.2012.02.016.

[4] P. Sermanet and Y. LeCun, “Traffic sign recognition with multi-scale convolutional networks,” in Proceedings of the International Joint Conference on Neural Networks (IJCNN), 2011, pp. 2809–2813, doi: 10.1109/IJCNN.2011.6033589.

[5] D. Cireşan, U. Meier, J. Masci, and J. Schmidhuber, “Multi-column deep neural network for traffic sign classification,” Neural Networks, vol. 32, pp. 333–338, 2012, doi: 10.1016/j.neunet.2012.02.023.

[6] Z. Zhu, D. Liang, S. Zhang, X. Huang, B. Li, and S. Hu, “Traffic-sign detection and classification in the wild,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 2110–2118.

[7] G. Neuhold, T. Ollmann, S. Rota Bulo, and P. Kontschieder, “The Mapillary Vistas dataset for semantic understanding of street scenes,” in Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2017, pp. 4990–4999.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[8] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779–788, doi: 10.1109/CVPR.2016.91.

[9] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," in Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2017, pp. 2961–2969.

[10] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017, doi: 10.1109/TPAMI.2016.2577031.



INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details