Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766338

REVIEW ON EARLY DETECTION OF STRESS MANAGEMENT USING ECG SIGNALS

Vanisha P.Vaidya[1*] Dr. Lokendra Singh Songare[2]
[1*] Department of Computer Science and Engineering Dr. A. P. J. Abdul Kalam University, Indore India Email:- vanisha.vaidya@gmail.com
[2]Department of Computer Science and Engineering Dr. A. P. J. Abdul Kalam University, Indore India Email:- lokendrasinghsongare@aku.ac.in
***Corresponding Author:-** Vanisha P.Vaidya
*Department of Computer Science and Engineering Dr. A. P. J. Abdul Kalam University, Indore India Email:- vanisha.vaidya@gmail.com

Abstract –
Stress has become a significant cause for many diseases in the modern society. According to research, stress should be managed as soon as symptoms appear to prevent long-term effects. In the other words, stress should be identified early on to prevent more harm and keep it from becoming chronic. Researchers have developed a concept to early identify the degree of stress in order to further limit the harm to human health as a result of the above-mentioned negative effects of stress upon human health as well as negative effects on social life and the economy. Heart rate, galvanic skin reaction, body temperature, and blood pressure are the fundamental indicators of stress and give precise information about a person's mental state. These characteristics differ from individual to individual depending on factors including age, gender, and physical condition. Our research's primary goal is to examine mental stress using physiological data from an electrocardiograph in various situations and states of mind. Numerous pre-processing techniques and algorithms, including artificial neural networks supported vector machines, Bayesian networks, as well as decision trees, can be employed to produce results that are more accurate.

Keywords: Stress Management, HRV, ECG Signals, Pre-Processing, ANN

1. INTRODUCTION

Today, managing stress has become crucial for people of all generations, and this issue requires extensive global attention since, according to the survey, 86% of people worldwide experience stress, compared to 89% of people in India. Approximately 75% of the local community lacks the confidence to discuss their pressures with a care provider and the expense of bringing up the issue as one of the challenges. Thus, the study of stress as well as its management is currently the most popular topic among scholars (*Source: 2018 Cigna 360° Well-Being Survey – Future Assured)*.

The body's significant, behavioural, and emotional reaction to stress is caused by both internal and external sources, including pressure from the job, interpersonal conflict, pollution, unfavourable physical and chemical circumstances, and illness (for instance, the prevalence of illness and contagiousness, lack of sleep, feeling exhausted, emotions, and expectation). One of things that causes stress is when a person encounters an unusual scenario and finds it challenging to handle the dread and worry that come with it. A person often experiences stress when the physical and physiological resources or instruments readily available to them don't meet their needs at that particular time [1].

Additional physiological elements include the acceleration of the heartbeat (Heart Rate Variability), a particular respiratory rate, galvanic skin, the subject's length, muscular tension, etc. Initially, the autonomic nervous system's (ANS) functions were supposed to be in response to the body's physiological reaction to stress. [2]. Under extended stress, the parasympathetic and sympathetic ANS divisions would go out of balance. While hyper-activating the sympathetic branch, one might limit the parasympathetic branch. The heart function should then be informed of this change in information, which is often calculated using electrocardiogram signals in medical equipment (ECGConsequently, significant global support has been given to the use of an ECG signal as a legitimate and trustworthy input signal for evaluating human stress.

just the variation in heart rate (HRV) [3], The most crucial signal variance detection for decoding Signal is nothing more than the difference between intervals of two subsequent ECG signal pulses. Since only R peaks are necessary for measurement and R levels always had the highest ECG intensity, HRV is impervious to interference and disruption[3]. Consequently, HRV is just a widely utilised stress management technique. Upon identification any of the R spikes, HRV characteristics for stress detection could be obtained[3].

2. Importance of Study

In popular society stress is a significant concern. It is an expanding disease that has permeated every aspect of our everyday life. Early diagnosis can reduce the risk of the injury, and prevent permanent harm. Researchers have learnt about the damage caused by stress on human well-being and there have lately been extensive attempts to develop an integrated stress management system by using several data sets and applying numerous algorithms.

Stress is a necessary bodily response to adversity that enables people to overcome some challenges or flee from some existential risks. Heart rates, tissue conductivity, respiratory rate, understudy length, body stiffness, and other related physiological markers alter. Depending on the person's body posture, age, gender, and experience, these needs are postponed. After calculating stress, the body then resumes its normal state of function. If the anxiety sign continues for a long time in either case, tension symptoms may become exceedingly incessant, which is associated with a large spectrum of well-being-related concerns such as cardiovascular disease, asthma, behavioral inadequacies, cerebrovascular disorders. As a result, the stress variables may be periodically observed to provide a person an early warning, which in turn enables them to modify their actions and behaviour and lower their stress levels.

But past research has failed to successfully classify anxiety levels reliably using machine learning models like Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT). That's why we agreed to come up with an idea of using ECG signals and using variance of HRV concentrations and defining ECG Signals' R-peak levels, we would develop our ANN model to detect mental stress earlier. This will make man take proactive steps to alleviate tension and lead a healthier life.

3.Literature Review.

Through the use of electrocardiographs in various locations and climates, Monika Chauhan et al. suggested adopting a variety of pre-planning tactics to identify stress. [4]. To identify a person's normal state and stress, the system employs Support Vector Machines (SVM) [5], Decision Trees, using linear discriminate analysis (LDA) [6]. They had found the accuracy of their model around 90%.

Emotion detection using a deep convolutional neural networks on such physiological signals Luz Santamria-Granados et al. conducted study on the identification of mental stress using a dataset (AMIGOS). Emotion identification is achieved by correlating these behavioral signs with the intensity and valence data of this dataset, to identify a person's effective condition. Additionally, it is encouraged to submit information for emotion analysis based on conventional machine learning methods in order to evaluate the characteristics of physiological signals in areas of time, frequency, and non-linearity. This application employs CNN to automatically extract physiological information, and totally connected network layers are used to forecast emotions (FCN). The experimental findings on the AMIGOS dataset demonstrate that, in comparison to the results previously acquired by the dataset's developers, the approach utilised in this research gives a superior precision in the classification of emotional states.

According to the triangulation theory, Wanqing Wu et alstudies .'s used a wearable sensor device to provide a quantitative assessment of one's own self-tracking of acute stress. In order to achieve high reliability and consistency when assessing stress, the author suggests a logistic regression-based model that combines information from the psychological (Stress Response Inventory, SRI), biochemical (salivary cortisol), and physiological (HRV measurements) domains. Using the suggested model, which is based on the correlation between salivary cortisol and time-/frequency-domain HRV properties, a measure of emotional stress (MSI) was created.

Electrodermal activity (EDA), electrocardiogram (ECG), and skin temperature (ST) have all been recorded throughout the treatment in attempt to determine sympathetic tension activation. Anusha A.S. And. Al. used these non-intrusive sensors to detect job tension dependant on physiological stimulation. The elicitation of the stress response was tested utilizing the amounts of salivary cortisol. In order to create classifier ensembles, multimodal stress detection techniques were used in conjunction with a fusion architecture that combined the advantages of feature fusion and decision fusion. The generated data sets had a class imbalance issue, thus three distinct class imbalance rectification schemes—undersampling, oversampling, and SMOTE—were investigated to see which may lead to the best classification results. One significant flaw in their research is the small sample size. For the stress tests in a lab setting, fixed environmental conditions were also applied, such as a constant room temperature and activity restrictions.

Minija Mi, and. Al suggested a system for real-time stress recognition utilizing peripheral physiological cues, aimed at reducing the errors induced by human variations and enhancing regressive stress recognition efficiency. The proposed paradigm was introduced as a transductive model centered on transductive learning which considered local learning to be a virtue of the community awareness of exemplary teaching.

In Evaluating acute response to stress by physiological signals: against, a quantitative examination of stress analysis paper by Adriana Arza and others, a multivariable method is suggested to comprehensively quantify the physiological stress response by using stress biomarkers extracted from skin temperature, heart rate, and pulse wave signals. Besides, five statistically varying stress thresholds caused by the tasks performed were also calculated using the proposed procedure.

Victoriano Montesinos et. Al. suggested a multimodal machine-learning stress detection strategy incorporating several physiological signals from two separate wearable devices to maximize the detection efficiency. The effect differs from the subjectivity of the individual and the degree and form of stimulation.

Mahesh Bhargavi et. Al. defines in their paper the criteria which a reference dataset for multimodal human stress detection should satisfy. Medical and scientific research reviews extract the criteria that are focused on current procedures that objective data. It was noticed that none of these data sets meet all criteria to register as a dataset of comparison. Future initiatives could also aim at building up such a dataset of comparison while addressing the current specifications.

Muhammad Adam et alstudy .'s A cutting-edge wavelet transform transform (DWT) approach is used in combination with nonlinear characteristics to automate the characterization of cardiovascular diseases (CVDs). Comparative wavelet nonlinear features are produced from ECG data. Five steps of the DWT are applied to the ECG indications of regular, dilated cardiomyopathy (DCM), hypertrophic cardiomyopathy (HCM), and cardiac infarction (MI). The proposed technique obtained overall accuracy of classification of 99.27 percent, versatility at 99.74 percent, and specificity of 98.08 percent using a K-nearest neighbour (kNN) classifier with the ReliefF method's 15 features. The drawback of this work is that more capacity and varied data are needed. Training the dataset calls for more time. Comparatively, researchers only employed 148 MI, 7 HCM, 8 DCM, and 52 safe patients. By increasing the amount of courses taught in class, you will get more consistent and reproducible results.

P. Madhan Mohan et al. [7] use variance information on pulse rate to assess a person's degree of stress. They have employed an optical photoplethysmography (PPG) sensor to forecast HRV. Three degrees of heart rate—high, low, and extremely low frequency—were used to characterise it.

Jie Zhang et al. determined the degree of stress using the metric Heart Rate[8]. A signal from electrocardiogram is used to calculate the values of RR interval (ECG). True +Ve and -Ve rates were used to calculate RR Values. SVM is utilised as a classification model both for positive and negative evaluations. The difference between the two ideas establishes a person's level of stress. The Sequential Backward Selection (SBS) method has been used to do additional repeats.

4. Proposed System Architecture

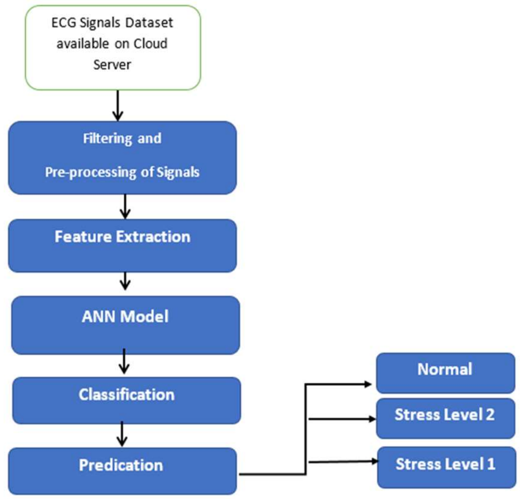

***Figure** 1:System Architecture*

5. Proposed Steps of Executions

5.1 Datasets

Initially we will be using the MIT-BIH dataset available from physionet.org website as well as from Kaggle.com website. This dataset consists of ECG Signal dataset from various level and conditions of human being. Later on we will be using real time dataset obtained from ECG signals of human being

Various algorithms will be implanted at different stages of our project.

5.2. Pre-processing:

To process the raw ECG signal, we will be implementing median filter, morphological filter to remove the noise available with ECG signals when it was recorded. We can try other filters like Butterworth as well to monitor the difference in the results and best result shown algorithm can be used.

5.3. Feature Extraction

The discrete wavelet transform has been used to complete the feature extraction. The importance of the wavelet change lies in its ability to highlight the most significant aspect of the ECG signal. The most remarkable abundance inside the ECG signal is the R peak, or QRS complex, which we first recognise. Q and S waves will then be identified. At that moment, the signal's distinct two-zero intersections well before Q and after S waves are selected. Finally, the difference between P & T waves is made.

We divide every channel of information into 30-second windows for each member's period of information to create the information window F1, F2,... up to F30. The element vector deleted from a information window is what we refer to as Fi. The jth highlight inside the element vector Fi is designated as Fi(j). We create a highlight vectors F layout for each member's informational collection. The trial convention includes ten highlight vectors for each part.

5.4. Feature Selection:

Selecting a collection of extracted features as results in the least amount of classification error is known as features selection. By deleting irrelevant and duplicate information, this process significantly improves classifier performance and speeds up the learning processes. As a result, this study employs a sequential forward feature selection (SFS) method. The evaluation function in SFS selects the features, lowering a mean square error (MSE). the final step is to progressively add the desired features to the original empty feature set. Following that, features are picked from the features available & added to the set of features at each iteration. Then, at each iteration, features are chosen from the available features and added to the list of features.

5.5. Classification and predication.

For each of the 20 subjects, we could use the same approach as described previously, applying classification after storing the different feature values in an array form. after which all feature vector values for all subjects were recorded in array form.

The dataset is split into two sets for classification, one of which is used to prepare the device and the other for testing. Information about members, in particular, that is applied for preparation and testing at a 50/50 ratio. To improve accuracy, we'll be utilising the most recent ANN artificial intelligence model. Following categorization, we determine if a person is under stress or is normal.

6. Conclusion

Electrocardiograms are among the most accurate tests for determining stress levels. Current research uses electrocardiogram measurements, which produce the expected precise findings, to identify people who are stressed. We can determine whether a person is under stress by adding measures like blood pressure and galvanic skin reaction. It is possible to create the execution with a certain level of precision using the vector support system order. Stress can help clients understand their anxiety symptoms better, and provide doctors with more reliable intervention knowledge. We compare decision trees of support vector machines, Bayesian networks, and artificial neural networks as real-time data-driven classification methods.

REFERENCES

1. National Safety Council of Australia, Stress: What causes it, how to manage it and how to reduce it in the workforce. National Safety Council of Australia
2. Rakesh Sharma, Deepak Goel, M. Shrivastav, Renu Dashmana, “Differences in Heart Rate and Galvanic Skin Response among Nurses Working in Critical and Non-critical Care Units” Journal of Clinical and Diagnostic Research, 2018, Nov, Vol-12(11): CC09-CC12 DOI: 10.7860/JCDR/2018/35602.12244

3. R. Castaldo, P. Melillo, U. Bracale, M. Caserta, M. Triassi, and L. Pecchia, ``Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-analysis," Biomed. Signal Process. Control, vol. 18, pp. 370_377, Apr. 2015
4. Monika Chauhan et al., "Effective Stress Detection using Physiological Parameters", IEEE International Conference on Innovations in Information, Embedded and Communication Systems, ISBN: 978-1-5090-3294, 2017.
5. M. Kusserow, O. Amft, and G. Tröster, ``Modeling arousal phases in daily living using wearable sensors," IEEE Trans. Affective Comput., vol. 4, no. 1, pp. 93_105, Jan./Mar. 2013.
6. P. Melillo, M. Bracale, and L. Pecchia, ``Nonlinear Heart Rate Variability features for real-life stress detection. Case study: Students under stress due to University examination," BioMed. Eng. Online, vol. 10, p. 96, Nov. 2011.
7. P. Madhan Mohan et al., "Stress measurement from wearable photoplethysmographic sensor using heart rate variability data", International Conference on Communication and Signal Processing, ISBN: 978-1-5090-0396-9, 2016.
8. Jie Zhang et al., "Recognition of Real-scene Stress in Examination with Heart Rate Features", International Conference on Intelligent Human-Machine Systems and Cybernetics, ISBN: 978-1-5386-3022-8, 2017
9. Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng in Med and Biol 20(3):45-50 (May-June 2001). (PMID: 11446209)
10. Pławiak, Paweł (2017), "ECG signals (1000 fragments)", Mendeley Data, V3, doi: 10.17632/7dybx7wyfn.3
11. Paul van Gent. (2018, July 31). Python Heart Rate Analysis Toolkit (Version V1.0.0). Zenodo. http://doi.org/10.5281/zenodo.1324311
12. Shaffer F and Ginsberg JP (2017) An Overview of Heart Rate Variability Metrics and Norms. Front. Public Health 5:258. doi: 10.3389/fpubh.2017.00258
13. R. Jan_e, P. Laguna, N. V. Thakor, and P. Caminal, \Adaptive baseline wander removal in the ECG: Comparative analysis with cubic spline technique," In Proceedings of Computers in Cardiology 1992, pp. 143{146. IEEE, 1992.