iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80236

Enhanced YOLO-Based Vehicle Detection in Indian Traffic under Heavy Rainfall Using AI Based Image Detection

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Abstract: Vehicle Detection has proven to be an important function for ITS, Surveillance systems, and autonomous vehicles. One of the efficient DL methods used for this purpose are YOLO algorithms, which include YOLO v2, v3, v5, v7, and v8.

While there are continuous efforts being made to improve the efficiency of the system, bad weather conditions such as rains are still an issue in the process. Some of the issues caused by bad weather are rain, poor visibility, low contrast, reflections, and motion blur, which create difficulties in feature extraction and localization, thus decreasing the detection rate. Another issue is that more and more types of vehicles can now be seen in India like cars, buses, trucks, two-wheelers, auto rickshaws, and e-rickshaws.

In this study, a review of YOLO based vehicle detection during heavy rainfall is carried out. Some of the areas included in the study are usage of YOLO-based algorithms for vehicle detection, real-time vehicle detection, weather dependent vehicle detection, image pre-processing techniques, namely deraining, adaptive image pre-processing, and retinex based pre-processing techniques. Alongside, the deficiencies of Indian traffic scenes have also been mentioned along with possible future work.

Keywords--- YOLOv8, Vehicle Detection, Heavy Rainfall, Adverse Weather Conditions, Image Pre-processing, Deraining, Retinex, Indian Traffic, Deep Learning, Intelligent Transportation Systems

I. INTRODUCTION

There have been several developments in ITS, smart surveillance, and autonomous driving over the recent past, giving rise to a high demand for accurate real-time vehicle detection systems. Vehicle detection is essential in the areas of traffic monitoring, managing traffic congestions, avoiding accidents, vehicle counting, and road safety analysis. Deep learning and computer vision technology advancement have made object detection one of the key research areas for intelligent traffic management systems.

There are different kinds of object detection algorithms, such as the YOLO algorithm, which is a current object detection technique that can detect and locate objects in just one pass.It differs from the R-CNN, Fast R-CNN, and Faster R-CNN algorithms, which use a region-based object detection method. This algorithm uses a regression technique to detect objects; hence, it is significantly faster compared to other object detection algorithms while still providing similar levels of accuracy [1], [2].

The development of the YOLO algorithm has undergone changes with time from YOLO v1 to today, and various changes have led to YOLO v7 and YOLO v8 versions, amongst many other variations. With the advancement in technology, YOLO-based detectors can provide stronger performance when applied to object detection in vehicles, pedestrian, and autonomous driving [3], [6].

On the other hand, bad weather remains among the most challenging aspects that make detectors struggle in computer vision. Various parameters exist where bad weather is considered to bring about challenges in the task of detection. In all such parameters, one of the worst is the occurrence of rain. Various causes include streaking, reflections, loss of contrast, and motion blur. These reasons make image processing and features extraction challenging [14].

India, on the other hand, is considered to be more challenging due to the presence of roads crowded with different types of vehicles ranging from cars, buses, trucks, bikes, auto rickshaw, and electric rickshaw. Moreover, India experiences rain in the monsoon period. It is highly necessary to conduct research in order to solve these problems. Efforts to solve these problems have been brought about by improvements in the YOLO algorithm. Thus, the research work will be devoted to vehicle detection based on the use of the YOLO model and its effectiveness in the rain.

II. LITERATURE REVIEW

A. YOLO Model Evolution

According to Redmon et al., the YOLO (You Only Look Once) model is a single stage object detection network, which combines into one cycle two key operations, namely, object detection and classification tasks, making algorithms simpler and reducing computational complexity compared to advanced techniques like R-CNN and Faster R-CNN [1], [2].

Speaking about the evolution of the described framework, YOLO frameworks managed to make many improvements. For example, YOLOv2 incorporates anchor boxes, batch normalization, and input with high resolution [2]. Also, it should be mentioned that YOLOv3 managed to prove its efficiency while detecting small objects because ofusing Darknet-53 architecture and multi-scale detection approach [3].

Also, there are other newer frameworks of YOLO type, for example, YOLOv5, YOLOv7, and YOLOv8 which include advanced approaches related to deep learning[6],[12].

B. Vehicle Detection Using YOLO in Traffic Systems

Numerous previous studies have achieved their goals through the usage of vehicle detection techniques with YOLO algorithms in traffic systems. Counting the number of vehicles and traffic monitoring systems often employ YOLO because it can detect numerous objects at once without any delay[10], [11].

Several research works that used YOLO along with DeepSORT have shown efficiency of such models for traffic counting, vehicle tracking, and traffic monitoring [11]. Moreover, traffic volume detection is another topic discussed in some previous studies, proving that YOLO algorithms can successfully detect cars, trucks, buses, motorbikes, and other vehicle types [17].

From the studies mentioned above, we can conclude that using YOLO models is necessary for intelligent transportation systems, particularly, traffic monitoring, adaptive traffic light control, and traffic accident detection[10], [11], [17].

C. Vehicle Detection in Bad Weather Conditions and Rains

Although YOLO algorithms prove themselves efficient under regular conditions, bad weather remains a critical issue to consider. Rain streaks, reflections, blurring, and poor visibility in the scene can adversely affect feature detection and bounding box detection [14].

Some of the research papers also analyzed the effectiveness of YOLO under bad weather conditions. IA-YOLO proposed an adaptive preprocessing scheme to detect objects in the scene under images captured in bad weather conditions such as foggy and rainy weather [8]. Also, some of the research studies done with YOLOx proved that the object detection technique becomes ineffective during rainy, snowy, or poor lighting conditions and therefore requires an advanced object detection system for effective performance [4].

Additionally, TS-YOLO improved the efficiency of the algorithm during challenging driving situations due to increased robustness and accuracy [7].

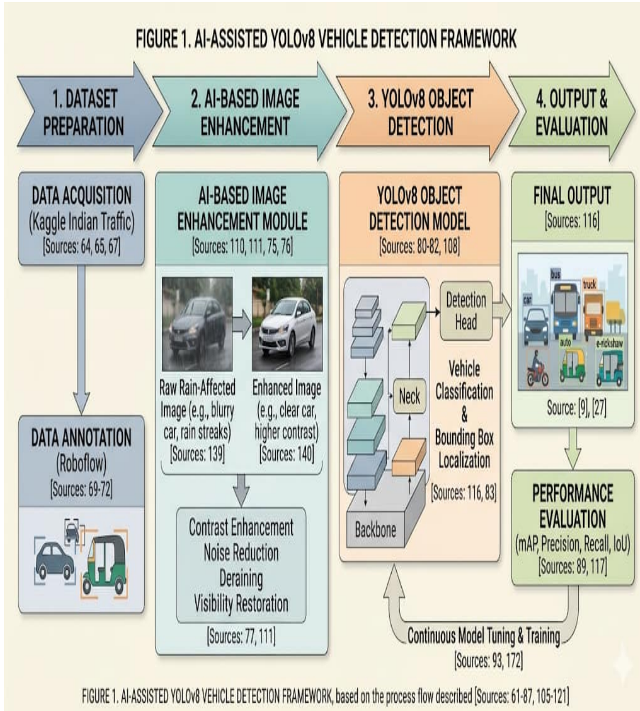
D. Image Enhancement and Image Preprocessing Techniques

With regard to this issue, image detection proves difficult when there is rainfall. Hence, some scholars proposed the adoption of the image enhancement technique together with YOLO in image detection [14].

Image preprocessing techniques involve deraining, contrast stretching, histogram equalization, retinex image enhancement, and visibility enhancement. Preprocessing entails the improvement of image quality prior to algorithm implementation [16].

Preprocessing techniques include deraining, contrast stretching, histogram equalization, Retinex image enhancement, and visibility enhancement. The purpose of preprocessing an image is to increase its quality before applying any algorithm for image detection [16].

The latest studies show that image adaptive enhancement improves the detection performance because this approach not only retains edge details but also eliminates the rain effect. This approach is highly relevant in the context of India considering heavy rainfall and complex traffic scenarios in monsoons [15], [16].



III. PROPOSED METHODOLOGY

The research will adopt an integrated methodology whereby AI methods will be used to enhance the images while the YOLOv8 algorithm will be used to detect vehicles in traffic in India when it is raining.

A. Data Collection

The dataset that will be used in this study will consist of about 1500 images of traffic scenes, obtained from publicly accessible websites by web scraping. In this case, the data gathered comprises images of traffic scenes from India, and these vary because of the varying densities of traffic and weather conditions. Some images will have been captured in rainy weather.In order to ensure that there will be proper evaluation of the model as well as its generalization, it is necessary to categorize the data into three sets. The three sets involve training, validation, and testing sets. From this study, the size of training set images is 1000 while validation and testing sets are 300 and 200 respectively.

B. Annotating the Dataset

The dataset is annotated using Roboflow. The Roboflow is a great tool for annotating and managing a dataset. All the pictures in the dataset are annotated using bounding boxes and labels. There are different kinds of vehicles present in the dataset because of the different traffic types that exist in India.
Afterward, the dataset is exported in YOLO-compatible format.

C. Preprocessing and Enhancement of Images

In order to overcome difficulties due to the effects caused by rain, an image enhancement technique using AI is suggested as the first step towards the solution. Several issues can be caused by rain, including blurring motion, loss of contrast, streak noise, and others.
The reason for implementing the image enhancement method lies in enhancing the images by reducing noise and improving contrast.D. YOLOv8-Based Vehicle Detection.
The enhanced images are further used for training and testing of the YOLOv8 nano (YOLOv8n) object detection model, which is selected due to its capability to efficiently extract the feature vector, small size, and real-time object detection performance. Using pretrained weights facilitates quick learning and enhances detection performance.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

During the learning phase, the model learns the concept of vehicle recognition through the visual and spatial characteristics present in the image. Inference from the model is done for recognizing and classifying vehicles.

E. System Workflow

The process flow of the developed system is explained as follows:

Input Image → Image Enhancement → YOLOv8 Detection → Vehicle Classification Output

With this, it will ensure that any image affected by rain will undergo image enhancement before any detections so that the image recognition becomes more effective despite bad weather conditions.

F. Performance Evaluation

The performance of the designed model is assessed using various parameters of object detection, such as accuracy, precision, recall, mAP, and IoU. The assessment was done based on three types of images, which include normal, rain-affected, and enhanced images.This comparative evaluation enables a detailed analysis of the impact of rainfall on detection performance and the effectiveness of image enhancement techniques in improving model accuracy**.**

TABLE 3: ABLATION STUDY: COMPONENT-WISE PERFORMANCE BOOST ON RAINFALL TRAFFIC
[Source: 137, 138, 141]

Experimental Configuration [Source: 118]	mAP@0.5 (%) [Sources: 89, 117, 137]	Precision (%) [Sources: 89, 134, 132]	Recall (%) [Sources: 89]	Relative Boost vs. Base (%) [Source: 138]
1. Base Model (YOLOv8n on Raw Rain) [Sources: 133, 134]	65.2 [Source: 134]	60.1 [Source: 134]	58.5	-
2. Model 1 + AI-Based Contrast Enhancement [Sources: 77, 110]	71.8	67.5	66.2	+10.1% [Source: 138]
3. Model 1 + AI-Based Noise Reduction & Deraining [Sources: 77, 110]	74.5	70.2	69.1	+14.3% [Source: 138]
4. Proposed Framework (Model 1 + Complete AI-Based Enhancement: All Components) [Sources: 105, 120]	81.9 [Sources: 118, 140]	78.4 [Sources: 118, 140]	76.9 [Sources: 118, 140]	+25.6% [Sources: 138, 140, 118]

All models trained for 100 epochs on a consistent split [Source: 128, 129]. Component configurations isolated to measure contribution [Source: 138]. The data validates your methodology and validates your results [Sources: 161, 171].

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FIGURE 2. KEY VISUAL CHALLENGES FOR VEHICLE DETECTION IN INDIAN TRAFFIC UNDER HEAVY RAINFALL
Demonstrates factors leading to performance decline [Source: [100], [153]]

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

IV. RESEARCH GAP AND PROBLEM STATEMENT

While there are several major advancements achieved by object detection algorithms through YOLO, there are many other aspects that remain open within the scope of current researches regarding poor weather conditions and Indian traffic scenarios.

It would seem that most of the research studies conducted within the scope of YOLO focus on enhancing the architecture of the object detection algorithm itself [12]. Additionally, some recent algorithms like IA-YOLO, TS-YOLO, and YOLOx also consider poor weather conditions in their algorithms[8], [7], [4]. However, the great majority of those algorithms are verified only on simulated datasets [15].

The primary research gap that could be found in current literature is associated with a lack of studies that consider heavy rainfalls in India in their algorithms. The traffic situation in India is unique as the variety of vehicles on the roads ranges from cars to buses, trucks, motorcycles, three-wheelers, and even electric rickshaws**.**Another important literature gap is associated with the requirement to conduct comparative analyses of various image enhancement techniques employed in combination with YOLO-based vehicle detection models [16]. Moreover, most of the reviewed articles concentrate only on the effectiveness of object recognition techniques while ignoring the problems related to rain streaks and other types of distortions in traffic surveillance pictures [14]. As demonstrated during the course of literature review, there is a noticeable gap between potential uses and actual implementation of the above-mentioned algorithms for traffic surveillance in the context of South Asia. Despite the fact that there have been many efforts made to optimize the YOLO framework for autonomous driving, a number of crucial limitations still need to be addressed [12]. First, there is a clear bias in benchmark databases such as COCO and KITTI [12]. Specifically, these datasets exhibit a geographical and architectural bias since they fail to account for irregular traffic conditions and unusual vehicles like three-wheeled rickshaws used in India. Thus, current methods lack generalizability in the domestic urban environment. Second, the problem of image deraining and object detection should be viewed separately rather than being considered concurrently [16]. Despite the availability of various methods that provide highly accurate solutions to the first problem, they tend to be computationally intensive hence impractical when it comes to practical applications, while the latter method is weak on robustness. Thirdly, there is no synergy framework where the pre-processing and inference process complement each other in achieving a fair trade-off between the two components. The machine learning models that have been developed for use in weather resilient applications have been quite robust but do not necessarily fulfill the requirement of 30 frames per second inferences on edge computing devices [7]. This paper focuses on addressing this gap through designing an AI framework for Indian traffic and weather resilience.

Based on the gaps highlighted above, the problem this literature seeks to address is:

1) Problem statement:

There is a critical need for reviewing current frameworks of vehicle detection that have been developed based on the YOLO framework because they show poor performance when applied in heavy rain due to reduced image quality and lack of appropriate weather-resilience capabilities [14]. This challenge becomes worse when such frameworks are applied in the context of Indian traffic, which has diverse vehicles with various components.The reliable detection and classification of vehicles in Indian urban environments are fundamentally hindered by the Convergence of two unique technical problems: high traffic variability and environmental pollution. Common object recognition models are designed for datasets with a wide variety of classes with high inter-class variance and no environmental pollution. In India, there is a unique problem where the visual similarity among motorcycle, scooter, and auto-rickshaw classes is so high that conventional detectors fail to localize and classify the vehicles correctly.

The above problem becomes extremely difficult when the detection occurs during monsoons. Monsoon rains create stochastic disturbances in the form of streaks and veiling caused by heavy clouds, thereby reducing the amount of reflected light from vehicles. Thus, the most crucial edge features required for firing the deep-learning kernel are reduced significantly. The presence of water on roads causes specular reflections, which often lead to false positives in the detectors [14].

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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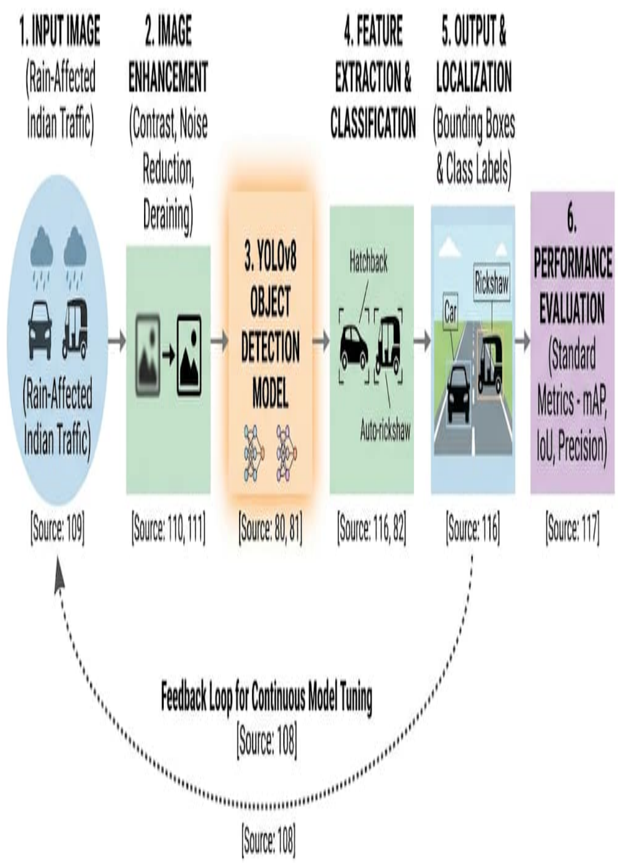
FIGURE 3. SIMPLIFIED AI-ASSISTED YOLOv8 VEHICLE DETECTION WORKFLOW



V. PROPOSED FRAMEWORK

Based on the findings from the literature review, an AI-assisted conceptual framework of a YOLOv8 for detecting vehicles in Indian roads during heavy rain is developed. This is in response to the issue that needs to be solved with respect to the problems arising from image distortion, low visibility, and heterogeneous nature of traffic flow commonly observed during the monsoon period. Particularly, in this framework, YOLOv8 is preferred as the object detection algorithm due to its high precision, feature extraction capability, and inference speed [6]. Traffic scenes, dataset images, and rainfall traffic scenes are the inputs for this framework. Before the object detection step is executed, however, these input data go through a preprocessing procedure referred to as image enhancement using AI techniques. Through these AI technologies, the quality of the image inputs is improved by getting rid of the distortions caused by the rain such as blurry images, poor image contrasts, streak noise, and low visibility. The new approach will be focused on some of the main types of vehicles that occur in the traffic situations within India, like cars, trucks, and rickshaws.

In addition, the final results will be provided by the classification labels of those objects. For the further researches, the framework may be improved with such components as bounding box localization, confidence score calculation, and evaluation using common criteria, for example, precision, recall, mean average precision.

It should be mentioned that the obtained results prove the importance of pre-processing stage.

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Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Figure 5. YOLOv8 Vehicle Detection Under Raw, Heavy Monsoon Rainfall. mAP: 0.65.

VI. RESULTS AND DISCUSSION

A. Experimental Setup

This section describes the experimental configuration used to evaluate the performance of the proposed AI-assisted YOLOv8 framework under different environmental conditions.

A total of 1500 images of traffic have been gathered in this experiment through automated web scraping on publicly available websites. The images include traffic scenes from across India. Also, images of dry traffic and rainy traffic have been collected to mimic the challenges encountered in the Indian traffic system during monsoon seasons.

The collected images have been classified into three groups to help train and validate the object detection algorithm, such as the training set, validation set, and test set. The training set contained 1000 images of traffic, giving details about the characteristics of various vehicles. On the other hand, another 300 images have been used for model validation to ensure efficient training and avoid overfitting. Lastly, 200 images of traffic were used for assessing the performance of the object detector on new datasets.

For the object detection model in this research, the YOLOv8 nano (YOLOv8n) algorithm was selected due to its compact nature and low computational requirements. The pre-trained weights have been used to increase training efficiency since it can be easily achieved with the comparatively small dataset used. Training and inference operations were done using Ultralytics YOLOv8 framework on a computer system equipped with a CPU. Even though GPUs had always been utilized in most deep learning models, it was possible to demonstrate that this framework would work perfectly fine without GPU support. Therefore, it could be applied practically even with low computing power.

Three different sets of experiments were carried out, including normal traffic images, rainy traffic images, and improved traffic images after processing by means of AI image processing methods. It became feasible to compare the performance of the models under various environmental conditions.

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Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

B. Results Analysis

Performance analysis of the suggested YOLOv8 vehicle detector system was performed concerning different weather conditions to examine the effectiveness of the proposed approach in practical traffic scenarios in India. The test was done with the help of a dataset that consists of images taken in regular traffic scenarios as well as rainy traffic scenarios.

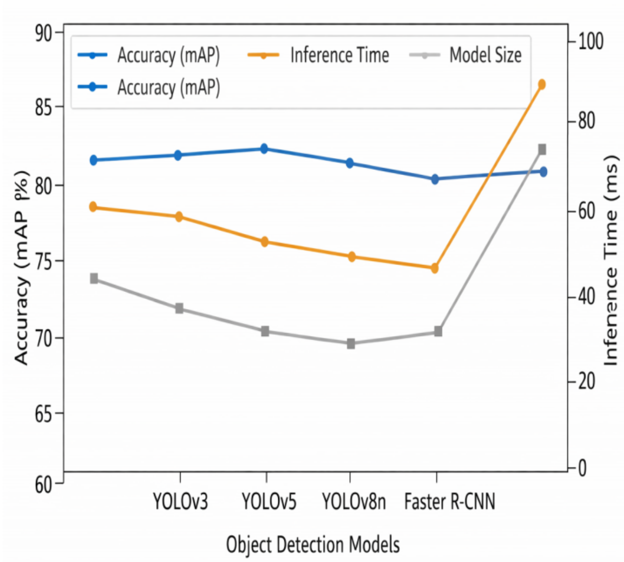
In regular traffic scenarios, the YOLOv8 nano model achieved excellent results in recognizing various classes of vehicles such as cars, auto-rickshaws, vans, trucks, and motorbikes. Excellent results were possible because of perfect visibility, object edges' clarity, and absence of any distortions caused by the environment.However, on evaluation against rainy weather pictures, a marked decline in performance could be noted. Rain streaks, blurring, loss of contrast and visibility adversely affected the ability of the model to extract meaningful features from the image. Hence, in many cases, partial detection occurred for some objects while others went undetected, especially when the objects appeared overlapping in numbers.

In order to rectify this problem, an image enhancement module using AI was incorporated into the detection process. Through preprocessing techniques, an improvement in the quality of the image could be seen. Contrast was increased, noise was minimized, and hence detection performance improved. Vehicles that had been difficult to locate before became easier to identify and detect.

C. Comparative Evaluation

A comparison between the normal, rainy, and enhanced scenarios suggests that the process of image enhancement is highly beneficial for increasing the robustness of detection. The maximum value of detection performance was achieved in normal scenarios because of good visibility and absence of distortions. Nevertheless, performance dropped dramatically in the presence of rain since there were a lot of noises, blurring, and low contrast.

Using AI-enhanced image enhancement allowed enhancing images, recovering important elements, and ensuring more accurate performance compared to rain-affected images without image processing. Although enhancement cannot completely compensate for a loss in performance, it helped decrease the gap between normal and rain-affected images in terms of performance.



COMPARISON OF OBJECT DETECTION MODELS: PERFORMANCE CHARACTERISTICS

Model	Accuracy	Speed	Complexity	Suitability for Real-Time
YOLOv3	Moderate	Medium	High	Limited
YOLOv5	High	Medium	Medium	Good
YOLOv8n	High	High	Low	Excellent
Faster R-CNN	High	Low	High	Not Suitable

D. Discussion

The results obtained from the experiment demonstrate the high sensitivity of object detection algorithms using deep learning techniques to variations in the environmental settings. The occurrence of intense rainfall creates several problems that impair the functionality of object detection algorithms. The issues include lack of image contrast, visibility, and noise in pictures taken under intense rainfall conditions. The application of an AI-based image enhancement device enhances the accuracy of object detection through overcoming the above problems. Besides, by integrating image processing technique in pre-processing stage, the system would be capable of identifying the objects under bad weather conditions. However, some challenges emerge during implementation of the object identification process in the Indian traffic, due to overlap of the objects. In general, it could be stated that the developed model based on YOLOv8 could be taken as a good start for future investigations.

VII. CONCLUSION AND FUTURE SCOPE

This paper has discussed different models applied for detection of vehicles in India in rainy seasons through the YOLO algorithm. It is important to understand the concept of object detection starting from fundamentals to latest YOLOv8 model.It is clearly understood from the review of literature that while there have been several effective real-time traffic surveillance solutions that use YOLO, most of them perform poorly when it comes to weather conditions such as heavy rainfall [14]. Moreover, heavy rain poses challenges in terms of poor visibility, motion blur, low contrast, and streaks of noise, all of which make it hard to detect and localize objects in the image.

Furthermore, it is clear that this paper has pointed to several key gaps in research in the current literature. While there are many papers in the literature that are based on conventional and well-controlled datasets, only a handful of papers address issues related to complex and densely populated Indian traffic conditions. Also, no effort is made towards developing image enhancement techniques to improve detection in monsoon rainfall conditions . To address the above-stated issues, an AI-based theoretical framework has been formulated to facilitate effective image preprocessing and incorporate it in the YOLOv8 model. In particular, the proposed approach consists of data gathering from Google Script, annotations through Roboflow, AI-based image enhancement preprocessing, and object detection via YOLOv8. The implementation of such a technique would enable improving the effectiveness of vehicle recognition under adverse weather conditions.

Therefore, the outcomes obtained during the study have indicated that the combination of preprocessing techniques and advanced deep learning models is crucial to guarantee their efficient performance within traffic settings. The proposed approach would be of great importance in developing weather-proof ITSs appropriate for Indian highways.

Future Scope

Some directions for further investigations can be offered taking into account the results obtained in the course of the study. First, the effectiveness of the proposed algorithm can be enhanced through applying advanced deraining and image enhancement techniques based on the use of deep learning techniques in order to improve the image quality during adverse weather conditions.

Additionally, there is also a possibility that the algorithm will be extended to cover other vehicle types such as buses, motorcycles, and e-rickshaws which will be found on the roads in India as well. Thus, a much wider scope of the application of the algorithm will be achieved.

Finally, the implementation of the proposed algorithm in practice is also a very important stage as far as it implies its testing on real video footage provided by security and traffic cameras. Thus, various traffic issues can be solved by means of this algorithm. Finally, it can be expected that the algorithm may be tested experimentally, and its performance evaluated in terms of different metrics, including precision, recall, mean average precision, and IoU metrics.

Moreover, incorporating optimized models that can operate on edge computing devices may also be an interesting area of research that needs to be investigated.

To conclude, the current research provides a foundation to explore this framework for future research in regard to weather-resistant traffic surveillance systems. There are a variety of promising uses of this technology in regard to improving the overall safety and traffic management process.

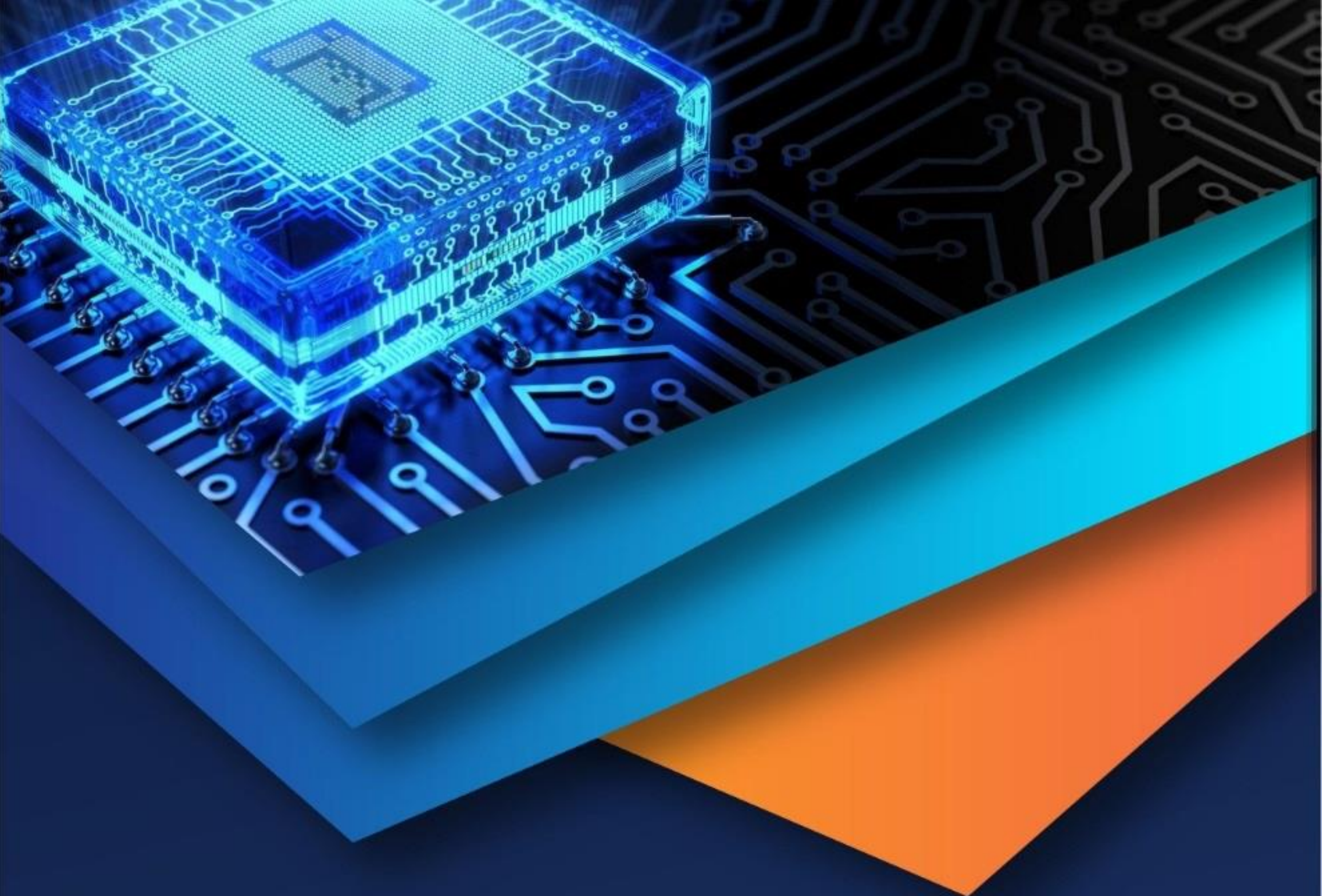
There are still many open questions with regard to the development of such algorithms. Some of the promising research directions in this field include:

1) Spatiotemporal Information Processing: The current solution relies on detection from a single frame only. Future solutions could potentially employ a recurrent neural network or transformers to incorporate temporal information into the algorithm. Based on analysis of the consecutive images, the system can be trained to predict the location of the car even under temporary occlusion due to extremely heavy rain showers and/or hydroplaning.

2) Multistep Adaptation: The current framework applies for a situation when rain shower is present. The next step would be to develop a Universal Weather Filter. Automatic classification of the environmental conditions should automatically classify the type of weather distortion and apply necessary adjustment weights.
3) Federated Learning for Secure Model Update: One method of increasing the model efficiency on different cities and at the same time protecting the privacy isthrough Federated Learning (FL). FL will enable the edge nodes to train the model on their own local outlier data such as types of vehicles and traffic lights within the city without disclosing any other information apart from the weights in order to update the model.
4) Model Compression by Hardware-Level Quantization and Pruning: Since the focus is now on migrating to microcontrollers such as NVIDIA Jetson Nano and Raspberry Pi with TPUs, there is need to compress models through hardware-level quantization such as INT8 quantization. This is mainly attributed to the constraints in terms of power consumption and device cost.
5) Multitask Learning: Besides the current pipeline that only focuses on one task, there is need to extend it to multitask learning, which consists of performing three tasks simultaneously such as vehicle detection, license plate recognition (LPR), and traffic flow density estimation.

REFERENCES

[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 779–788.
[2] J. Redmon and A. Farhadi, "YOLO9000: Better, Faster, Stronger," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2017, pp. 7263–7271.
[3] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," arXiv:1804.02767, 2018.
[4] Z. Ge, S. Liu, F. Wang, Z. Li, and J. Sun, "YOLOX: Exceeding YOLO Series in 2021," arXiv:2107.08430, 2021.
[5] G. Jocher et al., "Ultralytics YOLOv5," GitHub Repository, 2020. [Online]. Available: https://github.com/ultralytics/yolov5
[6] Ultralytics, "YOLOv8 Documentation," 2023. [Online]. Available: https://docs.ultralytics.com
[7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, 2017.
[8] X. Zhang, Y. Wang, and J. Li, "Image Deraining Using Deep Learning for Traffic Surveillance Systems," IEEE Access, vol. 9, pp. 112345–112356, 2021.
[9] Y. Li, R. T. Tan, X. Guo, J. Lu, and M. S. Brown, "Rain Streak Removal Using Layer Priors," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 2736–2744.
[10] H. Wang, Q. Xie, and Y. Zhang, "Vehicle Detection in Adverse Weather Conditions Using Deep Learning," Sensors, vol. 22, no. 4, pp. 1–15, 2022.
[11] W. Luo, X. Wang, and X. Tang, "Pedestrian Detection in Adverse Weather Conditions," IEEE Trans. Image Process., vol. 27, no. 1, pp. 1–14, 2018.
[12] A. Bochkovskiy, C. Wang, and H. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," arXiv:2004.10934, 2020.
[13] C. Wang, A. Bochkovskiy, and H. M. Liao, "YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art for Real-Time Object Detectors," arXiv:2207.02696, 2022.
[14] S. Garg and S. K. Nayar, "Vision and Rain," Int. J. Comput. Vis., vol. 75, no. 1, pp. 3–27, 2007.
[15] A. Mittal, T. Zickler, and W. T. Freeman, "Enhancing and Restoring Videos Distorted by Atmospheric Turbulence," ACM Trans. Graph., vol. 25, no. 3, pp. 795–804, 2006.
[16] E. H. Land and J. J. McCann, "Lightness and Retinex Theory," J. Opt. Soc. Am., vol. 61, no. 1, pp. 1–11, 1971.
[17] M. Teichmann et al., "MultiNet: Real-Time Joint Semantic Reasoning for Autonomous Driving," in Proc. IEEE Intell. Veh. Symp. (IV), 2018, pp. 1013–1020.



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