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Measuring anxiety level on phobia using electrodermal activity, electrocardiogram and respiratory signals

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ABSTRACT

People with spider phobia experience excessive anxiety reactions when exposed to spiders that will interfere with daily life. Diagnosing and measuring anxiety levels in patients with spider phobia is a complex challenge. Conventional diagnosis requires psychological evaluations and clinical interviews that take time and often result in a high degree of subjectivity. Therefore, there is a need for a more objective and efficient approach to measuring anxiety levels in patients. This study performs anxiety level classification based on electrodermal activity, electrocardiogram (ECG) and respiratory signals using the dataset of Arachnophobia subjects. Each raw data is preprocessed using 24 types of features. Feature performance is processed using the recursive feature elimination method. Data processing was performed in 3 anxiety levels (high, medium, low) and two anxiety levels (high, low) with the support vector machine method and hold-out validation method (7:3). The performance of the model is evaluated by showing the accuracy, precision, recall and F1 score values. The polynomial kernel can perform optimal classification and obtain 100% accuracy in 2 classes and three classes with 100% precision, recall, and F1 score values. This result shows excellent potential in measuring anxiety levels that correlate with mental health issues.

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1. INTRODUCTION

People with phobia experience an exaggerated anxiety reaction and this often interferes with their daily lives if not treated well. Feelings of fear or anxiety about something that does not cause actual harm are often referred to as phobias [1]. Approximately 7.4% of the human population has experienced a specific phobia at least once in their lifetime [2]. Specific phobias are persistent and excessive phobias of a specific object or situation, such as claustrophobia, which is the fear of closed or locked places, certain objects, such as needles and knives, and zoophobia. Zoophobia is generally defined as the fear of certain types of animals. Some phobias included in this group are arachnophobia (fear of spiders), scoliodentosaurophobia (fear of

lizards), ranidaphobia (fear of frogs), ophidiophobia (fear of snakes), katsaridaphobia (fear of cockroaches), musophobia (fear of rats), cynophobia (fear of dogs) and many others. Specific phobias are one of the most common psychological disorders, accounting for approximately 7%–11% of the general population [3]. All youngsters up to the age of 14 or 15 may develop school phobia, especially if they have a bad experience at school [4]. In addition, there is a survey that in one year, there were 9% of reported cases of specific phobia, with the prevalence of the possibility of individuals experiencing specific phobia around 10% to 13% [5]. In specific phobias, women are twice as likely [6].

Among the phobias are fear of heights [7], enclosed spaces [8], darkness [9], and insects [10]. The most common cause of specific phobia is spider phobia. People with spider phobia experience an exaggerated anxiety reaction when they are exposed to spiders, even if the spiders are harmless. This often interferes with their daily lives, such as keeping a distance from places where spiders may appear or having difficulty sleeping. The negative impact of spider phobia on quality of life highlights the importance of proper diagnosis and treatment. However, diagnosing and measuring anxiety levels in patients with spider phobia is a complex challenge. Conventional diagnosis requires psychological evaluations and clinical interviews that take time and often result in a high degree of subjectivity. Therefore, there is a need for a more objective and efficient approach to measuring anxiety levels in patients.

Some of the physiological measurement purposes that are widely applied in the medical field such as reducing stress or mental workload were cardiovascular, eye movement, electroencephalogram (EEG), respiration, electromyogram (EMG), and skin categories [11]; overcoming headaches, where EMG biofeedback therapy is successful in reducing the level of acute headaches [12]; emotion measurement, where biofeedback sensors can be used in emotion measurement and help control the speed and intensity of emotions felt. The literature offers a wealth of information regarding the effects of emotion regulation (ER) therapies on mental health and wellness [13]. In the use of biofeedback, special sensors are linked to devices that display information about the body's physiological functions in real-time. In addition, people are using digital technologies more and more to control and positively affect their affective states, which include their stress levels, emotions, and mood [14]. A person's anxiety level can be analyzed from physiological signals, as the human autonomic nervous system is capable of producing responses to regulate bodily functions, such as cardiac activity [15]. Critical physiological responses related to anxiety can be obtained from electrocardiogram (ECG), electrodermal activity (EDA), and respiration (RSP) signals [16]. The use of these signals in analyzing anxiety levels in patients with spider phobia has excellent potential. There is a need for new ways such as machine learning which has been proven to be used as an effective classification tool, such as using the method support vector machine (SVM), naive Bayes, and decision trees.

In a previous study, Healey concluded that using a linear discriminator in detecting stress levels based on EMG, ECG, EDA, and RSP signals, and breathing in 24 drivers in Boston obtained 97.4% accuracy [17]. Keshan and Chen using the same data but different classifiers and windowing durations (5 minutes and 10 seconds), showed that using the SVM method using ECG signals, EDA, and RSP signals obtained an accuracy of 89% in the detection of two levels of stress, and in the decision tree method to classify three levels of stress obtained an accuracy of about 70% [18], [19]. Ihmig *et al.* [20] using arachnophobia treatment data with six types of extraction features and a 10-fold cross-validation validation method in the bagged trees classification method, obtained an accuracy of 89.8% in two-level anxiety classes and 74.4% in three-level anxiety classes. Based on the above research, the accuracy value for the classification of phobic patients is still relatively low, especially in the three-level classification (low, medium, high). So, a classification method is needed that can provide a higher accuracy value.

In this anxiety level classification, researchers used the SVM model on data for spider phobia sufferers. The SVM method is a powerful tool in data class separation and has been widely used in classification problems. It is explained that the SVM method is suitable for the data classification process because it has a high-dimensional feature space [21]. In addition, SVM is an efficient classifier with several benefits, including a good generalization of new objects and a representation that relies on a small number of parameters [22]. Labeling method according to the source dataset to eliminate subjectivity, windowing size (10 s) to extract more data using features suitable for biofeedback signal distribution to improve the accuracy of the algorithm model. In the context of this research, SVM can be used to develop a classification model utilizing EDA, ECG, and respiratory data, which is processed using 24 extracted features and validated by the hold-out validation method. This model is expected to provide an objective and efficient classification system for early diagnosis, treatment, and monitoring of patients.

When such fear and anxiety arise, it becomes a problem that needs to be addressed, as it can be physically, cognitively, and morally disruptive. Therefore, phobias need to be addressed through appropriate treatment. Phobias can be eased or even eliminated by various methods, including drug therapy and psychological therapy [23]. One of the effective therapies used to overcome phobias is cognitive behaviour therapy (CBT), which consists of exposure therapy and cognitive restructuring needed for people who have

specific phobias. According to Mansell, CBT is a therapy that shows more effective results for anxiety disorders and phobias [24], [25]. In addition, a psychological therapy that can be used to reduce specific phobias or treatment of anxiety disorders is virtual reality exposure therapy (VRET) [26], [27]. Exposure therapy can be conducted in vivo, where patients are exposed to phobic stimuli in real life, or in sensu, where patients are exposed to phobic objects in their imagination [27]. Therefore, the main objective of this study is to develop a classification model that can identify anxiety levels in patients with spider phobia based on EDA and ECG signal data using the SVM method. As such, this research has the potential to provide new insights into the understanding of anxiety levels in patients with phobias. This research is expected to help mental health professionals in making decisions to design appropriate treatment, being able to better monitor the patient's condition during therapy with the use of these sensors and data processing methods.

2. MATERIALS AND METHODS

2.1. Data collection

Data of spider phobia patients who were treated were obtained through the open-access website of PhysioNet (*https://physionet.org/content/ecg-spider-clip/1.0.0/*) [20], [28], [29]. The dataset contains several raw data with biomarkers, such as ECG, EDA, and RSP. This data was collected using a Bitalino (r)evolution Bluetooth low energy (BLE) device (firmware version 5.1). This anxiety level classification study uses ECG and EDA signal parameters, as well as BR signals, as validation.

The dataset contains physiological EDA, heart rate variability (HRV), and breath rate (BR) data of 57 subjects aged 18-40 years. Data were collected at Saarland University, Germany, from July 2017 to July 2018. Each subject gave written informed consent. Before the data collection process, each subject was explained about the procedures and appeals to be done for each session. All subjects were interviewed and given some behavioral tests so that they could be grouped according to their phobia level. Participants were considered as individuals with intermediate phobia if they had at least 14 points on the German Spider Anxiety Screening test [30], which is a commonly used threshold point [31], [32], and had at least 50 points on the fear of spiders questionnaire test. In addition, having at least 4 points on the interview for mental disorders on the ADIS section 'specific phobias' [33]. Subject criteria were also based on the presence of other mental disorders besides arachnophobia (patient health questionnaire and beck depression inventory) and the presence of congenital cardiovascular disease.

The behavioural test session was conducted using the principles of the behavioural approach test method adapted from a previous similar study by Hennemann and Michael [34] consisting of a procedure in which participants were asked to stand in front of a closed room containing a house spider (Tegenaria atrica) measuring approximately 5 cm (including legs). The spiders were placed in a tight plastic container on a table at the end of the room. Next, participants were asked to enter the room, approach the container, open the lid, insert their hands, and try to pick up and hold the spider for at least 20 seconds. When participants tried to pick up or touch the spider or when they decided to stop the approach, the remaining distance was recorded. In detail, 13 steps were coded, including:

- Participant was unable to enter the test chamber will get 0 points.
- Participant stopped 5 m from the spider container, earning 1 point.
- Participants who stopped 4 m from the container will receive 2 points.
- Participants who stopped 3 m from the container will receive 3 points.
- Participants who stopped 2 m from the container will receive 4 points.
- Participant stops 1 m from the container, earns 5 points.
- Participant stops close to the table with the container, earns 6 points.
- Participant who is able to touch the container earns 7 points.
- Participant who is able to open the lid will receive 8 points.
- Participant who is able to put their hand into the container will receive a point 9.
- Participant who is able to touch the spider with one finger will receive 10 points.
- Participant who is able to hold the spider for less than 20 seconds will receive a point 11.
- Participants able to hold the spider for at least 20 seconds will get point 12.

This test was conducted before and after the subjects were given the treatment, and the difference between before and after the treatment was used as the primary outcome measure. This assessment lasted an average of 45 minutes, and participants who obtained a total of 14-50 points passed the screening stage. Participants who scored less than 14 or more than 50 were asked to attend the assessment at the Department of clinical psychology and psychotherapy for a consultation.

Participants who passed the screening stage were trained at home for one week and returned for bio-signal recordings during the stimulus. EDA, ECG, and RSP signals were recorded using a BITalino bio-signal measurement device with a sampling frequency set to 100 Hz per channel and 10-bit resolution,

which is sufficient for ECG rhythm monitoring. Three electrodes were placed according to the standard lead II configuration. For EDA measurements, two electrodes were placed on the proximal part of the palm of the participant's non-dominant hand. The electrodes used were gel-based disposable Ag/AgCl electrodes. The BITalino RSP sensor was an adjustable chest belt with an elasticated clamp and an integrated piezoelectric sensor. HRV biofeedback was obtained using a Rhythm+HR monitoring armband with a sampling frequency of 1 Hz. This armband was placed below the elbow of the participant's non-dominant arm. All sensor data was transmitted wirelessly to a personal computer (PC) via a smartphone (Nexus 5) using Bluetooth low energy (BLE) and wireless local area network (WLAN) interfaces.

At the data collection stage, participants were reintroduced to the stimulation method. This aims to give participants an idea of when they will be exposed to the feared object and help participants to decide again about the stimulation to be received. Each data collection was taken with an average duration of 35 minutes during the period from 2 p.m. to 6 p.m. to control cortisol levels that can affect the tapping value [34], where the subject will watch a spider video as a stimulus for two sessions displayed on a PC. Each session started with a question about what would appear in the following video clip. There were 16 different video clips of 1 minute each, which were taken from TV documentaries and showed details about spiders. These 16 clips were divided into two sessions. In session 1, eight videos were shown with low intensity of spider object appearance and slow movement.

The dataset included information to label the data based on the level of anxiety and the treatment given to the subject. HRV/EDA labeling is done based on clips [20]. In this study, classification will be carried out in 2 classes (high and low) and three classes (high, medium, and low).

2.2. Feature extraction

Data preprocessing consists of several steps, including cleaning, filtering, normalization, feature extraction, windowing, integration, and labeling. Cleaning and filtering were applied to the raw data. The processing and feature extraction stages were performed with Python. A total of 24 features were extracted to analyze the signal in the time domain for each biofeedback, as shown in Table 1. Analyses in the frequency domain were not taken into account because they used short windowing that could not display accurate spectral analyses.

Table 1. Feature extraction in the time domain

ECG	EDA	RSP
1. Heart beat normalized mean	1. Eda normalized mean	1. Breath rate normalized mean
2. Standard deviation	2. Standard deviation	2. Standard deviation
3. Mean of the absolute values of the normalized first differences (NFD)	3. Mean of the absolute values of the NFD	3. Mean of the absolute values of the NFD
4. Mean of the absolute values of the normalized second differences (NSD)	4. Mean of the absolute values of the normalized second differences **(**NSD**)**	4. Mean of the absolute values of the normalized second differences (NSD)
5. Heart rate variability (HRV)	5. Mean magnitude of orientation response (mmOR)	5. Breathing rate variability (BRV)
6. Average of normal-to-normal intervals (avNN)	6. Mean duration of orientation response (mdOR)	6. Average of normal-to-normal intervals (avNN)
7. Standard deviation of normal-to-normal intervals (sdNN)		7. Standard deviation of normal-to-normal intervals (sdNN)
8. Root mean square of successive normal-to-normal interval difference (Rmssd)		
9. Successive normal-to-normal intervals that differ by more than 50 ms (NN50)		
10. Proportion of NN50 divided by the total number of normal-to-normal intervals (pNN50)		
11. Proportion of NN20 divided by the total number of normal-to-normal intervals (pNN20)		

In ECG signals, the filtering process will be carried out with the frequency domain. Therefore, it is necessary to convert data from the time domain to the frequency domain using the discrete Fourier transform. In this data processing, the fast Fourier transform (FFT) algorithm is used to calculate the discrete Fourier transform quickly, where the advantage of using the FFT is that it can store signal information that allows for making a more straightforward inverse transformation. Filtering is performed because ECG signals often contain noise. This algorithm applies a lowpass filter to remove low-frequency noise. Then, the signal is filtered using a bandpass filter to highlight the QRS complex. The filtering uses a bandpass filter at a

frequency of 5-12Hz. The results of this FFT processing will be inverted to obtain the information needed for the QRS complex detection process.

QRS complex detection is then performed using the Pan-Tomkins algorithm, where this method detects the QRS signal by performing bandpass filtering first. In this algorithm, several stages are performed, including [35]:

- Differentiation where the signal is simplified to obtain information on the width of the QRS complex. This method uses five-point differencing to get the slope value of the QRS complex wave from the ECG signal.
- Squaring, where the signal is squared to increase the amplitude of the QRS wave to obtain only positive signal output and dampen the parts that are not part of the QRS complex.
- Moving window integration (MIW), where the algorithm calculates the total energy in a time range to obtain other information from the waveform besides the slope [20]. The signal from the squaring process is then combined in the MIW process, which aims to simplify the calculation of the QRS complex width.
- Thresholding separates the signal related to the QRS complex from noise and other parts. In this process, the signal is classified according to its amplitude value. If the signal value is 0, then it is classified as low, and if not, it is classified as high [35]. The threshold value is obtained, which is used as the value of the QRS width. From this stage, the RR interval and HR parameters can be obtained by performing peak detection.
- Peak detection, where signal peaks are identified to mark the on-set and off-set of the QRS complex. The average normalized heart rate (HR) value is obtained by calculating the average HR value during the resting phase of the stimulation session.

In the RSP signal, obtained from the sensor-shift value in percentage, the BR calculation is done by counting the number of times the chest expands. In processing this signal, it needs to be converted from percentage form to voltage form. Filtering is performed using a butter bandpass filter with a frequency of 0.1-24 Hz, which is equivalent to 6-24 breaths per minute to remove offsets and noise. In addition, peaks were identified using the 'ndpeaks' algorithm function.

On the EDA signal, filtering is performed using a second-order Butterworth low-pass filter with a cut-off frequency of 1.5 Hz for feature extraction. Then, a high-pass filter with a cut-off frequency of 0.05 Hz was applied to generate a phasic signal, the fluctuations in skin conductance that occur in response to a stimulus. Then the on-set, off-set, and peak are detected with a threshold of 0.03 Siemens where the number of responses is the number of peaks detected, the mean magnitude of response (mmOR) is the difference between the peak magnitude and its on-set, and the mean duration of response (mdOR) is the time difference between on-set and off-set.

3. RESULTS

In the data collection process, 57 raw ECG, EDA, and RSP data were obtained from 60 subjects aged between 18-40 years. The data obtained is in the form of numerical data, which is then used to facilitate processing. Figure 1(a) is an image of raw biosignal data on one of the subjects taken every 1/60 seconds. In ECG data, the value of voltage or electric potential in the heart with millivolt units has a value range of -1.5 to 1.5 mv; in Figure 1(b) EDA data can be seen the value of skin conductance with microsiemens (μS) units with a value range of -12.6 to 41 μS, and in Figure 1(c) RSP data, the value of pressure changes or vibrations that occur during breathing and convert them into electrical signals that can be recorded with a value range of -50% to 50%.

Data from the ECG signal is subjected to an FFT transformation process to convert the signal in the time domain to the frequency domain. Then, filtering is performed using a bandpass filter with a cut-off value of 5 to 12 Hz. The filtering process uses the 'firwin' function and then applies the filter to the raw ECG data using the 'lfiter' function. After filtering, the signal is inversed into the time domain; this is done because the Pan-Tompkins algorithm focuses on analyzing time-domain signals to detect QRS complexes in ECG signals. Next, we detect the QRS complex using the Pan-Tomkins algorithm. In this algorithm, the differentiation as shown in Figure 2 and squaring stages are performed on the filtered signal, where the amplitude of the QRS signal phase is increased and dampens the parts that are not included in the QRS complex as shown in Figure 3(a).

Moving window integration to calculate the total energy within 10 seconds as shown in Figure 3(b). Thresholding is performed to determine the signal associated with the QRS complex and separate other signals that exceed the threshold value, including noise, where a thresholding value of 0.01 is obtained as shown in Figure 4(a). From the determination of the threshold, peak detection can be performed on the signal where the peak is detected to mark the on-set and off-set as shown in Figure 4(b). Then, the RSP data is integrated with ECG processing data values, and feature extraction is performed. The size of ECG data

extraction features is 5652×11 features for two classes and 7461×11 features for three classes. Features that are used include Nmean, std, NFD, NSD, HRV, avNN, adNN, rMSDD, NN50, pNN50, and pNN20 as shown in Table 1. The use of these features is based on the purpose of preprocessing, which is to obtain HRV values from ECG signals.

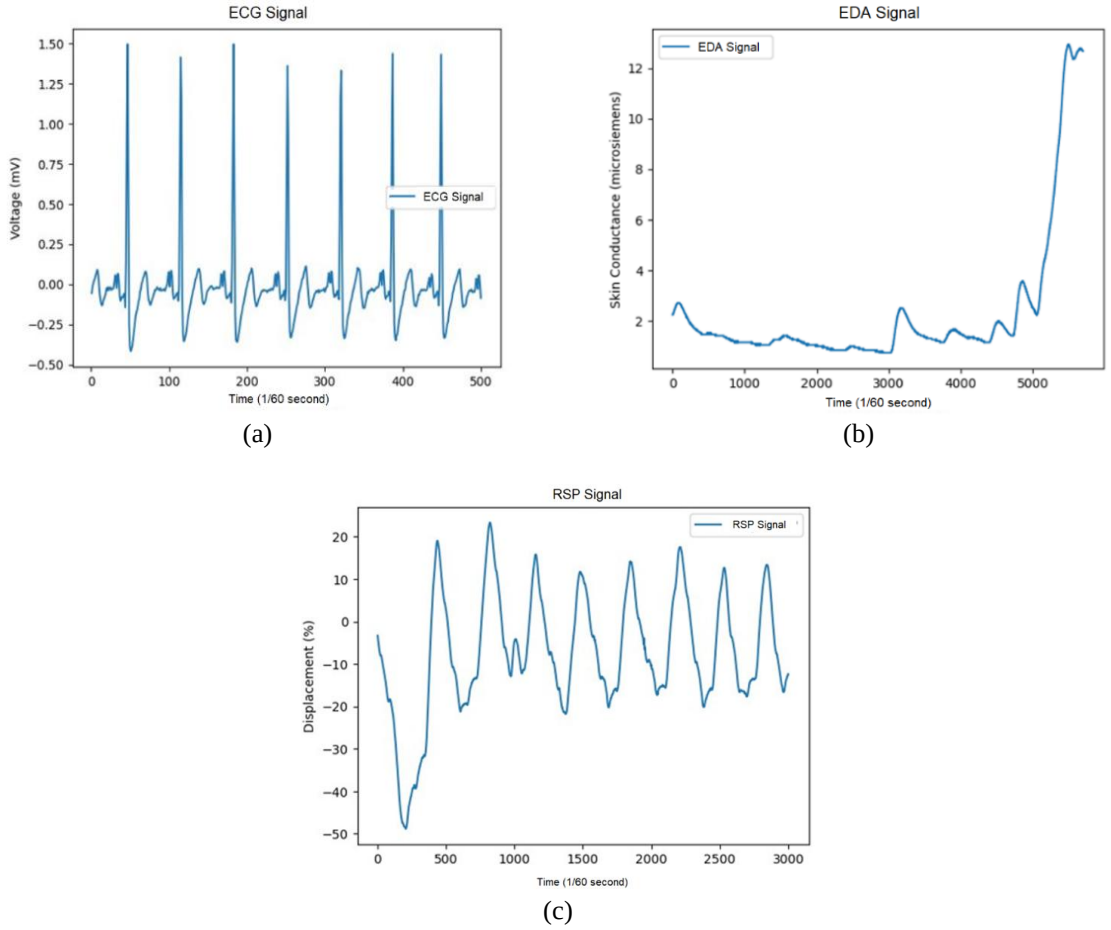


Figure 1. Biosignal plots (a) ECG signal, (b) EDA signal, and (c) RSP signal

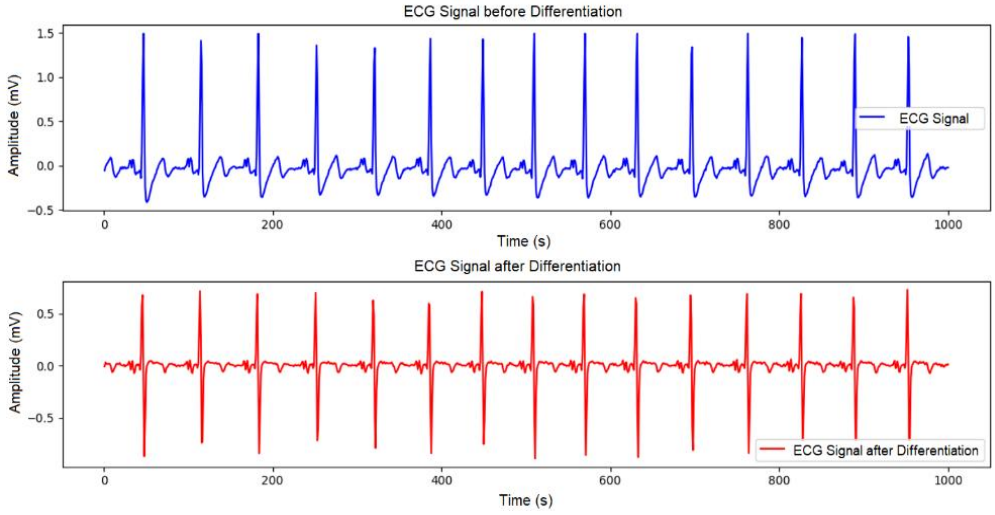
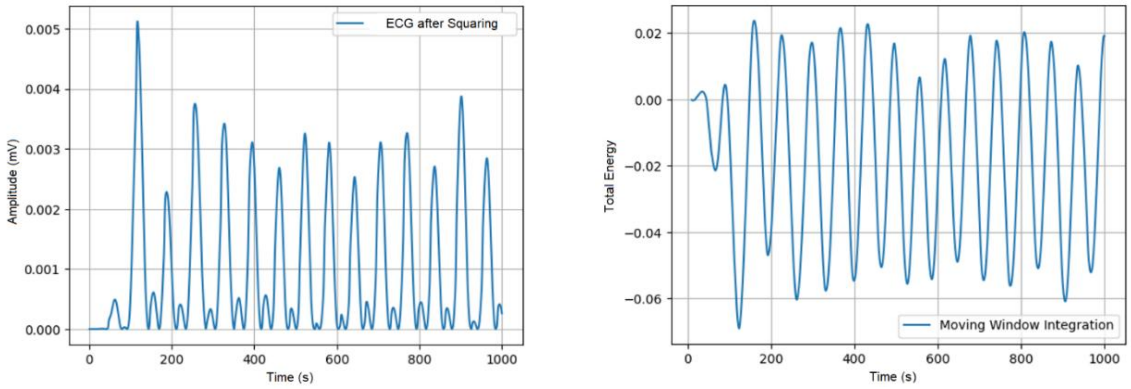
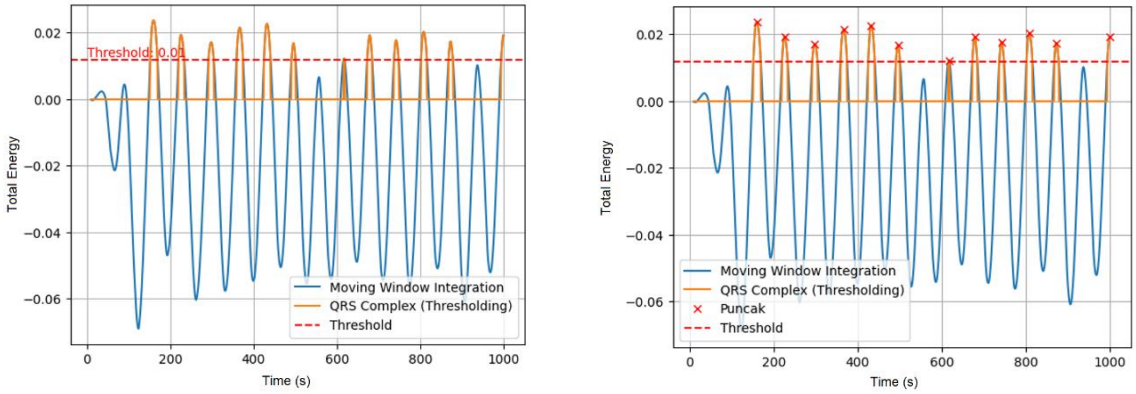


Figure 2. ECG signal after differentiation



(a) (b)

Figure 3. ECG signal after (a) squaring and (b) moving window integration



(a) (b)

Figure 4. ECG signal after (a) thresholding is performed and (b) ECG peak detection

The EDA data is transformed from the time domain to the frequency domain using the fast Fourier transform, which is an efficient method for solving the discrete Fourier transform that is widely used for signal analysis purposes such as filtering and spectrum analysis. Filtering was performed using a lowpass filter with a cut-off value of 10 Hz and 7th order to remove noise. The EDA filtering data was converted into phasic signals to obtain SCR data and skin conductance data information when there was a simulation. From the SCR signal, feature extraction is performed. The size of EDA data extraction features is the same as ECG data, which uses six types of features, including Nmean, std, NFD, and NSD. In this process, by calculating the value of off-set and on-set peaks, the mdOR and mmOR values are obtained. The mdOR value will describe the duration of the subject's response to the stimulus. At the same time, mmOR represents the magnitude value, which describes how much response the subject gives to the stimulus provided.

SVM is a learning algorithm that is very useful in data classification and separation. One of the key components of SVM is the kernel, which transforms the data into higher dimensions so that it can be separated linearly or non-linearly, depending on the type of kernel used. This classification is divided into two types, namely two classes (high and low) and three classes (low, medium, and high). It uses variations of several kernels, namely RBF, linear, polynomial, and sigmoid. The 2-class classification, Table 2 shows the optimal classification value using the polynomial kernel. This kernel provides optimal results with 100% accuracy on both data sets. The distribution of actual data in each class on the confusion matrix of the polynomial kernel is in accordance with the prediction. Therefore, this kernel has an accuracy value of 100%.

In the analysis of the 3-class classification using different types of kernels, there were variations in the results that showed differences in the ability of each kernel to classify the data effectively as shown in Table 3. The polynomial kernel was found to be the optimal kernel in this classification. This kernel achieved 100% accuracy on both data sets, with precision, recall, and F1-score reaching 100%. These results show that the classification process can be performed well by the model using the polynomial kernel.

Table 2. The 2-class classification result

Kernel	Accuracy		Precision	Recall	F1 Score
	Train	Test			
Polynomial	100.0%	100.0%	100.0%	100.0%	100.0%
Linear	71.9%	86.4%	87.0%	85.0%	85.0%
RBF	36.5%	66.0%	66.0%	65.0%	66.0%
Sigmoid	58.7%	57.2%	60.0%	59.0%	57.0%

Table 3. The 3-class classification result

Kernel	Accuracy		Precision	Recall	F1 Score
	Train	Test			
Polynomial	100.0%	100.0%	100.0%	100.0%	100.0%
Linear	58.7%	85.9%	84.0%	82.0%	83.0%
RBF	48.5%	67.7%	59.0%	60.0%	59.0%
Sigmoid	22.3%	27.4%	31.0%	31.0%	30.0%

To determine the type of feature extraction that is appropriate for the signal used, the most optimal feature selection is determined after classification. Due to the shortcomings of SVM, which cannot produce accurate predictions when it has many irrelevant features, not all features are used in the modeling process. This can be overcome by the feature selection method. This feature selection uses a random forest model with the recursive feature elimination (RFE) algorithm—feature selection module. Then, apply RFE with random forest to sort the features from the most important.

This assessment process is repeated until the order displayed does not change. In this stop criterion condition, the performance order of each feature will be shown where the top feature is considered the best feature. The higher the coefficient value, the better the ranking and the more likely to be selected. This is done to explore and want to know which features are the most prominent and dominant. This ranked feature method is highly dependent on the model algorithm used. If the model used is not accurate, the RFE process can also result in less-than-optimal feature selection. From the feature selection process, the three optimal feature combinations obtained in this study are Nmean, std, NSD, and two extraction features in EDA, including mmOR and mdOR as shown in Figure 5.

The Nmean extraction feature represents the normalized average value of the data. By using this feature, we can get information about the trend or tendency of values in the dataset. The use of mean normalization is used to compare data within a uniform range, thus simplifying the analysis and modelling process. The standard deviation (std) feature measures the spread or variation of a dataset. By knowing the standard deviation, it can assess how far the data is spread from the average value. NSD is the normalized standard deviation of a dataset. By using NSD, we can obtain information about the variability of the data in a uniform range, thus allowing better comparison between data.

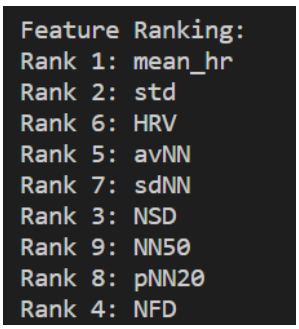


Figure 5. Feature extraction ranked

4. DISCUSSION

To develop a classification model that can identify anxiety levels in patients with spider phobia based on EDA and ECG signal data using the SVM method we need to evaluate the optimum kernel as well as the best feature. Thus, it could provide new insights into the understanding of anxiety levels in patients with phobias. If we look further into the variation of the kernel used before, both classifications (two-class and three-class) showed that polynomials is the best kernels compared to linear, RBF and sigmoid. The

polynomial kernel has a degree of use that can be adjusted to the complexity of the data being processed so that it can increase the possibility of data being classified linearly and quickly in high spatial dimensions [36]. This can be proven in the distribution of data in the confusion matrix, which indicates that the classifier is following the prediction and the actual data. However, this perfect result needs further validation to prove the absence of overfitting. The linear, RBF and sigmoid kernels were not effective in classifying the data, showing their limitations in handling complex patterns. This shows that this kernel does not fit the data. Therefore, kernel selection should be based on the characteristics, shape or pattern of data distribution.

Besides the kernel, features also contribute to the performance. The three optimum features based on the Figure 5 are normalized mean, standard deviation and normalized second differences based on ECG, EDA and RSP signals. Some previous studies have mentioned emotions affect heart rate. Moreover, breathing can also be used as an indication of emotional changes [16], [37]. Breathing rate (BR) increases with increasing levels of stress or anxiety which can lead to hyperventilation [38]. EDA can also be used as a biomarker of individual characteristics in emotional responses and as a potential method of treating psychosomatic conditions through biofeedback training [39]. When there is an event that triggers a phobia, emotional changes will automatically occur. Therefore, both EDA and ECG are physiological signals that can be used to detect stress and anxiety. Some studies used ECG, EDA and respiratory signals (RSP) to detect anxiety [40]. Heart rate variability (HRV) measured through ECG has been used to assess anxiety disorders.

In previous related research, classification using the SVM algorithm by Handouzi *et al.* [41], which classifies specific phobia/social phobia in VRET treatment into two anxiety classes with the holdout validation method, where there are 200 training data and 80 test data obtained an accuracy value of 76%. In addition, in the research of Ihmig *et al.* [20] conducted using the same dataset, an accuracy value of 74.4% was obtained using the bagged trees method. This study uses the same dataset with a varied windowing value of 5 and 10 sec and obtains a higher accuracy value at 10-sec windowing. Where this classification distinguishes anxiety levels in 3 classes using the 10-vold-cross-validation method in this study, which uses the SVM algorithm (polynomial kernel) and windowing of 10 seconds, with the hold-out validation method is considered superior because it can distinguish anxiety levels in 3 classes (‘high,’ ‘medium,’ and ‘low’) with an accuracy value of 100%, with precision, recall and F1 score values of 100%. This accuracy value is the same as the accuracy value in the 2-class classification. However, the 3-class classification is still superior considering the additional class so that it can display each anxiety class more precisely. From this research, it is known that the polynomial kernel is the most optimal kernel for the classification process; this is known from Table 1 and Table 2 that for each classification category, the polynomial kernel has the highest accuracy value compared to other kernels.

5. CONCLUSION

This study developed a classification of anxiety levels with ECG and EDA biosignals that can be done using the support vector machine method involving several optimal extraction features such as normalized mean, standard deviation, normalized second differences (NFD), and additional features on EDA, namely mmOR and mdOR, with a windowing of 10 seconds using the hold-out validation validation method. In the SVM method, the selection of kernel type is very influential on accuracy results. The kernel that provides optimal results for anxiety level classification is the polynomial kernel. This kernel is flexible because it has a polynomial degree that can be adjusted to the data used so that it can classify data with different complexities better than other kernels. The support vector machine method in the anxiety level classification process has good performance, especially in 3 classes that provide optimal results with a more specific classification. From the research, both in the classification of 2 classes and three classes, the accuracy value on test data and training data is 100%, with precision, recall, and F1 score values of 100%. In this study, the algorithm can provide information on the level of anxiety in subjects who have a specific phobia (arachnophobia) so that it can be applied as an additional therapy in the VRET/ARET treatment method with the aim of patients getting more efficient, optimal and comfortable treatment.

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REFERENCES

[1] V. Smith, J. Reddy, K. Foster, E. T. Asbury, and J. Brooks, “Public perceptions, knowledge and stigma towards people with schizophrenia,” *Journal of Public Mental Health*, vol. 10, no. 1, pp. 45–56, 2011, doi: 10.1108/17465721111134547.

[2] K. J. Wardenaar *et al.*, "The cross-national epidemiology of specific phobia in the World Mental Health Surveys," *Psychological Medicine*, vol. 47, no. 10, pp. 1744–1760, 2017, doi: 10.1017/S0033291717000174.
[3] American Psychiatric Association, *Diagnostic and Statistical manual of mental disorders, fourth edition, text revision (DSM-IV-TR)*, vol. 1, VA: American Psychiatric Association, 2000.
[4] M. Rettig and J. Crawford, "Getting past the fear of going to school," *The Education Digest*, vol. 9, no. 65, pp. 54–59, 2000.
[5] American Psychiatric Association, *Diagnostic and statistical manual of mental disorders*, 5th ed. American Psychiatric Association Publishing, 2022.
[6] J. S. Nevid, S. A. Rathus, and B. Greene, "Abnormal psychology : in a changing world," *World Sports Activewear*, vol. 8, no. 2, pp. 55–56, 2018.
[7] C. M. Coelho and G. Wallis, "Deconstructing acrophobia: physiological and psychological precursors to developing a fear of heights," *Depression and Anxiety*, vol. 27, no. 9, pp. 864–870, 2010, doi: 10.1002/da.20698.
[8] V. Rahani, A. Vard, and M. Najafi, "Claustrophobia game: design and development of a new virtual reality game for treatment of claustrophobia," *Journal of Medical Signals and Sensors*, vol. 8, no. 4, p. 231, 2018, doi: 10.4103/jmss.JMSS_27_18.
[9] E. Paulus, F. P. Yusuf, M. Suryani, and I. Suryana, "Development and evaluation on night forest virtual reality as innovative nyctophobia treatment," *Journal of Physics: Conference Series*, vol. 1235, no. 1, 2019, doi: 10.1088/1742-6596/1235/1/012003.
[10] A. de Jongh, "Treatment of a woman with emetophobia: a trauma focused approach," *Mental Illness*, vol. 4, no. 1, pp. 10–14, Jan. 2012, doi: 10.4081/mi.2012.e3.
[11] D. Tao, H. Tan, H. Wang, X. Zhang, X. Qu, and T. Zhang, "A systematic review of physiological measures of mental workload," *International Journal of Environmental Research and Public Health*, vol. 16, no. 15, pp. 1–23, Jul. 2019, doi: 10.3390/ijerph16152716.
[12] A. MARTINO CINNERA *et al.*, "Headaches treatment with EMG biofeedback: a focused systematic review and meta-analysis," *European Journal of Physical and Rehabilitation Medicine*, vol. 59, no. 6, pp. 697–705, Jan. 2024, doi: 10.23736/S1973-9087.23.07745-6.
[13] F. Jadhakhan, H. Blake, D. Hett, and S. Marwaha, "Efficacy of digital technologies aimed at enhancing emotion regulation skills: Literature review," *Frontiers in Psychiatry*, vol. 13, pp. 1–15, Sep. 2022, doi: 10.3389/fpsyt.2022.809332.
[14] D. Villani, C. Carissoli, S. Triberti, A. Marchetti, G. Gilli, and G. Riva, "Videogames for emotion regulation: a systematic review," *Games for Health Journal*, vol. 7, no. 2, pp. 85–99, Apr. 2018, doi: 10.1089/g4h.2017.0108.
[15] H. Yaribeygi, Y. Panahi, H. Sahraei, T. P. Johnston, and A. Sahebkar, "The impact of stress on body function: a review," *EXCLI Journal*, vol. 16, pp. 1057–1072, 2017, doi: 10.17179/excli2017-480.
[16] G. Giannakakis, D. Grigoriadis, K. Giannakaki, O. Simantiraki, A. Roniotis, and M. Tsiknakis, "Review on psychological stress detection using biosignals," *IEEE Transactions on Affective Computing*, vol. 13, no. 1, pp. 440–460, 2022, doi: 10.1109/TAFFC.2019.2927337.
[17] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 2, pp. 156–166, Jun. 2005, doi: 10.1109/TITS.2005.848368.
[18] N. Keshan, P. V Parimi, and I. Bichindaritz, "Machine learning for stress detection from ECG signals in automobile drivers," *Proceedings - 2015 IEEE International Conference on Big Data, IEEE Big Data 2015*, pp. 2661–2669, 2015, doi: 10.1109/BigData.2015.7364066.
[19] L. lan Chen, Y. Zhao, P. fei Ye, J. Zhang, and J. zhong Zou, "Detecting driving stress in physiological signals based on multimodal feature analysis and kernel classifiers," *Expert Systems with Applications*, vol. 85, pp. 279–291, 2017, doi: 10.1016/j.eswa.2017.01.040.
[20] F. R. Ihmig, H. Antonio Gogeascoechea, F. Neurohr-Parakenings, S. K. Schäfer, J. Lass-Hennemann, and T. Michael, "On-line anxiety level detection from biosignals: machine learning based on a randomized controlled trial with spider-fearful individuals," *PLoS ONE*, vol. 15, no. 6, 2020, doi: 10.1371/journal.pone.0231517.
[21] B. Ghaddar and J. Naoum-Sawaya, "High dimensional data classification and feature selection using support vector machines," *European Journal of Operational Research*, vol. 265, no. 3, pp. 993–1004, Mar. 2018, doi: 10.1016/j.ejor.2017.08.040.
[22] S. Maldonado, R. Weber, and F. Famili, "Feature selection for high-dimensional class-imbalanced data sets using support vector machines," *Information Sciences*, vol. 286, pp. 228–246, Dec. 2014, doi: 10.1016/j.ins.2014.07.015.
[23] S. G. Hofmann and J. A. J. Smits, "Cognitive-behavioral therapy for adult anxiety disorders: A meta-analysis of randomized placebo-controlled trials," *Journal of Clinical Psychiatry*, vol. 69, no. 4, pp. 621–632, 2008, doi: 10.4088/jcp.v69n0415.
[24] W. Mansell, *Coping with fears and phobias: a CBT guide to understanding and facing your anxieties*. New York: Oneworld Publications, 2007.
[25] S. Varadhila Peristianto and K. Astuti, "Decreasing symptoms of specific phobias with cognitive behavior therapy," *Malaysian Mental Health Journal*, vol. 1, no. 1, pp. 12–14, 2022, doi: 10.26480/mmhj.01.2022.12.14.
[26] K. B. Wolitzky-Taylor, J. D. Horowitz, M. B. Powers, and M. J. Telch, "Psychological approaches in the treatment of specific phobias: A meta-analysis," *Clinical Psychology Review*, vol. 28, no. 6, pp. 1021–1037, 2008, doi: 10.1016/j.cpr.2008.02.007.
[27] D. Boeldt, E. McMahon, M. McFaul, and W. Greenleaf, "Using virtual reality exposure therapy to enhance treatment of anxiety disorders: identifying areas of clinical adoption and potential obstacles," *Frontiers in Psychiatry*, vol. 10, pp. 1–6, Oct. 2019, doi: 10.3389/fpsyt.2019.00773.
[28] F. R. Ihmig, A. Gogeascoechea, S. Schäfer, J. Lass-Hennemann, and T. Michael, "Electrocardiogram, skin conductance and respiration from spider-fearful individuals watching spider video clips (version 1.0.0)," *PhysioNet*, 2020, doi: 10.13026/sq6q-zg04.
[29] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet," *Circulation*, vol. 101, no. 23, pp. 215-220, Jun. 2000, doi: 10.1161/01.CIR.101.23.e215.
[30] M. Rinck *et al.*, "Reliability and validity of German versions of three instruments measuring fear of spiders," *Diagnostica*, vol. 48, no. 3, 2002, doi: 10.1026//0012-1924.48.3.141.
[31] E. S. Becker and M. Rinck, "Sensitivity and response bias in fear of spiders," *Cognition and Emotion*, vol. 18, no. 7, pp. 961–976, 2004, doi: 10.1080/02699930341000329.
[32] M. Rinck and E. S. Becker, "Spider fearful individuals attend to threat, then quickly avoid it: Evidence from eye movements," *Journal of Abnormal Psychology*, vol. 115, no. 2, pp. 231–238, 2006, doi: 10.1037/0021-843X.115.2.231.
[33] E. Erdfelder, F. FAul, A. Buchner, and A. G. Lang, "Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses," *Behavior Research Methods*, vol. 41, no. 4, pp. 1149–1160, 2009, doi: 10.3758/BRM.41.4.1149.
[34] J. Lass-Hennemann and T. Michael, "Endogenous cortisol levels influence exposure therapy in spider phobia," *Behaviour Research and Therapy*, vol. 60, pp. 39–45, Sep. 2014, doi: 10.1016/j.brat.2014.06.009.
[35] Z. F. Mohd Apandi, R. Ikeura, S. Hayakawa, and S. Tsutsumi, "QRS detection in electrocardiogram signal of exercise physical activity," *Journal of Physics: Conference Series*, vol. 2319, no. 1, pp. 1–9, Aug. 2022, doi: 10.1088/1742-6596/2319/1/012021.

[36] A. Géron, *Hands-on machine learning with scikit-learn and tensorflow*. California: O'Reilly Media, Inc, 2019.
[37] D. McDuff, S. Gontarek, and R. Picard, "Remote measurement of cognitive stress via heart rate variability," in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug. 2014, pp. 2957–2960, doi: 10.1109/EMBC.2014.6944243.
[38] P. Grossman, "Respiration, stress, and cardiovascular function," *Psychophysiology*, vol. 20, no. 3, pp. 284–300, 1983, doi: 10.1111/j.1469-8986.1983.tb02156.x.
[39] Y. Liu and S. Du, "Psychological stress level detection based on electrodermal activity," *Behavioural Brain Research*, vol. 341, pp. 50–53, 2018, doi: 10.1016/j.bbr.2017.12.021.
[40] T. Christy and L. I. Kuncheva, "Technological advancements in affective gaming: a historical survey," *GSTF Journal on Computing (JoC)*, vol. 3, no. 4, 2014, doi: 10.7603/s40601-013-0038-5.
[41] W. Handouzi, C. Maaoui, A. Pruski, A. Moussaoui, and Y. Bendiouis, "Short-term anxiety recognition induced by virtual reality exposure for phobic people," in *Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013*, pp. 3145–3150, 2013, doi: 10.1109/SMC.2013.536.

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