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Application of ANFIS-based Non-Linear Regression Modelling to Predict Concentration Level in Concentration Grid Test as Early Detection of ADHD in Children

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Abstract. Concentration is the main asset for students and serves as an indicator of successful learning implementation. One of the abnormal disturbances that can occur in a child's concentration development is attention deficit hyperactivity disorder (ADHD). The prevalence of ADHD in Indonesia in 2014 reached 12.81 million people due to delayed management in addressing ADHD. Therefore, early detection of ADHD is necessary for prevention. ADHD detection can be done by testing the level of concentration using a concentration grid. However, a method is needed that can be applied to uncooperative young children who are not familiar with numbers. Therefore, research was conducted with an innovative approach using a combination of EEG-ECG to classify concentration levels. The data used in this study were primary data from 4 participants with 5 repetitions. The data were processed in the preprocessing stage, which involved noise filtering and Butterworth filtering. The features used in this study were BPM (beats per minute), alpha, theta, and beta EEG signals, which would later become inputs for the Adaptive Neuro-Fuzzy Inference System (ANFIS). The output shows that the combination of EEG-ECG has the potential to predict concentration test results. Using BPM, alpha, theta, and beta signals can serve as parameters for predicting the concentration grid test values using ANFIS effectively. In the ANFIS model with 4 features, an accuracy of 99.997% was obtained for the training data and 80.2142% for the testing data. This result could be developed for early detection of ADHD based on concentration levels so the learning implementation could be more effective.

Keywords: Concentration Level, ADHD, ECG, EEG, ANFIS

INTRODUCTION

Concentration is the focus of attention in the process of changing behavior which is expressed in the form of mastery, use, and evaluation of attitudes and values, basic knowledge and skills contained in various fields of study. If a student's concentration is low, it will also lead to low-quality activities and can lead to not being serious in learning. That lack of seriousness affects the power of understanding the material. Concentration is the main capital for students in receiving material and is an indicator of successful implementation of learning [3]. Learning in public schools where children live is the first step in building the future of this country. However, not all children are in good health and experience abnormal behavior disorders. One of the abnormal disorders that occur in child development is Attention Deficit Hyperactivity Disorder or ADHD. ADHD is a developmental disorder that increases motor activity in children, causing excessive and unusual activity [4].

Based on the American Psychiatric Association (2013), ADHD is described as a neurodevelopmental disorder with persistent behavior patterns in the form of lack of concentration and/or excessive hyperactivity/impulsivity [1]. In Indonesia, research on the prevalence rate of ADHD was conducted which stated that the prevalence of ADHD in Indonesia was 5% or around 12.81 million people of Indonesia's population [5]. Lack of parental knowledge about ADHD can result in slow treatment to overcome ADHD. In general, individuals who suffer from ADHD as children will inhibit some of these traits as adults such as difficulty focusing or concentrating on one activity. Therefore, prevention needs to be done by doing early detection of ADHD.

The simplest detection of ADHD is to test the concentration level of the children. Testing the level of concentration can be done in various ways. The most common way to do this is with a concentration grid. This method is done by ordering the numbers from 0 to 99 or from 1 to 100. However, this method cannot be done on children who are uncooperative in testing and also children who still cannot recognize numbers. ADHD detection needs to be done as early as possible so that concentration grid testing cannot be done. It is hoped that this research can detect ADHD as early as possible in order to reduce sufferers and improve the quality of life and education according to SDGs number 3 and 4. Therefore, a method that can be done on young children who are uncooperative and don't know numbers is needed. So an innovation was made for concentration testing using EEG and ECG.

EEG and ECG are used by combining the two signals as information to replace the concentration grid test. Based on research, a combination of EEG and ECG was carried out to determine the level or level of concentration in children using the Adaptive Neuro-Fuzzy Inference System (ANFIS). The results of the ANFIS training that has been carried out provide an accuracy value of 80.69% for training data and 65.88% for test data. This study uses EEG information in the form of changes in Max. Alpha and BPM change information from the ECG between normal conditions and concentration conditions [6]. Another research showed that theta and beta signals from the EEG had an effect on concentration. This is the basis for the development of ANFIS by using inputs in the form of BPM values, alpha, theta, and beta signals to determine the replacement value for the concentration grid level [7]. This research is expected to provide results in accordance with the concentration grid test by utilizing the EEG-ECG combination. In addition, with this innovation, it is hoped that the detection of ADHD can be done as early as possible in order to reduce sufferers and improve the quality of life and education according to SDGs number 3 and 4.

RESEARCH METHODOLOGY

In general, the research scheme is shown in Figure 1 by conducting the EEG and ECG signal from subjects then processing the features into the classifier. The result was also compared with the concentration grid to verify the concentration level of the subject.

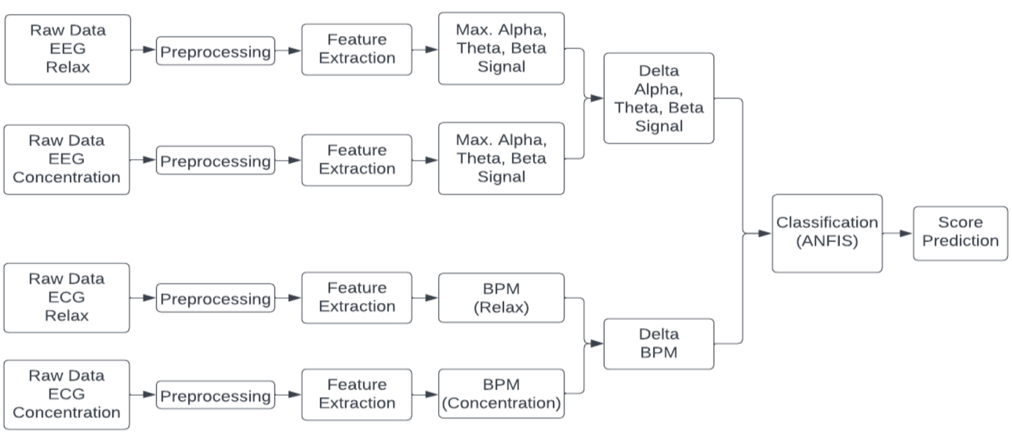

FIGURE 1. Research scheme flowchart

Data Collection

The data were collected from 4 subjects (male, 20 years age). In this research, each participant underwent five data collection sessions. During each session, simultaneous ECG and EEG data recording was performed using the BITalino device. The data was recorded for a duration of one minute, utilizing the autosave feature of the BITalino. For data acquisition, a specialized BITalino cable with three branches was used. The cable was color-coded, with red indicating the positive pole, black representing the negative pole, and white serving as the ground. The EEG electrodes were placed on the frontal part, specifically FP1 and FP2, with the ground electrode positioned behind the ear. These locations (FP1 and FP2) are known for their rich information content and their potential to identify concentration states [8]. The electrode placement is shown in Figure 2.

The data collection process consisted of two conditions: relaxation and concentration. During the relaxation condition, the participants will be in a relaxed state to assess the brain's activity. They will listen to specifically selected songs that promote relaxation while keeping their eyes closed. Listening to music has been shown to induce a relaxed state without causing drowsiness [9].

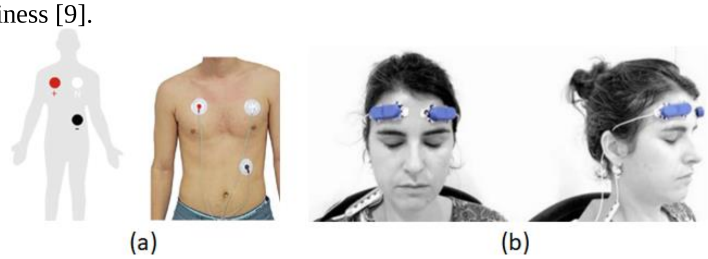

FIGURE 2. Electrode placement for (a) ECG and (b) EEG

The subjects were asked to do a concentration grid test (10 rows x 10 columns) during the concentration condition. The procedure consists of ordering numbers from 1 to 100 in ascending order [6]. Each participant was given one minute to do the test; their score will be the last number they reached. The assumption is that the more numbers an individual is able to order, the higher their concentration level is.

Signal Pre-Processing

The ECG signal was captured using the Bitalino software with the aVR lead configuration. The obtained data was saved as a .txt file for easy access and analysis. To enhance the data quality, a preprocessing stage was applied. The raw data went through a high-pass filter implemented with a Butterworth filter. This filtering process effectively eliminates the baseline drift present in the raw data. The Butterworth filter used is a commonly employed Infinite Impulse Response (IIR) filter in signal processing. In this case, a second-order filter with a cutoff frequency of 0.5 Hz was utilized. By implementing this filter, the detection and analysis of ECG waves associated with cardiac activity are significantly improved.

While for the raw EEG signal, the pre-processing involves eliminating noise and artifacts and enhancing the relevant signal components. This process ensures that subsequent analysis focuses on the brain's electrical activity and minimizes interference from external factors or physiological artifacts. The steps in the EEG preprocessing stage are; data selection, frequency sampling, filter design, filter coefficient, and filter application.

1. Data Selection

   The input data is assumed to be called a *data* matrix in the code, where each column represents a different signal. Biosignal The EEG is recorded in the 7th column of the data matrix. This selected EEG data is then assigned to a variable *eeg*. Additionally, to limit the analysis to a certain subset of data, the code truncates the EEG data to the first 45,000 samples of the data. This is because there are variations in the amount of recorded data obtained so the EEG data is limited to the first 45,000 samples to ensure consistency and fairness in data processing.

2. Sampling Frequency

   The code sets the sampling frequency (*fs*) to 1000 Hz, adjusting the BITalino setting during data capture. This value represents the number of samples recorded per second in the EEG signal.

3. Filter Design

   At this step, the bandpass filter Butterworth is designed for different frequency bands: alpha, theta, and beta. The butter function is used to design this filter, and the desired filter order is set to 3. Each frequency band is associated with a specific physiological phenomenon or brain activity.

4. Filter Coefficient

   The code calculates the filter coefficient based on filter design specifications and sampling frequency using the butter function to perform the actual filtering operation. This coefficient captures the filter characteristic for which it is designed and required for the next filtering step.

5. Filters Application

The designed filter is applied to the EEG signal using the '*filterfilt*' function. This function performs zero-phase forward and reverse filtering to remove any phase distortion that can occur during filtering. The filtered signal is then stored separately. Each variable stores the EEG signal, which is filtered according to a certain frequency band.

Feature Extraction

In the feature extraction phase, the R peaks of the aVR lead ECG signal are identified using the "*findpeaks*" algorithm. To ensure the accuracy of the detected peaks, a minimum peak height criterion, set at 0.3, is employed. Only peaks that reach this height threshold are considered valid R peaks. Any peaks falling below this threshold are disregarded.

To maintain appropriate spacing between the detected peaks, the "*MinPeakDistance*" parameter is utilized. It determines the minimum allowable distance between peaks during the search process. Specifically, the minimum distance is set as 0.6 times the sampling rate (fs) of the ECG signal. Consequently, peaks occurring closer to each other than 0.6 seconds are discarded to avoid double counting or misinterpretation.

Subsequently, measurements are conducted to calculate the time difference between consecutive R peaks on the ECG signal. This time difference is then converted from seconds to beats per minute (BPM) using appropriate formulas.

EEG, a non-invasive neuroimaging technique, enables the measurement of bioelectrical activity in the brain. EEG values are widely employed in neuroscience, psychology, and medicine and offer valuable insights into brain function and activity [10]. EEG signals provide valuable insights into various mental states, including concentration and relaxation. Feature extraction in EEG focuses on identifying and extracting relevant characteristics, which in this case is power spectral density and signal amplitude. It can reveal dominant frequency bands and overall brain activity patterns that are very important for identifying the characteristics of mental states of concentration and relaxation.

The steps in the EEG feature extraction stage are; amplitude extraction, *power spectral density* (PSD) calculation, extraction of the maximum value per EEG frequency band, and normalization.

1. Amplitude Extraction

The code uses Fast Fourier Transform (FFT) to calculate the amplitude of each filtered signal. FFT is applied to each filtered signal, `alpha_filtered`, `theta_filtered`, and `beta_filtered`, using the function `fft`. The result of the FFT operation is stored in a separate variable (`for`, `zt`, and `zb`).

2. Power Spectral Density (PSD) Calculation

The power spectral density is calculated based on the amplitude information obtained from the FFT. For each filtered signal (`alpha_filtered`, `theta_filtered`, and `beta_filtered`), the code calculates the power spectral density by squaring the absolute value of the FFT result. This is done using `abs` operation and `.^2`. The resulting power spectral density signal is stored in a separate variable (`PSa`, `PSt`, and `PSb`).

3. Extraction of Maximum Value per EEG Frequency Band

The code extracts the maximum value for each frequency band from the power spectral density signal. The maximum value represents the dominant power in a certain frequency range. To achieve this, the code uses the `max` function to find the maximum value of each power spectral density signal (`max(PSa)`, `max(PSt)`, and `max(PSb)`).

4. Normalization

The maximum values extracted are normalized by dividing by 10^10 to ensure consistent and concise feature values. This normalization step helps scale feature values appropriately. Additionally, normalized feature values are rounded to two decimal places for clarity and precision. The resulting normalized and summarized feature values are stored in separate variables (`maxAlpha`, `maxTheta`, and `maxBeta`).

Classification

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a machine learning approach that combines adaptive network systems with fuzzy system approximation. It utilizes a Sugeno fuzzy model trained using an adaptive network. This hybrid learning procedure enables modeling even in scenarios where expert knowledge is limited.

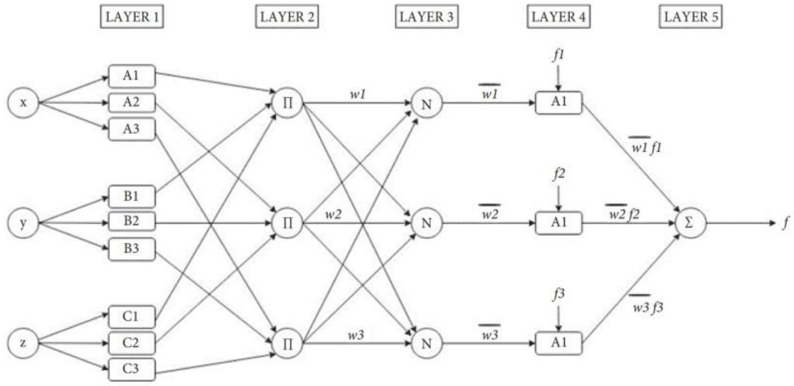

FIGURE 3. ANFIS architecture

ANFIS consists of 5 layers, each serving a specific function. The first layer is the fuzzification layer responsible for generating fuzzy sets using membership functions. The second layer is the implication layer, where the weights of the fuzzy rules are determined. The third layer is the normalizing layer, which displays the standard activation degree and normalizes the weights from the second layer. The fourth layer is the defuzzification layer, which is adaptive and computes the weighted multiplication of the previous layer's outputs. The final layer is the output or combining layer, where the results from the previous layers are summed [11].

Data evaluation is performed to assess the accuracy of the developed ANFIS system. The evaluation of ANFIS using regression model methods can utilize RMSE (Root Mean Square Error), MSE (Mean Square Error), and MAPE (Mean Absolute Percentage Error) [12]. RMSE indicates the magnitude of prediction errors. A smaller RMSE value, closer to 0, indicates more accurate predictions [13]. The MSE and MAPE methods are also employed to test the errors of each prediction system. The system with the smallest MSE and MAPE values is considered the best for making predictions [14]. MAPE values have specific ranges to assess the predictive capabilities of the model. Lower MAPE values indicate better prediction performance [15].

RESULT AND DISCUSSION

Based on the applied ECG processing that consists of two stages; preprocessing and feature extraction, the results are obtained in the form of BPM (beats per minute) of the heart rate. Heart rate (or pulse) is the frequency of heartbeats as measured by the number of heart contractions per minute (beats per minute, or bpm). The results of the bpm from several participants ranged from 71 - 76 bpm in a state of relaxation and 71 - 86 BPM in a state of concentration. This is in accordance with the American Heart Association, which states that the normal adult human heart rate at rest is 60-100 bpm.

During relaxation, the heart rate tends to decrease when the body is at rest, and the mind is calm. This is because the body's overall metabolic activity is lower, and the parasympathetic nervous system, which is responsible for promoting relaxation and recovery, becomes more active. Based on Figure 4, heart rate is often at the lower end of the normal range (about 60 to 80 bpm) while in a relaxation state. On the other hand, during mental concentration or focus, the heart rate may increase slightly. This is caused by activating the sympathetic nervous system, which is responsible for the response fight-or-flight body. When in a state of concentration that requires attention and focus, the body releases certain stress hormones that can increase heart rate and blood pressure. The increase in heart rate during concentration is usually not very high and can vary depending on the individual and the intensity of mental activity. However, the difference in heart rate between relaxation and concentration can vary between individuals. Factors such as overall fitness level, stress level, and underlying health conditions can affect variations in heart rate during different circumstances.

The experimental results showed differences in heart rate in different relaxation and concentration conditions. In some data, the heart rate in a relaxed state is higher than in a state of concentration. This is due to the accurate data collection when the relaxation state is due to the person only sitting in a room that is quite open. In addition, the program code for removing noise by filter and determining height and distance peak also affect the corresponding heart rate results.

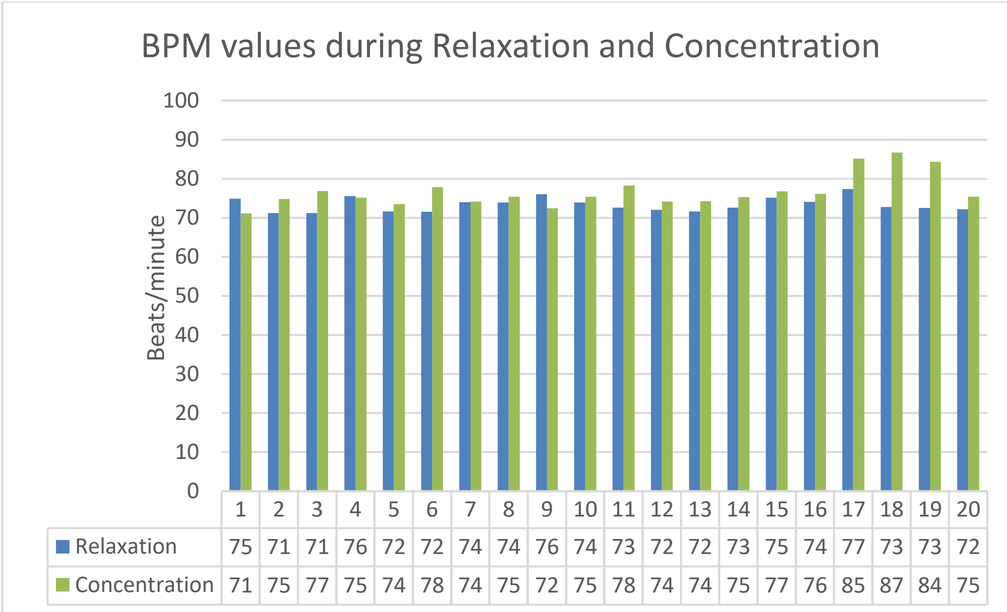

FIGURE 4. BPM values during relaxation and concentration

The result of the EEG processing stage, preprocessing, and feature extraction was obtained in the form of PSD (power spectral density) of the alpha, theta, and beta waves (Figure 5). During relaxation, it has been observed that alpha waves tend to increase in amplitude. Alpha waves are usually present in the 8-13 Hz frequency range and are associated with a relaxed and calm state of mind. An increase in alpha strength indicates a decrease in mental activity and can be an indication of a relaxed state [16]. During relaxation, the increase in the amplitude of alpha waves can be related to the physiological aspects of the brain's electrical activity. Alpha waves primarily originate in the thalamus, a brain structure involved in organizing sensory information. Increased alpha strength reflects decreased processing of sensory input and reduced cognitive engagement. This physiological state is associated with a relaxed and calm mental state [17].

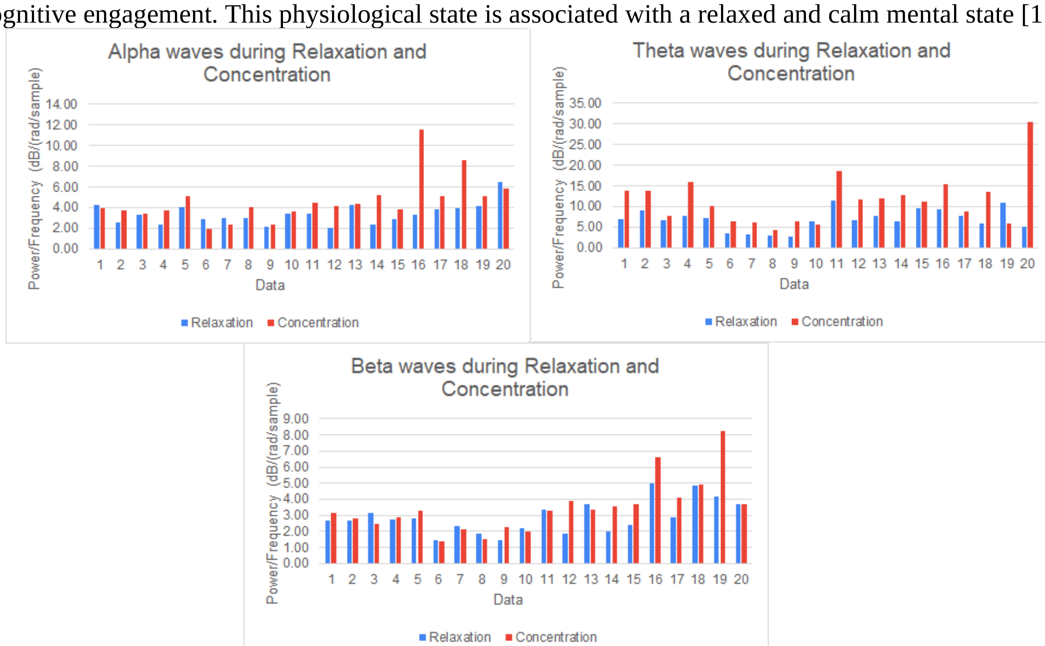

FIGURE 5. Power spectral density from several brain waves during relaxation and concentration

On the other hand, during concentration or cognitive engagement, it is often observed that alpha waves decrease in amplitude, whereas beta waves increase. Beta waves are generally associated with increased mental activity, focus and alertness. They have a frequency range of 13-30 Hz, and higher beta strength is associated with increased concentration and cognitive processing [16]. During concentration, the concomitant decrease in the amplitude of alpha waves and increase in beta waves can be explained by the increased cognitive processing demands of the brain. The neocortex, the brain's outer layer responsible for higher cognitive functions, generates beta waves. A decrease in alpha strength signals a shift from a relaxed state to a more focused and alert mental state. Increased beta power corresponds to increased cortical activation and increased cognitive processing, supporting concentration and mental engagement [18].

The theta waves, which are in the 4-8 Hz frequency range, are often associated with deep relaxation, meditation, and sleepiness. These waves tend to increase during states of deep relaxation or meditation [16]. Theta waves, on the other hand, play a role in states of deep relaxation, meditation, and sleepiness. An increase in theta power during deep relaxation or meditation is linked to decreased awareness and increased introspection. These waves are thought to originate from the limbic system and hippocampus, which are involved in emotional processing and memory consolidation. The increase in theta power during relaxation reflects the physiological changes associated with a more introspective and meditative state [19].

From this reference, we perform the calculation of alpha in a relaxed state minus alpha in a concentrated state (assuming higher relaxed alpha), theta in a relaxed state minus theta in a concentrated state (assuming theta in a higher relaxed state), beta in a relaxed state. concentrated minus beta in a relaxed state (assuming beta is in a higher concentrated state) for each data collection. The difference between relaxed alpha and intense alpha ranges from 0.35 to -8.28. The difference between relaxed theta and intense theta ranges from -25.55 to 4.88. The difference between concentrated beta and relaxed beta ranges from -0.69 to 4.07.

If we compare to the literature, there are some anomalies in the data that can be related to several factors, such as individual differences, cognitive strategy, measurement error, or other factors. Brain wave activity can vary significantly between individuals. Everyone has different neurophysiological characteristics, and their brain waves may respond differently to relaxation and concentration. These individual differences can manifest as anomalies in the data, where some individuals may show unexpected patterns or deviate from the general trend observed in the data set. Anomalies may also arise from various cognitive strategies used by individuals during concentration. People may use various approaches or mental techniques to increase their focus and concentration, which causes variations in brain wave activity. These strategies can involve different levels of mental effort, attention allocation, or cognitive control, which can influence the observed differences in alpha, theta, and beta strength. Measurement errors and other factors, such as environmental factors and emotional or physical condition, during data collection or analysis could also contribute to the anomaly of data.

After extracting all the features, we calculated the difference values from relaxation and concentration as input for ANFIS. So, the input became delta BPM, delta maximum Alpha, delta maximum Delta, and delta maximum Theta, as shown in Table 1 and Table 2. The predicted and actual results also show a slight difference in the resulting values. This difference was then also analyzed based on 4 data evaluation parameters, namely the value of RMSE, MSE, MAPE, and accuracy (Table 3).

TABLE 1. ANFIS Train Data Result

Training Data	Input				Actual	ANFIS Prediction
	BPM	Max. Alpha	Max. Theta	Max. Beta		
1	-3.81	0.35	-6.73	0.48	19.00	19.00
2	3.58	-1.21	-4.79	0.13	18.00	18.00
3	5.63	-0.17	-0.88	-0.69	18.00	18.00
4	-0.42	-1.32	-8.04	0.12	17.00	17.00
5	1.88	-1.08	-2.96	0.52	22.00	21.99
6	6.30	0.92	-2.83	-0.09	21.00	20.99
7	0.11	0.61	-2.89	-0.24	19.00	18.99
8	1.52	-1.11	-1.40	-0.35	23.00	22.99
9	-3.62	-0.25	-3.59	0.84	21.00	20.99
10	1.44	-0.17	0.59	-0.21	17.00	17.00

TABLE 2. ANFIS Test Data Result

Testing Data	Input				Actual	ANFIS Prediction
	BPM	Max. Alpha	Max. Theta	Max. Beta		
1	5.65	-1.04	-7.21	-0.13	19.00	14.76
2	2.19	-2.07	-5.05	2.04	12.00	19.91
3	2.63	-0.14	-4.05	-0.34	18.00	21.65
4	2.76	-2.84	-6.24	1.57	17.00	18.03
5	1.59	-1.01	-1.51	1.32	21.00	23.52
6	2.01	-8.28	-5.91	1.67	17.00	20.00
7	7.76	-1.36	-0.87	1.18	22.00	19.99
8	13.95	-4.60	-7.82	0.04	17.00	20.00
9	11.77	-0.98	4.88	4.07	22.00	20.00
10	3.24	0.62	-25.55	-0.01	17.00	20.00

TABLE 3. ANFIS Test Data Result

Data	RMSE	MSE	MAPE (%)	Accuracy (%)
Training	0.0001	0.0000	0.0008	99.9970
Testing	3.6900	13.6500	17.6500	80.2142

Based on the RMSE and MSE values from the ANFIS 4 feature training, a small value is obtained or close to 0. This value indicates that the predicted model that has been trained has a small error. The MAPE value of the 4 feature training data is less than 10%, which means that the predictive model's ability to train is very good. Calculating accuracy in ANFIS training with these 4 features produces an accuracy of 99.99% for training and 80.21% for testing. Based on the table it can also be seen that for each number of features for ANFIS training contributes to obtaining high accuracy. However, the test data obtained higher error values and lower accuracy than the training data. However, all of these values are still in the range of values, proving that the predictions made are good.

CONCLUSION

Based on research that has been done, the combination of EEG and ECG has the potential to be a substitute for the concentration grid test to predict concentration test scores. The use of BPM values, alpha, theta, and theta signals can be good parameters for predicting concentration grid test values using ANFIS. A higher accuracy value supports this compared to research with similar methods and has low RMSE, MSE, and MAPE values. Whereas ANFIS 4 features obtained an accuracy of 99.997% for training data and 80.2142% for test data is obtained. This result could be developed for early detection of ADHD based on concentration levels so the learning implementation could be more effective.

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