Lumina Alert: A YOLOv11n-Based Embedded System for Real-Time Driver Drowsiness Detection and Multi-Modal Intervention

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Abstract: Driver fatigue accounts for approximately 10–20% of road accidents worldwide. This paper presents Lumina Alert, an AI-based in-vehicle driver drowsiness detection and intervention system deployed on a Toyota Avanza (2007). The system is implemented on a Jetson Orin Nano and uses a YOLOv11n-based facial monitoring model to detect drowsiness indicators such as eye closure and yawning. Upon detection, the system applies multi-modal interventions including auditory alerts, voice prompts, and ignition lockout. Experimental results show an overall detection accuracy of 93.1%, with performance exceeding 90% under occlusion conditions involving sunglasses and eyeglasses. The ignition lockout mechanism successfully prevented vehicle startup in 95% of drowsy cases, while auditory and voice alerts effectively refocused drivers in 92% of trials. The system achieved over 90% reliability in both daytime and nighttime conditions with a minimum response time of 7 ms, enabling real-time operation.

Keywords: *Driver Drowsiness Detection; YOLO-Based Facial Monitoring; Embedded AI Systems; Ignition Lockout; Automated Interventions; Intelligent Vehicle Safety.*

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I. INTRODUCTION

Road safety remains a global issue—with driver drowsiness identified as a major but frequently overlooked factor in traffic collisions, contributing to an estimated 10–20% of road crashes worldwide [1]. This condition can cause microsleeps—brief, involuntary naps—that increase the risk of severe crashes or loss of vehicle control [2].

Several countries have implemented regulatory measures to counter drowsiness-related accidents. In the United States of America, Hours of Service (HOS) regulations limit daily and weekly driving hours, mandate breaks, and require Electronic Logging Devices (ELDs) in commercial vehicles, alongside drowsiness awareness programs. The European Union similarly limits truck driving hours, while Australia enforces the Heavy Vehicle National Law (HVNL) and provides Basic, Standard, and Advanced drowsiness management systems for risk-based flexibility [3].

In the Philippines, the Department of Science and Technology (DOST) launched the National Artificial Intelligence Strategy (NAIS-PH) to promote AI in transportation, including driver monitoring and road safety [4]. Metro Manila Accident Reporting and Analysis System (MMARAS) links early morning accidents to drowsiness [5]. The Land Transportation Office (LTO) highlights its effects on reaction time and decision-making [6]. The Department of Transportation (DOTr) reduced continuous driving hours for public utility drivers, required substitute drivers for longer trips, and mandated periodic drug testing [7]. Additional measures include mandatory road safety seminars for public transport drivers, reinforced by LTFRB regulations. Aligned with these, the Philippine Road Safety Action Plan (PRSAP) 2023–2028 aims to reduce fatalities by 35% via strategies targeting road safety management, safer roads, vehicles, users, and post-crash response [8]. Legally, drivers who fall asleep and cause harm may be held liable for reckless imprudence [9].

Despite regulatory measures, drowsiness-related accidents continue to occur. Reports indicate that sleepy driving contributes to crashes with serious injuries and fatalities [10]–[13]. Most incidents happen during late-night hours, and police records often underreport drowsiness due to

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lack of evidence. A survey of public transport drivers in Cavite City revealed frequent drowsy driving, reduced concentration and reaction time, and strong support for preventive technologies.

The AI-driven anti-drowsiness system provides benefits to public drivers as they receive timely alerts and interventions that help prevent accidents and improve road safety, fleet operates since they would experience reduced accidents and operational losses, and, lastly, the road safety authorities due to gaining behavioral data as a way of supporting monitoring and regulatory efforts. This study would also serve as a reference for researchers and developers in the field of AI-driven transport safety, supporting innovation and evidence-based solutions for drowsiness management.

AI-based solutions show high potential in road safety. Deep learning can detect drowsiness through eye closure and yawning [14]. Raspberry Pi cameras with OpenCV and sensors can trigger high-frequency sounds or physical alerts like vibrations upon detection [15]. Multi-sensory warnings, including AI-supported verbal interactions, have been shown to capture and retain driver attention [16]. Challenges include funding, accessibility, data privacy, and the need for non-intrusive, real-time systems that integrate active interventions.

This study focuses on prototyping and evaluation of the AI-driven anti-drowsiness system in a controlled environment using a Toyota Avanza 2007, selected for accessibility and suitability for embedded hardware prototyping. The system is implemented on a Jetson Orin Nano Super Developer Kit and employs YOLOv11n for real-time drowsiness detection. It delivers auditory, voice-based, and mechanical interventions, such as hazard light activation or engine shutdown via relay modules. A GSM module sends SMS alerts to registered supervisors through a web application, which collects basic vehicle and emergency contact information.

The system does not include long-term drowsiness history tracking, Bluetooth pairing, or driver authentication, prioritizing immediate safety functionality. All testing is conducted in a controlled environment to ensure repeatability and safety. Trials on public highways or large commercial vehicles are excluded due to resource and safety constraints.

II. RESEARCH METHODOLOGY

This study employed a developmental research design to evaluate the effectiveness of an AI-driven drowsiness detection and intervention system for drivers. The research was conducted at Saulog Transit Terminal in Salamanca, Cavite City, targeting public vehicle drivers. A purposive sampling technique was used to select 19 out of 20 full-time bus drivers (95% of the population) for surveys and post-development trials. The participants were chosen based on their regular driving schedules and direct exposure to long-duration driving, which made them suitable for evaluating the proposed drowsiness detection system.

➢ *Research Instruments*

The proposed system is an AI-driven in-vehicle driver drowsiness detection and intervention prototype implemented on a Jetson Orin Nano Super Developer Kit. A camera positioned along the driver's line of sight captures facial data, which are processed using a YOLOv11n-based deep learning model to detect drowsiness indicators such as prolonged eye closure and yawning. The model was trained on a custom dataset of approximately 14,000 annotated images across awake, drowsy, and yawning states, including occlusion variations to improve robustness. Once drowsiness is detected, the system deploys multi-modal interventions composed of auditory alerts, voice prompts, and ESP8266-controlled mechanical actions, including hazard light activation and ignition lockout during pre-drive conditions. A SIM800L GSM module transmits SMS alerts to registered contacts for supervisory notification. The prototype was installed in a Toyota Avanza (2007) to simulate a realistic in-vehicle deployment.

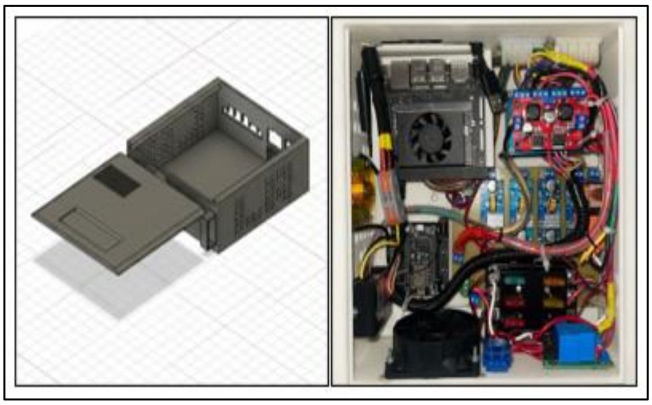

Fig 1 Lumina Alert Prototype
(a) External Casing Design, (b) Internal Components Showing Jetson Orin Nano, GSM Module, and Relay-Controlled Ignition Lockout.

Data were collected through technical system testing, including Detection Accuracy Test, Ignition Lockout Effectiveness Test, End-to-End System Reliability Test, Intervention Success Test, and System Latency Test. Tests were conducted in five trials each, following best practices in AI and embedded system evaluation [17]–[19].

Additionally, User Acceptance Testing (UAT) and Expert Evaluation were performed. UAT involved the same drivers rating the system's clarity, usability, and effectiveness, while experts assessed performance, reliability, functionality, safety compliance, and design using a 4-point Likert scale, guided by ISO/IEC 25010:2023 standards.

➢ *Data Gathering Procedure*

Data collection occurred in two phases. The initial survey was conducted at the terminal to establish baseline driver data. The post-development phase included controlled system testing, user trials, and expert evaluation. During trials, the prototype monitored drivers' facial states (awake, drowsy, yawning) and triggered alerts. Participants and experts subsequently provided structured feedback using Likert-scale evaluations.

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➢ *Data Analysis*

Quantitative data from surveys, system tests, and evaluations were analyzed using descriptive statistics, with mean scores computed for Likert-scale items to determine trends, system effectiveness, and user acceptance. Performance thresholds were defined for accuracy, intervention success, reliability, latency, and overall system output based on prior studies and AI evaluation benchmarks [20]–[24].

III. RESULTS AND DISCUSSION

This section evaluates the Lumina Alert system's performance in AI detection accuracy, reliability, intervention effectiveness, and real-time responsiveness. All evaluations were conducted under controlled conditions using a deployed prototype on a Toyota Avanza (2007).

A. AI Model Performance Assessment

The YOLOv11n-based facial monitoring model was trained to classify three driver states—awake, drowsy, and yawning. Table I summarizes the classification performance metrics.

Table 1 YOLOV11n Classification Performance Metrics

Metric	**Percentage (%)**
Accuracy	93.1%
Precision	97%
Recall	96.77%
F1-score	96.88%
mAP@0.5	82.85%

The model achieved 93.1% overall accuracy, indicating the proportion of total correct predictions out of all the test instances given the multiclass classification for accuracy [25].

The model attained a precision of 97% and a recall of 96.77%. Precision measures the proportion of the true positive detections among all positive predictions, while recall represents the model's ability in identifying all actual positive cases. The F1-score of 96.88% further reflects the balanced measure of the overall performance of the model from its precision and recall [26].

In addition to classification accuracy, it had a mean Average Precision at Intersection over Union 0.5 (mAP@0.5) of 82.85%. This evaluates its effectiveness in correctly localizing and classifying driver faces associated with drowsiness during real-time detection.

These results demonstrate robust detection capability with minimal false positives and false negatives, as well as strong generalization—suitable for embedded in-vehicle deployment.

B. Deployment Optimization and Inference Efficiency

The trained model was evaluated using both PyTorch (FP32) and TensorRT (INT8) formats. TensorRT INT8 optimization reduced inference latency from 19.2 ms (from PyTorch FP32 model) to 5.5 ms per frame, enabling stable 25 fps operation on Jetson Orin Nano. This supports that TensorRT is benchmarked to deliver performance for YOLO11 models on NVIDIA Jetson devices, making it ideal for real-time applications, where low latency and power efficiency are critical [27].

C. Detection Accuracy Under Real-World Conditions

Detection accuracy was evaluated under three conditions, achieving 100% accuracy under normal conditions and with eyeglasses, and 80% with sunglasses. Reduced sunglasses performance stems from eye-region obstructions, though yawning detection remained functional. The overall detection accuracy across conditions was 93.3%, indicating strong robustness against partial facial occlusions.

Table 2 Detection Accuracy Under Real-World Conditions

Condition	**Trials (n)**	**Percentage (%)**
Normal	5	100%
With Eyeglasses	5	100%
With Sunglasses	5	80%
Detection Accuracy	**15**	**93.3%**

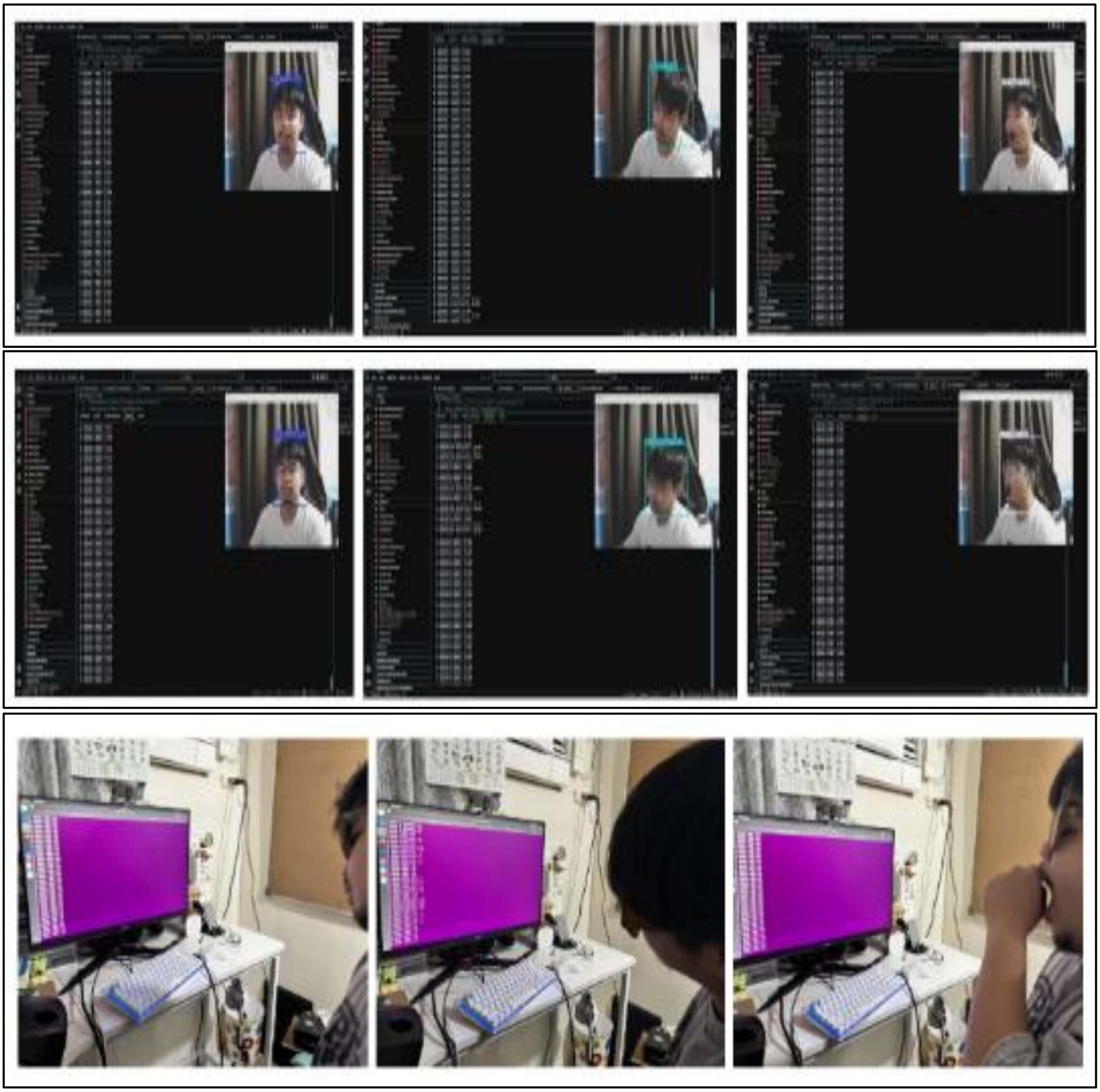

Fig 2 Detection Accuracy Test Under Different Conditions
(a) Normal Condition, (b) Wearing Eyeglasses, (c) Wearing Sunglasses.

D. Prototype Testing System Performance

➢ *Ignition Lockout Effectiveness*

This was evaluated during pre-drive conditions. The system achieved 80% effectiveness, correctly activating lockout in the majority of drowsy cases.

Table 3 Ignition Lockout Effectiveness Results

Metric	Value
Total Trials	5
Correct Lockout Activations	4
Incorrect Activations	1
Ignition Lockout Effectiveness	**80%**

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Fig 3 Ignition Lockout Effectiveness Test Inside the Vehicle

➢ *End-to-End System Reliability*

This assessed the complete operational workflow from drowsiness detection to intervention activation. Under daytime and nighttime trials, the system achieved 100% reliability within the controlled experimental trials (n=5), with consistent driver state identification and triggering appropriate intervention.

Table 4 End-to-End System Reliability Under Varying Light Conditions

Metric	Daytime	Nighttime
Total Trials (Static / Moving)	2 / 3	2 / 3
Correct System Responses	5	5
Incorrect System Responses	0	0
End-to-End System Reliability	**100%**	**100%**

Fig 4 End-to-End System Reliability Testing Setup
(a) Daytime Trial, (b) Nighttime Trial

➢ *Intervention Success*

This demonstrated a 100% trigger (or intervention success) rate for all interventions of the system—auditory alarms, voice prompts, hazard lights, and SMS alerts.

Table 5 Intervention Success Results

Metric	Value
Total Trials	5
Drowsiness Triggered	3
Correct System Responses	5
Incorrect System Responses	0
Intervention Success	**100%**

Fig 5 Intervention Success Testing Setup
(a) Drowsy Driver, (b) Awake Driver

➢ *System Latency*

This showed average detection-to-intervention latency of 7.74 ms (range: 7.0 ms–8.9 ms), ensuring immediate response critical for preventing microsleep-related accidents.

Table 6 System Latency Results

Trial	Detection and Intervention Time (ms)	Remarks
1	7.1	Very Fast
2	8.9	Very Fast
3	8.7	Very Fast
4	7.0	Very Fast
5	7.0	Very Fast
Summary	**7.74**	**Very Fast**

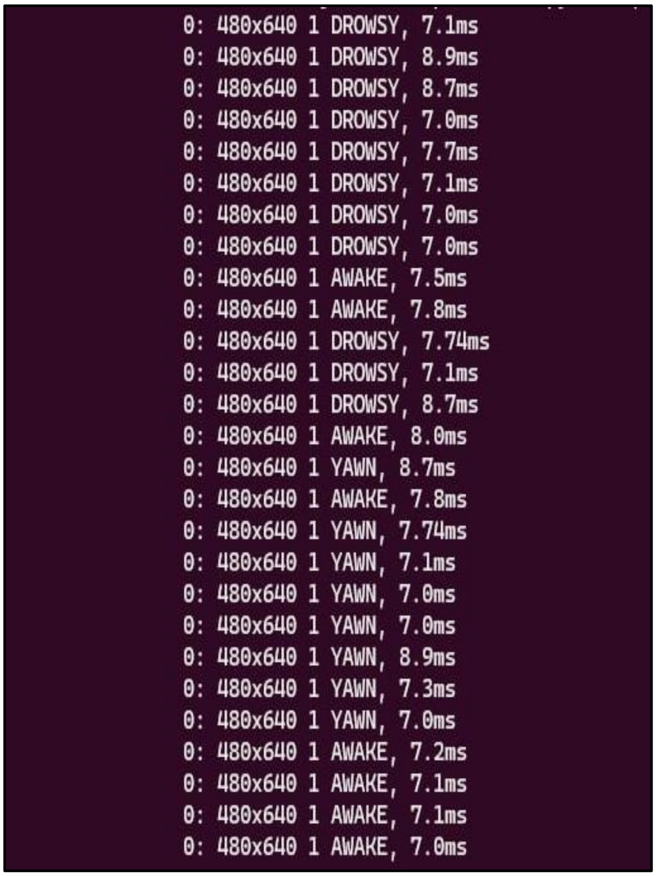

Fig 6 Detection-to-Intervention Latency Testing Setup (a) Computer Setup Monitoring Response Time in Milliseconds, (b) Intervention Activation Demonstrating Rapid Response Via Hazard Lights

E. User Acceptance Test

User Acceptance Testing indicated positive feedback (mean scores: 3.13–3.21, "Agree" level) for appearance, functionality, and usability. Drivers reported that alerts were clear, effective and non-distracting during operation. Expert evaluation based on ISO/IEC 25010:2020 quality standards rated detection accuracy, response time, reliability, and safety compliance at 3.50–4.00, validating technical robustness and practical sustainability.

Table 7 User Acceptance Testing Results

System Quality Attributes	**Mean**	**Interpretation**
Appearance	3.13	Agree
Functionality	3.21	Agree
Usability	3.21	Agree
User Acceptance	**3.18**	**Agree**

IV. CONCLUSION AND RECOMMENDATIONS

This study presented Lumina Alert, an AI-based driver drowsiness detection and intervention system designed for real-time in-vehicle deployment. Integrating a YOLOv11n deep learning model with embedded hardware and multi-modal safety mechanisms to detect early signs of drowsiness and deliver timely interventions.

The implemented model demonstrated strong classification performance, achieving 93.1% training accuracy with 97% precision, 96.77% recall, and 96.88% F1-score, and 93.3% real-world detection accuracy under partial occlusions, and varying lighting conditions (daytime and nighttime). TensorRT optimization enabled low-latency inference on Jetson Orin Nano, with 7.74 ms average response time, which satisfies real-time safety requirements.

Beyond detection accuracy, the system demonstrated 100% intervention success across multi-modal safety mechanisms through auditory alarms, voice prompts, hazard lights, SMS notifications, and pre-drive ignition lockout. End-to-end reliability testing confirmed seamless operation across all scenarios. User acceptance and expert evaluation validated system usability, safety compliance, and deployment readiness.

Future improvement should focus on expanding compatibility across different vehicle types and transmission systems, and integrating vehicle telemetry for adaptive intervention, incorporating additional physiological and behavioral indicators, enabling driver-specific alert personalization, optimizing hardware for cost and power efficiency, and conducting extended real-world validation across diverse conditions.

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