Journal of Engineering and Applied Research (JEAR)
National University of Skills
Summer & Autumn 2024, Vol. 1, No. 2, p. 135-150
Journal Homepage: https://jear.tvu.ac.ir/
doi:10.48301/JEAR.2024.472506.1035

Stress Leveling based on Physiological Parameters

Mohamad Reza Yazdani[1*], Haniyeh Baghdadi[2]

[1]Department of Electrical Engineering, National University of Skills (NUS), Tehran, Iran.
[2]Department of Electrical, Computer and Medical Engineering, Shahab Danesh University, Qom, Iran.

ARTICLE INFO

Article Type:
Original Research

Received: 08.09.2024
Revised: 08.16.2024
Accepted: 08.20.2024

Keyword:
Diagnosing
Physiological Signals
Non-invasive
Wavelet Features
Support Vector Machine
Ensemble Learning

***Corresponding Author:**
Mohamad Reza Yazdani
Email: *yazdani@nus.ac.ir*

ABSTRACT

Solar Diagnosing and controlling the level of stress to reduce health risks is vital. In this study, a system for detecting five levels of stress was presented: physical stress, semi-emotional stress, emotional stress, cognitive stress, and resting state in people based on physiological signals. In the proposed method, the Non-EEG Dataset for Assessment of Neurological Status database, which is available on the Physionet website, was used. This database contains physiological signals from twenty people. These data were collected using non-invasive wrist biosensors. A set of statistical frequency and wavelet features were calculated for electrodermal (EDA), temperature, acceleration, heart rate (HR) and arterial oxygen level (SpO2) signals. The determined features were applied as input to the classification units to detect the stress levels. Support vector machine (SVM), k nearest neighbor (kNN), decision tree (DT), ensemble learning and neural networks were evaluated as classification methods. Experimental results showed that neural networks can separate different neural states of 5 classes with 97% accuracy.

E-ISSN: 3060-6357

Introduction

Stress is a natural emotional state that humans experience when facing new situations and changes a person’s mental peace [1]. Excessive stress has negative consequences such as reduced concentration levels. When experienced for longer periods without being managed, stress can be harmful to health and cause problems such as high blood pressure, reduced sleep quality, constant fatigue, cardiovascular problems, diabetes, skin problems, and increased weight [2]. Stress affects the cardiovascular system, the brain and nervous system, the digestive tract and the immune and muscular systems of a person [3]. Therefore, no organ in the body will be safe from the risk of stress. Stress has much financial impact on society to diagnose and prevent these problems [4]. Therefore, measuring stress helps the health of society greatly. However, the results of this measurement are also used for other practical aims. For example, checking the stress level of drivers in real road conditions, the stress of drivers in competitions and increasing the security of users' access to banking systems. In the last few decades, many people have lost their lives due to increased sleepiness, fatigue and mental stress.

The study conducted by Healey and Pichard is a pioneer in the field of stress detection. In the study analysis, 5 physiological data during driving were considered to determine the driver's stress level [5]. Healey and Picard achieved an accuracy of 97.4% for two levels of high and moderate stress. This research aimed to identify the stress level using the signal fusion of multiple sensors. However, this method was not suitable for classifying stress into three levels, particularly when considering a single signal [6].

Akmandor and Jha introduced a stress detection and reduction system. This system used wearable medical sensors (SODA[1]) including ECG[2], GSR[3], breathing rate, blood pressure and blood oximetry signals for continuous monitoring of stress levels and reducing it, and achieved an accuracy of 95.8% [7].

In another study, Sobhani et al. presented a machine-learning structure for analyzing the EEG[4] signals of stressed participants [8]. In this paper, a computer-based mental calculation process was used to create stress. Montreal (MIST[5]) stress imaging was also used. The results showed that the designed system had an accuracy of 94.6% for identifying two levels of stress and an accuracy of 83.4%

[1] Stress detection and alleviation system
[2] Electrocardiogram
[3] Galvanic Skin Response
[4] Electroencephalogram
[5] Montreal imaging stress task

for identifying multiple levels. As a result, ML[1] structure based on the proposed EEG can create computerized diagnostic tools that help to diagnose stress [8].

choi and his colleagues proposed a system based on a wearable device to monitor the driver's abnormal conditions such as stress, fatigue and sleepiness. The proposed system measured the movement and physiological information of the driver using a wearable device placed on the wrist, and achieved a classification accuracy of 98.43% [9].

Liu and his colleagues investigated the use of linear discriminant analysis based on electrical activity of the skin (EDA[2]) signal to differentiate between three levels of low, medium and high stress. In this study, 11-foot EDA signals in the MIT Media Lab stress database were used [10]. The stress level was detected with an accuracy of 81.82% by the proposed system. The advantage of this system compared to systems designed with multiple signals is the reduction of its computational complexity [10].

Hssayeni et al. investigated the use of data-driven feature extraction based on deep learning to investigate the application of raw physiological signals for estimating PA[3] and NA[4]. Specifically, they proposed two multi-modal data fusion methods with deep Convolutional Neural Networks to estimate PA and NA and also classify baseline, stress, and amusement emotions [11].

In another study, Rachakanda et al. presented a new system based on deep learning to identify and manage stress in the context of smart healthcare. The designed system determines a person's stress level by using standards such as body temperature, movement and sweating. It achieved the best accuracy of 99.7%. In the present research, the use of the main parameter for the diagnosis and classification of stress was proposed called galvanic skin response (GSR) [5].

In the last decade, many articles have been presented in the field of detecting the level of stress using each of these signals. Sometimes a combination of physical and physiological signals has been used in people.

The first part of this paper deals with the research problem and existing research carried out in this field. The second part describes the tools and methods used in this research. In the third part, data analysis and data preprocessing to prepare for classification steps are presented. In the fourth part, features are extracted and the best ones selected. In the fifth section, data classification based on different algorithms and their performance evaluation using evaluation

[1] Machine learning
[2] Electro dermal activity
[3] Positive affect
[4] Negative affect

parameters are described. In the final section, conclusions and suggestions for future research are presented.

Methodology

In this study, the Non-EEG Dataset for Assessment of Neurological Status database was used. This database contains non-EEG physiological signals collected at the Quality of Life Laboratory at the University of Texas in Dallas, and used to infer the neurological status (including physical stress, cognitive stress, emotional stress and relaxation) of 20 healthy subjects [12]. The data was collected using non-invasive wrist-worn biosensors and consists of electrodermal activity (EDA), temperature, acceleration, heart rate (HR), and arterial oxygen level (SpO2) [12].

Today, due to the everchanging world, people are experiencing greater levels of physical stress, tension and nervous pressure which lead to increased levels of stress. According to psychologists, stress can be divided based on different situations and their impact [13].

One of the most common types of stress is physical stress, which refers to the set of physical activities that cause tension in people such as traveling [14]. Traveling disturbs a person's sleep and creates tension in them. One of the most common types of stress is emotional stress, which is also called psychological stress [15]. This type of stress includes different emotions such as anger, sadness, fear and frustration. Cognitive stress is a stress that directly affects the person's brain and mental resources and causes them to be disturbed to the extent that a person is not able to respond to their needs and desires.

The dataset consisted of 7 stages for 20 subjects:

- **First Relaxation:** five minutes.

Physical Stress: Stand for one minute, walk on a treadmill at one mile per hour for two minutes, then walk/jog on the treadmill at three miles per hour for two minutes.

- **Second Relaxation:** five minutes.

Mini-emotional stress: 40 seconds.

Cognitive Stress: Count backwards by sevens, beginning with 2485, for three minutes.

Performing the Stroop test for two minutes. The volunteer was alerted to errors by a buzzer. The Stroop test consisted of reading the names of colors written in different colored ink, and then saying what color the ink was.

- **Third Relaxation:** five minutes.

Emotional Stress: The volunteer was told he/she would be shown a five-minute clip from a horror movie in one minute. After a minute of anticipation, a clip from a zombie apocalypse movie, The Horde, was shown.

– **Fourth Relaxation:** five minutes.

Figure 1 shows a diagram of the physiological signals of each participant [12].

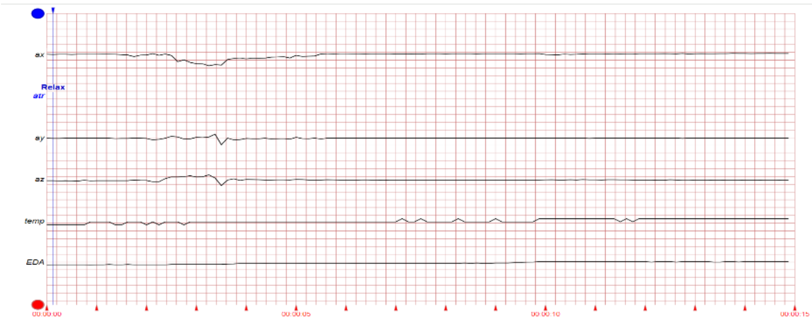

Figure 1. Diagram of signals for the 10th participant at the 15th minute.

In the next step, a questionnaire was designed to discover in which jobs the need was felt the most for this recognition and leveling system. In the questionnaire, people were first asked personal questions such as age, occupation, level of education, amount of working hours, amount of work experience and the need for a stress detection device in their workplace. The results were then presented in the form of pie charts and bar graphs. Figure 2 shows the age of the participants and Figure 3 shows the level of education of the participants.

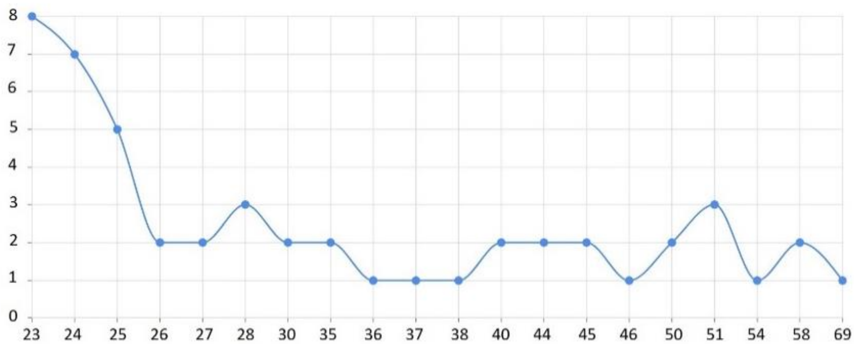

Figure 2. Line graph of the age of participants in the questionnaire.

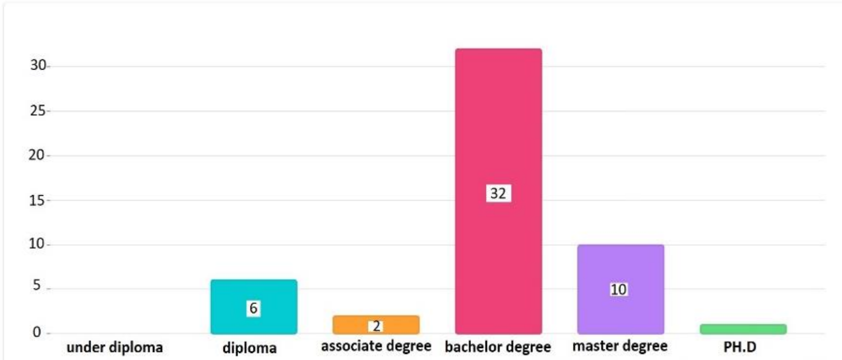

Figure 3. Bar graph of the education level of the participants in the questionnaire.

Then, questions were asked about the limitations and priorities if there was a system for stress detection and stress leveling. Figure 4 shows one of the questions in the questionnaire.

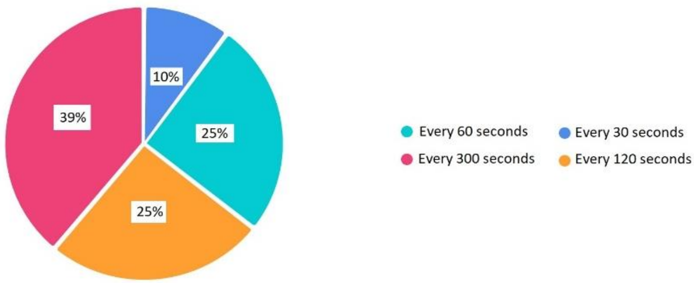

Figure 4. Bar graph of the answers of the participants in the questionnaire.

In this study, MATLAB software was used for data processing. Figure 5 shows the block diagram of the research. First, the database imported the software environment. The data was sorted based on the given timing. Then, the preprocessing and main processing of the data was carried out. In the next step, feature extraction was used from each signal. Then, the best features were selected using the ANOVA[1] technique, and in the last stage, the extracted features were classified and concluded.

Figure 5. Procedure for classification.

[1] Analysis of Variance

Preprocessing

In this study, electrodermal activity (EDA), temperature, acceleration, heart rate (HR), and arterial oxygen level (SpO2) were recorded. All the physiological signals in this database were recorded for a total duration of 35 minutes.

The SC signal indicates the electrodermal activity (EDA) measured by a non-invasive electrode on the skin. Figure 6 shows SC. The SC[1] signal consisted of two types of signals: slow-varying tonic activity and fast-varying phasic activity. They are called skin-conductance level (SCL[2]) and skin-conductance response (SCR[3]), respectively. SCL is a baseline level which is illustrated in Figure 7. It changes in the absence of any environmental events. On the other hand, SCR changes when environmental events occur. It is also known that changes in SCR are associated with the activity of the sudomotor nerves related to the sweat glands [16]. Figure 8 depicts SCR.

In this step, the EDA signal was analyzed and processed using coding in MATLAB and the Median filter.

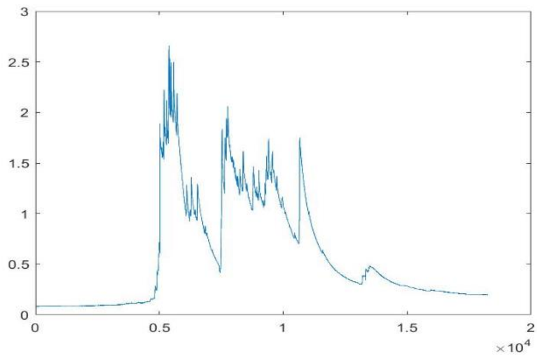

Figure 6. First subject SC signal.

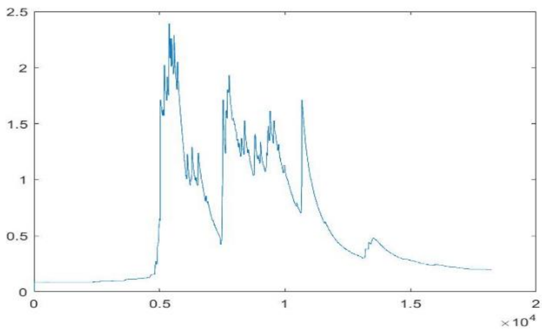

Figure 7. First subject SCL signal.

1 Skin Conductance
2 Skin-conductance level
3 Skin-conductance response

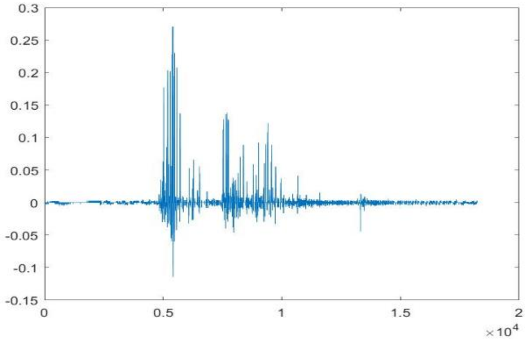

Figure 8. First subject SCR signal.

Feature extraction

Feature extraction aims to decrease noise and redundancy from input data and operate on the information of the data [17]. Several techniques have been employed to extract relevant features from the time, frequency, and wavelet domains. These features are extracted from the physiological parameters of EDA, HR[1], Temp[2], acceleration and SPO2 for leveling stress. After feature extraction, useful and significant data for classification is selected so that there are more reliable and accurate stress leveling [18]. In this step, many features are extracted from each signal in the time, frequency and wavelet domain. From the EDA signal, some features such as SC average, SCL average, SCR average, SCR maximum, number of peaks SCR, difference between maximum and minimum SCL, standard deviation, skewness, kurtosis, amplitude and peaks in the frequency domain and in the db10 wavelet domain are extracted. From Temp, HR, SPO2 and acceleration signals the mean, standard deviation, skewness, elongation, range and peaks in the frequency domain and the wavelet domain are extracted. Figure 9 shows Daubechies 10, level 4 and features extracted from the d4 signal. Figure 10 shows the reconstructed signal in level 3. Finally, 16 features were extracted from each of the 7 types of recorded signals, implying that that 112 features were extracted.

[1] Heart Rate
[2] Temperature

Figure 9. HR signal of the first subject in the wavelet domain in the state of physical stress.

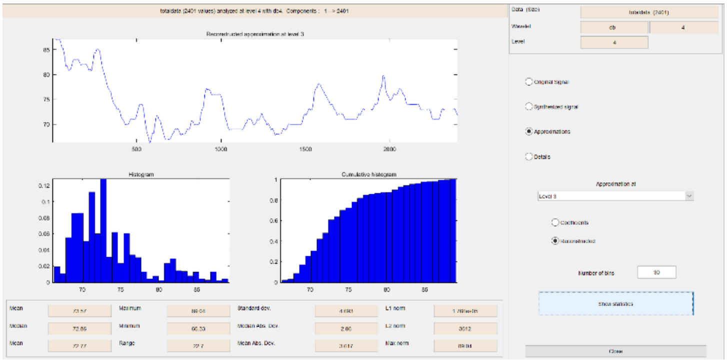

Figure 10. HR signal of the first subject in the wavelet domain at rest.

Feature selection is the process of identifying important and valuable features and also removing irrelevant and repetitive features. First, all features were extracted, and then the best features were selected. When the number of features decreases, in addition to reducing costs it increases the performance of the model. Feature selection methods are classified into filter methods and wrapper methods [19]. In this part, after extracting the best features from the signal, the variance analysis method was used to prepare the features for the classification stage.

One of the practical tools and statistical test is "Analysis of Variance" [20]. This method determines the difference between the averages of two or more independent statistical populations. Due to the scattered data, it is possible to analyze the variance between different groups in this method. It is performed in MATLAB with the anova1 command. The data includes 100 samples in 5 categories. The first category is related to the state of rest, the second category is related to the state of physical stress, the third category is related to the state of mini-emotional stress, the fourth category is related to the state of cognitive stress, and the fifth category is related to the state of emotional stress. Then, according to the p_value, good features are kept and bad features removed. Figure 11 shows the analysis of variance of the average HR. According to its p_value in Figure 12, it is a good feature.

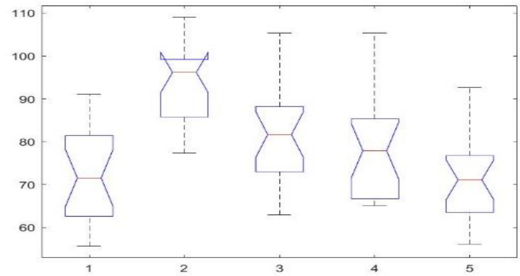

Figure 11. Analysis of variance of mean HR feature.

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	6898.4	4	1724.61	14.69	2.23767e-09
Error	11154.1	95	117.41		
Total	18052.5	99			

Figure 12. The analysis of variance table of the average HR feature.

According to the results obtained from the ANOVA method, 63 features were selected as the best features.

Classification

Classification is a science that creates a model for predicting the label of new data based on previous data that has labels. Classification is one of the basic branches of machine learning [21]. In classification, data are placed into certain categories based on their features. Classification algorithms can help organize data and identify patterns which in turn help make decisions based on data. Machine learning approaches are divided into three categories: supervised learning, unsupervised learning, and semi-supervised learning. In supervised learning, data has labels and the goal is to find the relationship between input and output, and it is divided into two categories, classification and clustering. In unsupervised learning data, there are no labels and data are divided into multiple clusters based on their similarity to each other. In this part, after selecting the best features, classification is carried out through analysis of variance to evaluate the results, compare the performance of different classifiers and obtain the best result. 63 features were selected. In this part, there is a feature matrix and a target matrix.

Cross-validation is a technique for evaluating a machine learning model and testing performance [22]. The dataset is divided into training data and test data. The goal is to use the maximum data capacity for training to learn the correct model and then evaluate the validity of the model on the test data. There are different techniques for validation. One of the most simple and practical models of evaluation methods is the Hold out method [23]. This method is used when there is big data for both testing and training. This method has less computational complexity but does not have good performance on small data. In the classification for the evaluation method the Hold out validation method is selected and 30 percent of the data is considered as test data. Then, classification is carried out using DT[1], SVM[2], KNN[3] and ensemble learning and neural networks method. Ensemble learning is a machine learning technique that aggregates two or more learners (e.g. regression models, neural networks) to produce better predictions [24]. In other words, an ensemble model combines several individual models to produce more accurate predictions than a single model alone [24]. The main types of ensemble methods in machine learning are Bagging (bootstrap-aggregating), Boosting or Stacking/Blending technique [25]. In this article, Bagging architecture was used. Bagging is commonly used to reduce variance within a noisy data set [26]. In bagging, a random sample of data in a training set is selected with replacement, meaning that the individual data points can be chosen more than once [27]. A neural network is a machine learning program, or model, that makes decisions in a manner similar to the human brain, by using biological neurons [28].

Figure 13 shows the confusion matrix and Figure 14 shows the ROC[4] diagram for the neural network method.

[1] Decision Tree
[2] Support vector machines
[3] K-nearest neighbors
[4] Receiver Operating Characteristic

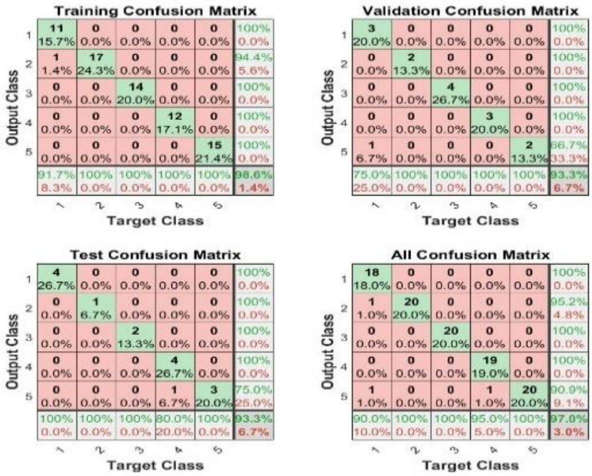

Figure 13. Confusion matrix.

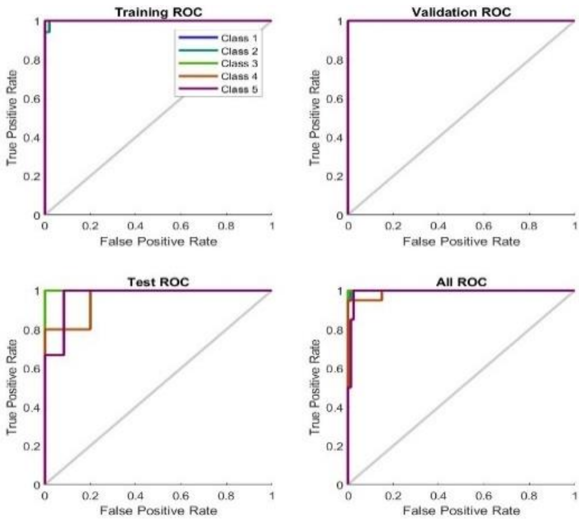

Figure 14. ROC.

The evaluation results demonstrated that the Ensemble learning method and the SVM method with an accuracy of 93.3% and the KNN method with an accuracy of 92% performed the classification of stress levels. The neural network method was the best classification method in this study with an accuracy of 97%. Table 1 presents the evaluation results.

Table 1. Evaluation values.

Algorithm	Accuracy	Precision	Sensitivity	Specificity
DT	86.7%	79.5%	86.6%	77.67%
SVM	93%	84.57%	93.2%	74.5%
KNN	92%	92.38%	92%	98%
Ensemble learning	93.3%	85.81%	93.8%	84.5%
Neural network	97%	100%	95.2%	90.9%

Conclusion

First, a questionnaire was designed and presented for selecting the research topic and people with different and particularly high-risk job groups completed this questionnaire. 52% of people felt the need for a stress detection device at their workplace. The data consisted of electrodermal activity (EDA), temperature, acceleration, heart rate (HR), and arterial oxygen level (SpO2) to infer the neurological status (including physical stress, cognitive stress, emotional stress and relaxation) of 20 healthy subjects. Emotions in people do not have specific limits. As a result, the classification of its levels does not have clear and linear boundaries. For each of the signals, 16 features were calculated including statistical features such as mean and standard deviation and features in frequency domain and wavelet domain. 112 features were calculated and then the best features were selected and prepared for the classification step using the variance analysis method. 62 features as the feature matrix were entered into classification units.

Several classification methods such as support vector machine, k nearest neighbor, decision tree, ensemble learning and neural networks were used for stress leveling. The results were evaluated in MATLAB software. The best performance by the optimal parameters in the design of the used classification methods was selected. The performance of the classifiers was evaluated by accuracy, sensitivity and specificity. According to the evaluation parameters, neural networks classified 5 levels of stress with an accuracy of 97%.

In future research, it is recommended that more efficient and useful feature extraction and feature selection methods by providing effective and stronger features are used, and with a smaller number of features and a higher speed, a better and higher percentage of accuracy, sensitivity and specificity can be obtained. According to the need for high-risk jobs for stress systems, it is expected to design and build systems such as wearable gadgets in the future. It is hoped that in the future, all workplaces can be equipped with these systems, which will help the health of the people in society and allow people to focus more on their activities.

Disclosure statement and funding

The authors declare no potential conflicts of interest. The present study received no financial support from any organization or institution.

Acknowledgment

I am very thankful to respected Professor Dr. Yazdani Kashani whose presence has always been the strength of his efforts. Without his valuable help and guidance, the completion of the article would not have been possible.

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