SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V11I11P112

Volume 11 Issue 11, 114-121, November 2024


*Original Article*

# Drowsiness Detection System in Drivers Using Micro-Maneuvers on the Steering Wheel and Machine Learning to Prevent Nighttime Traffic Accidents

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Received: 07 September 2024 Revised: 08 October 2024 Accepted: 06 November 2024 Published: 30 November 2024

***Abstract*** *- Traditional techniques to identify drowsiness, such as physiological sensors and camera-based eye tracking, often encounter difficulties in practice due to their intrusiveness, cost and vulnerability to other influences. This paper presents a novel non-invasive sleep detection system that accurately detects driver sleep indicators by combining machine learning approaches with driving micro-maneuvers. This method uses high-precision turning data obtained from sensors embedded in the vehicle's steering wheel. The system uses this data to extract characteristics related to driver drowsiness, relating small variations in the turning of the steering wheel, which, depending on whether they are present or not, determine the driver's state and classify it as "alert" or "drowsy" thanks to the use of sophisticated autonomic learning techniques, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). In order to validate the system, several tests were performed in controlled scenarios, with various drivers with different states of drowsiness previously verified. The tests showed that the proposed system obtained an overall accuracy rate of more than 92%, which allows it to be used in real scenarios without discomfort to the driver as it is a non-invasive measurement technique.*

***Keywords*** *- Drowsiness detection system, Micro-maneuvers on the Steering wheel, Machine Learning, SVM, CNN.*

## 1. Introduction

One of the main causes of road accidents worldwide, especially at night, is driver drowsiness. World Health Organization (WHO), in the Global Status Report on Road Safety 2023, shows that the number of annual deaths from road accidents has been 1.19 million. Additionally, among children and young adults aged 5 to 29, traffic-related injuries continue to be the primary cause of death. They end by saying that if the global target of cutting road traffic fatalities and injuries by at least half by 2030 is to be met, then immediate action is required [1]. These figures highlight the importance of effective real-time technologies that can identify and reduce driver fatigue. Current drowsiness detection systems primarily monitor three physiological signals: Electroencephalography (EEG), blink rate and eye movements. To measure the level of tiredness, for example, camera-based devices record head movements and eye closure [2, 3]. Although these techniques can be accurate, real problems often arise, such as discomfort and invasion of the driver's privacy.

Methods based on EEG measurements or analysis of the driver's head movement by means of cameras inside the vehicle cabin are very accurate in determining the driver's drowsiness state. Unfortunately, they are uncomfortable and invasive and are also limited by specific conditions such as lighting, so they are not practical for real scenarios [4]. Recent studies have investigated non-intrusive methods that do not necessitate direct physiological signal monitoring in response to these restrictions. Analyzing driver behavior using vehicle control inputs, including steering wheel movements, is one method that shows promise. Research has demonstrated that fatigue impacts motor function, resulting in discernible trends in driving behavior [5, 6]. Drivers make these patterns, often known as micro-maneuvers, involuntarily and subtly to maintain vehicle stability and lane position.

This paper presents a novel non-invasive sleep detection system that accurately detects driver sleep indicators by combining machine learning approaches with driving micro-maneuvers. This method uses high-precision turning data obtained from sensors embedded in the vehicle's steering wheel. The system uses this data to extract characteristics related to driver drowsiness, relating small variations in the turning of the steering wheel, which, depending on whether they are present or not, determine the driver's state and classify it as "alert" or "drowsy" thanks to the use of sophisticated autonomic learning techniques, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN).

The rest of the document is structured as follows: Section 2 presents the works related to the research. Section 3 presents the methodology used to perform the data acquisition. Section 4 presents the experimental development used for the classification of sleepiness. Section 5 shows the results obtained and their respective discussion. Finally, Section 6 contains the conclusions and the projection of future work.

## 2. Related Works

Due to the crucial role of driver fatigue in traffic accidents, drowsiness detection systems have been the subject of intense research. Three main categories compose the conventional techniques for identifying driver drowsiness: physiological signal monitoring, behavioral analysis, and vehicle-based metrics [2]. Measuring biological signals such as brain activity, heart rate, and eye movements is part of physiological signal monitoring. In this category, Electroencephalography (EEG) is a commonly used method because it directly measures brain activity related to various states of alertness [7]. However, these methods using EEG systems are uncomfortable and invasive for drivers, which precludes their daily use [8]. In addition, other methods, such as Heart Rate Variability (HRV) monitoring and Electrocardiography (ECG), have the same problem of being invasive, resulting in their low acceptance by drivers [9].

Another way of knowing the state of driver drowsiness is through behavioral analysis, which looks for external indicators of fatigue, such as head nodding, yawning and closed eyes. Among the most researched technologies in this category are camera-based systems that monitor blink rate and eye movements. In controlled environments, the paper by Zhao et al. designed a system that monitors eyelid movements using infrared cameras with high accuracy [10]. However, the effectiveness of these devices in practical situations may be limited by external lighting conditions and obstacles [11]. To increase the robustness of detection, Pup and Atzori investigated the use of head position and facial expressions as indicators of fatigue and thus achieved considerable improvement in detection accuracy [12].

Vehicle-based metrics are another method used to determine the state of driver drowsiness, which examines how the driver interacts with the car, including how he or she steers, deviates from the intended lane or accelerates. Research has indicated that drowsiness impacts vehicle handling, which can be affected by moving the steering wheel. In similar research, Chowdhury et al. examined a range of vehicle-based metrics and emphasized how they may be used to identify tiredness in real-time without requiring extra sensors [13]. In another paper, they analyzed, with specialized sensors, the vehicle's behaviour with respect to the lines painted on the side of the track and thus determined the driver's state; however, this method is very limited to tracks with lines on the tracks [14].

It was shown by Kim et al. [15] that steering performance might be utilized as a non-intrusive way to detect tiredness in drivers by tracking their level of attentiveness. This recent technique for tracking driver fatigue using micro-maneuvers on the steering wheel qualifies as non-intrusive. The little, frequently unconsciously made corrections drivers make to keep their cars stable are called micro-maneuvers. These little motions can indicate adjustments in motor function related to weariness.

In the article, Awais et al. used machine learning techniques to examine patterns in the steering wheel data, and they studied the use of the data to identify drowsiness [16]. Their findings suggested that micro-maneuvers made with the steering wheel could serve as a trustworthy gauge of tiredness and serve as a foundation for additional study.

Currently, there has been a growing interest in applying the methods described in this section to improve drowsiness detection systems due to the progress made in the field of machine learning. Machine learning methods are useful for identifying small indicators of drowsiness because they can examine intricate patterns in large data sets. In the paper by Fouad et al., drowsiness states were classified using fuzzy entropy measurements of EEG signals together with Support Vector Machines (SVM), with encouraging findings [17].

In the Almiron et al. paper, a system capable of determining the driver state was designed using fuzzy logic and EEG sensors to measure alpha brain waves [9]. Convolutional Neural Networks (CNN) were used by Florez et al. to interpret video data of driver faces to build a drowsiness detection system that demonstrated good accuracy in a variety of scenarios [18].

## 3. Methodology

The proposed drowsiness detection system leverages micro-maneuvers on the steering wheel combined with machine learning algorithms to accurately identify signs of driver fatigue. The complete system can be seen in Figure 1.

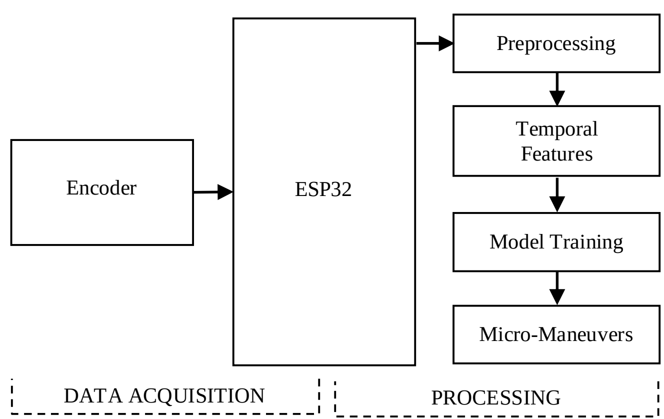



**Fig. 1 System flow diagram**

The proposed drowsiness detection system consists of two stages:

- Data Acquisition: In this stage, an encoder is in charge of sending to the ESP32 microcontroller the steering wheel rotation angles of the vehicle.
- Processing: The ESP32 microcontroller receives the data from the steering wheel rotation and processes it to determine the driver's state, whether the driver is awake or drowsy, by means of the stages:
  - Preprocessing: Preprocessing the angle signal captured by the encoder is essential to ensure the accuracy of the subsequent analysis. In addition, the signal is segmented into time intervals or "windows", which allows specific time periods to be analyzed and facilitates the identification of subtle changes in driver behavior.
  - Temporal Feature: Temporal features that capture the fluctuations of the angle signal in each time interval are recovered to identify driver fatigue. The frequency of steering wheel micro-corrections and angular variability are among the examined parameters. These measurements enable us to see patterns in the micro-maneuvers.
  - Model Training: Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) are two machine learning models used to categorize the retrieved features and identify the drowsiness state, respectively.
  - Micro-maneuvers: Steering wheel micro-maneuver detection is a critical system component, as these small corrections reflect the driver's attention and control over the vehicle. The system uses the given models to analyze the temporal features in each time window to identify the presence or absence of micro-maneuvers.

### *3.1. Participants*

A diverse group of 10 drivers, with varied on-road truck driving experience and ranging in age from 35 to 55 years (45 ± 6 years), was recruited. Participants were instructed to drive a test vehicle equipped with the proposed system to collect data under controlled, low-light nighttime conditions.

### *3.2. Equipment*

The test vehicle was equipped with high-resolution sensors integrated into the steering wheel to capture precise steering data. The encoder sensor recorded the steering wheel turning angle, allowing the driver's micro-maneuvers to be stored. A camera installed inside the cab allowed manual recording of a drowsiness event, information used to train the system and test accuracy. Figure 2 shows the truck where the tests were performed to validate this system.

### *3.3. Protocol*

The driving sessions were conducted on a closed test track to ensure safety. Each session lasted approximately 2 hours, during which drivers were subjected to monotonic driving conditions designed to induce drowsiness. Periodic breaks were provided to prevent extreme fatigue. Drivers' states were continuously monitored, and data was labeled as "alert" or "drowsy" based on visual inspection and participant self-reports.

**Fig. 2 Test vehicle**

## 4. Experimental Development

A prototype system was designed with the necessary hardware to record micro-manoeuvres of the steering wheel and the necessary software to process and analyze the data in real time to ensure accurate drowsiness detection. The design of the prototype was centered on selecting the appropriate components and implementing machine learning and processing algorithms that would function effectively in a moving vehicle.

### *4.1. Hardware Selection*

The process of selecting hardware for the driver sleepiness detection system was crucial. It required a careful assessment of many components to meet specific requirements for accuracy, dependability, and real-time operation in an automobile setting. The steering angle sensor, crucial for identifying minute motions in the steering wheel, was the first important part chosen. The AMT102-V series optical encoder, which has a resolution of up to 2048 pulses per rotation, was employed. The reason this particular sensor was selected is that it can record incredibly faint steering wheel movements, which is essential for seeing early indicators of fatigue.

Furthermore, optical encoders, like the AMT102-V, are not prone to mechanical deterioration or environmental interferences like dust or moisture, which are frequent in automotive settings, so they are also extremely reliable. An ESP32 microcontroller, chosen for its versatility and capacity to handle real-time processing applications, processes the collected data. The ESP32 is powerful enough to handle the signal processing and machine learning algorithms needed for the sleepiness detection system, thanks to its dual 32-bit core and clock frequency of up to 240 MHz. Furthermore, its low power consumption can be used in automotive applications where energy efficiency is essential. Additionally, the ESP32 incorporates connectivity components like Bluetooth and Wi-Fi, making it easier to send data to other servers for additional analysis or other car systems. Figure 3 shows the connections between the electronic components that capture the truck's rudder movement data.

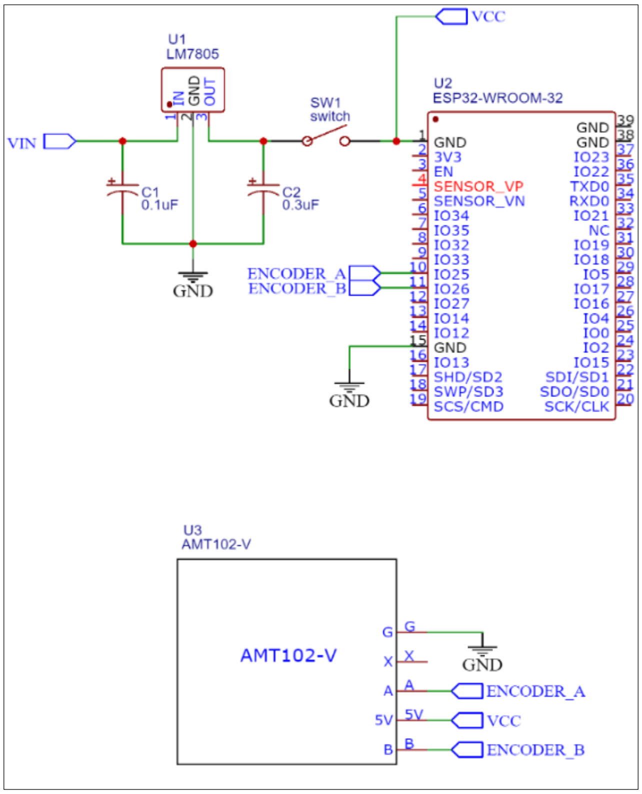



**Fig. 3 Connections of the electronic components**

### *4.2. Software Development*

The software development for the driver drowsiness detection system is based on a meticulous process that integrates signal reading from the AMT102-V optical encoder, real-time data processing and alert generation in case of drowsiness detection. Figure 4 describes in detail the software flowchart developed for this proposed system.

The ESP32 is first configured, with the required interrupts set up for effective signal collection and the GPIO pins identified for connection to the optical encoder. In order to count pulses and ascertain the flywheel's rotational direction, the ESP32 is set up to read the digital A and B signals from the encoder. The encoder generates square digital signals read through interrupts to ensure that rotational changes are captured accurately and instantly.

The encoder signal read cycle begins as soon as the ESP32 is configured. The program updates the pulse counter, which indicates the speed and direction of flywheel rotation at each interrupt by reading the current states of the A and B signals.

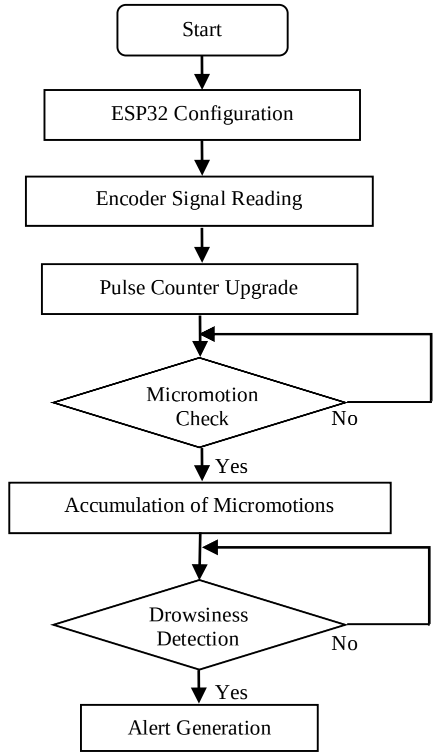



**Fig. 4 Software flowchart**

This counter, called ‘pulseCount’, is updated according to the phase relationship between the A and B signals. A quadrature algorithm detects changes and adjusts the counter accordingly. The software compares the current ‘pulseCount’ value with the value from the previous reading to verify the flywheel's micromovements once every second.

The micromovement counter is increased if there is a slight change in ‘pulseCount’, which suggests a micromovement. Identifying minute steering wheel movements that can be a sign of sleepiness depends on this verification procedure.

The collection of micromotions is the next stage of the software flow. In the event that the system detects more micro-maneuvers than a certain threshold in a given time frame (such as one minute), it is assumed that the driver is likely sleepy. Using the steering wheel rotation data, this logic enables the system to continuously evaluate the driver's condition. When drowsiness is identified, the driver receives an alarm from the software.

Depending on how the system is implemented, this alert may sound, vibrate on the steering wheel, or display a visual message. The purpose of the alert's creation is to inform the driver of potential fatigue so they can take appropriate action in a timely manner. The software then resumes the micro-maneuvers testing process and returns to the monitoring cycle's encoder signal reading step. This ongoing cycle guarantees ongoing observation of the driver's condition, enabling efficient and instantaneous identification of any sleepiness indicators.

### *4.3. Data Processing*

In order to guarantee that the signals recorded are precise and pertinent for sleepiness detection, data preprocessing is an essential step. In this stage, noise was eliminated from the data by applying filtering techniques, and the data was divided into temporal windows to enable continuous driving analysis and the extraction of important features for model training.

#### *4.3.1. Preprocessing*

The signals obtained from the sensors were subjected to a filtering process to remove high-frequency noise and other artifacts unrelated to drowsiness. Low-pass filters and smoothing techniques were used to ensure that variations in the data correlated with shifts in the driver's level of awareness and not with outside interferences like car vibrations or irregularities in the road.

#### *4.3.2. Temporal Features*

The data were filtered and then divided into time intervals of 30 seconds (T = 30s), which made it possible to analyze steering wheel micromotions in real-time and in great detail. Finding patterns of gradual tiredness during driving depends on this segmentation. Furthermore, sleepiness events in the video recordings were tagged by hand, making it easier to create a labeled dataset for training the algorithm. The steering angle signal is $(t)$ and is sampled at a frequency $f_s$ (in Hz). The duration of each epoch is T seconds, which is equivalent to $N = T \cdot f_s$ samples.

$$Epoch_i = [x((i-1).N), x((i-1).N+1), \dots, x(i.N-1)] \quad (1)$$

#### *4.3.3. Micro-Maneuvers Detection*

Micro-maneuvers were identified by analyzing small unintentional steering wheel adjustments. For each epoch, the steering angle variance was calculated to quantify the presence of micro-maneuvers. The following formula yields the variance of the $i$-th epoch (Variance$_i$):

$$Variance_i = \frac{1}{N}\sum_{n=0}^{N-1}(x_i(n) - \mu_i)^2 \quad (2)$$

Where $(n)$ represents the signal value at the $n$-th sample of the $n$-th epoch and $\mu_i$ is the mean steering angle at that epoch, calculated as:

$$\mu_i = \frac{1}{N}\sum_{n=0}^{N-1} x_i(n) \quad (3)$$

Variance was selected as the key characteristic because of its ability to reflect subtle changes in steering direction. An aware driver typically exhibits frequent micro-maneuvers, as a high variance indicates. On the other hand, a low variance may indicate drowsiness because it indicates smoother motions and less corrections. The threshold variance ($\text{Variance}_{\text{threshold}}$) was established to categorize each epoch based on the driver's level of attention. An epoch is considered indicative of sleepiness if its estimated variance is less than this threshold:

If $\text{Variance}_i < \text{Variance}_{\text{threshold}}$ then the driver is drowsy

#### *4.3.4. Model Training*

The labeled data were divided into training and test sets, and cross-validation techniques were applied to optimize the models and avoid overfitting. The training focused on improving the model's sensitivity to detect even early signs of fatigue by adjusting hyperparameters to maximize the accuracy of drowsiness detection. Two machine learning algorithms were tested:

- Support Vector Machine (SVM): An SVM with a Radial Basis Function (RBF) kernel is used to classify the state of the drivers as "alert" or "drowsy". SVM is known for its robustness in high-dimensional spaces and its ability to handle nonlinear relationships.
- Convolutional Neural Network (CNN): A CNN was developed to automatically learn features from address data. The CNN architecture consisted of three convolutional layers followed by max pooling layers and two fully connected layers. The input to the CNN was a time series of address data segments.

The data set was divided into training (70%), validation (15%), and test (15%) sets. A five-fold cross-validation strategy was employed to adjust the hyperparameters and avoid overfitting.

#### *4.3.5. Performance Evaluation*

Accuracy, recall, precision, and the F1 metric were among the metrics used to assess the detection system's efficacy. These metrics provide a thorough assessment of the system's capacity to detect sleepiness and reduce categorization errors.

## 5. Results and Discussion

The performance and efficacy of the driver sleepiness detection system were assessed under controlled conditions. An ESP32 and an AMT102-V optical encoder were used in its implementation. Early testing concentrated on the system's core features, such as its accuracy in signal reading, capacity to recognize micromotions, and efficiency in sending out notifications. Figure 5 shows a truck driver testing the system.

**Fig. 5 Test with a driver**

### *5.1. Signal Reading Accuracy*

When reading the digital signals produced by the optical encoder, the device demonstrated excellent precision. The flywheel's actual movements and the 'pulseCount', which measures the number of pulses produced by the flywheel's spinning, matched exactly. With a resolution of 2048 pulses per rotation, the AMT102-V encoder offered sufficient resolution for precise micromotion detection. Table 1 shows the accuracy of encoder measurements.

**Table 1. Accuracy of encoder measurements**

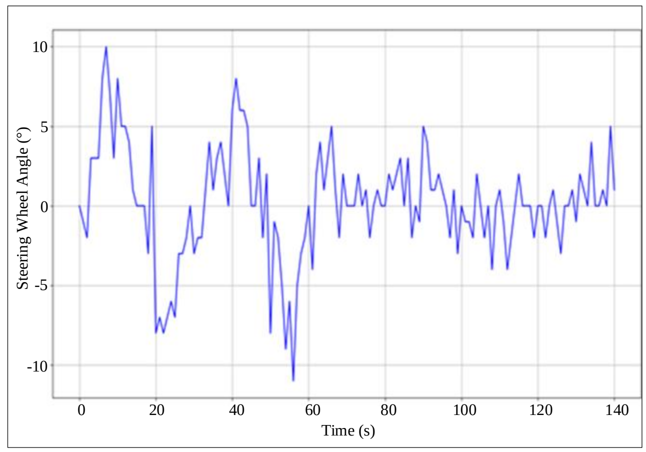
| Metric | Normal Driving | Drowsy Driving | Micro-Maneuver Detection |
|---|---|---|---|
| True Positive Rate (TPR) | 95% | 92% | 97% |
| False Positive Rate (FPR) | 3% | 6% | 2% |
| Accuracy | 94% | 91% | 96% |
| Recall | 95% | 92% | 97% |
| F1 Score | 94.5% | 91.5% | 96.5% |

The inclusion of additional metrics allows for a more comprehensive evaluation of the system. The accuracy and recall of the system are particularly important, as they allow an assessment of how effectively it identifies drowsy drivers while taking into account the frequency of false positives.

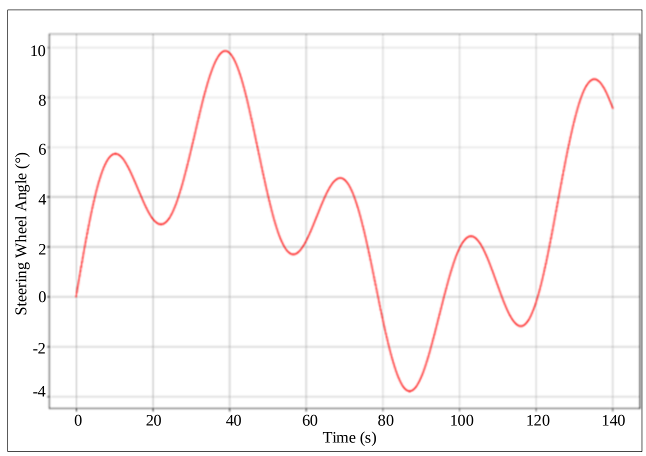
The F1 score, a unique and balanced rating that takes into account both accuracy and sensitivity, is determined using these criteria. In addition to having sufficient overall accuracy, this study shows that the system has a suitable balance between sensitivity and specificity, which is essential for road safety applications.

### *5.2. Micromotion Detection*

The software that was used could detect minute motions and could be adjusted in sensitivity. During testing, the system was able to identify variations in pulse counts of less than 10 pulses over a 1-second time span, enabling precise identification of minute steering wheel movements. Figure 6(a) shows graphs of a portion of data taken for 140 seconds corresponding to a driver in an awake state, and micro-corrections in the steering wheel are observed, and another graph of a drowsy driver shows in Figure 6(b), there are fewer or simply no micro-corrections in the steering wheel due to reduced physical faculties. This threshold for detection worked well enough to spot potential fatigue indicators without raising too many false alarms.




**(a)**




**(b)**

**Fig. 6 Graph of the angle measured by the encoder (a) 140-second steering wheel angle graph of an awake driver, and (b) 140-second steering wheel angle graph of a drowsy driver.**

### *5.3. Alert Generation*

During the simulated testing, the system's alert-generating capability was verified. The system sent out an alarm when it counted more micro-maneuvers than it had set in a given period of time. While the system was initially tested using serial communications, it is intended to be merged with visual or audio inputs in practical applications.

The results obtained demonstrate the effectiveness of the designed driver drowsiness detection system in tracking and assessing steering wheel movements. The resilience of the hardware and software designs is demonstrated by the great accuracy with which encoder signals may be read and the capacity to identify minute movements. The system has proven to process digital signals in real time and generate timely alerts based on the encoder pulse count.

## 6. Conclusion

The driver drowsiness detection system based on an ESP32 optical encoder and AMT102-V has proven effective in tracking the steering wheel's micro-movements to detect possible fatigue indicators. Test results show that the system can read encoder signals with high accuracy, detect micromotions with a sensitivity that can be adjusted, and produce useful notifications when it detects drowsiness. The software solution effectively processed the data in real time and produced signals based on a preset micro-movement threshold. Simulated driving tests confirmed the system could discriminate between normal activities and sleep signals. The suggested solution achieved an overall accuracy rate of over 92%, demonstrating a low false alarm rate and a high tiredness detection rate. These findings indicate that the system may prove to be a useful instrument for enhancing traffic safety. By identifying early warning signs of driver sleepiness, the system can lower the frequency of incidents connected to driver weariness and increase road safety.

Future work will focus on increasing the efficiency and usability of the drowsiness detection system. First, more sensors will be installed to provide a more comprehensive assessment of the degree of attention, including eye-tracking devices and driver-monitoring cameras. The detection system will be improved and can dynamically adjust to different driving behavior patterns by modifying the threshold and using machine learning techniques. The technology will be able to adjust to account for factors such as vibrations in the vehicle once it has been tested on various driver profiles and in varying real-world driving conditions, such as lighting varying over time.

## Acknowledgments

The authors would like to thank Universidad Nacional de San Agustin de Arequipa.

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