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Heart Rate-Based Fatigue Monitoring System with K-Nearest Neighbor Algorithm for Burnout Prevention

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ABSTRACT

The purpose of this study is to design a fatigue level monitoring system consisting of a monitoring device based on a Wemos D1 Mini microcontroller and a MAX30102 sensor, and a monitoring server with Thingsboard IoT Platform and Laravel PHP Framework using K-Nearest Neighbor Algorithm for burnout prevention. Design based research was used in this study. The monitoring system reads the activity level of the heart rate and the time interval between beats using the k-Nearest Neighbor algorithm, the heart rate variability value, and the questionnaire results. The monitoring results were delivered to the user's email and Telegram app. The monitoring system test results reveal that the entire system is functioning properly. However, there are still weaknesses in reading activities that require a lot of movement. This was attributed to the appearance of motion artifacts in heart rate sensor data obtained using photoplethysmography and/or PPG procedures at high wavelengths. From this research, a new alternative method was obtained to help maintain and monitor fatigue levels in order to prevent burnout. A fatigue monitoring system can be an alternative to preventing burnout in someone based on data received by the user.

Keywords:
Burn out; fatigue monitoring; heart rate; k-nearest neighbor algorithm

1. Introduction

Burnout is an individual response syndrome caused by stress from excessive work, causing changes in the health of sufferers [1-3]. The effects of burnout are not only limited to being physically tired or sick but can also be a syndrome that interferes with the sufferer's mentality [4, 5]. The phenomenon of burnout is a common occurrence among workers, especially those in the health sector [6, 7]. Based on a study conducted a decade earlier, approximately 11% of nurses experienced burnout, and many doctors also reported similar issues [3]. In addition to the Covid-19 pandemic, the risk of burnout for health workers increased due to the heavy workload, long working hours, lack of access to personal protective equipment, and reduced sleep time [8-10]. If not addressed promptly, burnout can adversely affect workers, not only in terms of their health but also in their performance

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outcomes, such as increased absenteeism, impaired cognitive function, decreased work ability, and reduced job satisfaction [11, 12].

Several researchers have previously conducted research to detect and prevent burnout using different methods and parameters. In the fatigue detection system using a smart vest, the parameter data analyzed includes ECG data, thoracic electroimpedance, inertia (IMU), SparkFun heart rate data, Galvanic Skin Response (GSR) from Grove, and accelerometers. The data analysis uses models based on penalized logistic regression and penalized regression [13-15]. In other studies, fatigue detection systems built using computer vision have been carried out by analyzing data on eye movements, eye and mouth movements, 3D movements, temperature differences, and IMU sensors. The data is processed using the Convolutional Neural Network (ConNN) algorithm and time series models such as the Naïve Method, Autoregression (AR), Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR), and Vector Error Correction Model (VECM) [16-21]. Many papers regarding K-nearest has been well-developed [22, 23]. However, there has been no research using the K-Nearest Neighbor algorithm to predict burnout based on several parameters, such as heart rate to determine activity level, Heart Rate Variability, and filling out individual data questionnaires to determine the fatigue level of each user.

Due to the problem of the level of fatigue that can cause burnout, it is necessary to find a solution to overcome it. Through this research, we propose a monitoring system that can monitor and predict the level of worker fatigue using the k-Nearest Neighbor algorithm, which is known as an algorithm that is simple, comprehensive, and has high prediction accuracy, so that it is efficient and effective in its use [24-26]. In addition, this research uses a device in the form of an activity tracker that is supported by a monitoring server for monitoring and predicting fatigue. Thus, in the future, the authorities can take preventive action and provide warnings to workers who have the potential to experience burnout.

2. Methodology

The design-based research method was applied in this study. This research was divided into four stages: a literature review, monitoring system design and manufacture, testing, and system evaluation.

2.1 Study Literature

The first stage of this research was to conduct a literature review, which included studies on the fatigue of supporting theories, similar research, and related tools, as well as looking for data related to field situations and constraints to add input to system development and technical specification requirements. Technical literature studies were sourced from articles and journals published in IEEE, ResearchGate, and a variety of other publication sources. The medical literature research cited papers and journals in PubMed NCBI.

2.2 Design and Manufacturing

In this study, the fatigue detection process carried out by monitoring heart rate parameters with a sensor based on the MAX30102 module. This component was an integrated SpO2 and HR monitoring module designed for low-noise electronics and equipped with ambient light rejection capabilities. The module had been fully validated and came in a compact physical size of 5.6 mm × 3.3 mm × 1.55 mm with 14 pins. It also had a low-power HR monitor, consuming less than 1 mW of power, and had an ultra-low shutdown current of 0.7 µA. One of its main features was its robust motion artifact resilience, which ensured consistent performance even in the presence of strong motion disturbances. Furthermore, the module was designed to operate over a wide temperature range, from -40 to +85 ◦C. It could be powered by a single 1.8 V supply or a separate 3.3 V supply [27]. In addition, we utilized the Wemos D1 Mini Microcontroller to measure heart rate and heart rate variability (HRV). Following that, the collected data was transmitted to the server for further processing before being presented to the user via the OLED display module. To achieve a small design, the third module was designed and constructed on a stacked PCB. Software for device monitoring and server monitoring was created during the software design process. On the monitoring server, software for monitoring and processing monitoring results was built based on the ThingsBoard and Laravel platform and framework. The software on the primary server component functioned as a recorder and processor of monitoring results, as well as device and user management and prediction based on the monitoring results collected. The Arduino IDE was then used to write and design software in the monitoring device's software. The Arduino IDE software was compatible with the microcontroller used in this study.

2.3 Testing System

At this stage, testing was performed on the complete system. A monitoring device was tested against a comparison device during the trial phase, and a monitoring server was also tested to monitor and anticipate fatigue levels. The sensor performance of the monitoring device was tested in static and non-static tests and compared to a comparator device, the Mi Band 3 tool. The tests included testing the performance of the prediction algorithm utilized as well as the results of the subsequent reports and forecasts on the monitoring server.

2.4 Evaluation

The whole system performance was evaluated. As part of the evaluation procedure, the performance of the device under development and the monitoring server under development were both compared. Then it was appraised based on the whole system's strengths and weaknesses to serve as the study's conclusion and suggestions for future research.

3. Results and Discussion

3.1 Result of Monitoring Device

Figure 1 shows the heart rate reading on the MAX30102 sensor which uses a combination of light from the 880nm Infrared LED and the 660nm Red LED to detect the heart rate.

Fig. 1. Heart rate reading

3.2 Result of Monitoring Device

The monitoring system was successfully created using the IoT Framework Thingsboard and Web Apps built using the PHP Framework Laravel, as can be seen in Figure 2. This monitoring system consists of two main components in order to make it easier in terms of device management, which is an advantage of using Thingsboard. As well as using Laravel to build supporting Web Apps, by building custom Web Apps, flexibility and customization of the required functions can be done more easily and specifically.

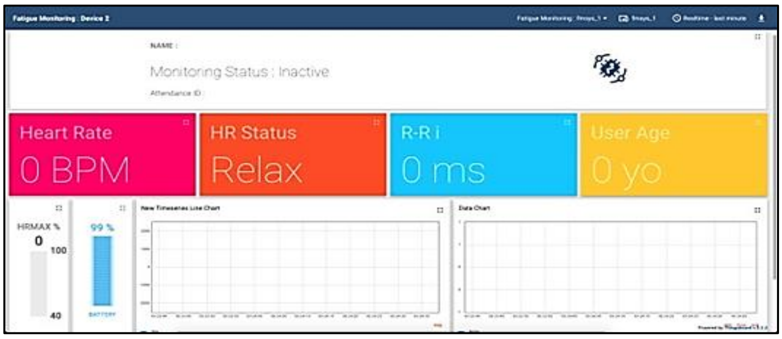


Fig. 2. Heart rate reading

The monitoring system can run smoothly both in operating scenarios on a local network using a PC device with 4 Cores and 8GB RAM, as well as non-locally using a Virtual Machinet2-micro cluster on Amazon AWS EC2 with 1 Core and 1GB RAM. However, due to the utilization of very big Thingsboard RAM capacity, two separate instances are required in testing utilizing the AWS EC2 t2-micro cluster for Thingsboard and Laravel Web Apps. Review Figure 2 shows the dashboard monitoring system.

3.3 Device Test

The device test is divided into two parts: a walking test and a running test, the results of which are compared to the MiBand 3 tacker.

3.3.1 Non-stress test

The test scenario is carried out on two different test groups. The test is performed by sitting quietly and taking readings every three seconds. Table 1 displays the results. There is a difference in readings between the two subject groups, with the second subject group having a greater percent difference in readings and a greater percent difference in average heart rate than the first group. There is more movement than when testing the first group subject due to the incorrect placement of the sensor. This influences the motion artifact in the reading of the second, larger subject, which influences the final reading.

Table 1
Walking test result

Non-Stress	Group 1	Group 2
Avg. difference read	8.10 %	16.34 %
Avg. heart rate on MAX30102	75.43 BPM	69.29 BPM
Avg. heart rate on Mi Band 3	79.98 BPM	81.37 BPM
%	5.69 %	14.85

3.3.2 Non-stress test

The test scenario is performed on two groups, one running and one walking, with readings taken at every 2-second interval. Table 2 displays the results. The results of the two non-static tests show that the motion artifact has a significant impact. This is because of the intensity of the movement or shift on the monitoring device.

Table 2
Running test result

Non-stress	Walking	Running
Avg. difference read	46.05 %	49.80 %
Avg. heart rate on MAX30102	106.25 BPM	103.08 BPM
Avg. heart rate on Mi Band 3	121.63 BPM	123.37 BPM
%	12.64 %	16.45 %

3.4 Prediction Test

Two key parameters are used in the predictions generated by this monitoring system, namely the level of fatigue or tiredness and the HRV or heart rate variability value, which is compared to the Elite HRV reference number.

3.4.1 Fatigue with k-nearest neigbor algorithm

Complete questionnaire data and monitoring data can be accessed on the Monitoring System Web Apps at the address http://www.l0wpass.site/questionary. The data used is the user "user-2023", because it has the most questionnaires with a range of data on numbers 1-16. Table 3 displays the results of the questionnaire obtained.

Table 3
Dataset of monitoring result and questions

Parameter level activity				Label
Duration (s)	Avg. Bpm	Intensive (s)	Light (s)	Relaxed (s)
735	98	120	240	360
1161	100	0	600	540
2586	90	0	240	2340
1879	103	60	1260	600
3603	87	60	480	3060
915	124	600	300	0
4863	76	0	120	4680
7440	76	0	180	7140
11124	78	0	0	11100
3054	89	0	360	2700
6727	84	120	300	6300
15788	82	0	120	15720
1493	98	60	720	720

The test results in Table 3 are carried out using every existing piece of data from the dataset, and then the data is attempted to be forecasted using a dataset that does not include the previously taken data. Table 4 shows the test findings.

Table 4 shows the test results, which obtained a maximum accuracy of 58% with a value of k = 1 and a total of 13 questionnaire data points, which is the maximum available questionnaire data for the user. In testing the k-Nearest Neighbor algorithm to forecast the level of fatigue, the maximum accuracy results are at a value of 53.846% at k = 1, however the accuracy results are still relatively far from the test results with other k values.

Table 4
Prediction accuracy test result

Accuration (%)				
N-data	k=1	k=2	k=3	k=4
1	0	0	0	0
2	0	0	0	0
3	33.3	0	0	0
4	0	0	0	0
5	0	0	0	0
6	16.7	16.7	16.7	0
7	28.6	14.2	14.2	0
8	37.5	25	37.5	25
9	44.4	33.3	44.4	33.3
10	60	50	30	30
11	45.5	27.3	27.3	27.3
12	41.7	25	16.7	16.7
13	53.8	23.1	23.1	23.1

The k-NN algorithm makes predictions by comparing data to k-data that is closest (nearest neighbor) in distance, and then taking the results from the label that appears the most from the closest k-data. As a result, for the same or close data distance, the k-NN algorithm ignores whether the data in the closest k-data are similar or not when compared to the raw parameter data. Because of the influence of this distance calculation, its accuracy can fluctuate as the number of datasets increases. However, when accuracy improves, it tends to produce a steadier average accuracy.

3.4.2 Monitoring result and final predictions

The results of monitoring and final predictions are sent as a notification to emails, as shown in Table 5.

Table 5
Prediction accuracy test result

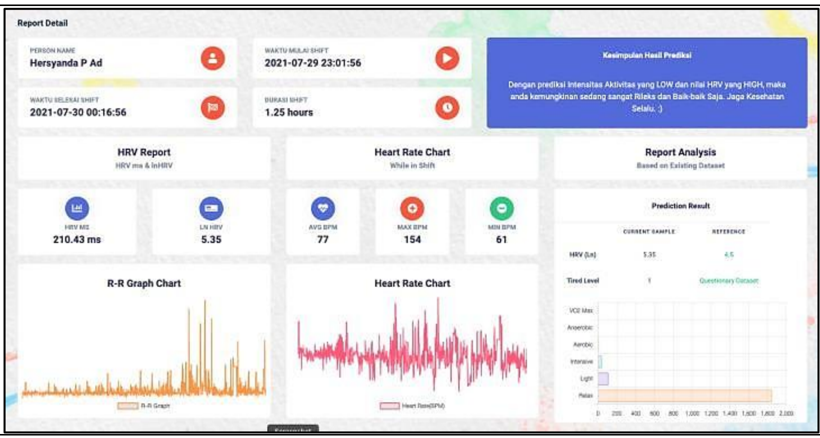
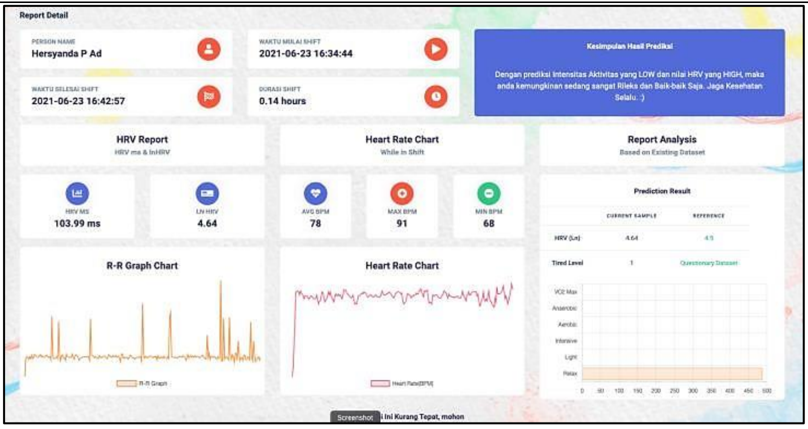
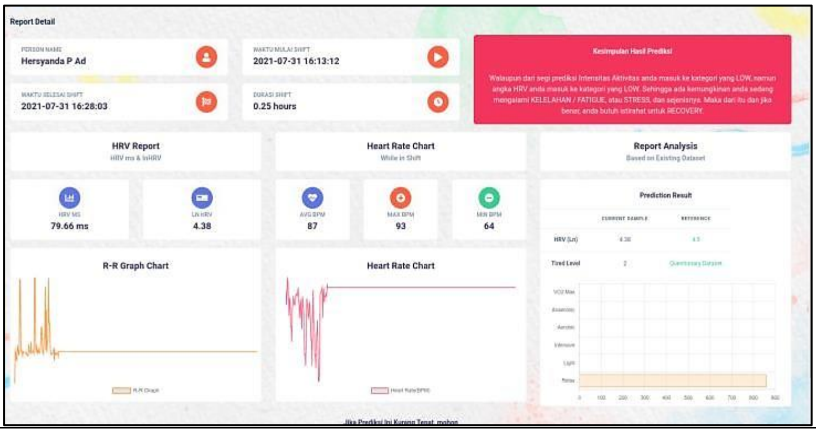
Activity	Result
Studying and working	

Table 5. Continued
Prediction accuracy test result

Activity	Result
Sitting down and static testing	
Browsing, rest and particular condition: lack of sleep in the last 3 days	

4. Conclusions

The monitoring device has been successfully created and can be used flexibly, and the device can also be operated properly with sufficient accuracy in the process of monitoring activities that do not involve a lot of intensive movement. The monitoring system server was successfully created and can be operated properly. The process of displaying monitoring data in real time, as well as providing the results of monitoring reports and predictions can be carried out as planned. In addition, the process of making fatigue predictions can also be carried out in accordance with expectations on the monitoring server that was developed, with the caveat that the number of available datasets influences the prediction accuracy outcomes.

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