Semiconductor Optoelectronics, *Vol. 41 No. 11 (2022), 161-170*
https://bdtgd.cn/

Semiconductor Optoelectronics
ISSN: 1001-5868

STRESSOCARE: AN NEXTGEN IOMT BASEDPHYSIOLOGICAL DATA ANALYSIS FOR ANXIETY STATUSPREDICTION

Bhupendra Ramani
Dept. of Information Technology, Parul Institute of Engineering & Technology, Parul University, Vadodara, India, bhupendra.ramani2817@paruluniversity.ac.in

Dr. Kamini Solanki
Dept. of IT & CS, Parul Institute of Computer Application, Parul University, Vadodara, India, kamini.solanki@paruluniversity.ac.in

Dr. Warish Patel
Dept. of Computer Science &Engg, Parul Institute of Engineering & Technology, Parul University, Vadodara, India, warishkumar.patel@paruluniversity.ac.in,

Abstract: Human mind involves a great many neurons which are accepting a huge part for controlling behavior of human body concerning inside/outer engine/tactile boosts. Human Brain makes various kinds of indications of different repeat in mindfulness or resting period. By using these unique kinds of frequencies mind waves can be perceived from each other. Besides, these electric signs can be assessed by an EEG (electroencephalograph) headset. The neuron goes about as information transporters between human body and psyche. Understanding scholarly lead of psyche ought to be conceivable by taking apart either signals or pictures from the brain. Human conduct can be imagined similar to engine and tangible states, for instance, eye development, lip development, acknowledgment, thought, hand getting a handle on, etc. these states are associated with express sign repeat which helps with understanding valuable lead of confusing brain structure. Electroencephalography (EEG) is a successful technique which helps with acquiring mind signals identifies with various states from the scalp surface district. These indications are classified as delta, theta, alpha, beta, and gamma based on signal frequencies ranging from 0.1Hz to more than 100Hz. This study primarily focuses on EEG indications and their portrayal in relation to various states of the human body. It similarly oversees preliminary course of action used in EEG examination. Previously, the EEG headset was not unassuming using any and all means and just used in medicine. Nonetheless, over the latest several years, there are various unassuming EEG contraptions available watching out. Along these lines, the investigation in BCI (Brain-Computer Interface) region has been widened. NeuroskyMindwave mobile II is an inconspicuous and easy-to-use EEG gadget available on the market that we employ in this evaluation.In this paper, NeuroskyMindwave convenient II used to find our work and moreover choose its comfort. The primary motivation driving this study is to demonstrate the accuracy of recognising mind wave announces the most recent version of this instrument (NeuroskyMindwave mobile II).

IndexTerms Machine learning, Random Forest, Hyper parameter tuning, Electroencephalogram, Anxiety detection

I. Introduction

Most countries around Electroencephalography (EEG) is a method for assessing synchronized neural activity by setting an assortment of terminals on the external layer of a subject's scalp. Since the recording of the fundamental EEG announces HansBerger in 1924 [1], EEG has been used in different clinical applications. For example, EEG is used as an illustrative mechanical assembly for epilepsy, mind harm and rest issues and is for the most part used in a variety of assessment settings, similar to the controlof neural development, the examination of human new development and the depiction of different illnesses [2]. Lately, an interest has similarly been begun in the usage of EEG for developing a prompt channel of correspondence between the psyche and a modernized device. These Brain Computer Interfaces (BCI) grant a customer to control an external contraption by unshakably changing their mental state while a model examination computation simultaneously tries to recognize the looking at change in the EEG signals. A device like a mouse cursor, robot or wheelchair can be told to take action that has been as of late associated with the recognized change in mental state. This methodology enough avoids our characteristic, motor based strategy for correspondence. BCI are of brief interest to individuals who have lost all ability to talk with the remainder of the world. This condition, referred to as known as secured disorder (LIS), can be achieved by different diseases, for instance, amyotrophic sidelong sclerosis, cerebral paralysis and stroke [3]. Mind has the ability to make power. Cerebral cortex could produce electrical recreation which is ceared by Fritsch and Hitzigv (1870) and later Ferrier (1875). The sign which we get by an EEG gadget is extremely perplexing; multi-component can be addressed by bend utilizing the frequencies. Mind has the ability to make power. Cerebral cortex could create electrical reproduction which is cleared by Fritsch and Hitzig (1870) and later Ferrier (1875). The sign which we get by an EEG gadget is extremely intricate; multi component can be addressed by bend utilizing the frequencies. The amplitudes are:

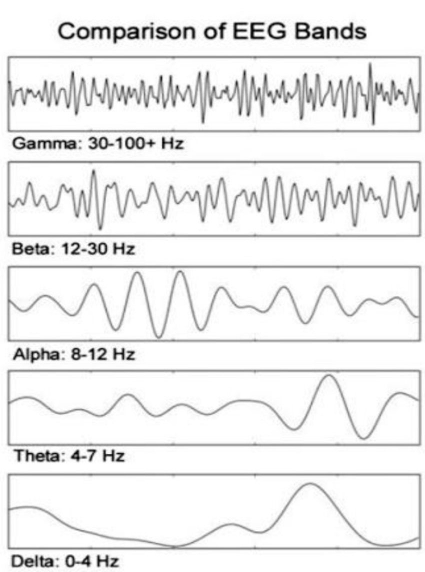


Figure 1: Example of Brain wave

Presently, numerous nervous system specialists face trouble inmakingtherightdeterminationforEEGexaminationanduneasinessdiscovery.Notwithstanding thisadditionally,the traditional strategy of visual examination is more confounded and requires experienced and time. The data got from an Electroencephalogram [4] can be utilized to find various sorts of cerebrum infections. It could be valuable for seeing presently well thepatientisreactingtotreatmentconsequentlyyourgoalistofosteranelectronicunderstanding of EEG and issues will work to investigate the diverse cerebrum-related issues utilizing ML calculations.

Create a device that can predict the state of anxiety in the initial stages.

- Interface all the sensors and components with a microcontroller.
- Send data to the server.
- Collect the data and apply the ML model for data analysis.

II.Architecture of Random Forest Algorithm

Random forest isanadaptable,easy-to-understandAIstrategy that,by andlarge,produces extraordinary outcomes even without hyper-boundary tweaking. It is likewisequite possibly the most widely used algorithm because of its straightforwardness andadaptability(itverywellmaybeutilizedforbotharrangementandrelapseundertakings).Random forest is a supervised learning algorithm. It produces a "forest"out of an assortment of choice trees that are frequently prepared to utilize the "bagging “strategy. The primary thought of the packing strategy is that joining many learning models improves all out yield. Random Forest is a supervised learning algorithm. It creates a "forest" out of a collection of decision trees that are regularly prepared to utilizethe"bagging"strategy.Thefundamentalthoughtofthepackingstrategyisthat consolidating many learning models upgrades complete results. Random forest deliversvarious choice trees and consolidates them together to produce a more genuine and solidexpectation. The random forest produces the benefit of having the option to address order and relapse issues, which are normal in AI frameworks these days. How about we see arbitrary woodland in characterization since the order is typically viewed as the structure square of AI. A random forest with two trees is portrayed in the chartbeneath: A random foresthyper parametersareverylikethoseof a random tree classifier.Rather than consolidatingachoicetreeandaclassifier,youcanutilize therandomforest'sclassifier class.To manage regression task undertakings with random forest, you can utilize thealgorithms regressor.The random forestadds more randomness to themodel asitdevelopsthetrees.Ratherthansearchingforthe mainelementwhilepartitioningahub,it looks for the best component from an irregular gathering of highlights. Accordingly,there is a lot of fluctuation, bringing about a superior model. Thus, the methodology forpartitioning a hub in the random forest just assesses an arbitrary subset of the elements. You can make trees significantly more irregular by assigning random edges to each component rather than searching for the best edges (like a typical choice tree does). One morebenefit of the random forest approach is that it is so clear to decide the general worth ofeachcomponentontheconjecture.

Sklearn has an incredible technique for deciding the significance of a component bylooking at how much impurity is diminished over the entire forest by tree hubs thatutilization it. It works out this score for each component after preparing andalters the outcomes with the goal that the general significance is one. Each internal mode in a choice tree addresses a property 'test,' each branch reflects the test'result, and each leaf node addresses a class mark (for example, whether a coin flip comes up heads or tails) (choice taken after figuring all ascribes). A leaf is a hub that doesn't have any posterity. '" You can erasehighlights relying upon their worth since they don't contribute enough (or none by anymeans) to the forecast interaction. This is huge because the more creditsyou have, the almost certain your model will be over fitted, as well as the other wayaround.

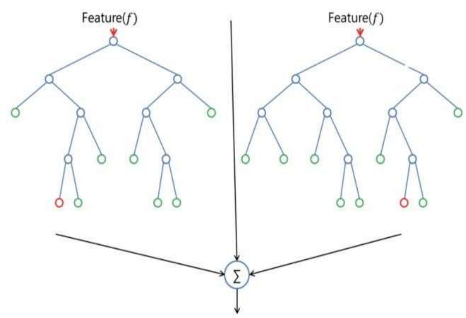


Fig 2: Random Forest Architecture

The proposed framework technique is addressed in the underneath figure, in which the information is gathered with the various sensors like Pulse Rate Sensor, Temperature Sensor, Accelerometer, GSR Sensor, and EEG Sensor. Two Machine learning Models (Random Forest calculation) are created from the gathered information. After gathering the information, it is preprocessed with the preprocessing procedures (standard scaler) and exploratory data analysis (EDA)[5] the handled information is taken care of into the Random Forest Algorithm. Thus end-product is the weighted normal of both models.

Fig 3: Proposed Methodology of the system

III. Experiment

A.DATADESCRIPTION

Neurosky Mindwave Mobile EEG Headset.

The Brainwave Starter Kit puts decades of study into laboratory EEG technology in your hands. Simply put the headset on your head and see your brainwaves alter in real-time. Keep track of your attention and relaxation levels, as well as how your brain reacts to your favoritemusic. There are plenty of options to pick from based on your age and particular interests, with over 100 brain training games and educational apps available through our store. It's a fantastic primer in the field of brain-computer interface! The MindWave Mobile headset uses Bluetooth/BLE to communicate wirelessly with your PC and mobile devices (iOS and Android). You can also use our free Development Tools to create your programs to interface with MindWave Mobile.This headgear records the electroencephalogram signal[6] generated by the brain as a result of brain activity.It is a single-channel device capable of outputting 12-bit raw EEG signals at 512 Hz sampling rate and a band range of 3-100 Hz.

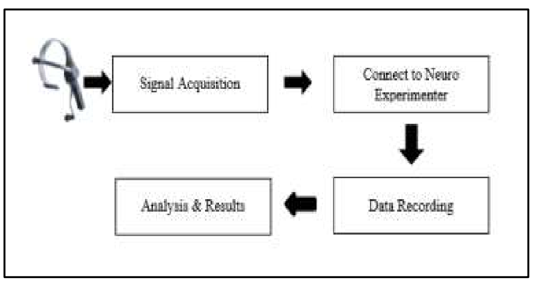


Fig 4: Data Collection through Neurosky brainwave

For this research, data was collected from numerous parts of our brain with multiple sensors. Data were collected utilizing a variety of sensors worn by several people. After that, the information is saved in a CSV file for further analysis. Before linking this device with a computer, we must first turn on Bluetooth on both devices. After being linked, Neurosky headsets Mindwave mobile II should be worn properly in the head. Hairy scalp necessitates the use of one probe. The earlobe is home to another. Then go to the software interface[7] and push the connect button to start generating data. In a calm and quiet environment, the examlastedroughly4-6minutesperparticipant.

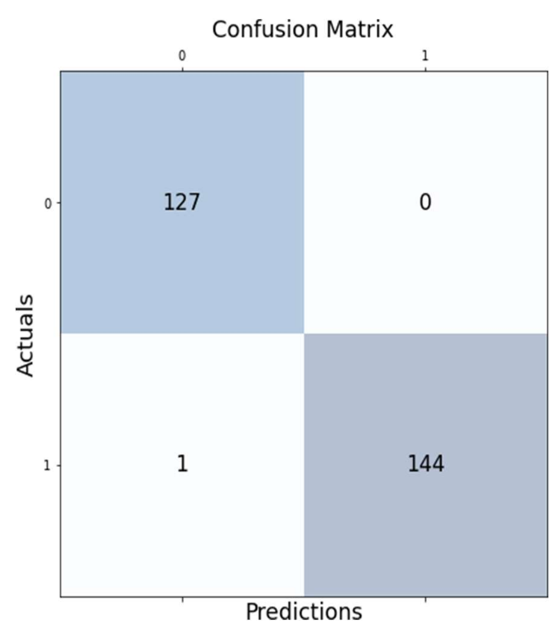
B.METHODOFEVALUATION

Dividing the dataset into two parts i.e., training dataset (70%) and testing dataset (30%)for the Machine learning model, the model is built using a Random algorithm using hyper parameter training and preprocessing the data with standard scaler technique so that the data can be normalized. Two models were created on the two datasets i.e. sensors data and EEG data, the evaluation is done based on the weighted average accuracy of both the models, in which more weightage is given to the EEG sensor to predict the anxiety in the person. Hence the weighted averages of the models are 86.03%. After training, true-positive,false-positive, true-negative, false negativeofthetestsetwererecordedsuccessively.

IV.Resultand Discussion

The electroencephalogram (EEG) has been generally used toconcentrateonupperintellectual capacities, mental states, and influence models. Since stress and nervousnessare convoluted feelings, there isn't a lot of examination on recognizing them with EEG.Moreover, the central systems by which these dispositions influence EEG information areobscure. We will likely give a reliable[8] way to deal with this issue. The discoveries of ourexamination into breaking down or recognizing nervousness in individuals. It is said thatpositive valence upgrades produce an expansion in left front-facing action, though badvalence boosts cause an increment in right front-facing action. The communication ofhandedness would be fascinating to examine, but there was just one remaining given individual. This work gives highlights and a dataset decrease process that can be utilizedforproficientpressure/uneasinessrecognizableproofutilizingEEG.Themodels'definitive acknowledgment exactness is 90% and 99 percent%. The model is deployed onthe server using Flask framework (Python)[9]through which we have created a UI of themodel. The graphs and data on the web change accordingly to the sensor data i.e. real-worlddata.

Fig 5: Confusion Matrix of Sensor Data



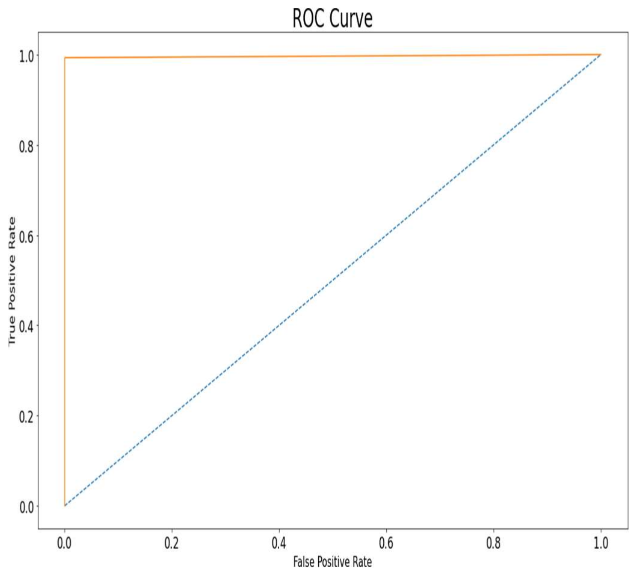
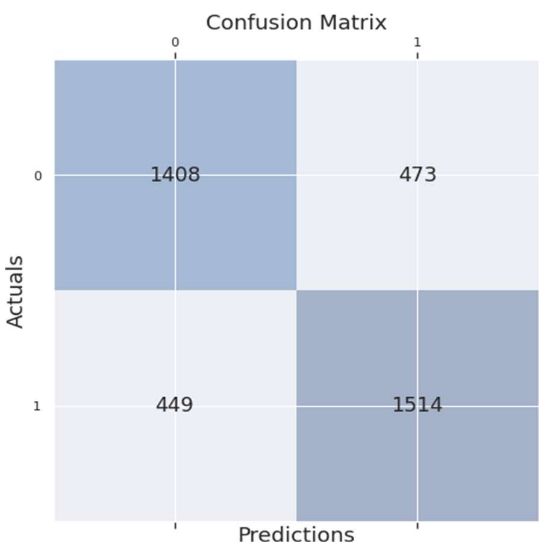


Fig 6: ROC Curve of Sensor Data



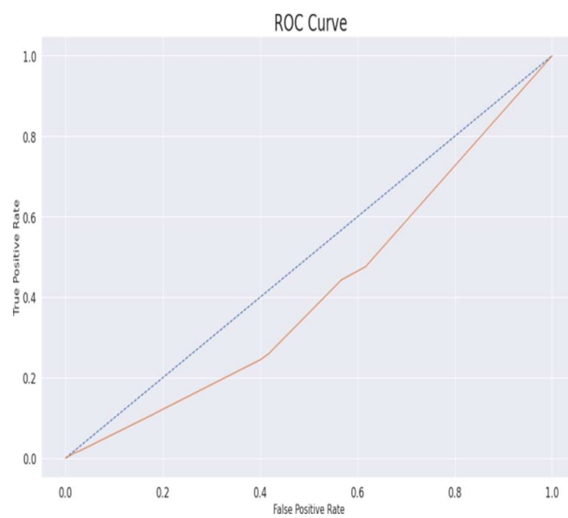


Fig 7: Confusion Matrix of EEG DataFig 8: ROC Curve of EEG Data

V.Conclusion

In this study, data was gathered in various stages of our brain, and samples were classified based on their level of worry and stress. The collected data is then stored in a csv file for future analysis. To link [10]this gadget to a computer, first switch on Bluetooth on both devices and then pair them. After connection, the Neurosky headset should be appropriately worn in the head. One probe must be placed on the hairy scalp. Another is located in the earlobe. The software interface should then be launched, and the connect button should be pressed to create data.The testing lasted roughly 4-6 minutes per participant in a calm and quiet environment. This approach required each participant to complete three tasks. Those are given below-Analytical reasoning- Participants were asked to do a couple of mathematical problems based on stress and anxiety level wearing the headset. To verify the task, they were asked to solve equation, calculus and matrix problems. Participants were instructed to focus their attention on a certain task. We requested to look at a picture[11] since our test was a basic control activity. This entails sitting in a calm and quiet place and closing their eyes to relax. Stress and anxiety are becoming increasingly prevalent in our daily lives, wreaking havoc on both individuals and society. Stress hurts various humanbodilysystems, including the neurological, immunological, cardiovascular, and gastro intestinalsystems. It also hurts hormone excretion, which is necessary for the healthy functioning of the immune system. Stress can also cause cardiac arrhythmias bycausing disruptions in the cardio-vascular system and amplifying or reducing heartbeatsand blood pressure.Meanwhile, it has GI side effects such as reduced appetite, disruption of normal GI tract function, and irritable bowel syndrome.As a result, mental stress evaluation and analysis are critical methods for detecting stressand preventing serious health problems. Despite a large number of research that hasused EEG signals to investigate this phenomenon, there are no comprehensive guidelineson the relationship between EEG features and their extraction methodologies. We did adetailed assessment of the approachesfor analyzing EEG signals based on mental stressin this paper.Our investigation focused on the type of data processingmethod andclassification model used. Because of the range of parameters used in the studies, wediscovered that choosing the proper method of analysis is difficult. Multiple sensors, suchas an EEG sensor, an accelerometer, a GSR sensor, a temperature sensor, and a pulse ratesensor,[12] as well as adequate EEG processing, feature extraction mechanisms, the numberof features, and the type of classifier, are among these parameters.

As a result, the mostimportantaspectof anxiety quantification is selecting themostappropriate features.Another cause for concern is the wide disparity in individual anxiety responses. We conducted a thoroughinvestigationintotheseanalysismethodologiesinthispaper. Meanwhile, we emphasizedthefundamentaldisparitiesfoundintheresearchfindingsand indicated that variances in data processing procedures could be a major contributor tomultiple contradicting results. In addition, the extraction of brain connection characteristics provided a clear picture of the brain and how its various areas interact with one another. As a result, studying brain connection feature extraction techniques provides a detailed picture of the brain and how its various areas interact with one another.

We deployed MLmodels (Random Forest with hyperparameter tuningi.e.,grid searchCV method) to detect anxiety[13] using real-world data from several sensors in our research...To train and test the model, we collected the data from the GSR sensor, pulse rate sensor,accelerometer sensor,[14] temperature sensor,[15] and EEG data from Neurosky brainwave. Aftersplitting the dataset into 70–30 (70% of whole data for training, 30% whole for testing),we achieved the best accuracy rate of 99.63% in sensor data, and 76.04% on EEGtheweighted average of both models will be taken into consideration i.e. 86.02%, which ismuchbetterthanotheralgorithms.

VI. References

[1] Selye, H. The stress syndrome. Am. J. Nurs. 1965, 65, 97–99.

[2] Giannakakis, G.; Grigoriadis, D.; Giannakaki, K.; Simantiraki, O.; Roniotis, A.; Tsiknakis, M. Review on psychological stressdetection using biosignals. IEEE Trans. Affect. Comput. 2019, 1–16. [CrossRef]

[3] Lazarus, J. Stress Relief & Relaxation Techniques; McGraw Hill Professional: New York, NY, USA, 2000.

[4] Bakker, J.; Pechenizkiy, M.; Sidorova, N. What's your current stress level? Detection of stress patterns from GSR sensor data. In Proceedings of the 2011 IEEE 11th International Conference on Data Mining Workshops, Vancouver, BC, Canada, 11 December 2011; pp. 573–580.

[5] Hou, X.; Liu, Y.; Sourina, O.; Tan, Y.R.E.; Wang, L.; Mueller-Wittig, W. EEG based stress monitoring. In Proceedings of the 2015 IEEE International Conference on Systems, Man, and Cybernetics, Hong Kong, China, 9–12 October 2015; pp. 3110–3115.

[6] Holmes, T.H.; Rahe, R.H. The social readjustment rating scale. J. Psychosom. Res. 1967, 11, 213–218. [CrossRef]

[7] A. P. Association et al., "Stress in america: Paying with our health,"Retrieved May, vol. 29, p. 2015, 2015.

[8] S. Cohen, D. Janicki-Deverts, W. J. Doyle, G. E. Miller, E. Frank, B. S. Rabin, and R. B. Turner, "Chronic stress, glucocorticoid receptor resistance, inflammation, and disease risk," Proceedings of the National Academy of Sciences, vol. 109, no. 16, pp. 5995–5999, 2012.

[9] R. S. Duman, "Neurobiology of stress, depression, and rapid acting antidepressants: remodeling synaptic connections," Depression and anxiety, vol. 31, no. 4, pp. 291–296, 2014.

[10] S. Cohen, T. Kamarck, and R. Mermelstein, "Perceived stress scale. measuring stress: A guide for health and social scientists. 1994."

[11] C. D. Spielberger, F. Gonzalez-Reigosa, A. Martinez-Urrutia, L. F. Natalicio, and D. S. Natalicio, "The state-trait anxiety inventory," RevistaInteramericana de Psicologia/Interamerican Journal of Psychology, vol. 5, no. 3 & 4, 2017.

[12] A. Deschenes, H. Forget, C. Daudelin-Peltier, D.Fiset, and C. Blais, "Facial expression recognition impairment following acute social stress," Journal of vision, vol. 15, no. 12, pp. 1383–1383, 2015.

[13] S. Gowrisankaran, N. K. Nahar, J. R. Hayes, and J. E. Sheedy, "Asthenopia and blink rate under visual and cognitive loads," Optometry and Vision Science, vol. 89, no. 1, pp. 97–104, 2012.

[14] A. Asif, M. Majid, and S. M. Anwar, “Human stress classification using eeg signals in response to music tracks,” Computers in biology and medicine, vol. 107, pp. 182–196, 2019.

[15] T. Pereira, P. R. Almeida, J. P. Cunha, and A. Aguiar, “Heart rate variability metrics for fine grained stress level assessment,” Computer methods and programs in biomedicine, vol. 148, pp. 71–80, 2017.