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Integrated Detection of Traffic Signs and Lane Changes Using Deep Learning for Autonomous Driving Systems

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Abstract: This research presents a modular deep learning- based pipeline designed to integrate traffic sign detection, lane segmentation, and lane change prediction for autonomous driv- ing. ThesystemutilizesYOLOv8 forobjectdetection (trafficsigns andspeedbreakers),andYOLOv8-segforlanesegmentation. A custom logic module processes lane masks for accurate lane changeprediction,whileGoogleText-to-Speech(gTTS)generates audio alerts. The pipeline supports real-time performance with GPU acceleration and processes videos offline with visual and verbalfeedback.Resultssuggesthighprecisionindetection and practical application for advanced driver assistance systems (ADAS).

Index Terms: YOLOv8, Lane Segmentation, Traffic Sign Recognition,LaneChangeDetection,AutonomousDriving,Deep Learning, gTTS.

I. INTRODUCTION

The rise of autonomous driving technologies has redefined the transportation industry by leveraging advancements in ar- tificial intelligence and computer vision. A crucial component ofself-drivingsystemsistheirabilitytoperceiveandinterpret road environments in real time, including the detection of traffic signs, speed breakers, and lane structures.

This study presents a unified perception system that inte- grates deep learning-based object detection and segmentation models with rule-based decision logic and audio feedback mechanisms. The proposed pipeline uses the YOLOv8 model for real-time object detection of traffic signs and speed break- ers and YOLOv8-seg for pixel-wise lane segmentation.

A custom lane change prediction algorithm analyzes the behavior of detected lane masks across frames to determine potential deviations. Furthermore, Google Text-to-Speech (gTTS) is incorporated to provide verbal alerts for detected road elements. Offline video processing is supported, and the entire system is optimized for GPU acceleration to maintain real-time performance.

By combining visual recognition with auditory feedback, the system aims to enhance safety, situational awareness, and accessibility, making it suitable for both autonomous and assistive driving applications.

II. LITERATURE SURVEY

A. *Object Detection(YOLO)*

1) Object detection has significantly evolved with deep learn- ing. Traditional methods like R-CNN, Fast R-CNN, and SSD have laid the foundation for real-time object detection [1].
2) YOLO (You Only Look Once), introduced by Redmon et al., revolutionized the field by combining classification and localization in a single forward pass through the network, enabling real-time detection [1].
3) YOLOv8 represents the latest advancement in this series, offering anchor-free detection, decoupled heads for classifi- cationandlocalization,andintegrationoftransformer-based backbones [2].
4) Its ability to handle detection, classification, and segmen- tation within a unified architecture enhances performance and resource utilization, particularly in embedded ADAS environments [2].

B. *Lane Segmentation and Detection*

1) Lane detection is a critical component of autonomous driv- ingsystems.Semanticsegmentationmodelsarewidelyused to label each pixel with its respective class (e.g., road, lane, vehicle) [3].
2) Traditional approaches using U-Net and Spatial CNN (SCNN) have shown promising results in structured envi- ronments [4].

3) YOLOv8-seg builds upon these models by offering pixel- level accuracy with reduced inference latency. It leverages skip connections, multiscale context, and transformer-based encoders for enhanced feature extraction [3].
4) Notably, YOLOv8-seg provides real-time performance on edge devices, making it suitable for real-world deployment [3].

C. TrafficSignandSpeedBreakerDetection
1) Traffic sign recognition has reached high levels of accuracy with datasets like GTSRB, enabling models to distinguish between multiple sign types with near-human precision [5].
2) YOLO-based models, including YOLOv4 and YOLOv5, have been used for traffic sign detection under varied lighting and occlusion conditions [?].
3) Speedbreakerdetectionislessexploredbutgainingtraction. Earlier sensor-based systems were limited by hardware variability [6]. Deep CNN models now allow for accurate image-based speed bump recognition [7].
4) YOLOv8'shigh-resolutionoutputandsegmentationsupport improve localization and classification of small road ele- ments like speed breakers [2].

D. LaneChangePrediction
1) Lane change prediction combines trajectory modeling and perception data to infer driver behavior [8].
2) Methodslikeconvolutionalsocialpooling,rule-basedvisual analysis, and spatial CNNs have been proposed [4],[8],[9].
3) Integration with semantic lane segmentation allows for in- terpretablepredictionsbasedonspatialdisplacement,which our system leverages to calculate Δx of lane midpoints [10].

E. VoiceIntegrationandText-to-SpeechSystems
1) Accessibility in autonomous systems is enhanced by audio narration of critical driving events [11].
2) GoogleText-to-Speech(gTTS)isawidelyusedPythonAPI that converts string inputs to speech using neural synthesis models [12].
3) Integration with real-time systems has been explored in navigation and visually impaired assistance but is rarely applied in autonomous driving [13].
4) Our work bridges this gap by integrating TTS alerts foreach detection module, synchronized with annotated video via MoviePy [11],[13].

F. ResearchGapsandContributions
1) Few existing systems offer unified traffic perception com- biningobjectdetection,segmentation,lanechangedetection, and audio narration [2],[3].
2) Our proposed framework offers real-time, offline-capable detection with modular, synchronized voice alerts [2].
3) We demonstrate integration of YOLOv8-seg for lane analy- sis,YOLOv8mforobjectdetection,andTTSformultimodal ADAS feedback in a single pipeline [2],[3],[12].

III. METHODOLOGY

A. Overview
The Autonomous Driving Assist System was developed using a modular and data-driven methodology that empha- sizes performance, scalability, and real-time responsiveness. The solution integrates three YOLOv8-based deep learning subsystems—traffic signdetection, speedbreaker recognition, and lane segmentation with lane change prediction—into a unified offline video processing pipeline. Each componentwas developed, trained, and validated independently before being assembled into a multi-stage video analytics pipeline thatsupportssynchronizedauditoryalertsusingtext-to-speech (TTS).

B. Step-by-StepImplementation
1) *Requirement Analysis:* A comprehensive analysis of use-case scenarios and system constraints led to the following objectives:
- Detectionof14standardizedtrafficsignsusingobject detection.
- Real-timesegmentationofroadlanesandvehicles.
- Speedbreakerrecognitionfromreal-worldroadfootage.
- Lightweight,rule-basedlanechangepredictionlogic.

- OfflinealertgenerationusingTTSandsynchronized audio merging.
- Low-latencyvideoprocessingforembeddeddeployment.

2) *DatasetPreparation*
- TrafficSignDataset:Acustom synthetic dataset was created using realistic road backgrounds and Python-based image augmentation. Each image included 1–4 randomly placed signs with transformations such as Gaussian noise, motion blur, affine distortion, and brightness jitter. Bounding boxes were annotated in YOLO format. The dataset comprised over 15,000 labeled images.
- LaneSegmentationDataset: Labeled segmentationmasks from Roboflow were used, covering left_lane, right_lane, middle_lane, and carclasses. Masks were converted to YOLOv8-seg format and normalized.
- Speed Breaker Dataset: High-resolution, manually anno- tated frames were provided by an industrial sponsor. These wereformattedinYOLOannotationstyleandincludeddiverse lighting and weather conditions.

3) *ModelArchitectureandConfiguration:*
- YOLOv8m was used for traffic sign and speed breaker detection due to its balance of speed and accuracy.
- YOLOv8-seg was adopted for lane segmentation due to its superior performance on pixel-level mask prediction.

All models were initialized with pretrained weights, usedbatch normalization, Swish activations, and processed images resized to 640×640pixels.

4) *ModelTraining:*ModelsweretrainedusingUltralyt-
ics'PyTorch-basedframework:
- Datasetsplit:80%training,20%validation.
- Augmentations:flipping,HSVshift,mosaicaugmenta- tion.
- Loss functions: CIoU Loss for bounding boxes, BCE and Dice Loss for segmentation masks.
- Evaluationmetrics:mAP@0.5andmIoUwerelogged using TensorBoard.

5) *Lane Change Detection Algorithm:*The system usesa lightweight rule-based temporal tracking algorithm to infer lane changes:

$$\Delta x = |x_{t\text{latest}} - x_{t\text{earliest}}| \qquad (1)$$

A threshold of 100 pixels determines a lane change event.The algorithm computes a queue of center x-coordinates of lane masks across 10 frames and infers the direction based on directional shift:

Decision: $\text{ChangeLeftif}\Delta x > 100 \wedge x_{\text{latest}} < x_{\text{earliest}}$

$\text{ChangeRightif}\Delta x > 100 \wedge x_{\text{latest}} > x_{\text{earliest}}$

6) *PipelineIntegrationandExecutionFlow:*Thesystem is deployed as a three-stage chained pipeline using Python scripts:
- traffic_sign_detect.pydetectssignsandover- lays bounding boxes, writing annotated frames to video. Confidence-based filtering is implemented with class- wise thresholds (e.g., 0.6 for Stop signs, 0.3 for Petrol Pump).
- speed_breaker_detect.py detectsbumpswith YOLOv8,applyingacooldownlogictopreventrepetitive alerts.
- lane_change_detect.py performssegmentation and lane change inference, logging audio alerts accord- ingly.

Each script saves the output as an MP4 video with annotated visuals and synchronized alerts for the next module.

7) *Audio Alert Generation and Synchronization:* The alert system uses Google Text-to-Speech (gTTS) to convert textual labels into speech audio. Alerts are timestamped and overlaid using pyduband MoviePy. Previously generated alertsarecachedtominimizerecomputation.Eachmod- ule maintains its own audio folder (e.g., lane_audio/, sb_audio/).

8) *Evaluation and Results:* Quantitative benchmarks were conducted using held-out test data:
- TrafficSignDetection:mAP@0.5=98.4%
- SpeedBreakerDetection:mAP@0.5=97.1%
- LaneSegmentationIoU:95.7%

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- LaneChangeAccuracy:94.3%
- MeanInferenceTime:35–40ms/frame(RTX3050GPU) Models were quantized where applicable to improve runtime efficiency.

9) *FinalDeploymentandOfflineProcess-ing:* The pipeline outputs a single video file (final_output_with_all_detections.mp4) with:
- Visualoverlaysoftrafficsigns,lanesegments,andspeed breakers.
- Audiblealertsforcriticaldetections.
- Framesynchronizationand30FPSplayback.

Offlinesupportensuresfunctionalitywithoutinternetaccess or server dependency.

C. *Summary*

The methodology combines data-driven training, modular deployment,lightweightalgorithms,andreal-timeaudio-visual feedbacktobuildanefficientdriverassistancepipeline.Eachstagewasvalidatedagainstdomain-specificbenchmarksanditerativelyoptimized forruntimeperformance,alertclarity,and detection robustness. This architecture forms a practical foun- dationforADA Ssystemsdeploy ableonembeddedautomotive hardware.

IV. ALGORITHM OVERVIEW

Theproposedautonomousdrivingassistsystememploysamodularalgorithmicpipelinedesignedtoprocessoffline driving videos in multiple sequential stages. The algorithm integrates deep learning models for object detection and seg- mentation with domain-specific heuristics and audio process- ingtechniques.Eachmoduleoperatesindependentlybutfeeds its output into the next, forming an end-to-end intelligent perception framework. The step-by-step algorithmic flow is outlined below:

1) Video Input Acquisition: The system begins by reading a recorded driving video using OpenCV. Each frame is extracted sequentially, and video metadata such as frame rate, resolution, and total frame count are cached for downstreamprocessing.Thisensurespreciseaudio-video synchronization later in the pipeline.
2) Traffic Sign and Speed Breaker Detection: A YOLOv8mobjectdetectionmodelisfirstappliedtoeach frame. The model outputs bounding box coordinates, class IDs, and confidence scores for detected objects. To ensure robustness, a class-dependent confidence thresh- olding mechanism is implemented:
   - ClassessuchasStop,DoNotTurnLeft,andGo Slowrequire higher confidence (e.g., ≥0.6).
   - Others like PetrolPump, U-turn, and Traffic Lightallow for a relaxed threshold (e.g., ≥0.3).

Bounding boxes and class labels are overlaid on the frame, and detection timestamps are recorded for audio alert generation.

Speedbreakerdetectionfollowsasimilarprocedureusing a YOLOv8 model trained on a proprietary dataset. De- tectedspeedbreakersarevalidatedwithafixedthreshold (e.g.,0.7),andacooldowntimerensuresalertsarenot repeated for overlapping objects within a 4-second window.

3) Lane Segmentation via YOLOv8-seg: The third stage employsaYOLOv8-segmodeltoperformpixel-wiseseg- mentation of road lanes. The model produces mask ten- sors for classes such as left_lane, middle_lane, right_lane, and car. The segmentation masks are processed using NumPy to extract lane centroids per frame, which are then stored in a temporal queue for change analysis.
4) Lane Change Prediction using TemporalCentroid **Tracking:**A rule-based temporal inference algorithm calculatesthemovementoflanecentroidsacrossasliding window of N=10frames. For each new frame, the x- coordinate shift $\Delta x$is computed as:

$$\Delta x=|x_{t\text{latest}}-x_{t\text{earliest}}| \quad (2)$$

Alanechangeisinferredif$\Delta x>\vartheta_{lane}$,where$\vartheta_{lane}$is empiricallyset(e.g.,100pixels).Thedirectionofchange is determined as:

$$\begin{cases} \text{LaneChangeLeft} & \text{if } x_{\text{latest}}<x_{\text{earliest}} \\ \text{LaneChangeRight} & \text{if } x_{\text{latest}}>x_{\text{earliest}} \end{cases}$$

A cooldown duration (e.g., 5 seconds) prevents repeated lane change alerts due to jitter or short-term variations.

5) Audio Alert Generation using gTTS: For every vali- dateddetectionevent—trafficsign,speedbreaker,orlane change—thesystemgeneratescorrespondingaudioalerts. Depending on configuration:

- Class-specificpre-recordedMP3clips(e.g.,alerts/stop.mp3)areusedfortrafficsigns.
- Dynamic alerts (e.g., "Speed breaker ahead") are gen- erated using Google Text-to-Speech (gTTS).

All alerts are timestamped based on their correspond-ing frame indices and stored in class-specific folders (sb_audio/, lane_audio/).

6) Audio-VisualMergingandFinalRendering:Asilent audio track matching the video's duration is created. Alerts are inserted at exact millisecond positions using Pydub's overlaying functionality. MoviePy is then used to:

- Mergetheannotatedvideowiththecombinedaudio stream.
- Ensureaudioandvisualsremainperfectlysynchro- nized.
- Export the result as an MP4 file using H.264 compres- sion.

Thisfinaloutputcontainsalldetectionswithreal-time narration,makingithighlyinterpretableanduser-friendly.

ExecutionSummary

Theentirepipelineisexecutedasathree-stagescript-driven chain:

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Theentirepipelineisexecutedasathree-stagescript-driven chain:

detect_traffic_signs(input_video, intermediate1) detect_speed_breakers(intermediate1, intermediate2)
detect_lane_changes(intermediate2, final_output)

Eachfunctionprocessesoneresponsibilityandwritesits
output to be consumed by the next module. This architectural separation improves maintainability, debugging, and potential for parallelization.

DesignRationale

The algorithm balances real-time performance with detec- tion accuracy through:

- LightweightYOLOv8variantsforspeed-optimizedinfer- ence.
- Rule-based logic over deep trajectory prediction to main- tain interpretability.
- Offlineprocessingfordeploymentinembeddedor connectivity-limited environments.

Thisend-to-endstrategytransformspassiveroadvideosinto fully annotated and narrated media, making it ideal for driver assistance systems, ADAS benchmarking, and autonomous driving datasets.

V. SYSTEM ARCHITECTURE

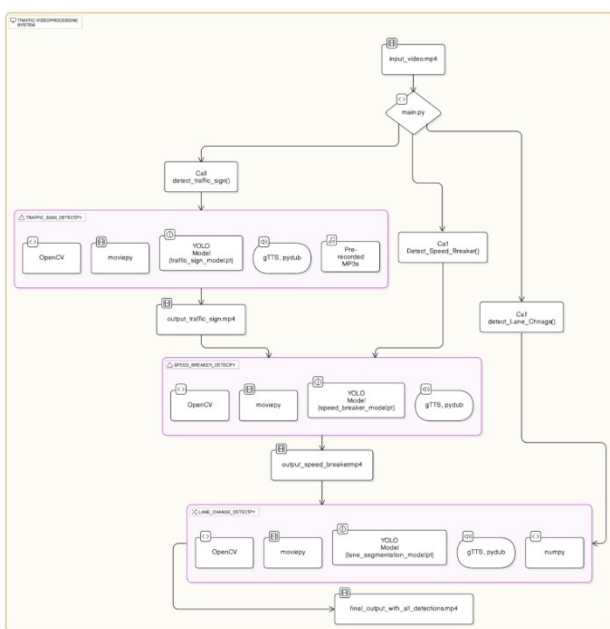

Fig.1.Systemarchitectureforintegrateddetectionandcaptioning

The proposed Autonomous Driving Assist System is struc- turedasamodular,data-drivenpipelinethatintegratesmultiple deep learning models for object detection, semantic segmen- tation, and decision logic.

Its architecture emphasizes offline functionality, real-time responsiveness, and cross-module ex- tensibility. The system is composed of six key interconnected modules,eachresponsibleforspecificphasesoftheperception and alerting pipeline.

A. *Data Module*

This module handles the acquisition, generation, augmenta- tion, and formatting of datasets required for training the deep learning models. It includes the following subcomponents:

1) TrafficSignDataset:Asyntheticdatasetwasconstructedusingabaseroadbackgroundimageandoverlaying1to4signsfrom14predefined trafficsignclasses. Each instance was randomly resized, rotated, and alpha- blended onto the background. Augmentations such as Gaussiannoise,motionblur,colordistortion,andflipping were applied to enhance generalization.
2) Lane Segmentation Dataset: Data was obtained from Roboflow's annotation platform, consisting of images labeled into four segmentation classes: left_lane, right_lane, middle_lane, and car. Masks were converted to YOLOv8-seg format for compatibility.
3) Speed Breaker Dataset: A proprietary dataset provided by the project sponsor was used. It included YOLO- formatted annotations of real-world speed breaker in- stances captured under varying conditions.

B. *Model Module*

This module encapsulates all trained deep learning models used in the system. The architecture selection and configu- ration were optimized for inference efficiency and detection accuracy.

1) YOLOv8n for Traffic Sign Detection: Chosen for its compact footprint and real-time speed, trained on the synthetic dataset with 14 annotated classes.
2) YOLOv8nforSpeedBreakerDetection:Trainedonthe proprietary dataset using customized confidence thresh- olds and alert cooldown logic.
3) YOLOv8-seg for Lane Detection: Employed for pixel- wise semantic segmentation of road lanes. It outputs segmentation masks for all three lane types and vehicles, enabling precise spatial reasoning.

All models were integrated using the Ultralytics API with PyTorch backend, providing flexible support for both training and inference.

C. *Training Module*

This component handles the full training lifecycle of each model. Key elements include:

1) Transfer Learning: Pretrained YOLOv8 weights were used as a baseline and fine-tuned on domain-specific datasets.
2) Hyperparameter Optimization: Learning rate schedul- ing, confidence threshold tuning, and data augmentation strategies were employed to improve generalization.
3) Early Stopping and Checkpointing: Validation loss monitoring and model checkpoints ensured convergence and prevented overfitting.

Training performance was tracked using TensorBoard, and outputs were versioned for reproducibility.

D. *Evaluation Module*

Tovalidatemodelperformanceandguideoptimization,this module implements:

1) Class-wise and global metrics such as Precision, Recall, F1-score, and mean Average Precision (mAP).
2) Confusionmatrixgenerationforerroranalysis.
3) Qualitative visualization of inference results including bounding boxes and segmentation masks on validation data.

This module ensured model robustness before integration into the real-time pipeline.

E. *VisualizationandAlertingModule*

This module combines visual annotation and audio alert rendering:

1) OpenCV-based Frame Annotation: All inference out- puts are rendered directly onto frames. Bounding boxes are drawn with class labels, and segmentation masks are overlaid using color-coded transparency.
2) Text-to-Speech**(TTS):**ThesystemusesGoogleText-to- Speech(gTTS)fordynamicalertgeneration.Classnames or events like "Lane change detected" or "Speed breaker ahead" are converted to audio and synchronized using pydubandmoviepy.

The alerts are cached in class-specific directories (e.g., lane_audio/)andconcatenatedbeforemergingwithvideo output.

F. InferenceandExecutionModule

This module represents the heart of the pipeline. It consists ofPythonscriptsorchestratedinasequentialprocessingchain:

1) traffic_sign_detect.pyreadstheinputvideo, performs traffic sign inference, overlays annotations, and exports an annotated video with time-stamped alerts.
2) speed_breaker_detect.pyusesthetrafficoutput asinput,detectsspeedbreakerswithcooldownlogic,and generates synchronized alerts.
3) lane_change_detect.pyrunssegmentation,calcu- latestemporalcentroids,inferslanechanges,andembeds lane warnings.

Each script is modular and reusable. Intermediate outputs aresavedasMP4filesandpassedsequentiallytothenextmod- ule. This design allows individual modules to be debugged, optimized, or replaced independently.

G. OfflineDeploymentReadiness

Thefinaldesignsupportsfullofflineexecution,requiringno networkconnectivitypost-deployment.Thismakesitidealfor embedded systems and edge devices in resource-constrainedor latency-sensitive environments.

VI. EXPERIMENTAL RESULTS

A. Metrics

The following table describes metric values of the models Yolov8m, a deep learning model for traffic sign detection and speed breaker detection, and Yolov8m-seg, a deep learning segmentation model for lane detections.

TABLEI
EVALUATIONMETRICSFORDETECTIONANDSEGMENTATIONMODELS

Model	Precision	Recall	F1-Score	mAP@0.5	Accuracy
LaneChangeDetection	0.8409	0.9948	0.9114	0.8656	0.9178
SpeedBreakerDetection	0.9495	0.9616	0.9555	0.9887	0.9560
TrafficSignDetection	0.9149	0.8196	0.8648	0.8709	0.8723

In fig 2, the confusion matrix demonstrates the training resultsoftheYolov8modelfortrafficsignsdetection.Fig 3 and fig 4, respectively represents the confusion matrix for Yolov8 segmentation model trained for lane detection and Yolov8 model for speed-breaker detection.

B. Qualitative Results

Annotated video frames show accurate detection overlays. Lane changes and speed breakers trigger correct audio alerts. The image shows the proof of detection of traffic signs and speed-breaker detection, as well as lane change predictions.

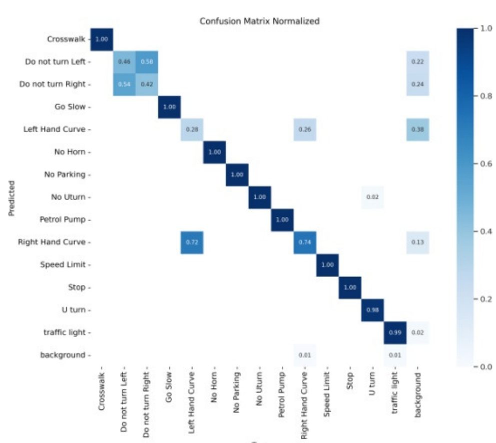

Fig.2.ConfusionMatrixforTrafficSignDetection

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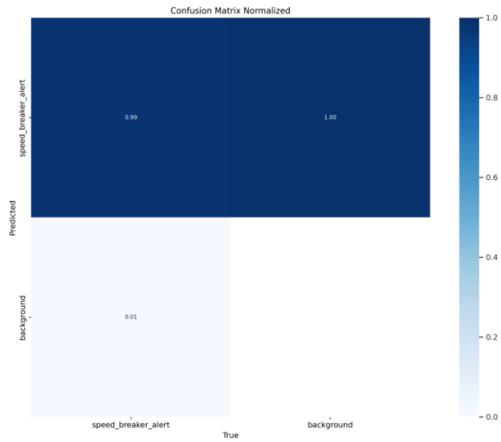

Fig.3.ConfusionMatrixforLaneDetection

VII.CONCLUSION AND FUTUREWORK

Thisworkpresentsamodularandefficientautonomous driving assistant system that integrates YOLOv8-based object detectionandsegmentationmodelswithvoicealertmech- anismsusinggTTSandMoviePy.Thesystemeffectively handlesreal-timelanedetection,lanechangeprediction,traffic signrecognition,andspeedbreakeridentification,allwithin anoffline,command-lineenvironment.Themodulardesign ensures that each component functions independently yet col- laboratively, offeringflexibilityforupgradesandoptimization.Theresultsdemonstratethatdeeplearningandcomputervisiontechniquescanbeappliedinp ractical,cost-effective waystoenhancedriverawarenessandroadsafety.High detection accuracy and real-time performance combined with intuitiveaudioalertsmakethesystemareliablefoundationforintelligenttransportationapplications.

For future work, we aim to extend support to live video streams and deploy the system on edge devices such as NVIDIA Jetson and Raspberry Pi. Additional improvements includeadoptingdeepreinforcementlearningforadaptivelane changelogic,expandingtraffic signcategories, andenhancing detection under low-light and adverse weather conditions.

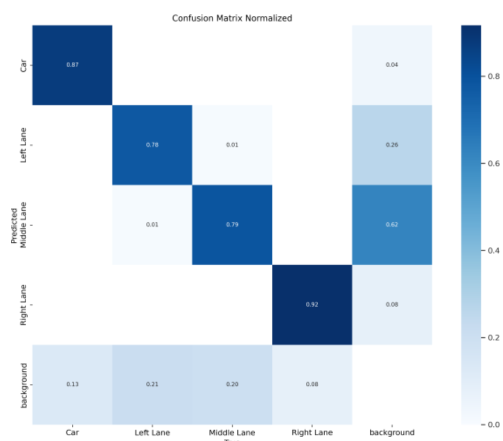

Fig.4.ConfusionMatrixforSpeed-breakerDetection

Furthermore, driver monitoring modules and a GUI or mobile interface could significantly improve usability.

With continued development, the proposed system holds potentialfordeploymentinadvanceddriver-assistancesystems (ADAS), fleet safety platforms, and autonomous research vehicles. Its scalability and adaptability make it suitable for both urban and rural driving environments, marking a step forward in intelligent road safety technology.

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