



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VIII **Month of publication:** August 2026

DOI: <https://doi.org/10.22214/ijraset.2026.84528>

www.ijraset.com

Call: ☎ 08813907089

E-mail ID: ijraset@gmail.com

Deep Learning Approach for Detecting and Classifying Traffic Signs and Potholes in Indian Roads

Gandu Gayathri¹, Ch Harika²

¹M.Tech Scholar, ²Assistant Professor, St. Mary's Womens Engineering College, Budampadu, Guntur, Ap-522213

Abstract: *The Advanced Driver Assistance Systems (ADAS) have a significance in enhancing road safety by identifying the traffic signs and road surface problems in real-time. This research paper compares three models of object detection that are based on YOLO algorithm and are YOLOv5, YOLOv7, and YOLOv8 for detecting Indian traffic signs and potholes. The approach used in this research involved the steps of collecting dataset, annotating the data, processing the data, augmenting the data, and training the model. The results after conducting the experiments show that every model has its own particular functionalities. In case of traffic signs detection, YOLOv5 got the highest precision of 99.3 percent, however, YOLOv8 got the highest recall of 83.3 percent and mAP50 of 88.7 percent, showing the capability of identifying the sign on different road conditions. In case of pothole detection, YOLOv5 gave the best precision of 83.1 percent, but YOLOv7 performed best overall with retrieval of recall of 76.7 percent and mAP of 79.0 percent and mAP range from 50 to 95 of 48.3 percent. The comparison proves that the YOLO models of object detection are of great use in real-time ADAS and show good efficiency in road scene perception.*

Keywords: *Traffic Sign Detection, Pothole Detection, Deep Learning, Computer Vision, Intelligent Transportation Systems.*

I. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) refers to technology that is designed to improve the safety from accidents that are caused by human error and driving experience of vehicles by providing assistance to drivers. The role of ADAS is to prevent deaths and injuries by reducing the number of car accidents and the serious impact of those that cannot be avoided. This system uses sensors, cameras, and other technologies to detect and analyse the environment around the vehicle, and provide alerts or automatic actions to help the driver avoid accidents. In ADAS there are many models like Pedestrian detection, Lane detection, Traffic sign recognition, Automatic emergency braking, Pothole detection, Driver drowsiness detection. we are developing this project on traffic sign and potholes detection for INDIAN roads using You Only Look Once (YOLO).

Vehicle perception systems are new consumer technology application that is being developed over time with the goal of extending safety benefits and reliable means of transportation. Intelligent vehicular systems are closely related to a number of important technologies, such as sensor fusion for real-time data logging and object/obstacle detection and tracking systems using machine learning algorithms. A machine is said to be learning from past Experiences (data feed in) with respect to some class of Tasks, if it's Performance in a given Task improves with the Experience. Supervised learning is when the model is getting trained on a labelled dataset. Labelled dataset is one which have both input and output parameters. In this type of learning both training and validation datasets are labelled.

Within supervised learning, we can indicate the presence of input variables (x) and output variable (y). The algorithm will find the proper mapping function for the input variables and output variable. This means that we can express that y is equal to f(x). This means that the learning process is supervised as we know the output. The algorithm gets corrected every time to improve its performance. The training takes place until the algorithm becomes efficient enough. The ideal case is the situation in which the output variable is unknown. The algorithm learns on its own and finds a certain pattern within the data. By using unsupervised learning, we succeed in decoding the data. Reinforcement learning implies that we train machine learning models to make a number of decisions based on the feedback they receive from the actions they implement. The machine becomes capable of making accurate decisions without any training dataset. Figure 1 presents the samples of potholes and traffic signs obtained in the process.



Figure: 1 Sample traffic sign and pothole images

II. LITERATURE SURVEY

Traffic signs are an essential component of the driving assistance system. They provide critical information and advice to the drivers, which successively requires them to change their driving behaviour. A pothole is commonly designated as a bowl-shaped road surface. Potholes are caused due to Aging of the foundation, Heavy traffic conditions, Narrow Road level structure and Fragile foundation.

Merkle et al [1] has developed a novel model to detect the traffic signs. This model uses popular *Histogram of Oriented Gradients* (HOG) algorithm. It is trained and evaluated on dataset consists of 33, 409 street-level panoramic images. It attained accuracy of 0.9 recall. Ge et al [2] has developed a novel model to recognize the traffic signs. This model uses YOLO and R-CNN methods. It is trained and evaluated on dataset contains 726 images and 1847 traffic signs. It attained accuracy of 99%. Wang, C et al [3] has developed a novel model to detect the traffic signs. This model uses color-based methods and shape-based methods. It is trained and evaluated on GTSDDB dataset. It attained accuracy of 95%.

Fernando et al [4] has developed a novel model to detect the traffic signs. This model uses YOLO and CNN methods. It is trained and evaluated on set of 835 images. It attained a mean average precision of 84.7%. Zhang, Z et al [5] has developed a novel model to detect the traffic signs. This model uses a CO-TRAINING METHOD. It is trained and evaluated on dataset with 3553 positive samples and 5116 negative samples. It attained accuracy of 94%.

Sharma et al [6] has developed a novel model to recognise the traffic signs. This model uses CNN methods. It is trained and evaluated on GTSRB dataset. It attained an accuracy of 99.85%. Oza et al [7] has developed a novel model to detect the traffic signs. This model uses deep learning algorithms. It is trained and evaluated on GTSRB dataset. It attained accuracy of 97.86 percent precision. Zarrouk et al [8] has developed a novel model to recognise the traffic signs. This model uses tracking method. It is trained and evaluated on GTSRB dataset. It attained accuracy of an average improvement of 2.53% in the Recall rate, 3.56% in the Precision rate.

Tabernik et al [9] has developed a novel model to detect the traffic signs. This model uses YOLOV3 method. It is trained and evaluated on GTSRB dataset. It attained accuracy of a mean averaged precision of 88%. Dhar et al [10] has developed a novel model to recognise the traffic signs. This model uses deep learning algorithm. It is trained and evaluated on GTSRB dataset. It attained accuracy of 97%. Reddy et al [1] has developed a project on detection of potholes and methodology YOLO v7 algorithm is utilized for pothole categorization, and the Google API and Accelerometer are utilized for pothole counting on dataset that consists of approximately 289 images, and acquired an accuracy of 90.01%.

Saranya et al [2] has developed a project on an Intelligent Convolutional Neural Network based Potholes Detection. This model uses YOLOv7. It is trained and evaluated on Roboflow pothole detection dataset with a total of 289 photographs and acquired an accuracy a confidence level of 0.5 mAP is appropriate, recall is 0.95 and precision is 1.

Kang et al [3] has implemented a model on automatic Pothole detection system using 2D Light Detection and Ranging (LiDAR) and Camera method. This model is trained on GTSRB dataset. And this model obtained an accuracy of 99%. Singh et al [4] have implemented a project on Image-based Road Pothole Detection. This project is implemented on ResNet50 method and trained on dataset has two classes named positive and negative with a total of 1281 images and obtained an accuracy of 98.05%.

Dharneeshkar et al [5] has developed a project on Detection of potholes in Indian roads. Project uses YOLOv2 and YOLOv3 methodologies and is trained on new dataset with 1500 images. It obtained an accuracy of 0.5 recall on YOLOv2 and 0.4 recall on YOLOv3. Kuan et al [6] has proposed a project on Pothole Detection. This project uses YOLOv3 method and trained on GTSRB. It obtained an accuracy in energy efficiency on Xilinx ZCU104 is 0.86 FPS/W in pothole detection and energy efficiency on Xilinx ZCU104 is 0.91 FPS/W in pothole avoidance.

Rohitaa et al [7] has proposed a project on Pothole Detection. This model uses YOLOv3 methodology. It is trained on new dataset with 899 images. It obtained an accuracy of 97%. Madli et al [8] has developed project on pothole Detection. This model uses yolov2 methodology. It is trained on new dataset with 600 images. It obtained an accuracy of 95%. Wang et al [9] has developed project on pothole detection. This model uses ultrasonic sensors to detect the presence of potholes. It obtained an accuracy of 97%.

III. PROPOSED METHODOLOGY

One of the most well-liked model architectures and object detection method is You Only Look Once (YOLO). In order to achieve high accuracy and overall processing speed, it employs one of the best neural network architectures. YOLO suggests using an end-to-end neural network that simultaneously predicts class odds and bounding boxes. YOLO is a single stage detector, handling both the object identification and classification in a single pass of the network. The proposed model implementation block diagram is depicted in Figure 2. The proposed traffic sign and pothole detection architecture is depicted in Figure 3.

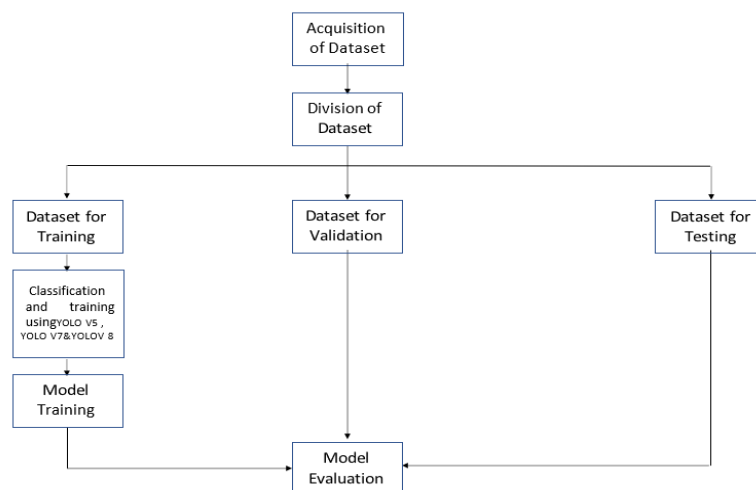


Figure 2: Block diagram of implementation

A. Data Acquisition

The Indian Cautionary Traffic Signs (ICTS) dataset is collected from various places in India with different cautionary signs present besides roads, at railway stations, etc. And Potholes dataset is collected from various places in the country to make model more efficient. The dataset for detection of traffic sign consists of 6670 images and dataset for potholes of 1800 images. These images were divided into 3 subgroups 4700, 1300 and 670 images for training, validation and testing respectively in traffic sign dataset and 413, 116 and 69 images for training, validation and testing respectively in pothole dataset. Samples acquired for training.

B. Data Augmentation

In order to train a more efficient neural network, an extensive database is needed to support the results. Data augmentation is a technique used to increase the size and diversity of a dataset by creating new samples through various modifications or transformations of existing data. In the proposed datasets data augmentation is done by zooming and rotating few images.

C. Deep Learning Models for Detecting Traffic Signs and Potholes

1) YoloV5

YoloV5 is a neural network that has the capacity to detect images and videos in real time. Its architecture is made up of three main components. They are given below.

- a) Backbone: Cross Stage Partial Network has been integrated into Darknet, thus forming CSPDarknet which is the backbone of YoloV5. CSPNet resolves the issue of repeating gradient information in large backbones. It further integrates the changed gradient information in the feature map, which allows reducing the number of parameters and FLOPS (floating-point operations per second) of the model. In so doing, it offers both fast inference and high accuracy, along with a smaller size of the model.
- b) Neck: YoloV5 applies Path Aggregation Network, also known as PANet, to increase information flow due to the structured nature of this approach. PANet uses the enhanced FPN structure that improves the bottom-up path. Thanks to this, the process of low-level features propagation becomes better. The neural system also employs adaptive feature pooling that connects the feature grid with all feature levels in order to make useful information of the feature level propagate through to the next subnetwork. PANet makes it possible to utilize the localization signal in low levels better, thus significantly improving accuracy.
- c) Head: YoloV5 employs the head called the yolo layer that generates 3 different sizes (18×18 , 36×36 , 72×72) of feature maps that are essential multi-scale prediction of the objects.

2) YOLOV7

ELAN (efficient layer aggregation network) is the foundation of the YoloV7 design. In order for deeper networks to converge and train efficiently, ELAN takes into account constructing an efficient network by managing the shortest and longest gradient paths. E-ELAN is a modification to the ELAN architecture made by YOLOv7. To enhance model learning while preserving gradient flow routes, ELAN employs the cardinality operations of expand, shuffle, and merge. Regarding the architecture, it solely makes changes to the computational block, leaving the transition layer's design as ELAN. Group convolution is used by E-ELAN to increase the computational block's cardinality and number of channels.

All the computational blocks in a computing layer are subject to the same channel multiplier and group parameter. Each computing block's feature map will be divided into groups of size g , concatenated, and then combined. In order to perform merge cardinality, a group feature map will be added and shuffled. YoloV7 Neck builds feature pyramids by gathering feature maps that the Backbone has retrieved. YOLOv7 isn't restricted to just one head. The lead head is in charge of producing the ultimate product, while the auxiliary head is utilised to support middle-layer training. The head's output layers with final detections make up the head in the end.

3) YOLOV8

The architecture of YOLOv8 builds upon the previous versions of YOLO (You Only Look Once) object detection models. YOLOv8 utilizes a fully convolutional neural network that contains two main parts: the backbone and the head. The backbone of YOLOv8 is a modified version of the CSPDarknet53 architecture.

This architecture consists of 53 convolutional layers and employs a technique called cross-stage partial connections to increase flow of information between the different layers of the network.

A number of convolutional layers and a string of fully connected layers make up the head of the YOLOv8 algorithm. These layers are in charge of forecasting the bounding boxes, ratings, and probabilities for each class of objects found in a picture. The usage of a Self attention mechanism in the network's brain is one of YOLOv8's distinguishing characteristics. This method enables the model to shift its attention to various areas of the image and the significance of certain elements in accordance with the task at hand. The ability to do multi-scale object recognition is yet another crucial aspect of YOLOv8. To identify objects of various shapes and sizes in an image, the model makes use of a feature pyramid network.

The model can recognise both large and small items in an image because to the several layers of its feature pyramid network that recognise objects at various scales.

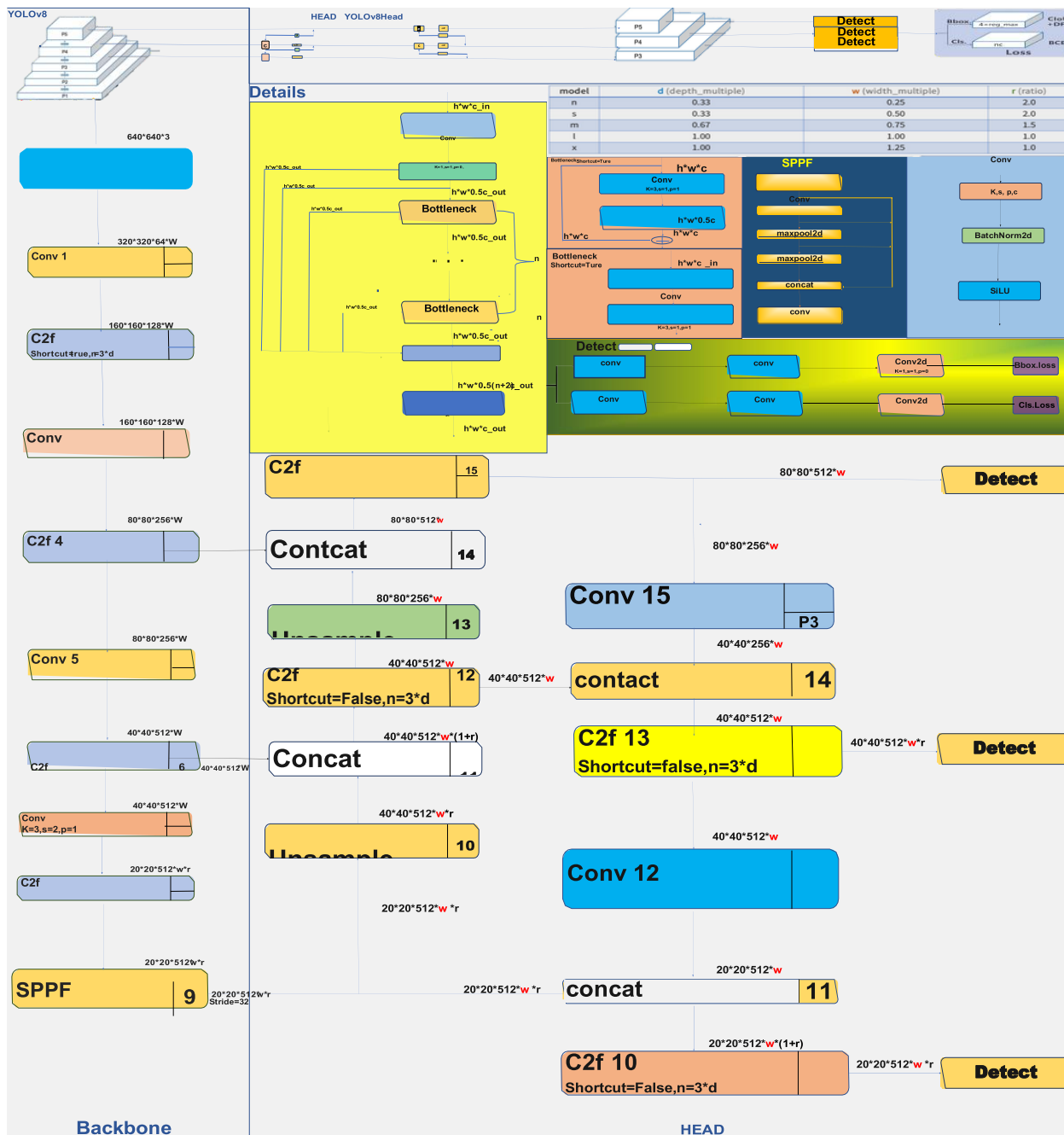


Figure 3: Proposed deep learning Architecture for detecting traffic signa and Potholes

IV. RESULTS AND DISCUSSION

The proposed methodology is trained and evaluated on both the traffic sign datasets and pothole datasets. The datasets such as ICTS and from Kaggle are adopted. All the models are run using the python. The Figure 4 depicts the precision and recall curves of the proposed model on traffic sign detection. Figure 5 shows the confusion matrix of the proposed model on traffic sign detection. Figure 6 shows the sample traffic sign detection results obtained from the proposed model.

In the same way, Figure 7 depicts the confusion matrix of the proposed model on pothole detection. The figure 8 depicts the sample pothole detection outcomes of the proposed model.

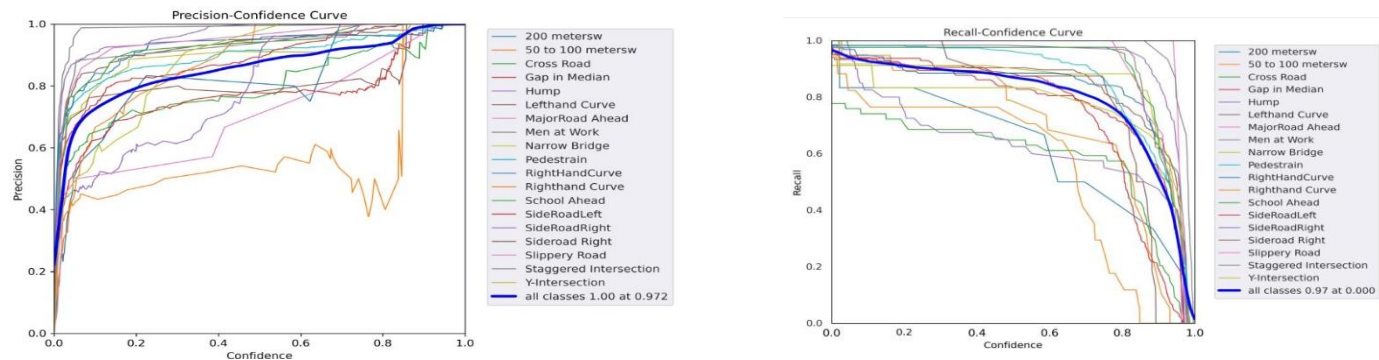


Figure 4: Precision Curves and Recall Curves

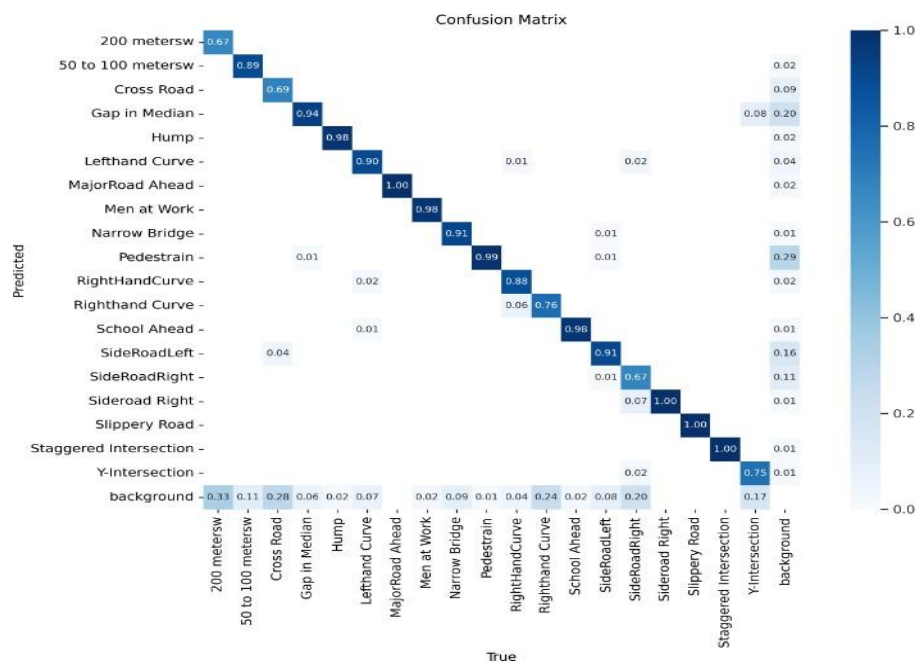


Figure 5: Confusion Matrix of proposed traffic sign detection model

Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
All	1339	1429	0.880	0.902	0.914	0.780
200 meters	1339	6	0.856	0.667	0.775	0.612
50 to 100 meters	1339	19	1.000	0.891	0.995	0.737
Cross Road	1339	54	0.771	0.648	0.740	0.551
Gap in Median	1339	127	0.806	0.961	0.884	0.715
Hump	1339	126	0.995	0.984	0.995	0.931
Lefthand Curve	1339	135	0.952	0.926	0.972	0.846
MajorRoad Ahead	1339	4	0.872	1.000	0.995	0.922
Men at Work	1339	85	0.990	0.976	0.990	0.909
Narrow Bridge	1339	34	0.948	0.941	0.970	0.847
Pedestrian	1339	348	0.911	0.951	0.982	0.862

RighthandCurve	1339	156	0.969	0.885	0.971	0.849
Righthand Curve	1339	17	0.612	0.882	0.585	0.413
School Ahead	1339	43	0.950	0.977	0.988	0.866
SideRoadLeft	1339	180	0.900	0.939	0.980	0.834
SideRoadRight	1339	40	0.896	0.675	0.858	0.811
Sideroad Right	1339	16	0.754	1.000	0.818	0.696
Slippery Road	1339	12	0.954	1.000	0.995	0.814
Staggered Intersection	1339	15	0.975	1.000	0.995	0.882
Y-Intersection	1339	12	0.600	0.833	0.887	0.725

Table1 : Class wise performance results of traffic sign detection model



Figure 6: Sample traffic sign detection outcomes

The comparative performance of the YOLOv5, YOLOv7, and the proposed model is illustrated in Table 2 for pothole detection at using four standard metrics, namely, Precision, Recall, mAP@50, and mAP@50:95. It is observed that YOLOv5 has been able to achieve the maximum precision (83.1%) indicating the least number of false positives in comparison to the other two models making it more suitable in situations where accurate object localization is needed. On the contrary, YOLOv7 demonstrated the highest recall (76.7%), which indicates its ability to detect the maximum number of potholes therein leading to better detection capacity in terms of reducing missed detections. In addition to this fact that YOLOv7 achieved the highest mAP@50 (79.0%) and mAP@50:95 (48.3%), indicates that it yielded better overall localization and detection results across the different IoU thresholds.

As for the case of the proposed model, it was found to reach precision statistics of 82.1%, which is comparable to that of YOLOv5 indicating successful maintenance of a low false positive rate. However, the proposed model reaches its recall (64.7%) and mAP values (75.3% and 46.6%) that are lower than those obtained by YOLOv7. This implies that the proposed model is able to detect a substantial number of potholes with high confidence although the total number

Model	Precision (%)	Recall (%)	mAP@50 (%)	mAP@50:95 (%)
YOLOv5	83.1	68.1	77.5	47.7
YOLOv7	69.6	76.7	79.0	48.3
Proposed Model	82.1	64.7	75.3	46.6

Table2 : Comparative analysis of proposed model

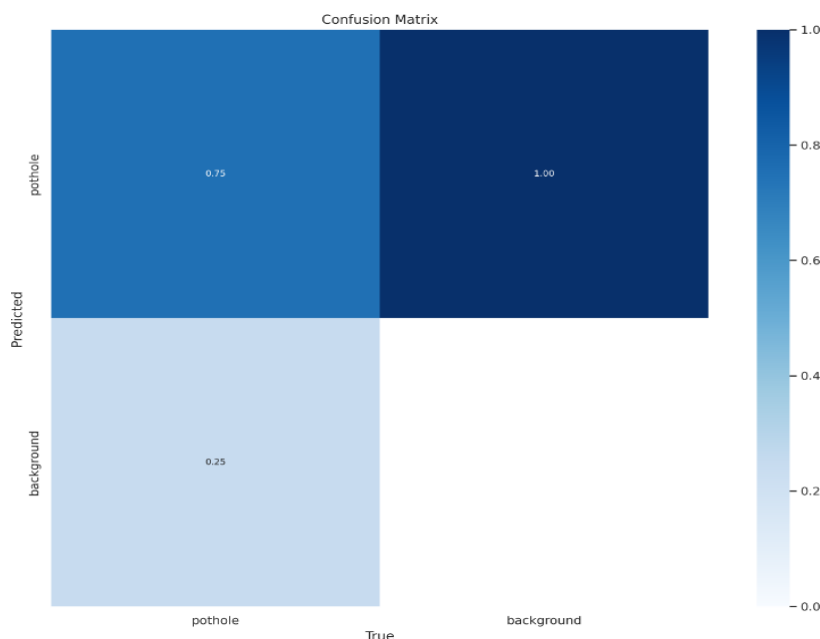


Figure 7: Confusion matrix of pothole detection model

According to Figure 7, it can be inferred from the confusion matrix that there is a detection rate of 75% for the model when spotting potholes. This means that the model is capable of identifying potholes correctly in the majority of scenarios. Nevertheless, around 25% of the pothole cases are flagged as background; when this occurs, it creates a false negative situation. In addition, it should also be noted that confusion matrix has confirmed that all images with background have been identified as potholes, which points to a substantial false positive indication regarding this class. Based on these findings, it can be concluded that the model is good in detecting potholes; however, distinguishing between potholes and similar-looking road environments needs to be refined. More diverse training set, better data augmentation strategy, and application of attention mechanisms can help decrease the rate of erroneous identifications both from false positives and negatives.



Figure 8: Sample pothole detection outcomes

As illustrated in Figure 8, the results of the qualitative detection signify that the proposed model can identify potholes of all dimensions, shapes, and surface textures in various conditions around the road. Most of the potholes are correctly detected with confidence scores in the range of 0.4-0.9, indicating effective detecting skills under the real-world conditions. The model performs very well for large potholes which can be seen very clearly. However, some images show multiple detections of the same pothole leading to the same bounding box being used twice. Moreover, detection of a few potholes is spotted with less confidence score due to their unusual shapes or lack of light.

V. CONCLUSION AND FUTURE SCOPE

The present work compared the performance of YOLOv5, YOLOv7, and YOLOv8 in terms of detecting potholes and traffic signs on Indian roads. The findings of the experiments demonstrated that although all three models produced good results, each of the models has some specific advantages. YOLOv5 achieved the highest precision; YOLOv7 peculiarly showed the best performance in terms of detecting potholes while YOLOv8 manifested high values of recall in detecting the traffic signs. Overall, it can be said that the YOLO models prove to be effective in the process of detecting hazards on the roads practically in real time or enhance the capabilities of ADAS. In the future, the performance of the system can be improved with the help of the incorporation of larger datasets and conducting the experiments in various weather conditions. Besides that, usage of larger datasets which consist of images taken in different lighting conditions can be selected in the project. Additionally, the system can be deployed on edge devices which can help making the process completely real-time.

REFERENCES

- [1] Merkle, P., Morvan, Y., Smolic, A., Farin, D., Mueller, K., De with, P. H. N., & Wiegand, T. (2009). The effects of multiview depth video compression on multiview rendering. *Signal Processing: Image Communication*, 24(1-2), 73-88.
- [2] Ge, S. S., & Wang, C. (2004). Adaptive neural control of uncertain MIMO nonlinear systems. *IEEE Transactions on Neural Networks*, 15(3), 674-692.
- [3] Wang, C. (2018, May). Research and application of traffic sign detection and recognition based on deep learning. In *2018 International Conference on Robots & Intelligent System (ICRIS)* (pp. 150-152). IEEE.
- [4] Fernando, W. H. D., & Sotheeswaran, S. (2021, September). Automatic road traffic signs detection and recognition using 'You Only Look Once' version 4 (YOLOv4). In *2021 International Research Conference on Smart Computing and Systems Engineering (SCSE)* (Vol. 4, pp. 38-43). IEEE.
- [5] Zhang, Z., Xin, L., Sun, K., & Li, W. (2011). Pd-Ni electrocatalysts for efficient ethanol oxidation reaction in alkaline electrolyte. *International Journal of Hydrogen Energy*, 36(20), 12686-12697.
- [6] Sharma, A., Bhatt, N. S., St Martin, A., Abid, M. B., Bloomquist, J., Chemaly, R. F., ... & Shah, G. L. (2021). Clinical characteristics and outcomes of COVID-19 in haematopoietic stem-cell transplantation recipients: an observational cohort study. *The Lancet Haematology*, 8(3), e185-e193.
- [7] Oza, R. M., Geisen, A., & Wang, T. (2021, September). Traffic Sign Detection and Recognition using Deep Learning. In *2021 4th International Conference on Artificial Intelligence for Industries (AI4I)* (pp. 16-20). IEEE.
- [8] Zarrouk, A., Vejux, A., Mackrill, J., O'Callaghan, Y., Hammami, M., O'Brien, N., & Lizard, G. (2014). Involvement of oxysterols in age-related diseases and ageing processes. *Ageing research reviews*, 18, 148-162.
- [9] Tabernik, D., & Skočaj, D. (2019). Deep learning for large-scale traffic-sign detection and recognition. *IEEE transactions on intelligent transportation systems*, 21(4), 1427-1440.
- [10] Dhar, P., Abedin, M. Z., Biswas, T., & Datta, A. (2017, December). Traffic sign detection—A new approach and recognition using convolution neural network. In *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)* (pp. 416-419). IEEE.
- [11] Reddy, E. S. T. K., & Rajaram, V. (2022, December). Pothole Detection using CNN and YOLO v7 Algorithm. In *2022 6th International Conference on Electronics, Communication and Aerospace Technology* (pp. 1255-1260). IEEE. [8] Madli, R., Hebbar, S., Pattar, P., & Golla, V. (2015). Automatic detection and notification of potholes and humps on roads to aid drivers. *IEEE Sensors journal*, 15(8), 4313-4318.
- [12] Saranya, G., & Pravin, A. (2020). A comprehensive study on disease risk predictions in machine learning. *International Journal of Electrical and Computer Engineering*, 10(4), 4217.
- [13] Kang, B. H., & Choi, S. I. (2017, July). Pothole detection system using 2D LiDAR and camera. In *2017 ninth international conference on ubiquitous and future networks (ICUFN)* (pp. 744-746). IEEE.
- [14] Singh, S., & Gupta, P. (2014). Comparative study ID3, cart and C4. 5 decision tree algorithm: a survey. *International Journal of Advanced Information Science and Technology (IJAIST)*, 27(27), 97-103.
- [15] Dharneeshkar, J., Aniruthan, S. A., Karthika, R., & Parameswaran, L. (2020, February). Deep Learning based Detection of potholes in Indian roads using YOLO. In *2020 international conference on inventive computation technologies (ICICT)* (pp. 381-385). IEEE.
- [16] Kuan, C. W., Chen, W. H., & Lin, Y. C. (2020, November). Pothole detection and avoidance via deep learning on edge devices. In *2020 International Automatic Control Conference (CACS)* (pp. 1-6). IEEE.
- [17] Rohitaa, R., Shreya, S., & Amutha, R. (2021, September). Intelligent Deep Learning based Pothole Detection and Reporting System. In *2021 Fourth International Conference on Electrical, Computer and Communication Technologies (ICECCT)* (pp. 1-5). IEEE.
- [18] Madli, R., Hebbar, S., Pattar, P., & Golla, V. (2015). Automatic detection and notification of potholes and humps on roads to aid drivers. *IEEE sensors journal*, 15(8), 4313-4318.
- [19] Wang, X., Hegde, S., Son, C., Keller, B., Smith, A., & Sasangohar, F. (2020). Investigating mental health of US college students during the COVID-19 pandemic: Cross-sectional survey study. *Journal of medical Internet research*, 22(9), e22817.
- [20] Meng, Y., Xu, J., Jin, Z., Prakash, B., & Hu, Y. (2020). A review of recent advances in tribology. *Friction*, 8, 221-300.



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)