Automated Seat Belt Detection Using Surveillance Cameras for Indian Traffic

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ABSTRACT

Road accidents continue to rise at an alarming rate across India, highlighting the urgent demand for robust traffic safety enforcement systems. Among various preventive measures, seat belts remain one of the most effective means of reducing crash-related injuries, yet widespread non-compliance persists as a significant concern. This paper introduces an automated deep learning-based framework designed to identify seat belt violations within Indian traffic scenarios. The system leverages lightweight YOLOv8 model variants to perform vehicle detection, directional classification, and windshield-level analysis to assess whether occupants are wearing seat belts. To address performance degradation under adverse lighting and environmental conditions, Contrast Limited Adaptive Histogram Equalization (CLAHE) is integrated into the pipeline, yielding a 5.7% improvement in detection accuracy. The proposed system attains a precision of 87.5% and a recall of 86.5% for seat belt detection, with an inference speed of 13.9 ms per frame, demonstrating its viability for real-time traffic monitoring and enforcement applications. This work advances the field of intelligent transportation systems by offering a scalable and efficient solution toward safer urban road environments.

Keyword : - *Seat Belt Detection, YOLOv8, Deep Learning,Traffic Safety, CLAHE.*

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1. INTRODUCTION

Road traffic fatalities continue to pose a global challenge,with seat belt non-compliance being a major contributing factor. Although regulations exist, manual enforcement remains inefficient, error-prone, and difficult to scale. This has driven growing interest in automated detection systems that combine deep learning and computer vision to support law enforcement.

Existing solutions, however, struggle with poor lighting, interior occlusions, and variability in seat belt appearance. To overcome these limitations, this paper proposes a three-stage YOLOv8-based pipeline enhanced with Contrast Limited Adaptive Histogram Equalization (CLAHE) for robust seat belt violation detection. The key contributions are:

- A lightweight real-time pipeline covering vehicle detection, windshield segmentation, and seat belt classification.
- Integration of CLAHE to boost accuracy under adverse lighting.
- Evaluation on a diverse dataset yielding high precision and recall.

2. RELATED WORKS

Several deep learning-based approaches have been proposed for seat belt detection, each demonstrating varying levels of accuracy, computational efficiency, and real-time applicability. However, most prior models struggle with key challenges such as poor lighting conditions, occlusions, and variations in seat belt appearance due to different clothing and seat colours.

A Gated Bi-LSTM model with part-to-whole attention achieved 72.3% accuracy but required extensive hyperparameter tuning, making it computationally expensive and less viable for real-time applications [1]. Similarly, a pre-trained Xception model demonstrated high accuracy (99.42%) but had slower inference times, limiting its deployment in traffic surveillance systems [2].

Traditional CNN-based models such as ResNet50, VGG16, and InceptionV3 were tested for feature extraction, with ResNet50 and VGG16 achieving 72% accuracy and InceptionV3 has 56% accuracy. However, these models exhibited lower performance in real-world traffic conditions with complex backgrounds [3]. The YOLOv8 family has shown promise in real-time object detection tasks, with YOLOv8m achieving 96% accuracy in windshield detection and YOLOv8l-cls obtaining 88.46% accuracy for seat belt classification and 89% accuracy for passenger classification [4]. But with this method, limited contextual information may lead to misinterpretations since it directly detect the windshields of vehicles without detecting the vehicles that are suitable for seat belt detection. Meanwhile, MobileNetV2 attained 89% accuracy, though its performance was highly dependent on dataset quality, limiting its generalisability across diverse traffic conditions [5].

Hybrid approaches, including YOLOv5, ResNet34 with Spatial Pyramid Pooling (SPP) and Power Mean Transformation (PMT), achieved a high seat belt detection accuracy of 98.9%. However, such architectures require significantly more computational power, making them impractical for real-time processing in traffic surveillance systems [6]. Additionally, YOLOv5 for windshield detection and AlexNet for seat belt classification is used in [10]. After detecting the windshield, the hough transformation technique is applied on the windshield to detect its boundaries more precisely for further seatbelt classification. Windshield detection is performed with 93.3% accuracy and classification has obtained 87% accuracy, though the mandatory image processing step increases the overall processing time and makes the model less practical for real-time implementations. Lightweight models like Tiny YOLO (93% accuracy) were computationally efficient but suffered from classification instability in dynamic real-world conditions [7].

Another promising approach, NADS-Net, developed for in vehicle monitoring, achieved 89% accuracy in seat belt detection with ResNet50 with Feature Pyramid Network (FPN). But adding FPN increases the computational load, resulting in higher memory consumption. [9]. Lastly, a hybrid CNN-SVM model reached an 85% Correct Identification Rate (CIR) by leveraging CNN for initial detection and SVM for post- processing refinement [8].

These studies highlight the trade-offs between accuracy, computational efficiency, and real-time applicability. The proposed approach builds upon these insights, utilising YOLOv8- based models with CLAHE image enhancement to improve seat belt detection under challenging real-world conditions.

3. METHODOLOGY

3.1 Dataset Details

A custom dataset was created using surveillance cameras with minimum 5MP ZTP (Zoom, Tilt and Pan) for overall surveillance. From the collected real-time videos, a total of 2,000 frames were extracted which covering occlusions, variable lighting, heavy traffic, and partial obstructions. Annotations on these frames were performed using Label Studio for five vehicle classes: two-wheeler, three-wheeler, four-wheeler, bus, and truck. Windshield detection and passenger classification annotations were also included. The data set was divided into an 80:10:10 ratio for training, validation and testing.

3.2 Proposed Method

The proposed system consists of a multi-stage deep learning pipeline, as illustrated in Fig.1 and Fig.2.

Hyper parameter tuning of YOLOv8 models are performed on the vehicle detection validation dataset, for object detection, and best result obtained for YOLOv8n and YOLOv8s, with 50 epochs, 32 batch size, Adam optimizer and a learning rate of 0.001111, considering both accuracy and processing time. Since lightweight models of YOLOv8 provide better trade-off between the speed and accuracy in object detection, these models along with other lightweight models of YOLO are trained in the training dataset for vehicle detection and the result is shown in Table I.

Hyper parameter tuning for object classification is per- formed on the vehicle classification validation dataset and best result achieved with the YOLOv8n-cls model with 21 epochs, 16 batch size and 0.001667 learning rate. Hence, all the object detection and object classification tasks are performed with YOLOv8n and YOLOv8n-cls models respectively with these optimal parameter values using NVIDIA T4 GPU.

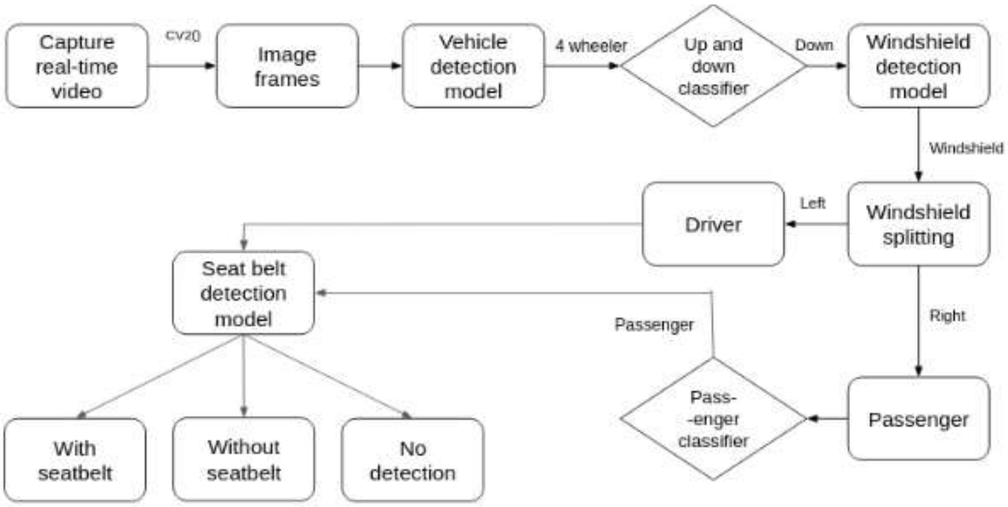


Fig -1:Proposed System for Seatbelt Detection

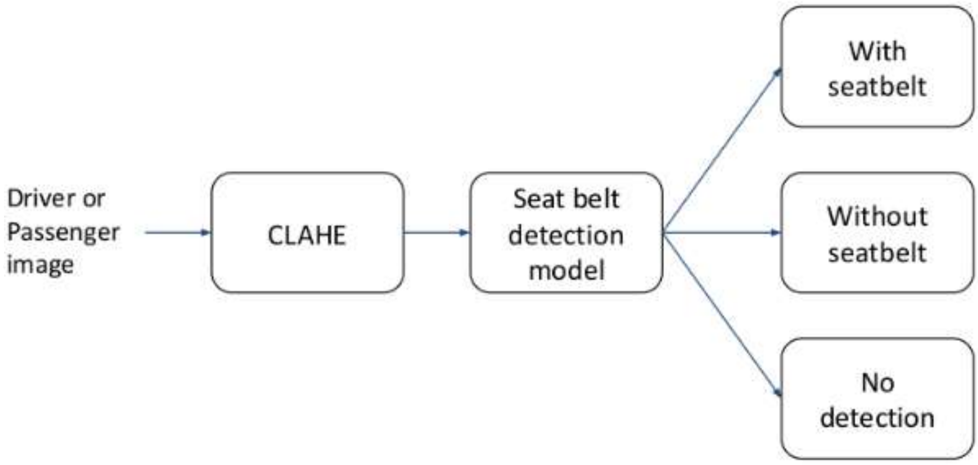
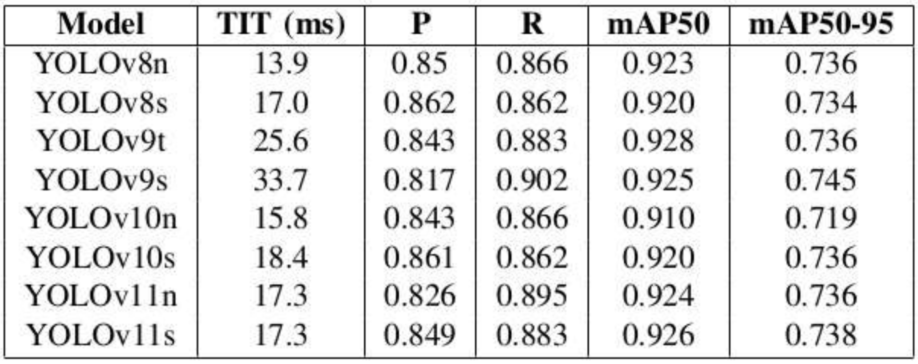


Fig -2:Case of Without Seatbelt or No Detection Predictions

The proposed system follows a multi-stage deep learning pipeline for seat belt violation detection. It begins with vehicle detection, where the YOLOv8n model identifies four wheelers from traffic footage. A movement classification model, YOLOv8n-cls, then determines whether the vehicle is moving towards or away from the camera, ensuring seat belt analysis is conducted only on vehicles with a clearly visible windshield and occupants. Next, a windshield detection model isolates the driver and passenger sections for further analysis. If a passenger is detected, a seat belt classification model evaluates the presence of a seat belt, categorising images as “with seat belt” or “without seat belt”. For cases with low confidence scores or poor contrast between the seat belt and garments, CLAHE enhancement is applied to improve visibility. Since the proposed model is designed for real-time processing, it balances accuracy and computational efficiency using lightweight YOLOv8 models for detection and classification, making it suitable for large-scale traffic surveillance and enforcement applications.

Table -1: Performance Comparison of YOLO Models for Vehicle Detection



Model	TIT (ms)	P	R	mAP50	mAP50-95
YOLOv8n	13.9	0.85	0.866	0.923	0.736
YOLOv8s	17.0	0.862	0.862	0.920	0.734
YOLOv9t	25.6	0.843	0.883	0.928	0.736
YOLOv9s	33.7	0.817	0.902	0.925	0.745
YOLOv10n	15.8	0.843	0.866	0.910	0.719
YOLOv10s	18.4	0.861	0.862	0.920	0.736
YOLOv11n	17.3	0.826	0.895	0.924	0.736
YOLOv11s	17.3	0.849	0.883	0.926	0.738

3.3 Evaluation Metrics

Standard object detection metrics were used to assess model performance:

- Precision (P): Measures the proportion of correctly detected seat belts among all detections. It is given by [4]: $P = TP / (TP+FP)$
  where TP is True Positives, and FP is False Positives. High precision indicates a low false-positive rate.
- Recall (R): Indicates how many actual seat belt instances are correctly detected. It is calculated as [4]:
  $R = TP/ (TP + FN)$
  where FN is False Negatives. A high recall ensures that most seat belt violations are identified.
- F1 score: The F1 score is the harmonic mean of precision and recall, providing a balanced measure of a model's accuracy, especially in imbalanced datasets.
- Mean Average Precision (mAP@50): Measures detection performance by computing the average precision (AP) at an Intersection over Union (IoU) threshold of 0.50 [4]. It evaluates how well the model differentiates between seatbelt and non-seat belt instances.
- Mean Average Precision (mAP@50-95): Assesses the model's performance across multiple IoU thresholds (0.50 to 0.95, in 0.05 increments), providing a more comprehensive measure of detection robustness across varying degrees of object overlap.

These metrics collectively evaluate the accuracy, reliability, and effectiveness of the seat belt detection framework, ensuring its applicability for real-world deployment in traffic monitoring systems.

4. RESULTS AND DISCUSSIONS

The proposed automated seat belt detection system was evaluated on a custom dataset using various YOLOv8 models. The system's effectiveness was assessed based on precision, recall, F1-score, and inference time, ensuring a comprehensive evaluation of both accuracy and computational efficiency.

- Vehicle Detection

According to Table-1(where TIT implies Total Inference Time), YOLOv8n is the better model of vehicle detection in real-time as it takes only 13.9 ms for processing. The model achieved 85% precision and 86.6% recall, demonstrating robust vehicle detection capabilities in diverse traffic conditions.Additionally, YOLOv8n maintained a high preci- sion of 94.9% for four-wheeler detection, ensuring reliable classification.

An example output from the YOLOv8n model detecting four-wheeler vehicles in traffic footage is shown in Fig. 3

Fig -3:Detected Four Wheeler Vehicles

- Vehicle Movement Classification

After detecting vehicles, YOLOv8n-cls was used to classify their movement direction. Vehicles moving towards the camera are detected as “Down”, and those moving away from the camera as “Up” with an accuracy of 98%. Vehicle movement classification results on the detected four wheeler vehicles are illustrated in Fig. 4.


(a) Up (b) Down

Fig -4:Vehicle Movement Classification Results

- Windshield Detection and Passenger Classification

To ensure accurate seat belt detection, windshield regions were extracted from detected vehicles. The YOLOv8n model achieved 99.7% precision, ensuring high-quality segmentation. The confusion matrix [Fig. 5], Precision–Recall curve, and F1 score curve [Fig. 6] represent the performance of the YOLOv8n model in detecting windshields. Fig. 7 showcases detected windshields from down-moving vehicles, demonstrating the accuracy of windshield segmentation.

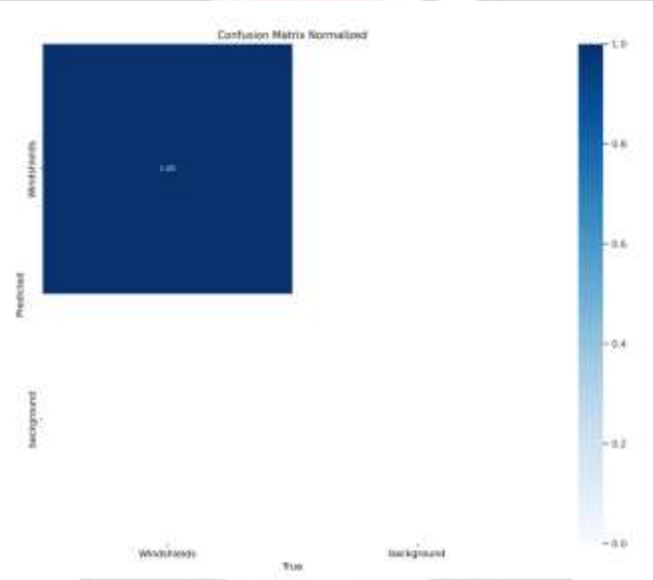


Fig -5:Windshield detection - Normalized Confusion Matrix

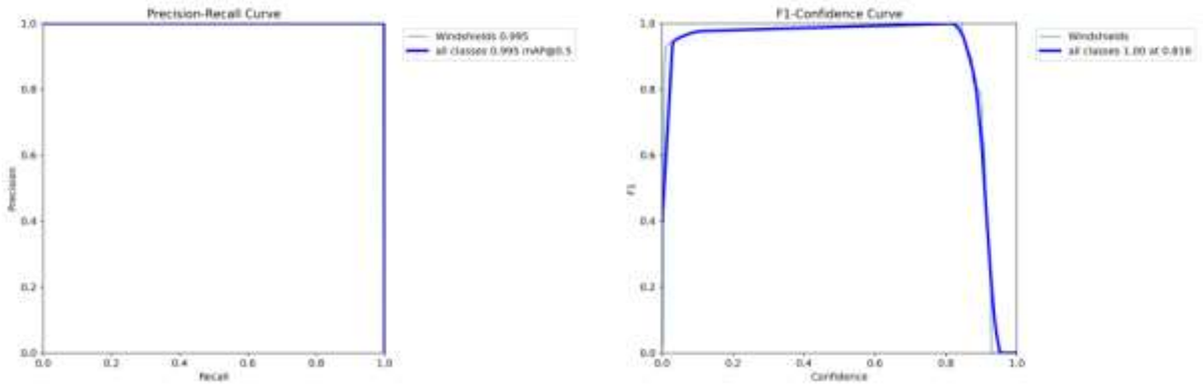


Fig -6:Windshield Detection - Precision-Recall and F1 Curve

Fig -7:Examples of Detected Windshields

Following windshield segmentation, the passenger classification model was applied to determine whether an occupant was present in the passenger seat. The performance of the passenger classification model is given in Table 2, and it confirms the ability to flawlessly identify passengers.

Table -2: Performance Comparison of YOLO Models for Vehicle Detection

Classes	top1_acc	top5_acc
all	0.99	1.00

Fig. 8(a) represents an example of a detected windshield with a passenger and 8(b) represents a windshield without a passenger.

(a) with_passenger (b) without_passenger

Fig -8:Passenger Classification Results

- Seat Belt Detection

The seat belt detection model classified images into two categories: “with seatbelt” and “without seatbelt”. The model achieved 87.5% precision and an F1-score of 85.9%, indicating high reliability. Additionally, CLAHE preprocessing significantly improved detection accuracy from 82% to 88%, especially in cases where seat belts were difficult to distinguish due to low contrast or similar-coloured clothing.

If the model’s confidence score fell below 0.25, the image underwent CLAHE enhancement before final prediction. This enhancement significantly improved visibility and reduced false negatives.

Table -3: Seat Belt Detection Performance of YOLOv8n Model

Model	P	R	mAP@50	mAP@50-95
all	0.933	0.797	0.875	0.472
with_seatbelt	0.906	0.761	0.912	0.522
without_seatbelt	0.961	0.833	0.838	0.423

The following images show accurate detection of seat belt usage using the proposed YOLOv8n model [Fig. 9], and a case where the model fails to detect a seat belt due to the low contrast between clothing and the seat belt [Fig. 10]. The same image from Fig. 14 after CLAHE pre-processing and successfully improving seat belt visibility and correcting the mis-classification is illustrated in Fig. 11.

Fig -9:Successful Seat Belt Detection Results

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Without seatbelt or no detections, applying CLAHE...
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Fig -10:Example of Misclassified Seat Belt Detection

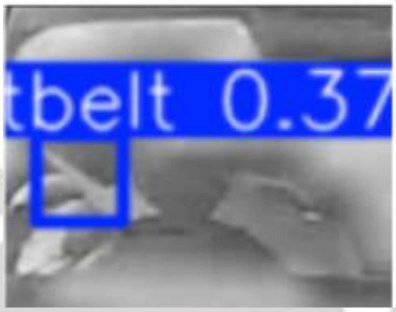

Fig -11:Seatbelt Detection After CLAHE Enhancement

5. CONCLUSION

This paper presents an automated seat belt detection frame- work leveraging YOLOv8 models and CLAHE enhancement to improve classification accuracy. The proposed system effectively detects four-wheelers, classifies their direction, isolates windshield regions, and determines seat belt usage with high reliability. Experimental results confirm that YOLOv8n is well-suited for real-time traffic enforcement applications, balancing accuracy and speed. Future work will focus on expanding the dataset to include more diverse traffic and light conditions, integrating additional occlusion handling techniques, and exploring hybrid approaches combining YOLO with transformer-based architectures to further enhance model robustness.

6. REFERENCES

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