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Stress Recognition Using Machine Learning

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ABSTRACT

Stress is a normal phenomenon in today’s world and it causes people to respond to a variety of factors, resulting in physiological and behavioral changes. If a person is stressed for a long time, it will have an effect on bodies. Many health conditions are associated with stress, can be avoided if stress is detected soon. When a person is stressed, a pattern can be detected using various bio-signals such as thermal, electrical, impedance, acoustic, optical and stress levels can be identified using these bio-signals. The main objective of this work is to detect stress among people using Machine Learning techniques. Due to the importance of stress detection and prevention, many traditional and advanced techniques were developed. In this proposed system, logistic regression is used for stress detection. The key indicators of stress are heart rate, respiratory rate, skin conductance, RR interval, heart rate variability in the electrocar- diogram, and muscle activation measured by electromyography are evaluated based on a publicly available WESAD (Wearable Stress and Affect Detection) dataset. The data preprocessing is done by interquartile range, feature selection is done by sequential forward selection method and classification is done by logistic regression algorithm. The proposed classifier gives a better accuracy.

Index Terms—Physiological signals, electromyography, electro- cardiogram, interquartile range, logistic regression

I. INTRODUCTION

In psychology, stress is a feeling of emotional strain and pressure. Stress is a type of psychological pain. Small amounts of stress may be beneficial, as it can improve the athletic performance, motivation and reaction to the environment. Excessive amounts of stress can increase the risk of strokes, heart attacks, ulcers, and mental illnesses such as depression and also aggravation of a pre-existing condition.

Stress can be external and related to the environment, but may also be caused by internal problems .The term "eustress" comes from the Greek root eu which means "good" (as in "euphoria"). Eustress results when a person perceives a stressor as positive. "Distress" stems from the Latin root dis (as in "dissonance" or "disagreement"). Medically defined distress is a threat to the quality of life. It occurs when a demand vastly exceeds a person’s capabilities. Stress may cause headacheand other critical problems and may lead to death.

It has four variations of stress. The first one is good stress (eustress) and the second one is bad stress (distress). The next one is over-stress (hyper stress) and under stress (hypo stress). The ultimate goal would be to balance hyper stress and hypo stress perfectly and have as much eustress as possible. The stress is predicted by machine learning techniques.

The data were collected using two multimodal devices such as chest-worn device that is Bio Signal Plux RespiBAN Professional and a wrist-worn device and Empatica E4. The data includes a high-resolution measurement of EMG, EDA, ECG, RESP, TEMP and movement from ACC. There were 12 males and 3 females in the remaining 15 subjects with a mean age of 27.5 (SD) years. Thus all analyses for this were completed using 14 subjects. In the dataset, there are 11,500,000 baseline (non-stress) samples and 6,400,000 stress samples.

The remainder of the paper is organized as follows. Section II presents the related work. The proposed method is described in Section III. The obtained results are reported in Section IV. Conclusions are drawn in Section VI.

II. RELATED WORK

Muhammad Zubair et al., (2020) in Multilevel mental stress detection using ultra-short pulse rate variability series sug- gested the prolonged exposure to mental stress reduces human work efficiency in daily life and may increase the risk of diabetes and cardiovascular diseases. The identification of the true degree of stress in its initial stage can reduce the risk of life threatening diseases. In this, the multilevel stress detection system using ultra-short term recordings of a low cost wearable sensor. The experimental paradigm based on Mental Arithmetic Tasks (MAT) to properly stimulate different levels of stress. In Photoplethysmogram (PPG) signals were recorded along with subjective feedback for validation of stress induction. The beat-to-beat interval seriesnestimated from sixty seconds long segments of PPG signals were used to extract different features based on their reliability. In order to capture the temporal information in the ultra-short term segments of PPG, a new set of features which have the potential to quantify the temporal information at point-to- point level in the Poincare plot. The Sequential Forward Floating Selection (SFFS) algorithm to mitigate the issues of irrelevancy and redundancy among features is used. The two classifiers based on quadratic discriminate analysis (QDA) and Support Vector Machine (SVM) is used. The results of the proposed method produced 84.33% accuracy with SVM for five-level identification of mental stress. Moreover validation was done by evaluating its performance on a dataset recorded with a different stressor (Stroop). The proposed multilevel stress detection system in conjunction with new parameters of the Poincare plot has the potential to detect five different mental stress states using ultra-short term recordings of a low- cost PPG sensor.

Namho Kim et al., (2021) proposed Electrogastrogram Demonstrating Feasibility in Mental Stress Assessment Using Sensor Fusion. This covers the feasibility of ElectroGas- trogram (EGG) in multi-modal mental stress assessment in conjunction with electrocardiogram (ECG) and respiratory signal (RESP). In this twenty-one healthy participants were repeatedly relaxed, stressed, and highly stressed according to our experimental protocol, which was based on combined arithmetic, Stroop tasks, and their EGG, ECG, and RESP were simultaneously captured. Subsequently various features were extracted from the signals and correlation analysis was performed between mental stress levels and the features espe- cially the EGG features. The conventional machine learning models were optimized and validated to verify the feasibility of EGG in mental stress detection. Some EGG features exhibited significant correlation to mental stress levels. The correlation degree was comparable to that of the RESP features. The EGG features largely reflected individual differences regarding mental stress response compared to the ECG and RESP features. The logistic regression exhibited moderate accuracy in detecting mental stress 70.15% accuracy EGG monitoring could significantly contribute in depth mental stress evaluation and potentially be used for the development of real-time men- tal stress monitoring system and personalized mental stress assessment modality.

Pamela Zontone et al., (2020) proposed Car Driver's Sympa- thetic Reaction Detection through Electrodermal Activity and Electrocardiogram Measurement. In this study a system is used to detect a subject's sympathetic reaction, which is related to unexpected or challenging events during a car drive is used. The Electrocardiogram (ECG) signal and the Skin Potential Response (SPR) signal, which has several advantages with respect to other Electrodermal (EDA) signals. The record of one SPR signal for each hand and use an algorithm that, se- lecting the smoother signal is able to remove motion artifacts. The extraction of statistical features from the ECG and SPR signals in order to classify the signal segments and identify the presence or absence of emotional events via a Supervised Learning Algorithm. The experiments were carried out in a company which specializes in driving simulator equipment, using a motorized platform and a driving simulator. Different subjects were tested with different challenging events happen- ing on predetermined locations on the track. It's accuracy is 79.10% .

III. METHODOLOGY

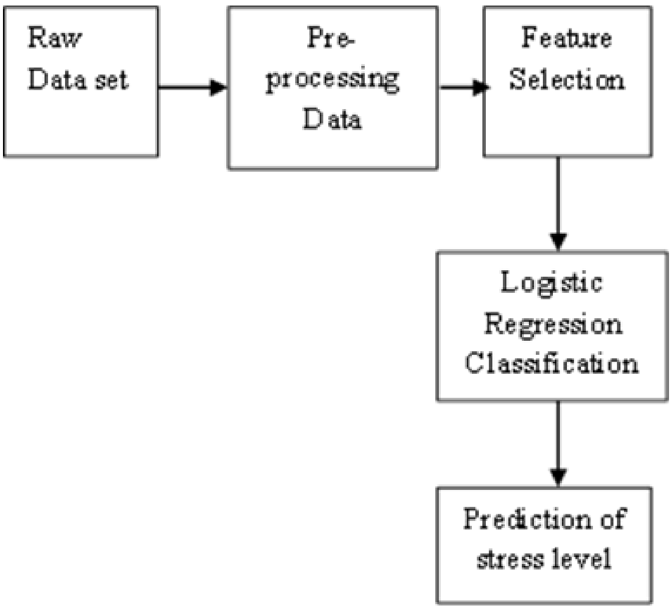


Figure 1 Flow chart of the proposed system

A. Preprocessing of Data

Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. Real world data is often incomplete, inconsistent and lacking in certain behaviors or trends and is likely to contain many errors. Data preprocessing is a proven method of resolving such issues. Noise containing outliers is present in the data. Inconsistent containing discrepancies in codes or names are used to overcome the noise. Outliers are the value that lies outside the data. If the data contain outliers the data is skewed. So there is an extreme of smallest values in data columns. Inter Quartile Range is used to measure variability by dividing a data set into quartiles. The data is sorted in ascending order and split into three equal parts. Q1, Q2, Q3 called first, second and third quartiles are the values which separate the three equal parts. It equally divides the distribution into four equal parts called quartiles. Q1 represents the 25th percentile of the data. Q2 represents the 50th percentile of the data. Q3 represents the 75th percentile of the data.

The data set has $2n$ $2n+1$ data points, then Q1 = median of the dataset. Q2 = median of n smallest data points.. Q3 = median of n highest data points. The second quartile (Q2) divides the distribution into two equal parts of 50%. So it is same as Median. The interquartile range is the distance between the third and the first quartile that is IQR equals Q3 minus Q1 .It is given by the equation IQR = Q3- Q1

B. Feature selection

Sequential feature selection algorithms are a family of greedy search algorithms that are used to reduce an initial d- dimensional feature space to a k-dimensional feature subspace where k < d. The motivation behind feature selection algorithms is to automatically select a subset of features that is most relevant to the problem. The goal of feature selection is two-fold that is used to improve the computational efficiency and reduce the generalization error of the model by removing the irrelevant features or noise. A wrapper approach such as sequential feature selection is especially useful in embedded feature selection. The Sequential Forward Selection (SFS) is used for feature selection

Input: $Y = \{y1, y2, \ldots., yd\}$

The SFS algorithm takes the whole d-dimensional feature set as input. The output is

$Xk = \{xj|\ j = 1,2, \cdots, k; xj \in Y\}$

where $k = (0,1,2, \ldots, d)$.SFS returns a subset of features; the number of selected features k, where k<d, has to be specified a priori. Initialization $X0 = \emptyset$, $k = 0$

Initialize the algorithm with an empty set ∅ ("null set") so that k=0 (where k is the size of the subset).

Step 1 (Inclusion)

$x+ = \arg max\ J(Xk + x), where\ x \in Y - Xk$

$Xk+1 = Xk + x+$

$k = k + 1$

In this step, add an additional feature, x+, to the feature subset Xk. x+ is the feature that maximizes the criterion function, that is, the feature that is associated with the best classifier performance if it is added to Xk.Repeat this procedure until the termination criterion is satisfied.

Termination: k=p

Then add features from the feature subset Xkuntil the feature subset of size k contains the number of desired features p that we specified a priori. The mathematical equations are given below. The physiological signals are x and xi is an i-th sample of the signal within the sliding window, where i= 1…n. Mean is denoted by $\bar{x}$ and represents the mean value of a raw signal within a sliding window. Mean is calculated by the following equation

1 n

$\bar{x}$ = $\sum$ xi

i=1

The standard deviation is denoted by S and represents the deviation of raw signal around the mean of the signal within

the sliding window. Standard deviation is calculated using the following equation

1 n

S= √ $\sum$ $(xi - \bar{x})2$

i=1

Median corresponds to the cumulative percentage of 50% that is middle reading in a dataset. It is calculated using the equation as

Median =(n + 1)$th\ value$ 2

For the statistical analysis, only two-state data (Baseline and Stressed states) were used to evaluate the relative importance of each physiological indicator of stress in stress prediction.

Two types of analysis were performed

(i) An independent analysis for each bio physiological indicator via a two-sample t-test under the null hypothesis that the mean bio physiological indicator is equal during the Baseline and the stressed states.

(ii) A multivariable (deviance) analysis to rank the contribution of each bio physiological indicator in a logistic regression model are as follows

$p(stress)$

log = ($p(baseline)$)

= $c0 + c1EDA + c2EMG + c3ECG + c4RsPr$

The logit link function log ($p(stress)$) is used (p is the $p(baseline)$ probability) to relate the log odds of being stressed to the linear predictor where $c0$, $c1$, $c2$, $c3$, $c4$ are the coefficients showing the direction of the relationship. The logistic regression classification analysis to determine the mean, median and classification accuracy of the model.

C. Classification

Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable although many more complex extensions exist. In regression analysis, logistic regression (or logit regression) is estimating the parameters of a logistic model (a form of binary regression). Mathematically, a binary logistic model has a dependent variable with two possible values, such as pass or fail which is represented by an indicator variable, where the two values are labeled "0" and "1".

In the logistic model the log odds (the logarithm of the odds) for the value labeled "1" is a linear combination of one or more independent variables ("predictors") the independent variables can each be a binary variable (two classes, coded by an indicator variable) or a continuous variable (any real value). The corresponding probability of the value labeled "1" can vary between 0 (certainly the value "0") and 1 (certainly the value "1") hence the labeling function that converts log-odds to probability is the logistic function. The unit of measurement for the log-odds scale is called a logit from logistic unit. Analogous models with a different sigmoid function instead of the logistic function can also be used such as the probit model the defining characteristic of the logistic model that increases one of the independent variables multiplicatively scales the odds of the given outcome at a constant rate with each independent variable having its own parameter for a binary dependent variable this generalizes the odds ratio.

In a binary logistic regression model the dependent variable has two levels. One is the outputs with more than two values are modeled by multinomial logistic regression and if the multiple categories are ordered by ordinal logistic regression. The logistic regression model itself simply models probability of output in terms of input and does not perform statistical classification, though it can be used to make a classifier for instance by choosing a cutoff value and classifying inputs with probability greater than the cutoff as one class below the cutoff as the other this is a common way to make a binary classifier. The coefficients are generally not computed by a closed form expression unlike linear least squares.

The logistic regression is by considering a logistic model with given parameters then finding how the coefficients can be estimated from data. Consider a model with two predictors, x_{1} and x_{2}, and one binary (Bernoulli) response variable Y, with parameter p=P(Y=1). Assume a linear relationship predictions for a binary dependent variable. There is a way to between the predictor variables and the log-odds (also called convert a binary variable into a continuous one that can take on logit) of the event that Y=1. This linear relationship can be any real value (negative or positive). For that binomial logistic written in the following mathematical form where ℓ is the log- regression first calculate the odds of the event happening for odds, b is the base of the logarithm, and β{i} are parameters of different levels of each independent variable, and then takes its the model. The second equality followed by dividing the numerator and the denominator of fraction by $b\beta 0+\beta 1x1+\beta 2x2$ and where Sb is the sigmoid function with base b. The above formula shows that once β{i} are fixed, it can easily be computed either the log-odds Y=1 for a given observation, or the probability that Y=1 for a given observation.

The main use-case of a logistic model is to be given an observation (x_1,x_2), and estimate the probability p that Y=1. In this the base b of the logarithm is usually taken to be e. However, in some cases it can be easier to communicate results by working in base 2 or base 10.

Logistic regression can be binomial, ordinal or multinomial. Binomial or binary logistic regression deals with situations in which the observed outcome for a dependent variable can have only two possible types, "0" and "1" (which may represent, for example, "stress" vs. "relaxed" or "win" vs. "loss"). Multinomial logistic regression deals with situations where the outcome can have three or more possible types (e.g., "disease A" vs. "disease B" vs. "disease C") that are not ordered. Ordinal logistic regression deals with dependent variables that are ordered.

In binary logistic regression, the outcome is usually coded as "0" or "1", as this leads to the most straightforward interpretation. If a particular observed outcome for the dependent variable is the noteworthy possible outcome (referred to as a "stress" or a "relaxed" or a "highly stressed") it is usually coded as "1" and the contrary outcome (referred to as a "failure" or a "non instance" or a "non case") as "0". Binary logistic regression is used to predict the odds of being a case based on the values of the independent variables (predictors). The odds are defined as the probability that a particular outcome is a case divided by the probability that it is a non instance.

Like other forms of regression analysis, logistic regression makes use of one or more predictor variables that may be either continuous or categorical. Unlike ordinary linear regression, however, logistic regression is used

for predicting dependent variables that take membership in one of a limited number of categories (treating the dependent variable in the binomial case as the outcome of a Bernoulli trial) rather than a continuous outcome.
Given this difference the assumptions of linear regression are violated. In particular, the residuals cannot be normally distributed. In addition, linear regression may make nonsensical logarithm to create a continuous criterion as a transformed version of the dependent variable. The logarithm of the odd is the logit of the probability, the logit is defined as follows:
Although the dependent variable in logistic regression is Bernoulli, the logit is on an unrestricted scale. The logit function is the link function in this kind of generalized linear model that is $logit\ \varepsilon(Y) = \beta 0 + \beta 1x$
where, Y is the Bernoulli-distributed response variable and x is the predictor variable; the β values are the linear parameters.
The logit of the probability of success is then fitted to the predictors. The predicted value of the logit is converted back into predicted odds by the inverse of the natural logarithm that is exponential function. Thus the observed dependent variable in binary logistic regression is a 0 or 1 variable, the logistic regression estimates the odds, as a continuous variable, that the dependent variable is a 'success'.
In some applications, the odds are all that is needed. In others, a specific yes-or-no prediction is needed for whether the dependent variable is or is not a 'success', this categorical prediction can be based on the computed odds of success, with predicted odds above some chosen cutoff value being translated into a prediction of success. The Logistic regression equation can be obtained from the Linear Regression equation. The mathematical steps to get Logistic Regression equations are given below
The equation of the straight line can be written as
$y = b0 + b1x1 + b2x2 + b3x3 + \cdots + bnxn$
As $b0$ is the coefficient not associated with any input feature,
$b0$= log-odds of the reference variable, x=0 (x=male). Here,
$b0$= log odds(male graduating with honours). The coefficient of the input feature 'female', $b1$= log-odds obtained with a unit change in x= female. This is followed till it reach the last data.
The logistic regression coefficient β associated with a predictor x is the expected change in log odds of having the outcome per unit change in x. So increasing the predictor by 1 unit (or going from 1 level to the next) multiplies the odds of having the outcome by eβ. In Logistic Regression y can be between 0 and 1 only, so for this let's divide the above equation by (1-y)
{ ; 0 for y=0 and ∞ for y=1}
$1-y$
The range between -[∞] to +[∞] the equation will become:
log [
$1 - y$
$] = b0 + b1x1$
$+ b2x2 + b3x3$
$+ \cdots + bnxn$

IV. EXPERIMENTAL RESULTS

The raw data is taken and the dataset used here is WESAD. The data pre processing is done by IRQ method .The features of each data are selected by sequential forward selection method. The classification and prediction is done by logistic regression algorithm.The software used here is python. Following are the Figure 5 shows the data preprocessing in stress prediction is by variables included in the data file ACC includes Raw data from interquartile range IQR. In this get the data and extract the the three axis accelerometer ECG includes raw signals of ECG, dependent and independent variables from the WESAD dataset. the heart rate was calculated using the Hamilton peak detection The Q1, Q2 and Q3 values are calculated for each data set . Then algorithm . The EDA signals were recorded from the abdomen . split the dataset into training and test set.
EMG was recorded from the muscles of the upper trapezius on both sides of the spine. In addition, Empatica E4 was worn on the dominant hand by all subjects.BVP, EDA, TEMP, and ACC signals were recorded at the sampling rate of 64Hz, 4Hz, 4Hz, and 32Hz, respectively.

A. Input images

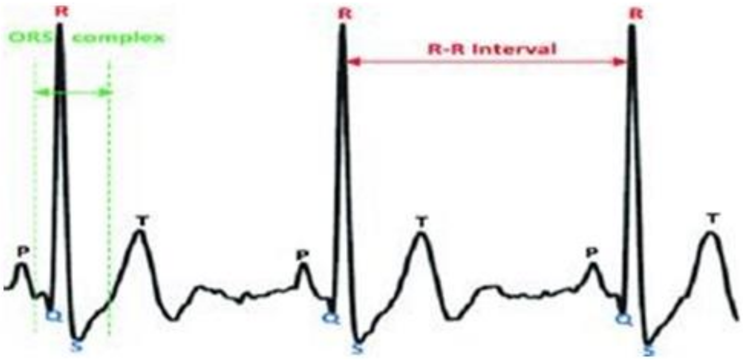


Figure 2 shows the ECG input signal

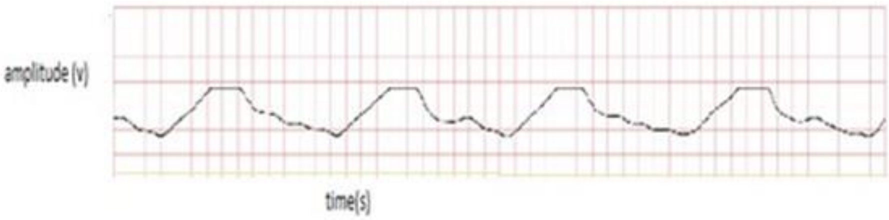


Figure 3 shows the respiratory signal

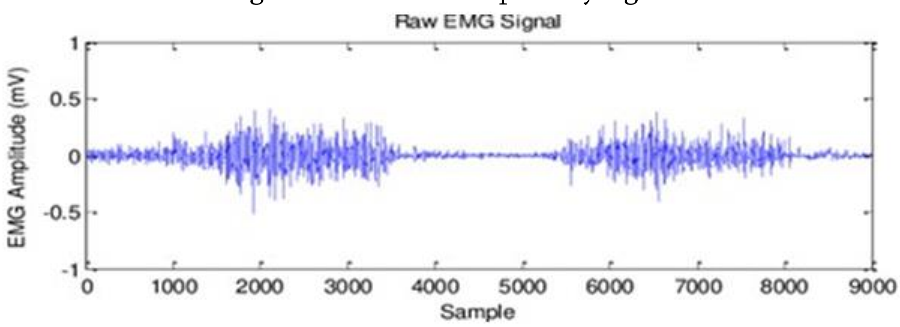


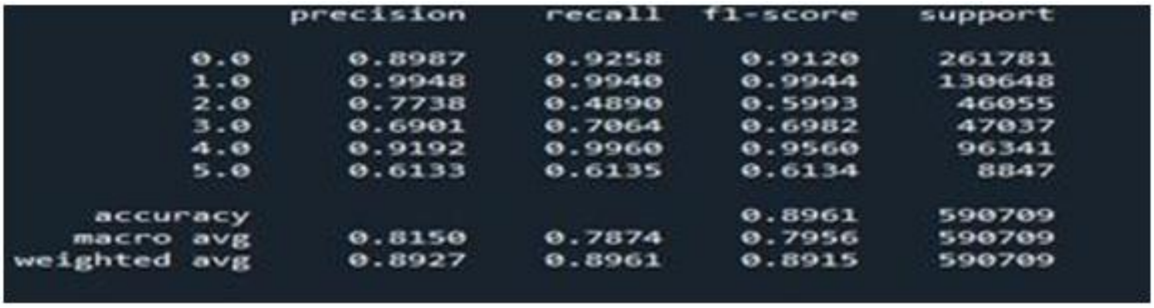
Figure 4 shows the EMG signal

B. Performance analysis

The performance of the classifier is evaluated using the performance measures. Some of them are Accuracy, Precision, Recall, F1 score. They are calculated.The proposed classifier achieves an accuracy of 89.2% with the five signals.

C. Results

Figure 5 shows the output of preprocessing



	precision	recall	f1-score	support
0.0	0.8987	0.9258	0.9120	261781
1.0	0.9948	0.9940	0.9944	130648
2.0	0.7738	0.4890	0.5993	46055
3.0	0.6901	0.7064	0.6982	47037
4.0	0.9192	0.9960	0.9560	96341
5.0	0.6133	0.6135	0.6134	8847
accuracy			0.8961	590709
macro avg	0.8150	0.7874	0.7956	590709
weighted avg	0.8927	0.8961	0.8915	590709

Figure 6 shows the output of stress level.

The classification is done by logistic regression. The accuracy can be calculated as the ratio of the number of correct predictions made by the classifier to all number of predictions made by the classifiers.

V. CONCLUSION

Several human bio physiological variables have been explored to evaluate and monitor both physical and mental stress levels in recent literature. Many of these variables have been independently used in wearable sensor-based devices. A logistic regression-based classifier was also trained and validated during this study to determine the classification accuracy of the model. The results of two types of statistical analysis and classification model suggest that respiratory rate is the strongest (stand-alone) predictor of stress compared to other commonly used physiological variables that include heart rate, RR interval, heart rate variability in the ECG, skin conductance (electro dermal activity) and muscle activation (electromyogram). The prediction model consisting of the combination of respiratory rate, heart rate and heart rate variation, derived from a single sensor gives accurate classification results as a combination of EDA, EMG, RspR, Temp, and ECG. It is important that all efforts were focused to provide a fair comparison by using data from the same device and participants. However, there may be other excitation sources (of similar responses) that these experiments failed to capture. Therefore, including context to the data will be a key to effective monitoring of stress on a daily basis.

VI. REFERENCES

[1]. Muhammad Zubair A. and Changwoo Yoona (2019), ‘Multilevel mental stress detection using ultra-short pulse rate variability series’, Biomedical Signal Processing and Control, Science direct, Vol. 113, No. 9, pp. 1221-1387.
[2]. Luntian Mou A. and Chao Zhou A. (2021), ‘Driver stress detection via multimodal fusion using attention-based CNN- LSTM’, Expert Systems With Applications on Science direct, Vol. 23, No. 45, pp. 69-81.
[3]. Sergio A. and Usechea Boris E. (2016), ‘Stress-related psychosocial factors at work, fatigue, and risky driving behavior in bus rapid transport (BRT) drivers’, Accident of a analysis and prevention Elsevier, Vol. 10, No. 23, pp. 98- 114.
[4]. Namho Kim and Sung-Min Park (2021), ‘Electrogastrogram Demonstrating Feasibility in Mental Stress Assessment Using Sensor Fusion’, IEEE Sensors Journal, Vol. 21, No. 1, pp. 34-60.
[5]. Yan ding and Shan zhong (2020), ‘A Depression Recognition Method for College Students Using Deep Integrated Support Vector Algorithm’ ,IEEE Transactions on Science and Engineering , Vol. 4, No. 4, pp. 1284-1294.
[6]. Pamela Zontone and Antonio Affanni (2020), ‘ Car Driver’s Sympathetic Reaction Detection through Electrodermal Activity and Electrocardiogram Measurements’ IEEE Transaction on Biomedical Engineering , Vol .5, No. 6,pp. 134-167.
[7]. Mario Munoz Organero and Victor Corcoba-Magana (2016), ’Predicting Upcoming Values of Stress While Driving’, IEEE Transactions on Intelligent Transportation Systems , Vol. 7, No. 5, pp. 1524-9050 .
[8]. Ahmad rauf subhani and Wajid mumtaz, (2017), ‘Machine Learning Framework for the Detection of Mental Stress at Multiple Levels’,IEEE Transaction on Biomedical Engineering , Vol.6 ,No. 6 , pp. 1234-1278.
[9]. Sara Taylor and Natasha Jaques (2017), ‘Personalized Multitask Learning for Predicting Tomorrow’s Mood, Stress, and Health’, IEEE Transactions on Affective Computing, Vol. 14, No. 7, pp. 13-50.
[10]. Mert Sevil and Mudassir Rashid (2021), ‘Physical Activity and Psychological Stress Detection and Assessment of Their Effects on Glucose Concentration Predictions in Diabetes Management’ , IEEE Transactions on Biomedical Engineering, Vol. 13, No. 5, pp. 4116-4123.
[11]. Kenneth Lai and Svetlana N. (2021), ‘Intelligent Stress Monitoring Assistant for First Responders’, IEEE Access Special Section on Behavioral Biometrics for e-Health and Well-being, Vol. 51, No. 4, pp. 4476-4488.
[12]. Gonzalez and Castellanos (2021), ‘Machine Learning for Personalised Stress Detection: Inter-individual Variability of EEG-ECG Markers for Acute-Stress Response’, Elsevier, Computer Methods and Programs in Biomedicine, Vol. 41, No. 10, pp. 12-56.
[13]. Dae Seok Lee and Chong, (2016), ‘Stress Events Detection of Driver by Wearable Glove System’, IEEE Sensors Journal Vol. 23, No. 24, pp. 45-87.

[14]. Z. Zainudin and Hasan (2019), 'Stress Detection using Machine Learning and Deep Learning', Journal of Physics, Vol. 56, No . 60, pp. 78-99.

[15]. Jharna Agrawal and Hitendra Garg (2020), 'Early Stress Detection and Analysis using EEG signals in Machine Learning Framework' , IOP Conf. Series in Materials Science and Engineering.

[16]. Rajdeep Kumar Nath and Himanshu Thapliyal (2021), 'Smart Wristband-Based Stress Detection Framework for Older Adults With Cortisol as Stress Biomarke', IEEE Transactions on Consumer Electronics, Vol. 67, No. 1, pp.123-140.

[17]. Saskia Koldijk Koldijk and Wessel Kraaij (2016), 'Detecting work stress in offices by combining unobtrusive sensors' , IEEE Transactions on Affective Computing, Vol. 2, No. 5, pp.456-487.

[18]. Joao Rodrigues and Mariana Kaiseler (2020) , 'A Mobile Sensing Approach to Stress Detection and Memory Activation for Public Bus Drivers', IEEE Transactions on Intelligent Transportation Systems, Vol. 14 No. 12, pp. 271- 285.

[19]. Ayten Ozge Akmandor and Niraj K. Jha, Fellow (2017), 'Keep the Stress Away with SoDA: Stress Detection and Alleviation System', IEEE Transactions on Multi-Scale Computing System, Vol. 7, No.4, pp. 43-61.

[20]. SEONGSIL HEO Boon Giin Lee and Wan-Young Chung(2016), 'Wearable Glove-Type Driver Stress Detection Using a Motion Sensor', IEEE transactions on Intelligent Transportation Systems , Vol. 14, No. 2, pp. 34-50.

[21]. Seongsil heo and Jaekoo lee (2021), 'Stress Detection With Single PPG Sensor by Orchestrating Multiple Denoising and Peak-Detecting Methods', IEEE Transaction on Biosignals, Vol. 156, No. 5, pp. 1669-181.

[22]. Alberto Hernando and Jesus azaro (2015), "Inclusion of respiratory frequency information in heart rate variability analysis for stress assessment Alberto Hernando", IEEE Journal of Biomedical and Health Informatics, Vol. 7, No. 4, pp. 236-257.

[23]. Houtan Jebelli and SangHyun Lee(2020), 'A Continuously Updated, Computationally Efficient Stress Recognition Framework Using Electroencephalogram (EEG) by Applying Online Multitask Learning Algorithms (OMTL)', IEEE Journal of Biomedical and Health Informatics, Vol. 23, No. 5 ,pp. 202-222.

[24]. Bin Hu and Philip Moor (2020), 'Signal Quality Assessment Model for Wearable EEG Sensor on Prediction of Mental Stress', IEEE Transactions on Nano Bioscience, Vol. 14, No. 5, pp. 107-119.

[25]. Philip Schmidt, Attila Reiss (2018), 'Introducing WESAD, a Multimodal Dataset for Wearable Stress and Affect Detection', ICMI on Science Direct, Vol. 5, No. 3, pp. 123-150.