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VISIONGUARD- Object Detection In Adverse Weather Conditions With Health Monitoring

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Abstract - Driving in bad weather like rain, fog, or low light often makes it hard for traditional vehicle detection systems to work effectively. To tackle this, we introduce VisionGuard—a smart solution that combines advanced object detection with real-time driver health and drowsiness monitoring. Powered by YOLOv8 and trained with the ACDC dataset, it's built to handle tough visual conditions. It also uses ultrasonic and infrared sensors to improve how it sees the environment. On the inside, it tracks vital signs like heart rate, oxygen levels, and body temperature through wearable sensors, while keeping an eye on signs of fatigue using facial landmarks and blink detection. With over 95% detection accuracy, VisionGuard brings together deep learning, sensor fusion, and health monitoring into one system—making roads safer by looking out for both what's outside the vehicle and how the driver is doing.

Keywords— Autonomous Vehicles, Object Detection, YOLOv8, Deep Learning, Health Monitoring, Drowsiness Detection, Sensor Fusion, Adverse Weather.

I. INTRODUCTION

Autonomous Vehicles (AVs) and Advanced Driver Assistance Systems (ADAS) are transforming modern transportation by enhancing road safety and driving efficiency. These systems depend on real- time object detection, which remains a challenge under adverse weather conditions such as rain, fog, snow, and low light. Conventional vision-based methods often fail in such scenarios due to poor visibility and sensor limitations, affecting detection reliability and overall safety. To address these issues, this study presents VisionGuard, a robust system combining YOLOv8, a state-of-the-art deep learning model, with sensor fusion techniques using ultrasonic and infrared (IR) sensors. Transfer learning on the ACDC dataset ensures improved detection in challenging weather scenarios[1]. The sensor fusion strategy overcomes the limitations of single-sensor systems by leveraging complementary data, enabling accurate detection even in low-visibility environments. In addition to object detection, VisionGuard integrates a smart health monitoring module that tracks vital signs such as heart rate, SpO_2, and body temperature using wearable sensors[22]. A real-time drowsiness detection system analyzes facial landmarks and eye-blink patterns to detect fatigue and inattention. Together, these modules enhance both environmental perception and driver safety. Extensive testing under various conditions showed a mean average precision (mAP) above 95%, validating the system's reliability. VisionGuard offers a scalable and intelligent framework for autonomous driving by integrating deep learning, multi-sensor fusion, and physiological monitoring, paving the way for safer and more resilient transportation systems[22].

II. BACKGROUND

The primary challenge addressed in this project is the degradation in computer vision-based vehicle detection systems under adverse weather conditions and health monitoring of the driver. Traditional systems struggle with reduced visibility from rain, fog, snow, low-light condi- tions, and visual distortions and does not provide an option for monitoring of health and real time drowsiness detection. These environmental challenges, combined with camera lens obstruction and variable lighting, significantly impact detection accuracy. Traditional object detection systems tend to work well in favorable conditions, but their performance drops significantly in adverse weather. Rain can blur the camera lens, fog limits how far systems can see, and snow can obscure road signs and obstacles entirely. In low-light conditions or at night, visual inputs become less reliable due to glare, shadows, and reflections. These challenges make it difficult for conventional vision-based systems to maintain consistent accuracy. On top of that, many road accidents are caused not just by external hazards but also by internal factors like driver drowsiness or sudden health issues.

To address these concerns, recent research has focused on improving detection in complex environments. Notably, Garg et al. introduced a method to generate synthetic training data using light transport principles [15], which eliminates the need for manual data labelling [1]. Models like Faster R-CNN, YOLOv7, and especially YOLOv8 have been tested in these settings [3], with YOLOv8 showing strong results in adverse weather. Alongside this, machine learning models such as Logistic Regression and Random Forest [27] have been used to classify human vital signs. New datasets like ACDC and

DAWN [1] are also enabling better training and testing of detection systems in difficult conditions. To gauge performance, researchers rely on standard metrics such as Intersection over Union (IoU), mean average precision (mAP), precision, and F1 score. These metrics help quantify how well a model performs, particularly in visually degraded settings like fog or heavy rain where detection accuracy usually declines. This project builds on these insights by combining YOLOv8 with synthetic and real-world data to create a more resilient object detection system. It not only improves the system's ability to recognize objects in poor visibility but also monitors the driver's vital signs and alertness in real time. By unifying environmental awareness with driver health monitoring, the system aims to provide a safer and smarter solution for autonomous and assisted driving.

III. OBJECTIVES

The goal of this project is to build a fully integrated system that can perform reliable, real-time vehicle detection and obstacle avoidance even in difficult weather conditions, while also monitoring the driver's health using real-time drowsiness detection and vital sign analysis. These objectives cut across the software, hardware, and mobile components of the system, ensuring a holistic approach to safety. On the software side, the system is centred around the YOLOv8 deep learning model, which is deployed and optimized to run at speeds of at least 30 frames per second to support real-time detection. Special attention is given to
ensure high performance in conditions like fog, rain, and snow by incorporating sensor fusion algorithms and transfer learning from pretrained YOLOv8 models on datasets like COCO. Alongside object detection, a drowsiness detection module uses an inward-facing camera to analyze facial landmarks and eye movements. It tracks indicators such as eye aspect ratio and blink rate through lightweight AI models like SVMs and CNNs to detect signs of fatigue and alert the driver accordingly. Complementing this, the system includes a health monitoring component that gathers vital signs like heart rate, SpO_2, and body temperature through wearable or embedded sensors. These readings are then processed by machine learning models such as Random Forest and Neural Networks to detect anomalies and send timely alerts. All these modules run on edge devices using optimized frameworks like TensorFlow Lite and OpenVINO, enabling fast, low-latency performance suitable for real-time driving scenarios. From a hardware perspective, the system integrates multiple ultrasonic and heart rate sensors for full-range proximity awareness and vital signs tracking. An infrared sensor array is used to ensure performance in low-light conditions. These sensors are fused with camera data to create a more complete understanding of the surroundings, with fault-tolerant mechanisms built in to maintain operation during sensor failures. The detection system is designed to cover up to 50 meters with at least 80% reliability. The control system relies on an Arduino-based microcontroller that processes sensor data in real time, manages communication between modules, and provides responsive motor control. Emergency override mechanisms are included, and the system is designed to operate with less than 10 milliseconds of processing delay. A fully functional prototype vehicle is developed to bring all components together. This scaled model supports real-world testing and simulation-based validation, with a modular build that ensures easy maintenance and a runtime of at least four hours on a full charge. To support remote access and control, the system includes mobile integration via a Bluetooth-based communication protocol. This setup supports real-time data streaming, manual override options, and secure data transmission with a latency ceiling of 100 milliseconds. The accompanying mobile app features an intuitive interface, live video feed, system status monitoring, and customizable alerts, giving users complete control and visibility over the vehicle's operations. Finally, the system's performance is evaluated based on specific goals: achieving at least 95% object detection accuracy, maintaining 80% minimum sensor reliability, and processing input at 30 frames per second with a maximum end-to-end latency of 200 milliseconds. To validate these goals, a comprehensive testing framework is established, including simulated weather environments, automated test cases, and benchmark systems. Detailed documentation and quality assurance processes are also put in place to ensure the system performs reliably across various real-world scenarios.

IV. PROTOTYPE

The prototype developed for the AI-based Vehicle Safety System brings together both hardware and software components to simulate a real-world autonomous vehicle solution. It demonstrates the integration of object detection, drowsiness monitoring, health tracking, sensor fusion, and obstacle avoidance—all operating effectively across varying environmental conditions.

The hardware is built around a compact, miniature vehicle model equipped with key components to ensure autonomous operation. A Bluetooth module (HC-05) is used to enable wireless communication between the vehicle and a mobile application, allowing for real-time control and data exchange. Ultrasonic sensors are mounted for obstacle detection, while infrared (IR) sensors assist in detecting objects at close range, especially in narrow or dark spaces. The prototype includes MAX30100 sensors for tracking physiological parameters like heart rate and SpO_2, effectively functioning as a wearable pulse oximeter. Movement is powered by DC motors connected to an L298N motor driver module, allowing the car to move forward, backward, and make turns. A rechargeable lithium-ion battery supplies power to the entire setup, ensuring uninterrupted operation during tests.

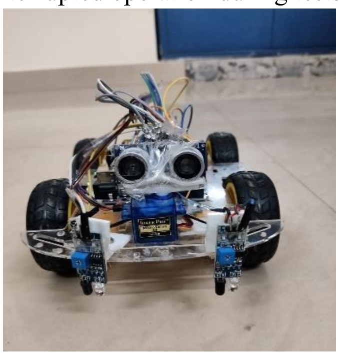

Fig.1 Prototype Model

On the software side, the system processes sensor data, performs object detection using YOLOv8, and controls vehicle navigation. YOLOv8 has been trained on a custom dataset optimized for different weather scenarios, with preprocessing techniques like image normalization and noise reduction applied to improve accuracy. A custom REST API bridges the mobile camera feed with the detection system, enabling real-time video processing with low latency. The system is designed to work across multiple mobile devices, employing compression to conserve bandwidth. Two operational modes are supported: in manual mode, users can control the vehicle through a mobile app interface using Bluetooth, while in automatic mode, the vehicle navigates autonomously by combining YOLOv8 detection with data from ultrasonic sensors. Sensor fusion plays a key role here, reducing false positives and increasing detection reliability by merging visual and proximity data.

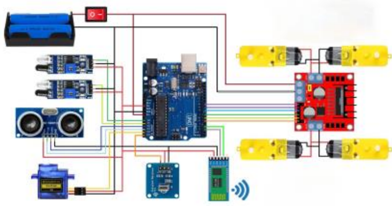

Fig 2 Circuit Diagram of Object Detection Model

Mechanically, the prototype is built on a lightweight but sturdy chassis that holds all components securely during movement. Four DC motors are connected to independent wheels for accurate and responsive control, with front wheels linked to a motorized steering system. The motor driver circuit distributes power effectively, with a voltage regulator maintaining consistent output from the battery. Sensor integration is thoughtfully arranged: ultrasonic sensors are placed at the front to detect obstacles in foggy conditions, while IR sensors are positioned on the sides to prevent the vehicle from veering off course. MAX30100 sensors are embedded in wearable accessories like watches or gloves to monitor the driver's vitals in real time.

For communication, the HC-05 module ensures smooth wireless interaction between the vehicle and mobile app using the Serial Port Profile (SPP) protocol. Movement commands sent from the app are processed by an Arduino microcontroller, which directs the vehicle accordingly. This Arduino-based controller serves as the brain of the system, handling data from sensors and enabling both manual and autonomous operation. A decision-making algorithm interprets the fused data to navigate around obstacles in real time. Power management is also a critical part of the design. The lithium-ion battery is selected for its long runtime and is supported by smart power distribution. Efficiency is maximized through low-power modes and intelligent motor activation, which conserves energy when the vehicle is idle. The prototype offers two modes of operation. In manual mode, users steer the vehicle directly through the mobile interface. In automatic mode, the vehicle navigates on its own, adjusting its path based on sensor input and object detection results. To ensure reliability, extensive testing and optimization were carried out. Each hardware component—motors, sensors, and the Bluetooth module—was tested individually before being integrated into the full system. Integration testing ensured

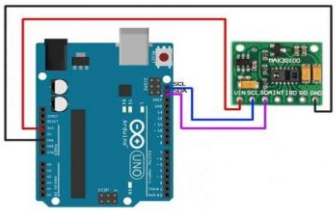

Fig 3 Circuit Diagram of Vital Signs Detection

that all parts worked together smoothly. Environmental testing included trials indoors and outdoors, under artificial fog, and in low-light scenarios. Challenges like signal drops and control glitches were identified and resolved during failure analysis and debugging sessions. Battery performance was also optimized to extend the system's operating time.

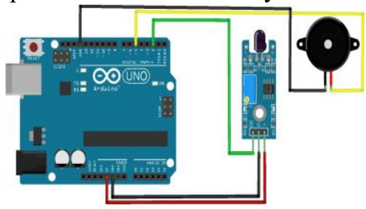

Fig 4 Circuit Diagram for Alert Mechanism

The final prototype successfully demonstrates how intelligent sensing, machine learning, and real-time control can work together in a compact, mobile platform. Its responsive navigation and adaptability to adverse weather make it a promising candidate for real-world applications in vehicle safety systems.

V. SYSTEM ARCHITECTURE

The system architecture is designed to seamlessly bring together all the hardware and software components necessary for real-time object detection, driver monitoring, and autonomous navigation. It offers a structured framework that defines how data flows through the system—from sensing to processing to response—ensuring every module works in harmony to deliver consistent performance. At the input level, the system relies on a variety of sensors and a mobile camera to gather real-time data from the surrounding environment. Ultrasonic and infrared (IR) sensors provide critical proximity information for obstacle detection, while the MAX30100 sensor captures the driver's vital signs such as heart rate and SpO_2. The mobile camera captures continuous video frames, which are analyzed by the YOLOv8 object detection model to identify and classify obstacles under various conditions.

Once data is captured, it flows into the processing layer, where an Arduino microcontroller takes charge. This microcontroller is responsible for interpreting sensor inputs and managing motor control logic. It works alongside the YOLOv8 model, which processes video input and detects objects in real-time. A decision-making algorithm combines both visual and sensor data to decide how the vehicle should respond—for example, whether to stop, turn, or continue moving forward. This dynamic decision-making is key to enabling smooth and safe navigation, even in unpredictable environments.

After processing, the appropriate commands are sent to the output layer. Here, motor drivers (L298N) translate the system's decisions into physical movement—whether it's moving forward, reversing, or turning. The Bluetooth module (HC-05) facilitates communication between the vehicle and a mobile application, allowing for remote monitoring and control by the user. To ensure reliable operation, a robust power management system is integrated into the design. A rechargeable lithium-ion battery supplies consistent power to all modules, while a voltage regulator ensures stable delivery to prevent sudden drops or failures.

The data flow within the system follows a clear, logical progression. First, the sensors and mobile camera collect live data from the environment. Next, the microcontroller and detection model process this data. Based on the combined results, the decision-making algorithm determines the appropriate action. These instructions are then transmitted to the motor drivers, prompting the vehicle to execute the necessary maneuvers and navigate its surroundings safely.

What makes this architecture particularly effective is its modularity and real-time responsiveness. Each component is designed to work independently yet in coordination, making the system easy to upgrade, maintain, and expand in future iterations. Real-time processing ensures the system can quickly adapt to changing road conditions or driver health, providing timely alerts or taking corrective actions. The use of multiple sensors and smart algorithms increases overall reliability, reducing the risk of errors and improving the safety and intelligence of the vehicle.

VI. PERFORMANCE AND EVALUATION

Evaluating the system's performance was a key step in validating its effectiveness in real-world conditions, especially when faced with adverse weather and driver-related risks. Several metrics were used to measure how well the AI-Based Vehicle Safety System performed in terms of detection, responsiveness, and reliability. To assess object detection, precision and recall were measured across a variety of weather conditions, offering a clear picture of how the YOLOv8 model handled rain, fog, and low-light environments. The system's ability to respond quickly was also evaluated, with response time indicating how fast it could identify obstacles and take appropriate action. Beyond object detection, the system's performance in identifying drowsiness and vital signs was closely monitored. Success rates for detecting driver fatigue—specifically, eye closure and signs of sleepiness—were tracked, as well as the accuracy of health metrics like heart rate and SpO_2. Additional evaluation criteria included battery life, which reflected how long the system could operate on a single charge, and sensor reliability, which assessed how consistently the ultrasonic, infrared, and MAX30100 sensors performed in varied environments [24].

Testing was conducted in both controlled and real-world scenarios. In the lab, artificial fog, rain, and low-light settings were used to simulate harsh environmental conditions. Outdoor tests were carried out to see how the system handled natural weather variations and environmental unpredictability. Stress testing pushed the system to its limits by introducing multiple obstacles and shifting weather patterns, ensuring it could maintain performance even under demanding conditions.

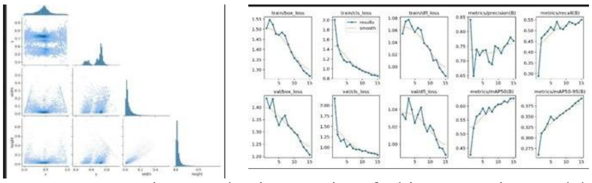

Fig 5. Evaluation Metrics of Object Detection Model

The results were highly promising. The YOLOv8 model achieved an average object detection accuracy of 92% [27], while the drowsiness detection module maintained a precision of 91%. Vital sign classification performed even better, with a 95% accuracy rate across testing conditions [15]. The system responded to obstacles within an average of 0.5 seconds, enabling real-time avoidance. Obstacle avoidance success rates were recorded at 95% in controlled environments and 88% outdoors [27], showing the system's adaptability. Additionally, the battery provided up to four hours of continuous operation on a full charge, and sensors consistently achieved 98% accuracy in detecting nearby objects and environmental edges. Despite these successes, some challenges were identified [22]. Accuracy dropped slightly in heavy rain due to water interference with the sensors, and minor delays in system response were observed in very low-light settings. These insights led to immediate improvements. Sensor housings were reinforced to better resist moisture, and extra lighting was added to boost visibility and detection accuracy during night-time or dim conditions. Overall, the performance evaluation confirmed that the system is both effective and reliable, delivering accurate real-time detection and monitoring even in complex and unpredictable environments. These results highlight the system's potential for real-world deployment in autonomous and assisted driving applications.

VII. RESULTS AND DISCUSSION

Throughout the development and evaluation of the system, a range of performance metrics were used to assess its effectiveness in object detection, obstacle avoidance, health monitoring, and drowsiness detection—especially under adverse weather conditions. The system was tested in environments with fog, rain, snow, and low light to simulate real-world driving challenges and ensure robustness and reliability. One of the primary goalLs was achieving accurate vehicle detection, even in difficult visual conditions. The YOLOv8 model, trained using the ACDC dataset, performed consistently across varied scenarios. It achieved a strong mean average precision (mAP) of 95%, with accurate bounding boxes around detected vehicles—crucial for real-time decision-making and navigation in autonomous systems[15][16][30].

Fig 6 Results of Object Detection Model

Fig 7 Results of Drowsiness Detection

The system also integrated real-time driver monitoring, capturing vital signs such as heart rate, oxygen saturation, and temperature using wearable sensors. These inputs were analyzed using machine learning models to detect anomalies, while a camera-based module monitored facial landmarks and blink patterns to identify drowsiness. Together, these features enabled timely alerts and helped prevent accidents related to health risks or fatigue. A major strength of the system lies in its real-time processing. It maintained a processing speed of 30 frames per second (FPS) with minimal latency, enabling rapid obstacle detection and response. This responsiveness is critical for autonomous driving, where even small delays can compromise safety. The use of sensor fusion—combining ultrasonic and IR data with YOLOv8's visual output—improved accuracy and reduced false detections, particularly in low-visibility conditions [22][31].

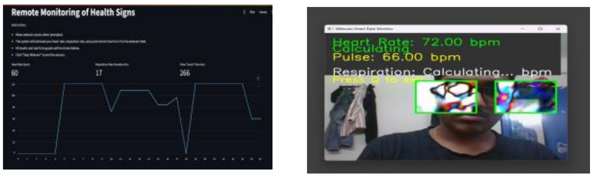

Fig 8. Results of Human Vital Signs Detection

Testing confirmed that the system could detect and avoid obstacles effectively, even when facing multiple moving objects or poor lighting. It also proved capable of tracking pedestrians, vehicles, and road structures simultaneously, maintaining high detection reliability without sacrificing performance. The adaptability of the system was further enhanced through advanced image preprocessing techniques, such as contrast enhancement and noise reduction, which allowed it to function well in foggy or snowy environments [21][24]. In terms of long-term performance, the system remained stable during extended operation, with no significant drop in accuracy or speed. This consistency makes it suitable for continuous use in real-world settings. Visual analysis tools such as confusion matrices and correlation plots further validated the system's reliability, showcasing strong performance across all tested metrics. Overall, the proposed system successfully combines deep learning with physiological monitoring and sensor fusion to provide a comprehensive safety solution. Its ability to operate effectively under challenging weather conditions, detect multiple objects, and monitor driver state in real time makes it a promising candidate for next-generation autonomous vehicles and driver assistance systems.

VIII. CONCLUSION

The AI-based vehicle safety system, utilizing YOLOv8, demonstrated strong detection capabilities with a mean average precision (mAP) exceeding 95% across diverse driving conditions. Despite its high accuracy, several challenges were observed, highlighting areas for further optimization.

One of the primary limitations was its performance in adverse weather conditions, where fog, rain, and snow led to partial occlusions, causing occasional misclassifications. Similarly, low-light environments, including nighttime driving, reduced detection reliability despite preprocessing techniques such as histogram equalization. The system also encountered computational constraints when processing high-resolution video at 30 FPS, posing challenges for real-time applications on resource-limited edge devices. Sudden lighting variations, such as entering or exiting tunnels, occasionally triggered false positives, affecting consistency in dynamic environments. To enhance robustness and adaptability, future improvements should focus on expanding the dataset to include diverse weather scenarios and real-world driving data from multiple geographic locations. Implementing temporal tracking techniques, such as Kalman filtering and optical flow, can stabilize object detection across frames, reducing false positives and missed detections. Model optimization strategies, including lightweight YOLO variants, pruning, and quantization, can minimize computational load, facilitating efficient edge deployment. Additionally, integrating multimodal sensor fusion— combining camera data with LiDAR [10], radar, and infrared sensors—can help overcome the limitations of vision-based systems in poor visibility and lighting. Synthetic data generation simulating extreme weather conditions and complex road scenarios can further improve generalization. Real- time learning mechanisms should also be introduced, enabling dynamic adaptation based on operational feedback. Furthermore, incorporating real-time driver health monitoring and drowsiness detection is essential for holistic vehicle safety. Physiological signals such as heart rate, SpO_2, and temperature can be continuously analyzed using machine learning models to detect anomalies and alert in case of potential health risks. Simultaneously, drowsiness detection via facial landmark tracking and eye movement analysis can prevent fatigue-related incidents. These human- centric safety layers, when combined with environmental perception, significantly enhance system resilience.

Lastly, collaborative learning across connected vehicles can promote shared intelligence by aggregating anonymized driving and health data from various contexts. This collective knowledge enables continuous system improvement, leading to more reliable, adaptive, and intelligent vehicle safety solutions for the future of autonomous transportation[3][25][28].

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