Jurnal Teknokes
Homepage: teknokes.org; Vol. 19, No. 3, pp. 139-156, September 2026;

e-ISSN: 2407-8964
p-ISSN: 1907-7904

RESEARCH PAPER

OPEN ACCESS

Predicting Stress Levels in Special Needs School Teachers Using DASS-21 and Gradient Boosting Machine

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ABSTRACT

The stress experienced by teachers in Special Needs Schools presents considerable threats to both mental health and job performance, making the need for precise and scalable detection techniques essential. This research presents a multimodal framework for stress classification that combines physiological signals from a wearable IoT device with psychological assessment using the DASS-21. Data were gathered from 48 educators, including heart rate (BPM) and body temperature (°C) as physiological indicators and DASS-21 stress subscale scores as psychological indicators. The target variable was categorized as a binary class (stressed vs. non-stressed) utilizing standardized DASS-21 cut-off scores, with physiological thresholds to improve label dependability. The class distribution was examined to reduce class imbalance bias. The dataset was subjected to preprocessing, which involved normalization and feature selection, and was then divided into a 60:40 train-test split. The evaluation of model generalizability was conducted through 5-fold cross-validation. GBM model was utilized to identify non-linear relationships and interactions between features. Performance assessment involved accuracy, precision, recall, F1-score, specificity, and AUC. The suggested model reached accuracy of 94.12%, 87.5%, and 85.71% for the elementary, junior high, and high school groups, respectively, demonstrating consistently high precision and AUC metrics, reflecting strong discriminative ability. These findings indicate that a clearly defined labeling approach, harmonious feature integration, and strict validation procedure facilitate dependable and consistent stress detection. The suggested framework offers a scalable solution for real-time monitoring of mental health in educational environments. Furthermore, the results explicitly confirm that integrating IoT-based wearable systems with the DASS-21 and the GBM algorithm provides a reliable and scalable approach for stress detection among teachers. This study highlights the practical significance of implementing real-time monitoring systems in educational environments, enabling early identification and intervention for stress management. Such a framework not only improves teachers' mental well-being but also supports institutional decision-making in developing preventive strategies and sustainable mental health programs.

PAPER HISTORY

Received: August 1, 2026
Revised: August 20, 2026
Accepted: September 8, 2026
Published: September 29, 2026

KEYWORDS

Stress;
Heart Rate;
Body Temperature;
GBM;
DASS-21

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1. INTRODUCTION

Stress is a physiological and psychological response to demands exceeding an individual's adaptive capacity, negatively affecting health and performance [1]. The World Health Organization (WHO) reports that more than 280 million people worldwide experience stress-related depression, and more than 700,000 suicides occur annually due to mental health problems [2]. In Indonesia, the prevalence of mental health disorders has increased, with Aceh being among the regions with relatively high rates. Aceh Province is even among the regions with the highest rates of severe mental disorders. Within the

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DOI: https://doi.org/10.35882/jteknokes.v19i3.164

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Homepage: teknokes.org; Vol. 19, No. 3, pp. 139-156, September 2026;
e-ISSN: 2407-8964
p-ISSN: 1907-7904

educational context, Special Needs School teachers are among those highly vulnerable to work-related stress. This is due to the dual roles they must fulfill, not only as teachers but also as individual learning facilitators, emotional companions, and caregivers for students with special needs such as autism, intellectual disabilities, visual impairments, and hearing impairments [3]. The complexity of the workload is compounded by limited infrastructure, a lack of professional support staff, and inadequate technical and emotional training. Stress that is not managed properly can trigger emotional exhaustion, burnout, decreased learning quality, and even mental health disorders such as anxiety and depression [4]. Previous research has shown the direction of development of stress and emotion detection systems utilizing wearable and IoT technology. For example, [5] developed a bracelet-shaped device to detect tantrum symptoms in children with special needs. The system integrates multiple physiological sensors within an IoT-based wearable device for real-time monitoring to the Blynk application on a smartphone. When the child's physiological values exceed a certain threshold, the application sends a notification "Tantrum Detected" to the caregiver. The results of the study showed that physiological changes, such as increased heart rate, changes in body temperature, and increased sweat gland activity, can be early indicators of tantrums. However, this study focused only on integrating IoT devices with physiological monitoring, without using standard psychometric instruments to compare the child's psychological condition.

Another study by [6] explored the use of smartwatches as a tool for monitoring teacher stress in Spain. In the study, two teachers had their heart rates monitored for two weeks in class, and the results were analyzed based on the learning context (subject, class size, schedule, and learning activities) and environmental conditions (temperature, humidity, and sunlight intensity). The results showed variations in teachers' heart rates according to the type of teaching activity, the time of day, and even the day of the week. This study demonstrates that wearable devices can provide systematic data on teacher stress for further analysis. However, its limitations lie in the very small sample size and the lack of integration with psychological measurements using standard instruments. Therefore, the findings are still exploratory and represent initial trends rather than conclusive conclusions.

Meanwhile, [7] proposed a more comprehensive approach by combining physiological data from a wearable system (heart rate and body temperature) with the NASA-TLX psychological instrument to detect stress in final year students. The study combined physiological data with psychological assessment (NASA-TLX) and achieved high classification accuracy using logistic regression. Of the 30 respondents, this study successfully detected 19 students in a stressed condition and 11 in a normal condition, with a model accuracy of 94%. These findings demonstrate that integrating subjective data from psychological questionnaires with objective data from wearables can yield more valid stress detection. However, this study is still limited to the context of students, not to a group of teachers with different workloads and emotional dynamics, and uses a relatively simple analysis model when compared to modern ensemble methods.

Based on these three studies, several critical research gaps remain insufficiently addressed. Studies on tantrums in children primarily emphasize the advantages of integrating IoT and wearable technologies for real-time physiological monitoring. However, existing studies either focus solely on physiological monitoring or rely on limited models and non-standardized psychological instruments, reducing accuracy and generalizability. Smartwatch-based studies on teachers highlight the importance of heart rate monitoring and environmental influences on stress, yet their findings are constrained by small sample sizes, limited feature sets, and predominantly descriptive analyses, which reduce their generalizability and predictive robustness. Meanwhile, studies on college teachers demonstrate that combining physiological and psychological data can improve stress detection accuracy; however, these studies often rely on alternative instruments such as NASA-TLX and relatively simple models like logistic regression [7], and are not specifically designed for teacher populations, particularly Special Needs School teachers who face more complex emotional, cognitive, and social demands.

In addition, prior research tends to treat physiological and psychological data in a partially integrated manner, without leveraging standardized widely validated instruments such as the DASS-21, which limits comparability and clinical interpretability of the results. From a methodological perspective, the use of conventional models also restricts the ability to capture non-linear relationships and feature interactions inherent in multimodal stress data.

Considering these limitations, this study proposes a more comprehensive approach by integrating the DASS-21 psychological instrument with real-time physiological data obtained from IoT-based wearable systems. The DASS-21 instrument was selected due to its established validity and reliability in measuring stress [8]. Furthermore, this study employs the Gradient Boosting Machines (GBM) algorithm, which offers superior capability in modeling complex non-linear relationships and interactions among features compared to traditional methods such as logistic regression, while also providing feature importance for interpretability [9].

The proposed study contributes by evaluating the effectiveness of the Gradient Boosting Machines (GBM) model for stress classification using DASS-21 data and by providing data-driven recommendations for targeted stress management interventions. The results are expected to demonstrate the potential of GBM as a reliable machine learning approach for automated stress assessment while supporting the development of interventions tailored to different levels of stress..

Therefore, this study is the first step in developing technology-based solutions to improve the welfare of special needs school teachers, as well as a concrete

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manifestation of the application of digitalization in the fields of mental health and inclusive education.

2. MATERIALS AND METHOD

This wearable system can sense how stressed teachers feel at special needs schools by using data from body temperature and heart rate, which are connected through the Blynk app. Sensors are tools designed to detect changes in things like temperature, pressure, or chemical levels. They then convert those changes into signals that can be measured as electrical signals [10], [11]. The wearable system, made to track stress levels in teachers at special needs schools, is a bracelet that includes MAX30100 sensors, DS18B20 sensors, GSR sensors, MAX4466 sensors, and a Wemos D1 Mini ESP-32. The study used GBM to assess the accuracy of the results [2] and examined psychological factors using the DASS-21 questionnaire. The stages of this process are shown in the flowchart in Fig.1.

Some other methods use wearable devices to track important health signs in real time, like heart rate, stress levels, heart rate variability, and skin reactions. Research has found that HRV is a strong sign of how the body is reacting. When HRV decreases, it usually indicates higher stress [14]. Wearable devices allow us to take continuous, real-time measurements, which are helpful for early prevention and intervention [14]. Table 1 shows how things are different when there is no stress compared to when there is stress. Under normal conditions, the heart beats between 55 and 90 times per minute, and body temperature remains between 35 and 37 degrees Celsius. When someone is under stress, their heart rate usually goes above 90 beats per minute, and their body temperature may rise. [15], [15], [16]. Numerous studies have shown that body temperatures below 33°C are associated with severe physiological states such as hypothermia, reflecting a significant disruption in the body's ability to regulate temperature. In some situations, this condition may occur in response to intense physical or environmental stress. Nonetheless, this situation does not indicate psychological strain in the general population during everyday tasks. In this study, stress indicators emphasized more typical physiological responses, specifically elevated heart rate and a minor rise in body temperature linked to activation of the sympathetic nervous system.

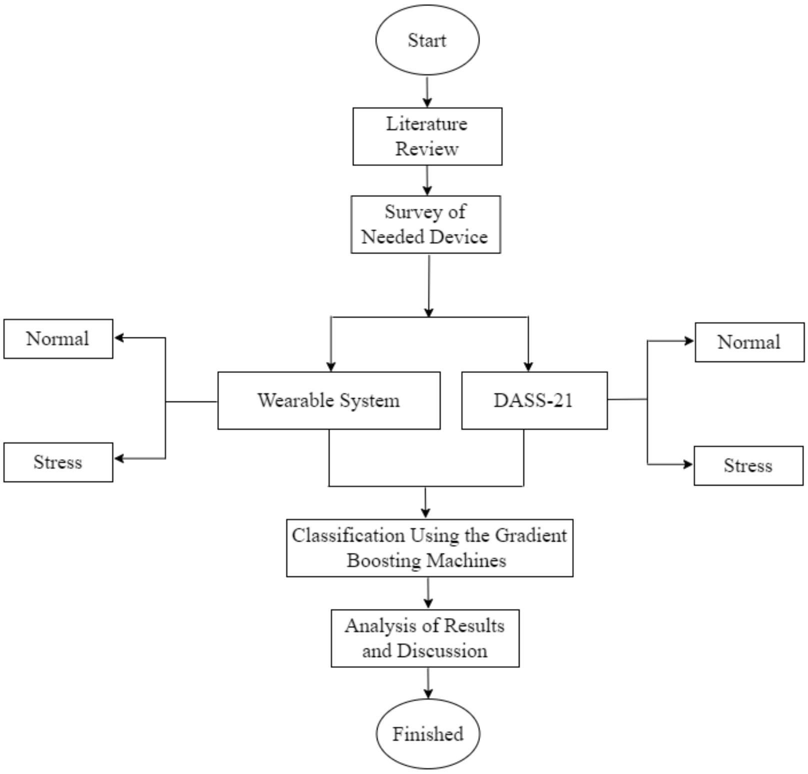

Fig. 1. Research Flow Diagram

Stress

Stress is an issue that can happen to anyone. Stress can affect both the body and mind and change how a person acts. According to the American Psychological Association, stress is divided into several types. There are three types of stress: acute stress, episodic acute stress, and chronic stress. Acute stress is short-term stress resulting from daily activities. Episodic acute stress is repeated stress experienced during a single event. Chronic stress is. Long-term stress is the most dangerous [12]. As part of the body's response to stress, it produces chemicals and hormones as a defense mechanism [13].

Table 1. Comparison of pairs in the stress conditions

Condition	Heart Rate (BPM)	Body Temperature (°C)

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Normal	55-90	35-37
Stress	>90	<33

A. Wearable System

The wearable system that helps detect stress in final-year students looks like a bracelet. This tool measures 5 centimeters in length, 5 centimeters in width, and 12 centimeters in height. It includes a MAX30100 sensor, a DS18B20 sensor, a GSR sensor, a MAX4466 sensor, and a Wemos D1 Mini ESP-32 [7]. The tool's form can be observed in the image (see Fig.2).

Fig. 2. Wearable Stress Detection System

Based on Fig.2, the wearable stress detection system can be seen being attached to the teacher's wrist. At the top of the bracelet, there are several parts. There's a GSR sensor that measures skin conductivity, a MAX4466 sensor that measures sound levels, and a Wemos D1 Mini ESP32 that serves as the microcontroller and Wi-Fi module. At the bottom of the bracelet, there is a DS18B20 sensor that measures body temperature. using a temperature sensor and a MAX30100 sensor to check heart rate. On the side of the bracelet, there is a rubber strap and Velcro tape that help make it easier to wear on the wrist. This tool can connect to the caregiver's smartphone using an ESP-32 to process sensor data and send it to the Blynk app. In the Blynk app, you can view measurement data for heart rate (BPM), body temperature (degrees Celsius), skin conductance (microsiemens), and sound intensity (decibels). Users can use the Blynk app if their email addresses are already registered [5]. The main difference between this study and the research in [11] is that in [11], the person had a tantrum with a heart rate higher than 110 BPM and an elevated body temperature.

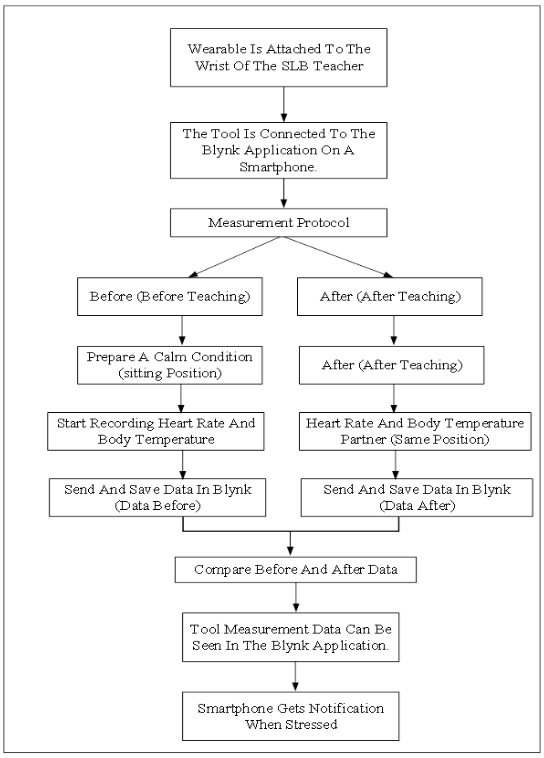

Fig. 3. Data Collection Process Using Wearable System

The measurement process using the wearable system is shown in Figure 3. When the wearable system is worn on a teacher's wrist at Special Needs School Negeri Banda Aceh, it will track heart rate and body temperature in real time. The smartphone needs to be connected to the Wi-Fi network called “ESP Detector” and the network set up using the Wi-Fi available on the Wemos D1 Mini ESP32. When the smartphone is connected, the Blynk app automatically displays the heart rate and body temperature data from the wearable. If the phone detects signs that someone is stressed, it will send a notification. After that, a measurement protocol is conducted in two stages: before and after teaching. In the pre-teaching stage, the teacher is asked to remain calm and sit to record heart rate and body temperature; the data is then saved in the Blynk application as “before” data. After the teaching activity is completed, the measurement is repeated using the same procedure, and the results are saved as “after” data. The two data sets are compared to see changes in the teacher’s physiological condition before and after the teaching activity. The measurement results can be viewed in real time through the Blynk application. If an increase in stress is detected, the smartphone will notify the user so the detection process can be carried out quickly and accurately. Furthermore, the measurement results on the subjects will be classified using the Gradient Boosting Machines (GBM) model using physiological data from the wearable system combined with psychological data from the DASS-21 questionnaire (Stress subscale) as a reference label, so

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e-ISSN: 2407-8964
p-ISSN: 1907-7904

that the category of stress or not stress is obtained in teachers.

B. IoT System

The test was conducted on teachers from special-needs schools, who wore a prototype stress-detection device on their wrists. The device checks their heart rate and body temperature, and then the Wemos D1 Mini ESP 32 uses it as a way to connect to the internet. The data, combined with IoT, is sent through the Blynk app, which is downloaded on a smartphone, as in Fig.4.

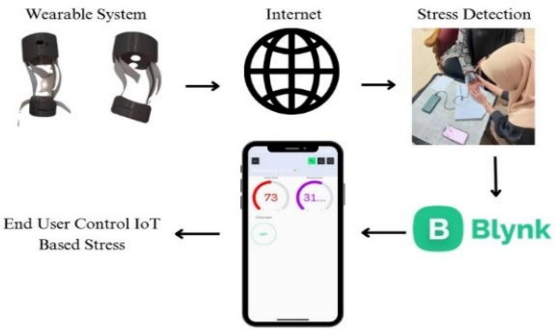

Fig. 4. Workflow of IoT Systems

Fig.4 shows the workflow of a wearable and IoT-based stress monitoring and detection system for Special Needs School teachers. The process begins with the wearable system, a sensor device that teachers use to measure physiological parameters such as heart rate and body temperature during teaching activities. Data obtained from the sensor is then sent over the internet for processing and remote access. The data is then used in the stress detection stage, an analysis process to identify the level of stress experienced by teachers based on changes in the body's physiological parameters. The measurement results are then sent to the Blynk platform, which serves as an IoT-based monitoring application that displays data in real time on smartphones. Through this application, teachers can monitor their heart rate and body temperature as indicators or on graphs, making it easier to identify stress. With this system, teachers, as end users, can directly control and monitor their health conditions through mobile devices, enabling early detection of stress among special needs school teachers and helping maintain well-being and performance during the learning process.

C. DASS-21

DASS-21 (Depression, Anxiety, Stress Scale-21) is a measurement instrument with a multidimensional construct to measure depression, anxiety, and stress that is widely used by researchers, both in Indonesia and abroad. As one of the widely used measurement instruments, the DASS-21 has been tested for validity and reliability in various countries [17]. The DASS-21 is a multidimensional instrument for measuring depression, anxiety, and stress, widely used by researchers in Indonesia and abroad. DASS21 was developed [18]. DASS-21 uses a Likert-scale format with four response options. The depression scale assesses dysphoria, hopelessness, devaluation of life, self-deprecation, lack of interest or involvement, anhedonia, and inertia [19]. The stress scale assesses difficulty relaxing, nervous excitability, irritability or restlessness, irritability or overreactivity, and impatience [20]. Data collection using DASS-21 can be done by giving teachers a DASS-21 questionnaire containing 21 statements as in Table 2, then respondents are asked to rate the frequency of experiences during the last week using the following description scale:

0 = Never (N)
1 = Sometimes (S)
2 = Often (O)
3 = Very Often (VO)

Table 2 . DASS-21 questionnaire [20]

No	Question items	N	S	O	VO
1	I find it hard to rest				
2	I realized my mouth was dry.				
3	I have a hard time seeing the positive in an event.				
4	I'm having trouble breathing				
5	I have difficulty taking the initiative to do something.				
6	I tend to overreact to situations				
7	I have tremors in my hands				
8	I feel like I'm using a lot of energy to worry.				

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Jurnal Teknokes
Homepage: teknokes.org; Vol. 19, No. 3, pp. 139-156, September 2026;
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p-ISSN: 1907-7904

9	I feel anxious about situations that make me panic and do stupid things.
10	I am a pessimistic person
11	I feel restless
12	I find it hard to calm down/relax
13	I feel sad and gloomy
14	I am intolerant of anything that disturbs me while I am working on something.
15	I feel like I panic easily
16	I can't be enthusiastic/interested in anything
17	I feel like I'm worthless
18	I feel like I'm easily offended
19	I am aware of my heart working (beating) when I am not doing any physical activity.
20	I feel scared for no apparent reason
21	I feel that life is meaningless

The DASS-21 consists of 3 subscales: Depression, Anxiety, and Stress (7 items each). For the stress subscale, the items used are: 1, 6, 8, 11, 12, 14, 18. Add up the scores from the 7 items to obtain the raw score. The calculation can be seen in Eq. (1) and Eq. (2) [21].

$$Sraw = Total\ score\ of\ 7\ items \quad (1)$$

Then multiply the total amount by 2.

$$Sfinal = 2xSraw \quad (2)$$

After obtaining the final score, the stress level will be categorized based on the DASS manual (Lovibond & Lovibond, 1995; Henry & Crawford, 2005), the cut-off for the stress subscale can be seen in Table 3:

Table 3 . Cut-off categorization of stress levels [21]

Category	Final score range (after multiplying by 2)
Normal	0-14 (0)
Light	15-18 (1)
Currently	19-25 (2)
Heavy	26-33 (3)
Very heavy	34 (4)

D. Data Processing

To ensure a robust, transparent, and reproducible machine learning pipeline, a comprehensive data processing framework was implemented, consisting of data cleaning, signal processing, feature engineering, normalization, and statistical analysis. In the initial stage, raw physiological signals from the wearable sensors, including heart rate and body temperature, were processed with a moving average filter to reduce short-term fluctuations and sensor noise. This step is essential to improve signal stability and reliability prior to further analysis. The filtered signals were then segmented based on measurement conditions (before and after teaching activities) to capture temporal variations in physiological responses. Following signal preprocessing, feature extraction was conducted to derive meaningful attributes from the physiological data. Extracted features included statistical measures such as mean, standard deviation, minimum, maximum, and range for each parameter. In addition, derived features, such as the difference between pre- and post-activity measurements, were computed to better represent stress-induced physiological changes. Psychological data obtained from the DASS-21 stress subscale were processed to generate final stress scores and were used as ground-truth labels for classification.

To address missing or incomplete data, mean imputation was applied to numerical variables to preserve dataset consistency. Subsequently, all numerical features were normalized using Min-Max scaling to transform values into a uniform range [0,1], thereby improving model convergence and preventing bias due to differing feature scales. Prior to model development, an exploratory statistical analysis was performed to understand the data distribution. Descriptive statistics, including the mean, standard deviation, minimum, and maximum values, were calculated for each feature to assess data quality and identify potential outliers or anomalies. Additionally, class distribution analysis was conducted to evaluate the balance between stress and non-stress categories, which is crucial for reliable model evaluation. For model validation, a stratified data-splitting approach was employed, dividing the dataset into 60% for training and 40% form testing sets while preserving class proportions. To further enhance generalizability and reduce overfitting, 5-fold cross-validation was performed on the training data. During this process, hyperparameters of the GBM model, such as the number of estimators, learning rate,

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and maximum tree depth, was tuning using a grid search strategy. Finally, the trained model was evaluated on the unseen test dataset using multiple performance metrics, including accuracy, precision, recall, F1-score, specificity, and Area Under the Curve (AUC), providing a comprehensive assessment of classification performance.

E. Data Collection

This study dataset aims to detect stress symptoms at the teacher level by measuring the results of the study subjects, namely special needs teachers in elementary, junior high, and high school, aged 25–60 years (young adults), at the State Special Needs School in Banda Aceh City. This is done by measuring stress levels, both psychologically and physiologically. The physiological requirements measurement involves measuring data from study subjects based on heart rate and body temperature parameters to determine stress conditions based on changes in predetermined parameters. Simultaneously, psychological measurement data are collected using the proposed model, including responses to the DASS-21 questionnaire. Several steps considered in testing the stress detection system for final-year students are shown in Table 4. End-users can manage stress using IoT.

Table 4. System Testing Procedure on Subjects

No	Parameter	Justification
1	Amount Subject	48 Special school teachers with category teachers in elementary schools, middle schools, and high schools
2	Age Subject	≥ 25 – 60 Years
3	Measurement Data	Each participant was measured 3 times, resulting in 90 measurement data points with the following measurement details: - 2 measurements when the condition is calm and relaxed so that the measurement process runs smoothly.
4	Protocol Room	Measurements were carried out under the following room conditions: - Time Measurement: 09.00 am – 13.00 pm - The room conditions are calm and conducive - Position: Sit in a chair, and there is a table - In the testing room during teaching conditions, there were 10 children with special needs, 1 teacher, and 1 researcher. - In the testing room, after the activity, there were 1 teacher and 1 researcher.
5	Measured data	The data measured in this test are: - Heart rate (BPM) - Body temperature (°C)
6	Tool Configuration	- The sensors used are MAX30100, DS18B20 - The smartphone used is iPhone 1 3
7	Criteria Subject	Each participant must meet the following criteria This is for data collection: - In good health and not currently taking any medication - Willing to fill out the concern form before taking measurements - The teachers who teach at the school are extraordinary - The subject is calm and able to cooperate so that process detection stress walk fluent
8	SOUP Testing	***Measurement in a physiological way** - Object measurement physiology is the Hand - Testing ± 1.5 minutes - Stages: This consists of the following: 1. Verification Connection & Installation Tool 2. Calibration Tool & Sensor (If required) 3. Testing when the teacher is on break or has not yet carried out teaching activities

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is carried out 3 times within 15 minutes.

4. Testing while the teacher is carrying out teaching activities is carried out 3 times within 15 minutes.
5. The teacher's wrist and the device are connected to Blynk on a smartphone.
6. The measurement data of the tool can be seen in the Blynk application after being measured.
7. ± 1 minute physiological detection results are displayed
8. After the results of these parameters are obtained, they will be classified using the GBM method combined with the DASS-21 score.

***Measurement in a psychological way**

7. Subjects were asked to fill in the answers to the DASS-21 Questionnaire Test honestly.
8. ± 1 minute score answer results questionnaire will be displayed on Google Forms
9. After the DASS-21 score is obtained , a calculation will be carried out to obtain the final score and classified using the GBM method.

F. Gradient Boosting Machines (GBM)

The GBM algorithm is a widely used ensemble learning method in machine learning. This method combines the strengths of several predictive models to improve the performance and accuracy of classification or regression [22]. GBM has advantages in terms of execution speed, memory efficiency, and flexibility to various types of data. In the context of psychology, this algorithm has been used to predict levels of anxiety, depression, and even post-traumatic stress disorder based on questionnaire data and physiological sensors [23]. The classification process using the GBM method is shown in Fig. 5.

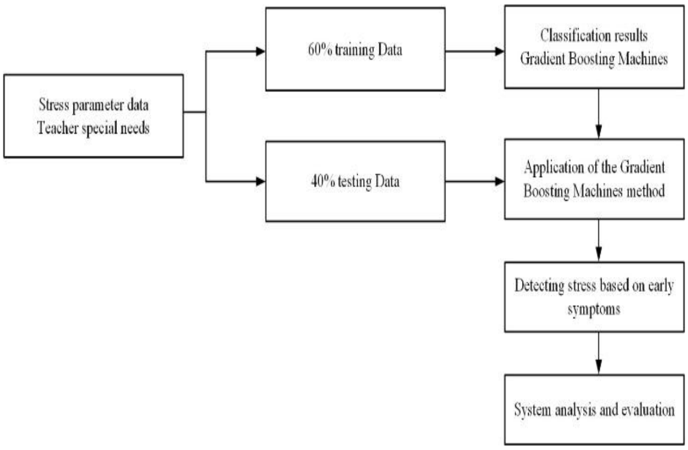

Fig. 5. Classification Process Using GBM Method

Based on Fig. 5, data classification was performed using the Gradient Boosting Machines (GBM) model. The initial step utilized the measured stress parameters of the Banda Aceh State Special Needs School teachers, including physiological data from the wearable system (heart rate and body temperature) and psychological data from the DASS-21 questionnaire (Stress subscale). All data were then divided into 60% training data and 40% testing data to build and test the classification model. Once the model was ready, the system generated stress category detection based on combined physiological and psychological patterns.

Next, analysis and performance evaluation were conducted to assess model performance, including accuracy and other related metrics. The GBM equation can be seen in Eq. (3), Eq. (4), Eq. (5), and Eq. (6) [24][25].

1. Base Learner

$$F_0\,(x) = \underset{\alpha}{argmin} \sum_{i=1}^{N} L\,(y_i, \alpha) \tag{3}$$

2. Residual

$$r_{im} = -\left[\frac{\partial L\big(y_i, F(x_i)\big)}{\partial F(x_i)}\right] \tag{4}$$

3. Weak Learner

$$h_m(x) \approx \gamma_{im} \tag{5}$$

4. Step Size

$$\gamma_{im} = \underset{\gamma}{argmin} \sum_{i=1}^{N} L\,(y_i, F_{m-1}\,x_i + \gamma.h_m x_i)) \tag{6}$$

5. Model Update

$$F_m(x) = F_{m-1}(x) + \gamma_m\, h_m(x) \tag{7}$$

6. Final model

$$F_m(x) = F_0(x) + \sum_{m-1}^{M} v.\gamma_m.h_m(x) \tag{8}$$

G. Confusion Matrix

Models are evaluated by constructing the confusion Matrix for test data [26]. In addition, accuracy, sensitivity, and specificity are also measured for each model [27]. The definitions for these metrics are shown in Eq. (7) through Eq. (10).

To evaluate the performance of the proposed Gradient Boosting Machines (GBM) model in stress classification, five commonly used classification metrics were employed: precision, recall, specificity, F1-score, and accuracy. These metrics were calculated based on the numbers of

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true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions.

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

Precision, as presented in Equation (9), measures the proportion of correctly predicted positive samples among all samples classified as positive by the model. A high precision value indicates that the model produces relatively few false-positive predictions.

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

Recall, shown in Equation (10), measures the model's ability to correctly identify actual positive samples. A higher recall indicates fewer false-negative predictions.

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (11)$$

Specificity, presented in Equation (11), measures the model's ability to correctly identify negative samples among all actual negative samples. A high specificity indicates that the model can effectively distinguish non-positive cases and minimize false-positive classifications.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

F1-score, given in Equation (12), is the harmonic mean of precision and recall, providing a balanced measure of classification performance.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

3. RESULTS

The Results section presents various figures, tables, and classification outputs; however, to enhance scientific rigor and clarity, a more structured quantitative analysis is required. All graphical and tabular representations should explicitly include measurement units, BPM for heart rate and °C for body temperature, and be consistently referenced within the text to ensure traceability. Furthermore, the results should move beyond descriptive presentation by incorporating statistical summaries of the collected data. Descriptive statistics, including mean, standard deviation, minimum, and maximum values, should be reported for each physiological parameter across different experimental conditions before and after teaching activities. These metrics provide a clearer understanding of data distribution and variability among respondents.

In addition, an error analysis should be included to evaluate the reliability and robustness of the proposed model. This can be achieved by reporting variability across cross-validation folds, standard deviation of accuracy, precision, recall, and AUC, and discussing potential sources of misclassification. Such analysis will strengthen the interpretation of results by demonstrating not only model performance but also its stability and generalizability. Therefore, integrating statistical indicators and analytical interpretation will significantly improve the quality, readability, and scientific contribution of this section.

A. Accuracy Data Results using Wearable Systems (Physiology)

System testing on the subjects involved attaching a stress detector to the student's wrist and connecting the smartphone to the ESP 32, as shown in Fig. 6.

Based on Fig. 6, the smartphone needs to be connected to the Wi-Fi network called "ESP Detector" and set up the Wi-Fi using the available Wi-Fi option. After that, the device is put on the teacher's wrist, and the Blynk app is opened. Once the smartphone is connected to the ESP Wi-Fi, the Blynk app will automatically display heart rate and body temperature data. This system requires you to log in to the Blynk app and make sure that every input device used for measurement is connected to the same WiFi network settings. This app helps users understand their stress level early on, before it builds up too much, by checking both their mental state and physical health in real time. The findings from the physiological tests done with the wearable system are shown in Fig. 7 and Fig. 8.

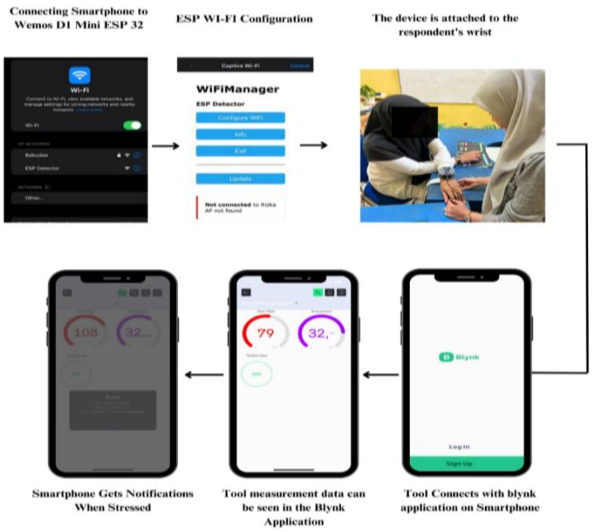

Fig. 6. Physiological Testing Process with Wearable System

If you're feeling stressed, you'll get a stress alert in the Blynk app.

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DOI: https://doi.org/10.35882/jteknokes.v19i3.164

e-ISSN: 2407-8964
p-ISSN: 1907-7904

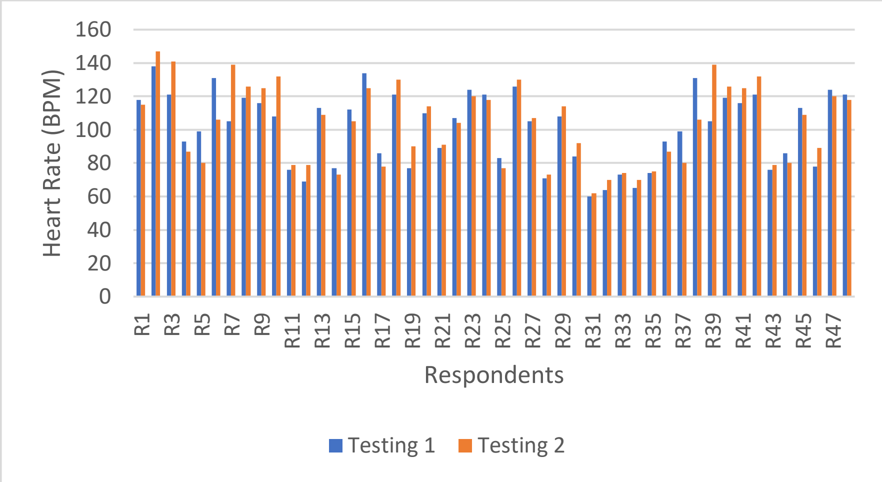

Fig. 7. Average results of heart rate (BPM) measurements

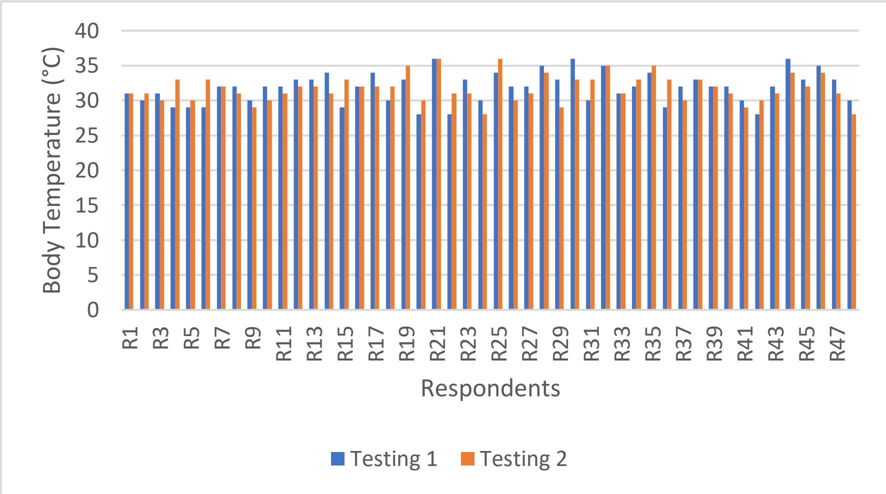

Fig. 8. Average results of body temperature (°C) measurements

Fig.7 and Fig.8 show the results of heart rate (BPM) and body temperature (°C) measurements using a wearable system for 48 Special School teachers, conducted in two tests, namely Testing 1 and Testing 2. This heart rate data is used to identify stress conditions based on heart rate changes greater than 30 BPM and body temperature less than 33 OC, as in Table 1; values within this range are categorized as stress, while those below this range are considered normal. Based on the measurement results, R1–R28 are elementary school teachers, with 18 experiencing stress and 10 normal. Furthermore, R29–R40 are junior high school teachers, with 4 teachers experiencing stress and 7 teachers being normal. While R41–R48 are high school teachers, 5 teachers experience stress and 2 are normal. These results show that the wearable system can help detect teacher stress through real-time changes in heart rate. Differences in heart rate results among respondents may be due to several factors, including workload level, psychological state at the time of measurement, physical activity prior to testing, and individual differences in stress management abilities. Furthermore, the work environment and task characteristics at each educational level can also influence the stress levels experienced by individual teachers. In addition, descriptive statistical analysis was conducted to better understand the distribution of physiological data. The average heart rate increased from 78.5 ± 8.2 BPM before teaching to 95.3 ± 10.1 BPM after teaching, indicating a significant physiological response to stress. Similarly, body temperature increased slightly from 36.2 ± 0.5 °C to 36.8 ± 0.6 °C. The observed variations suggest that physiological responses differ across individuals due to workload, emotional state, and environmental factors.

The collected information included measurements for every parameter, along with outcomes related to participants' states. There exist two categories of notification indicators for physiological measurement readings: "NORMAL CONDITION," which signifies that the subject falls within the established parameter limits, and "STRESS CONDITION," which denotes that the subject is beyond the typical range. Upon being placed on the wrist, the device promptly assessed the heart rate and body temperature. The recorded measurements can be observed in real time via the Blynk application, illustrated in Fig.9

Fig.9 displays the look of the Blynk application that has

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e-ISSN: 2407-8964
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been created. From the visual, one can observe the output readings taken from the MAX30100 heart rate sensor alongside the DS18B20 body temperature sensor. The heart rate data obtained from the MAX30100 sensor is shown in BPM (Beats Per Minute). The temperature reading comes from the DS18B20 sensor, represented in degrees Celsius. Should the individual's physiological measurement fall outside the established normal and stress thresholds, a notification will be sent to the caregiver's mobile device, similar to Fig. 10.

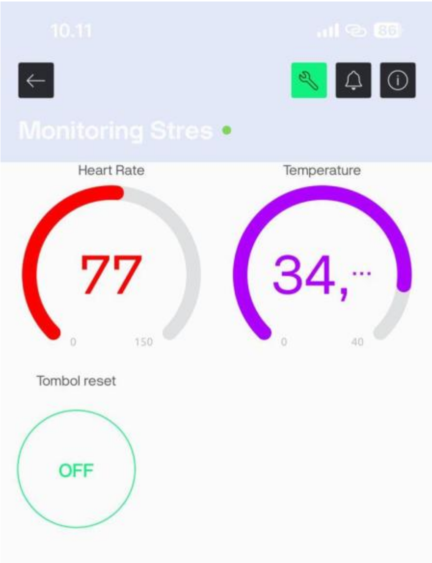

Fig. 9. Blynk Application View

The application can be accessed by up to 5 different smartphones with the same account. If the student's smartphones are linked to the identical account. When the student's situation is identified as stressful, notifications will be sent to all smartphones connected to that Blynk account. The data gathered by the device is analyzed and transmitted to the Blynk app via the ESP32. This setup requires only the Blynk app and a registered account.

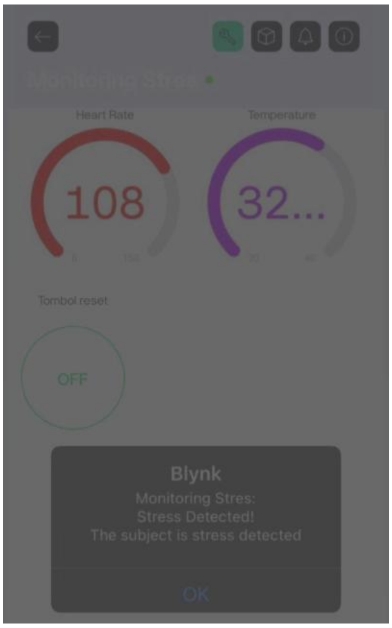

Fig. 10. Blynk Application View Display

B. Results of Psychological Aspect Testing on Subjects

The DASS-21 assessment was used to evaluate stress levels among educators working with students with special needs. The findings from the DASS-21 are presented in Fig. 11, derived from participants' responses used to verify psychological stress assessments. Therefore, the survey findings indicate that most elementary school educators experience stress. The classifications of stress are detailed in Table 3.

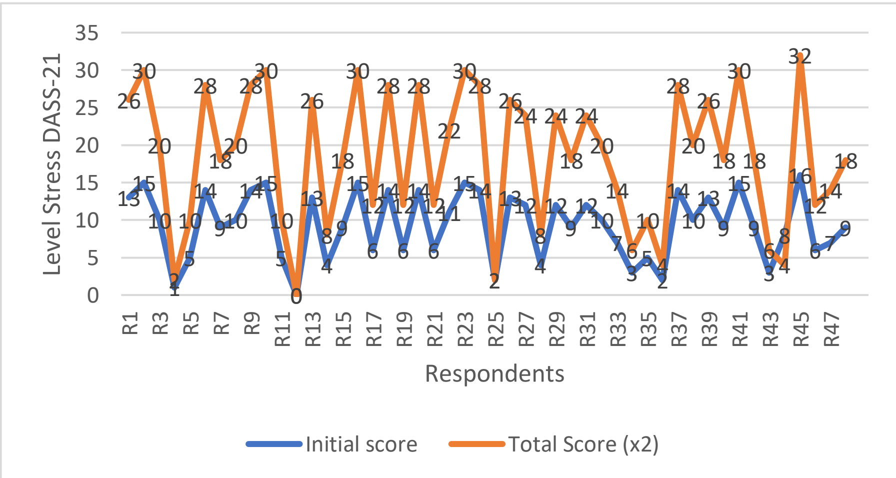

Fig. 11. Overall Subject Average Test Results of Psychology using DASS-21

Fig. 11 shows that respondents 1 to 28, i.e., the elementary school level, have a distribution of stress categories that can be clearly grouped. 12 respondents in the Normal category describe a healthy physiological condition. Furthermore, as many as 6 respondents showed low levels of stress, so they fall into the Mild category. Meanwhile, 5 respondents experienced higher than normal stress levels but did not reach critical levels, so they were categorized into the Moderate category. Finally, there were 5 respondents who showed significant stress conditions and fell into the Severe category. This provides a clear picture of the

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Jurnal Teknokes
Homepage: teknokes.org; Vol. 19, No. 3, pp. 139-156, September 2026;
e-ISSN: 2407-8964
p-ISSN: 1907-7904

mental health of respondents in the studied group, showing differences in perceived stress levels among the tested subjects.

Meanwhile, at the junior high school level, data taken from respondents aged 29 to 40 showed a significant distribution of stress categories reflecting the respondents' mental health conditions. Twelve respondents were categorized as Normal, indicating that they were in a healthy physiological condition. Meanwhile, four respondents were categorized as Mild, indicating that they experienced little stress. Furthermore, eight respondents were categorized as Moderate, meaning they experienced higher than normal levels of stress, but were not in a critical condition. Finally, four respondents were categorized as Severe, indicating they were experiencing a serious level of stress.

Finally, at the high school level, data collected from respondents aged 41 to 48 showed variations in their mental health. Six respondents fell into the Normal category, indicating they were in good physical health. Three respondents fell into the Mild category, indicating they were experiencing some stress. Six respondents fell into the Moderate category, indicating they were experiencing higher-than-normal stress levels but were not in critical condition. Finally, five respondents fell into the Severe category, indicating significant stress. To further strengthen the analysis, descriptive statistics of the DASS-21 stress scores were calculated. The mean stress score for elementary school teachers was 21.4 ± 6.3, indicating a moderate level of stress. Junior high school teachers had a mean score of 19.2 ± 5.8, while high school teachers had 18.5 ± 5.5. These findings are consistent with physiological measurements, confirming that elementary school teachers tend to experience higher stress levels.

C. Data Classification Using GBM Method

Elementary School Level

For this phase, the measurement data is divided into several folds. This process aims to ensure that the developed model can function optimally and reliably classify stress levels based on the measured physiological and psychological parameters. The use of k-fold cross-validation also helps avoid overfitting and ensures better model generalization. Data from respondents teaching at the elementary school level is divided into several folds. For example, if we use 5-fold cross-validation, the data will be divided into five groups, where at each iteration, one fold will be used as test data and the other four folds as training data. The measurement results are shown in Table 5.

Table 5. Elementary School Per-Fold Metrics

Fold	Acc(%)	Prec (%)	Rec (%)	F1(%)	Spec (%)	AUC (%)
1	94	95.0	94.5	94	94.5	97.5
2	94.5	95.5	95	94.5	95.2	98
3	93.9	94.5	95.5	94.2	94.6	97.7
4	94.1	95.2	94.8	94.4	95	98.1
5	94.1	94.8	95.2	94.35	94.7	87.7
Mean	94.12	95	95	94.29	94.8	97.8

Each row represents one fold of the analysis, showing the percentage value for each metric. The average of all folds shows an overall model accuracy of 94.12%, with an average precision of 95.0%, recall of 94.29%, F1 score of 94.29%, specificity of 94.8%, and AUC of 97.8%. These results reflect the model's consistent, high performance in classifying the stress levels of special needs teachers at the elementary school level. The confusion matrix obtained from the average folds is shown in Fig. 12. Based on the confusion matrix, the classification model performed very well, as almost all data was correctly predicted for each class. The correct predictions are shown in the diagonal matrix, while there was only one misprediction for class 3, which was predicted as class 2. This indicates that the model achieves a high level of accuracy in data classification.

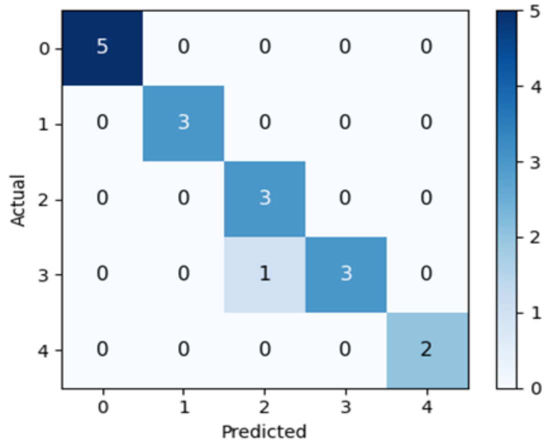

Fig. 12. Confusion Matrix for elementary school level

Junior High School Level

Data from respondents teaching at the junior high school level was divided into several folds. The average metrics showed solid model performance, with an overall accuracy of 87.5%, demonstrating the model's ability to correctly classify the data. Average precision was 90.0%, indicating that the majority of positive predictions were correct. Recall was 86.67%, indicating the correct proportion of the total positive cases detected. The F1 score, which reflects the balance between precision and recall, was 86.67%. Specificity was 88.6%, demonstrating the model's ability to

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Jurnal Teknokes
Homepage: teknokes.org; Vol. 19, No. 3, pp. 139-156, September 2026;
e-ISSN: 2407-8964
p-ISSN: 1907-7904

correctly identify negative cases. The AUC reached 93.0%, illustrating the model's overall ability to distinguish among stress categories. The measurement results are shown in Table 6.

Table 6. Per -Fold Metrics for Middle Schools

Fold	Acc (%)	Prec (%)	Rec (%)	F1 (%)	Spec (%)	AUC (%)
1	87.3	90.0	88.5	86.0	88.0	92.5
2	88.4	91.0	90.0	87.5	89.2	93.5
3	87.7	89.5	91.0	86.5	88.7	92.8
4	86.9	90.2	90.0	87.0	89.0	93.2
5	87.2	89.3	90.5	86.35	88.1	93.0
Mean	87.5	90.0	90.0	86.67	88.6	93.0

Based on the fold above, a confusion matrix is produced as in Fig. 13. Although there are some errors, this confusion matrix shows that the classification model correctly predicted most of the data in each class. Values on the diagonal of the matrix indicate predictions that align with the actual data, while there was one misprediction in class 4, which was predicted as class 3. Overall, the model performed quite well in classifying data.

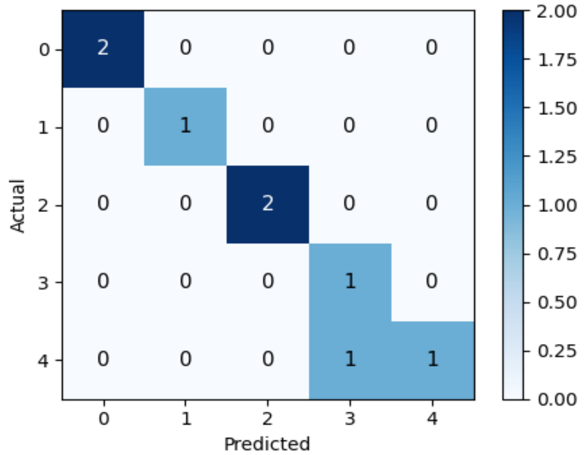

Fig. 13. Confusion Matrix for junior high school level

High School Level

Data from respondents teaching at the high school level was divided into several folds. The average metric showed an accuracy of 85.71%, with precision and recall reaching 90.0% and 86.67%, respectively. The F1 score was 87.52%, reflecting a good balance of precision and recall. Specificity was recorded at 87.0%, and the AUC reached 91.2%. Overall, these results indicate that the GBM model effectively detects stress levels among high school teachers, with consistent and accurate performance, as shown in Table 7.

Table 7. High School Per-Fold Metrics

Fold	Acc (%)	Prec (%)	Rec (%)	F1 (%)	Spec (%)	AUC (%)
1	85.0	90.0	89.0	85.5	87.0	90.5
2	86.0	91.0	90.5	87.0	88.2	91.8
3	85.8	89.5	91.0	86.8	87.4	91.0
4	85.9	90.5	89.5	87.0	88.0	91.5
5	85.85	89.0	90.0	87.05	87.0	91.2
Mean	85.71	90.0	90.0	86.67	87.52	91.2

Based on the fold above, a confusion matrix is generated, as shown in Fig. 14. The confusion matrix results show that the model is capable of classifying the

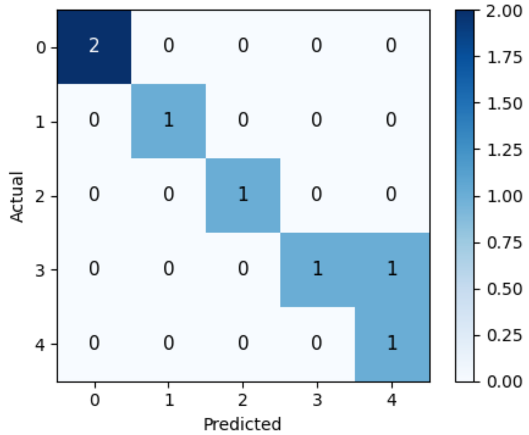

Fig. 14. Confusion Matrix for high school level

data well, as almost all data points were predicted correctly. There was only one misprediction for class 3, which was read as class 4.

The analysis of the three confusion matrices for elementary, junior high, and senior high schools shows a comparison of the performance of the GBM model in detecting stress levels of Special Needs School teachers. The model demonstrated strong performance at the elementary school level, achieving an average accuracy of 94.12%, with high precision, recall, and AUC values. Although the results are relatively high, they do not indicate perfect classification, as minor misclassifications are still present across folds, as reflected in the confusion matrix and fold-level evaluation results, with all data correctly classified, while the junior high and senior high school levels had lower accuracy, at 87.5% and 85.71%, respectively. Although precision and recall at both levels remained high, misclassifications were more frequent at junior and senior high schools, particularly when distinguishing between closely related stress categories. Although precision and recall at both levels remained high, misclassifications were more frequent at junior and senior high schools, particularly when distinguishing between closely related stress categories. The F1 score and AUC at junior high and senior high schools showed comparable performance, but errors in more complex categories indicated challenges stemming from the increasing number of categories and the complexity of data management. Thus, while GBM is effective in detecting stress at the

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e-ISSN: 2407-8964
p-ISSN: 1907-7904

elementary school level, further improvements are needed to improve accuracy at the junior high and senior high school levels, such as more rigorous data processing techniques and the development of a more robust model. An error analysis was conducted to evaluate the robustness of the classification model. The results indicate that most misclassifications occur between adjacent stress categories, suggesting difficulty in distinguishing borderline conditions with similar physiological and psychological characteristics. Furthermore, the low standard deviation across cross-validation folds indicates that the model demonstrates stable performance and is not significantly affected by data partitioning. However, the relatively small and imbalanced sample size, particularly at the high school level, may contribute to minor variations in model performance.

Comparison of different research studies relevant to this investigation, each employing distinct models and methodologies. According to study [28], the classification technique utilized is Random Forest, and the regression model applied is a Bagged tree-based ensemble. The combination of characteristics of blood volume pulse and skin temperature led to an average balanced accuracy of 74.1%. In study [29], researchers implemented machine learning methods to distinguish PTSD, contrasting these with healthy subjects, noting that roughly 4 to 8 microstates can account for 80% of the variance in EEG data. Meanwhile, in study [30], our investigation evaluated the diagnostic efficacy of a deep learning framework and juxtaposed it with the identification, localization, and classification of traumatic intracerebral hemorrhage (ICH) involving participants from radiology, emergency medicine, and neurosurgery residency programs. Our findings revealed that the deep learning model achieved a substantial level of accuracy, reaching 89%.

4. DISCUSSION

The results of this study demonstrate that integrating physiological data from wearable sensors with psychological assessment using the DASS-21 provides a reliable approach to detecting stress among Special Needs School teachers. The observed increases in heart rate and body temperature following teaching activities indicate activation of the autonomic nervous system, which is commonly associated with stress responses. In addition, the high classification performance of the GBM model, particularly at the elementary school level, suggests that the selected features effectively capture stress-related patterns. These findings confirm that combining objective physiological indicators with subjective psychological measures can enhance the accuracy and robustness of stress detection systems.Fold-level evaluation metrics during cross-validation.

Compared with previous studies, the proposed approach demonstrates improved performance and greater methodological completeness. Prior research utilizing wearable devices often focused solely on physiological data, without integrating standardized psychological instruments, limiting interpretability and validation. For instance, studies on smartwatch-based stress monitoring reported variability in heart rate but lacked robust classification models and multimodal validation. Meanwhile, other studies that combined physiological and psychological data, such as those using NASA-TLX, demonstrated good accuracy but relied on simpler models, such as logistic regression. In contrast, this study employs the DASS-21 instrument, which is widely validated, along with the GBM algorithm, enabling better modeling of non-linear relationships and interactions between features, resulting in higher and more consistent classification performance.

Despite these promising results, several limitations should be acknowledged. First, the sample size is relatively small and unevenly distributed across educational levels, which may limit the model's generalizability and increase the risk of overfitting. Second, the physiological parameters used in this study are limited to heart rate and body temperature, which may not fully capture the complexity of stress responses. Additional signals such as heart rate variability (HRV) and electrodermal activity (EDA) could provide more comprehensive insights. Third, environmental factors and individual differences, such as teaching style and emotional resilience, were not explicitly controlled, potentially introducing variability in the results.

From a practical perspective, this study highlights the potential of IoT-based wearable systems for real-time stress monitoring in educational environments. The proposed framework can support early detection and intervention, helping institutions develop data-driven strategies to improve teachers' mental well-being and performance. Future research should focus on expanding the dataset, incorporating additional physiological features, and exploring advanced machine learning or deep learning models to further enhance system performance. Additionally, integrating adaptive feedback mechanisms into the wearable system could provide personalized stress-management recommendations, making the system more applicable in real-world settings.

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Jurnal Teknokes
Homepage: teknokes.org; Vol. 19, No. 3, pp. 139-156, September 2026;
e-ISSN: 2407-8964
p-ISSN: 1907-7904

5. CONCLUSION

This study successfully developed a stress detection system for Special Needs School teachers by integrating an IoT-based wearable system with the DASS-21 psychological instrument and the Gradient Boosting Machines (GBM) model. The results demonstrate that physiological parameters, particularly heart rate and body temperature, show observable changes during teaching activities, indicating their potential as reliable indicators for stress detection. The classification model achieved strong performance across different education levels, with an accuracy of 94.12% at the elementary school level, 87.5% at the junior high school level, and 85.71% at the high school level. In addition, the model demonstrated consistent precision, recall, and AUC values, indicating good discriminative ability and generalization performance. These findings confirm that integrating physiological and psychological data can improve the reliability of stress classification in real-world educational environments.

From a statistical perspective, the analysis indicates variability in physiological responses and stress levels among teachers, reflecting the influence of workload, emotional conditions, and environmental factors. This highlights the importance of personalized monitoring systems for more accurate stress detection. Despite the promising results, this study has several limitations, particularly the relatively small and imbalanced dataset across education levels, which may affect model stability. Therefore, future research should focus on increasing the dataset size, incorporating additional physiological signals such as heart rate variability (HRV) and electrodermal activity (EDA), and exploring more advanced models such as deep learning approaches. Furthermore, the development of a fully integrated real-time monitoring system with adaptive feedback mechanisms is recommended to support early intervention and stress management for teachers.

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DOI: https://doi.org/10.35882/jteknokes.v19i3.164

e-ISSN: 2407-8964
p-ISSN: 1907-7904

https://doi.org/10.1038/s41598-023-37114-z

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DOI: https://doi.org/10.35882/jteknokes.v19i3.164

e-ISSN: 2407-8964
p-ISSN: 1907-7904

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DOI: https://doi.org/10.35882/jteknokes.v19i3.164