NON-EEG METHOD TO PREDICT A PSYCHIATRIC DISORDER AND PROPOSED PREVENTIVE METHOD

Farhad Nassehi[1], Ege Kırıcı[1], Andaç Budak[1], Refika Dilara Aşcı[1], Osman Eroğul[1]
Department of Biomedical Engineering, TOBB University of Economics and Technology, Ankara, Turkey
(f.nassehi, e.kirici, a.budak, rasci, erogul)@etu.edu.tr

***Abstract*— Social anxiety disorder (SAD) involves an intense fear of social interactions, leading to distress and impaired daily functioning. This study aims to develop a wearable technology to predict and mitigate anxiety attacks in SAD patients using Photoplethysmogram (PPG) and Electrocardiogram (ECG) signals. The system analyzes data from 135 participants, using the Liebowitz scale and State-Trait Anxiety Inventory to select 30 individuals for detailed analysis. Key features from ECG and PPG signals were input into a Naive Bayes algorithm, achieving an 84.24% accuracy in predicting anxiety states. The system also provides sound and vibration stimuli to help calm patients, potentially improving their quality of life.**

Keywords*— *Anxiety; Prediction; Electrocardiogram; Photoplethysmography; Machine Learning.

I. INTRODUCTION

Social anxiety disorder (SAD), also known as social phobia, involves intense fear or anxiety in social situations where individuals feel scrutinized or judged. This anxiety can lead to avoidance of social interactions and significantly impact daily life, such as work or school. According to the DSM-V, key diagnostic criteria include intense fear of being evaluated or judged, leading to avoidance behavior or enduring social situations with distress. SAD is prevalent, with lifetime rates around 12% and varying prevalence in different populations, including 1.8% among adults in Turkey and 9.8-22% among university students. [1,2,3]

Anxiety typically triggers physiological responses like increased heart rate and muscle tension. While EEG is commonly used to study brain activity related to mental disorders, it has limitations in portability and instant data collection. Therefore, this research focuses on ECG and PPG sensors, which are better suited for measuring physiological changes like heart rate and respiratory rate in social anxiety, offering advantages in terms of immediate data collection and practical application.[4]

The Liebowitz Social Anxiety Scale (LSAS) is a popular questionnaire for assessing social anxiety, consisting of 24 questions about anxiety and avoidance in social situations. Responses are scored from 1 to 4, with a maximum possible score of 144. Higher scores indicate greater anxiety. The LSAS is known for its reliability and validity in measuring social anxiety. [5]

The State-Trait Anxiety Inventory (STAI) includes 40 self-report questions rated on a 4-point scale, measuring state and trait anxiety. Higher scores indicate greater anxiety, with low scores reflecting mild anxiety and high scores indicating severe anxiety. The STAI assesses both the presence and absence of anxiety through questions like "I feel safe" (absence) and "I feel anxious" (presence). Both the LSAS and STAI were used to evaluate participant conditions in the study, and their results were analyzed statistically.[6]

Bilateral stimulation involves alternating stimulation of the left and right sides of the brain. One method is bilateral touching, where gentle touches are applied to each side of the body in succession. This technique has been shown to normalize physiological changes associated with social anxiety and improve connections between brain regions involved in sensory regulation and attention, potentially reducing symptoms of depression and stress.[7]

Another method is voice stimulation, which uses calming or familiar voices to help normalize physiological responses and reduce anxiety. This can involve soothing messages from a therapist or a loved one, which can lower anxiety levels and help return heart and respiratory rates to normal.[8]

II. MATERIALS AND METHODS

A. Participants

The study, approved by the TOBB Economy and Technology University Human Research Evaluation Board, took place in the university's medical imaging and instrumentation laboratory. Participants first completed the Liebowitz Social Anxiety Scale, with 135 individuals participating. Those scoring above 80 were eligible, and 30 were selected for the experiment. Additionally, 30 individuals with scores below 80 were invited as observers to enhance the simulation's effectiveness. All participants and observers provided written informed consent.

B. Data Acquisition

The BIOPAC MP36 is a device designed for students to record, measure, and analyze basic physiological signals in real-time. It allows for the collection and transfer of data to MATLAB for

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further analysis, making it ideal for academic research and laboratory experiments.

The study simulated an anxiety-inducing scenario to collect data on participants' physiological responses. Participants were informed about the task via a PowerPoint presentation and then asked to sing for one minute in front of an audience. ECG and PPG data were recorded during a 2-minute rest period and a 2-minute task period. The singing task was designed to trigger anxiety, as people with social phobia often struggle with performing in front of others. This scenario allowed the study to capture real physiological changes associated with social anxiety.

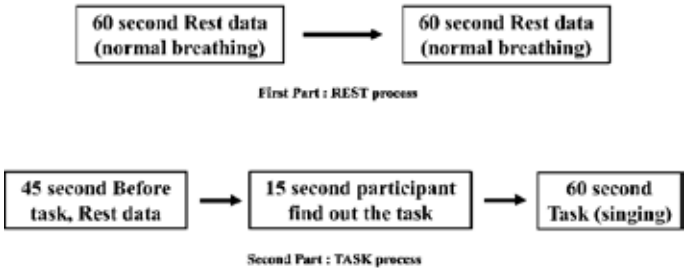


Fig 1: Anxiety simulation processes

The data from thirty participants was imported into MATLAB, a powerful software platform for numerical computing and data analysis. MATLAB was used for various operations, including matrix handling, data analysis, signal processing, and graph generation. The signal data underwent several preprocessing steps to ensure accuracy.

C. Preprocessing

To ensure accurate analysis, the signal data was first preprocessed. This involved correcting noise and irregular oscillations caused by sensor movement during the experiment. The ECG and PPG signals, originally recorded at 1000 Hz, were downsampled to 250 Hz to simplify processing without losing essential information. Baseline correction was applied to remove artifacts caused by movement and environmental factors, using MATLAB's 'polyfit' and 'polyval' functions to fit and correct the data.

D. Feature Extraction

Key features, such as mean, standard deviation, variance, skewness, kurtosis, median, interquartile range, QRS complex, and R-R interval, were extracted from the ECG and PPG signals. These features are essential for analyzing changes in breathing and heart rate related to anxiety, which were then used in machine learning models to predict anxiety states.[9]

E. Classification

Data was split into training and test subsets using a 5-fold cross-validation method. We employed several machine learning techniques: a support vector machine (SVM) with a Gaussian, K-nearest neighbors (KNN) with Euclidean distance metric and K value of K=7, a Decision Tree classifier, Random Forest classifier and Naïve Bayes classifier. Model performance was evaluated using accuracy, sensitivity, specificity, and area under the curve (AUC). All analyses were conducted using MATLAB R2021b.

F. Feature Selection

This section employed two feature selection techniques to refine the dataset by prioritizing features based on their relevance to classification outcomes. Nearest neighbor-based methods, including Nearest Component Analysis (NCA) and Relief, were utilized. [10,11]

G. Hardware

In this project phase, signals from PPG and ECG sensors were captured using an Arduino MEGA 2560 and processed in MATLAB. The DFROBOT Gravity ECG and PPG sensors, along with a buzzer, were connected to the Arduino for data collection and patient alerting.

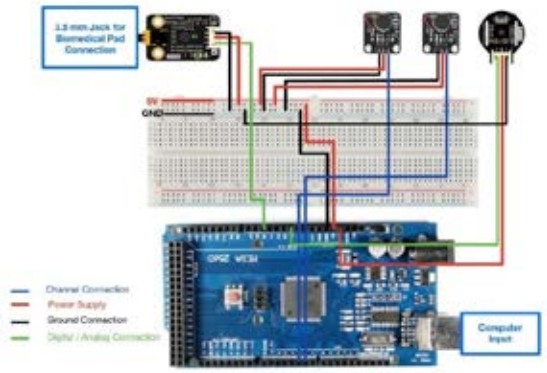


Fig 2: Block Diagram of the Hardware System

H. Communication Between Software and Hardware

In our project, we seamlessly transferred physiological signals from PPG and ECG sensors to MATLAB using an Arduino MEGA 2560. We wrote and uploaded the necessary code on the Arduino board and established a connection to the host computer via COM4 using a USB cable. To ensure communication between Arduino and MATLAB, we utilized the "MATLAB Support Package for Arduino Hardware," enabling reliable data transfer and analysis in MATLAB.

III. Statistical Analysis

Statistical analysis of the project data was conducted using paired t-tests and correlation methods. The paired t-test was used to assess changes in data between the rest and task states, revealing a significant difference in the IQR feature from the ECG measurements. Although some features didn't show

significant differences, they were still relevant for machine learning models, as verified by feature selection methods.

Correlation analysis examined the relationship between the STAI State 2 scores and other scales. Significant correlations were found between STAI State 2 and both trait anxiety (STAI Trait and Liebowitz scores) and pre- and post-measurement STAI State scores. These findings confirm the effectiveness of the experimental task in influencing anxiety levels.

IV. RESULT

This section presents the results of all classifiers across different input types. Tables summarize the average and standard deviation of accuracy, sensitivity, and specificity from the 10-fold cross-validation, while figures display the average AUC rates for all classifiers

Table I and Figure 3 illustrate the performance of classifiers when all 20 extracted features were used. The Naïve Bayes classifier achieved the highest accuracy and AUC.

TABLE I. PERFORMANCES OF CLASSIFIERS FOR ALL FEATURES

	Accuracy(%)	Sensitivity(%)	Specificity(%)
SVM(Gaussian)	57.42±21.01	62.67±26.81	52.67±20.6
Random Forest	70.91±15.2	66.00±28.42	76.67±19.0
KNN(k=7)	69.24±8.7	49.33±19.06	90.00±9.13
Decision Tree Method	74.09±16.91	76.67±25.28	71.33±22.31
Naive Bayes	82.73±5.95	78.86±21.44	93.33±9.13

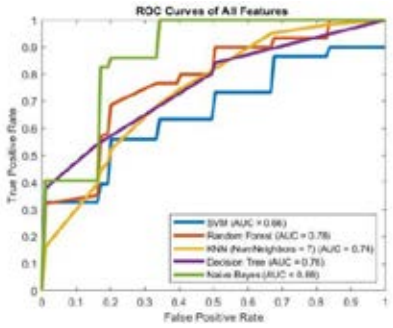


Fig 3: AUC of classifiers for all features

Figure 4 shows the features selected using the NCA method. NCA is applied with "fsnca" function in MATLAB.

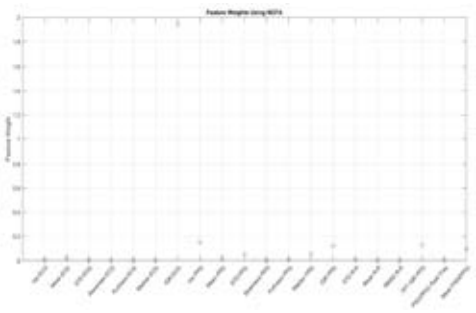


Fig 4: Selected Features by NCA

Table II and Figure 5 illustrate the performance of classifiers when NCA selected 11 features were used. The Naïve Bayes classifier achieved the highest accuracy and AUC.

TABLE II. PERFORMANCES OF CLASSIFIERS FOR NCA SELECTED FEATURES

	Accuracy(%)	Sensitivity(%)	Specificity(%)
SVM(Gaussian)	65.61±5.24	69.33±13.21	62.00±13.86
Random Forest	79.09±11.74	76.00±14.61	82.00±18.5
KNN(k=7)	69.09±9.33	38.67±16.77	100.00±0
Decision Tree Method	77.42±14.5	76.67±25.28	78.00±25.34
Naive Bayes	82.73±6.48	78.86±21.44	89.33±9.83

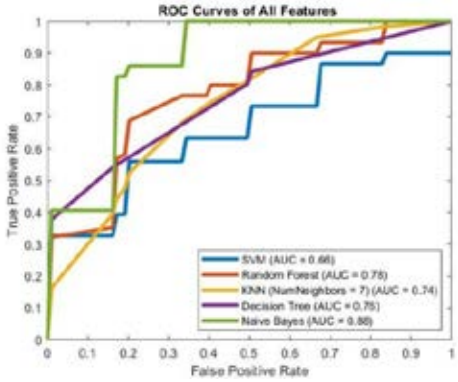


Fig 5: AUC of classifiers for NCA selected features

Figure 6 shows the features selected using the Relieff method. In MATLAB, it is used with the "relief" command from MATLAB's statics and machine learning toolbox.

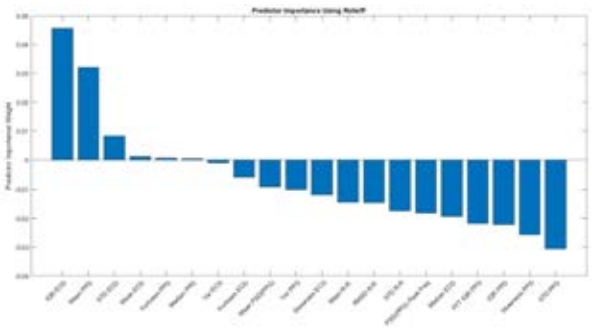


Fig 6: Selected Features by Relief

Table III and Figure 7 illustrate the performance of classifiers when Relieff selected 6 features were used. The Naïve Bayes classifier achieved the highest accuracy and AUC.

TABLE III. PERFORMANCES OF CLASSIFIERS FOR RELIEFF SELECTED FEATURES

	Accuracy(%)	Sensitivity(%)	Specificity(%)
SVM(Gaussian)	65.61±5.24	69.33±13.21	62.00±13.86
Random Forest	79.09±11.74	76.00±14.61	82.00±18.5
KNN(k=7)	69.09±9.33	38.67±16.77	100.00±0
Decision Tree Method	77.42±14.5	76.67±25.28	78.00±25.34
Naive Bayes	82.73±6.48	78.86±21.44	89.33±9.83

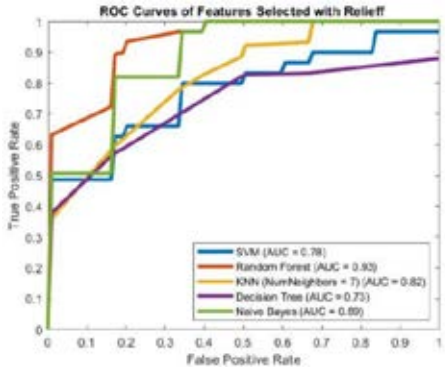


Fig 7: AUC of classifiers for Relieff selected features

Table IV and Figure 8 show the performance of all classifiers using the common features selected by both methods as inputs. With the feature set reduced to 5, the Naïve Bayes classifier achieved the highest accuracy and AUC.

TABLE IV. PERFORMANCES OF CLASSIFIERS FOR MUTUALLY SELECTED FEATURES

	Accuracy(%)	Sensitivity(%)	Specificity(%)
SVM(Gaussian)	77.73±9.49	83.33±11.79	72.00±15.92
Random Forest	82.58±8.95	76.00±14.61	88.67±17.58
KNN(k=7)	76.06±8.6	56.00±21.4	96.67±7.45
Decision Tree Method	77.42±14.5	76.67±25.28	78.00±25.34
Naive Bayes	84.24±7.9	80.60±20.24	85.33±20.22

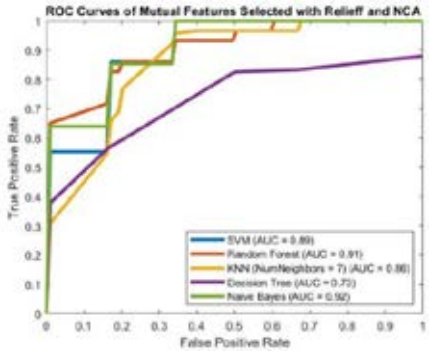


Fig 8: AUC of classifiers for mutually selected features

V. DISCUSSION AND CONCLUSION

Anxiety disorders, including social anxiety, are widespread, with a higher prevalence among women. Our study developed a wearable device to predict social anxiety using physiological data. We found that the Naive Bayes (NB) algorithm achieved the highest accuracy of 84.24% with ECG and PPG data, which is comparable to existing research.

John et al. achieved a maximum accuracy of 65% using ECG and BVP signals with SVM, RF, and XGBoost.[12] Ruksana et al. reached up to 99% accuracy using SVM for anxiety detection with heart rate, skin temperature, and EDA sensors.[13] Our approach is unique in providing real-time predictions and alerts using both ECG and PPG sensors, addressing a gap in current research.

REFERENCES

[1] NHS. (2021, February 16). Social anxiety (social phobia). Nhs.uk; NHS. https://www.nhs.uk/mental-health/conditions/social-anxiety/

[2] Mayo Clinic. (2017). Social anxiety disorder (social phobia) - Diagnosis and treatment ,Mayo Clinic. https://www.mayoclinic.org/diseases-conditions/social-anxiety-disorder/diagnosis-treatment/drc-20353567

[3] Gültekin, B. K., & Dereboy, İ. F. (2011). Üniversite öğrencilerinde sosyal fobinin yaygınlığı ve sosyal fobinin yaşam kalitesi, akademik başarı ve kimlik oluşumu üzerine etkileri. Türk Psikiyatri Dergisi, 22(3), 150-158.

[4] Al-Ezzi, A., Kamel, N., Al-Shargabi, A. A., Al-Shargie, F., Al-Shargabi, A., Yahya, N., & Al-Hiyali, M. I. (2023). Machine learning for the detection of social anxiety disorder using effective connectivity and graph theory measures. Frontiers in psychiatry, 14, 1155812.

[5] Beard, C., Rodriguez, B. F., Moitra, E., Sibrava, N. J., Bjornsson, A., Weisberg, R. B., & Keller, M. B. (2011). Psychometric properties of the Liebowitz Social Anxiety Scale (LSAS) in a longitudinal study of African Americans with anxiety disorders. Journal of anxiety disorders, 25(5), 722-726.

[6] Grös, D. F., Antony, M. M., Simms, L. J., & McCabe, R. E. (2007). Psychometric properties of the state-trait inventory for cognitive and somatic anxiety (STICSA): comparison to the state-trait anxiety inventory (STAI). Psychological assessment, 19(4), 369.

[7] Bilateral Stimulation: What It Is and How to Use It | The Balance App. (n.d.).Balanceapp.com.https://balanceapp.com/blog/bilateral-stimulation#:~:text=Because%20of%20its%20relaxing%20benefits

[8] Mallik, A., & Russo, F. A. (2022). The effects of music & auditory beat stimulation on anxiety: A randomized clinical trial. Plos one, 17(3), e0259312.

[9] Singh, A.K., Krishnan, S. ECG signal feature extraction trends in methods and applications. BioMed Eng OnLine 22, 22 (2023). https://doi.org/10.1186/s12938-023-01075-1.

[10] Rank importance of predictors using ReliefF or RReliefF algorithm - MATLAB relieff. (n.d.). Www.mathworks.com. https://www.mathworks.com/help/stats/relieff.html

[11] Agrawal, A. K., & Chakraborty, G. (2023, November). Neighborhood component analysis to leverage the class label information during feature selection to enhance the damage classification performance. In Structures (Vol. 57, p. 105174). Elsevier.

[12] Priya, A., Garg, S., & Tigga, N. P. (2020). Predicting anxiety, depression and stress in modern life using machine learning algorithms. Procedia Computer Science, 167, 1258-1267.

[1] Henry, J., Lloyd, H., Turner, M., & Kendrick, C. (2023). On the robustness of machine learning models for stress and anxiety recognition from heart activity signals. IEEE Sensors Journal.