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FATIGUE DETECTION SYSTEM BASED ON HEART RATE VARIABILITY USING MOBILE DEVICE AND SENSOR

SANTONY*[1] and SANI MUHAMAD ISA[2]

[1, 2] Computer Science Department, Binus Graduate Program - Master of Computer Science, Bina Nusantara University, Jakarta, Indonesia. *Corresponding Author Email: santony@binus.ac.id

Abstract

The potential for sleepiness due to fatigue can actually be detected using an analysis of heart rate variability known as HRV (Heart Rate Variability). HRV can be analyzed using various methods, one of which uses a frequency domain analysis where the ECG data of the subject obtained from the Polar H10 sensor can be used to determine the LF/HF ratio. The resulting LF/HF ratio can be classified into several sleep stages to label the subject whether the subject is awake or asleep. The result of LF/HF ratio will be compared with the threshold classification used in Herzig's research in 2018 so that it can determine whether the subject can be categorized as awake or asleep. If the subject is indicated to be asleep, which is marked by a decrease in the value of the LF/HF ratio, a notification will be given from the system to take a short break.

Keywords: ECG, HRV, Sensor Polar H10, Frequency Domain, Sleep Stage Classification

1. INTRODUCTION

Statistics show that the number of accidents involving motorized vehicles in Indonesia is quite high. The accident rate data released by the KNKT (National Transportation Safety Committee) states that from 2010 to 2016 there have been 41 accidents with 443 deaths. Data from the World Health Organization (WHO) in 2018 stated that the number of deaths caused by traffic accidents in the world reached 1.35 million people. This places traffic accidents as the second leading cause of death in the world, where the majority of victims are aged 5 to 29 years [1].

In Indonesia, one of the causes of these accidents comes from driver error (human error). 69.7% of motor vehicle accidents were caused by human error, while the rest were caused by inadequate facilities and infrastructure. The cause of human error that is most often found is the condition of the driver who experiences fatigue which leads to drowsiness while driving. Drowsiness is a transitional condition between wakefulness and sleep that causes decreased function of all senses.

The risk or potential for accidents caused by tired or drowsy drivers may be four to six times higher than that of awake drivers [2]. The increased risk of traffic accidents cannot be separated from the subjective nature of drivers who are tired and sleepy when they experience sleep apnea or sleep duration is not sufficient [3]. To prevent accidents due to tired and sleepy drivers, a driver assistance system is needed that can detect driving when drowsy and can provide effective warnings.

In medical, electroencephalography (EEG) is needed to assess the level of sleepiness because sleep stages are defined based on EEG [4]. Although EEG-based drowsiness detection methods have been developed [5], it is difficult to record EEG accurately during driving because the

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EEG recording itself is intolerant of noise caused by the driver's movement. Therefore, currently many fatigue and sleepiness detection systems have been developed that do not use EEG [6].

Changes in body condition caused by fatigue and drowsiness can affect the Autonomic Nervous System (ANS) and heart activity, so that cardiac signals can be used to detect fatigue and drowsiness [7]. Therefore, it is necessary to have a computer-based analysis system that can real-time monitor the condition of fatigue and sleepiness of the driver, detect fatigue based on heart rate variability quickly, precisely, and accurately, and make an analysis of fatigue levels automatically. This system will later run on Android-based smartphone devices where this system will process and analyze cardiac activity data sent by sensors connected to it [8]. The system will be combined with the sleep stage range generated from Herzig's research in 2018 [9], where the research obtained a sleep stage classification based on HRV data, starting from sleep stage 2, SWS (Slow Wave Sleep) or sleep stages 3 and 4. , as well as REM (Rapid Eye Movement Sleep) with their respective ratio levels and obtained 87% accuracy results for SWS (Short Wave Sleep) or sleep stages 3 and 4. The level of fatigue in this system will be measured by measuring activity when sleepy / sleep because activity during sleepiness / sleep affects physiological signs that can be detected and measured, such as heart rhythm data, especially heart rate variability (HRV) which is closely related to sleepiness [10].

2. RESEARCH METHOD

2.1 Literature Review

In 2015, research conducted by Peng, R.-C., Zhou, X.-L., Lin, W.-H., and Zhang, Y.-T proved that Heart Rate Variability data can be extracted from heart data. Rate by using the Photoplethysmorgrams sensor on a smartphone. This research provides an alternative to obtain HRV data apart from ECG data [11].

Then in 2017, research conducted by Gonzalez, K., Sasangohar, F., Mehta, R. K., Lawley, M., & Erraguntla, M, concluded that a person's level of fatigue is very dependent on the activities he does. They measure the level of fatigue by doing Activity Recognition using Machine Learning. The data used as the research base is Heart Rate Variability (HRV) data [12].

Research conducted by SGE Brucal, GKD Clamor, LAO Pasiliao, and J. P in 2016 seeks to develop technology for independent ECG checking by doing several things, such as using smaller and more accurate tools, converting from analog signals to digital signals accompanied by with the addition of a filter to make the signal cleaner from noise. The results of this research showed that the margin of error for the R-R interval and heart rate was 7.61% and 5.35%, respectively [13].

Still in the same year, research conducted by Vicente, J. , Laguna, P. , Bartra, A. , and Bailon attempted to develop a system that was used to detect fatigue using Heart Rate Variability (HRV) data. The results of this research provide an accuracy of P+ of 0.96, Se of 0.59 and Sp of 0.98 [10].

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Then in 2018, research conducted by Venkatesan, C., Karthigaikumar, P., & Satheeskumaran, S attempted to develop an ECG checking technology based on cloud computing mobile [14]. Although in terms of the ECG sensor, wearable-based ECG is still not used, the resulting data can already be centralized in the cloud, so that the data can be processed and displayed on several mobile devices connected to it. The use of mobile cloud computing is a means of sharing data between users and health workers who handle it. The results of this research can show a maximum accuracy of 98.75% for the proposed ANFIS method.

Research conducted by Herzig, D., Eser, P., Omlin, X., Riener, R., Wilhelm, M., & Achermann, P. in 2018 resulted in the classification of sleep stages based on the LF/HF ratio values obtained from frequency domain feature extraction [9]. The level of accuracy obtained is about 87% to determine the sleep stage starting from sleep stage 2, SWS (Slow Wave Sleep) or sleep stages 3 and 4, and REM (Rapid Eye Movement Sleep).

In 2019, research conducted by Lee, H., Lee, J., and Shin, M. which focused on detecting driver fatigue using ECG and PPG sensors could conclude that a person's level of fatigue can be calculated using data from sensors. ECG and PPG [15].

In the same year, research conducted by Walch, O., Huang, Y., Forger, D., & Goldstein, C. focused on detecting sleep stages using heart rate data from PPG sensors on wearable devices, obtaining an accuracy rate of up to 81% [16].

In this research, author will specialize in the use of the sleep stage classification produced by Herzig (2018) [9] research because this research uses ECG signal data so that it is expected to provide higher accuracy when compared to using PPG signals as in the Walch research (2019) [16]. This research is also based on Gonzalez's research (2017) which concludes that the level of fatigue can be measured using the Heart Rate Variability (HRV) and depends on the activities that have been carried out [9]. So that by combining the two methods, it is hoped that a system can be produced that can predict the level of fatigue for each activity carried out and can categorize whether the subject is in a tired condition or not based on the classification of sleep or awake.

Research conducted by Herzig, D., Eser, P., Omlin, X., Riener, R., Wilhelm, M., & Achermann, P. in 2018 [9] resulted in the classification of sleep stages based on the LF/HF ratio values obtained from frequency domain feature extraction. The level of accuracy obtained is about 87% to determine the sleep stage starting from sleep stage 2, SWS (Slow Wave Sleep) or sleep stages 3 and 4, and REM (Rapid Eye Movement Sleep).

Table 1: Sleep Stage Classification by Herzig (2018)

	Stage 2	**SWS (3 dan 4)**	**REM**
	Median	**Median**	**Median**
Heart Rate (bpm)	51.6 (47.9, 58.3)	51.5 (47.9, 55.3)	53.6 (49.7, 58.3)
HF Power (ms^2)	1095 (660, 1841)	1167 (595, 2438)	1322 (689, 2326)
LF Power (ms^2)	1303 (683, 2578)	651 (385, 1199)	2541 (1585, 4001)
LF/HF Ratio	1.11 (0.68, 2.02)	0.51 (0.31, 0.90)	2.02 (1.30, 3.22)

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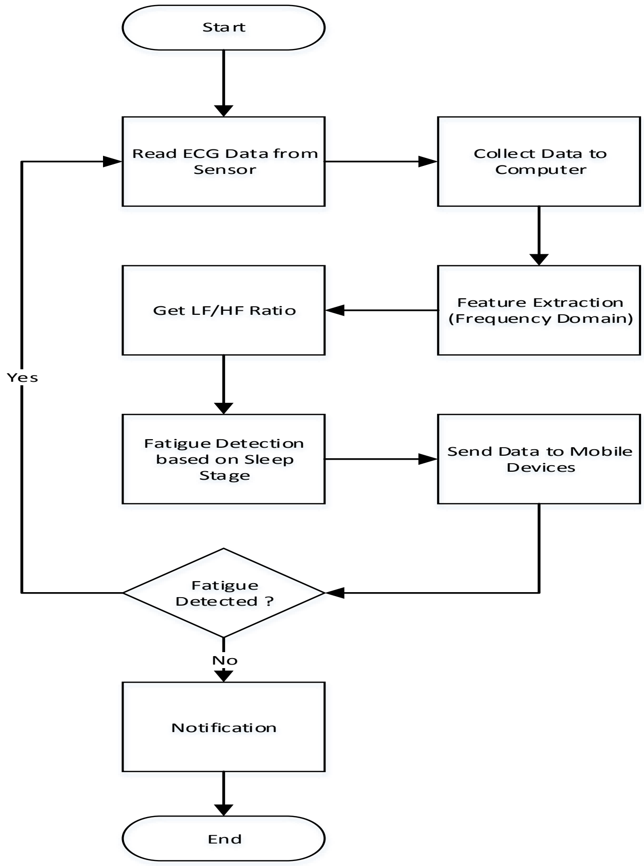
2.2 Data Research Stage

This Research Method is using Polar H10 HR sensor device, mobile device, ECG data and LF/HF ratio of HRV (Heart Rate Variability) to can detect sleepiness due to fatigue that can cause the accidents. The following illustrates the research activities that will be carried out to detect fatigue, starting from collecting ECG data from subjects using the ECG sensor. Then a feature extraction will be carried out on the data to obtain Heart Rate Variability (HRV) data which will be used to detect whether there is fatigue in the driver.

The process of detecting fatigue is done by comparing the user's HRV data when relaxed and when doing activities. If in the detection process there is a decrease in the HRV level which refers to fatigue, then the system will give a warning or alarm for the users to rest.

Figure 1: Research Stages



2.3 System Design

The proposed system design is to use an ECG sensor from Polar H10 which will be worn on the subject's chest when doing activities. The following figure will provide an initial overview of the proposed system design:

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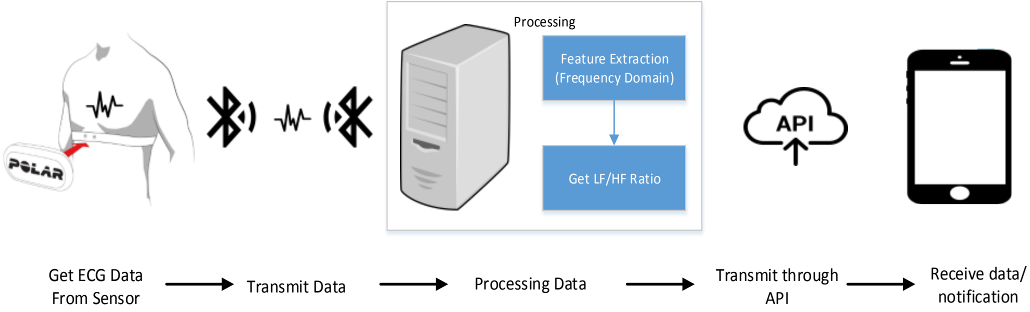
Figure 2: System design



The Polar H10 sensor was chosen because apart from being able to issue raw ECG and heart rate data, this sensor is also a fairly accurate sensor marketed to consumers. ECG data from the sensor will be transmitted and stored into the computer in the form of a file. The ECC data generated from the sensor consists of the timestamp and the ECG measurement value in microVolts. This ECG data will be obtained every second from the subject when doing activities / waking up and sleeping with a maximum data length of 5 minutes. The following picture shows an example of the data obtained from the sensor:

Figure 3: Data from Polar H10 sensor.

```
Phone timestamp;sensor timestamp [ns];timestamp [ms];ecg [uV]
2022-03-17T09:52:22.559;599616026585845216;0.0;5903
2022-03-17T09:52:22.566;599616026593533661;7.688445;6045
2022-03-17T09:52:22.574;599616026601222106;15.37689;6770
2022-03-17T09:52:22.582;599616026608910551;23.065336;7305
2022-03-17T09:52:22.589;599616026616598996;30.75378;7473
2022-03-17T09:52:22.597;599616026624287441;38.442223;7826
2022-03-17T09:52:22.605;599616026631975886;46.130672;8179
2022-03-17T09:52:22.612;599616026639664331;53.819115;8349
2022-03-17T09:52:22.620;599616026647352776;61.50756;8568
2022-03-17T09:52:22.628;599616026655041221;69.19601;8827
2022-03-17T09:52:22.635;599616026662729666;76.884445;9002
2022-03-17T09:52:22.643;599616026670418111;84.5729;9163
2022-03-17T09:52:22.651;599616026678106556;92.261345;9350
```

On a computer, the received ECG data will then be extracted using a frequency domain (frequency domain analysis) HRV feature so that it can generate several HRV values that will be used such as power VLF, power LF, and power HF using the NeuroKit2 library in Python. The value of LF power and HF power will then be compared so that the LF/HF ratio will be obtained. The 5 minute ECG data that is entered into the calculation will be taken every 30 seconds, the ratio is calculated and then averaged so that the LF/HF ratio is obtained for 5 minutes of data with a total of 10 epochs (5 minutes / 30 seconds). The following figure shows the results of calculating HRV features using the frequency domain.

Figure 4: HRV feature extraction using frequency domain analysis

	HRV_ULF	HRV_VLF	HRV_LF	HRV_HF	HRV_VHF	HRV_LFHF	HRV_LFn	HRV_HFn	HRV_LnHF
0	NaN	0.004795	0.002282	0.000962	0.000107	2.373366	0.280162	0.118044	-6.946981

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The following table will show a comparison of the LF/HF ratio values for two different activities:

Table 2: LF/HF ratio for different conditions

Parameter	Condition			
	Relax	**Label**	**Sleep**	**Label**
ULF (ms^2)	-	AWAKE	-	SLEEP - SWS
VLF (ms2)	0.00944		0.01458	
LF (ms2)	0.01360		0.02780	
HF (ms2)	0.00942		0.05410	
VHF (ms2)	0.00089		0.00782	
LFn	0.56165		0.26652	
HFn	0.59291		0.51872	
LnHF	-4.58948		-2.91688	
LF/HF Ratio (%)	**1.27514**		**0.51380**	

After the HRV data is obtained, especially the LF/HF ratio, it will be compared with the median sleep stage range that has been classified by Herzig as shown in tabl below. If the LF/HF ratio falls into one of these stages (stage 2, SWS, or REM) it will be classified as a sleep condition (sleep), either light sleep (light sleep) or deep sleep (deep sleep). However, when the LF/HF ratio scores outside this range, it will be classified as an awakened state.

Table 3: LF/HF median ratio for different sleep stages

	Stage 2	**SWS (3 dan 4)**	**REM**
	Median	**Median**	**Median**
LF/HF Ratio	$0.68 \leq x \leq 2.02$	$0.31 \leq x \leq 0.90$	$1.30 \leq x \leq 3.22$

If the system detects a decrease in the HRV level which is indicated by the LF/HF ratio which is included in one of the median classifications in table above so that it has the potential for fatigue, the system will give a warning or alarm to the user so that they can take a break. With this warning, it is hoped that the user can quickly recover from his fatigue condition, and avoid potential dangers that may arise, for example if the driver experiences fatigue while driving which can lead to an accident.

The image below shows a description of a mobile device that is connected to a processing device via an API. The mobile device will store the LF/HF ratio data which is sent every five minutes by the processing device. On this mobile device, it is determined if the LF/HF ratio data sent is classified as sleep stage or not. If it is classified as sleep, then the mobile device will provide alerts / warnings as shown in the following image:

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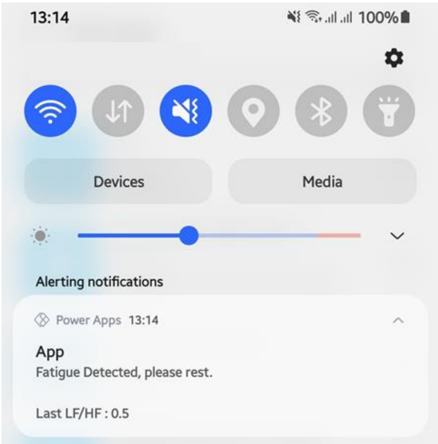
Figure 5: User interface

Figure 6: Fatigue warning



2.4 Variable

The variable used in this research is the ECG signal obtained from the Polar H10 sensor which is equipped with a chest strap, where the data generated is raw ECG data. The quality of the ECG signal used in the analysis will determine the resulting output. Therefore, the use of poor quality ECG signals can reduce the accuracy of the resulting output.

Figure 7: Good quality ECG signal

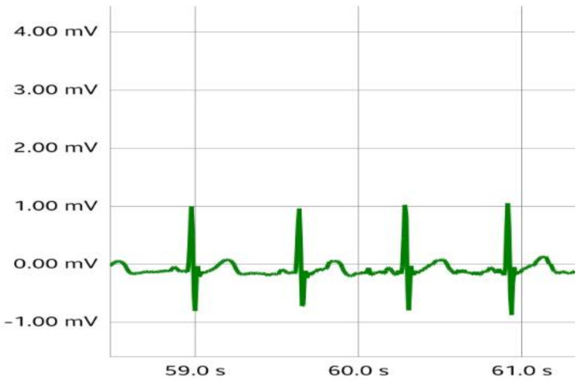


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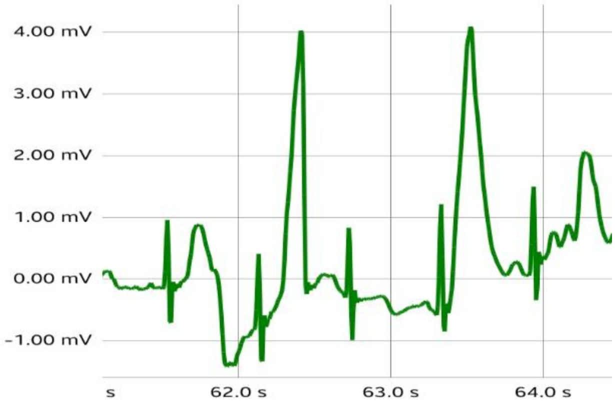
Figure 8: Poor quality ECG signal



2.5 Population and Sample

The sample of ECG data used in this research was obtained from 3 subjects groups. Group 1 consists of men aged between 30 to 35 years, group 2 consists of women aged between 30 to 35 years, and group 3 consists of children aged between 5 to 10 years, where in each group consists of 5 people. Gender and age variations were used in collecting sample data to see differences in the HRV produced and according to several studies it was reported that HRV levels were also influenced by gender and age.

From each subject, 2 activity data were obtained, namely activities during relaxation and during sleep for 5 minutes each. From these 2 activities, 10 data epochs were also obtained each with a length of 30 seconds. Epoch data for 30 seconds is the data range used in special research for single lead ECG data that only comes from 1 sensor. With such a sample configuration, for this research, 60 samples were used.

2.6 Data Collection

The data collection method in the form of ECG signals from sensors is carried out using a sensor logger which will generate raw data for ECG signals from the subject. The ECG sensor worn on the subject's chest will pick up electrical signals from the heart. ECG signal data was obtained from the subject when he was relaxed or doing light activities and while sleeping.

ECG data when relaxed will be used to describe the variability of normal ECG signals without any fatigue that the subject may experience. Data collection for relaxed conditions will be carried out for 5 minutes where the subject is sitting relaxed and breathing at a normal rhythm.

ECG data while sleeping will be used to describe the variability of the ECG signal when the body is tired and needs rest. Data collection for sleep conditions was carried out on average within 3 to 4 hours. The data with a range of 3 to 4 hours will then be cut to produce a 5 minute piece of data. The criteria for conducting this 5-minute data collection will take the time when the subject is in a deep sleep condition which is characterized by the lack of movement activity during sleep.

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2.7 Experimental

In conducting experiments for the system that has been designed, several stages will be carried out, starting from collecting ECG data using sensors on several subjects in relaxed and sleeping conditions, calculating the LF/HF ratio of the subjects, to sending ratio data to mobile devices.

ECG data collection for subjects in relaxed conditions was carried out during the day when the subject was resting or doing light activities which would be classified as awake. While the ECG data on sleep conditions is carried out when the subject is asleep which will be classified as sleep (Sleep). The ECG data for both conditions will calculate the LF/HF ratio using the frequency domain, so that the variability of changes from a relaxed state (Awake) to a sleep state (Sleep) will be illustrated.

Data collected every 5 minutes from each activity (wake up and sleep) will calculate the LF/HF ratio using the average for each data epoch for 30 seconds. So that from every 5 minutes the data will be averaged as much as 10 epochs (per 30 seconds). The data will then be sent to the mobile device, where the mobile device will determine whether it is classified as sleepy or not by looking at the LF/HF ratio value compared to the median value for each sleep stage. If the value of the LF/HF ratio is outside the classification / median sleep stage, it will be categorized as awake.

A decrease in HRV level will be indicated as a potential for fatigue, which is indicated by a decrease in the subject's LF/HF ratio. This happens because the sympathetic branch of the Autonomic Nervous System (ANS) activates stress hormones and increases the rate and strength of heart contractions and decreases the HRV required during mental or physical stressful activities and situations. The decrease in HRV level will be detected by the system as an indicator of fatigue in the subject, and will make the system give a warning or alarm to the user so that they can take a break.

3. RESULTS AND DISCUSSION

This research recorded ECG data using the Polar H10 HR Sensor device on 3 subject groups. Group 1 consists of men aged between 30 to 35 years, group 2 consists of women aged between 30 to 35 years, and group 3 consists of children aged between 5 to 10 years, where in each group consists of 5 people. ECG data was recorded for 5 minutes for each relaxing activity (activity 1) and during sleep (activity 2). Then the recorded ECG data is processed using the HRV extraction feature to detect the values of LF, HF, and LF/HF ratio.

Table 4 is the result of the HRV frequency domain analysis for group 1 in each activity. Based on the table, the shift in activity from relaxing to sleeping resulted in a decrease in the level of the LF/HF ratio, which was marked by a decrease in the LF value and an increase in the HF value.

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Table 4: HRV Result in group 1

Parameter	Condition (Average for 5 minutes data)			
	Activity 1	**Label**	**Activity 2**	**Label**
ULF (ms^2)	-	AWAKE	-	SLEEP - SWS
VLF (ms2)	0.00944		0.01458	
LF (ms2)	0.01360		0.02780	
HF (ms2)	0.00942		0.05410	
VHF (ms2)	0.00089		0.00782	
LFn	0.56165		0.26652	
HFn	0.59291		0.51872	
LnHF	-4.58948		-2.91688	
LF/HF Ratio (%)	**1.27514**		**0.51380**	

Figure 9: Frequency domain group1 when relax

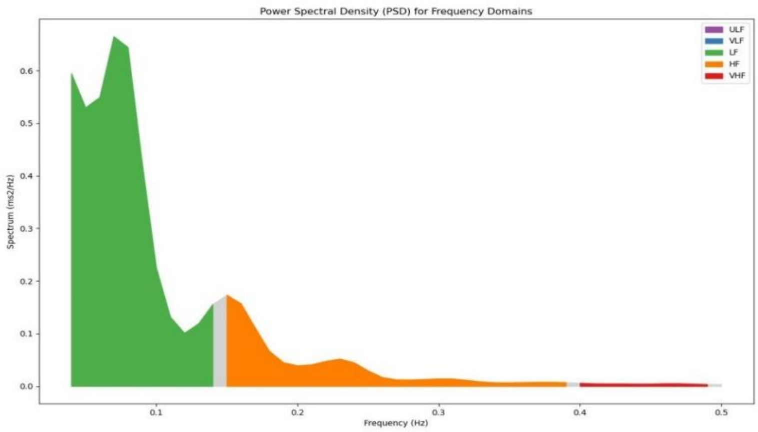

Figure 10: Frequency domain group1 when sleep

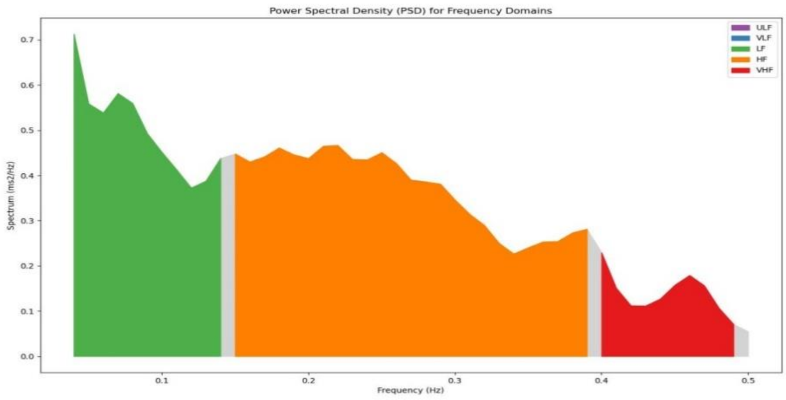

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Table 5 is the result of the HRV frequency domain analysis on group 2 for each activity. Based on the table, the shift in activity from relaxing to sleeping resulted in a decrease in the level of the LF/HF ratio, which was marked by a decrease in the LF value and an increase in the HF value.

Table 5: HRV Result in group 2

Parameter	Condition (Average for 5 minutes data)			
	Activity 1	**Label**	**Activity 2**	**Label**
ULF (ms^2)	-	AWAKE	-	SLEEP – SWS
VLF (ms2)	0.00788		0.00719	
LF (ms2)	0.00692		0.00155	
HF (ms2)	0.00600		0.00372	
VHF (ms2)	0.00086		0.00026	
LFn	0.51265		0.12189	
HFn	0.46333		0.29228	
LnHF	-5.31956		-5.59522	
LF/HF Ratio (%)	**1.41729**		**0.41703**	

Figure 11: Frequency domain group 2 when relax

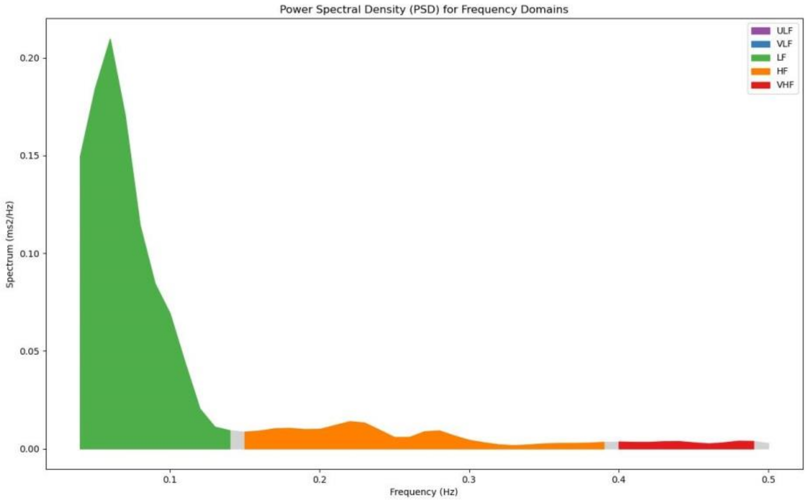

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Figure 12: Frequency domain group 2 when sleep

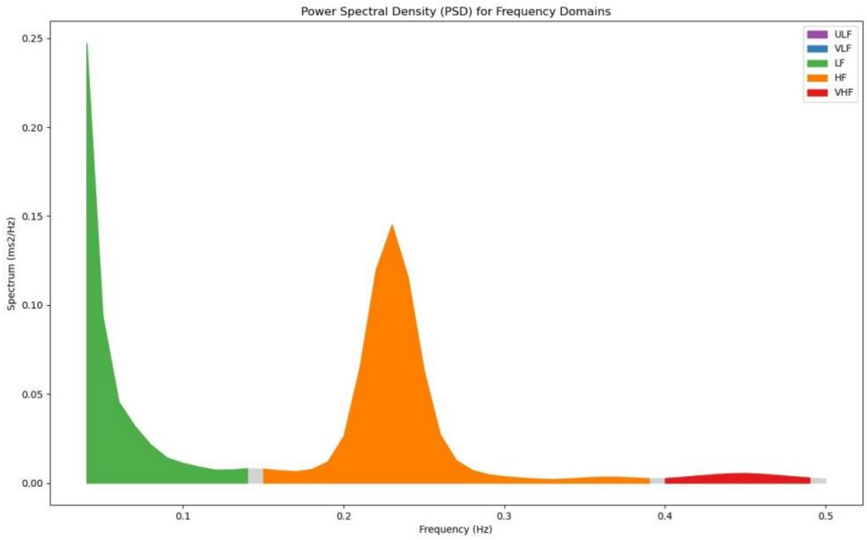

Table 6. is the result of the HRV frequency domain analysis for group 3 for each activity. Based on the table, the shift in activity from relaxing to sleeping resulted in a decrease in the level of the LF/HF ratio, which was marked by a decrease in the LF value and an increase in the HF value.

Table 6: HRV Result in group 3

Parameter	Condition (Average for 5 minutes data)			
	Activity 1	**Label**	**Activity 2**	**Label**
ULF (ms^2)	-	AWAKE	-	SLEEP
VLF (ms2)	0.00554		0.00894	
LF (ms2)	0.00852		0.00632	
HF (ms2)	0.01403		0.02117	
VHF (ms2)	0.00242		0.00597	
LFn	0.42273		0.14900	
HFn	0.54010		0.49937	
LnHF	-4.69509		-3.85501	
LF/HF Ratio (%)	**1.14240**		**0.29838**	

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Figure 13: Frequency domain group 3 when relax

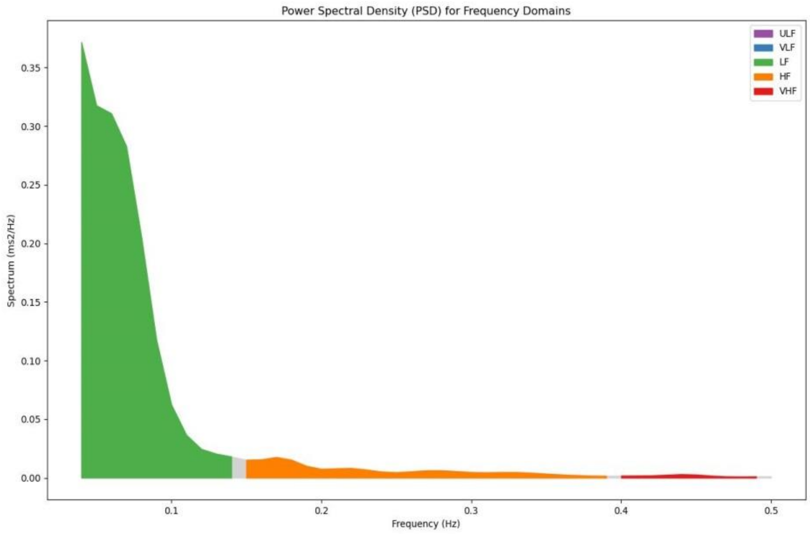
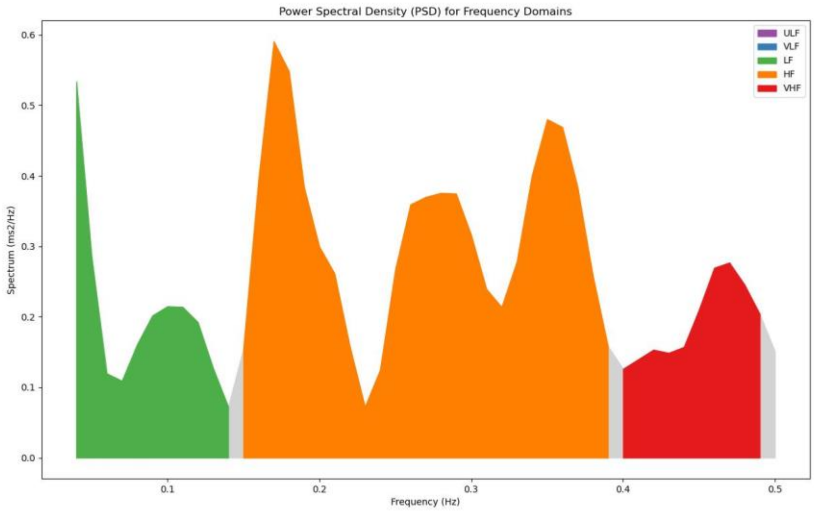


Figure 14: Frequency domain group 3 when sleep



Based on the results of HRV analysis in the frequency domain using the LF/HF ratio shown in tables 4 and 5 for sleep conditions, the LF/HF ratio value is close to the value of the sleep stage classification conducted at Herzig in 2018, where the median value for sleep stage 2 is 1.11, SWS is 0.51, and REM sleep is 2.02. However, in table 6, based on the results of HRV analysis, the values are far below those of stage 2 sleep, SWS, and REM sleep, so that currently they are only classified with the sleep label with reference to the condition of the subject at the time of

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measurement. Meanwhile, for relaxed conditions, the normal value of the LF/HF ratio is in the range of 1 to 2.

The following is a table of evaluation results for three group above:

Table 7: Condition labeling based on LF/HF ratio for all groups

	Group 1		Group 2		Group 3	
	Activity 1	Activity 2	Activity 1	Activity 2	Activity 1	Activity 2
Average LF/HF Ratio	1.27514	0.51380	1.41729	0.41703	1.14240	0.29838
Median	-	$0.31 \leq x \leq 0.90$	-	$0.31 \leq x \leq 0.90$	-	-
Sleep	-	SWS	-	SWS	-	-
Label	**AWAKE**	**SLEEP**	**AWAKE**	**SLEEP**	**AWAKE**	**AWAKE**

In group 1 and group 2, when doing activity 2, the evaluation results show the value of the average LF/HF ratio which indicates that they are in a sleeping state, while for group 3 when they are doing activity 2 it is labeled as AWAKE because the value of the LF/HF ratio does not fall into the range regardless of the sleep stage classification used, even though the real condition when doing activity 2 is sleeping.

4. CONCLUSION

The results of the research that has been done regarding the detection of fatigue levels associated with the activities carried out by the subject both when awake and during sleep resulted in several conclusions both from the method used and the results from the variability of the data used. The conclusions generated include:

- The decrease in HRV levels is closely related to activities carried out both while awake and while sleeping.
- The LF/HF ratio value can be used to determine the sleep stage of the subject by referring to the ratio range obtained from previous studies [9].
- The sleep stage ratio range used only classifies sleep stages for stage 2 sleep, SWS (Slow Wave Sleep) or sleep stages 3 and 4, and REM (Rapid Eye Movement Sleep), so that the results of HRV classification outside of that range can be classified as awakening.
- Gender, and age affect the resulting HRV ratio value, because based on the ratio range used, there is 1 group of children subject whose ratio value does not approach the existing sleep stage classification.

From the results of this research methodology, we design a fatigue detection system with notifications, with hope that users especially drivers can take a short break when experiencing fatigue while driving.

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