Driver Fatigue Detection And Warning Application

BOSCH CodeRace Challenge Round 1

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I. Topic Research

1. Business Context

Driver fatigue is widely recognized as a major hidden risk behind road accidents, causing thousands of serious injuries and significant economic losses every year. In Vietnam and worldwide, statistics show that 20– 25% of traffic accidents are related to drowsy or fatigued driving (WG-17 Transport Safety, 2023), often caused by long driving hours, poor sleep, medication, or health conditions.

Most modern cars are equipped with smart features, such as lanekeeping assistance or collision warnings. However, few systems are capable of detecting driver fatigue, a major contributor to accidents at night and long distances. Many drivers remain unaware of their fatigue levels until it is too late, yet affordable fatigue detection systems are still rare outside of premium vehicle models.

Bridging this gap is vital for protecting drivers, passengers, and other road users, as well as reducing the social and economic costs of preventable crashes.

2. Vision

Our vision is to develop a simple yet highly reliable driver fatigue detection and warning system that utilizes steering wheel angle (SWA) and yaw rate (YR)—two types of data already available in most modern vehicles. This approach avoids the need for additional expensive hardware or intrusive devices attached to the driver.

The system will be:

- **Affordable**: Designed for widespread adoption, even in older vehicles.
- **Non-intrusive**: Requires no physical contact with the driver.
- **Easy to install**: Seamlessly integrates with existing vehicle systems.

By providing early and clear warnings when signs of fatigue are detected, the system encourages drivers to take timely actions, such as pulling over to rest before accidents occur. This proactive approach can help prevent thousands of avoidable accidents, ultimately saving lives and reducing property damage and insurance claims.

In the long term, we envision this technology being integrated directly into new vehicles as part of advanced driver assistance systems (ADAS). In combination with features such as lane keeping, automatic emergency braking, and adaptive cruise control, it can contribute to a future in which no lives are lost due to drowsy driving.

3. Goals

To realize this vision, we aim to achieve the following practical goals:

- **Data Collection and Analysis:** Collect and analyze key driving behavior data, specifically SWA and YR. Research shows that subtle changes in steering control and vehicle turning dynamics are strong early indicators of driver fatigue.
- **Model Development:** Build a smart detection model using data analytics and machine learning techniques. This model will learn normal driving patterns and detect deviations that suggest fatigue or loss of attention.
- **Real-Time Alerting:** Design a real-time alert system that notifies the driver through sound, or vibration when fatigue is detected. The alert must come early enough for the driver to react safely.
- **Field Testing:** Conduct thorough testing in real-world conditions, covering various road types (urban, highway, long-haul) and a diverse set of drivers and vehicles. The system must perform reliably outside of lab environments, under real traffic scenarios.
- **System Integration:** Develop the system as a support feature that works with the vehicle's built-in human-machine interface (HMI) display. The solution should require no additional devices or complicated installation.

4. Market and Scientific Research

4.1. Market Research:

Brands like **Tesla** (Model 3, Model Y), **Volvo** (EX90, XC90), **BMW** (iX, 7 Series), and **Mercedes** (S-Class, EQS) have equipped premium models with in-cabin camera-based Driver Monitoring Systems (DMS). However, these solutions are:

- Expensive and mainly limited to high-end vehicles.
- Obstructed by the driver or interior objects.

Wearable devices such as headbands or smart glasses also exist, but are generally uncomfortable and impractical for widespread or long-term use.

The market clearly demands a cost-effective, non-intrusive solution that is compatible with existing vehicle infrastructure, can be easily installed in both new and older vehicles.

Many modern vehicles are already equipped with Advanced Driver Assistance Systems (ADAS) such as automatic lane keeping, adaptive cruise control, emergency braking. For example, the Toyota Corolla Cross model has lane tracing and dynamic radar cruise control features. Despite these advancements, there is currently no widely adopted solution that estimates or predicts the driver's condition using non-intrusive analysis of existing CAN (Controller Area Network) signals.

4.2. Scientific Research

Scientific studies have demonstrated that **steering wheel movements** and **yaw behavior** of a vehicle are reliable indicators of a driver's mental and physical state. When drivers become fatigued:

- Steering stability decreases
- Small corrective movements become more frequent and erratic
- Yaw rate — the way the vehicle turns and responds — shows noticeable deviations

These signals can be accurately captured through the vehicle's existing built-in sensors, eliminating the need for additional intrusive equipment [1, 2, 3].

In practice, many drivers are unaware of their fatigue levels or fail to react in time. Prior research [4, 5] shows that tired drivers exhibit distinct abnormalities in vehicle control behavior, such as increased fluctuation range, altered frequency and speed of SWA and YA, and consistent deviations from normal driving patterns.

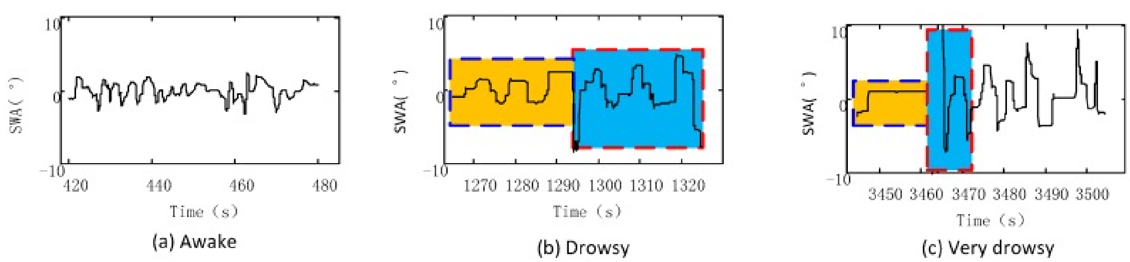


Figure 1

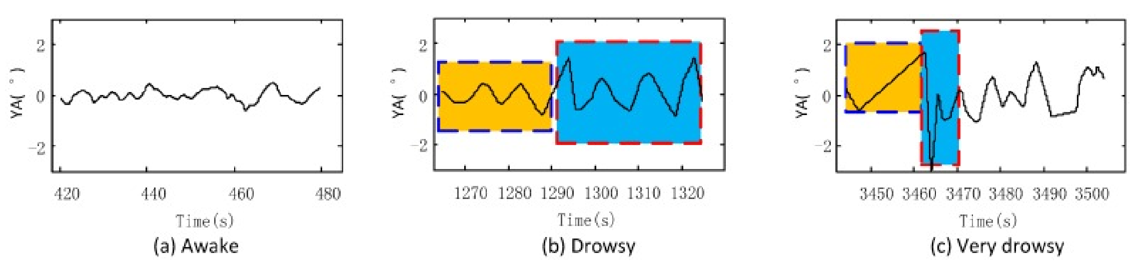


Figure 2

Waveforms in Figure 1 and Figure 2 are used to visually express how the driver's fatigue levels affect his operation features. Figure 1 shows the SWA waveforms at different fatigue levels, from which we can see that when the driver is sober, as shown in Figure 1a, he will modify the steering wheel angles frequently in a small range. When he is tired, as shown in Figure 1b, the frequency of modification is low, as indicated by the waveforms in the yellow block, while the modification amplitude becomes larger and velocity higher, indicated in the blue block. If the driver is severely tired, as shown in Figure 1c, steering wheel angles remain unchanged for a period of time, as indicated by the yellow block, followed by quick fluctuations with big amplitude, as indicated by the blue block [6].

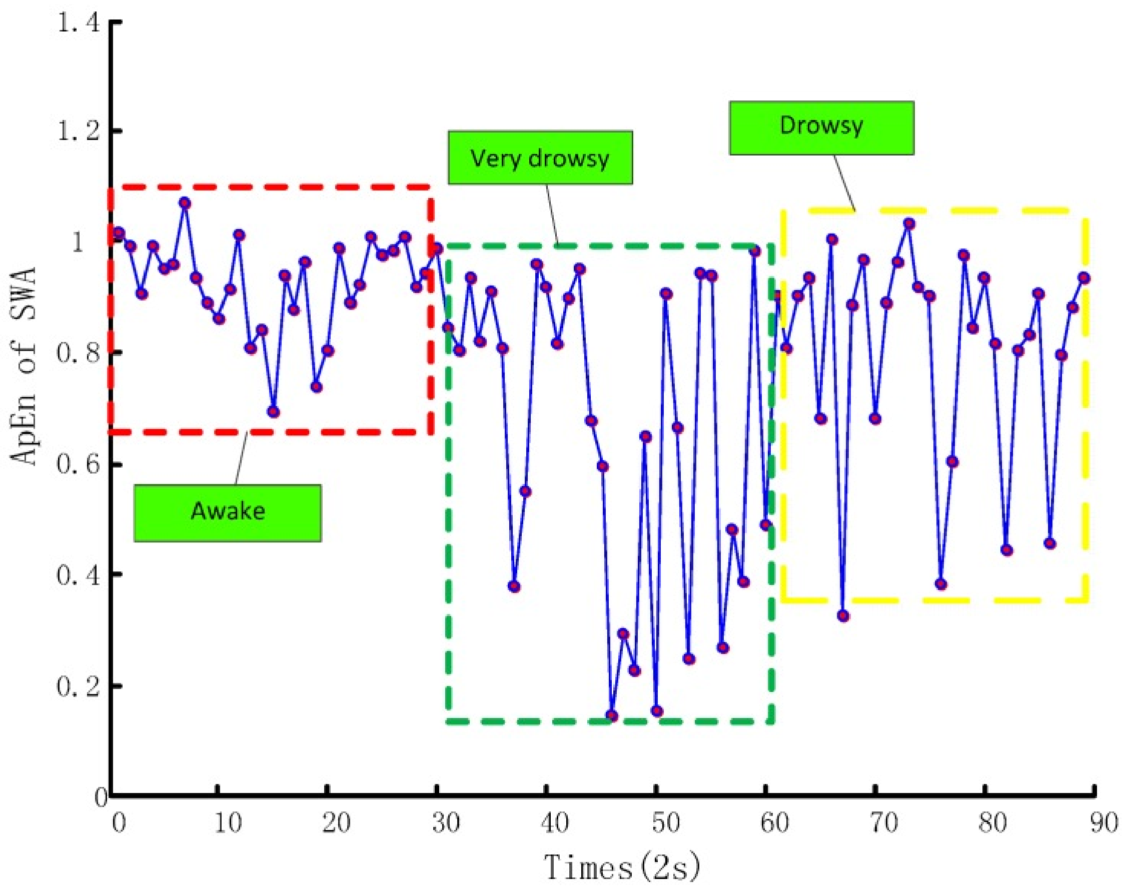


Figure 3

About the experiment results, Figure 3 and Figure 4 illustrate the ApEn distributions of SWA and YA time series (recorded every 2 seconds), showing clear differences when the driver is at distinct fatigue levels. This demonstrates that ApEn values of SWA and YA can effectively reflect the driver's operational behavior and help identify fatigue states. A three-level fatigue identification test in research achieved an accuracy of 88.02%. Data in the experiment were collected in real driving conditions, thus may be practical for our approach [6].

To summarize, the drivers' behaviors under fatigue can be reflected in identifiable patterns through the amplitude, velocity, and frequency of changes in the SWA and YA parameters. These findings provide a solid foundation for the development of an effective real-time driver

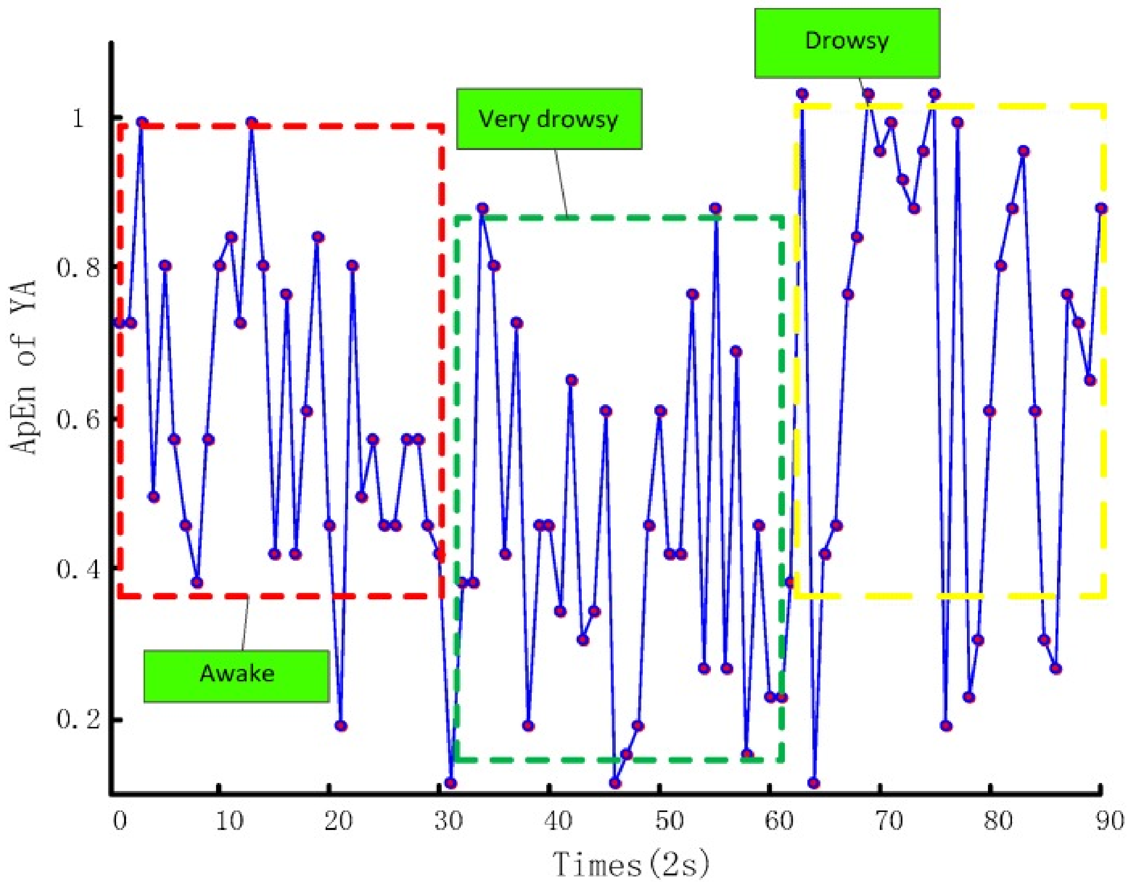


Figure 4

fatigue warning application.

II. Software Design

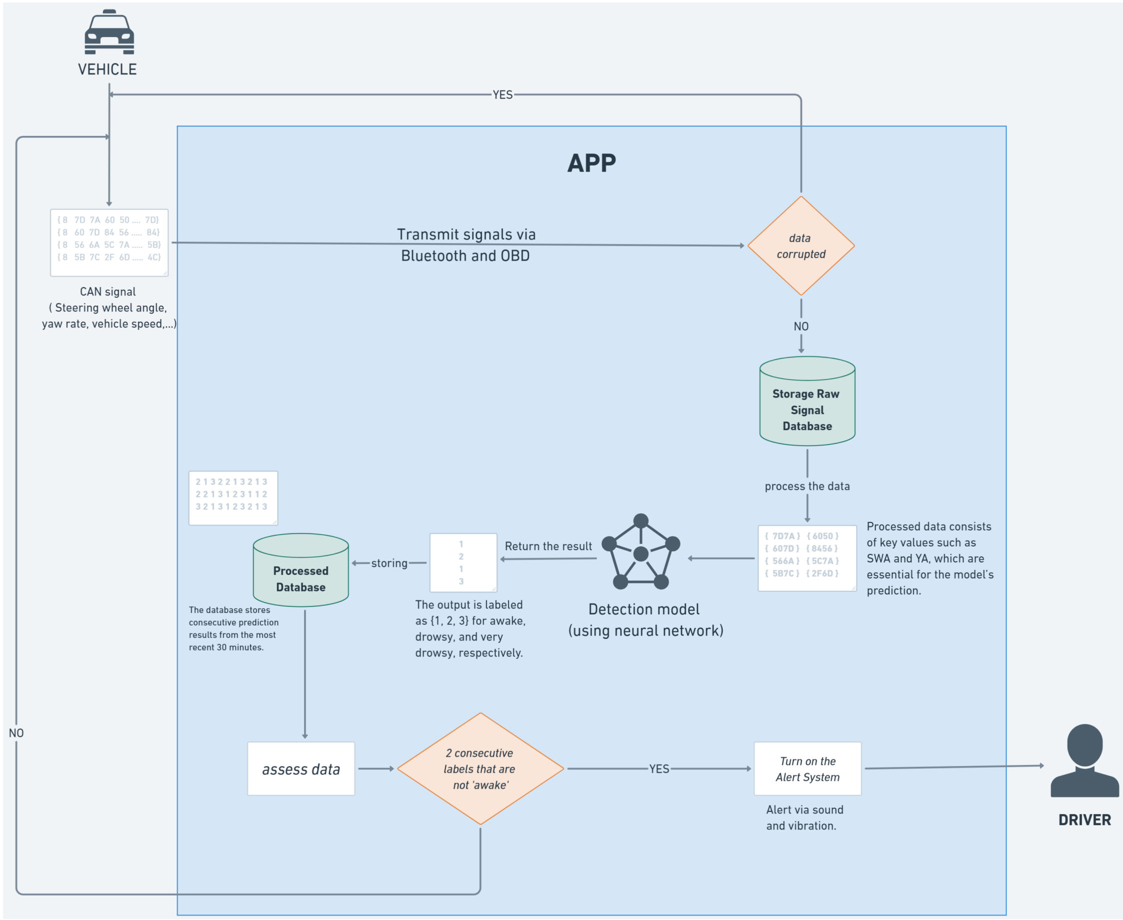
1. System Architecture Explanation

The proposed software system aims to detect driver drowsiness by analyzing real-time data retrieved from the vehicle's CAN. Key signals collected include YA, and vehicle speed, which are transmitted to a mobile application via Bluetooth or OBD interfaces.

Upon reception, the application conducts an initial data integrity check. If the data is found to be corrupted, it is immediately discarded to preserve system accuracy. Valid data is stored in the raw signal database for temporary retention and further processing. During preprocessing, relevant features—particularly SWA and YA—are extracted, as they are critical indicators of steering behavior and lateral dynamics associated with fatigue.

The processed data is then fed into a neural network-based detection model, which outputs a classification corresponding to the driver's alertness level: 1 for awake, 2 for drowsy, and 3 for very drowsy. These predictions are stored in the processed database, which maintains a sliding window of results over the most recent 30-minute period.

To determine whether the driver is at risk, the system continuously analyzes the stored



System Architecture for Driver Drowsiness Detection

outputs. If it detects two consecutive predictions indicating a non-awake state, the system automatically activates the alert system. The alert mechanism consists of auditory and vibrational feedback, such as sound from the phone's speaker and vibration signals, to prompt the driver to regain attention.

Overall, the architecture ensures that vehicle data is reliably collected, effectively analyzed, and acted upon in a timely manner to enhance road safety and reduce the risk of fatigue-related incidents.

2. Design Properties

The foundational principles of the development process:

- Scalability: the design accommodates potential future expansions, such as adding more sensors (e.g., heart rate or eye tracking), upgrading the detection algorithm, or integrating with cloud-based analytics.

- Portability: the application is built to run on standard smartphone platforms and supports data input via commonly available interfaces like Bluetooth or OBD-II adapters.

- Reliability: error handling is implemented at every stage—from corrupted signal detection to model confidence assessment—to ensure system stability and robustness.
- Security and Privacy: all collected data is stored temporarily, anonymized if necessary, and transmitted securely to prevent misuse or unauthorized access.

III. Algorithm Development

1. Sensors/ECUs in Use

- Steering Wheel Angle Sensor
- Yaw Rate Sensor

2. Data

a. Raw Data Example

```
CAN ID: 0x0CFF1234
Data:  00 FA 01 F4 01 00 00 5A
```

b. Data Breakdown (Bytes 0–3)

Byte	Description	Example Hex	Value	Notes
0–1	Steering Angle (°)	00 FA	0x00FA = 250 (signed)	SWA
2–3	Angular Speed (°/s)	01 F4	0x01F4 = 500 (unsigned)	YA

c. Convert Raw Data Example To Decimal

$$\mathrm{SWA} = \texttt{0x00FA} = 250^\circ$$
$$\mathrm{YA} = \texttt{0x01F4} = 500^\circ/\mathrm{s}$$

3. Algorithm Rationale

Driver behavior during vehicle operation is dynamic and non-linear. Under fatigue, response time and precision decrease, leading to measurable changes in the SWA and YA, such as:

- Reduced frequency
- Increased amplitude
- Greater variability

To quantify these behavioral patterns, the algorithm uses **Approximate Entropy (ApEn)**, a statistical measure of signal irregularity, to measure predictability in the time-series data.

- High ApEn: more variable and adaptive driving (sober state)

- Low ApEn: more repetitive and delayed actions (fatigued state)

ApEn is computed by reconstructing the data into vectors and analyzing how often similar patterns recur within a given tolerance.

These ApEn features are then input into a **Backpropagation Neural Network (BP-NN)**, trained on labeled data (manually, using facial video assessments) to detect fatigue levels: *awake*, *drowsy*, and *very drowsy*.

4. Algorithm Steps

4.1. Acquire Sensor Data

Collect raw time-series data from SWA sensor and YR sensor.

4.2. Feature Extraction [6]

a. Reconstruct time-series into vectors
From input as time series:

$$u(n) = [u(1), u(2), \ldots, u(N)]$$

Form m-dimensional vectors:

$$X(i) = [u(i), u(i+1), \ldots, u(i+m-1)]$$

Goal: captures local patterns in the signal using delay embedding.

b. Compute vector distances and count valid vectors
Distance metric:

$$d|X(i), X(j)| = \max_{1 \le k \le m} |u(i+k-1) - u(j+k-1)|$$

Count how many vectors $X(j)$ are within distance r:

$$B_i = \{j \mid d|X(i), X(j)| \le r\}$$

Then compute:

$$C_i^m(r) = \frac{B_i}{N-m+1}$$

Goal: measures how frequently patterns of length m repeat within tolerance r.

c. Calculate ApEn

$$\text{ApEn}(m, r, N) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \log C_i^m(r) - \frac{1}{N-m} \sum_{i=1}^{N-m} \log C_i^{m+1}(r)$$

Goal: quantifies the irregularity and unpredictability of the time series.

4.3. Classification Using Neural Network Model

a. Input Layer
Receives input feature vector $P = [\mathrm{ApEn}_{\mathrm{SWA}}, \mathrm{ApEn}_{\mathrm{YR}}]$.

b. Hidden Layers
Each neuron computes:

$$A^{(l)} = f\left(W^{(l)} A^{(l-1)} + B^{(l)}\right)$$

- $A^{(l)}$: Activation at layer l
- $W^{(l)}$: Weight matrix
- $B^{(l)}$: Bias vector
- f: Activation function (e.g., tanh, ReLU)

c. Output Layer
Generates a 3-element vector of class probabilities:

$$[O_{\text{awake}}, O_{\text{drowsy}}, O_{\text{very drowsy}}]$$

Computed softmax function:

$$O_k = \frac{e^{z_k}}{\sum_{j=1}^{3} e^{z_j}}, \quad k = 1, 2, 3$$

d. Prediction
Choose the fatigue level corresponding to the maximum value in $[O_k]$.

5. Technical Evaluation Metrics

5.1. Detection Reliability

a. Accuracy, Precision, Recall, and F1-Score
Evaluate how well the model distinguishes between different fatigue levels by analyzing standard classification metrics.

b. False Positive and False Negative Rates
Minimize false positives to reduce unnecessary warnings, and minimize false negatives to maintain safety.

5.2. Performance

a. Computational Efficiency
Ensure the system operates within the constraints of embedded automotive hardware, use moderate resource.

b. Real-Time Capability
Process input data and generate fatigue predictions with minimal delay.

5.3. User-Centric Evaluation

a. Driver Feedback

Collect driver perceptions of usefulness and satisfaction through surveys or interviews.

b. Behavior Analysis

Track changes in driving habits (increased rest breaks after alerts, etc.) to evaluate behavioral impact of fatigue warnings.

c. Incident Reduction

Perform long-term testing to observe reduction in fatigue-related driving incidents.

6. Considerations

6.1. Latency Constraints

Approximate Entropy (ApEn) is computationally intensive, especially with high-frequency data. Program may be in need of further optimization for ApEn computation.

6.2. Over-Warning Risk

Excessive sensitivity may lead to frequent or false alerts, potentially causing irritation or distrust of drivers.

6.3. Environmental and Road Condition Adaptability

The application need further data of variations in lighting, weather, road types, and vehicle dynamics to maintain detection reliability under diverse real-world conditions.

6.4. Fail-Safe Mechanisms

Include safeguards for handling sensor failures, low-quality data, or uncertain model predictions to prevent erroneous warnings or system behavior.

6.5. Need for Diverse Labeled Data

High-quality, expert-labeled datasets are essential for model training and validation.

References

[1] Wang, J.Q., Zhang, L., & Zhang, D.Z. (2013). An adaptive longitudinal driving assistance system based on driver characteristics. *IEEE Transactions on Intelligent Transportation Systems*, **14**, 1–12.

[2] Sahayadhas, A., Sundaraj, K., & Murugappan, M. (2012). Detecting driver drowsiness based on sensors: A review. *Sensors*, **12**, 16937–16953.

[3] Wang, J.Q., Li, S.E., & Zhang, Y. (2015). Longitudinal collision mitigation via coordinated braking of multiple vehicles using model predictive control. *Integrated Computer-Aided Engineering*, **22**, 171–185.

[4] Zhang, X., Cheng, B., & Feng, R. (2010). Real-time detection of driver drowsiness based on steering performance. *Journal of Tsinghua University*, **7**, 1072–1076.

[5] Qu, X., Cheng, B., Lin, Q., & Li, S. (2013). Drowsy driving detection based on driver's steering operation characteristics. *Automotive Engineering*, **35**, 288–291.

[6] Awais, M., Badruddin, N., & Drieberg, M. (2017). A hybrid approach to detect driver drowsiness utilizing physiological signals with steering wheel movement. *Sensors*, **17**(12), 2874.

Work Package	Note	Members	Start Date	Due Date	
Brainstone ideas	- List potential ideas - Analyze practicality of ideas - Finalize the team's topic	ALL	27-Thg6	27-Thg6	ROUND 1
Topic Research	- Define context, vision, and goals - Research market landscape and related scientific studies	Trọng	28-Jun	29-Jun	
Software Design	- Research and design overall system architecture (diagram) - Define data flow from input signals to prediction to alert output	Trà	28-Jun	29/06 AM	
Algorithm Development	- Research and develop core algorithm logic - Choose appropriate ML methods for SWA + YR - Draft model workflow	Uyên	28-Jun	29/06 AM	
Create PPT slides	- Organize research, design, and algorithm into slides	Trọng	29-Jun	29-Jun	
Presenstation	- Script, record	Uyên	29-Jun	30-Jun	
Edit video	- Compile recorded clips - Add visuals, graphics, and subtitles if needed - Finalize within time limit (≤ 3 mins)	Trà	30-Jun	30-Jun	
Submission	- Final check of all deliverables (PPT, video, documents)	Uyên	30-Jun	30/06, 08:00 AM	
Data Collection	- Collect CAN signal data: SWA, YR, Speed, Pedals, etc. - Store raw data in organized format (CSV/Database)	Trọng, Trà	5-Jul	7-Jul	ROUND 2
Data Pre-processing & Labeling	- Clean and filter noise signals - Label data with driver states (awake, drowsy, very drowsy) - Perform sample validation	Trọng, Trà	7-Jul	9-Jul	
Model Development	- Code core ML model - Train initial prediction model - Evaluate model	Uyên	9-Jul	11-Jul	
Model Testing & Validation	- Test model on separate test sets - Monitor overfitting or underfitting - Adjust hyperparameters to optimize performance	ALL	11-Jul	15-Jul	
Basic Software Integration	- Build a simple user interface (HMI dashboard mockup) - Connect model to UI - Implement alert mechanisms (vibration/audio) - Set up a basic database for session logs	ALL	15-Jul	20-Jul	
Full System Testing	- Test entire workflow: real CAN input → model → alerts - Run stress tests for real-time performance - Identify and fix bugs or crashes	Trà, Trọng	20-Thg7	26-Thg7	ROUND 3
PRESENTATION	- Prepare for presentation	Uyên	27-Thg7	28-Thg7	