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Monitoring Physiological State of Drivers Using In-Vehicle Sensing of Non-Invasive Signal

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Abstract

Eighty percent of traffic accidents are caused by human error, called hypo vigilance, stemming from drowsiness, stress, or distraction while driving. This poses a significant threat to road safety. An electrocardiogram (ECG) is often used to monitor drivers' health. Thus, enhancing vehicles with Internet of Things (IoT) sensors and local analytical databases becomes crucial for real-time detection and transmission of relevant health data to avoid things that compromise road traffic safety. This study introduces a cost-effective in-vehicle ECG sensing prototype using an AD8232 sensor integrated with an Arduino Uno and an AD8232 Wi-Fi module placed on the steering wheel to monitor the driver's heart signal while driving. Short-term heart rate variability (HRV) features were computed through Python from the acquired ECG data, and supervised machine learning techniques such as AdaBoost, Random Forest, Naïve Bayes, and Support Vector Machine (SVM) classified the features into normal and abnormal classes. Naive Bayes exhibited the highest accuracy (90.91%) and F1 score (85.71%), surpassing Random Forest's lower accuracy (63.64%) and F1 score (50.00%). These findings indicate the prototype's potential as a valuable tool for ensuring safe and efficient driving, proposing integration into standard vehicle safety systems for enhanced road traffic safety.

Keywords: ADAS; Driver Monitoring System; ECG; Vehicle Safety.

1. Introduction

Road accidents pose a significant threat to car drivers. Despite the various efforts made by the authorities to improve traffic and road safety, traffic accidents have increased in recent years. According to a study conducted by the Malaysian Institute of Road Safety Research (MIROS), one of the main causes of road accidents is human behavior, namely hypo-vigilance among drivers, a condition when individuals experience decreased sensory sensitivity and responsiveness due to factors such as drowsiness, fatigue, the influence of alcohol or drugs, stress, excessive cognitive demands, or distraction from the use of smartphones or GPS devices while driving [1–4]. In addition, the driver's health condition can also trigger a state of hypo-alertness. If an emergency occurs while driving, the driver only has 0.15 seconds to respond to the situation to prevent unwanted things from happening [2]. Thus, upgrading vehicles with Internet of Things (IoT) sensors connected to the Internet and local analytical databases to identify and address cognitive and physiological problems in real-time becomes an innovative approach that could revolutionize road safety by providing new perspectives on driver-related challenges [5].

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The latest research and theoretical approach for monitoring the physiological state of drivers using in-vehicle sensing of non-invasive signals involves biometric sensors, artificial intelligence (AI), and virtual reality (VR) technologies. These approaches aim to detect and classify stress levels in drivers in real-time [6]. One study explores the neurophysiological effects of visual, auditory, and higher-order cognitive distraction on young drivers using electroencephalograms (EEG) [7]. Another study also utilized EEG to calculate the correlation between brain neural activity and driving behavior [8]. The proposed scheme in Yang et al.'s study accurately detects driver alertness using face landmarks, head poses, and gaze direction, offering high classification accuracy in actual road driving conditions [9].

While EEG and facial point features are the most studied physiologic measures of vigilance while driving, photoplethysmography (PPG) and other biometric sensors are integrated into the in-vehicle sensing of non-invasive signals for the driver's monitoring system. One study explores remote photoplethysmography (rPPG) to monitor drivers' cardio-respiratory functions, focusing on upgrading the single-wavelength NIR setup to multi-wavelength for more robust heart-rate monitoring [10]. Another study also employed rPPG with quality-guided spectrum peak screening that allowed tracking of the driver's heart rate under realistic driving conditions [11]. Besides, the study from Gharamohammadi et al. focuses on using Frequency Modulated Continuous Wave (FMCW) radars incorporated in a vehicle for breathing pattern monitoring to detect breathing abnormalities during driving [12]. Additionally, a proposed approach suggests using selected biosignals, such as EMG, GSR, and respiration rate, combined with machine learning models to classify stress levels in drivers [13].

The electrocardiogram (ECG) signal is also one of the methods often used to track a driver's health or attention. The ECG has several phases: the P signal, the QRS complex, and the T signal [5]. The driver's physical condition is commonly evaluated using the QRS complex because it has a higher amplitude and signal-to-noise ratio (SNR) than the P and T signals [14, 15]. Based on measurements of electrical properties, the ECG continuously records cardiac changes in heart rate, offers cardiac response information that describes cardiac activity, and measures the body's level of physical, psychological, and physical fatigue [16]. The signals have received increased attention and have been included in the in-vehicle sensing of advanced driver monitoring systems that detect, record, and transmit relevant health information to avoid things that could compromise traffic safety [5, 14].

Furthermore, the driver's physical condition can be evaluated non-invasively using parameters such as heart rate and heart rate variability (HRV), eliminating the need to put the driver at risk [17]. The HRV power spectrum analysis of the R-to-R time series (0.15–0.4 Hz) from two to five minutes of recording gives three frequency bands: the very low-frequency band (0.003-0.04 Hz), the low-frequency band (0.04-0.15 Hz), and the high-frequency band [18]. In a healthy state, the instantaneous heart rate fluctuates within a specific range of variation [19]. However, HRV data also fluctuates between individuals and over time within individuals, depending on internal and external conditions [20].

Several studies have used HR and HRV from the ECG as primary data to investigate the driver's condition. For example, Mathissen et al. [21] investigate tasks that could potentially induce stress in the driver to assess the driver's condition. These tasks included sequential memory tasks, sing-a-song stress tests, and noise exposure tests. Their study used Ag/AgCl (ECG) electrodes to obtain HR and HRV for further research. They found that sequential memory tasks strongly activated the sympathetic nervous system, resulting in increased HR and decreased HRV in response to stress-inducing secondary tasks. Aswathi et al. [22] developed a drowsiness detection system based on HRV. They compared several machine learning algorithms, including random forests, support vector machines, decision trees, Naive Bayes, and 1-dimensional convolutional neural networks. The algorithm was tested on the Physikalisch-Technische Bundesanstalt's (PTB) diagnostic ECG data set. The authors claim that the CNN 1D approach is superior to traditional machine learning, with an accuracy difference of 0.94 to 14 percent. They also noted that analyzing HRV could help reduce accidents caused by drowsy driving. A study by Arefnezhad et al. [23] used eleven features extracted from the HRV collected from the ECG using the g.NautilusTM device classifies drowsiness into three different classes: alert, moderate drowsy, and extremely drowsy. HRV characteristics were classified using random forest and K-nearest neighbor techniques and obtained 62% and 64% accuracy, respectively. Ebrahimian et al. [24] propose a multi-level classification of drowsiness using two types of signals: ECG and respiratory signals. The signals were attached to the driver using several electrodes, and the experiment was performed in a controlled setup using a driving simulator by K. N. Toosi University of Technology. HRV, power spectral density, and respiration rate were considered for the classification using CNN-LSTM of a three-level classification (wakeful, moderately drowsy, and extremely drowsy) and a five-level classification (wakeful, slightly drowsy, moderately drowsy, very drowsy, and extremely drowsy). The accuracy obtained for three- and five-level classification is 91% and 67%, respectively.

Previous studies about driver performance have demonstrated a connection between these measurements and variations in drivers' attention [25, 26]. Consequently, in-vehicle gadgets and cameras are projected to dominate the detection process. At the same time future uses are expected to include equipment that can identify health issues and irregularities by driving as usual. For instance, a comparison study was conducted to compare the contact Biopac system with the non-contact Plessey Electric Potential Integrated Circuit (EPIC) system to understand levels of vehicle autonomy affecting human behavior and public perception. The study demonstrates that the inside-seat EPIC sensor can be used to accurately replicate autonomous driving scenarios with minimal movement artifacts [27].

Driver applications led to the development of non-invasive ECG recording techniques, such as the integration of sensors into the steering wheel [28]. To enable long-term electrocardiogram (ECG) monitoring and continuous in-vehicle heart rate monitoring while driving, thin, flexible polyurethane electrodes were developed [29]. Another study proposed a system that integrates a heart-rate sensor, Global Positioning System (GPS), and Global System for Mobile Communications (GSM) modules into the steering wheel to detect the driver’s pulse rate and dynamically inform the rescue party about the driver's wellness to avert accidents [30]. Similarly, an unobtrusive monitoring approach was applied to track the vital signs of drivers, including heart-rate activities and breathing activities. Sensors were placed at the steering wheel and backseat of the vehicle [31].

Since the number of accidents worldwide keeps increasing yearly, knowing the driver’s heart condition in advance may help avoid accidents on the road. However, equipment or hardware that can test heart conditions is very expensive. Therefore, many drivers are unaware of their heart conditions because they are unwilling to go to the clinic or hospital to check their heart condition due to time and cost constraints. Additionally, previous studies mostly focused on classifying hypo-vigilance states such as fatigue, drowsiness, or stress. In the current system, drivers are not equipped with an indicator to receive warnings if their heart rate is irregular. This caused the driver not to notice if they had heart problems like chest pains or, even worse, loss of consciousness, which makes them unable to contact a health provider for assistance [5]. Therefore, this study will build a low-cost in-vehicle sensing system for ECG signals and monitor the driver’s heart rate variability. This study will collect the data while the driver is driving and gather information from HRV using built-in ECG sensors on a steering wheel to classify the driver’s cardiac health as normal or abnormal. The system developed in this study hoped to enable users to monitor their heart condition regularly, even while driving.

This paper is organized as follows: Section 2 describes the related works, while Section 3 presents the research method applied in this study. Section 4 presents the results and analysis of this study. The discussion is elaborated in Section 5, and lastly, Section 6 provides the conclusion of this study.

2. Research Methodology

The project's primary goal is to develop an automatic heart rate variability monitoring device for passenger vehicle drivers that does not involve human interference to determine and alert the driver immediately with a light signal when the heart rate variability is abnormal. Hence, a prototype of the HRV monitoring device was developed to demonstrate the in-vehicle sensing of ECG signals and monitoring the driver’s heart rate variability. Figure 1 shows a circuit diagram of the system for a clearer view of the prototype components. The hardware used to build this prototype consists of several IoT devices and microcontroller sensors, which are:

- Silver-colored woven conductive material
- Car steering wheel
- Steering cover
- ECG AD8232 sensor
- Arduino Uno
- ESP 8266 Wi-Fi Module
- USB 2.0 Cable Type A/B
- 8.5 × 5.5 cm mini breadboard
- 40pin Men to Men, 40pin Women to Women, Breadboard Jumper Wires, Ribbon Cables Kit
- Adafruit Neo Pixel LED Ring
- 12V Battery

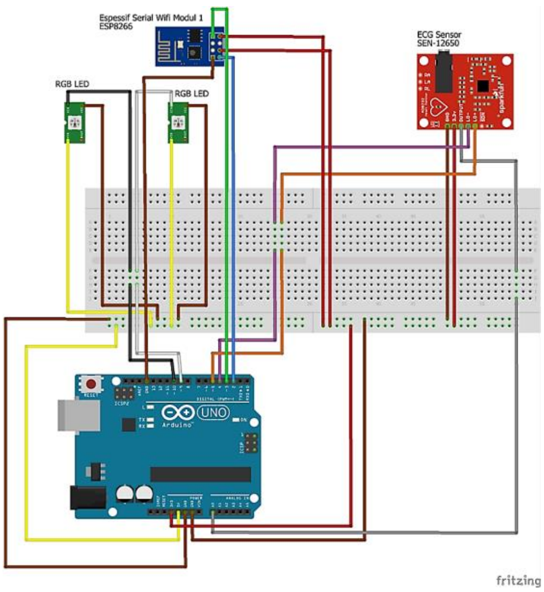


Figure 1. System Circuit Diagram

Two 7×7 pieces of silver-colored woven conductive material made of Copper and Nickel-plated nylon were placed at the 9-3 position of the steering wheel. The ECG AD8232 sensor was stuck together at the steering wheel to enable the transmission of the physiological signal from the conductive paper to the sensor when drivers are holding the steering wheel. The Arduino Uno Rev3 development board is utilized here to connect the ECG AD8232 sensor and AD8232 WiFi module via an 8.5×5.5cm mini breadboard packaged in a 4.8×3.2×1.5-inch enclosure. Once the AD8232 sensor begins to monitor the driver's ECG signals, the data is sensed and sent to the Arduino to process and analyze the variability of the heartbeat every 5 minutes before being saved to a database using the ESP8266 WiFi Module. In this stage, the R-R interval will be computed based on the difference between the second peak time (ms) and the first peak time (ms), and the HRV features will be calculated based on the R-R interval obtained. An Adafruit Neo Pixel LED Ring was placed at the center of the steering wheel to provide visual alerts to the driver regarding the current situation and to respond appropriately (refer to Figure 2). For example, if the result shows a heart rate lower than the normal rate of "60" or higher than "120", the light will turn yellow; if there are any severe heart problems detected, the light will turn red; if there are no problems with the heartbeat, the light will remain green. All lights will refresh every 20 seconds. The result and signal data will be sent to ThingSpeak and saved to a local Excel file.

Figure 2. LED ring placement on the steering wheel

In an actual driving situation, the prototype of the HRV monitoring device will technically start as soon as the vehicle begins the engine. The prototype device will detect the driver's heartbeat once it senses the driver's hand gripping the steering wheel. The signal collected is transmitted to the Arduino for data processing and analysis of the heart rate variability every five minutes. This will trigger the alert signal when any event or problem suddenly occurs to the driver while driving. The system will also classify, store, and provide real-time heart rate results to the driver. Figure 3 shows an overview of the system flow. In addition, before implementing this monitoring tool in real-life driving situations, an experiment is carried out in a controlled laboratory environment for the performance evaluation of the prototype. The following subsection will provide more details about the project and prototype.

2.1. Electrocardiogram (ECG) Signals Acquisition

A call for voluntary participants was made a week before the actual experiment took place. On the experimental day, the volunteers were briefed on the experimental setup and processes. The volunteers were asked to determine if they were unfit, which would make them unsuitable to participate. Ten of the volunteers had to be declined since they were feeling stressed and showed signs of not feeling well or tiredness, which would affect the data collection. Out of 35 volunteers, 25 of them (13 male and 12 female) agreed to participate and complete the experiment. The participants were asked to read and sign a consent form to indicate their agreement to take part in the experiment as approved by the organization’s Ethical Committee. In addition, based on a brief preliminary questionnaire administered to the participants, they reported no history of heart-related problems, including shortness of breath, asthma, or experienced tight chest. The participants were asked about their food and beverage intake before data recording.

Each participant was asked to sit upright and hold the steering wheel for 5 minutes while listening to music or watching a short video that made them feel calm and peaceful. The average temperature of the experimental laboratory was set to 25 degrees Celsius and adjusted if necessary. During this period, their ECG signals were obtained, and the system's behavior was monitored by one of the research team members. The raw ECG data is available at the Zenodo repository (10.5281 / zenodo.7546094).

In addition, to prove the basic correctness and applicability of the prototype device with existing ECG devices, clinical ECG equipment (ADInstruments ML856 PowerLab 26t) was used for testing purposes and to compare the similarity of the collected data. A standard 3-electrode ECG signal is recorded for 5 minutes using a PowerLab with a positive electrode attached to the left wrist, a negative electrode to the right wrist, and a ground electrode to the right leg.

The acquired ECG signals were pre-processed to remove noise from the individuals' movement, respiration, and muscle electrical activity. In this study, 50 Hz notch filtering and a bandpass filter of 0.75 Hz to 35 Hz were applied to remove the noise and minimize the environmental noise or technological aberrations caused by analog and digital signal processing that might affect heart rate variability measurements as recommended by Hejjel [32]. Moreover, HRV values' accuracy for short-term recordings depends on robust digital infinite impulse response (IIR) filters, such as analog models, which can provide an NN-interval series adequate to reflect physiological signals [33].

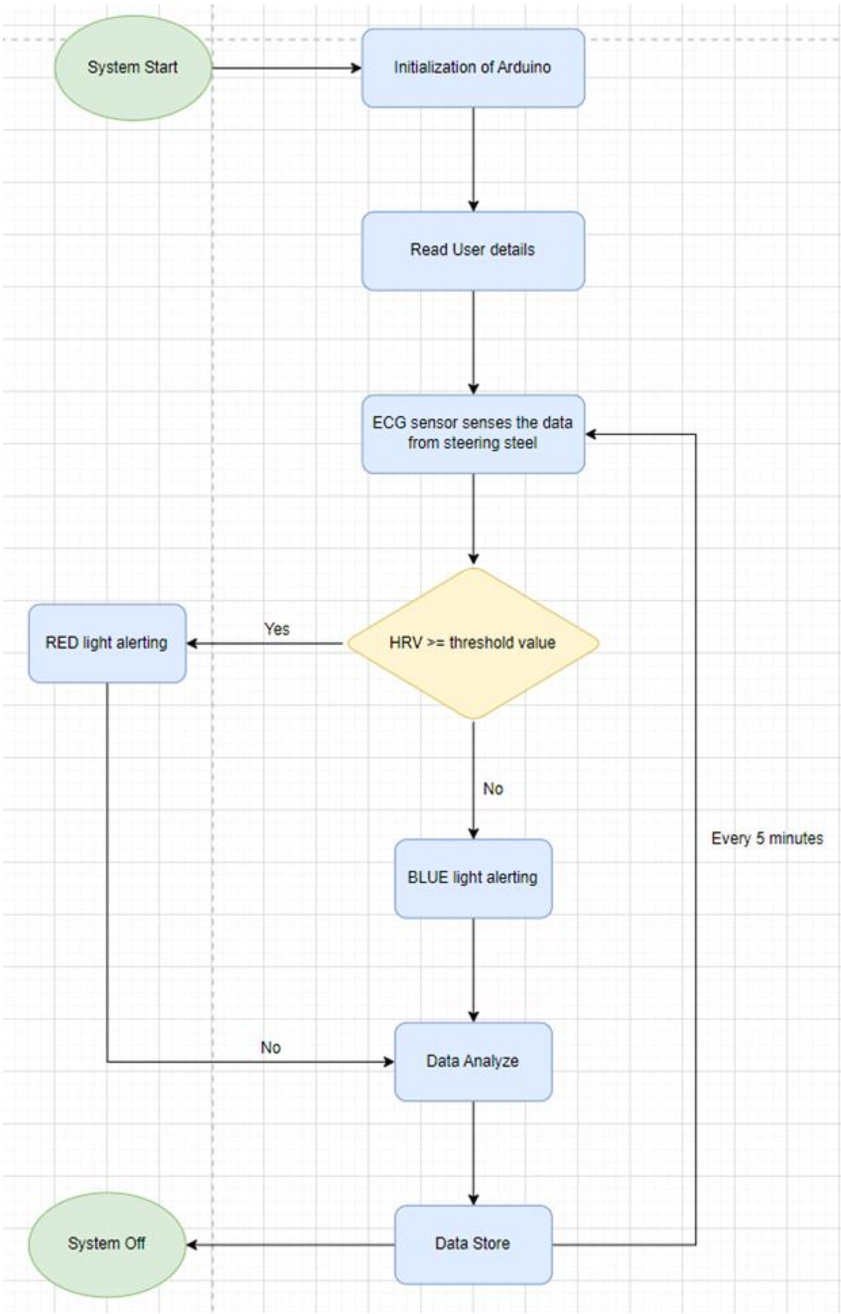
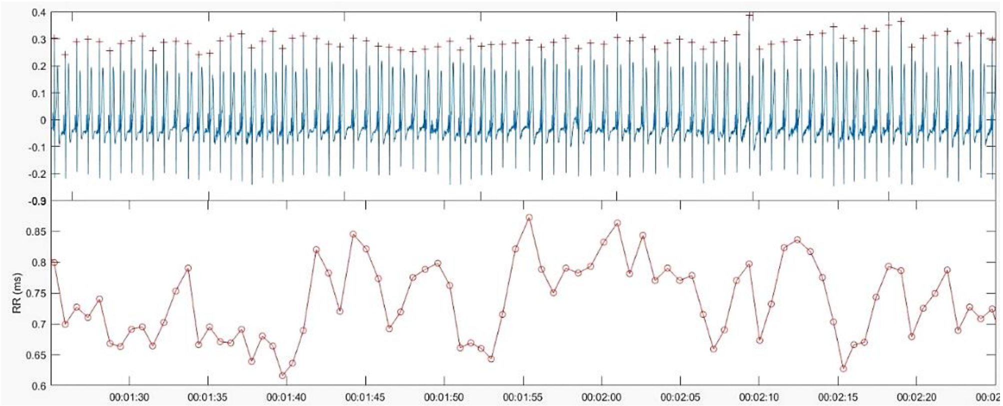


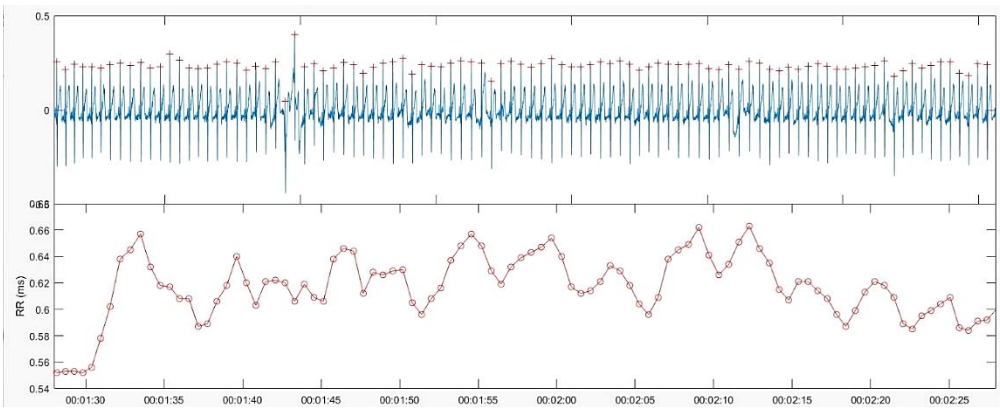
Figure 3. System flow chart

2.2. Computation of Heart Rate Variability (HRV)

The R-R interval, RR*i*, is usually computed based on the difference between the peak, R*i*+n, and the previous peak, R*i*, where *i* is the order of the peaks (*i=1, 2,…, n*). This study used two settings to compute the RR*i*: 1) a Python code, and 2) the HRVAnalysis Toolkit 1.2 [34]. In the first setting, Python code was written to automatically convert all the filtered ECG data and get the R-R interval values from the ECG data into an Excel file. For the second setting, the R-R interval was computed by feeding the raw ECG data into the toolkit, and it will automatically give the R-R interval as the output. LabChart Lightning software extracted and visualized the raw data from both settings. The ECG patterns and sample RR plots based on participants from PowerLab (refer to Figure 4) were compared with those from the prototype device (refer to Figure 5).

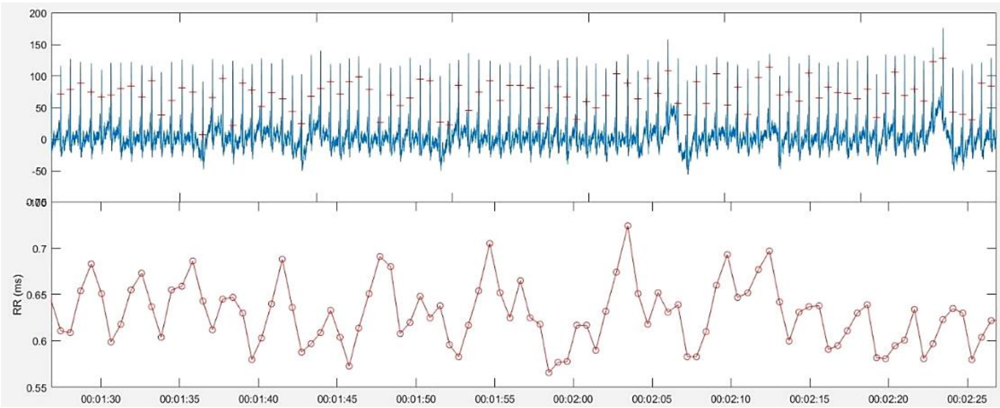


(a) Subject 1

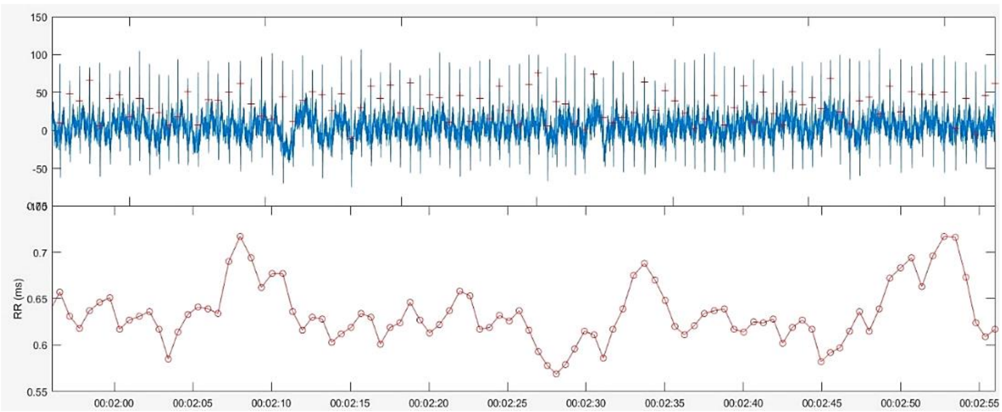


(b) Subject 2

Figure 4. Sample RR plots from PowerLab



(a) Subject 1



(b) Subject 2

Figure 5. Sample RR plots from the prototype device

In line with the ADInstruments ML856 PowerLab 26T, we observed a zero autocorrect RR value for all participants when utilizing our prototype system. Consequently, there is no requirement to identify and rectify abnormal RR intervals that deviate substantially from the expected pattern to enhance the accuracy and dependability of consequent HRV measures. The ECG sensors integrated into the prototype device effectively obtain ECG signals with minimal noise, artifacts, and other error types that may introduce spurious RR intervals.

HRV can be quantified in the time-domain, frequency-domain, and nonlinear analyses. In general, younger people have a higher HRV score than older people, and men frequently have a higher HRV score than women. Athletes have higher heart rate variability than non-athletes; within that category, endurance athletes have a higher HRV than strength athletes. The HRV score referred to in this study is based on the published age-gender-specific HRV range derived from the Elite HRV platform, accessible at https://elitehrv.com/normal-heart-rate-variability-age-gender and shown in Table 1. The normal range for males aged 18–25 is between 60.16 and 77.2, whereas the normal range for females is between 55.1 and 75.08.

Table 1. Age-gender specific HRV score

Age Range	Gender	Ln (RMSSD)	HRV Score
18-25	Male	4.46 ± 0.55	68.68 ± 8.52
	Female	4.23 ± 0.65	65.09 ± 9.99
26-35	Male	4.19 ± 0.63	64.48 ± 9.69
	Female	4.02 ± 0.69	61.83 ± 10.59
36-45	Male	3.92 ± 0.64	60.26 ± 9.92
	Female	3.82 ± 0.68	58.72 ± 10.45
46-55	Male	3.68 ± 0.65	56.65 ± 9.94
	Female	3.73 ± 0.69	57.35 ± 10.57
56-65	Male	3.46 ± 0.72	53.27 ± 11.07
	Female	3.48 ± 0.68	53.50 ± 10.44
65-75	Male	3.42 ± 0.83	52.66 ± 12.70
	Female	3.21 ± 0.72	49.35 ± 11.10
Above 75	Male	3.50 ± 0.98	53.88 ± 15.09
	Female	3.24 ± 1.09	49.85 ± 16.79

To further validate the effectiveness of the prototype device in obtaining ECG signals, the short-term HRV features proposed by Nunan et al. [35] were extracted using the open-source Python library and toolkit for analyzing HRV from ECG data, known as HeartPy [36]. Table 2 tabulates the extracted short-term HRV features using HeartPy, along with the associate description, mean value, standard deviation value, and normal range HRV features from Nunan et al. [35]. The class labeling process is done by marking the values within the normal range as zero, and values outside the normal range are scored 1 for all HRV features. If the total mark is below 4, the HRV is labeled normal; if the total mark is four or higher, the HRV is labeled abnormal.

Table 2. Short-term HRV features

Feature Name	Units	Description	Mean	Standard Deviation	Range
IBI	ms	Interbeat interval	926	90	785 - 1160
SDNN	ms	Standard deviation of NN intervals	50	16	32 - 93
RMSSD	ms	Root mean square of successive R-R intervals differences	42	15	19 - 75
LF	ms^2	Absolute power of the low-frequency band	519	291	193 - 1009
LF	nu	Relative power of the low-frequency band in normal units	52	10	30 - 65
HF	ms^2	Absolute power of the high-frequency band	657	777	83 - 3630
HF	nu	Relative power of the high-frequency band in normal units	40	10	16 - 60
LF/HF	ms^2	Ratio of LF-to-HF power	2.8	2.6	1.1 - 11.6

3. Results and Discussion

In this study, a range of supervised machine learning approaches, including AdaBoost, Random Forest, Naïve Bayes, and Support Vector Machine (SVM), were utilized to classify the HRV features. These four supervised machine learning approaches were chosen due to the excellent performance achieved in various monitoring systems, such as emotion, stress, and fatigue monitoring [13, 22]. AdaBoost is an ensemble learning method that combines multiple weak learners (usually decision trees) and assigns greater weight to misclassified data points in each repetition, allowing subsequent weak learners to focus on previously misclassified examples. The final prediction is a weighted combination of predictions from all weak students, with the more accurate weak students having a higher influence. Random forests are another ensemble learning algorithm that combines multiple decision trees for classification tasks. Models make predictions by following some rules or results, where the final prediction is obtained by aggregating the predictions of all individual trees by a majority vote.

Naive Bayes is a simple probability classification based on Bayes' Theorem and the assumption of independence between features. This theorem is a mathematical formula that can calculate the probability of an event occurring, given that another event has occurred. It works by calculating the probability of each data point belonging to each class and then assigning the data points to the class with the highest probability. SVM is a supervised learning algorithm that looks for hyperplanes in the data that best separate the data points between classes.

The performance of the models was evaluated using two widely used metrics in machine learning: accuracy and F1 score. Accuracy, being an intuitive measure of model performance, is commonly used in balanced datasets where false positives and false negatives are equally costly. The harmonic means of precision and recall, or the F1 score, provides a fair assessment of the two measurements. Given the small dataset, leave-one-out cross-validation was implemented. The accuracy and F1 score of the various techniques are summarized in Table 3.

Table 3. Classification results

Feature Name	Accuracy	F1 Score
AdaBoost	81.82	83.33
Random Forest	63.64	50.00
Naïve Bayes	90.91	85.71
Support Vector Machine	72.73	66.67

The Naïve Bayes method demonstrated strong performance with both high precision and recall, achieving the maximum accuracy and F1 score. In particular, the accuracy of 90.91% shows an almost 91% correct classification percentage for the entire dataset. This result implies that they are quite informative despite the small number of traits. The Naive Bayes technique can produce great generalization performance because it is based on a probabilistic model that represents the underlying data distribution. The Random Forest technique, in contrast, may show bias towards the dominant class, resulting in lower precision and F1 scores.

As a result of its ease of use and convenience, the prototype can acquire non-invasive signals from the steering wheel without disturbing the driver. The steering wheel is always within easy reach, and drivers do not have to wear additional devices, which can be uncomfortable or cumbersome. Thanks to its simplicity and convenience, the prototype can collect non-invasive signals from the steering wheel without upsetting the driver. Drivers do not have to wear extra equipment, which might be uncomfortable or heavy, and the steering wheel is always within easy reach. This enables continuous HRV monitoring without disrupting the driver's daily duties or making them uncomfortable.

4. Conclusion

Drivers' physiological states can be usefully gleaned via in-vehicle monitoring of non-invasive data from the drivers. In the present study, we suggest a prototype for detecting and monitoring heart rate variability (HRV), which is the fluctuation in the interval between heartbeats and regulates the body's response and relaxation response. A drop in HRV may occur when a motorist is stressed or exhausted. Therefore, tracking HRV can reveal details about the physiological state, amount of weariness, and general stress of the driver. Using this data, interventions can be created to support drivers in operating their vehicles safely and effectively. This technology can detect signs of driver impairment, such as drowsiness or distraction, allowing for timely alerts or interventions to prevent accidents. Additionally, monitoring non-invasive signals can help minimize distractions by enabling hands-free and voice-controlled interactions.

Additionally, as the use of autonomous vehicles spreads, it will be crucial to ensure that they are built with the utmost consideration for the security and comfort of their passengers. To achieve cost-effective goals, the ECG sensors in this investigation were mounted on the steering wheel. Data from the sensor and data from the lab instrument were compared. Machine learning techniques were also used to demonstrate the effectiveness of the approaches utilizing the prototype's obtained data because the use of non-invasive signals for HRV monitoring in driving scenarios is still relatively new.

The early results are encouraging, and this prototype has a great deal of promise to help promote safe and effective driving. This method might be included in the typical car safety systems as technology develops, giving drivers input in real-time, assisting in accident avoidance, and enhancing overall road safety. The prototype can also be improved by incorporating more sophisticated signal processing techniques, such as quality-guided spectrum peak screening (QSPS), to increase the precision and dependability of HRV measurements during the driving monitoring process. For instance, machine learning approaches could accomplish the automatic detection and elimination of noise, artifacts, and other defects that can skew HRV readings. Additionally, the temporal and frequency domains of HRV measurements might be modeled using sophisticated statistical techniques, which could increase the precision and dependability of subsequent analysis. Additional physiological sensors could be included to track physiological variables like skin conductance and pupil dilation, as well as other vital signs like blood pressure and oxygen saturation. This would provide a more thorough evaluation of the driver's physiological condition and could assist in spotting any health problems before they worsen.

5. Declarations

5.1. Author Contributions

Conceptualization, S.F.A.R. and S.Y.; methodology, S.F.A.R. and S.N.M.S.I.; software, B.H.B.B. and S.Y.; formal analysis, S.F.A.R., S.N.M.S.I., and B.H.B.B.; investigation, N.H.K.; resources, M.F.A.A.; writing—original draft preparation, S.F.A.R. and S.N.M.S.I.; writing—review and editing, S.F.A.R., S.N.M.S.I., and S.Y.; visualization, B.H.B.B.; supervision, S.F.A.R.; project administration, M.F.A.A.; funding acquisition, S.F.A.R. and S.Y. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are openly available in Zenodo: ECG datasets of young healthy adults at doi:10.5281/zenodo.7546094.

5.3. Funding

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5.4. Acknowledgements

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5.5. Conflicts of Interest

The authors declare no conflict of interest.

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