Efficient Object Detection Framework for Indian Road Scenarios Under Foggy Conditions Using YOLOv8

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Abstract: Effective congestion management and safe navigation depend on accurate object detection , especially for autonomous vehicle systems. Indian roads pose unique challenges, including high traffic density, erratic driving behaviors, diverse vehicle types, and adverse weather conditions such as fog. This paper presents a robust solution using YOLO (You Only Look Once) models for object detection tailored to Indian road conditions. The YOLOv8 nano (YOLOv8n) model is used for daylight images, while the YOLOv8 medium (YOLOv8m) model addresses performance in foggy scenarios by training on a synthetic fog enhanced dataset. The framework also incorporates video analysis for real time object detection, leveraging YAML configuration, pre trained weights, and fine tuned models. Results demonstrate reliable performance across images and videos, providing an efficient solution for autonomous driving in complex environments.

1 INTRODUCTION

Object detection play a crucial role in the development of autonomous vehicles, enabling them to navigate safely and efficiently through dynamic and unpredictable environments. These systems are fundamental to intelligent transportation technologies by ensuring that vehicles can make decisions in real time, avoid obstacles, and comply with traffic regulations. However, designing robust object detection frameworks becomes particularly challenging when addressing the unique characteristics of Indian roads. High traffic density, erratic driving behaviors, diverse vehicle types, and infrastructure inconsistencies exacerbate the difficulty. In addition, adverse weather conditions, such as fog, significantly reduce visibility, further complicating the task of reliable object detection.

Indian roads pose challenges that differ significantly from those found in more structured road systems commonly found in developed nations. Unlike these environments, Indian roads feature a heterogeneous mix of motorized and non motorized traffic, including cars, buses, motorcycles, bicycles, and pedestrians. The unpredictability of traffic patterns, combined with frequent obstructions such as parked vehicles, stray animals, and roadside vendors, requires detection systems that are not only accurate but also highly adaptive. Adverse weather conditions, particularly fog, add another layer of complexity by obscuring visual data and reducing the effectiveness of traditional object detection systems. Although existing models such as YOLOv5, YOLOv7, and YOLOv8 have shown promise in structured settings, their performance often falters when applied to the dynamic and unstructured environments characteristic of Indian roads.

The current research adopts a two stage approach to address these challenges. In the first stage, the lightweight YOLOv8 nano (YOLOv8n) model is utilized for daylight scenarios. With its compact architecture and computational efficiency, YOLOv8n is well suited for real time deployment in resource constrained environments, such as onboard vehicle systems. However, its performance under foggy conditions revealed certain limitations, prompting the transition to YOLOv8 medium (YOLOv8m) in the second stage. The YOLOv8m model, with its enhanced architecture, delivers improved detection accuracy and robustness, particularly in low visibility scenarios.

Unlike traditional approaches that rely heavily on data augmentation to enhance model performance,

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this study focuses on leveraging pre trained weights and fine tuning techniques. The dataset, derived from the DATS 2022 collection, is augmented with synthetic fog layers to simulate real world weather conditions, ensuring the model's ability to handle low visibility scenarios without requiring additional raw data. The ability of the framework to detect and classify 35 different object categories, including vehicles, pedestrians, and cattles, underscores its versatility and applicability.

This study represents a significant step forward in developing practical solutions to the unique challenges faced by Indian roads. By addressing issues such as high traffic density, unpredictable driving behavior, and adverse weather conditions, the proposed framework contributes to the development of intelligent transportation systems. Furthermore, it demonstrates the potential to deploy scalable and efficient object detection systems in autonomous vehicles, even in resource constrained settings.

The rest of this paper is organized as follows: Section 2 reviews related works, highlighting the limitations of existing models in handling dynamic road conditions. Section 3 details the methodology, including model selection, dataset preparation, and fine tuning processes. Section 4 presents the experimental results, analyzing the performance of the proposed framework across various scenarios. Finally, Section 5 concludes with a summary of findings, contributions, and future research directions.

2 Literature Survey

Deep learning models and tailored datasets have advanced the analysis of Indian road traffic, addressing challenges like diverse vehicles and unstructured traffic. This survey highlights methods such as YOLO and faster RCNN, focusing on their effectiveness in traffic monitoring and autonomous systems.

In(Pimpalgaonkar et al., 2024),proposed a YOLO based system for detecting lanes and objects on Indian roads. It tackles challenges like faded markings, dense traffic, and varying weather, making it suitable for ADAS. The system is robust but struggles under extreme weather conditions like heavy rain or dust storms. In(Sai Srinath et al., 2020),introduced the NITCAD dataset for autonomous vehicle navigation, focusing on unstructured traffic and unique Indian road conditions. The work uses faster RCNN for object detection and CNNs for depth estimation. Key limitations include misclassification of similar vehicle types and the need for more complex scenario data. In (Fujitake and Sugimoto, 2022),developed a video representation learning framework leveraging stochastic video prediction for online object detection. The method achieved superior speed and accuracy on datasets like ImageNet VID, though its reliance on computationally expensive pre training limits scalability.

In(Lim et al., 2024),conducted a performance analysis comparing SSD and faster RCNN models for object detection in autonomous vehicles. Faster RCNN achieved higher accuracy but had lower recall, emphasizing precision at the cost of localization in challenging scenarios. In(Taher and Tuaimah, 2020),designed a system for moving object detection using background subtraction and K Nearest Neighbors for classification. The system achieved high accuracy in static environments but faced challenges with multimodal backgrounds. In(Xu et al., 2024),proposed an area aware attention mechanism for detecting small abandoned objects on highways. While it enhanced segmentation accuracy, the computational overhead posed challenges for real time deployment.

In(Madhan and Shanmugapriya, 2024),presented the EMOD system for detecting moving objects using shadow detection and CNNs optimized by Manta Ray optimization. The system excels in noisy environments but has limitations in real time large scale applications due to computational complexity. In(Esmaeil Abbasi et al., 2024),proposed a hyper parameterized YOLOv8 model for object detection in foggy conditions. The method showed improved detection accuracy but required extensive computational resources for hyperparameter tuning. In(Srin and Baydeti, 2022),developed a deep learning model combining CNN and LSTM for video classification. The approach enhances spatial and temporal feature recognition but introduces complexity and potential overfitting challenges.

In (Guo and Chen, 2024),the study presents a method for enhancing object detection accuracy by leveraging stereoscopic vision to improve the identification of waste objects on roads, contributing to better urban waste management and autonomous vehicle navigation. In(Adegun et al., 2024),introduced an ontology based deep learning model integrating YOLOv8 for object detection and classification in smart city environments. While enhancing interpretability through semantic reasoning, the complexity of ontology construction limits its scalability. In(Ding et al., 2024),developed the SCD-YOLO model for efficient road crack detection. The system integrates advanced feature extraction techniques, achieving high accuracy, but the added computational cost limits real time application.

In(Liu et al., 2024),proposed the ProEqBEV network for 3D object detection using multi sensor fusion data. The network excelled in handling motion patterns in Bird's Eye View representations but faced challenges with extremely complex rotational scenarios. In(Cheng and Liu, 2024),improved YOLOv3 for video surveillance, effective under noise but limited in low light and occlusions. In(Khare et al., 2023),proposes an advanced detection system using YOLOv8 to identify road hazards such as potholes, sewer covers, and manholes. The study focuses on enhancing real time detection accuracy under challenging conditions, contributing to improved road safety and maintenance.

In(Kumari et al., 2023),introduces method that emphasizes high accuracy and real time performance, aiming to facilitate proactive road maintenance and enhance vehicular safety. In(Wang et al., 2023),presents an enhanced YOLOv8 model optimized for detecting road defects. By integrating advanced feature extraction techniques, the model achieves improved accuracy and robustness in identifying various road imperfections, supporting efficient infrastructure maintenance. In(Biswas et al., 2023),the study addresses the challenges of diverse road conditions and complex traffic scenarios, aiming to enhance real time traffic management and autonomous vehicle navigation.

In(Anvitha et al., 2023),examines the application of YOLOv8 for analyzing traffic management systems. The study focuses on detecting vehicles, pedestrians, and traffic signals in real time, contributing to efficient traffic flow and safety improvements. In(Jha et al., 2023),presents techniques to mitigate overfitting in vehicle classification models using YOLOv8. It highlights optimization strategies such as data augmentation and regularization, improving model generalization for real world applications.

The reviewed works showcase advancements in deep learning for Indian road traffic analysis, addressing challenges like unstructured traffic, diverse vehicles, and varying conditions. YOLO-based systems and the NITCAD dataset enhance lane detection and object classification but face limitations under extreme weather and misclassification. Advanced methods, such as hybrid CNN-LSTM models and area-aware attention mechanisms, improve accuracy and detection speed but struggle with scalability and computational demands. YOLOv8 models excel in detecting foggy conditions, road defects, and traffic elements, contributing to safety and maintenance, though complexity limits scalability. Overall, these methods demonstrate progress in balancing accuracy with real-world applicability.

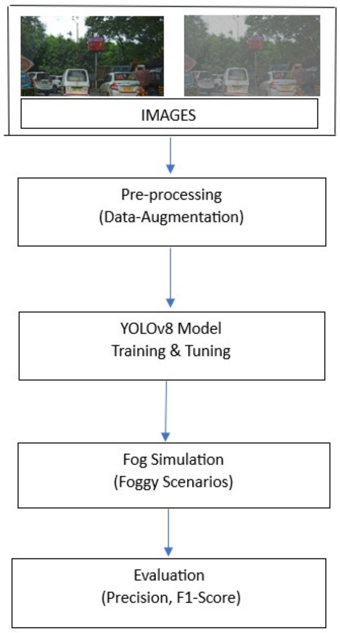

Figure 1: Proposed Methodology

3 Proposed Methodology

The proposed framework aims to develop a robust object detection and classification system tailored for Indian road conditions, addressing challenges such as high traffic density, erratic driving patterns, diverse object types, and infrastructural inconsistencies. It employs the DATS 2022 dataset, comprising 2048 training images and 802 test images, including urban landscapes, vehicles, pedestrians, and traffic signs across 35 different object classes. The methodology integrates image and video analysis to ensure real time adaptability and performance under dynamic conditions.

The workflow of the proposed approach, as illustrated in Figure (1), outlines the methodology adopted for object detection in Indian road scenarios. The process begins with the collection of images, followed by pre-processing, where data augmentation techniques are applied to enhance the dataset's diversity. Next, the YOLOv8 model is utilized for training and tuning, leveraging two versions of the model—YOLOv8nano (YOLOv8n) for daylight scenarios and YOLOv8medium (YOLOv8m) for challenging conditions like fog. A fog simulation step is incorporated to generate synthetic foggy conditions, preparing the model to perform effectively in low-visibility environments. The final phase involves evaluation, where metrics such as precision and F1-score are used to assess the performance of the object detection framework. This systematic approach ensures robustness and adaptability in varying visibility conditions on Indian roads.

Phase 1 - Training using daylight images : The YOLOv8n model is trained on daylight images from the DATS 2022 dataset, chosen for its lightweight architecture and computational efficiency, making it ideal for resource constrained environments such as onboard vehicle systems. Pre trained weights from the COCO dataset, a large scale benchmark with diverse annotations across multiple object categories, are fine tuned over 210 epochs on GPU accelerated hardware to adapt to Indian road conditions. This phase optimizes hyperparameters, such as learning rate and batch size, to improve detection performance.

Phase 2 - Training for foggy scenarios : To address challenges in low visibility conditions, a synthetic fog layer is applied to the dataset. The fog simulation is formed using the following equation (1) :

$$f_i = (1-i) * o_i + i * f_l \tag{1}$$

where:
fi is the foggy image,
i is the intensity of image selected,
oi is the original image,
fl is the fog layer.

where the intensity parameter controls the fog density, ranging from 0 (clear) to 1 (dense). The fog layer is generated with random noise, adjusted for realistic variability, and applied programmatically to all dataset images, producing multiple fog intensity levels.

The YOLOv8m model, with its advanced architecture, is then employed for these foggy scenarios. As depicted in Figure(2), the process begins with the application of a fog simulation equation to the original images, generating foggy images of varying intensity levels. These fog-affected datasets undergo data augmentation to enhance diversity and robustness. Using transfer learning, the YOLOv8m model is fine-tuned on this augmented dataset over 100 epochs with re-optimized hyperparameters. This systematic approach ensures improved model performance in low-visibility conditions caused by fog. The framework extends to video analysis, enabling real time object detection in dynamic traffic footage. Video frames are processed sequentially using the trained YOLOv8 models, maintaining high detection accuracy and computational efficiency across various conditions. This integration demonstrates the system's adaptability for real world deployment in autonomous vehicles.

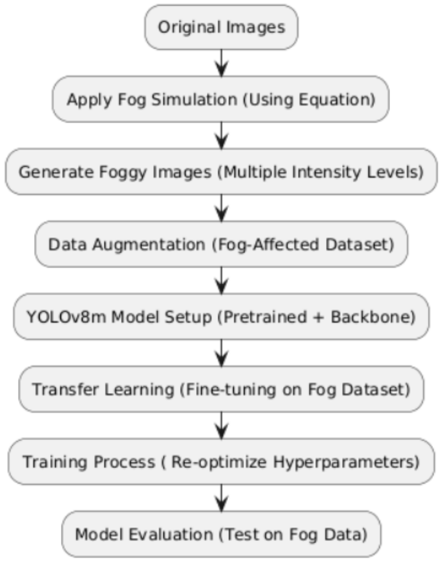

Figure 2: YOLOv8m architecture for fog image.

Implementation workflow : Data preprocessing is performed by organizing daylight and foggy datasets with structured labels and image paths. Model configuration is performed by creating YAML files specifying dataset paths , number of classes, and object names. Training execution is performed utilizing GPU accelerated hardware for efficient computation and saving model checkpoints for evaluation. Video processing is performed by extracting and analyzing frames from videos, ensuring consistent detection performance.

Figure 3: Image before detection.

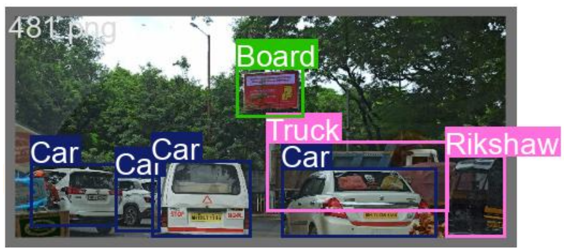

Figure 4: Image after detection.

The key challenges includes accurately simulating real world fog conditions and optimizing model per-

Algorithm 1 YOLOv8-Based Object Detection Framework for Indian Road Scenarios

Input: Dataset $D_{\text{daylight}}, D_{\text{fog}}$; Pretrained weights w_{COCO}; Hyperparameters H; Video stream V
Output: Trained models $M_{\text{daylight}}, M_{\text{fog}}$
 # Phase 1: Training for Daylight Conditions
Train YOLOv8 Nano (M_{daylight}) on D_{daylight} with w_{COCO}, using GPU and hyperparameters H
Save M_{daylight}
 # Phase 2: Training for Foggy Conditions **for** *each image o_i in $D_{daylight}$* **do**
    end
    Apply synthetic fog layer to create fogged image f_i using the formula:

$$f_i = (1-i) \cdot o_i + i \cdot f_l$$

Add f_i to D_{fog}

Train YOLOv8 Medium (M_{fog}) on D_{fog} with w_{COCO}, using GPU and hyperparameters H
Save M_{fog}
 # Video Analysis Integration **for** *each frame F in the video stream V* **do**
    end
    Extract F from V
Preprocess F and determine conditions (e.g., daylight or foggy)
Apply:

$$\text{Detection Result} = \begin{cases} M_{\text{daylight}}(F) & \text{if daylight image} \\ M_{\text{fog}}(F) & \text{if fog image} \end{cases}$$

 # Evaluation
Evaluate $M_{\text{daylight}}, M_{\text{fog}}$ on test datasets
Calculate precision, recall, and F1-score
Return: $M_{\text{daylight}}, M_{\text{fog}}$

Figure 5: Fog Image before detection.

formance across scenarios. These are addressed by fine tuning fog intensity parameters and leveraging transfer learning with efficient GPU resources.

The models are evaluated using metrics such as

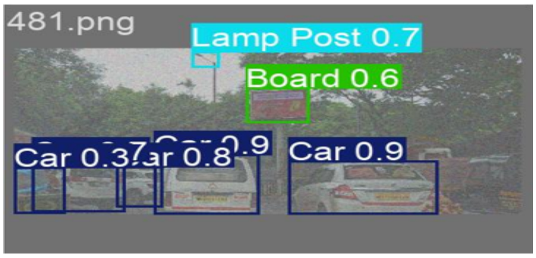

Figure 6: Fog Image after detection.

precision, recall, and F1 score , alongside qualitative analysis of detection results in both image and video formats. YOLOv8m demonstrates superior performance in low visibility scenarios, validating its robustness for real world deployment.

The proposed framework effectively integrates advanced deep learning techniques with image and video analysis, offering a scalable and robust solution for object detection and classification tailored to Indian road conditions. By addressing unique challenges such as fog and dynamic traffic patterns, it contributes to the development of intelligent and efficient autonomous vehicle systems.

4 Results and Discussion

The implementation of the YOLO based object detection framework is conducted iteratively, emphasizing efficient resource utilization and incremental improvements. Python served as the primary programming language, with the ultralytics library utilized for YOLO, along with supporting libraries like YAML for dataset configuration and OS for file management. All experiments are executed on Google Colab, leveraging a Tesla T4 GPU with 12 GB of memory to accelerate training and inference. Intermediate model weights are stored and managed using Google Drive to streamline workflow management.

The dataset comprised 35 object classes specific to Indian road conditions, including categories such as Traffic Signal, Car, Zebra Crossing, and Tree. A custom configuration file, config.yaml, is used to define the dataset structure, specifying paths for training and validation images and labels. The YOLOv8 nano (YOLOv8n) model is initially employed for daylight image detection, leveraging its lightweight and efficient architecture for faster training and inference.

To process video data, the input videos are converted into individual frames at a specified frame rate using openCV. These frames are then treated as input images for the object detection model. After detection , the processed frames are reassembled into videos to visualize the results of object detection. This frame by frame approach enabled efficient and adaptable object detection for dynamic road scenarios captured in real time videos.

The training process spanned 200 epochs, ensuring steady optimization of model performance. No data augmentation techniques are applied to the daylight dataset since the raw dataset closely mirrored real world Indian road conditions during daylight hours. However, to simulate challenging weather conditions, a synthetic fog layer is applied to a subset of images, creating a fog dataset. For this dataset, the YOLOv8 medium (YOLOv8m) model is used instead of YOLOv8n due to its enhanced capacity to capture subtle features and handle the reduced visibility in foggy conditions. The YOLOv8n model, while efficient and lightweight, is less effective in such scenarios, whereas the YOLOv8m model balances speed and accuracy, making it more suitable for complex environments.

The batch size is set to five, and default YOLOv8 hyperparameters were used to establish a reliable baseline without extensive manual tuning. During training, both YOLOv8n for daylight images and YOLOv8m for foggy images demonstrated steady improvements in learning, achieving consistent reductions in both training and validation losses over time. The framework also displayed effective generalization, as evidenced by its performance on unseen data, achieving high accuracy in detecting and classifying objects under various conditions.

In Figures (3) and (4), images illustrate a road scene under daylight conditions before and after object detection. Figure (3) shows the unprocessed frame, while Figure (4) highlights detected objects such as cars, a rickshaw, a truck, and a signboard, with each enclosed in colored boxes. Metrics such as precision, recall, and mean average precision (mAP) are tracked throughout the training process to evaluate learning trends. Precision stabilized as training progressed, while recall improved consistently, indicating enhanced detection of true positives. The mAP metric displayed initial variations but eventually converged, demonstrating reliable performance.

In Figures (5) and (6), the images display a foggy road scene before and after object detection. The fog layer introduces a challenge, but the model successfully detects and identifies key objects despite the reduced visibility.

In Figure (7), the precision trend for daylight conditions (YOLOv8n) is depicted, where the x-axis represents the epochs (number of training iterations) and the y-axis shows the precision values. Initially, the precision decreases but eventually stabilizes and improves. By the final epoch, there is a noticeable upward trend in precision, highlighting the model's ability to adapt and perform better as training progresses. In Figure (8), the precision trend for foggy conditions (YOLOv8m) is shown, with the x-axis representing epochs and the y-axis representing precision values. Unlike the daylight condition, the precision in foggy conditions exhibits more variability and sharp oscillations, reflecting the challenges posed by low visibility. Despite this, the overall precision trend demonstrates a steady improvement over time, indicating that the model progressively adapts to the challenging conditions.

In Figure (9), the recall trend for daylight conditions is shown, where the x-axis represents epochs and the y-axis represents recall values. Initially, recall drops but then recovers and improves as training progresses. This trend highlights the model's ability to stabilize and enhance its detection of true positives over time. In Figure (10), the recall trend for foggy conditions is depicted, with the x-axis representing epochs and the y-axis representing recall values. Unlike daylight conditions, the recall under foggy conditions shows a steady increase with fewer fluctuations. This suggests that the model effectively adapts to the challenges posed by low visibility and consistently improves its ability to detect objects despite the adverse conditions.

In Figure (11), the mAP trend for daylight conditions (YOLOv8n) is shown, where the x-axis represents epochs and the y-axis represents the mean average precision (mAP). Initially, the mAP exhibits variability, but as training progresses, it converges toward a higher value, indicating improved and consistent performance as the model stabilizes. In Figure (12), the mAP trend for foggy conditions (YOLOv8m) is depicted, with the x-axis representing epochs and the y-axis representing mAP. The mAP steadily increases with minor fluctuations, particularly for the mAP50-95 metric, which demonstrates the model's robustness and its ability to generalize well despite the challenges presented by foggy conditions.

In Figures (7, 9, and 11), the performance metrics—precision, recall, and mean average precision (mAP) are evaluated across training epochs to analyze the model's learning trends under daylight conditions. Precision initially decreased but later stabilized and improved, showcasing the model's adaptability and its increasing ability to minimize false positives as training progressed. Recall demonstrated an initial drop followed by consistent improvement, highlighting the model's growing capacity to detect true positives over time. The mAP metric exhibited variability in the early epochs but gradually converged to a higher value, indicating stable and reliable object

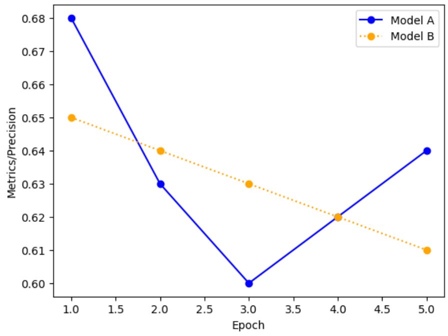

Figure 7: Precision trend across epochs for YOLOv8n Model.

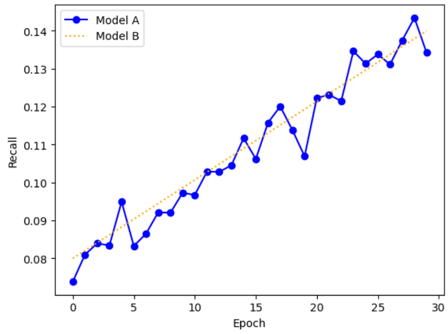

Figure 10: Recall trend across epochs for fog image using YOLOv8m.

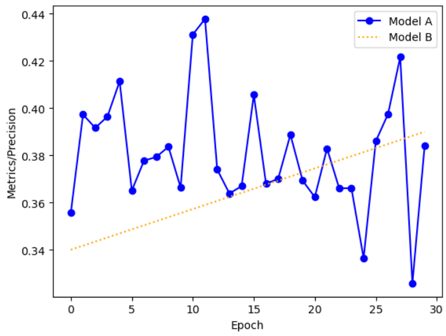

Figure 8: Precision trend across epochs for fog image using YOLOv8m.

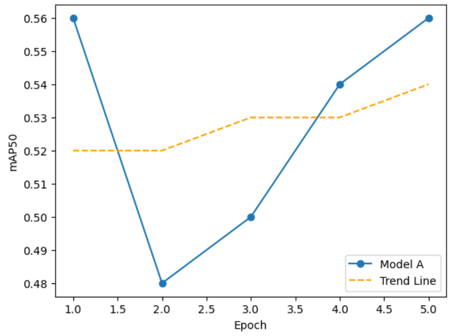

Figure 11: mAP trends across epochs for YOLOv8m Model.

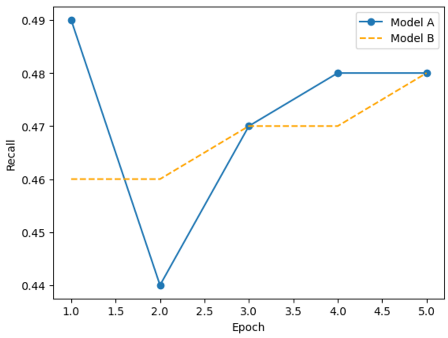

Figure 9: Recall trends across epochs for YOLOv8n Model.

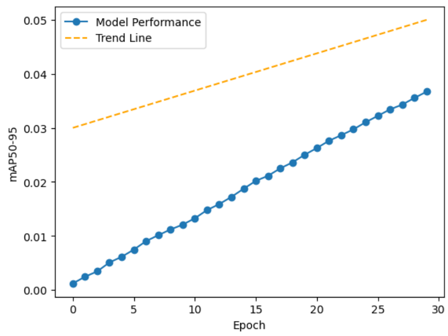

Figure 12: mAP trends across epochs for fog image using YOLOv8m Model.

detection performance under daylight scenarios.

In Figures (8, 10, and 12), the metrics—precision, recall, and mean average precision (mAP)—were analyzed across training epochs to evaluate the model's performance under foggy conditions. Precision trends exhibited significant fluctuations across the epochs, reflecting the challenges in minimizing false positives under low-visibility conditions. The recall trends showed an initial decline followed by a steady increase, demonstrating the model's improving ability to detect true positives as training progressed. The mAP trends started with lower values but gradually converged, indicating the model's capability to achieve consistent and reliable object detection performance even in foggy scenarios.

Table 1 compares the performance of the model for daylight and foggy conditions. The YOLOv8n model excelled in daylight, while the YOLOv8m model performed better under foggy conditions, addressing low visibility challenges effectively. Compared to the baseline paper, which used YOLOv8 with roboflow for extensive data augmentation to tackle faded lane markings and lighting variations, the approach focused on frame by frame video processing and weather specific adaptations. Both studies affirm YOLOv8's suitability for Indian road conditions, with the work emphasizing scalability across diverse weather scenarios and real time ADAS applications.

Overall, YOLOv8n outperforms YOLOv8m across precision, recall, and mAP metrics. Daylight conditions show steady improvements and stability, while foggy conditions exhibit greater fluctuations and lower performance, highlighting the challenges of object detection in reduced visibility.

Table 1: YOLOv8 Models Performance under Effects

Effect	**Model**	**Accuracy**
Daylight	YOLOv8n(nano)	56%
Fog	YOLOv8m(medium)	42%

5 Conclusion

The proposed methodology introduces a YOLOv8-based object detection framework for analyzing video data from Indian road conditions, integrating real-time video analysis for dynamic scenarios. The lightweight YOLOv8n model outperforms YOLOv8m across precision, recall, and mAP metrics, demonstrating steady improvements and stability, particularly under daylight conditions. Meanwhile, the robust YOLOv8m model excels in low visibility scenarios like fog, addressing challenges posed by reduced visibility. Incremental training in 5-epoch cycles reduces training loss and ensures stable validation, enhancing generalizability. Frame-by-frame video analysis ensures temporal consistency and adaptability to challenges like motion blur. While smaller objects such as manholes and dogs remain difficult to detect, the framework shows strong potential for applications in autonomous driving, traffic monitoring, and road analysis, with notable improvements over the baseline through incremental training and video analysis.

6 Future Scope

The proposed framework offers significant opportunities for future advancements. Integrating it into advanced driver assistance systems (ADAS) can enable real time object detection and classification, enhancing road safety on Indian roads. Expanding the dataset to include night time scenarios and extreme weather conditions like heavy rainfall can improve the model's robustness and generalization. Furthermore, employing model compression techniques such as pruning and quantization can optimize the framework for deployment on edge devices with limited computational resources. Lastly, extending the framework to include multi lane detection and object tracking can make it a more comprehensive solution for autonomous driving applications.

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