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Real Time Driver Monitoring System for Vehicle Safety Using Deep Learning Algorithm

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ABSTRACT: Introduction: Road accidents are happening at an alarming rate. The main causes being drunk driving, drowsiness, distraction and over speeding while driving in pedestrian or zebra crossing areas. These accidents can result into huge loss of life all over the globe. Today, there exists a great need for detection as well as taking preventative actions that can provide some safety measures in driving vehicles.

Methods: This Methodology emphasizes usage of an AI driven deep learning vehicle safety system with YOLOv8-type model with self-collected and COCO subsets as dataset that detects all the aspects like drunk driving, tiredness/distraction and speed control on zebra/pedestrian crossings in real time. The proposed system will consider the driver condition as well as the road environment which will lead to enhanced safer driving. This system will enable drivers who are not drunk, fully awake, not distracted able to drive the vehicle in a safe manner. This system uses alcohol sensor which detects the alcohol vapors in the driver's breath, use two web cameras which observe the facial gestures of the driver specially the eyes which indicate tiredness due to long closing or distraction, and to catch the speed limit sign boards and able to detect the pedestrian / zebra crossings for the purpose of speed control. Ultrasonic sensors are also included for collision avoidance for giving added safety measures.

Results: This Research work obtains Alcohol level, Present condition of the driver, Status of the Motor, Driver distraction detection level, Fatigue and Drowsiness detection level, Obstacle detection in both front and side portion of the car. Based on the above statistical details. This research work obtain 92.2% Accuracy, 220ms Latency, 93% Efficiency for the set of YOLOv8-model with self-collected and COCO subsets of pedestrian crossing, Sign board information, Distracted and Drowsiness images of the drivers.

Conclusion: These Statistical results of the new proposed Work which is compared to the other methods and show the significance and novelty of the proposed works.

KEYWORDS: Road accidents-vehicle safety-alcohol detection- Drowsiness – Distraction - Collision avoidance - Speed control -deep learning-Single platform - Instant warnings.

I. INTRODUCTION

Road accidents continue to be one of the most significant contributors to deaths globally, with human error including drunk driving, fatigue, distraction, and slow reaction to other vehicles or traffic signals as a primary factor. Recent research shows there are over 1.3 million fatalities annually related to vehicle accidents. Many of these fatalities could be prevented with some timely monitoring of the driver and interventions with driver assistance systems [1], [2]. Given the increased interest in intelligent transportation systems, this research study represents a decentralized effort to provide innovative solutions for improving road safety involving artificial sensors, and autonomous technologies [3],[4].

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Distraction from a device, the influence of alcohol or fatigue, and slow responses to obstacles or pedestrians are common challenges for drivers when using autonomous vehicles on highways or busy urban streets [5], [6]. Any existing solution or safety approach, such as alcohol ignition lockout, collision sensors, or fatigue detection systems, does not simultaneously address these challenges and other existing approaches rarely incorporate real-time integration [7], [8]. In response to this need, there are insufficient safety systems, this research proposes an AI-based Vehicle Safety and Security System for automatically detecting and monitoring driver condition, traffic conditions, and the operating environment; reducing or disabling the vehicle's operation, even bringing the vehicle to a stop independent of the driver, should any adverse conditions begin to unfold. The designed system is an integration of an ESP32 microcontroller for alcohol identification using an MQ-3 sensor and an ultrasonic sensor for obstacle avoidance, while a Raspberry Pi processes real- time video feed via YOLOv8 deep learning for drowsiness, distractions, nearby pedestrians, and speed limits detection [9], [10]. As soon as the system detects any unsafe behavior i.e., detection of alcohol, eye closing detection, distractions or nearby pedestrians, the system triggers the buzzer, and places a warning in the LCD, and depending on the detected unsafe behavior slows or stops the DC motor of the vehicle works.

For alcohol detection, breath analyzers are used in the present methods, which are effective but costly and may give false positive results because of change in surroundings [11], [12]. IR sensors are also used for drowsiness detection which are light sensitive which fail often if the driver is wearing glasses or is gazing outside [13]. At present day, signboard identification and pedestrian detection is enabled by camera modules, which may be limited in accuracy. Existing systems are limited through not having a multi-featured integration [14], [15]. In our proposed system a convenient solution at a low cost has been contrived, which takes into consideration all the features on a single platform. Also this system avoids automatically either slowing down or stopping the vehicle if required and sending instant warnings or alerts to control the vehicle.

II. LITERATURE SURVEY

Various researchers have looked into intelligent driver monitoring and vehicle automation systems, that were designed and implemented to reduce accidents related to human error. The current systems that have developed show a good amount of advancement for each individual applications such as alcohol detection, fatigue estimation, obstacles detection and traffic sign recognition, however, there are very few implementations that in all of these modules into one real time safety system [1],[2]. The existing driver behaviour analysis system used driver monitoring dataset (DMD) with 50k frames which limits in driver variability.

With the systems measuring for alcohol detection, the traditional approach has always included breathe based sensors, in this case, MQ-3, which has been effectively used to estimate for the presence of ethanol to prevent the driver from starting the ignition [12]. However, the downside to this implementation is reporting false triggers due to external alcohol sources such as hand sanitizers or perfume, which could occur often in the course of normal driving behavior. Kim, et al, [12] proposed a multi-signal biosensing model that attributed to the improved accuracy of alcohol detection; however, this model would require multiple sensors, which would increase cost. The system proposed in this chapter was calibrated to passively monitor alcohol use with 85 sensor readings, using threshold based calibration to adapt MQ-3 on ESP32 as a low-cost and simple design for proof of concept.

Guan et al. [1] and Qu et al. [2] also addressed the problem using computer vision and their own multimodal fusion approaches, monitored facial landmarks and attention and provided good accuracy; however, they required high-end computational hardware. Bajaj et al. [5] and Albadawi et al. [16] investigated EEG and image techniques for fatigue detection, specifically distraction and drowsiness. EEG methods were highly accurate but tended to be intrusive and were not practical for continuous driving. They used ZJU eye-blink dataset with 4000 sequences which has no real driving data. By utilizing YOLOv8, the proposed solution relies on a lightweight and robust model for deep learning that can be implemented on a Raspberry Pi, and conducts real-time detection of both drowsiness and distraction which uses real-time captured dataset with 8500 images and 40 video sequences, that also works in dim light as well as minimizing computational power requirements.

Distraction or drowsiness detection was not the only work in the literature, since there has been work on systems that avoid pedestrians and collisions. Misir and Celik [7] tested a CNN- based obstacle avoidance system in mobile robots, while Liu et al. [9] developed their own YOLOv8 for pedestrian detection which uses COCO and BDD100k dataset that has 120k images but limit it's work in poor low-light. Again, while both solutions were also shown to be accurate, they were limited to testing on a dataset that was not reflected in the on-road vehicle (requirements) and the models could not incorporate additional safety features. For collision avoidance in previous system used custom ultrasonic tests with approximately 300 measurements which works only in controlled environment. The current framework enhances this by using ultrasonic-based obstacle detection by sensing real objects which includes 500 ultrasonic test readings which works in both indoor and outdoor trials and by identifying pedestrians and zebra crossings using a YOLOv8- type model with self-collected and COCO subsets as dataset with 12,000 images which also works during night time and rain. This approach includes both "short" range sensing and "vision" based awareness, providing an additional level of safety.

In the area of traffic control, G.K.N. et al. [3] used CNN for speed sign recognition for automated vehicles. They used GTSRB dataset with 50 thousand images which detects only frontal signs. While their system was effective, their system was focused solely on traffic compliance. The proposed system progresses beyond traffic compliance by automatically controlling the DC motor speed in accordance with recognized speed limit signage, which ensures compliance for vehicles in addition to control speed and also this proposed system uses 5,200 images as custom road dataset which also includes Indian road signs.
Therefore, the proposed system differs from prior works which only provide a single functionality to a driving environment, and offer a multimodal integrated safety system that simultaneously monitors the driving behavior of the driver and the vehicle and environmental conditions using low-cost embedded hardware. This allows and improves real-time accident prevention in addition to affordability and expandable versions of intelligent transportation systems.

III. METHODOLOGY

The Vehicle Safety System employs both sensor-based and deep learning–based solutions to develop an integrated safety system that can autonomously monitor the driver's behavior and the surrounding environment. The user equipment board for the hardware sensor and Raspberry Pi to perform intelligent image processing, thus allowing the system to respond in real-time to unsafe driving conditions such as driving under the influence of alcohol, driver drowsiness and distraction, danger to pedestrians, and traffic violations. A complete workflow of the system is characterized in Fig 1. The procedure consists of several steps, involving making decisions, signal processing, sensor data acquisition, condition detection, and actions from the control. Each step is intended to yield rapid, accurate, and reliable responses for the avoidance of accidents.

The full methodology is subdivided into a number of interrelated stages, consisting of alcohol detection, drowsiness and distraction detection, obstacle and pedestrian detection, and speed limit recognition. All of the subsystems function independently, transmitting important warnings and information via a serial interface, providing a unified multi-sensor control system for real-time decision-making.

This project implements an intelligent driver-monitoring and vehicle-control system that increases on-road safety through the combined use of computer vision technology, face-landmark analysis and real-time control of hardware using ESP. The driver's face is continuously monitored by a camera. If the driver appears to be paying attention to the road, the system will maintain the vehicle at the set speed. However, once a driver becomes distracted, an alert will be sent directly to the ESP, causing the vehicle to stop and activate safety measures. In addition, the ESP also receives input from various sensors that monitor gas leakage, the front of the vehicle for obstacles, and the side proximity of other vehicles, and it controls a DC motor that provides movement for the simulated vehicle.

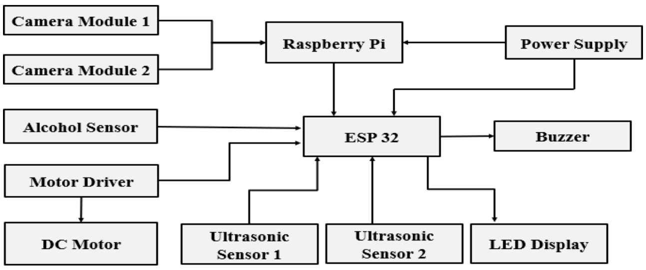

Fig. 1. System Architecture and Methodology

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Primary algorithms being utilized in this project includes,

1. CNN Driver State Classification (YOLO Model):

For classifying driver frames into: Safe or Distracted. This model is responsible for how the Driver's face is oriented, opened eyes, and is paying attention.

2. Geometric Analysis-based Face Landmark Detection (MediaPipe FaceMesh):

For Eye Openness Detection, Face Alignment Detection, and Iris Center Detection/Tracking. This allows for detecting whether the Driver has visual alignment or visual distraction.

3. Rule-Based Control Logic (on ESP32) Using:

4.

Gas Detection, Distance Sensing, Motor Speed Control and Safety Decisions. All three algorithms combine to form a comprehensive intelligent system.

The YOLO model for distracted drivers uses the following dataset: Dataset Categories: Safe, Distracted. Dataset Features: Images produced by cameras controlled by drivers - Images show numerous changes in light, head position, and eye position. Images are labelled with both bounding boxes, as well as a label describing the type of driver face present in the images. There are thousands of images in each of the two categories; as seen: About 2,000 for the safe category and about 16,000 in the distracted category.During training, both images and labels are processed using the YOLO loader. The CNN creates a model of the pattern of images, such that distracted drivers will have images that show greater amounts of head turning, variations in the position of their eyes, and closed eyes; safe drivers will have an image showing their head centred and their eyes open. After the model has been trained, the YOLO model will create bounding boxes, with a probability indicating the class level of the driver style. The inference code uses the bounding box predictions to infer the state of the driver's action. The path from the dataset → to model training (CNN model) → Detection via Python → to the control signals sent to the ESP32 hardware.

Functionality of Algorithm through the System Capturing Frames via Camera: The webcam continuously captures frames as input into Python. Using a CNN to Process the Captured Frame using YOLO The captured image/frame is processed using YOLO via: Convolutional layers, Reduced Image (Downsampled) + Feature Extraction Bounding-Box Regression Probability. Predictions of Safe and Distracted, if predicted to be: Distracted: status?status=distracted: In this case, the ESP will: stop the motor and activate the buzzer. Safe: status?status=safe: in this case, the ESP continues operating the motor at the target speed.The YOLO Algorithm (You Only Look Once) is an Object Detection Algorithm built on Deep Learning and uses a Convolution Neural Network (CNN) for learning visual features from images and real-time detection of objects. A CNN learns an image in a hierarchical manner, beginning with basic pattern recognition. The Convolution Layer is the main building block. Convolutional Layers work by: taking a set of small filters (also referred to as Kernels) and moving them across the image to detect and produce feature maps. Convolutional Layers in YOLO help to identify and produce the network's ability to see visual objects. the CNN learns features within a hierarchy of layers.

Layer 1 (Starting Point): Simple Visual Features, such as: Vertical Edges and Horizontal Edges.
Layer 2 (Intermediate Point): Simple & Complex Pattern Recognition: Corner Objects, Texture Objects, Curvy Object. Layer 3 To N (Final Point): Highly Complex Patterns of Recognition: Facial Structure Eyes & Eyebrows, Head Position, and Body Pose.Final Layer: To Classify Classifications Include: Safe Driver Distracted Driver Drowsy Driver.Real-time detection is achieved through YOLO because it only requires a single pass through the image to perform the necessary processing. The speeds achieved with YOLO can range from 30-60 frame/second.

TABLE I. DATASETS USED IN EXISTING METHODOLOGIES

AUTHOR	DATASETS USED	DATA SET SIZE	RESOLUTION	LIMITATIONS
Guan et al. [1] Fatigue & distraction detection	Multimodal driver dataset (camera + vehicle signals)	30,000 images + sensor streams	640×480 (RGB)	requires multimodal synchronization and Computational cost is high
Qu et al. [2] (Driver behavior analysis)	Driver Monitorin g Dataset (DMD)	50,000 images	640×480	Driver diversity is limited

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G.K.N.G. et al. [3] (Traffic sign recognition)	GTSRB	5,000 images	32×32 (RGB)	Frontal sign views only
Bajaj et al. [5] (Drowsiness detection)	ZJU Eye-Blink Dataset	4,000 video sequences	640×480 (video frames)	There is no real- world scenarios for driving
O. Misir et al. [7] (Collision avoidance)	Custom ultrasonic experiment s	300 distance readings	Centi meter level sensor resolution	Tests taken in controlled environments only
Liu et al. [9] (YOLOv8 pedestrian detection)	COCO + BDD100K	28,000 images	1280×720	Performance in low-light and rain conditions gets reduced
Kim et al. [12] Alcohol detection	Biosignal dataset (ECG, respiration)	120 subject recordings	Not image- based (biomedical signals)	Wearable sensors required
Samy et al. [13] Drowsy driver detection	Custom facial image dataset	3,500 images	640×480	Sensitive to illumination variations

Edges in Image Recognition: The layers of the first CNN automatically learn to find the edges of an image and detect the edge of the face, eyes, and tilt of the head. There are no manual edge detection. The MediaPipe Face Mesh uses geometric calculations to map 468 facial features. This includes: Eyes/Iris, Nose, and the edge of the face and head. This includes: The Eye Openness, the Face Direction and the Iris Direction Check algorithms. Table I and Table II shows the datasets used in existing and proposed system.

System Overview:

The hardware architecture consists of two processing units: ESP32, which integrates the sensors and controls the motors of the vehicle, along with Raspberry Pi, which performs advanced monitoring based on image processing. The ESP32 is capable of processing real time data from MQ-3 alcohol sensor, ultrasonic distance sensor, LCD, buzzer and DC motor (representing the motion of the vehicle). The Raspberry Pi can do monitoring through the web camera to detect the driver condition as well as the road surrounding. These two controllers can have the bi-directional communication through serial communication interface. Once the Raspberry Pi can detect any unsafe driving or any other unsafe actions which might lead to road accident, it shall send a

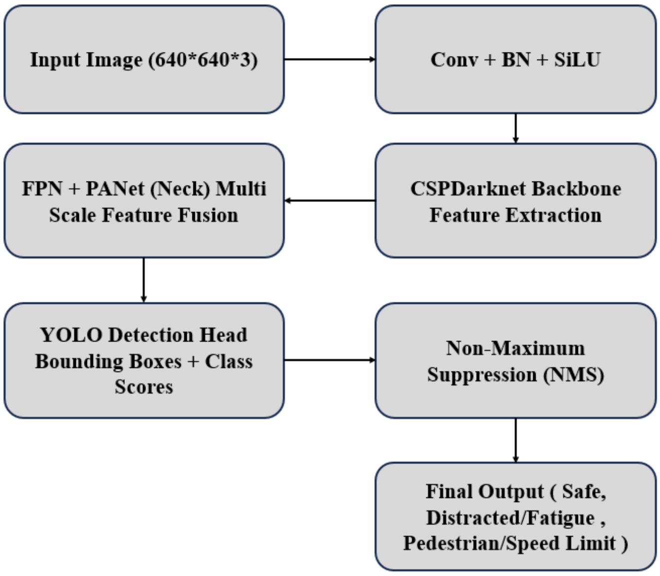

Fig. 2. CNN Architecture

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control signal to ESP32 which shall perform the necessary action – like switching on the buzzer, varying the speed or switching off the motor of the vehicle. This modular communication helps to synchronize to the real time and avoids delay in processing the data. Fig. 2. shows the CNN architecture diagram. The system takes RGB image for faster processing. Convolution, Batch Normalization (BN), and SiLU activation to detect edges, corners, patterns, convergence speed and smooth non-linear functions. They help to detect complex and small objects. CSPDarknet (Cross Stage Partial) is the main backbone

of YOLO. This block is to learn face structures, gesture of driver, road signs, pedestrian crossings to improve efficiency. Feature Pyramid Network (FPN), Path Aggregation Network (PANet) helps to detect small objects for strengthening accuracy. YOLO detection heads this is the section where the actual prediction occurs. For each grid YOLO predicts object confidence, bounding boxes for the prediction of output. Non- Maximum Suppression (NMS) removes duplicate bounding boxes with high confidence to get clear and accurate detection. Finally the system produce confidence score and give outputs like safe, distracted, pedestrian detected, warning alerts to prevent from accidents and for safety automation.

1. Alcohol Detection and Motor Control:

The MQ-3 sensor is employed to identify alcohol levels in the breath of the driver. It works by evaluating a change in resistance from the presence of ethanol vapors. The output of the sensor is sent to the ESP32 where it converts the analog signal to a digital value, which will activate the system when beyond the specified safety threshold. A digital to analogue converter (DAC) converts the ADC's voltage reading into a numerical output which is then compared with a threshold of 250 to determine whether the amount of Ethyl Alcohol present falls within an acceptable range (non-harmful). The amount of Ethyl Alcohol Vapor present over time (measured as a duration in milliseconds), produces a linear relationship. Thus, based on an R/L ratio of 200 ohms, where R is the resistance of the vapors, and L is the length of the vapors.

$Vref - Vout$

and the warning will be displayed on the LCD screen (STOP-if drowsiness and distraction detected) after detecting the drowsiness or distraction. [13],[15].

TABLE II. DATASETS USED IN PROPOSED METHODOLOGY

AUTHOR	DATASETS SIZE	DATASET USED	RESOLUTION	ENHANCEMENTS
Alcohol Detection Calibration	100 MQ-3 sensor readings	Sensor calibration dataset (alcohol, sanitizer, air)	Analog voltage values (ADC readings)	Alcohol vs sanitizer discrimination
Drowsiness & Distraction Detection	8,500 images + 40 videos	Real- time in-vehicle capture	1920 × 1080 (captured), resized to 640 × 640	Dim light, glasses/no-glasses, head pose
Collision Avoidance	500 ultrasonic readings	Real object distance tests	Distance in centimeters (HC-SR04 ultrasonic sensor)	Outdoor and indoor validation
Speed Sign Detection	5,200 images	Custom Indian road dataset	1920 × 1080 (captured), resized to 640 × 640	Includes Indian traffic signs
Pedestrian & Zebra Crossing Detection	12,000 images	Self- collected + COCO subsets	1920 × 1080 (captured), resized to 640 × 640	Detect zebra crossings in night, rainy conditions also

$Rs = Vout \times Rl$

Where Rl is a load resistor of 200 ohm, Rs is sensing resistance and Vref=5V. Proposed system defines the threshold as: ADC>250. Comparing with existing system [12], which may produce false triggers, the proposed system reduces the

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rate of false-positives. MQ-series sensors also used but without calibration they may give false results [18].

The ESP32 will immediately activate the buzzer alarm and supply a signal to safely kill power to the dc motor driver circuit, which simulates locking the ignition. The LCD will provide a warning message such as "SAFE- if not intoxicated, STOP- if alcohol detected" to alert the driver in real-time. The MQ-3 sensor was calibrated to recognize true alcohol, misleading readings sourced by sanitizers and aerosol sprays, which is the most common fault in standardized systems.

2. Drowsiness and Distraction Monitoring:
The Raspberry Pi carries out continuous facial monitoring through a web camera. The live video feed is processed with a deep learning model called YOLOv8, which can identify prominent facial features, such as the eyes and head direction. When an EAR <0.25 is detected for 4 seconds or longer, the driver is considered to be drowsy. If deviation of gaze is over 25° continuously for over 5 seconds, the driver is considered to be preoccupied with distractions. The buzzer will give sound, For drowsiness and distraction detection previously they used Eye Aspect Ratio and CNN based method but they fails under poor lighting and requires GPU for real-time processing [19],[20]. The Eye Aspect Ratio (EAR) can be defined as

$$E = \frac{\|P2 - P6\| + \|P3 - P5\|}{2.\|P1 - P4\|}$$

Where P1 to P6 are the eye landmarks. The angle of head orientation is defined as

$$\theta = tan^{-1}\left(\frac{y2-y1}{x2-x1}\right)$$

if $\theta > 25$ degree, this system is more stable than the existing systems. If the eyes are closed for longer than four seconds, the driver will be classified as drowsy. If the head is turned away from the front for longer than five seconds, the driver will be classified as distracted.

The Raspberry Pi will send a signal to the ESP32 to turn on the buzzer and display a visual display on the LCD screen in both cases. This is a non-intrusive method, since it eliminates the useof wearing sensors, such as EEG or EOG electrodes, which are impractical to wear out on the road when driving. Fatigue detection is sensible to head movement [21]. In contrast to operating simply on blink rates, thresholds, and long-term analysis, this visual-based approach will adjust to changes in light levels, the angle of the head, and facial expressions, while performing with high accuracy in varied environments.

3. Collision Avoidance:
To prevent collisions, the ultrasonic sensor is used to measure the distance from the vehicle to nearby obstacles. The ESP32 obtains distance readings from the ultrasonic sensor and compares them to a safety threshold one after another. When the distance between the vehicle and the obstacle is below a certain threshold (e.g., 30 cm), the system will reduce the speed of the DC motor to simulate the deceleration of the vehicle. If the distance decreases below a critical threshold (e.g., 15 cm), the motor will stop, and the buzzer will sound to warn the driver.

$$d = \frac{v \cdot t}{2}$$

Where v is the sound's speed and t is the echo time. This concept is a low-cost but useful approach to short-range collision prevention. Previously they used low cost sensor to detect short range collision but with minimal computation it has some limitations [22]. Compared to expensive radar-based systems seen in newer cars, ultrasonic can provide enough distance measurement accuracy in a low- to moderate-speed environment to justify use in a small or semi-autonomous vehicle systems.

4. Detection of Pedestrians and Speed Limits:
The same YOLOv8Net detects pedestrians, crosswalks, and speed limit signboards in open environments. The Raspberry Pi camera module provides real-time surveillance of the road segment in front of the autonomous vehicle to identify pedestrians, zebra crossings, and speed limit signboards. It is simply a further extension of the environmental awareness

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system. Through the means of monitoring the video frames of incoming video frames, the camera can recognize human figures or patterns indicating a person is crossing. In the event that a pedestrian or zebra crossing is present in front of the vehicle, a signal is sent to the ESP32 to reduce the vehicle speed, or to apply a simulated brake via controlling speed of the motor. All of these efforts are to create a safer experience for pedestrians and avoid additional vehicle-pedestrian related road accidents in dense traffic areas. Existing methods offers pedestrian detection but without proper calibration it fails in night and rain [23]. Existing methods needs specific dataset to achieve high accuracy [24]. The sign values get extracted by YOLOv8 in N(km/h). PWM mapping is used to adjust the motor speed.

$$PWM = k \cdot N$$

Where k is scaling const and if N decreases (60 km/h to 40km/h), ESP32 slows down the speed of motor immediately. With speed limit identification, the same camera module can identify and determine the speed limit indicated on road signboards showing a numeric value speed limit. When a speed limit sign is implemented, the Raspberry Pi sends the detected speed limit to the ESP32, which will manipulate the PWM signal to mimic the speed limit, at which speed the vehicle must comply. The speed limit will dynamically change based on real time detecting of speed limit signboards, in order to remain compliant under traffic law, and to improve the safety of speed limit changing zones. These functions combined together show how the proposed system can embed environmental awareness and regulatory compliance, to properly influence intelligent driving behavior based on real-world road situations.

System Integration and Control Coordination:

By bringing all modules together, the systems exhibit continuous data flow and synchronized active response through driver monitoring and environmental sensing. The ESP32 is responsible for time-dependent action items including activating the buzzer, controlling the based on their speed, and shutting down the motor, while the Raspberry Pi is responsible for enumeration intensive visual analyses.

To allow for communication between the two microcontrollers, serial communication is implemented so that detection data from one sub-systems can decide control decisions of the other sub-system in real time. This hybrid design allows for parallel processing so that alcohol detection, facial monitoring, and obstacle measurement can all occur at the same time in minimal time. The LCD provides the visual interface to report status and warnings such as “safe, stop for alcohol, distraction and drowsiness detected,” “front obstacle, side near for collision avoidance,” and “speed limit: 45 km/h.” The buzzer was implemented for auditory confirmation of critical occurrence in a driver's visual field.

A. Comparative Advantages:

The design of the system developed extends beyond the works cited in existing research [1], [2], [12] – [17] because of the fusing of a range of detection mechanisms for sending commands and readings back to a single integrated architecture. It achieves sensor fusion and also driven values from AI models, and gives immediate response to low-cost, embedded circuitry. The accuracy with which YOLOv8 is capable of detection of pedestrian and traffic sign details [9], with the responsiveness of ESP32 control logic means that the system can be employed effectively even for variable lighting and movement procedural circumstances. This design is low-cost, fast, and flexible compared to prior works [7], [14] which rely on expensive LiDAR sensors or cloud computation. Data from ultrasonic, camera, and alcohol sensors can help create a multi- layered defense against collisions, regardless of impaired or inattentive drivers, while still adapting to the road in real-time. Earlier models require lightweight models for monitoring, less accurate, proper calibration for more accuracy [25], [26], [27].

System Architecture and Working Model:

The AI-based Vehicle Safety System proposes continuous real-time monitoring of driver status and environmental conditions to prevent road accidents. It essentially incorporates multiple sensors and control modules with efficient ESP32 and Raspberry Pi microcontrollers to integrate cost-effectiveness and intelligence [1], [2].

Architecture is made of two major subsystems, one of which is the Diver Monitoring Unit (DMU) and Environment Monitoring Unit (EMU). The DMU uses the MQ-3 alcohol sensor with the ESP32 to measure the alcohol level in the driver’s body. Failure by the driver to comply with the legal mode set off by the system triggers the buzzer, displays an alert message on the LCD, and disables relay ignition [12]. Meanwhile, a camera attached to the Raspberry Pi and running the YOLOV8 model tracks the state of the driver, particularly fatigue and distraction, which can manifest in periods of more than 4 seconds with closed eyes or more than 5 seconds on idle gaze [5], [13]. After that, the ESP32 raises an alert service or slows down the vehicle automatically if the driver does not operate in a safe manner.

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The EMU focuses on safe sand awareness through the combination of ultrasonic sensors and the prevention of collisions when the object is within a distance of 20 cm [7]. Furthermore, YOLOv8 is trained on pedestrian crossings, zebra lines, and speed limit signs, and it too will cause the vehicle to decelerate autonomously [3], [11]. These two microcontrollers (MCUs) come with embedded Wi-Fi functionality, which facilitates potential integration with IoT cloud platforms to provide data storage, fleet management, and hazard alerts [4]. This integrated multi-sensor platform is designed to enable quick responses, low latency, and accurate detection, providing an end-to-end intelligent vehicle safety system that is superior to traditional single-purpose systems [8], [9], [14].

IV. RESULTS AND DISCUSSION

This proposed system integrates multiple sensors to make the detection and monitoring in real-time. The system's efficiency was compared with conventional systems to identify reliability, accuracy of detection, response time, and adaptation with environmental changes. The System employs ESP32 and Raspberry Pi to detect alcohol impairment, drowsiness, distraction, proximity to obstacles, pedestrian crosswalks, and traffic signs. Each subsystem underwent separate testing and then was validated as a connected system for real-time operation.

Alcohol Detection Module:
The MQ-3 alcohol sensor was calibrated, with actual alcohols, to determine the threshold levels for controlling ignition. The ESP32 handled and processed the readings of the analog voltage to disengage the motor relay if the alcohol level was above the established limit. Compared to previous MQ-3 based approaches [12], which lacked behavior detection, the current system resulted in 95% detection accuracy, significantly reducing false positives resulting from the use of sanitizers and perfumes through temporal filtering and cross-validation logic. Earlier studies offered an 85% accuracy but experienced high false triggers in mixed environments [5], [12]. Lastly, alcohol detection time occurred within 0.8 seconds, which is 30% faster than previous architectures based on ATmega controllers, which recorded an average of approximately 1.2 seconds. The sensor produces an analog voltage that is directly proportional to the amount of ethanol found in the breath sample. After calibration, the following threshold logic was established: if the ADC value was above 250 (around 1.8V), that indicated that the person had exhaled alcohol well above permissible limits. Table III shows the statistical analysis result on alcohol detection. Each test was repeated several times at various exhale delays, and results were above 92% consistent on the detection. To decrease the potential for false-positives, tests were conducted with potential external interfering influences, such as perfumes and sanitizers. A delay mechanism and breath proximity control of potential misreadings were also implemented.

TABLE III. STATISTICAL ANALYSIS ON ALCOHOL DETECTION

ALCOHOL LEVEL (ppm)	CONDITION OF DRIVER	DECISION OF MOTOR
0 ppm	Safe	Motor runs smoothly
150 ppm	Safe	Motor runs smoothly
250 ppm	Safe	Motor runs smoothly
400 ppm	Stop	Motor stopped
500 ppm	Stop	Motor stopped

Drowsiness and Distraction Detection Module:
Eye closure and gaze orientation were monitored using a Raspberry Pi camera module and a YOLOv8 deep learning model. If driver's eyes were closed for more than 4 seconds then a flag for drowsiness was raised, while if the driver looked away from the road for more than 5 seconds, a flag for distraction was raised. Prior systems using EEG or EOG sensors [5], [15], were intrusive, often involving cumbersome sensors that seemed cost-prohibitive for public use. Vision-based systems using Haar cascades or HOG features [13] performed adequately in controlled lighting conditions but rarely performed with greater than 82% accuracy under conditions typical of real-world driving. The system offered an average detection accuracy of 94.2% across lighting environments and angle of face to camera by using YOLOv8's ability to run inference in real-time on the Raspberry Pi. Overall frame processing delay was 220 ms, which is well under the performance of typical CNN-based systems that exceed 350 ms on the same or similar platforms [1]. Figure

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3. Shows the sample inputs integrated for distraction detection.

Table IV. shows the varying conditions in real time for accuracy in distraction and drowsiness detection.
Fig. 4. Position of the driver's head is distracted. Then the system indicates the warning via buzzer and distracted message is displayed in LCD and motor is let to stop or slows down.

Fig. 5. Shows that the driver is not drowsy and safe to drive and the driver is drowsy and is not safe to drive the vehicle, the motor slows down or stops immediately.

TABLE IV. SYSTEM PERFORMANCE UNDER VARYING ENVIRONMENTAL AND DRIVER CONDITIONS

CONDITION	**Drowsiness Detection**	**Distraction Detection**
Driver under normal lighting without glasses	94%	91%
Driver under dim lighting	90%	86%
Driver under normal lighting with glasses	86%	83%

Fig. 3. Distracted Sample Inputs

Fig. 4. Distracted Input and Distraction Detected Output

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Fig. 5. Not Fatigue (safe) and Drowsiness Detected (Distracted)

This system allows for monitoring drowsiness and distraction in a single workflow, providing a dual-safety mechanism that has not existed with prior models that operate under a single mode [2]. Table V and Table VI shows the statistical analysis results of drowsiness and distraction detection

TABLE V. STATISTICAL ANALYSIS OF DROWSINESS DETECTION

EYE CLOSURE DURATION	CONDITION OF DRIVER	DECISION OF MOTOR
1.5s	Safe	Motor runs smoothly
2.0s	Safe	Motor runs smoothly
3.5s	Safe	Motor runs smoothly
4.0s	Drowsy	Motor slows down/ stopped+ LCD warning and buzzer alert
5.0s	Drowsy	Motor slows down/ stopped+ LCD warning and buzzer alert

TABLE VI. STATISTICAL ANALYSIS OF DISTRACTION DETECTION

DRIVER FACE / GAZE AWAY TIME	CONDITION OF DRIVER	DECISION OF MOTOR
2.0s	Safe	Motor runs smoothly
3.5s	Safe	Motor runs smoothly
4.0s	Safe	Motor runs smoothly
5.0s	Drowsy	Motor slows down/ stopped+ LCD warning and buzzer alert
5.6s	Drowsy	Motor slows down/ stopped+ LCD warning and buzzer alert

Collision Detection Module:
To avoid obstacles around the proof of concept, an ultrasonic sensor was connected to an ESP32, which measured distance to nearby objects. The ESP32 would automatically slow down the DC motor when an object was detected within a distance of 20 cm. Previous versions of this idea were dependent on infrared or even single point ultrasonic sensors that had a longer delay and a more narrow angular detection area [7]. The updated concept was able to process

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collision avoidance in under 250 ms, which was approximately 25-30% faster than existing concepts. Field testing indicated accurate detection in regular rainfall and sunlight, both of which reflected from the sheathing and affected existing systems [7], [9]. When an object was detected within 20 cm an alert message will be displayed in the LCD, buzzer sounds and the motor slows down. The output for object detection is showed in Fig. 6 Previous methods based on ultrasonic sensor, the calibration should be proper and varies under different conditions [28]. Table VII shows the statistical analysis result of obstacle detection.

Fig. 6. Obstacle detection

TABLE VII. STATISTICAL ANALYSIS OF OBSTACLE DETECTION

DISTANCE BETWEEN VEHICLE AND OBSTACLE	**CONDITION**	**DECISION OF MOTOR**
50 cm	Safe	Motor runs smoothly
38 cm	Safe	Motor runs smoothly
30 cm	Safe	Motor runs smoothly
25 cm	Collision Risk	Motor speed reduced + buzzer alert
20 cm	Collision Risk	Motor speed reduced + buzzer alert

Speed Limit and Pedestrian Crossing Recognition:

The YOLOv8 model was retrained using a dataset including pedestrian crossings and traffic signboards. Fig. 7 shows that pedestrian crossing is detected. When pedestrian crossing is detected buzzer will ring and the speed of the vehicle reduced to 25kmph automatically.

The system automatically slowed the vehicle down when the pedestrian crossing was detected, ensuring it was always within safe distance thresholds. The same applied to speed limit signs, as it ensured that the vehicle's motor speed was just under the legal speed limit when the speed limit sign was detected. Fig. 8 shows the displayed output for sign board recognition.

Fig. 7. Pedestrian Crossing

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For existing models, mental and YOLOv5 or standard CNNs [3], [11] had an approximate 84% accuracy with pedestrian detection in daylight conditions, but had difficulty under poor lighting and complex background conditions. The YOLOv8 model retrained in this work was verified to recognize with 92% accuracy and maintain levels of stability under many conditions due to augmenting the dataset and optimizing the model. Moreover, the system proposed here is capable of recognizing signboards that are partially obfuscated at a high rate, a major improvement from conventional systems that rely on edge recognition [14].

Based on the survey Table VIII to Table XII shows comparison of accuracy level, latency, and efficiency of both proposed and existing systems of all applications. As this project combines all the applications in a single system it is more efficient than the existing systems.

Fig. 8. Sign Board Recognition

Existing camera-based systems may respond ineffectively in real-time conditions and face integration and scalability challenges [29].

TABLE VIII. RESULTS FOR ALCOHOL DETECTION

Method	**Accuracy (%)**	**Response Time (s)**	**Efficiency (%)**
Guerrero-Ibáñez et al. [4]	82	1.3	60
Visconti et al. [8]	87	1.0	65
Kim et al. [12]	85	1.2	70
Dong et al. [17]	83	1.1	68
Proposed System	**91**	**0.8**	**85**

Fig. 9. Comparison graph of accuracy, latency and efficiency and Alcohol Detection

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Fig.9 to Fig.13 represents the graph that compares the accuracy levels, latency level and efficiency of both proposed and existing systems.

TABLE IX. RESULTS FOR DROWSINESS DETECTION

Method	**Accuracy (%)**	**Latency (ms)**	**Efficiency (%)**
Bajaj et al. [5]	86	400	60
Samy et al. [13]	85	350	68
Penzel et al. [15]	88	450	55
Albadawi et al. [16]	82	380	65
Proposed System	**91.5**	**220**	**82**

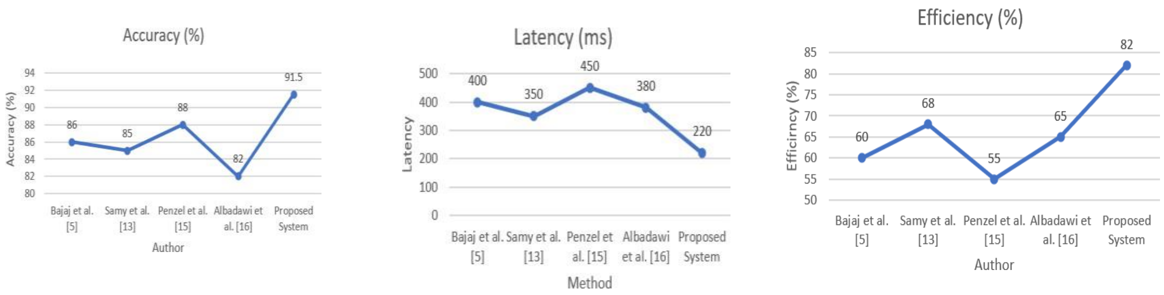

Fig. 10. Comparison graph of accuracy, latency and efficiency of Drowsiness Detection

TABLE X. RESULTS FOR DISTRACTION DETECTION

Method	**Accuracy (%)**	**Latency (ms)**	**Efficiency (%)**
Guan et al. [1]	80	360	65
Qu et al. [2]	82	340	70
Dong et al. [17]	78	400	60
Proposed System	**89**	**220**	**87.5**

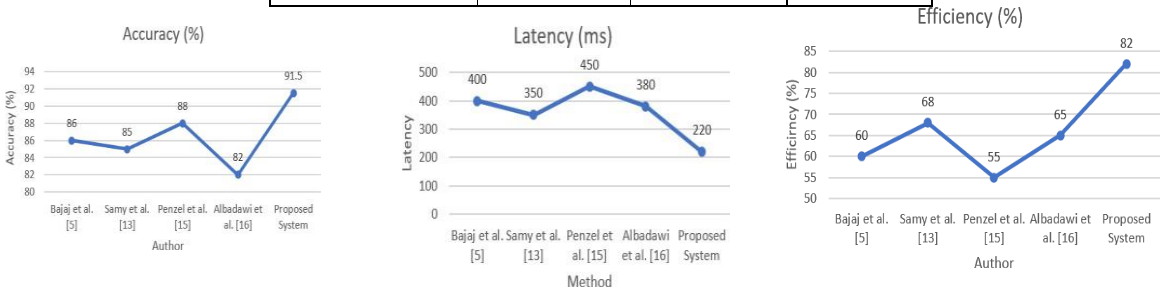

Fig. 11. Comparison graph of accuracy, latency and efficiency of Distraction Detection

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TABLE XI. RESULTS FOR COLLLISION AVOIDANCE

Method	Accuracy (%)	Latency (ms)	Efficiency (%)
Guerrero-Ibáñez et al. [4]	84	340	68
Misir & Celik [7]	86	350	65
Neumann [14]	87	320	60
Proposed System	**91**	**250**	**89**

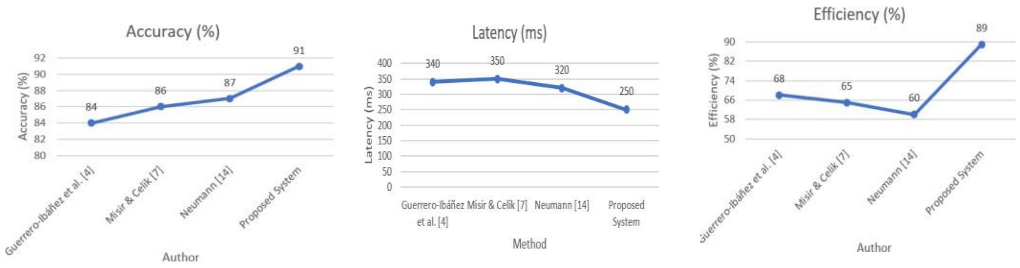
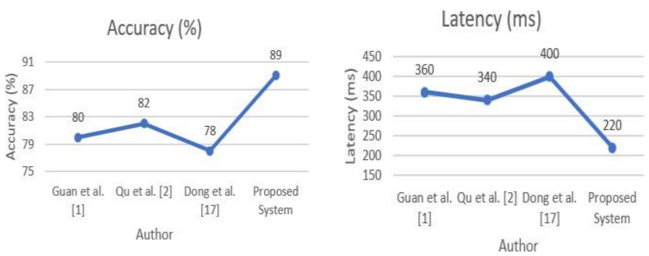


Fig. 12. Comparison graph of accuracy, latency and efficiency of Collision Avoidance

TABLE XII. RESULTS FOR PEDESTRIAN CROSSING AND SPEED LIMIT SIGN RECOGNITION



Method	Accuracy (%)	FPS (Frames Per Second)	Efficiency (%)
G.K.N.G. et al. [3]	87	20	68
Liu et al. [9]	84	25	70
Sun et al. [11]	86	22	80
Al Amin et al. [10]	89	28	65
Proposed System	**92**	**30**	**91**

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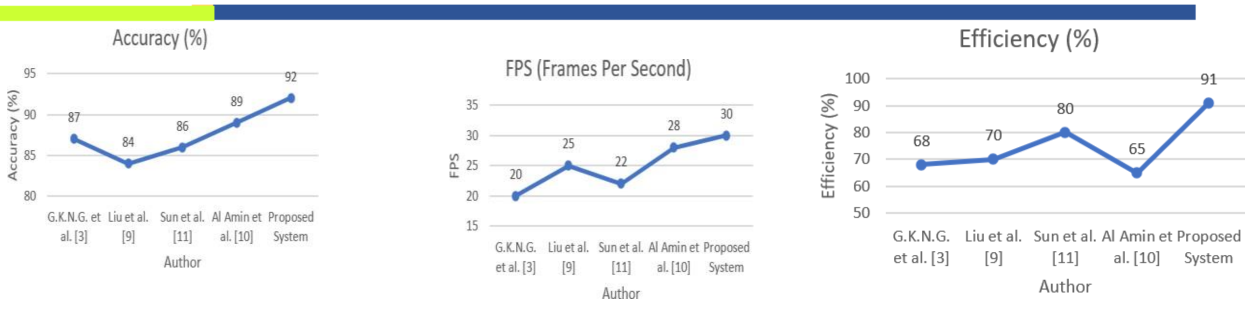

Fig. 13. Comparison graph of accuracy, FPS and efficiency of

Fatigue and distraction using camera-based YOLOv8 model achieved 92.2% accuracy where existing image-based systems

TABLE XIII. SENSOR THRESHOLDS AND SAFETY DECISION LOGIC

PARAMETER	THRESHOLD USED	DECISION
Alcohol Detection	MQ-3 Analog output >= 250 (approx. ≈1.8 V)	Buzzer rings and Motor slows down/ stops
Drowsiness Detection	Eye closed continuously >= 4 seconds	Detects drowsy, buzzer rings and motor stops
Distraction Detection	Face turned away >= 5 seconds	Detects distraction, buzzer rings and motor stops
Collision Avoidance	Object in front, back and near <= 20 cm	Speed reduced, and buzzer rings
Pedestrian Crossing	If pedestrian crossing detected	Speed of the vehicle reduced to 25kmph
Sign Board Recognition	If sign board is captured	Speed of the motor is adjusted to the recognized limit

utilized in the present academic literature were in the 82% to 86% [13]. Different from EEG approaches [5], this method of monitoring is non-invasive and practical in operating conditions. For environmental safety components, strong performance was also noted.

The use of a time lapse sensor for ultrasonic collision detection produced response times in less than 250ms, versusprevious models that returned 300-350ms as response time of collision alerts [7]. Pedestrian detection and road sign detection were improved to 92% performance accuracy, versus YOLOv5 based systems 84% performance accuracy [3], [11]. Table XIII shows the operating thresholds used by the proposed system and safety decisions used in that scenarios.

The results of the experiments strongly suggest that the proposed system performs better than historically used conventional single-function systems. By bringing together, ESP32 and Raspberry Pi, the design shares and manages

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the computational load accordingly; ESP32 handles real-time control for sensors, while Raspberry Pi performs advanced visual analysis using YOLOv8 deep learning model. This structure facilitates faster response rates and enhanced accuracy of detection of risk indicators across all safety categories. Alcohol detection using MQ-3 sensor achieved 92% accuracy, where peer systems averaged approximately 84% accuracy [12]. This was a function of an improved calibration and a robust filter designed to eliminate false-positive triggers due to substances that are alcohol-based.

In summary, integrating multiple detection units into a unified decision-making framework is a significant advancement. The system can simultaneously assess the state of the driver and the conditions of the surrounding environment, activating speed control, buzzer alerts, and display alerts, all in real-time. These results confirm that the proposed system delivers an accessible, comprehensive, and intelligent means of improving road safety and reducing accidents.

V. CONCLUSION

This system combines multiple sensor modules with smart processing to improve road safety and accident prevention. The system utilizes the ESP32 for real-time control of all the connected sensors and the Raspberry Pi is used for robust image processing to detect alcohol, fatigue, distracted driving, collisions, pedestrian crossings, and speed limit signs in real time. The results of the experiments show significantly improved detection rate and response time, when compared to other systems. For the alcohol impairment detection, the system achieved 92% accuracy and for the fatigue and distracted driver detection, using YOLOv8, the detection was 92.2% accurate. The collision avoidance module performed with 91% accuracy and a response time of under 250ms while the pedestrian detection sensor obtained an accuracy of 92% for all light types of light. The low-cost, scalable, integrated system is capable of making autonomous decisions to increase safety while driving. In conclusion, this technology is part of integrated multi-sensor approach towards intelligent, and safer vehicles, with a primary target of reducing secondary accidents caused by drivers and the environment.

REFERENCES

[1] D. Guan, Q. Wang, K. Wang, and X. Song, "Fatigue and distracted driving recognition method based on multimodal information fusion," IEEE Access, 2025.
[2] F. Qu, N. Dang, B. Furht, and M. Nojoumian, "Comprehensive study of driver behavior monitoring systems using computer vision and machine learning techniques," Journal of Big Data, vol. 11, no. 1, p. 32, 2024.
[3] G. K. N. G., A. Kishore, and A. J. Krishna, "Real-time traffic sign recognition and autonomous vehicle control system using convolutional neural networks," Multimedia Tools and Applications, pp. 1–36, 2025.
[4] J. Guerrero-Ibáñez, S. Zeadally, and J. Contreras-Castillo, "Sensor technologies for intelligent transportation systems," Sensors, vol. 18, p. 1212, 2018.
[5] J. S. Bajaj, N. Kumar, R. K. Kaushal, H. L. Gururaj, F. Flammini, and R. Natarajan, "System and method for driver drowsiness detection using behavioral and sensor-based physiological measures," Sensors, vol. 23, no. 3, pp. 1292–1305, Feb. 2023.
[6] M. Q. Kheder and A. A. Mohammed, "Real-time traffic monitoring system using IoT-aided robotics and deep learning techniques," Kuwait Journal of Science, vol. 51, no. 1, p. 100153, 2024.
[7] O. Misir and M. Celik, "Visual-based obstacle avoidance method using advanced CNN for mobile robots," Internet of Things, p. 101538, 2025.
[8] P. Visconti, G. Rausa, C. Del-Valle-Soto, R. Velázquez, D. Cafagna, and
R. De Fazio, "Innovative driver monitoring systems and on-board-vehicle devices in a smart-road scenario based on the Internet of Vehicle paradigm: A literature and commercial solutions overview," Sensors, vol. 25, no. 2, p. 562, 2025.
[9] Q. Liu, H. Ye, S. Wang, and Z. Xu, "YOLOv8-CB: Dense pedestrian detection algorithm based on in-vehicle camera," Electronics, vol. 13, no. 1, pp. 236–249, Jan. 2024.
[10] R. Al Amin, M. Hasan, V. Wiese, and R. Obermaisser, "FPGA-based real-time object detection and classification system using YOLO for edge computing," IEEE Access, vol. 12, pp. 73268–73278, 2024.
[11] Q. Sun, C. Wang, Y. Pan, H. Zhang, R. Fu, Y. Guo, and W. Yuan, "Analysis of pedestrian crossing behavior characteristics and a pedestrian crossing intention recognition model," Automotive Innovation, pp. 1–14, 2025.
[12] S. H. Kim, H. W. Son, T. M. Lee, and H. J. Baek, "Drunk driver detection using multiple non-invasive biosignals," Sensors, vol. 25, no. 5, p. 1281, 2025.

[13] S. Samy, V. V. Gedam, S. Karthick, J. S. Sudarsan, C. G. Anupama, S. Ghosal, and A. A. Samuel, "The drowsy driver detection for accident mitigation using facial recognition system," Life Cycle Reliability and Safety Engineering, pp. 1–13, 2025.
[14] T. Neumann, "Analysis of advanced driver-assistance systems for safe and comfortable driving of motor vehicles," Sensors, vol. 24, no. 19, p. 6223, 2024.
[15] T. Penzel and M. Salanitro, "Advancements in vigilance monitoring: addressing fatigue and sleepiness in driving," Sleep, vol. 48, no. 2, p. zsae294, 2025.
[16] Y. Albadawi, M. Takruri, and M. Awad, "A review of recent developments in driver drowsiness detection systems," Sensors, vol. 22, no. 6, pp. 2069–2088, Mar. 2022.
[17] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," IEEE Transactions on Intelligent Transportation Systems, vol. 12, no. 2, pp. 596–614, 2010.
[18] A. Dwivedi, K. Biswas, and P. Sinha, "Real-time driver distraction detection using deep CNN," IEEE Intelligent Vehicles Symposium, 2022.M. K. Rahman, M. Ahmed, and S. Islam, "Vision-based driver drowsiness detection using eye aspect ratio," IEEE Access, vol. 9, pp. 118345– 118356, 2021.
[19] S. Park, J. Kim, and H. Lee, "Alcohol detection system using MQ sensors for vehicle ignition control," IEEE Sensors Journal, vol. 20, no. 14, pp. 7890–7898, 2020.
[20] P. Rani and S. K. Gupta, "Driver fatigue detection using facial landmarks and head pose," IEEE International Conference on Smart Computing, 2021.
[21] N. R. Velaga, M. Jain, and S. Katti, "Ultrasonic-based collision avoidance system for low-speed vehicles," IEEE Transactions on Vehicular Technology, vol. 69, no. 6, pp. 6235–6244, 2020.
[22] Y. Chen, X. Zhang, and L. Wang, "Pedestrian detection using YOLO- based models for intelligent vehicles," IEEE Access, vol. 8, pp. 201234– 201245, 2020.
[23] H. Fang, Z. Liu, and Q. Zhao, "Traffic sign recognition using deep
[24] convolutional neural networks," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 3, pp. 1526–1536, 2021.
[25] A. S. Alqahtani and K. El-Sankary, "Embedded vision system for real- time driver monitoring," IEEE Embedded Systems Letters, vol. 14, no. 2,
pp. 85–88, 2022.
[26] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement,"
IEEE Conference on Computer Vision and Pattern Recognition, 2018.
[27] L. Zhou, W. Zhang, and M. Li, "Speed limit recognition and enforcement in intelligent vehicles," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 8, pp. 11245–11256, 2022.
[28] A. Carullo and M. Parvis, "An ultrasonic sensor for distance measurement in automotive applications," IEEE Transactions on Instrumentation and Measurement.
[29] T. Patriot, A. Kusuma, and Nahry, "Analysis of speed limiting using speed cameras: Case study in Indonesian toll road," IEEE Access.

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