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Deep Learning Model To Detect Driver Hand Gestures And Vehicle Signals in Indian Traffic

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Abstract: This research aims to improve road safety by developing a deep learning-based system capable of detecting and recognizing tail lights, brake lights, and driver hand gestures in Indian traffic conditions. Using the YOLOv8 object detection architecture, the system has been designed and implemented in two key phases: training and inference. During the training phase, a comprehensive custom dataset of traffic images - carefully labelled with seven distinct classes - was used to train the YOLOv8 model. This dataset includes real-world conditions such as varying lighting, complex backgrounds, and occlusions. In the inference phase, the trained model processes new images or videos, automatically detecting the presence of vehicle signals and hand gestures. The output consists of bounding boxes and class labels that are visually rendered and saved, ensuring traceability and ease of analysis.

Keywords: Brake Light Detection, Tail Light Detection, Hand Gesture Recognition, Object Detection.

I. INTRODUCTION

Effective communication between vehicles and their environment has become increasingly important as advanced driver-assistance systems (ADAS) and autonomous vehicles become more common. Vehicles, pedestrians, and drivers all rely on hand gestures, brake lights, and tail lights to communicate important information. By reducing accidents and promoting improved vehicle interactions under a variety of driving circumstances, accurate, real-time detection of these indicators is essential to improving road safety. However, environmental factors like poor lighting, obstacles, and changing traffic situations frequently limit the effectiveness of conventional detection techniques.

In order to address these issues, this project uses the YOLOv8 deep learning model to present a reliable method for identifying and detecting hand gestures, tail lights, and brake lights. One state-of-the-art object detection framework that is well-known for its high accuracy and real-time processing capabilities is called YOLO (You Only Look Once). As the most recent iteration, the YOLOv8 model seeks to improve upon the precision, speed, and effectiveness of its predecessors, making it especially appropriate for real-time applications such as ADAS and autonomous driving systems.

Training and testing are the two main stages of the detection and recognition process. The YOLOv8 model is trained on a dataset of pictures showing hand gestures, brake lights, and tail lights during the training phase. To improve model performance, preprocessing methods like resizing, normalization, and data augmentation are used. Through the extraction of spatial features from the input images and their association with the appropriate class labels, the model gains the ability to recognize these signals. After training, the model is evaluated on a different testing dataset to confirm its accuracy and real-time performance.

II. RELATED WORKS

In order to improve road safety, recent research has made significant strides in identifying vehicle signals and gestures, especially for ADAS and autonomous vehicles.

Detecting Brake Lights: Previous methods mostly used color-based detection, but more recent developments have moved toward using deep learning models, such as CNNs, for more reliable and accurate detection under a variety of circumstances. For instance, to improve collision avoidance, Rampavan and Ijjina (2023) developed a genetic algorithm to optimize brake light detection models.

Tail Light Detection: YOLO-based models, such as those developed by Li et al. (2024), have significantly enhanced the speed and accuracy of tail light detection, particularly in automated lane change scenarios.
Hand Gesture Recognition: To efficiently identify hand gestures in dynamic environments, Mishra et al. (2021)

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combined CNNs with pose estimation. Better communication between pedestrians and drivers is made possible by this method's success in recognizing gestures like stop signals.

III. PROPOSED WORK

The proposed work emphasizes the real-time detection and recognition of brake lights, tail lights, and hand gestures through the YOLOv8 deep learning model. The process is segmented into two main phases: Training and Testing.

A. *Training Phase:*

1) *Input Images:* The dataset comprises labeled images of brake lights, tail lights, and hand gestures captured under various environmental conditions.

2)Preprocessing: Techniques such as image resizing, normalization, and augmentation (including rotation and scaling) are applied to enhance model performance.

3)Model Training: YOLOv8 is trained to detect the specified objects by processing the preprocessed images and learning their spatial features.

4)Model Evaluation: The trained model is evaluated against a validation dataset to determine its accuracy.

B. Testing Phase:

1)Input: Real-time camera input is provided to the trained model.

2)Preprocessing: Consistent preprocessing steps are applied to ensure uniformity in input data.

3)Detection: YOLOv8 detects brake lights, tail lights, and hand gestures in real-time, generating bounding boxes and classifying objects.

4)Output: For instant visualization, the system displays the detected signals along with class labels and bounding boxes.

IV. METHODOLOGY

The proposed system for detecting and recognizing brake lights, tail lights, and hand gestures utilizes the YOLOv8 deep learning model, divided into two primary phases: training and testing.

A. Training Phase:

1) *Dataset Creation:* The dataset comprises labeled images of brake lights, tail lights, and hand gestures captured under various environmental conditions.

2) *Data Preprocessing:* Techniques such as image resizing, normalization, and augmentation (including rotation and scaling) are applied to enhance model performance.

3) *Model Training:* YOLOv8 is trained to detect the specified objects by processing the preprocessed images and learning their spatial features.

4) *Model Optimization:* The trained model is evaluated against a validation dataset to determine its accuracy.

B. Testing Phase:

1) *Real-time Input:* The trained model is evaluated using real-time input from a vehicle-mounted camera, allowing it to process live video or individual frames.

2) *Image Preprocessing:* Similar preprocessing steps from the training phase are applied to maintain consistency in data format.

3) *YOLOv8 Detection:* The model recognizes hand gestures, brake lights, and tail lights. It then creates bounding boxes and class labels to indicate the type and location of objects it has detected.

4) *Post-processing:* Low-confidence detections are filtered out and redundant bounding boxes are removed using Non-Maximum Suppression (NMS). A graphical user interface displays the final output, which includes detected objects with confidence scores and class labels.

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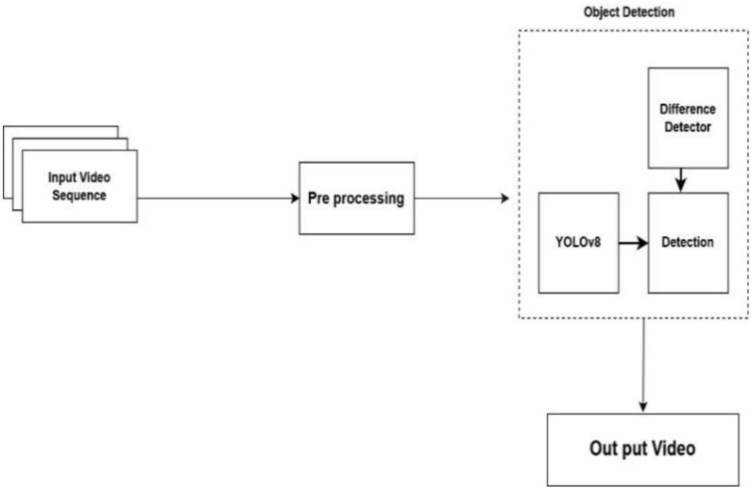

Fig.1 Architecture Design for Object Detection Using YOLOv8

V. MATHEMATICAL MODEL

The advanced object detection model YOLOv8 splits the input image into a grid of cells, each of which predicts a set number of bounding boxes and the class probabilities that go along with them. YOLOv8's loss function is a combination of multiple elements:

A. Prediction Head:
Every grid cell forecasts a number of bounding boxes, each of which is distinguished by:
1) (x, y): The bounding box's center coordinates in relation to the grid cell.
2) w, h: The bounding box's width and height.
3) C: Confidence score, which shows how likely it is that an object will be inside the bounding box.
4) P(Class_i|Object): The likelihood that the object is a member of class i.

B. Loss Function:
The weighted sum of the following elements makes up the overall loss function for YOLOv8:
Loss = λ1 * Classification Loss + λ2 * Box Regression Loss + λ3 * Object Loss

C. Classification Loss:
Encourages the model to correctly predict the correct class for each detected object by classifying the object inside the bounding box using cross-entropy loss.

D. Box Regression Loss:
This technique penalizes the differences between predicted and ground-truth bounding box coordinates, usually using a combination of L1 and L2 loss. This helps to ensure that object size and location predictions are accurate.

E. Object Loss:
This feature encourages the model to accurately identify cells that contain objects by using binary cross-entropy loss to ascertain whether an object is present in a grid cell.
Mathematical Formulation:
Let, p_i is the predicted probability of class i,
y_i is the ground truth label for class i,
b_i is the predicted bounding box coordinates,
b*_i is the ground truth bounding box coordinates.

The loss function can be expressed as:
Loss = λ1 * Σ(y_i * log(p_i) + (1-y_i) * log(1-p_i)) + λ2 * Σ(λ1 * |b_i - b*_i|_1 + λ2 * (b_i - b*_i)^2) + λ3 * Σ(y_i * log(p_obj) + (1-y_i) * log(1-p_obj))

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VI. RESULTS

The YOLOv8n and YOLOv8s models were used to identify hand gestures, left and right turn signals, and brake lights in automobiles. Google Colab's GPU resources were used to train on a dataset. Critical metrics such as mean Average Precision (mAP), recall, precision, and inference speed were used to assess the models' performance. The purpose of comparing the two models is to evaluate how well they work in real-time applications where timely and precise vehicle signal detection is crucial, like ADAS and autonomous driving.

Table 1 summarizes the trial implementation, contrasting the performance of YOLOv8n and YOLOv8s across five classification types. The evaluation results indicate that the YOLOv8s model consistently outperformed the YOLOv8n model, achieving superior recall and mAP values across all classes. While hand sign detection demonstrated high accuracy, with recall rates of 92-94% and mAP values of 97-98%, the detection of brake and turn lights proved more challenging with recall rates ranging from 41-55% and mAP values between 48-62%. Factors contributing to these challenges include data imbalance, occlusions, adverse weather effects, and intra-class variability. Future research should prioritize data augmentation, advanced model architectures, domain adaptation, and real-time object tracking to enhance performance

Table 1. Result

Name of Class	Yolo Model	Recall	mAP	Precision
Brake	YoloV8n	55%	60%	62%
	YoloV8s	55%	62%	64%
Left turn light	YoloV8n	46%	56%	45%
	YoloV8s	47%	58%	48%
Right Turn Light	YoloV8n	41%	48%	50%
	YoloV8s	46%	51%	49%
Left Hand sign	YoloV8n	93%	93%	92%
	YoloV8s	94%	92%	93%
Right Hand sign	Yolo V8n	92%	93%	92%
	Yolo V8s	93%	92%	93%

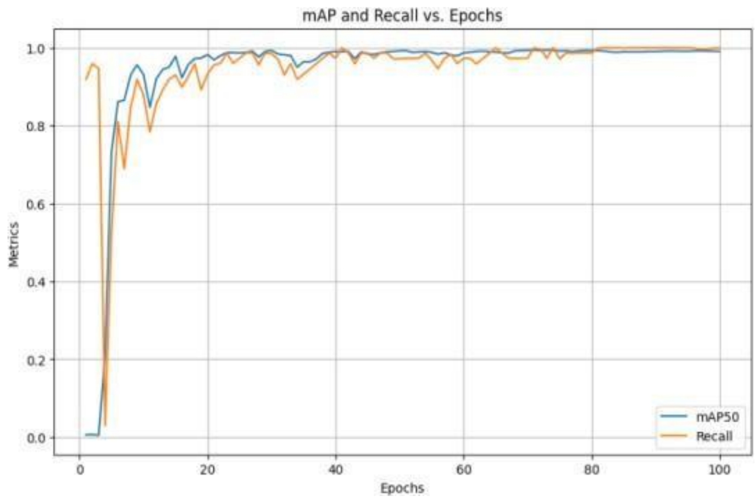

Fig.2. Right Hand signal Recall vs Epochs

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Fig.3. Brake light

Fig.4. Indicator Right

Fig.5. Left Hand sign

VII. CONCLUSION AND FUTURE WORK

The suggested system has demonstrated encouraging results in hand gesture detection, reaching a 93% recall rate; however, it encounters difficulties in precisely identifying turn and brake light signals.

These signals' lower recall rates point to possible overfitting problems and constraints in controlling for changes in camera angles and lighting. Future studies should focus on enlarging the dataset to include more scenarios, exploring sophisticated data augmentation methods, and optimizing the YOLO model's hyperparameters.

Additionally, the integration of real-time object tracking and contextual information could further enhance the system's overall performance.

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