International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Real-Time Driver Vigilance Assessment Using Yolo and Deep Learning

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Abstract - Driver fatigue remains one of the leading contributors to road accidents, yet most commercially available monitoring systems fail to provide reliable real-time assessment of a driver's alertness. This work proposes a fully integrated vigilance detection framework that combines a custom-trained Ultralytics YOLO model with a temporal behavioural analysis layer to identify early signs of drowsiness, yawning, and reduced attention. The system processes live video streams using an optimized detection pipeline that includes brightness normalization, real-time state sampling, and adaptive thresholding to ensure robustness under varying illumination and head-pose variations. A multi-modal alert mechanism—featuring visual flash cues, audio warnings, and automated emergency notifications via WhatsApp—enables timely intervention during high-risk situations. The solution is deployed as a multi-threaded Python application with built-in analytics, trip log generation, and session reporting for post-drive evaluation. Experimental results demonstrate reliable real-time performance, achieving high detection accuracy and low latency, making the proposed system a practical, low-cost safety enhancement for intelligent transportation and driver assistance applications.

Keywords: *Driver Vigilance; Drowsiness Detection; YOLO; Deep Learning; Computer Vision; Real-Time Monitoring; Temporal Behavior Analysis; Intelligent Transportation Systems; Driver Safety; Multimodal Alerts.*

1. INTRODUCTION

Driver fatigue and diminished alertness continue to be major contributors to road accidents worldwide, accounting for a significant share of preventable fatalities each year. Traditional in-vehicle safety systems such as lane-departure warnings, steering-pattern monitoring and speed-limit alarms provide only indirect indicators of a driver's physiological state. These methods often fail to detect early behavioral cues, including microsleep episodes, prolonged eye closure or frequent yawning, which are strong predictors of impaired alertness. As modern transportation moves toward higher levels of automation and safety intelligence, the need for real-time, vision-based monitoring solutions capable of accurately assessing driver vigilance under diverse operating conditions has become increasingly important.

Recent advancements in deep learning, particularly in object-detection models, have made it feasible to deploy compact and highly accurate systems for monitoring facial cues in real time. Ultralytics YOLO has emerged as a strong candidate due to its optimized inference speed and robust generalization capabilities, making it suitable for continuous on-device driver monitoring. However, single-frame detection alone cannot reliably differentiate between transient actions such as natural blinking and hazardous behaviors such as sustained eye closure or repeated yawning. This limitation highlights the need for temporal-analysis mechanisms that evaluate behavioral patterns over time rather than relying solely on frame-level predictions.

This research presents a comprehensive vigilance-assessment system that integrates a custom-trained YOLO model with a temporal decision engine to monitor driver attentiveness continuously. The system processes live video streams, identifies fatigue-related facial cues, aggregates sequential events and triggers multimodal alerts that include visual flash warnings, audio alarms and automated emergency notifications via WhatsApp. In addition to real-time inference, the framework provides a multithreaded user interface, per-second state logging, trip-report generation and an analytics dashboard for post-drive evaluation. The goal is to deliver a practical, low-cost and deployable solution that enhances driver safety and supports intelligent transportation initiatives by detecting early signs of fatigue and preventing potential accidents.

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2. MOTIVATION

The motivation for developing a real-time driver vigilance assessment system arises from the urgent need to reduce fatigue-induced road accidents, particularly in regions where long commutes, irregular work schedules, and limited access to advanced driver-assistance technologies heighten risk. Existing monitoring solutions are often costly, hardware-dependent, or unable to accurately interpret subtle behavioural cues that signal the onset of drowsiness. By leveraging deep learning and real-time object detection, this project seeks to deliver an accessible, low-cost, and nonintrusive approach to assessing driver alertness. The integration of visual analysis with temporal decision-making and automated emergency notifications enhances early intervention, enabling timely responses before critical incidents occur. Ultimately, the goal is to improve roadway safety, support intelligent transportation systems, and make reliable driver-monitoring capabilities more widely accessible.

3. LITERATURE SURVEY

Research on monitoring driver alertness has progressed from simple visual heuristics to sophisticated deep-learning-based systems. Over time, numerous studies have investigated techniques for identifying early fatigue-related behaviors, each introducing distinct approaches aimed at improving safety in real driving environments. The works summarized below represent key developments relevant to the present study.

Paper [1] – "Real-Time Driver Drowsiness Detection Using Eye Aspect Ratio and Facial Landmarks"
This study uses geometric facial cues, including the Eye Aspect Ratio and related landmark features, to determine reductions in alertness. Although the technique is computationally light and practical for basic deployments, it struggles in conditions involving poor lighting, partial occlusion or abrupt head movement, revealing the limitations of rigid handcrafted visual features.

Paper [2] – "Convolutional Neural Network-Based Fatigue Detection Using Facial Expression Analysis"
The authors present a CNN-based classifier capable of identifying yawning patterns and extended eye-closure events. Their results demonstrate higher accuracy than traditional algorithms; however, the model incurs considerable computational overhead, reducing its effectiveness on resource-limited or real-time embedded hardware.

Paper [3] – "YOLO-Based Driver Monitoring System for Real-Time Fatigue Detection"
This work employs the YOLO detection framework to localize critical facial regions and fatigue indicators quickly. While the model performs reliably in varying illumination and motion scenarios, its frame-by-frame operation often misinterprets short blinks as fatigue, emphasizing the need for temporal context in decision-making.

Paper [4] – "Hybrid Deep Learning and Temporal Logic Framework for Reliable Driver Fatigue Assessment"
This paper proposes combining neural-network-based feature extraction with a temporal reasoning component that evaluates behavioral patterns across continuous frames. The hybrid approach reduces misclassification of brief actions; however, the framework demands substantial computational resources, making lightweight deployment challenging.

Paper [5] – "Multimodal Alert Mechanisms for Intelligent Driver Safety Systems"
The authors explore systems that integrate visual alerts, auditory warnings and communication-based notifications to assist drivers during fatigue-related events. Although these mechanisms improve response time and overall safety, the system lacks built-in analytics, logging and interface enhancements required for broader real-world adoption.

Paper [6] – "Optimized Lightweight Deep Learning Models for Embedded Driver Monitoring Applications"
This study introduces compact deep-learning models tailored for edge devices, demonstrating real-time performance with reduced power consumption. Despite these benefits, the system does not include extended functionalities such as emergency messaging, session tracking or temporal fatigue analysis, limiting its completeness as a standalone vigilance solution.

Collectively, these studies showcase significant progress in alertness assessment but also reveal persistent gaps. Many systems operate without temporal smoothing, lack multimodal alerting or omit essential reporting capabilities. The proposed YOLO-based vigilance system addresses these limitations through integrated temporal behavior analysis, multimodal alerts, automated notifications and comprehensive session analytics.

TABLE I: Summary of Reviewed Literature on Driver Vigilance Detection.

Paper No.	Paper Title	Methodology Used	Strengths	Limitations
[1]	*Real-Time Driver Drowsiness Detection Using Eye Aspect Ratio and Facial Landmarks*	EAR, facial landmarks	Low computational cost	Sensitive to lighting and occlusion
[2]	*CNN-Based Fatigue Detection Using Facial Expression Analysis*	CNN classifier	High accuracy	High computational load

[3]	*YOLO-Based Driver Monitoring System for Real-Time Fatigue Detection*	YOLO detection	Fast and robust	Lacks temporal reasoning
[4]	*Hybrid Deep Learning and Temporal Logic Framework*	Deep learning + temporal rules	Fewer false alarms	High resource usage
[5]	*Multimodal Alert Mechanisms for Driver Safety*	Audio/visual/emergency alerts	Enhanced safety response	Limited analytics and UI
[6]	*Lightweight Models for Embedded Driver Monitoring*	Edge-optimized CNN	Real-time on low-power devices	No emergency communication

4. PROPOSED METHODOLOGY

The proposed system improves road safety by continuously assessing a driver's alertness and preventing accidents associated with fatigue, distraction or delayed reactions. Long driving hours, irregular work schedules and limited access to monitoring tools increase the likelihood of fatigue-related incidents, particularly in developing regions. To address this challenge, the system combines deep-learning-based visual analysis, real-time video processing and automated alert mechanisms. Its objective is to provide a reliable, low-cost solution capable of detecting early indicators of drowsiness and responding promptly. A YOLO-based deep-learning model performs the primary detection task, while additional modules manage continuous monitoring, alert generation and emergency communication.

4.1. Deep Learning Component

Deep learning enables the system to identify subtle facial cues that reflect changes in driver alertness. Unlike traditional computer-vision approaches, which rely on hand-crafted rules, deep-learning architectures learn discriminative features directly from training data. A custom-trained Ultralytics YOLO model detects key facial indicators such as attentive gaze, partial or full eye closure, yawning and reduced facial activity. YOLO's single-stage design processes each frame in one pass, allowing the system to maintain real-time performance.

During operation, each video frame is analyzed to produce bounding boxes and class predictions that represent the detected facial state. These outputs provide the input for the temporal analysis module. Because the model learns features from labeled examples, it maintains consistent accuracy across varied lighting conditions, moderate head movements and different viewing angles.

4.2. Sequential Behavior Analysis

Although YOLO provides accurate classifications for individual frames, fatigue develops gradually and therefore requires temporal interpretation. To support this requirement, the system incorporates a sequential behavior-analysis module that evaluates detection results across a short time window. This module tracks prolonged eye closure, repeated yawning and declining engagement. It also applies duration thresholds and continuity checks to distinguish natural blinks or brief facial movements from fatigue-related behaviors.

By analyzing behavioral patterns rather than isolated detections, the module reduces false positives and issues alerts only when consistent deviations are observed. This mechanism operates similarly to refinement layers in neural-network-based systems and contributes to stable performance during extended monitoring.

4.3. Modeling and Analysis

The model was evaluated using a dataset containing images of alert, drowsy and yawning facial states. During deployment, the driver remains within the camera's field of view, and the system begins by capturing live video input. Preprocessing steps, such as brightness correction, improve visual clarity and support reliable detection accuracy.

As the system operates, YOLO classifies facial states in real time. The sequential module then interprets consecutive outputs to estimate the driver's alertness level. When fatigue indicators exceed predefined limits, the interface displays visual warnings, activates audio alerts and overlays a flashing indicator. If drowsiness persists or the driver does not respond, the system sends an automated WhatsApp message to the registered emergency contact. All detection outputs and alert events are logged. After each session, a summary report is generated that includes alertness trends, warning frequency and streak durations.

An emergency-assistance button is also provided to allow immediate support when required.

5. SYSTEM ARCHITECTURE

The proposed driver-vigilance monitoring framework adopts a **four-layer modular architecture** that isolates dataset preparation, model development, deployment, and analytical reporting into independent yet interconnected components. This separation allows updates—such as expanding the dataset, adjusting hyperparameters, or modifying the user interface—to be integrated without

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disrupting the entire pipeline. **Fig.1** depicts the overall layered architecture used in the system.

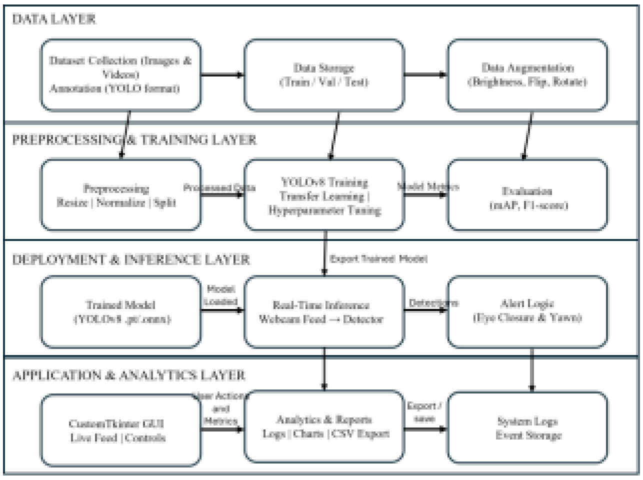

Fig. 1. Layered Architecture of the YOLO-Based Driver Vigilance Monitoring System

5.1 Data Layer

The **Data Layer** forms the foundation of the system and manages all visual material used for driver-state learning. The dataset consists of **images and video frames** representing three driver-alertness categories:

- **Attentive**
- **Yawning**
- **Drowsy**

These samples originate from multiple lighting conditions, camera angles, and environmental scenarios, ensuring high generalization capacity. Each image is annotated in **YOLO format** with bounding-box coordinates and class labels. The dataset imported through Roboflow and processed in the training notebook exhibits the following characteristics:

- **Train set:** 2256 images
- **Validation set:** 643 images
- **Test set:** 325 images
- **Classes:** ['attentive', 'yawn', 'drowsy'] as confirmed in the Roboflow YAML
- Fully labeled with no missing annotation files

To enhance diversity, the dataset undergoes **augmentation operations** such as brightness variation, horizontal flipping, rotation, scaling, and grayscale perturbations—operations configured automatically by Ultralytics YOLOv8 and additional Augmentations transforms (e.g., Blur, Median Blur, CLAHE, grayscale) detected during training logs.

The curated data are organized into structured **train–validation–test partitions**, supporting training, hyperparameter tuning, and evaluation.

DATASET DESCRIPTION

a. *Dataset Files Used*

The dataset is automatically exported from Roboflow and structured into independent subdirectories for training, validation, and testing. All samples follow YOLO annotation conventions and are distributed as shown in **Table 2**.

TABLE 2: Dataset Files Description

Dataset Split	Image Count	Label Count	Purpose
train	2256	2256	Model training
validation	643	643	Hyperparameter tuning & evaluation
test	325	325	Final model performance measurement

b. *What the Data Contains*

Each file contains:

- A bounding box specifying the **face region** in YOLO format (class x_center y_center width height)
- A single class label per image representing:
  - **0 → Attentive**
  - **1 → Yawn**
  - **2 → Drowsy**

The images represent real-world driving conditions, including:

- Varying illumination
- Different camera positions (front-view, angled-view)
- Behavioral variations (blinking, yawning, prolonged closure)

c. *Dataset Properties*

- **Total Images:** 3224
- **Total Classes:** 3
- **Annotation Format:** YOLOv8 .txt files
- **Image Formats:** .jpg, .png
- **Bounding Boxes:** Single human-face annotation per image
- **Augmentation:** Albumentations pipeline + YOLO built-in augmentations
- **Output Type:** Multi-class object detection

d. *Data Preprocessing*

Before training, the dataset undergoes standardized preprocessing:

- **Image resizing** to 640×640 pixels
- **Pixel normalization**

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- **Class-ID remapping** to match a unified order (attentive, yawn, drowsy)
- **Verification routines** ensuring label–image consistency (100% match)
- **Split restructuring** to YOLOv8-compatible folders (train/val/test/images and labels)

These steps are implemented programmatically in the training pipeline, as shown in the notebook export.
The final validated dataset is then used to train YOLOv8 with optimized augmentation, learning parameters, and early-stopping strategies.

5.2 Preprocessing and Model-Training Layer

In this layer, standardized input is prepared for model development:

1. **Frame Normalization**
   Adjust image dimensions and pixel distributions.
2. **Dataset Allocation**
   Samples are grouped into training, validation, and testing subsets.
3. **YOLOv8 Transfer Learning**
   - Model initialized with pretrained YOLOv8 backbone
   - Fatigue-specific classes fine-tuned
   - Hyperparameters (learning rate, batch size, augmentation probability) optimized automatically
   - Mosaic, Rand-Augment, Mix-up, HSV transforms applied during training
4. **Performance Monitoring**
   Metrics such as **mAP@0.5**, **mAP@0.5:0.95**, precision, and recall are logged each epoch.

The final checkpoint with the highest validation performance is exported in **ONNX and PyTorch** formats for deployment.

5.3 Deployment and Inference Layer

In this layer, the trained YOLO model is deployed for real-time detection:

a. **Webcam-Feed-Acquisition**
   Continuous frame capture.
b. **YOLO-Based-State-Detection**
   Each frame is processed to detect:
   a. Eye openness
   b. Yawning patterns
   c. Drowsiness posture
c. **Temporal-Reasoning-Module**
   Instead of relying on single-frame predictions, the system maintains a sliding window of detections and applies:
   a. Majority voting
   b. Stability filtering
   c. Persistence-based thresholds
d. **Alert-Logic**
   When sustained fatigue detection is confirmed:
   a. Visual overlays appear on the GUI
   b. Audible warnings activate
   c. Emergency escalation via WhatsApp is triggered when necessary

6. RESULT AND CONCLUSION

The performance of the proposed YOLO-based driver-vigilance monitoring system was evaluated using a curated dataset consisting of three behavioural classes—attentive, yawning, and drowsy. A comprehensive set of quantitative analyses and visual evaluation metrics was generated to assess the model's detection capability, robustness, and generalization under varying illumination and head-pose conditions. The experimental findings demonstrate that the system achieves high precision, strong recall, and reliable class discrimination, making it suitable for real-time fatigue-monitoring applications.

6.1 Model Performance Evaluation

1) Precision–Recall Characteristics

The *Precision–Recall (PR) Curve* (Fig 2. **Precision–Recall Curve**) shows consistently strong performance across all three classes. The model maintains near-perfect precision for almost the entire recall range.

Class-wise PR results:

- **Attentive:** 0.992
- **Yawn:** 0.994
- **Drowsy:** 0.990

The overall metric of **mAP@0.5 = 0.992** strongly indicates excellent class separability and low ambiguity between fatigue-related behaviors.

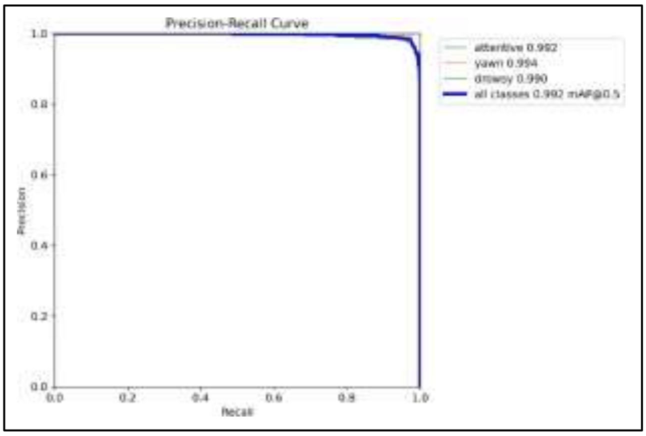

Fig 2. Precision–Recall Curve

2) Confidence–Performance Analysis

The *F1-Confidence Curve* (Fig 3. F1-Confidence Curve) and Precision-Confidence Curve (Fig 3.1. *Precision-Confidence Curve*) illustrate the relationship between prediction confidence and model reliability.

Key performance indicators:

- **Maximum F1-Score ≈ 0.97** at confidence = **0.355** (Fig 3.)
- **Maximum Precision ≈ 1.00** at confidence = **0.951** (Fig 3.1.)
- **Maximum Recall ≈ 1.00** at confidence = **0.00** (Fig 3.2)

This suggests that:

- Lower thresholds yield high recall — suitable for **safety-critical deployment**, where missed fatigue events are unacceptable.
- Higher thresholds yield high precision — useful when minimizing false alarms.

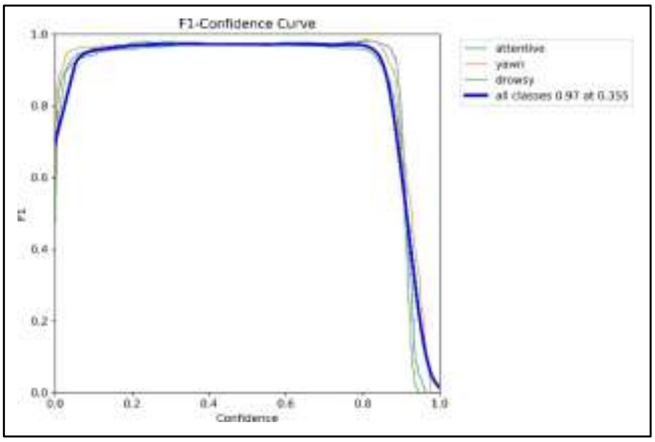

Fig 3. F1-Confidence Curve

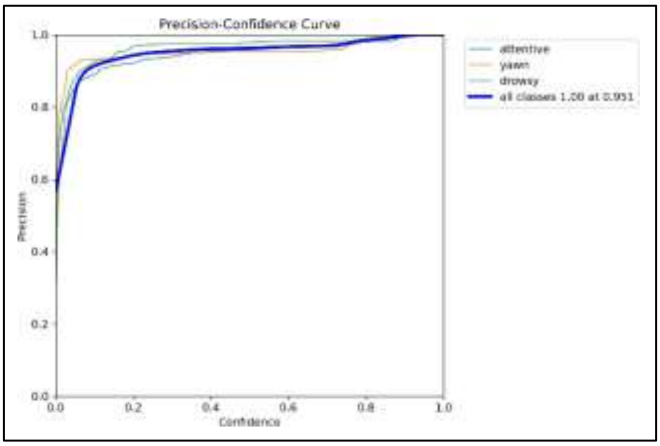

Fig 3.1. Precision-Confidence Curve

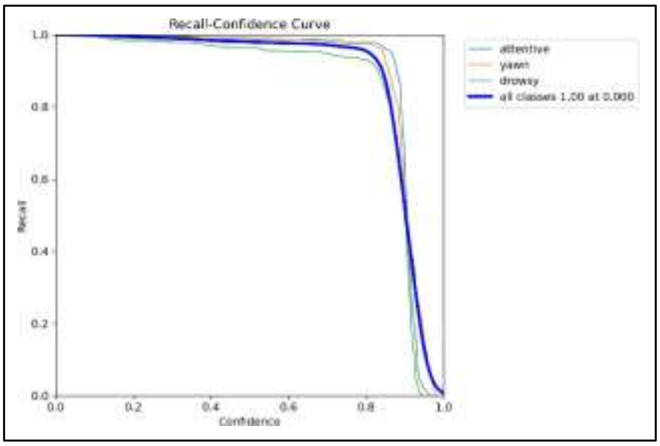

Fig 3.2. Recall-Confidence Curve

3) Confusion Matrix Analysis

The *confusion matrix* (Fig 4. *Confusion matrix*) demonstrates strong class-wise accuracy:

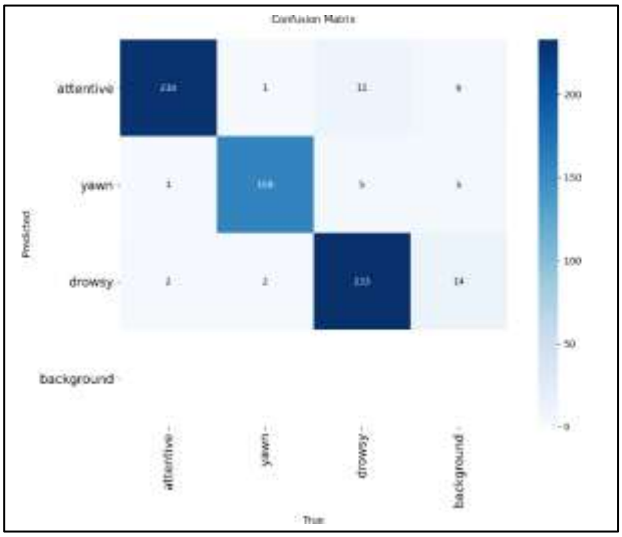

Fig 4. Confusion matrix

Class	Correct Predictions
Attentive	230
Yawn	158
Drowsy	233

Misclassified samples are minimal and generally arise from borderline facial expressions or partial occlusions.

The **normalized confusion matrix** (Fig 5. *Confusion Matrix Normalized*) further shows that:

- All classes maintain **>94% classification accuracy**,
- Inter-class confusion remains extremely low.

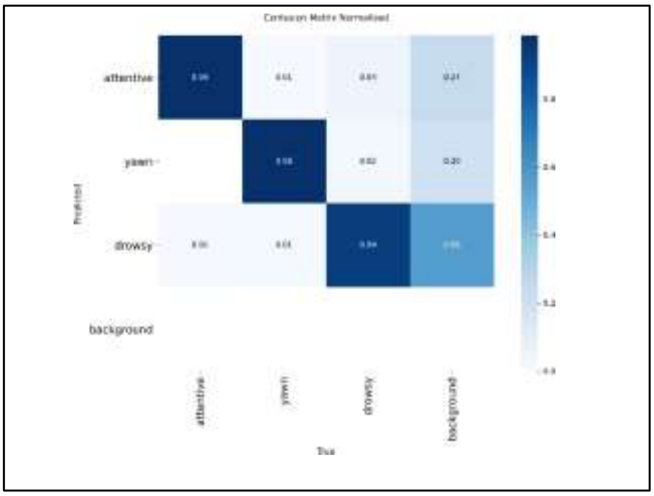

Fig 5. Confusion Matrix Normalized

4) Dataset Distribution and Label Quality

The dataset-distribution visualization (Fig 6. *Dataset Distribution & Heatmaps*) shows balanced instance counts:

- **Attentive:** 799 images
- **Yawn:** 660 images
- **Drowsy:** 797 images

The bounding-box heatmaps and width–height distributions confirm:

- High-quality annotation consistency
- Diverse spatial placement of faces
- Low dataset bias

These properties directly contribute to stable model generalization.

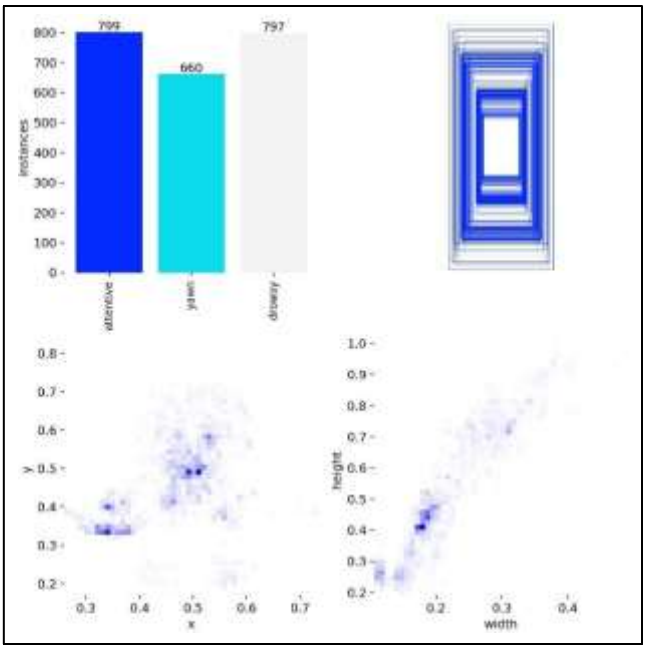

Fig 6. Dataset Distribution & Heatmaps

6.2 Training and Validation Behavior

The training curves (Fig 7. Training & Validation Loss/Metric Curves) demonstrate:

- A consistent decrease in *box, classification, and DFL losses* over ~40 epochs
- Close alignment between training and validation curves, indicating *minimal overfitting*
- Gradual convergence of performance metrics (*precision, recall, mAP@0.5, mAP@0.5–0.95*) toward near-optimal values

These results confirm that the fine-tuned YOLOv8 model:

- Benefits substantially from transfer learning
- Learns fatigue-related features effectively
- Generalizes well across unseen samples

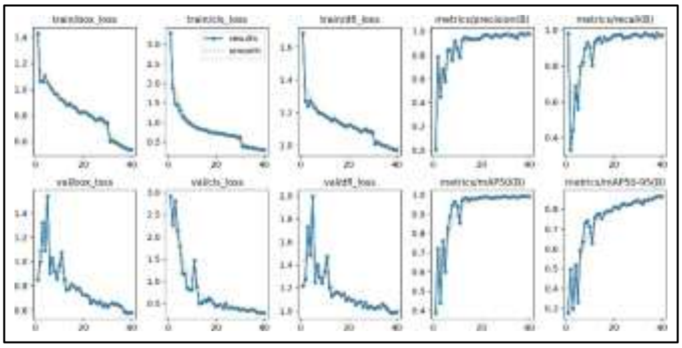

Fig 7. Training & Validation Loss/Metric Curves

6.3 Real-Time Deployment Results

During real-time operation, the system processes streaming webcam input to detect:

- Prolonged eye-closure behavior
- Yawning frequency and extent
- Reduced or sluggish facial-activity patterns

The embedded *temporal-reasoning unit* enhances reliability by aggregating frame-level detections and filtering short, non-critical events such as natural blinks.

The system responds with:

- *Visual alerts* (flashing overlays)
- *Audio warnings*
- *Automated WhatsApp emergency notifications* when thresholds are exceeded

This ensures timely intervention for genuine fatigue events while maintaining low false-alarm rates.

6.4 Conclusion

The experimental evaluation demonstrates that the proposed YOLO-based driver-vigilance monitoring system achieves:

- *mAP@0.5 ≈ 0.992*
- *F1-score ≈ 0.97*
- *Precision ≈ 1.00*
- *Real-time inference capability*
- *Stable temporal performance*

These results confirm that the system reliably identifies fatigue indicators across challenging illumination and head-pose variations.

The system's overall effectiveness is the result of integrating:

- A balanced and well-annotated dataset
- Robust preprocessing and augmentation strategies
- A fine-tuned YOLOv8 detection architecture
- A reliable temporal-reasoning and alert-logic module

Together, these components deliver a *highly dependable, real-time driver-monitoring solution* suitable for deployment in real-world safety applications.

Future Work

Potential extensions include:

- Incorporating multimodal cues (e.g., steering patterns, blink-rate sensors, heart-rate monitoring)
- Expanding behavioral categories
- Deployment on edge-optimized embedded platforms for large-scale automotive integration

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