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Design-Build a Smart Health Device to Measure Stress Levels Based on the Internet of Things (IoT) Using the K-Nearest Neighbor (KNN) Algorithm

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ABSTRACT

Mental health plays an important role in daily life. However, many factors can affect mental health, one of which is stress. Students are one group that is prone to stress. Academic stress is common among students. Currently, physiological stress screening devices are available, but most of them still work separately and are quite expensive. Therefore, this study aims to design an IoT-based stress detection device with a KNN algorithm that can measure physiological symptoms to detect stress levels in a practical and economical manner. This research is a type of engineering research, which involves the process of designing hardware and software for the system in an IoT-based stress level detection tool. The tool is designed to measure three physiological parameters, namely skin conductance, heart rate, and body temperature. Sensor data is processed using the KNN algorithm to classify stress levels into four categories, namely normal, mild, moderate, and severe. The results are displayed on an OLED and ThingSpeak platform so that they can be accessed remotely through IoT integration. Testing was carried out by collecting stress condition data from several subjects. The test results show that the device has an average accuracy and precision value of 83.33% to 99.82%. In addition, the average prediction computation time produced by the system was only 0.44 seconds, this computation time falls within an acceptable range for real-time applications. Thus, this stress level detection tool is expected to be an alternative solution and facilitate remote condition monitoring through the IoT feature.

1. INTRODUCTION

Mental health plays an important role in influencing an individual's mindset, feelings, and behavior in their daily lives. There are many factors that affect a person's mental health, one of which is stress, which has the potential to reduce quality of life and cause disorders such as depression [2]. Students are one group that is prone to stress. The majority of students have experienced stress during their education, and academic stress is a common occurrence [3].

Academic stress is the body's reaction when academic demands exceed a student's ability to adapt, especially when they do not receive social support [4]. The results of the Indonesia-National Adolescent Mental Health Survey (I-NAMHS) show that 39.30% of Indonesian adolescents experience mental disorders in school or work environments [5]. A study explains that academic stress can reduce academic achievement and motivation to learn, leading to the risk of dropping out of school and even the long-term impact of a decrease in workers with quality human resources [6].

Currently, stress levels are generally measured using psychological questionnaires. This method has limitations, such as dependence on self-reporting and subjectivity of results [7]. In addition, devices for physiological stress screening are available, but most of them still work separately and are quite expensive. From the user's perspective, there are factors that make people reluctant to undergo examinations, such as time constraints and lengthy administrative procedures [8].

To overcome these problems, researchers have begun developing low-cost and practical stress detection devices by integrating electronic components such as sensors and microcontrollers. In a previous study conducted by Aritonang et al. [9], a stress level detection device was developed using a DS18B20 temperature sensor and an MPX5700AP pressure sensor integrated with an Arduino microcontroller. The study achieved a sensor accuracy of 96.00%; however, it had several limitations that should be considered in future research. One of the main limitations was that the device was only capable of measuring two parameters and did not employ machine learning techniques.

Subsequently, Wijayanti et al. [10] developed a stress detection device using an MLX90614 temperature sensor and a MAX30102 heart rate sensor. The system achieved an accuracy of 70.00%. However, the study was limited to measuring only two parameters, namely body temperature and heart rate. Although both parameters are physiological indicators of stress, this limitation may reduce the device's capability to accurately detect stress conditions. In addition, the system was not integrated with Internet of Things (IoT) technology.

Another study conducted by Raimun [11] developed a stress detection device using a Galvanic Skin Response (GSR) sensor. The study utilized only a single physiological parameter, namely GSR, and achieved an accuracy of 99.35%. Furthermore, Dinasty et al. [12] developed a human stress level detection device using GSR and MAX30102 sensors combined with a decision tree algorithm. The system achieved an accuracy of 75.00% with a computation time of 36.80 seconds. However, the device was not integrated with IoT technology, and therefore the measurement results could only be displayed locally through an LCD. The absence of IoT functionality prevented remote monitoring and reduced the overall effectiveness of the system.

To overcome the limitations of previous studies, further development of human stress detection devices is required. Previous studies generally utilized only one or two physiological parameters. Moreover, several studies did not implement machine learning techniques or IoT technology, resulting in measurement data that could only be displayed locally and did not support remote monitoring. In this study, three physiological parameters, namely GSR, heart rate (MAX30102), and body temperature (DS18B20), are utilized and integrated with the K-Nearest Neighbor (KNN) algorithm to improve stress level classification performance. In addition, IoT integration enables measurement data to be transmitted and monitored in real time via the Internet.

Based on the aforementioned background, this research is entitled “Design-Build a Smart Health Device to Measure Stress Levels Based on the Internet of Things (IoT) Using the K-Nearest Neighbor (KNN) Algorithm.” The objective of this study is to determine the design specifications and performance specifications of the proposed stress detection device. This study utilizes IoT technology and the KNN algorithm to enable a more comprehensive analysis of an individual's stress level. Therefore, the proposed system is designed to improve classification accuracy and accelerate decision-making processes, thereby contributing to the development of innovative healthcare technologies.

2. METHOD

The type of research conducted is engineering research aimed at designing and building a specific tool or product. This research is designed to create a product to improve the performance of existing products. This research was conducted at the Electronics and Instrumentation Physics Laboratory, Faculty of Mathematics and Natural Sciences, Padang State University.

This research has three main variables, namely independent variables, dependent variables, and controlled variables. The independent variable in this research is the user, while the dependent variables include the output of the GSR, MAX30102, and DS18B20 sensors, which measure skin conductance, heart rate, and body temperature, respectively. The controlled variable is the electronic components used. The stages carried out in this study can be seen in Fig. 1.

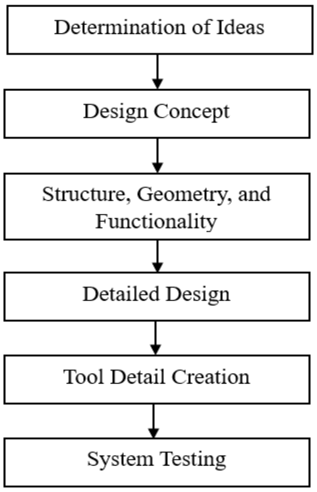


Fig. 1. Research Flowchart

2.1 System Design

The device is designed by combining a GSR sensor, MAX30102 sensor, and DS18B20 sensor, which will then be processed by an NodeMCU ESP32 microcontroller. The processed data will be displayed on an OLED and monitored online using ThingSpeak. The system will be equipped with a KNN algorithm to improve the accuracy of the device. The block diagram of the device system can be seen in Fig. 2.

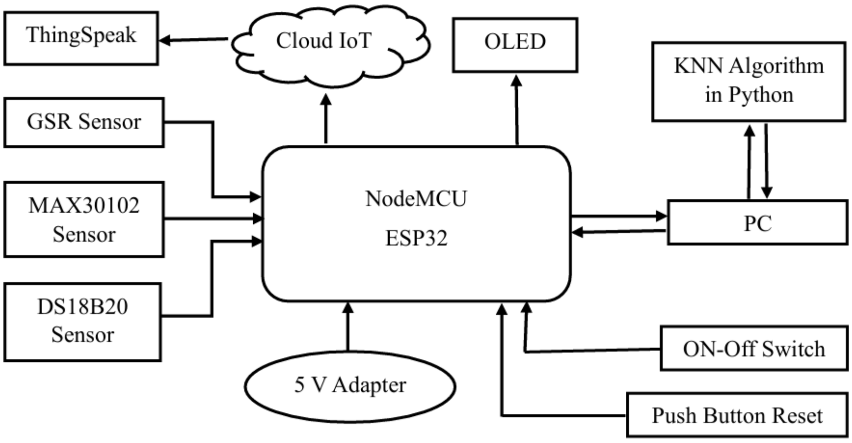
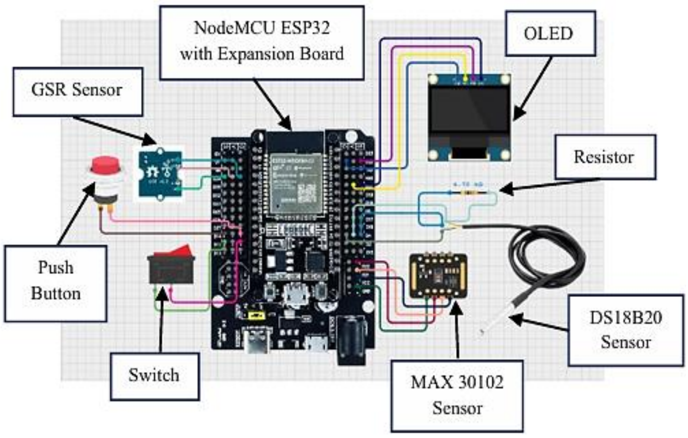


Fig. 2. Block Diagram of Stress Level Detection Device System

The IoT-based stress level detection device system works by using NodeMCU ESP32 as the control center. To turn on the device, a 5V adapter power supply is used. In addition, the system is equipped with a switch to activate (On) and deactivate (Off). The system's input is obtained from a GSR sensor to measure skin conductivity, a MAX30102 sensor to measure heart rate, and a DS18B20 sensor to measure body temperature. The three sensors are connected to the NodeMCU ESP32 to send data on the individual's condition. The data from the sensors is collected by the ESP32 and then sent to a PC to be classified using the KNN method using the Python programming language. After the stress level classification is obtained, the results are sent back to the ESP32 to be displayed on the OLED and also sent to the IoT cloud platform, which in this study uses ThingSpeak via the Wi-Fi connection on the ESP32.

2.2 Hardware Design

Hardware design is a combination of electronic circuits and mechanical design of the device. The electronic circuitry serves to connect and regulate the operation of sensors, microcontrollers, and supporting components so that the system can run properly. Meanwhile, the mechanical design acts as a container or mounting place for components. In this study, the hardware design of the device can be seen in Fig. 3.



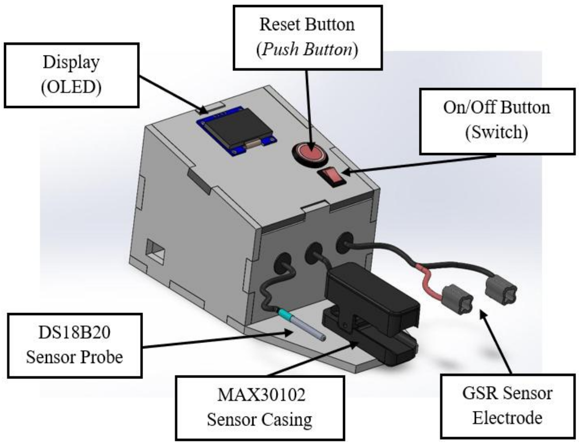


Fig. 3. (a) electronic circuitry, and (b) mechanical form of the device

2.3 Software Design

Software design is the design of programs that will be entered into a microcontroller to execute instructions. Generally, software design is defined using flowcharts. The flowchart for this stress level detection tool can be seen in Fig. 4.

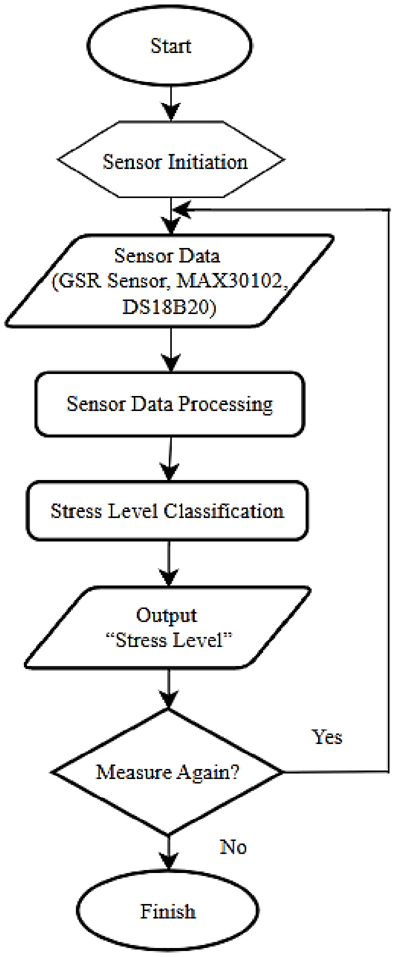


Fig. 4. Work Equipment System Flowchart

Based on the flowchart, after all data from the sensors has been collected, the sensor data will be classified using the KNN algorithm. The classification results will be displayed as output in the form of stress levels such as normal, mild stress, moderate stress, and severe stress. Once the stress level is known, the system will ask "Measure Again?". If yes, the system will return to reading the sensors, but if not, the process will end (complete).

2.4 Data Collection Techniques

Data collection techniques are systematic steps taken by researchers in gathering data to achieve specific objectives. Data collection techniques are systematic steps taken by researchers in gathering data to achieve specific objectives. Before data collection, clients are prepared to be in a calm and stable condition by asking them to sit in a comfortable position and refrain from physical activity for 5 minutes to stabilize their heart rate and body temperature. Once calmer, the device is attached to the client. The client is given a controlled trigger to obtain data on different conditions.

First, a situation is designed to trigger the client's stress reaction by giving them math problems with a time limit for each question. While working on the problems, additional pressure is applied in the form of the sound of a ticking clock to increase the client's psychological burden. After the time to complete the questions has expired, the client is instructed to calm down by breathing slowly. The client is asked to sit in a comfortable position and perform breathing relaxation. Data collection in this study was obtained through physical measurements on the device. Some of the data measured and calculated in this study were accuracy, error, and precision.

2.5 Technical Data Analysis

Technical data analysis is a procedure used to process, analyze, and interpret data to obtain information and support conclusions. Accuracy is the degree of closeness between the predicted value and the actual value. The accuracy percentage can be calculated using Equation (1).

$$A\% = \left(1 - \left|\frac{Y_n - X_n}{Y_n}\right|\right) \times 100\% \qquad (1)$$

Where Y_n is the actual value measured by the SNI measuring device and X_n is the value measured by the stress level detection device.

Precision is the closeness of the values produced from repeated measurements of a data set. The percentage of precision can be calculated using Equation (2).

$$P\% = \left(1 - \left|\frac{X_n - \bar{X}}{\bar{X}}\right|\right) \times 100\% \qquad (2)$$

Where X_n is the nth measurement value and $\bar{X}$ is the average value of all

Error, also known as measurement deviation, is the percentage difference between the measured variable value and the actual value. The percentage error can be calculated using Equations (3) and (4).

$$\%KSR = \left|\frac{(Y_H - X_U)}{Y_H}\right| \times 100\% \qquad (3)$$

Where Y_H is the calculated conductance value and X_U is the conductance value measured by the stress level detection device.

$$\%\ error = \left|\frac{(Y_n - X_n)}{Y_n}\right| \times 100\% \qquad (4)$$

Where Y_n is the actual value measured by the SNI measuring device and X_n is the value measured by the stress level detection device.

3. RESULTS AND DISCUSSION

The research results were obtained through a series of stages, including system design, hardware and software integration, device testing, and performance evaluation. The collected data are presented in tables and graphs to facilitate the interpretation and analysis of the device's performance. The analysis of these results was conducted to achieve the research objectives, namely to determine the design specifications and performance specifications of the Internet of Things (IoT)-based stress level detection device using the K-Nearest Neighbor (KNN) algorithm.

3.1 Device Design Specifications

Design specifications describe the required performance standards and functionality of a system [13]. To ensure that the developed device met these specifications, characterization was conducted on the sensors used in the system. Sensor characterization is an evaluation process performed to analyze sensor responses to input variations and to assess their stability and reliability in producing outputs. In this study, three sensors were characterized, namely the GSR sensor, the MAX30102 sensor, and the DS18B20 sensor. The characterization results demonstrated that all three sensors exhibited good performance, with coefficients of determination (R^2) ranging from 0.9951 to 0.9997.

These sensors were subsequently integrated into a stress level detection device controlled by a NodeMCU ESP32 microcontroller. The developed system was also equipped with an OLED display as a local interface and the ThingSpeak platform as a cloud-based interface for displaying measurement results. In addition, the device was equipped with a switch functioning as an ON/OFF button and a push button functioning as a reset button. All components were assembled and interconnected according to the designed system architecture. After the integration process was completed, the electronic circuit was housed in a 5-mm-thick acrylic enclosure in the shape of a trapezoidal prism, as shown in Fig. 5.

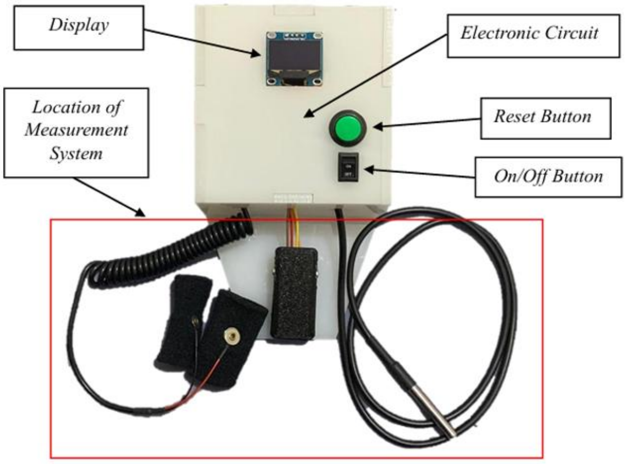
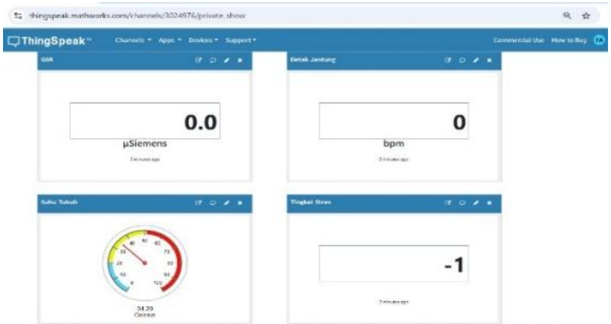


Fig. 5. Overall Mechanical Design of the Device

This device uses two interfaces: OLED as a local display and ThingSpeak as a cloud-based interface. The data displayed on the OLED includes skin conductance values, heart rate, body temperature, and stress level classification results. In addition, the OLED also displays the operational status of the device, such as ON/OFF status, reset indicator, and Wi-Fi network connection information required by the ESP32 to receive and send data to the cloud platform. Furthermore, measurement data for each parameter is displayed every 15 seconds on the ThingSpeak platform via the ESP32's Wi-Fi connection. A dedicated channel is created on ThingSpeak to display the data sent by the system. The device interface design can be seen in Fig. 6.

(a) (b)



(c)

Fig. 6. (a) OLED display, (b) Graphical display on ThingSpeak, (c) Measurement value display on ThingSpeak

3.2 Device Performance Specifications

Performance specifications are a measure of the quality and quantity of system components that affect the level of ease of use of a device [14]. Accuracy data was obtained by comparing the values displayed on the stress detection device with the values displayed on the standard measuring device. Errors were obtained from the percentage difference between the measured variable values and the actual values. The accuracy of the GSR was evaluated by comparing the skin conductance values generated by the device with the theoretical conductance values calculated using the voltage divider circuit principle. Measurements were performed simultaneously on the same subject under identical hand conditions. The GSR electrodes were attached to the index and middle fingers of the left hand, while the voltage divider circuit measurements were conducted on the index and middle fingers of the right hand. The skin resistance values obtained from the voltage divider circuit calculations were subsequently converted into conductance values. The accuracy and error data for skin conductance on the stress level detection device can be seen in Table 1.

Table 1. Accuracy Data and Skin Conductance Measurement Errors in Stress Level Detection Devices

Measurement of	Skin Resistance Value ($k\Omega$)	Calculated Conductance Value ($\mu Siemens$)	Measured Conductance Value ($\mu Siemens$)	$A\%$	$\%RE$
1	597.289	1.67	1.74	95.81	4.19
2	269.230	3.71	3.59	96.77	3.23
3	500.000	2.00	2.05	97.50	2.50
4	386.555	2.59	2.55	98.46	1.54
5	658.291	1.52	1.40	92.11	7.89
6	448.004	2.23	2.11	94.62	5.38
7	692.308	1.44	1.40	97.22	2.78
8	422.413	2.37	2.40	98.73	1.27
9	333.872	2.99	2.95	98.66	1.34
10	269.231	3.71	4.09	89.76	10.24
Average				95.96	4.04

The accuracy of heart rate measurements was evaluated by comparing the measurements obtained from the developed device with those obtained from the Yuwell Fingertip Pulse Oximeter YX-102 as the reference device. Measurements were performed simultaneously on the same subject under identical conditions. The measurement using the developed device was conducted on the middle finger of the left hand, while the measurement using the reference device was conducted on the middle finger of the right hand. The accuracy and error data for heart rate measurement on the stress level detection device can be seen in Table 2.

Table 2. Accuracy Data and Heart Rate Measurement Errors in Stress Level Detection Devices

Measurement of	Heart Rate Measured by Device (bpm)	Yuwell *Fingertip Pulse Oximeter* YX-102 (bpm)	$A\%$	$\%\ error$
1	102	105	97.14	2.86
2	100	98	97.95	2.05
3	88	91	96.70	3.30
4	96	92	95.65	4.35
5	88	86	97.67	2.33
6	76	80	95.00	5.00
7	86	84	97.62	2.38
8	100	102	98.03	1.97
9	92	94	97.87	2.13
10	91	94	96.80	3.20
Average			97.04	2.96

The accuracy of body temperature measurements was evaluated by comparing the measurements obtained from the developed device with those obtained from the Omron MC-246 Digital Thermometer as the reference device. Measurements were performed simultaneously on the same subject under identical conditions. The accuracy and error data for body temperature measurement on the stress level detection device can be seen in Table 3.

Table 3. Accuracy and Error Data for Body Temperature Measurement on Stress Level Detection Devices

Measurement of	Body Temperature Measured by the Device (°C)	Thermometer Digital Omron MC-246 (°C)	$A\%$	$\%\ error$
1	35.41	35.40	99.97	0.03
2	36.47	36.40	99.80	0.20
3	35.97	36.00	99.92	0.08
4	33.04	32.90	99.57	0.43
5	35.47	35.40	99.80	0.20
6	32.54	32.60	99.82	0.18
7	36.16	36.10	99.83	0.17
8	33.47	33.50	99.91	0.09
9	35.41	35.50	99.75	0.25
10	35.85	35.80	99.86	0.14
Average			99.82	0.18

The device has a high level of accuracy for each parameter measured. Skin conductance measurements are accurate to 95.96%, heart rate measurements are accurate to 97.04%, and body temperature measurements are accurate to 99.82%. However, the device has a measurement error of 4.04% for skin conductance measurements, 2.96% for heart rate measurements, and 0.18% for body temperature measurements.

The precision of the stress level detection device was determined by measuring each parameter and determining a single value to be measured repeatedly 10 times. The precision of the device was determined by the closeness of the values in each experiment. Data on the precision of the stress level detection device in measuring skin conductance was collected 10 times by placing electrodes on the index and middle fingers while the body was in a relaxed state. The precision data of the device in measuring skin conductance values can be seen in Table 4.

Table 4. Skin Conductance Measurement Precision Data

on Stress Level Detection Devices

Measurement of	Skin Conductance (μS)	$P\%$
1	0.81	92.04
2	0.87	98.86
3	0.81	92.04
4	0.86	97.73
5	0.86	97.73
6	0.91	96.59
7	0.96	90.90
8	0.88	100.00
9	0.94	93.18
10	0.86	97.73
Average	0.88	95.68

The precision data of the device in measuring heart rate values can be seen in Table 5.

Table 5. Heart Rate Measurement Precision Data on Stress Level Detection Devices

Measurement of	Heart Rate (bpm)	$P\%$
1	101	97.77
2	98	99.19
3	100	98.78
4	100	98.78
5	100	98.78
6	98	99.19
7	97	98.17
8	99	99.79
9	98	99.19
10	97	98.17
Average	98.80	98.78

The precision data of the device in measuring body temperature values can be seen in Table 6.

Table 6. Body Temperature Measurement Precision Data on Stress Level Detection Devices

Measurement of	Body Temperature (°C)	$P\%$
1	36.60	99.75
2	36.60	99.75
3	36.72	99.92
4	36.60	99.75
5	36.66	99.92
6	36.79	99.72
7	36.72	99.92
8	36.79	99.72
9	36.79	99.72
10	36.66	99.92
Average	36.69	99.81

The precision of the device was tested by taking data 10 times under the same conditions. The skin conductivity measurement showed a precision of 95.68%, the heart rate measurement showed a precision of 98.78%, and the body temperature measurement showed a precision of 99.81%. These results indicate that the device as a whole has good measurement capabilities, although there are several parameters that require special treatment to ensure stable measurements and good precision results.

The stress level classification process was carried out using machine learning with the KNN algorithm. In this study, 200 training data with a value of k=3 were used. The results of the KNN classification of all data for k=3 had an average success rate of 95.80% [15]. The results of the KNN algorithm classification evaluation can be seen in Fig. 7.

```
              precision    recall  f1-score   support

           0       0.99      0.96      0.97       205
           1       0.97      0.96      0.96       245
           2       0.85      0.98      0.91        41
           3       0.00      0.00      0.00         0

    accuracy                           0.96       491
   macro avg       0.70      0.72      0.71       491
weighted avg       0.97      0.96      0.96       491


Jumlah Benar: 470 | Jumlah Salah: 21 | Total: 491
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Fig. 7. Results of KNN Algorithm Classification Evaluation.

Based on the test results of 491 data obtained from measurements stored in ThingSpeak, the KNN algorithm has an accuracy rate of 96%. The computation time required by KNN to calculate each data is 2.20 ms on average, with a total processing time of 0.44 seconds. Based on the test results, the KNN algorithm has excellent performance.

To determine the accuracy of the stress level classification results in this study, testing was conducted by comparing the classification results with the STAI Form Y-1 questionnaire. Testing was conducted on 6 subjects under two conditions, namely before an examination and after a Basic Physics examination. Data regarding the accuracy of the stress level classification results are presented in Table 7 and Table 8.

Table 7. Agreement Data of Stress Level Classification Results Under Pre-Examination Conditions

Subject	Stress Level Detection Device				Stress Class by STAI Form Y-1	Compliance (Yes/No)
	Skin Conductance ((μS)	Heart Rate (bpm)	Body Temperature (°C)	Stress Class		
1	0.84	88	34.22	Mild	Mild	Yes
2	0.80	103	28.98	Severe	Moderate	No
3	1.35	96	30.04	Moderate	Moderate	Yes
4	1.09	86	30.91	Moderate	Moderate	Yes
5	2.12	105	33.41	Mild	Severe	No
6	1.35	114	30.66	Moderate	Moderate	Yes
Appropriate Amount						4

Table 8. Agreement Data of Stress Level Classification Results Under Post-Examination Conditions

Subject	Stress Level Detection Device				Stress Class by STAI Form Y-1	Compliance (Yes/No)
	Skin Conductance ((μS)	Heart Rate (bpm)	Body Temperature (^oC)	Stress Class		
1	1.06	67	30.60	Mild	Mild	Yes
2	0.98	69	32.85	Mild	Mild	Yes
3	1.29	85	35.41	Mild	Mild	Yes
4	1.80	96	35.66	Mild	Mild	Yes
5	1.18	98	32.85	Moderate	Moderate	Yes
6	1.30	67	30.16	Mild	Mild	Yes
Appropriate Amount						6

The developed stress level detection device achieved an accuracy of 83.33%. System performance evaluation was conducted on six participants under two measurement conditions, namely pre-examination and post-examination conditions, resulting in a total of 12 test samples. The evaluation results indicated that 10 out of 12 classification outcomes generated by the system were consistent with the reference assessments obtained from the STAI Form Y-1 questionnaire, whereas 2 classification outcomes were inconsistent.

4. CONCLUSION

Based on the research results, it can be concluded that the design specifications of the smart healthcare device for stress level measurement based on the Internet of Things (IoT) using the K-Nearest Neighbor (KNN) algorithm consist of an electronic circuit system comprising a NodeMCU ESP32, ESP32 expansion board, GSR sensor, MAX30102 sensor, DS18B20 sensor, OLED display, and other supporting components. The system is housed in an acrylic enclosure in the form of a trapezoidal prism measuring 10 × 10 cm, with a front height of 6 cm and a rear height of 8 cm. The device provides two types of interfaces, namely a local interface using an OLED display and a cloud-based interface using ThingSpeak. This study was conducted to address the limitations of previous stress detection devices, which generally employed only one or two physiological parameters, lacked integration with Internet of Things (IoT) technology, and did not optimally utilize machine learning methods for stress level classification. The results demonstrate that the developed device successfully integrates three physiological parameters, namely skin conductivity (GSR), heart rate (MAX30102), and body temperature (DS18B20), with the K-Nearest Neighbor (KNN) algorithm and the ThingSpeak IoT platform. The developed device achieved high measurement performance, with accuracy and precision values ranging from 83.33% to 99.82%, and an average computation time of 0.44 seconds per measurement.

This study still has several limitations, including the device's dependence on a PC for stress level classification decision-making, the relatively limited number of test samples, the use of a stress induction protocol that has not been clinically validated, the lack of control over external factors, and the absence of testing on individuals with clinical anxiety disorders. Therefore, future studies are recommended to employ microcontrollers with greater computational capabilities than the ESP32, enabling the device to operate independently without reliance on a PC, involve a larger and more diverse participant population, implement a validated stress induction protocol, control factors that may influence physiological responses, and evaluate the device's performance in clinical populations. Furthermore, future research may explore the use of alternative machine learning algorithms to improve classification accuracy and system reliability.

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DECLARATIONS

Authorship contribution

Tiara Ayunda: Conceptualized the research, designing and building tools, formal analysis, implemented the software, and drafted the manuscript. **Asrizal and Leni Aziyus Fitri**: Provided feedback to improve it, and validated the manuscript

Competing Interest

There are no personal or financial interests that could influence the results of this study.

Funding statement

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Ethical Clearance

This research was conducted with due regard for ethical considerations, including participant consent and protection of personal data.

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