# Applying artificial neural network on heart rate variability and electroencephalogram signals to determine stress

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**ABSTRACT**

Emotions are mental states, categorizes them into positive and negative feelings, and uses stress as an example of a negative emotion. Research demonstrated that acute and chronic stress can change physiological variables, such as heart rate variability (HRV) and electroencephalography (EEG). This research aims to early prevention and management of stress that is comfortable to use, reliable and accurate for stress detection. The Einthoven triangle rule was used to gather electrocardiogram (ECG) signals, while EEG signals were obtained from Fp1 and F3 connected to mikromedia 7 with the STM32F746ZG chipset. Various parameters were examined, including ECG signals in the time domain, frequency domain, non-linear analysis, and EEG signals in the frequency domain. Healthy subjects aged 18-23 undergoing different stress-inducing stages, with stress levels validated through the STAI-Y1 questionnaire. To process the HRV and EEG features, Pearson's correlation function (PCF) was employed to select appropriated features into classification method. The proposed classification method in this research is the artificial neural network (ANN) with stratified K-fold, which yielded a stress level output accuracy of 95%. Additionally, the STAI-Y1 questionnaire results evaluation indicated a similarity score of 90.91%. This research has potential applications for individuals experiencing stress, providing a valuable tool for stress detection.



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## 1. INTRODUCTION

Nowadays, an increasing number of individuals are experiencing psychological distress. Extensive surveys have demonstrated a robust correlation between individuals' overall health and the prevalence of stress [1]. In general, stress refers to a series of physiological responses that aid the human body in coping with threatening situations. Stress triggers an endocrine reaction to release cortisol. Moreover, it regulates various physiological processes such as metabolism, anti-inflammatory response, and fat metabolism [1]. Activating the endocrine system simultaneously releases catecholamines, which exert regulatory effects on the cardiovascular system, myocardial infarction, depression, and hypertension [1], [2] . Furthermore, stress can increase cardiovascular disease risk, particularly when combined with smoking habits, excessive eating, and a lack of physical activity.

The sympathetic nervous system (SNS) activation triggers the release of stress hormones, namely epinephrine and cortisol, eliciting a physiological response in emergencies. This response manifests as accelerating heart rate, blood pressure elevation, and lung air volume. Moreover, heightened oxygen supply to the brain enhances sensory acuity, promoting increased alertness and elevated energy levels. These physiological changes contribute to enhanced strength, endurance, and improved focus. Once these adaptations are concluded, the parasympathetic nervous system (PSNS) reduces the stress response and restores the body to homeostasis [2]. Stress is a process that burdens an individual's capacity and induces psychological and biological changes, which can potentially increase the risk of diseases. Stress can be classified into short-term acute stress and long-term chronic stress. Acute stress is more common, and most individuals have experienced this type of stress at some point [2]. According to a survey conducted by the American psychological association, more than half of the population in America has reported that stress is a significant source of health problems. Research has also indicated approximately 760 cases of depression, stress, and work-related anxiety per 100,000 workers. Furthermore, while most individuals agree that stress can negatively impact health, they lack a proper understanding of preventing or effectively managing it. Consequently, stress can affect an individual's environment, economy, and overall well-being. According to the survey conducted by the American Psychological Association, a significant majority of the American population has reported that stress constitutes a prominent determinant of their health-related issues. Research has also revealed seven hundred and sixty cases of depression, stress, and job-related anxiety per one hundred thousand workers [3]. Consequently, stress can have far-reaching implications on the environment, economy, and the overall well-being of individuals involved [4].

Previous research indicated that human physiological signals could serve as sensors for detecting psychological stress [1]. Electroencephalography (EEG) studies show that an elevation in cognitive workload or stress levels leads to an increase in theta activity and a decrease in alpha activity [5]. Additionally, significant differences in theta activity have been observed, indicating the impact of stress on neural oscillatory patterns [6]. The long-term consequences of stress necessitate the need for reason when the initial symptoms arise. Detecting and addressing stress at its earliest stages is crucial to other damage or worsening of the condition [7].

Generally, in-store, three or more physiological signals are commonly utilized in stress detection, Attar *et al.* [2]. Also, it is still rare in the stress detection process to be carried out in an embedded system [4]. Rachakonda *et al.* [4] measured using the temperature, humidity, and accelerometer sensors without using physiological signals [8], [9]. Gonzalez-Carabarin *et al.* [1] found that classification accuracy has also not been reported. Tang *et al.* [10] argued that discrete wavelet transform (DWT) will consume less power. A study conducted in [2], [6], [11] affirmed that stress can be seen through the correlation between and heart rate variability (HRV), providing supplementary information regarding stress levels [11], [12]. From all the background above, it is proposed that all devices are embedded ones that take two physiological signal [13]. Typically, questionnaires are used to identify individuals prone to stress [1].

It is crucial to protect human resources worldwide from the escalating impact of stress, as the effects of stress are unavoidable. Therefore, early detection and management of stress are of utmost importance to enhance emotional well-being and overall human welfare [2]. To improve the previous research, as mentioned before, this study aims to enhance the efficiency and effectiveness of stress detection systems by employing a more streamlined approach. While previous studies have commonly utilized three or more physiological signals for stress detection, this research takes a novel direction by focusing on utilizing only two key physiological signals: EEG and electrocardiogram (ECG) signals. This strategic reduction in the number of signals is motivated by the need to create a more practical and resource-efficient embedded system for stress detection. The utilization of these two key signals allows us to gather comprehensive data on physiological responses while minimizing the complexity of signal acquisition and processing.

In addition, this study involves harnessing the power of computational methods to process physiological signals efficiently, catering to the specific requirements of embedded systems with limited memory capacity. By doing so, we aim to make significant strides in the field of stress detection, ultimately contributing to the well-being of individuals and the broader human community. Therefore, this study presents the analysis of ECG signals using Einthoven's rule, which is processed using DWT framework scale 1 to 3 to extract various features from the time domain, frequency domain, and non-linear analysis. Additionally, EEG signals are analyzed using four electrodes, which are processed using a band pass filter (BPF) to extract the frequency domain. The changes in these features from ECG and EEG signals will be utilized in applying the artificial neural network (ANN) method for stress level classification. Consequently, the system's output is expected to indicate three stress levels, enabling the identification of an individual's stress condition.

## 2. MATERIAL AND METHOD

Objective and subjective assessments were employed to gather information regarding the stress level. The conducted research involved 20 male subjects aged between 21 and 22 years. An accurate evaluation was carried out by capturing ECG and EEG signals. The ECG signal acquisition process utilized surface electrodes following Einthoven's lead I, placed on the left arm (LA), right arm (RA), and left.

Leg (LL) as depicted in Figure 1. The ECG signal was recorded at a sampling frequency of 250 Hz, and the HRV analysis was performed on the ECG signal. ECG click as a module was used to retrieve ECG signals was utilized for acquiring the 7-block circuitry, including a protection circuit, preamplifier, high pass filter #1, amplifier, high pass filter #2, low pass filter, DRL, and voltage reference circuit.

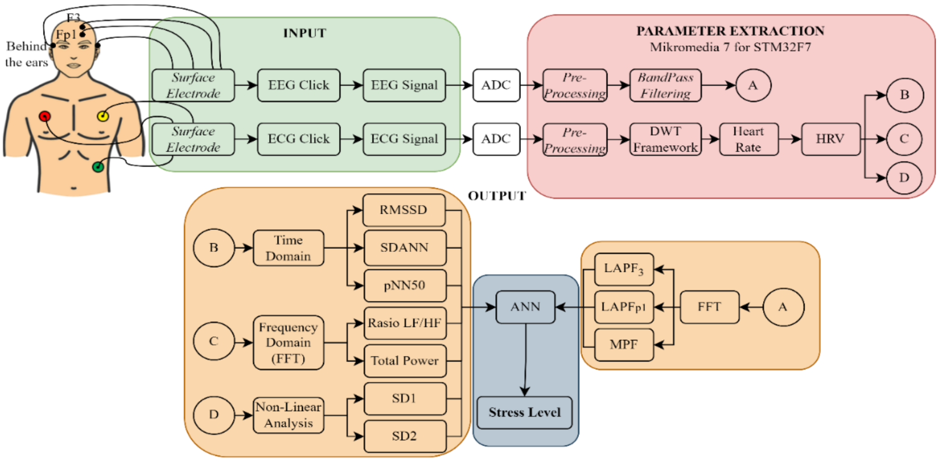



Figure 1. Overall system diagram

### 2.1. Data acquisition scenario

The data acquisition scenario is conducted several moments after the subjects wake up to ensure a consistent initial condition. This study used 20 male subjects from ITS University, aged between 21 and 22. The process of collecting physiological information from the body was carried out simultaneously during the seven stages of stress induction, which lasted for 14.5 minutes, as shown in Table 1. Collecting physiological information signals was repeated five times for each subject. The data collection for both ECG and EEG was performed while the subjects were seated. At the end of each round of retrieving physiological signals, subjective data would be gathered by having the subject fill out a questionnaire using the STAI-Y1 again. The testing and data collection were conducted after waking up, assuming all subjects had the same initial conditions.

Table 1. The sequence of the seven experiments used for the induced-stress

| Procedure | Time (min) | Test |
|---|---|---|
| P1 | 2 | Standard questionnaire |
| P2 | 1.5 | Period of relaxation |
| P3 | 2 | Time-limited arithmetic test |
| P4 | 5 | Images and unpleasant noise |
| P5 | 3 | Fake interview |
| P6 | 0.5 | Time-limited memory test |
| P7 | 0.5 | Time-limited logical test |

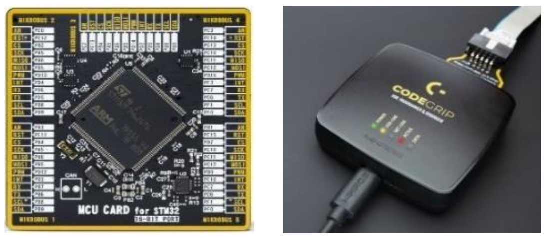
### 2.2. Hardware system

In that research, the objective assessment entailed utilizing various hardware components, which served the purposes of data acquisition and data processing. The data acquisition process involved placing Ag/AgCl electrodes on the skin's surface. These electrodes were subsequently connected to the ECG and EEG click modules. The precise positioning of these click modules can be referenced in Table 2. Importantly, it should be noted that these click modules were seamlessly integrated with mikromedia 7 for STM32F7 capacitive [14], as depicted in Figure 2. Mikromedia 7 for STM32F7 capacitive utilized in this study was equipped with the STM32F746ZG microcontroller chipset, as depicted in Figure 3(a). However, to upload the program to the STM32F746ZG on mikromedia 7, it was necessary to connect it with the CODEGRIP debugger, as depicted in Figure 3(b). Additionally, mikromedia 7 featured an LCD TFT capacitive screen that enabled the display of a graphical user interface (GUI), facilitating the observation of the process results at each stage in data processing. Therefore, when an analog sensor from ECG and EEG click enters the STM32F746ZG microcontroller, it is converted using an analog-to-digital converter (ADC) to be read by the microcontroller. The transmitted data has been multiplied by 3.3 and can retrieve data obtained from sensor recording results, where the existing data can be seen on the USART terminal device with a baud rate of 115200 so that later data can be saved in ".txt" and ".csv".

Table 2. Click placement on MikroBUS

| No. | MikroBus shuttle | Click |
|---|---|---|
| 1 | MikroBUS shuttle 1 | ECG click |
| 2 | MikroBUS shuttle 2 | EEG click |
| 3 | MikroBUS shuttle 3 | USB UART click |
| 4 | MikroBUS shuttle 4 | EEG click |

Figure 2. Instrumentation of mikromedia 7 STM32F7




(a) (b)

Figure 3. Additional equipment for mikromedia 7 STM32F7: (a) MCU card STM32F746ZG as microprocessor and (b) CODEGRIP as upload connector

### 2.3. The acquisition of ECG signals

In the preceding section, it was elucidated that the acquisition of ECG signals necessitated the utilization of a sensor module, namely the ECG click module. The ECG Click module constituted an ECG sensor that could be interfaced with a click board, as depicted in Figure 4. The raw ECG signal was acquired at a minimum sampling frequency of 250 Hz. Subsequently, the filtered ECG signal was subjected to the DWT level 1 to 3 framework to extract the R-R intervals [10], [15], enabling heart rate determination. R-R intervals can be obtained from the peak Q, peak R, and peak S (QRS) wave, the QRS Wave is the dominant feature in the ECG signal and has a high amplitude pattern and a power spectrum that varies from 0 to 62.5 Hz and a mid-frequency of 20 Hz.

DWT is based on multi-resolution analysis resulting from decomposition at different scales. The decomposition is performed by a combination of the fundamental, dilation (a), and translation (b) functions of the basic wavelet with dyadic factor ($2^j$) shown in (1):

$$\psi_{2^j,b}(t) = \frac{1}{2^{\frac{j}{2}}}\psi\left(\frac{t-b}{2^j}\right) \quad (1)$$


Figure. 4 ECG click module

From (1) the wavelet transform (ψ) as the mother wavelet represents the scale parameter in the equation above, and b represents the time shift parameter. Each level of the DWT decomposition (levels 1-3) has a low pass filter (LPF) and a high pass filter (HPF). The formula is then derived using the filter bank technique. The filter coefficient (Q) can be computed using (2) and (3) from the transfer function $H(\omega)$ and $G(\omega)$, which is the frequency response of the LPF and HPF:

$$H(\omega) = e^{j\omega/2}(cos\frac{\omega}{2})^3 \tag{2}$$

$$G(\omega) = 4je^{j\omega/2}(sin\frac{\omega}{2}) \tag{3}$$

the values $H(\omega)$ and $G(\omega)$ are used to calculate the coefficient values for each scale starting from scale one to scale three as in (4) to (6):

$$Q1(\omega) = G(\omega) \tag{4}$$

$$Q2(\omega) = G(2\omega)H(\omega) \tag{5}$$

$$Q3(\omega) = G(4\omega)H(2\omega)H(\omega) \tag{6}$$

After all the stages have been carried out, the next stage is thresholding. Thresholding is applied to detect the beginning of a complex QRS. Thus, zero crossing is detected if the filter coefficient exceeds a given threshold. A delay is also required by following each scale, meaning that there is delay 1 to 3. The delay equation can be formulated in (7):

$$\mathrm{Ta} = 2^{j-1} - 1 \tag{7}$$

The AND logic gate process is the following process for each discovered delay. The quadratic spline function is selected as the mother wavelet because it produces the best procedure for QRS detection.

Once the QRS complex is found, HRV can be further analyzed. The analysis of HRV encompassed the domains of time, frequency, and non-linear analysis [16]–[19]. Indicators of HRV within the time domain encompassed RMSSD, SDANN, and pNN50 [20], [21]. Meanwhile, the LF/HF ratio and total power served as HRV indicators within the frequency domain utilizing the fast fourier transform (FFT), specifically employing welch's method. Determining the LF/HF ratio might have required utilizing the total power (TP) value in Table 3.

Table 3. HRV feature calculations in time, frequency domain, and non linear analysis

| Feature | Equation | Description |
|---|---|---|
| RMSSD | $\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(RR_{n+1} - RR_n)^2}$ | Square root of the mean squared differences of successive RR intervals |
| SDANN | $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\overline{RR_5} - \overline{\overline{RR}})^2}$ | Standard deviation of all normal RR in 5 minutes |
| pNN50 | $\frac{Number\ of\ RR > 50}{N-1} \cdot 100\%$ | Percentage of adjacent RR intervals that differ from each by more than 50 ms |
| LF/HF Ratio | $\frac{Summation\ of\ power\ from\ 0.04\ to\ 0.15\ Hz}{Summation\ of\ power\ from\ 0.15\ to\ 0.40\ Hz}$ | Ratio of low frequency to high frequency of HRV |
| Total Power | Summation of power from 0-1 Hz | Total summation from 0 until 1 Hz |
| SD1 | $\sqrt{\frac{1}{2}SDSD^2}$ | Minor axis of the cloud |
| SD2 | $\sqrt{2SDNN^2 - \frac{1}{2}SDSD^2}$ | Major axis of the cloud |

*N*: number of *RR* intervals, *RR*: interval between two R peak

### 2.4. The acquisition of EEG signals

The acquisition of EEG signals from the subjects involved the utilization of the EEG click as a sensor, which featured an onboard 3.5 mm audio socket for connecting electrode cables to the sensor board. The EEG click module, although not suitable for comprehensive clinical brain condition examinations, provided adequate capabilities for studying, and analyzing brain activity. It was equipped with a high-sensitivity circuit that amplified faint electrical signals from the brain. The configuration of the EEG click module utilized in this research can be observed in Figure 5. The module consisted of various circuitry components that supported the performance of the EEG click in providing insights into EEG signals and utilizing EEG signals to assess stress conditions involved working with raw brain signals sampled at 512 Hz. EEG signals were processed to determine the frequency characteristics of the existing EEG signals, providing information about the types of EEG signals. Filtering was applied to the EEG signals to remove noise caused by eye movements and other muscle activities. A BPF with 1 and 35 Hz cutoff frequencies was used. The processing of EEG signals began with baseline restoration, followed by applying the FFT, specifically welch's method, to the EEG signals. This was followed by calculating the MPF, which provided information about the dominant frequency components in the EEG signals in Table 4.


Figure 5. EEG click module [14]

Table 4. EEG features

| Feature | Equation | Description |
|---|---|---|
| LAPFP1 | $\frac{Summation\ of\ power\ from\ 8\ to\ 13\ Hz}{Total\ Power} * 100$ | Normalized left hemisphere alpha band power (Fp1) |
| LAPF3 | $\frac{Summation\ of\ power\ from\ 8\ to\ 13\ Hz}{Total\ Power} * 100$ | Normalized left hemisphere alpha band power (F3) |
| Median power frequency (MPF) | $\frac{\sum_{i=1}^{K} f_i P_i}{\sum_{i=1}^{K} P_i}$ | Mean power frequency |

$P_i$ is the power spectrum, $f_i$ is the frequency parameter, and $K$ is the length of frequency

### 2.5. Questionnaire STAI-Y1

The relationship between stress and emotions can be examined through survey methods using questionnaires. Surveys and assessments utilizing questionnaires are subjective examinations and observations that serve as the ground truth. One commonly used questionnaire is the state-trait anxiety inventory (STAI), which consists of STAI-Y1 and STAI-Y2. STAI-Y1 assesses the conscious experience of unwanted stress and is associated with the autonomic nervous system (ANS). On the other hand, STAI-Y2 measures enduring personality traits related to consistent individual differences. While numerous questionnaires have been proposed to measure stress, the STAI is one of the most popular tools for assessing anxiety and has been widely used in stress-related research [22], in this study, and STAI-Y1 was utilized.

### 2.6. Stress detection with ANN using K-fold cross validation

Once all the features for stress detection had been obtained, a detection or classification system was required to be implemented on a computer. Machine learning enables machines or computers to learn and generate desired outcomes through supervised, unsupervised, or semi-supervised learning approaches [23]. When discussing supervised has been chosen, especially machine learning, it was inevitable to mention one of its popular models, the ANN. ANN simulates information processing in the human brain by learning from data via interconnected neurons and storing information with weights.

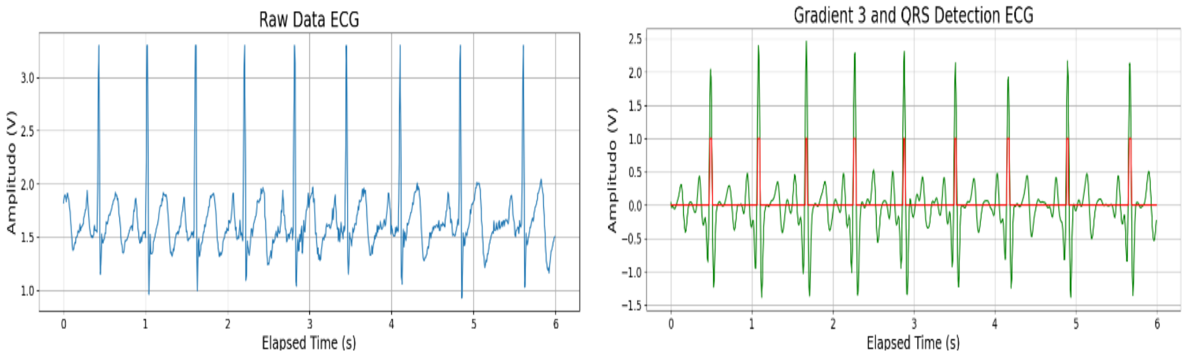
One of the advantages of ANN was that the model did not need to be explicitly defined before starting the experiment. ANN could recognize relevant data and patterns, while statistical models required prior knowledge of the relationships between the studied factors [4]. ANN consists of an input, hidden, and output layer. The features of the ECG and EEG data determined the number of nodes in the input layer. The number and nodes were selected in the hidden layer based on the relationships among different data. The number in the hidden layer connected to the input layer could combine input variable values, assign weights, extract new values, and send them to the output layer. Based on the features calculated in the hidden layer, the output layer enables classification and prediction for a given problem [24]. The dataset was divided into various folds or partitions in K-fold cross validation. To maintain a balanced class distribution in the test data for each fold, the type of K-fold used was stratified K-fold [15], [18], [22].

## 3. RESULTS AND DISCUSSION

The data generated by the objective and subjective evaluation of the research are assembled into a standardized dataset for use in machine learning algorithms. On each existing signal, multiple phases of signal processing tests are done to obtain parameter values that will be used as analytical features. Each signal includes unique stages based on parameters connected with stress detection evaluation. ECG and EEG signals are signal processed in the results and discussion of signal processing. The following subsection will review the outcomes of each physiological signal processing and stress detection categorization.

### 3.1. Result of ECG signal processing

The initial stage of processing the ECG signal was to obtain a QRS complex detection to calculate the R-R interval. The algorithm for detecting QRS complexes was adapted from the research framework [25]. Signal processing of ECG is carried out through several steps, starting from the microcontroller using UART. The subsequent steps include decomposition 1, decomposition 2, decomposition 3, gradient 1, gradient 2, gradient 3, and thresholding. The gradients represent the gradient thresholding. The plotted results of the raw signal can be seen in Figure 6(a). Gradients 1 to 3 facilitate the thresholding process, and the thresholding process is illustrated in Figure 6(b).




(a) (b)

Figure 6. ECG raw signal and gradient thresholding for QRS detection: (a) ECG raw signal and (b) level 3 gradient and QRS detection

### 3.2. Result of ECG signal processing

As one of the two physiological signals utilized in this study, the EEG signal also undergoes signal processing to extract the relevant information from the EEG signal itself. The EEG signal processing involves several steps, starting with plotting the obtained signal from the microcontroller, baseline restoration, and fourier transform. The plotted results of the raw EEG signal can be observed in Figure 7(a). After obtaining the EEG signal, the next step is to perform a filtering process, as there may still be noise in the EEG signal. The filtering process uses a second-order LPF with a cut-off frequency of 35 Hz and a second-order HPF with a cut-off frequency of 0.1 Hz. The output of the EEG signal after the filtering process is depicted in Figures 7(b) and 7(c). This cut-off frequency value was selected based on the spectrum of the EEG signal.

Figure 7(c) shows the HPF EEG signal in quiet conditions. The amplitude and frequency of the EEG signal remain relatively stable and consistent. Figure 7(d) depicts the HPF EEG signal in noisy conditions. The EEG signal exhibits increased amplitude and frequency variations, indicating higher brain activity due to external stimuli.

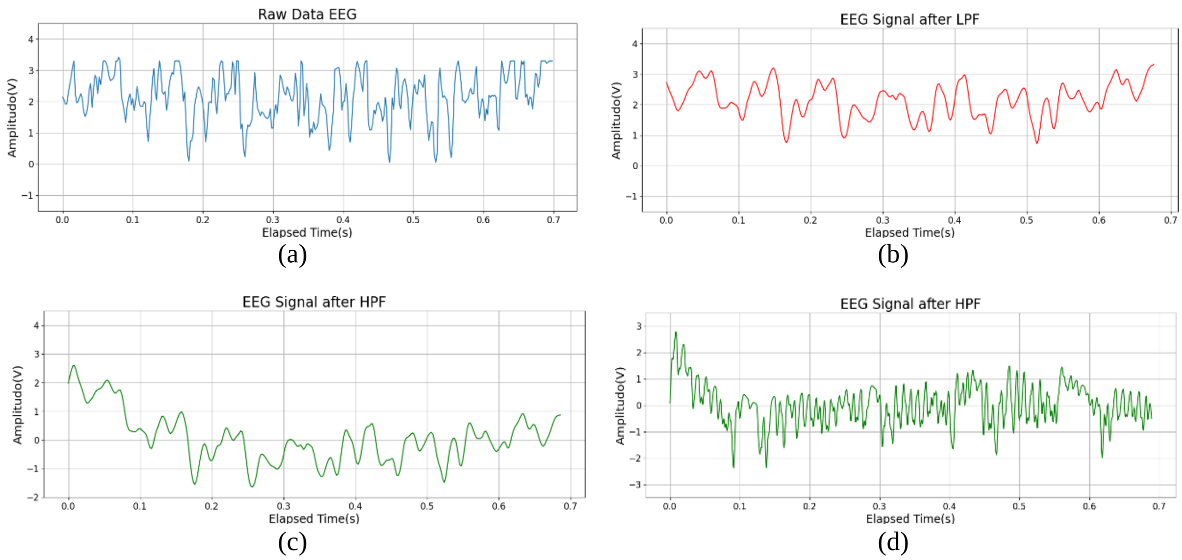



Figure 7. EEG signal processing stages: (a) Raw EEG signal, (b) LPF EEG signal, (c) HPF EEG signal in quiet condition, and (d) HPF EEG signal in noisy condition

– Assessment of the questionnaire state-trait anxiety inventory (STAI–Y1)

The STAI-Y1 questionnaire was administered to each subject shortly after they underwent the collection of ECG and EEG physiological signals. This research observed that the issues involved had a relatively even distribution of stress levels across the low, medium, and high categories. The distribution of the STAI-Y1 questionnaire results into the three existing classes are 33%, 33%, and 34%, respectively.

– Detection system testing

In this study, the dataset was divided into three classes: low (0), medium (1) and high (2). The detection system used in this research is ANN. ANN is a machine-learning method that can be used for classification tasks. In its usage, the classification method with ANN requires a large amount of data to train the model. However, open-source datasets designed explicitly for stress classification with only two signals and seven features are scarce, as used in this research. Therefore, a dataset was created based on the collected data from the subjects and previous research in section 2.1. This dataset consists of three labels and was designed for supervised machine learning algorithms, allowing the machine to learn patterns from input-output pairs.

The first layer of this model is the input layer, which has seven neurons expressing the data from Pearson’s correlation function, reducing the initial 11 features to 7, and as shown in Table 5. This is followed by the hidden layer, where in this research, different models with varying numbers of nodes in the hidden layer and other activation functions were experimented with and compared. Among the many experiments, the chosen ANN model uses stratified K-fold, with 32, 16, and 8 nodes in the hidden layer, and rectified linear unit (ReLU) as the activation function. The output layer consists of three nodes with three levels and softmax as the activation function.

Table 5. Pearson’s correlation function result to level

| Feature | Pearson’s correlation function |
|---|---|
| LAPF3 | 0.575970 |
| MPF F3 | 0.568574 |
| MPF Fp1 | 0.544803 |
| LAPFp1 | 0.415694 |
| SD2 | 0.217372 |
| RMSSD | 0.195142 |
| SD1 | 0.191544 |
| TP | 0.177927 |
| SDANN | 0.131496 |
| LF/HF | 0.073565 |
| pNN50 | 0.049090 |

Based on the conducted testing, it can be observed that the ANN successfully created a model with a reasonably good accuracy using stratified K-fold. However, the classification results for each individual may vary according to their respective stress level at that time. The result obtained from this instrumentation system with the ANN model, as shown in Table 6, indicates that an individual's stress level depends on their mental condition at that moment. A subject whose data was collected while performing the research and/or those contained while relaxed will exhibit different stress values and levels. Therefore, the classification results in this research are more dependent on the individual's stress level at that time, what they were doing at that moment, their experiences on that day, and other external influences that can affect their mood and stress levels.

Table 6. Classification report on the selected ANN form

| | 0 | 1 | 2 | Average |
|---|---|---|---|---|
| Precision | 0.97 | 0.94 | 1.00 | 0.97 |
| Sensitivitas | 0.94 | 0.97 | 1.00 | 0.97 |
| Spesifitas | 0.956 | 0.955 | 0.945 | 0.952 |
| Amount of data | 33 | 33 | 34 | 100 |

## 4. DISCUSSION

This research's stress evaluation process was undertaken through subjective and objective approaches. Before delving into the subject matter, it is crucial to acknowledge that stress triggers an endocrine response leading to cortisol secretion [1]. Determining an individual's stress condition in this study leveraged physiological information from the subjects, specifically the ECG signals and EEG. The acquisition of ECG signals involved using surface electrodes placed according to Einthoven's standard leads, and the ECG signals were recorded at a sampling frequency of 250 Hz, which is considered optimal for capturing ECG signals for subsequent analysis of HRV. Furthermore, the EEG signals were obtained using surface electrodes, with four electrodes placed accordingly. Two electrodes were positioned at the back of the ears, while the other two were placed on the upper and lower left forehead. The EEG signals were recorded at a sampling frequency of 512 Hz, considered the optimal frequency for EEG signal analysis. These physiological data will undergo a pre-processing stage, where the ECG signal will be processed using DWT. DWT will be applied with a scale of 1, a cutoff frequency of 0–250 Hz, and a mid-frequency of 125 Hz. Subsequently, a decomposition level 2 will be performed by applying a scale of 2 with a cutoff frequency of 0-125 Hz and a mid-frequency of 42 Hz. The next step is decomposition level 3, which involves a scale of 3 with a cutoff frequency of 0-62.5 Hz and a mid-frequency of 20 Hz. This process aims to obtain time-domain, frequency-domain, and nonlinear analysis of HRV. The EEG signal is processed using a BPF with a second-order design and cutoff frequencies of 1 Hz and 35 Hz to eliminate eye movement artifacts from the EEG signal, as depicted in Figure 1. This filtering process allows us to obtain left hemisphere alpha power frequency (LAPF) and MPF frequency domain features. The value of MPF determines the waveform type of the EEG signal, where the delta signal corresponds to the range of 0.2-3 Hz, Theta signal corresponds to 3-8 Hz, alpha signal corresponds to 8-13 Hz, beta signal corresponds to 13-30 Hz, and gamma signal corresponds to a frequency above 30 Hz [2]. The processed from DWT levels 1 to 3 can be seen in Figure 6, making it a HRV tachogram. The processed from bandpass filtering can also be seen in Figure 7.

The subjective assessment is conducted using the STAI-Y1 questionnaire and used as the ground truth for stress detection or classification systems. The scores obtained from this questionnaire will determine the stress level, with the following breakdown: the score ranges from 20 to 80 and is divided into three classifications. If the score falls within the range of 20-37, it is classified as low stress. Scores ranging from 38-44 indicate medium stress, while scores between 45-80 are classified as high stress [26].

Next, combining the two outputs from the subjective data collection is used as parameters for classifying stress conditions using the ANN method. The output layer employs the softmax activation function because the output of the ANN model consists of more than two classes, precisely three [22]. There are three classes for stress levels: low, medium, and high, but it is a single label because the classification only includes one stress level. The accuracy using the ANN above parameters is 95%, as indicated by the performance evaluation in the classification report, as shown in table.

This research found that the subjects involved had the highest stress distribution level, namely medium, followed by low and high, which were taken from 11 male subjects. Where is the distribution of the results of the STAI-Y1 questionnaire into the three existing classes. Differences occur in subject number 5, as shown in Table 7. Filling in the STAI-Y1 questionnaire was carried out after an objective review. From the results of the comparison between the STAI-Y1 questionnaire and an objective review, a similarity value of 90.91% was obtained.

Table 7. Comparison of questionnaire with an objective

| Subject no. | STAI-Y1 | Objective |
|---|---|---|
| 0 | Low | Low |
| 1 | Medium | Medium |
| 2 | High | High |
| 3 | Low | Low |
| 4 | Medium | Medium |
| 5 | High | Medium |
| 6 | Medium | Medium |
| 7 | Medium | Medium |
| 8 | Low | Low |
| 9 | High | High |
| 10 | High | High |

## 5. CONCLUSION

This research proposes an instrumental device that can identify stress levels by utilizing objective and subjective assessments of an individual's body condition. The study successfully achieved a consistent output for stress levels, with a 95% accuracy in subjective and objective evaluations based on testing available sample data. The objective assessment process for detecting stress levels as an indicator, aided by machine learning, specifically ANN with stratified K-fold, was successfully performed using the available parameters, and resulting in an ANN accuracy of 95%. The process of evaluating the results of the STAI-Y1 questionnaire with an objective review of stress levels provided a similar level, which was 90,91% of the sample owned.

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