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University Students Stress Detection During Final Report Subject by Using NASA TLX Method and Logistic Regression

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Abstract

Stress is a psychological response that occurs when someone faces pressure or demands that exceed their ability to adapt. In the context of a final-year student, stress is often a significant problem due to academic pressure, such as completing final assignments, as well as demands to immediately prepare to enter the workforce and demands to immediately prepare to enter the workforce. Research shows that stress that is not managed properly can cause various negative effects, such as sleep disorders and decreased cognitive function. This study aimed to identify and analyze stress levels among final-year students who completed a final report by integrating physiological and psychological data. In this study, 30 students were assessed using a wearable system to obtain physiological data, such as heart rate and body temperature, while subjective assessments were carried out using the NASA-TLX method to measure mental workload. The results showed that 19 out of 30 respondents experienced significant levels of stress and 11 respondents were in normal conditions, with the main causal factors including high academic pressure and distance regarding the future. In addition, the logistic regression analysis applied in this study succeeded in developing a predictive model with an accuracy of 94% in identifying students' stress conditions. This shows that this method is sufficiently accurate for detecting stress symptoms in final-year students.

Keywords: stress; wearable system; NASA-TLX; heart rate; body temperature

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1. Introduction

The introduction section sets the stage for your study by providing context, defining the problem, highlighting its significance, and outlining your contribution. It should engage the reader, establish the relevance of your work, and clearly articulate the objectives of the research.

Stress is a typical physiological and psychological reaction that arises when individuals encounter pressures or demands that surpass their capacity to cope. For final-year students, stress frequently becomes a major issue due to academic pressures such as the need to complete final assignments and prepare for immediate entry into the workforce [1]. Studies indicate that if stress is not managed, it can lead to various adverse effects, including sleep disturbances, reduced cognitive abilities, anxiety, and depression, which can ultimately impede both academic and personal achievement [2].

Various methods have been developed to measure and detect stress. Conventional methods typically use psychological questionnaires, such as the Perceived Stress Scale (PSS) and the Depression Anxiety Stress Scales (DASS), which provide subjective assessments of stress levels. Although these methods have advantages, such as ease of use and accessibility, they rely on self-reports that could be affected by subjective bias and are unable to detect real-time changes in stress [3].

Based on research [4] using the Support Vector Machine (SVM) method, Heart Rate (HR), Skin Conductance, Body Temperature, and

Photoplethysmography (PPG) obtained an accuracy of 67%. In a study using the WESAD dataset, 81.65% were obtained for the classification of three classes, demonstrating the effectiveness of combining multimodal data. In [5] the CapsNets model is used to monitor stress in real-time by analyzing biometric data, including physiological signals and behavioral patterns. CapsNets is designed to capture hierarchical relationships in data, making it more effective in recognizing complex patterns than traditional CNN models. CapsNets achieved an accuracy of 92.76% with excellent precision, recall, and F1 score values (around 91-92%). in research [6] A cross-sectional survey design was used among students of a University of Applied Sciences, A total of 875 university students (37.2% male, 62.3% female, mean age 21.6) participated. Perceived stress had a strong negative association with mental well-being (unstandardized regression coefficient (b) = -.848, p < .001; r = -.667, p < .01), explaining 45% of the variance. Academic pressure (b = -8.014, p < .01), family pressure (b = -3.189, p < .01), side-activity pressure (b = -3.032, p < .01) and financial pressure (b = -2.041, p < .01) that has a negative impact on mental wellbeing.

Alternatively, physiological measurements have been developed with the use of wearable devices that allow real-time monitoring of parameters such as heart rate stress, heart rate variability (HRV), and electrodermal activity. These studies have shown that HRV, in particular, is a powerful indicator of response; decreases in HRV are often associated with increased stress levels [7]. The use of wearable devices allows for continuous, real-time measurements, providing advantages in the context of early prevention and intervention of stress [7]. Table 1 shows the differences between normal and stress conditions. Normal conditions have a heart rate of 55-90 BPM and a body temperature of 35-37ºC, while stress conditions often show a heart rate >90 BPM and body temperature of 37-38ºC [8], [9].

Table 1. Comparison of pairs in the NASA-TLX indicator [8], [9]

Condition	Heart Rate (BPM)	Body Temperature (°C)
Normal	55-90	35-37
Stress	>90	<33

Based on the above problems, this research carried out the development of a more comprehensive wearable system to detect stress in final year students, where subjective data from NASA-TLX and objective data from the wearable system. NASA-TLX has proven to be a reliable tool in measuring mental workload and has been used in various studies to measure stress levels in a person in certain situations [10] wearable system that uses a DS18B20 temperature sensor, MAX30100 sensor to measure beat heart. Physiological measurement data is viewed on *a* smartphone via the Blynk application in real-time. The Blynk application can be accessed by users who have a registered username and password [11]. This system is then analyzed using the logistic regression method to predict the likelihood of students experiencing high stress. This approach not only takes advantage of the advantages of real-time physiological measurements but also considers the subjective aspects of stress, providing better stress detection [12].

The predictive model developed through logistic regression will allow the identification of significant factors influencing stress levels, as well as provide a solid basis for more targeted interventions [13]. Thus, this system is expected to assist in early detection and more effective management of stress among final-year students, which in turn can improve their overall well-being [14].

The application of technology in stress detection in final-year students must involve two aspects of body condition, so a prototype that can detect heart rate and body temperature is needed. The method used is logistic regression and stress conditions are compared based on the results of psychological measurements using the NASA-TLX method so that optimal and accurate conditions are obtained in the two aspects.

The proposed study offers several significant contributions: (1) the detection of stress in final-year students through a wearable system that monitors heart rate, body temperature, and skin conductance; (2) the integration of physiological data from wearable systems with NASA TLX scores to assess stress levels; and (3) the evaluation of the logistic regression model's performance in identifying stress among students based on collected data.

In this study, the primary contributors took several crucial steps to meet the research objectives. One contributor gathered physiological and psychological data from the participants. Additionally, the development of the research methodology, which included the wearable system and the NASA-TLX questionnaire, enhanced the accuracy of stress detection. Through statistical analysis and logistic regression, a prediction model was created that achieved 94% accuracy in identifying stress conditions among college students. Other contributors have concentrated on developing and testing a wearable system to assess its effectiveness in real-time stress monitoring. Finally, the analysis of the NASA-TLX questionnaire revealed that students' mental load was categorized as high, offering further insight into the effects of academic stress.

2. Methods

This wearable system is capable of detecting stress levels in final-year students by utilizing IoT-based body temperature and heart rate data connected to the Blynk application. Sensors are devices designed to detect physical or chemical changes and produce outputs in the form of variables that are converted into electrical quantities [15], [16]. The wearable system, designed to monitor stress in final-year students, takes the form of a bracelet equipped with MAX30100 sensors, DS18B20 sensors, GSR sensors, MAX4466 sensors, and a Wemos D1 Mini ESP-32. Logistic regression was employed to assess the level of accuracy [2], along with the psychological aspects evaluated using the NASA-TLX questionnaire. The stages of this process are illustrated in the flowchart in Figure 1.

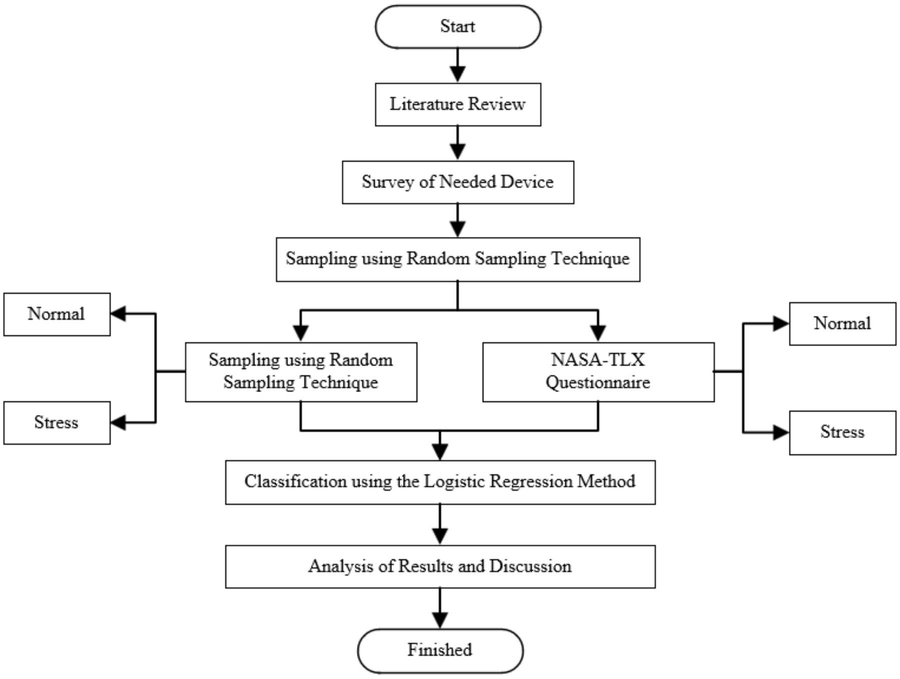


Figure 1. Research Flow Diagram

2.1 Wearable System

The wearable system used to detect stress in final-year students is shaped like a bracelet. This tool has dimensions of length x width x height, namely 5 x 5 x 12 cm. It consists of a MAX30100 sensor, DS18B20 sensor, GSR sensor, MAX4466 sensor, and Wemos D1 Mini ESP-32. The shape of the tool can be seen in Figure 2.

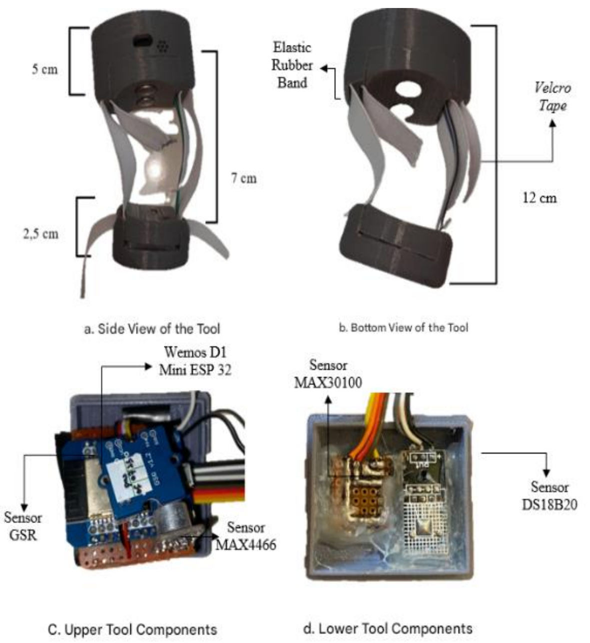


Figure 2. Wearable Stress Detection System

Based on Figure 2, it can be seen that the wearable stress detection system will be attached to the student's wrist. This study uses a wearable system such as in research [11] using *the Galvanic Skin Response (GSR)* Sensor MAX30100 Sensor DS18B20 Sensor MAX4466 Sensor Wemos D1 Mini ESP 32 Velcro Tape 12 cm Elastic Rubber Band 36 the top of the bracelet contains several components, such as the GSR sensor to measure skin conductance, the MAX4466 sensor to measure sound intensity and the Wemos D1 Mini ESP 32 as a microcontroller and WiFi module. However, in the research, this is only used on the part lower bracelet. There is a DS18B20 sensor to measure body temperature and an MAX30100 sensor to measure heart rate. On the side of the bracelet, a rubber strap and Velcro tape are used to facilitate its use on the wrist. This tool can be connected to the caregiver's smartphone by processing the data generated from the sensors using the ESP-32 and sending it to the Blynk application. In the Blynk application, you can see the measurement data from heart rate in the form of BPM, body temperature in units of ^{o} C, skin conductance in units of µS, and sound intensity in units of dB. The Blynk application can be accessed by users whose email is Already registered [11]. The difference between the range of research [11] and this study is in[11] had a tantrum with a heart rate >110 BPM and body temperature <36^{o}C while this study can be seen in Table 1, then the detected stress displayed in the blynk application.

The measurement process using the wearable system is illustrated in Figure 3. As shown, when the wearable device is attached to the student's wrist, it measures both heart rate and body temperature. The smartphone must connect to the WiFi network "ESP Detector" and configure the WiFi using the available network on the Wemos D1 Mini Esp 32. Once connected, the Blynk application automatically displayed the heart rate and body temperature data. If a student experiences stress, the smartphone receives a notification. The results from testing the system on the subject will be classified using the logistic regression method in conjunction with psychological data from the NASA-TLX questionnaire.

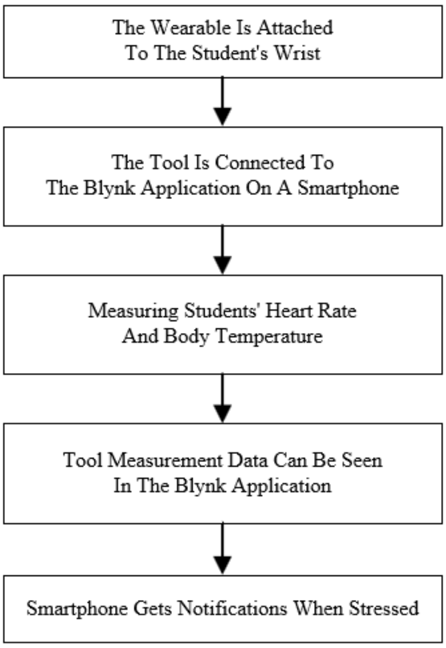


Figure 3. Data Collection Process Using Wearable System

2.2 IoT System

The test was conducted on final-year students using a prototype stress detector device attached to their wrists. The device measures heart rate and body temperature, which is then processed by the Wemos D1 Mini ESP 32 as an internet module. The data integrated with IoT is sent via the Blynk application downloaded on a smartphone, as in Figure 4.

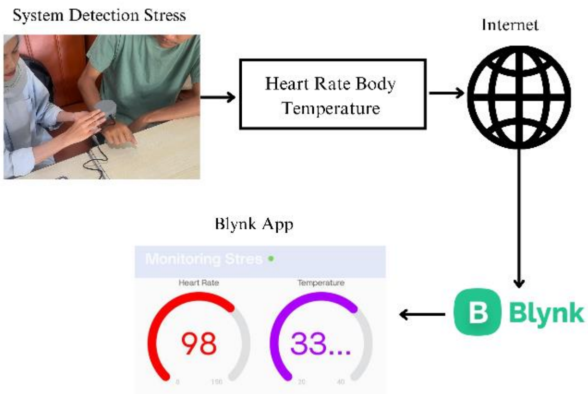


Figure 4. Workflow of IoT Systems

Figure 4 illustrates the process of collecting student data. First, the wearable system is attached to the student's wrist, then the heart rate sensor and body temperature are measured as shown in Table 5. Measurements with the wearable system were carried out twice within 5-10 minutes. The results of this tool, especially regarding the physiological condition of final-year students, can be tracked using a smartphone through the blynk application. The blynk app presents measurement data obtained from the MAX30100 heart rate sensor and the DS18B20 body temperature sensor. The heart rate, measured by the MAX30100 sensor, is displayed in BPM (Beats Per Minute). Temperature readings are provided by the DS18B20 sensor and are displayed in degrees Celsius (°C).

2.3 NASA-TLX

The NASA Task Load Index (NASA TLX) method is a method to measure mental workload subjectively. This method can be used to analyze the mental workload of workers and provide recommendations for ergonomic improvements. This method establishes a multidimensional assessment procedure that provides quantification of workload based on assessment weights consisting of 6 subscale indicators: Mental Demand (MD), Physical Demand (PD), Temporal Demand (TD), Performance (P), Effort (EF), and Frustration (FR) [17]. The following are the steps that must be taken in measuring workload using the NASA-TLX method [18]. In the weighting stage, in this section, respondents are asked to choose one of the two indicators that are considered more dominant than the activities carried out by workers [19].

There are 15 comparisons from 6 assessment dimensions. The total number of each dimension will be the dimensional weight [20]. Filling out the questionnaire is carried out based on the measurement standards in Table 5, there is a 5 minutes pause after measurement with the wearable system. The NASA-TLX questionnaire was filled in 5 minutes, then the NASA-TLX score was calculated to see the category of stress levels experienced by final year students. The following is a comparison of indicators in the NASA TLX method found in Table 2.

Table 2. Comparison of pairs in the NASA-TLX indicator [20]

No	Weighting Indicator		
1	Mental Demand (MD)	Or	Mental Demand (MD)
2	Mental Demand (MD)	Or	Temporal Demand (TD)
3	Mental Demand (MD)	Or	Performance (P)
4	Mental Demand (MD)	Or	Frustration (FR)
5	Mental Demand (MD)	Or	Effort (EF)
6	Physical Demand (PD)	Or	Temporal Demand (TD)
7	Physical Demand (PD)	Or	Performance (P)
8	Physical Demand (PD)	Or	Frustration (FR)
9	Physical Demand (PD)	Or	Effort (EF)
10	Temporal Demand (TD)	Or	Performance (P)
11	Temporal Demand (TD)	Or	Frustration (FR)
12	Temporal Demand (TD)	Or	Effort (EF)
13	Performance (P)	Or	Frustration (FR)
14	Performance (P)	Or	Effort (EF)
15	Frustration (FR)	Or	Effort (EF)

In this section, the respondents were asked to assign a value to six subscale dimensions: mental demand, physical needs, temporal demand, performance, effort, and stress level (frustration). These ratings range from 0 to 100, reflecting the workload experienced by the respondent [21]. Table 3 lists the dimensions used in the rating-determination stage. Subsequently, the product value was calculated by multiplying the weight and rating provided by the respondents, resulting in a product value for each indicator as shown in Equation 1 [22].

$$\text{Product Value} = \text{Rating} \times \text{Weight} \quad (1)$$

Then, calculate the Weighted Workload (WWL) adding the six indicators for each Respondent as shown in Equation 2.

$$\text{WWL} = \sum \text{Product Value} \quad (2)$$

The average WWL value is determined by dividing the value WWL with total weight, which is equal to 15 as shown in Equation 3.

$$Score = \frac{\sum \text{Product Value}}{15} \quad (3)$$

Output from a calculation using the NASA-TLX method is the level of mental workload experienced by respondents.

The average mental workload is divided into five categories. In Table 4, the interpretation score workload of the NASA-TLX method [23].

Table 3. NASA-TLX dimension description [21]

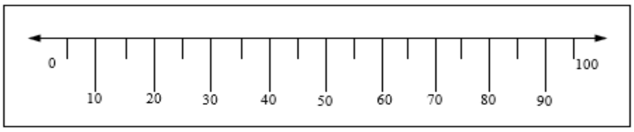
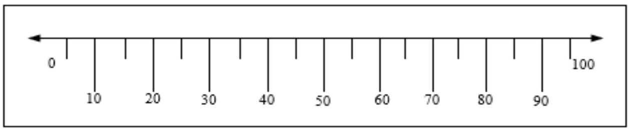
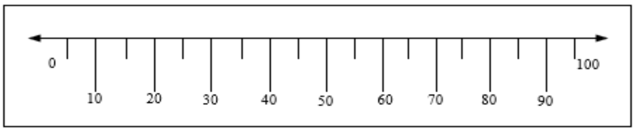
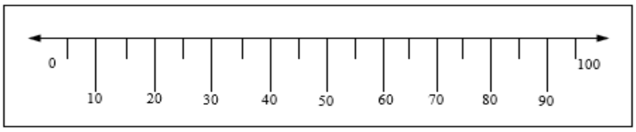
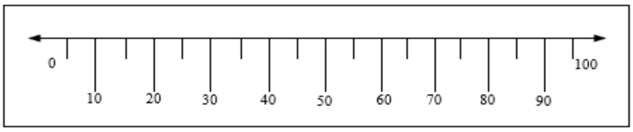
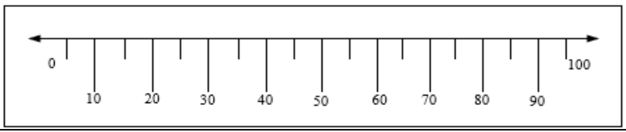
No	Dimensions	Scale
1	Mental Demand How much effort is required for your work, such as remembering, seeing, deciding, and considering whether the work is easy or difficult, loose or strict, simple or complicated?	(Low – High) 
2	Physical Demand How much physical activity do you need to do for your job (such as controlling, pushing, twisting, running, and other activities)? Is the work simple or challenging, fast or quiet?	(Low – High) 
3	Temporal Demand How much stress do you feel when working or doing part of your job? Is the work pace relaxed and slow or fast and paced?	(Low – High) 
4	Performance How satisfied are you with your performance to achieve your work goals? How much of your success is your ability to achieve targets on your job?	(Low – High) 
5	Effort How much mental and physical effort do you put into doing your best?	(Low – High) 
6	Frustration How do you feel at work when you feel insecure, discouraged, offended, stressed, and annoyed?	(Low – High) 

Table 4. NASA-TLX Score Interpretation [23]

No.	Workload Class	Mark
1.	Very Low	0 – 20
2.	Low	21 – 40
3.	Currently	41 – 60
4.	High	61 – 80
5.	Very High	8 1 – 100

2.4 Data Collection

Research dataset This aims to detect symptom stress in student-level results measurement from subject research, which is student-level final years (final years 9 – 14) aged 20 – 30 years (Young Adult Age) in the Industrial Engineering Study Program and Electrical Engineering Study Program at Universitas Syiah Kuala with measure level stress, both psychologically and also physiological. Measurement physiological requires measurement data from a subject study based on pulse parameters of the heart and temperature body to know condition stress based on changes in the parameters that have been determined. At the same time, the measurement data is psychologically collected using the proposed model, covering results answered from the NASA-TLX questionnaire. Some of the steps considered in testing the stress detection system for final-year students can be seen in Table 5.

Table 5. Test Parameters

No	Parameters	Justification
1	Amount Subject	30 student final level years, 20 men and 10 women (9-10 a final year)
2	Age Subject	≥ 20 – 30 years (young adult age)
3	Measurement Data	Each participant was measured twice with a wearable system, 60 measurement data with the following measurement details: 2 measurements when in a calm and relaxed state so that the measurement process runs smoothly. After a 5 minutes break after measuring with the wearable system, data measurements were carried out by filling out the NASA-TLX questionnaire.
4	Protocol Room	Measurements were taken under the following room conditions: Time measurement: 09.00 am– 3.00 pm The room conditions are calm and conducive Sit position is in on chair and there is table In the testing room there were final year students and 1 researcher.
5	Data measured	The data measured in this test are: Heart rate (BPM) Body temperature (^{O}C) Mental workload (questionnaire filling)
6	Tool Configuration	The sensors used are MAX30100, DS18B20, GSR, and MAX4466 The smartphone used are iPhone 11 pro and Vivo Y15
7	Criteria Subject	Each participant must meet the following criteria, as follow: They are in good health and are not taking any medication. Willing to fill out the concern form before the measurement is carried out. Students who are currently do end task. The subject is calm and able to cooperate so that process detection stress is running well.
8	Standards of Testing	Testing was carried out on students with a wearable system, the measurement was carried out 2 repetitions in the range of 5-10 minutes Testing by filling out the NASA-TLX questionnaire was carried out after a 5-minute pause after testing with the capable system, and fill out the questionnaire with 5 minutes.

2.5 Sampling Techniques

The sampling technique used is stratified sampling (random stratified), where the student population is divided into strata based on certain characteristics, such as year of enrollment and study program [24]. This approach ensures that each subgroup in the population is represented proportionally in the sample so that the data obtained is more accurate and representative [25]. In the sampling technique, determining the population first as in Equation 4 where N is the population from students whose samples were taken.

$$N = N_1 + N_2 \tag{4}$$

Then, calculate the Proportion for each stratum and determine the number of respondents from each stratum, the distribution of respondents based on class in each stratum, and

$$P_i = \frac{N_i}{N} \tag{5}$$

$$P_i = P_i \times n \tag{6}$$

$$n_{ij} = \left(\frac{N_{ij}}{N_i}\right) \times n_i \tag{7}$$

Based on Equations 5, 6 and 7 its component is P_i is the Proportion from the i -th stratum, N_i is the population in stratum i, n_i namely the number of Respondents from the i-th stratum, then n is the total number of respondents determined, N_{ij} is amount Respondent from batch j in stratum i while N_{ij} is the sum population in batch j in stratum i

2.6 Logistic Regression

Logistic regression is an analysis that explains the correlation between one or more independent variables and one dependent variable, which is a dichotomous variable [26]. A form of mathematical analysis whose use can observe the correlation between several independent variables and one dependent variable, which is dichotomous. Dichotomous variables are variables that only have two meanings, such as high/low or prosperous/not prosperous. Logistic regression uses quantitative independent variables to predict the probability of the occurrence of binary dependent variables [27]. Furthermore, it can use categorical or numeric variables as its independent variables. Logistic regression uses a non-linear logarithmic transformation approach to predict relationships, which are expressed as odds ratios [28]. The classification process of the LR method can be seen in Figure 5.

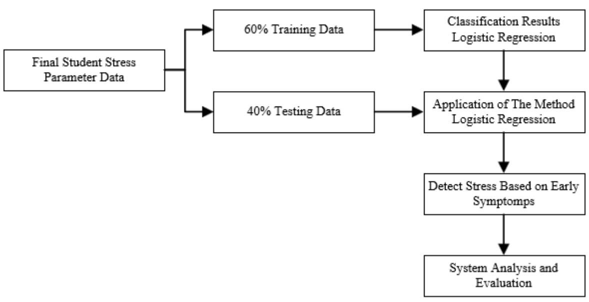


Figure 5. Classification Process Using RL Method

Based on Figure 5, data classification is carried out using the logistic regression method. The initial step in this classification is the final student stress parameter data that has been measured, namely data physiology (wearable system) and Psychology (NASA-TLX Questionnaire). Then, the data is divided into two, namely 60% training data and 40% testing data. This data is used to build the model that will be used for classification. When the model is ready to be used, the detection results are obtained. Stress is based on early symptoms. Analysis is carried out, and system evaluation is performed to determine system performance.

2.7 Confusion Matrix

Models are evaluated by constructing the confusion matrix for test data [29]. In addition, accuracy, sensitivity, and specificity are also measured for each model [26]. The definitions for these matrices are shown in Equations 8 through 11.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{8}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{9}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{10}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{11}$$

3. Results and Discussions

3.1 Data Results using Wearable Systems (Physiology)

System testing on subjects was carried out by attaching a stress detector to the student's wrist and connecting the smartphone to the ESP 32, as shown in Figure 6.

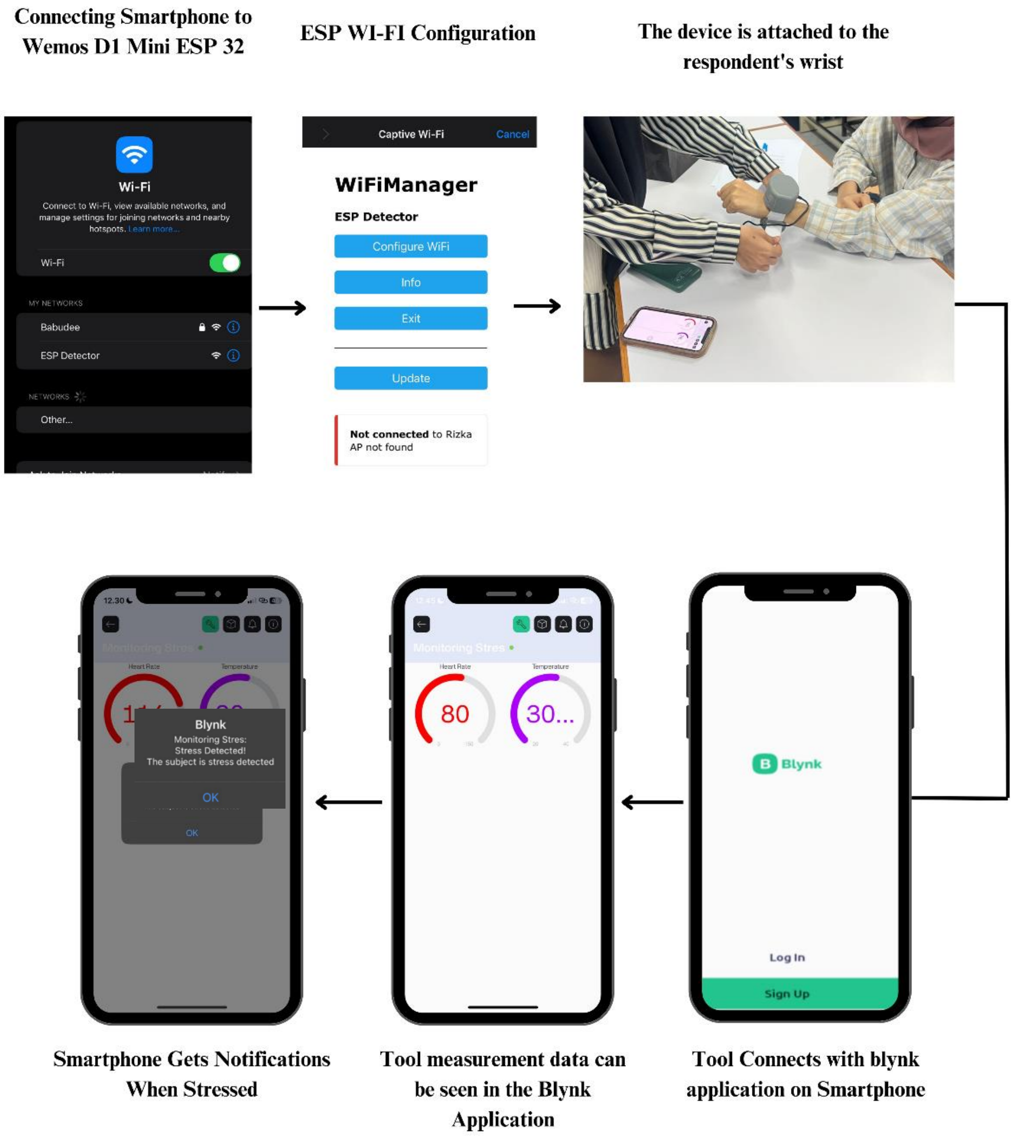


Figure 6. Physiological Testing Process with Wearable System

As shown in Figure 6, the smartphone must first connect to the "ESP Detector" WiFi and be configured using the available network. Once this is completed, the device is secured to the student's wrist, and the Blynk application is launched. When the smartphone is connected to the ESP WiFi, the Blynk app automatically displays data on the heart rate and body temperature. In the event of stress, a notification appeared in the Blynk application. This wearable system was affixed to the research subject's hand by measuring two predetermined parameters. Consequently, the heart rate and body temperature were assessed, providing the user with information on stress conditions.

The percentage of the results is then displayed on the blynk application, which is sent via the Esp detector from the Wemos D1 Pro Esp 32 microcontroller and connected to the Arduino program code and Internet connection (WiFi). This system only requires logging in to the Blynk application and ensures that each input device in the measurement has been connected to the WiFi configuration that has been set. This application is very helpful for users to know the stress condition as an early anticipation of stress accumulation based on two conditions, namely, psychology and body physiology, in real time. The results of physiological testing using the wearable system are shown in Figures 7 and 8.

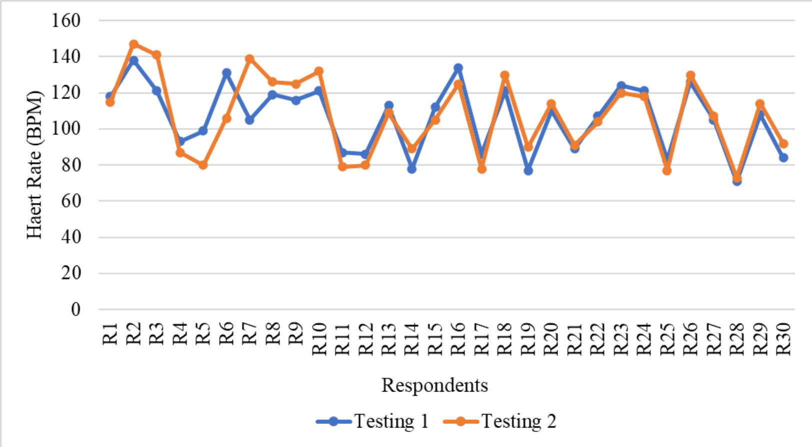


Figure 7. Average results of heart rate measurements

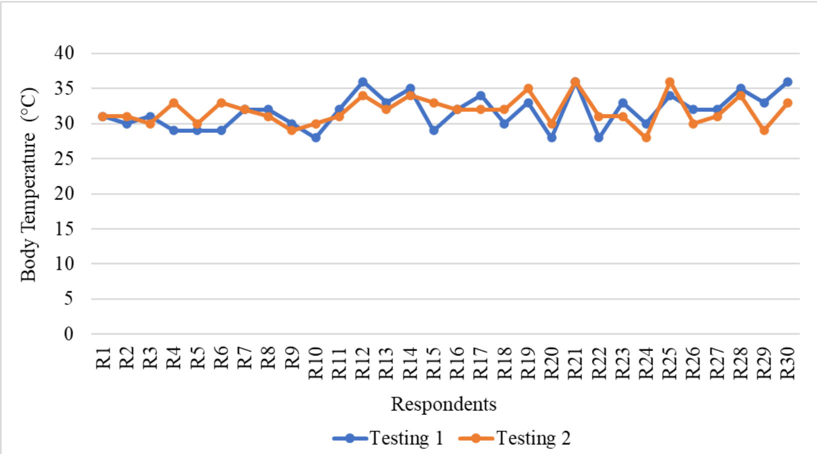


Figure 8. Average results of body temperature measurements

Testing was conducted in the Industrial Engineering and Electrical Engineering Study Program at the Universitas Syiah Kuala. Prior to testing, participants were required to complete a consent form to agree with the measurements. The testing involved two measurements taken under calm and relaxed conditions to ensure a smooth process. Physiological testing of the subjects was conducted as illustrated in Figures 7 and 8. Figure 7 presents the pulse data, indicating stress when the heart rates exceed the parameter range outlined in Table 1. Among the 30 respondents, stress was detected in 19 when their heart rates surpassed the normal range of 100-147 BPM. Figure 8 shows the body temperature data, where stress is indicated if the temperature falls below the parameter range listed in Table 1. Stress was detected in 19 of 30 respondents when their body temperature was lower than the normal range of 28-33°C. The recorded data included the values of each parameter and the results of the participants' conditions. There are two types of notification displays for physiological measurement values: "NORMAL CONDITION," indicating the subject is within the specified parameter range, and "STRESS CONDITION," indicating the subject is outside the normal range. When the device was worn on the wrist, it immediately measured the heart rate and body temperature. The measured values can be viewed in real time using the Blynk application, as shown in Figure 9.

Figure 9 shows the appearance of the blynk application produced. Based on the image, the measurement results from the MAX30100 heart rate sensor and the DS18B20 body temperature sensor can be seen. Heart Rate is the measurement result from the MAX30100 sensor, which is displayed in the form of BPM (Beats

Per Minute). Temperature is the measurement result of the DS18B20 sensor in the form of ºC. If the measurement value of the subject's physiology exceeds or is less than the parameters specified as normal and stress limits, the caregiver's smartphone will receive a notification, as in Figure 10.

Figure 9. Blynk Application View

The application can be accessed by up to 5 different smartphones with the same account. If the student's condition is detected as stressed, all smartphones with the same Blynk account will receive a notification. The measurement value from the tool is processed and sent to the Blynk application using ESP 32. This system only requires the Blynk application and has a registered account.

Figure 10. Stress Detected Notification Display

3.2 Results of Psychological Aspect Testing on Subjects

The NASA-TLX questionnaire was used to measure the mental workload of final-year students. The data results using NASA-TLX are shown in Figure 10. Based on the answers of the research subjects used as validation of psychological stress measurement. So, the results of the NASA-TLX questionnaire of the subject testing conducted showed that overall, the majority of subjects experienced stress in the high category, while only a few were in the moderate category, and 11 people were in the low-stress range. This shows differences in the level of stress perception among the subjects tested.

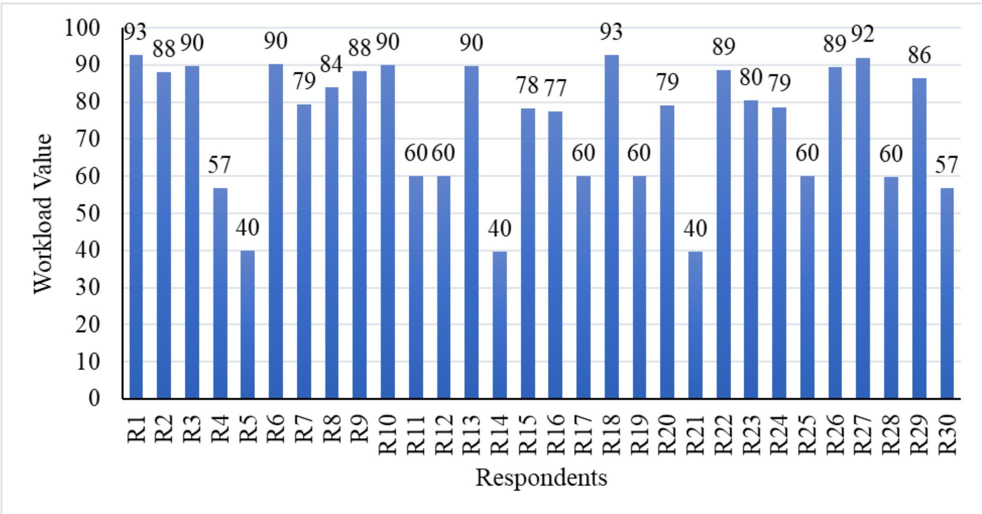


Figure 11. Overall Subject Average Test Results of Psychology

Based on Figure 11, the average WWL value and results of the NASA-TLX workload category can be seen based on Table 4. 23 respondents have marked burden mental work with a range value of 40-89, while 7 respondents have a total value of >90. Based on the load-interval scale NASA-TLX mental work, the Respondent should be in the category of burden-high mental work because the result of burden mental work is in the rental interval 61 – 80. Based on the measurement burden Respondent's mental work using the NASA-TLX Method, that burden Respondent's mental work is in the category tall. So, it can be concluded that the burden of student mental work levels ends up being in the category tall with a total average WWL value of 74. Condition This appears Because work Respondents need significant mental effort to achieve optimal performance. Physical needs, time, performance, level of effort, and level of high frustration also influence this.

3.3 Data Classification Using Logistic Regression Method

At this stage, the classification of stress detector measurement results data on final year students from the physiological and psychological aspects using the logistic regression classification method is carried out. The data used in this classification are 60 data from 30 students, with details of 19 data in stress conditions and 11 data in normal conditions. Data classification using this method is carried out based on the stages that have been explained in Figure 5, so the confusion matrix can measure the accuracy of classification testing obtained using the logistic regression method. The results of the performance accuracy analysis can be seen in Figure 12.

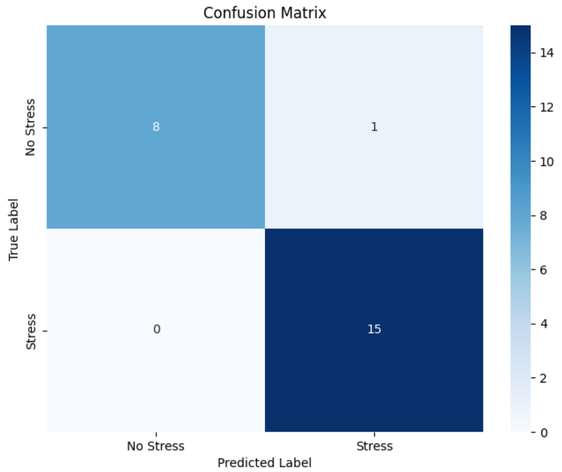


Figure 12. Accuracy Results Using Confusion Matrix

Based on Figure 12. it can be seen that there are 0 data categorized as False Negative (FN), 1 data categorized as False Positive (FP), 32 data categorized as True Positive (TP), and 37 data categorized as True Negative (TN). From the 4-quadrant data, the accuracy value of the RL method is obtained as in Table 5.

Table 6. RL Method Classification Accuracy Results

Precision	Recall	F1-Score	Accuracy
92.0	1.00	96.0	94.0

Based on Table 6. The classification of test data in this study using the logistic regression method produces an accuracy value of 94%, which means that this method is good enough to detect stress symptoms in final-year students. This study successfully demonstrated that the developed wearable system can effectively detect stress levels in final-year university students, with 19 out of 30 subjects identified as experiencing significant stress levels. Analysis using the NASA-TLX questionnaire showed a high mental load, while the logistic regression model achieved 94% accuracy, proving that combining physiological and psychological data provided valid results. These findings are in line with previous research [5] who emphasized the importance of stress monitoring through wearable technology. The NASA-TLX method has also been shown to be effective in various contexts, including academia. The results supported the initial hypothesis that a wearable system integrating such data could improve the accuracy of stress detection, with the majority of subjects experiencing higher stress due to academic pressure in the final year. However, the study also revealed additional factors, such as time management and social support, that may have influenced stress levels, opening up opportunities for further research into this issue among university students.

Comparison of various studies related to this study, each using different models and techniques. Based on research [30], the research method used is the Random Forest classification model, and the regression model is a Bagged tree-based ensemble. Using a combination of blood volume pulse and skin temperature features, the average balanced accuracy is 74.1%. In [31] Physiological Signals is Heart Rate from Various Movements and using fuzzy logic techniques, The results of the study showed that stress has a significant negative relationship to well-being ($\beta 1 = -0.788$; $p < 0.05$), while gratitude can moderate the relationship between stress and well-being ($\beta 3 = 3.257$; $p < 0.05$). Meanwhile, in the study [32], FFT was applied to obtain PSD, especially the ratio of relative differences of Beta power and Alpha power as features, and fed into the SVM classifier with 4-fold cross-validation to achieve 75% classification accuracy on three-level stress. Based on several comparisons in previous studies, it can be said that the logistic regression method's accuracy in predicting stress in final-year students is very high, at 94%. This shows that this study is very promising compared to previous studies because the accuracy level is very high.

3.4 Analyzing the Results Physiology and Psychological

Based on Figures 7, 8, and 9, Subjects were measured based on two aspects, namely physiology heart rate, heart rate, and body temperature, integrated with the blynk application and psychology data taken based on the NASA-TLX questionnaire. The results of testing subjects based on two aspects showed that 19 subjects were in a state of stress with variations in stress levels, and 11 subjects were in a non-stress condition. This shows that academic pressure is one of the main causes why students are faced with final assignments, such as theses, and intense exam preparation. In addition, uncertainty about the future, including job searches after graduation, can add to the mental burden.

Many students feel stressed by uncertain economic conditions, so more attention is needed to the physiological and psychological aspects of the subject, such as environmental factors. This study also shows the importance of considering physiological and psychological aspects in evaluating conditions of overall stress. In addition, the analysis of the logistic regression applied in this study successfully developed a predictive model that showed an accuracy of 94% in identifying students' stress conditions. This shows that this method is good enough to detect stress symptoms in final-year students.

4. Conclusions

This study successfully developed an innovative wearable system to detect stress levels in final-year students by integrating subjective data from the NASA-TLX method with physiological data obtained from wearable devices. The results indicated that out of 30 participants, 19 experienced varying levels of stress, primarily driven by high academic pressure and uncertainty about the future. Logistic regression analysis performed on the collected data yielded a predictive model with an accuracy of 94%, demonstrating the effectiveness of the system in identifying stress symptoms. This study highlights the importance of combining physiological and psychological assessments for a comprehensive understanding of student stress. Ultimately, this system aims to facilitate early detection and effective stress management, thereby enhancing the overall well-being of final-year students as they transition to the workforce. The findings of this study have significant implications for both the research field and the community. In the realm of academic research, they underscore the value of interdisciplinary approaches that merge technology with psychological assessments, paving the way for future studies to explore similar integration in other contexts. For the community, particularly educational institutions, these findings emphasize the urgent need to proactively address students mental health. By implementing such wearable systems, schools and universities can support students better, ultimately fostering a healthier academic environment. Future work should focus on expanding the sample size and diversity to improve the applicability of the system across different educational contexts. Additionally, this study can provide recommendations to the university through the guidance of the counseling field to take further action against students who experience stress and improve performance for those working on their final assignments so that the stress they experience can be anticipated.

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