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Analysis of Heartbeat Signals to Detect Sleep Disorders Using Artificial Neural Network Methods

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Abstract

Abstract Sleep disorders such as Central Sleep Apnea (CSA) and Obstructive Sleep Apnea (OSA) can have adverse health effects if not treated properly. This research aims to design a sleep disorder detection device using the Internet of Things (IoT)-based artificial neural network method. This system uses AD8232 sensor to acquire electrocardiogram (ECG) signal which is then extracted High Frequency and Low Frequency features. Feature extraction is performed using the Fast Fourier Transform method. Classification of normal, CSA, or OSA conditions is performed using the Multilayer Perceptron artificial neural network method which is trained using data from Physionet. The ESP32 microcontroller is used to process the feature extraction and classification. The classification results are then sent to the database via the ESP32 WiFi module and displayed on the website interface. From testing the performance of the AD8232 sensor, an accuracy of 96.85% was obtained, the classification accuracy using the Artificial Neural Network was 80%, and the average computation time was 7.6 ms. This system has the potential to help early detection of sleep disorders so that they can be treated early by medical personnel.

Keywords: *Artificial Neural Network Method; Obstructive Sleep Apnea; Sleep Disorder; ECG Signals; Central Sleep Apnea*

1. Introduction

Sleep is a very important activity for humans because it allows the brain to give the body time for complete rest [1]. Poor sleep quality can increase the risk of depression, immune system disorders, chronic diseases, and even death [2]. One of the causes of poor sleep quality is the presence of sleep disorders. According to research data, more than 28 million people or 10% of the population in this country are reported to suffer from sleep disorders [3]. Sleep disorders in Indonesia are very high, especially in children aged 0-36 months, with a prevalence rate of 31% [4]. The World Health Organization (WHO) states that types of sleep disorders in humans include Sleep-Disordered Breathing (SDB), REM Behaviour Disorder (RBD), and Restless Legs Syndrome (RLS) [5]. Of the three types of sleep disorders, SDB is the most commonly experienced, reaching 20% - 40% [6]. SDB encompasses Obstructive Sleep Apnea (OSA) and Central Sleep Apnea (CSA). The standard diagnostic tool for identifying sleep disorders or sleep apnea in the medical world is Polysomnography (PSG). However, this tool is not always effective because it requires the installation of many electrodes on the patient's body, takes a considerable amount of time to administer, and requires the patient to sleep in the hospital [7]. Therefore, alternative diagnostic techniques are needed that can be carried out practically at home without the need for hospital care through the analysis of Electrocardiogram (ECG) signal recordings [8].

Several studies have been conducted related to the detection of sleep disorders, including one carried out by The study conducted by Ratnasari in 2022 [9] analyzed sleep disorders using QRS duration and RR

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interval and analyzed them using the Artificial Neural Network method. The system was designed as a cardiac electrical activity detector with 3 electrodes attached to the chest to record and extract RR interval and QR duration features, the results of which are displayed on a smartphone with Bluetooth connectivity. However, this device can only transmit data when connected within one Bluetooth device, and if the distance is more than 5 meters indoors and 10 meters in different rooms, it cannot transmit data. Another study was conducted by Qonita in 2022 [10] study designed a central sleep apnea detection system using the AD8232 ECG sensor and the HC-05 Bluetooth module. The accuracy achieved in the testing of this research using the K-NN method was 83.33% and the average computation time was 78.7 ms. Further development of research related to sleep disorder detection systems can still be done by increasing accuracy and reducing computation time.

Based on existing issues and related research, a portable home diagnostic technique for sleep apnea is needed, eliminating the need for a hospital sleep laboratory. The proposed system, using a microcontroller, can detect sleep disorders like CSA and OSA and allows real-time monitoring by doctors through a website. This aids in initial diagnosis by recording patient signals overnight. The system utilizes an ESP32 microcontroller for ECG feature extraction and classification, with the AD8232 module as a sensor for ECG signals. Three electrodes are placed on the upper and lower chest and a reference point, using the Fontaine bipolar precordial lead technique. The system offers good accuracy and computation time, suitable for home use. The ESP01 WiFi module sends classification results to a database, accessible via the website. This portable, fast, and accurate detection system helps doctors monitor patient conditions during sleep, with stored results available for further examination.

2. Methods

This research involves hardware programming, integrating sensors, microcontrollers, and IoT interfaces with machine learning methods, specifically Artificial Neural Networks (ANNs). The researcher considered the main parameters and limitations of previous studies, such as the use of QRS duration and RR interval features recorded by Ratnasari (2022), and the use of the AD8232 ECG sensor by Qonita (2022). These studies highlighted the issues of Bluetooth data transmission range and computational efficiency.

The researcher chose the AD8232 ECG sensor due to its reliability in capturing heart signals and explored alternative connectivity options to improve range and reliability. Sensor and method selection was based on a careful assessment of the pros and cons, including the need for precise placement and limited Bluetooth range, to ensure robust data collection and analysis.

2.1. System Design

The system design model explains how the system works in a structured manner. In a basic model of a system, there are 3 main processes, namely input, process and output. The system workflow design can be seen in Figure. 1.

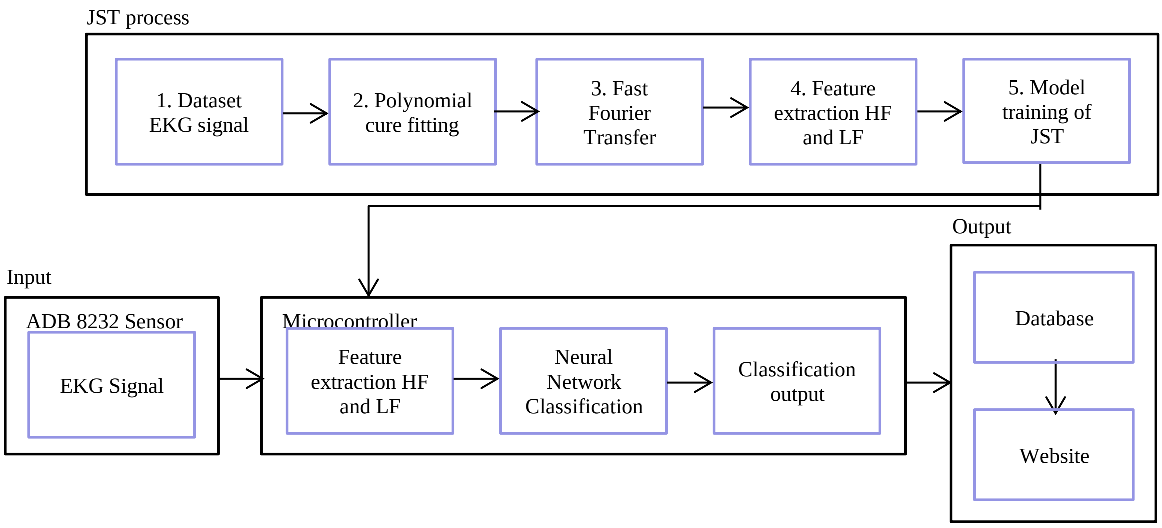

Figure 1. System Design Model

Figure 1 is an illustration of the hardware block diagram designed in this research. In the input diagram, there is an 18650 battery used to power the ESP32, then there is an AD8232 sensor used as input to read the electrical signal activity in the heart using 3 electrodes. Furthermore, in the processing diagram, the Arduino will extract features from the AD8232 sensor, then perform Artificial Neural Network classification, where the weight values of the Artificial Neural Network are obtained from the training process using MATLAB software. The dataset is obtained from Physionet, which is then processed using polynomial curve fitting to ensure the middle value of the signal is zero. After that, a Fast Fourier Transfer feature extraction process is performed, and the High Frequency and Low Frequency features are taken to train the Artificial Neural Network model. The classification results will be sent to the database. In the output diagram, the data sent by the ESP32 will be received and displayed on a website using the Laravel framework. The sequence of the system's operation can be described in the flowchart in Figure 2 as follows:

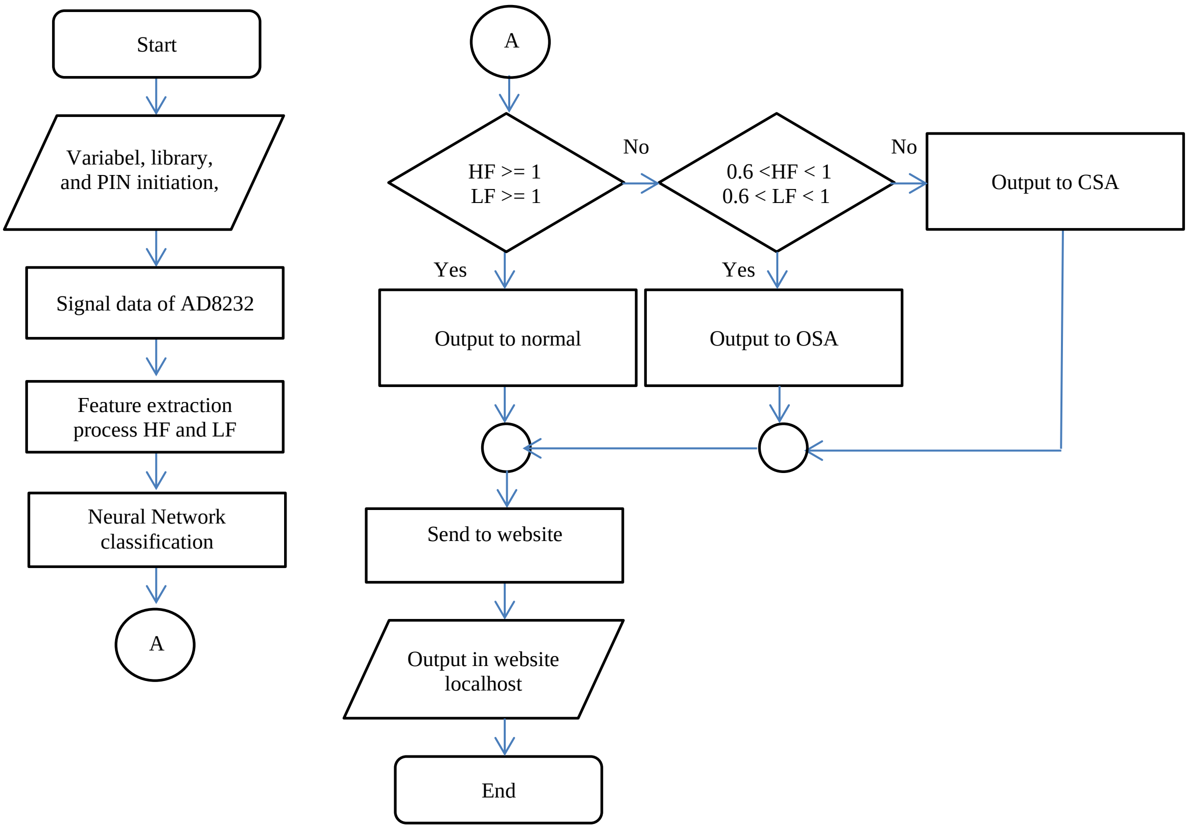

Figure 2. Flowchart of systems

The classification of normal, OSA, and CSA classes is based on the references as shown in the following Table 1 [11]:

Table 1. Reference values for normal, OSA, and CSA

No	HF	LF	Class
1	1.81	1.38	Normal
2	0.78	0.85	OSA
3	0.57	0.45	CSA

2.2. System Analysis

The analysis in the system to determine the normal, OSA, or CSA class is using an Artificial Neural Network (ANN). The ANN method is a Machine Learning (ML) method whose working mechanism is similar to the human brain. This method performs the learning process by calculating the weight values based on its layers. There are 3 layers in ANN: the input layer, the hidden layer, and the output layer. The input layer represents the number of features that will be input into the architecture, usually the input layer is expressed in the form of a vector P with L rows [12]. The hidden layer is the layer between the input layer and the output layer. In this hidden layer, the neurons will be determined, which will have a set of weights from the input layer to produce the output layer. The output layer is the final layer of neurons, which is the result of the system output. The illustration of the ANN can be seen in Figure 3.

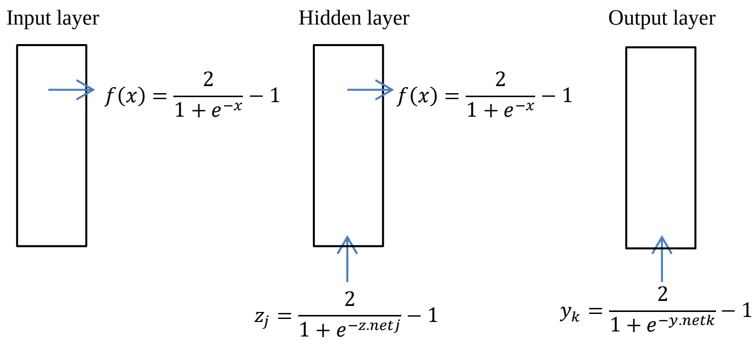

Figure 3. Artificial Neural Network architecture

The Artificial Neural Network used in this research is a feedforward type called a multilayer perceptron (MLP). MLP has a nonlinear activation function that allows the ANN to learn activities based on past data and make decisions on data that has not been learned before. The details of each layer can be seen in Figure 4.

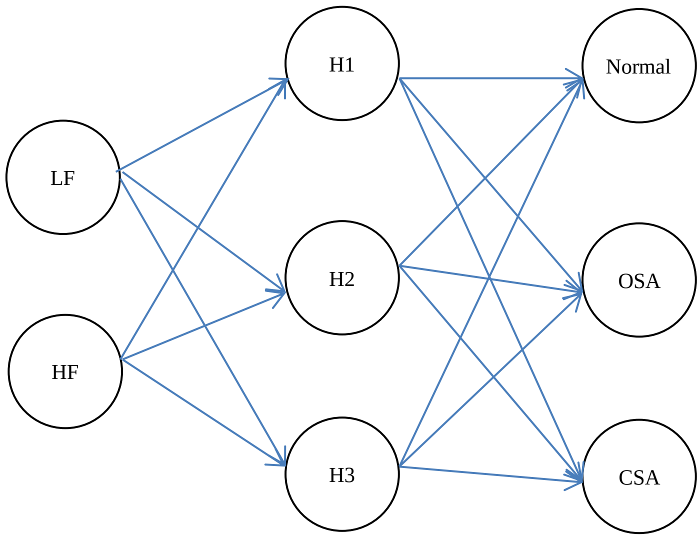

Figure 4. Artificial Neural Network with Multilayer Perceptrons (MLP)

3. Result and Discussion

The sleep disorder detection system that has been designed and integrated with the internet network (IoT) has been tested with the aim of testing the functionality and validity of each system component, including: sensor detection, method performance, and output in the website display.

3.1. Sensor Testing

The testing of the AD8232 sensor reading aims to determine the error rate of the AD8232 sensor reading. The test is carried out by comparing the number of heartbeats or Bits Per Minute (BPM) through sensor readings and manual readings for 10 seconds, then multiplied by 6. The BPM from the sensor reading will be compared with the manual calculation BPM. The test was carried out on 10 different subjects with a time of 10 seconds per subject. Based on the comparison in Table 2, there is a difference between manual measurement and using the AD8232 sensor with an average data error of 3.15% and the accuracy level of the AD8232 sensor reading can be calculated at 96.85%. The calculation of the percentage of error and accuracy uses the following formulas:

$$\%\varepsilon = \left|\frac{N_m - N_B}{N_m}\right| \times 100\% \tag{1}$$

$$\%A = 100\% - \%\varepsilon \tag{2}$$

Where N_m is number of BPM manually and N_B is value of BPM AD232 sensor

Table 2. AD8232 Sensor validation test

Subject	BPM Manually	BPM AD8232 Sensor	Error (%)
1	72	72	0
2	72	72	0
3	84	78	7.14
4	72	72	0
5	72	66	8.33
6	78	78	0
7	78	72	7.69
8	84	84	0
9	78	78	0
10	72	78	8.33

3.2. System Testing

The testing is carried out according to the block diagram that has been applied previously, starting from the reading of the AD8232 sensor, then Fast Fourier Transform (FFT) calculations will be performed and Artificial Neural Network (ANN) calculations will be carried out with the following steps:

1. The patient must be fitted with electrodes according to the initial design of the electrode placement. It can be seen that the electrodes are set according to the following Table 3:

Table 3. Electrode displacement

Colour	Placement	Function
Red (RA)	Upper middle chest	To determine the electrical activity in the heart.
Yellow (LA)	Lower middle chest (last rib)	To determine the direction and magnitude of the signals passing through the heart
Green (LL)	Right chest (below nipple)	To see the overall interpretation of the ECG

2. After ensuring that the electrodes are installed, the reading of the signal is done using the AD8232 sensor, which will then undergo an FFT calculation process on the ESP32. Here is an example of the signal generated on the AD8232 sensor.

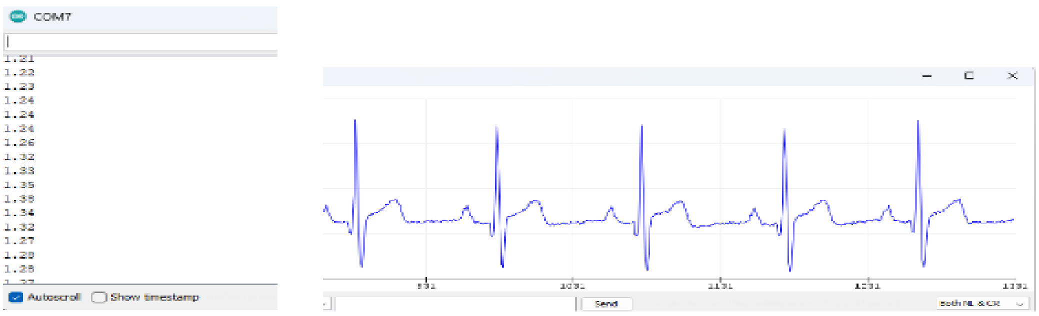

Figure 5. AD8232 AD8232 Sensor Signal Reading

3. After obtaining data from the AD8232 sensor reading, an FFT calculation is performed, which will result in the values of High Frequency (HF) and Low Frequency (LF). The Power Frequency from LF ranges from 0.04 - 0.15 Hz and HF ranges from 0.15 - 0.4 Hz, which will be averaged, and that data will be used as input for the ANN

Table 4. AD8232 sensor reading data between 2 R-Peaks

No	Data
1	1.12
2	1.26
3	1.77
4	1.76
.....	.....
79	1.20

For the calculation on the ESP32, the EasyFFT library directly from Arduino is used. Where the function is already provided, just need to enter the data according to the provided function. The library can be read and viewed at the following link: https://projecthub.arduino.cc/abhilashpatel121/easyfft-fast-fourier-transform-fft-for-arduino-03724d

4. After obtaining the HF and LF values, the weight calculation will be performed, where the training weight values are obtained in the training process using the MATLAB software with the Neural Network Start (NNS) tools which can be seen in Figure 6.

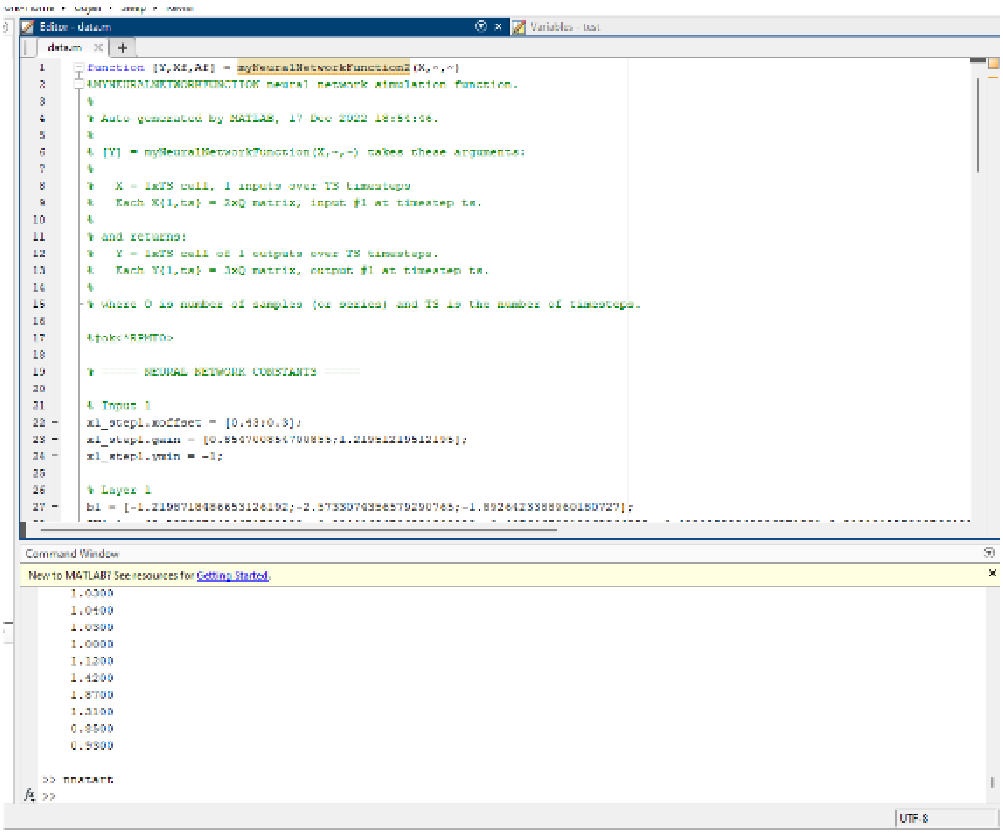

Figure 6. Function Output in NNstar

5. After obtaining the weight values in MATLAB, the calculation process is carried out until it produces the class based on the highest probability value.

3.3. Training Data Testing

The training data testing is a test to see the ability of an algorithm used with the resulting model whether it has an effective level or otherwise. This test uses a dataset obtained from Physionet and is compared with the sensor calculations using the ANN, which can be seen in Table 5

Table 5. Results of training data testing

No	LF	HF	Classification results	Actual class
1.	0.90	0.97	Normal	Normal
2.	0.77	0.92	Normal	Normal
3.	0.82	0.88	Normal	Normal
4.	0.81	0.88	Normal	Normal
5.	0.93	0.88	Normal	Normal
6.	1.01	1.03	Normal	Normal
7.	1.02	1.03	Normal	Normal
8.	0.91	1.03	Normal	Normal
9.	0.75	1.03	Normal	Normal
10.	0.79	1.03	Normal	Normal
11.	0.89	0.97	Normal	Normal
12.	1.05	0.97	Normal	Normal
13.	0.92	0.97	Normal	Normal
14.	0.92	1.00	Normal	Normal
15.	0.89	1.02	Normal	Normal
16.	0.89	1.04	Normal	Normal
17.	0.90	1.04	Normal	Normal
18.	0.87	1.04	Normal	Normal
19.	0.96	1.03	Normal	Normal
20.	0.89	1.02	Normal	Normal
21.	0.85	0.90	OSA	OSA
22.	0.96	0.90	OSA	OSA
23.	0.96	0.90	CSA	OSA
24.	1.00	0.90	OSA	OSA
25.	1.01	0.89	OSA	OSA
26.	1.22	0.68	OSA	CSA
27.	1.12	0.68	CSA	CSA
28.	1.01	0.67	CSA	CSA
29.	1.09	0.67	CSA	CSA
30.	1.12	0.67	CSA	CSA

From the test results of 30 times using the dataset for testing the data class, the error value can be calculated using the following formula

$$\%\varepsilon = \left|\frac{N_v - N}{N}\right| \times 100\% \tag{3}$$

with N_v is the number of valid values and N is the total number of tests. The percentage of error obtained is 6.67%, so the accuracy is 93.33%.

3.4. The Test Data Testing

The test data testing is carried out on 20 random subjects using the ANN method and based on the training data, it can be grouped whether it is included in normal, OSA, or CSA. The test results have been validated by direct testing by filling out the Stop-Bang questionnaire and the Epworth Sleepiness Scale to determine whether the tested subject is a normal patient or experiencing symptoms of sleep disorders. The results of the classification method testing can be seen in Table 6 below

Table 6. Results of test data testing

No	LF	HF	Classification	Actual class

			results	
1.	2.36	0.83	Normal	Normal
2.	1.02	1.22	Normal	Normal
3.	1.72	1.29	Normal	Normal
4.	2.49	1.57	Normal	Normal
5.	1.98	1.28	Normal	Normal
6.	1.05	0.90	OSA	Normal
7.	2.02	1.36	Normal	Normal
8.	1.38	1.12	Normal	Normal
9.	2.38	1.90	Normal	Normal
10.	1.78	1.24	Normal	Normal
11.	1.45	0.98	OSA	OSA
12.	1.34	1.11	OSA	OSA
13.	1.23	1.23	OSA	OSA
14.	1.45	1.05	Normal	OSA
15.	1.18	1.26	OSA	OSA
16.	1.48	1.21	OSA	OSA
17.	1.23	1.10	Normal	OSA
18.	1.36	1.40	OSA	OSA
19.	1.76	1.12	OSA	OSA
20.	1.19	1.03	Normal	OSA

The accuracy result obtained from Table 6 is 80%, which indicates that this system is highly effective for detecting sleep disorders. Reading errors in the system are usually caused by sensors that are susceptible to magnetic interference or objects with metallic properties.

3.5. Interface Testing

The interface of this system is a representation of the software design using MS. Office, Google Chrome, Fritzing, Arduino IDE 1.8.10, Visual Studio Code software, and the programming language used is C++. The testing is carried out to prove the results of the patient classification class calculation with the manual calculation using the steps of the ANN method which can be seen in Figure 7.

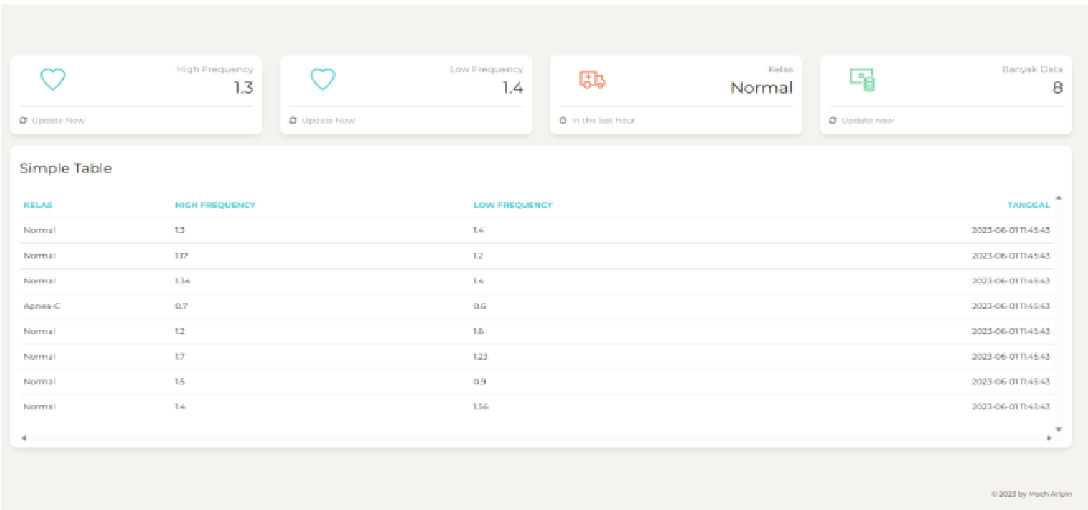

Figure 7. System application

3.6. The Computation Time Testing

The computation time testing is a test to determine the time required to perform classification using the Artificial Neural Network method until the output is generated which can be seen in Table 7.

Table 7. Results of Computation Time Testing

Test data	t (ms)
1	6
2	7
3	8
4	10
5	6
6	7
7	7
8	8
9	9
10	8

From the test results in Table 7, the average computation time for 10 subjects to obtain the results is 7.6 ms. This speed value is influenced by the feature value output, if the feature value is higher, it will result in a fairly high computation of around 10 ms. This is because the ESP32 requires time to calculate the existing weight values.

4. Conclusion

Based on the measurement results, the AD8232 ECG sensor on the ESP32 successfully detected electrical activity and obtained accurate heart signal data. The accuracy level obtained from testing the performance of the AD8232 sensor in detecting cardiac electrical activity is 96.85%. The classification accuracy level using the Artificial Neural Network is 80% based on the classification process using the Artificial Neural Network on 20 test data, which is calculated based on the number of Normal, OSA and CSA classes. This accuracy level is considered quite good. The average computation time of the Sleep-disordered Breathing detection monitoring system using the Artificial Neural Network method is 7.6 ms, based on the computation time range of 6 ms to 10 ms obtained after testing.

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