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CONTENT

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REVIEW OF STRESS RECOGNITION TECHNIQUES AND MODALITIES

BISERKA SIMONOVSKA, NATASA KOCESKA, SASO KOCESKI

Abstract. Stress is a major problem of the modern society, as it is the cause of many health problems and huge economic losses in companies. It is a growing issue, and it has become an inescapable part of our daily lives. The early detection of stress will decrease the damage it causes and prevent it from becoming chronic. The scientific community is aware of this, and much progress has been made in the last years towards the development of an automatic stress detection system. In this review study, we will examine the recent works on stress detection, looking over the measurements executed along different modalities. Only studies involving human participants were taken into account, as no such analysis has been made so far. The performed analysis gives us hints about the future development of appropriate methods for automatic stress recognition systems.

1. **Introduction**

Stress can be defined as a physical, mental, or emotional factor that causes bodily or mental tension. The causes of stress are extremely diverse, ranging from difficulties to handle everyday experiences and changes to traumatic events such as surviving a natural disaster. Under stress, the body is flooded by stress hormones including adrenaline and cortisol, which rouse the body for emergency action. The heart pounds faster, muscles tighten, blood pressure rises, the breath speeds up, and senses become sharper. These physical changes increase body's strength and stamina speed reaction time and enhance focus.

Stress can be divided into two main categories: eustress and distress. Eustress can have a positive (e.g. motivating) effect on a person, while distress can be really harmful and can carry negative consequences. A person experiences distress when he/she is facing stress due to some stressors and is not able to cope with that stress. As a result, the person creates a stress-related tension, which affects his/her lifestyle. To prevent stress from becoming chronic and provoking irreversible damages, it is necessary to detect it in its early stages.

Much progress has been made in the last years towards the development of an automatic stress measuring and detection system. Various approaches exist that involve the use of physiological signals (heart rate variability, hormone levels, electrocardiograms, etc.), behavioural responses (keystroke and mouse dynamics, posture, mobile phone usage, etc.), contextual events, and multi-modal techniques (which are the combination of multiple types of data).

This paper is a survey of recent works (published in the last 5 years) carried out in the field of automatic stress detection. Publications were retrieved by means of a computerised search of the Science Direct and IEEE Xplore databases, with the search keywords: "stress recognition" OR "stress detection". The duplicated and non-relevant references (papers that that did not work with human participants) were excluded. A total of 26 articles were considered for further analyses.

2. Related work

There are some surveys already available in the area of stress recognition. Some of them investigate the literature related to stress recognition only in office environments [27], some investigate the usage of smartphones and wearable devices for stress detection [28], others are focused only on physiological parameters for stress detection [29], or they make a comparison between subjective and objective measures [30]. There are reviews that used limited papers only and gave a brief analysis, so the research outcomes were considered inadequate due to a lack of comprehensive study [31, 32]. In all these surveys, articles that use publicly available databases were also considered relevant. These databases contain the data obtained under strictly controlled conditions, which is not the case in real life. Because of this, we have decided, in our paper, to analyse only articles where stress recognition is performed using the data obtained through experiments with human participants. To the best of our knowledge, no such study has been done so far. Also, some of the above-mentioned surveys are written and published 5 years ago, so they do not analyse the articles reviewed in this paper.

3. Literature survey on the existing stress recognition systems

Over the years, researchers have developed different methods and techniques for the detection of human stress. Various approaches exist that involve the use of psychological signals, physiological signals, behavioural responses, contextual events, as well as multi-modal techniques.

The psychological way of measuring stress can be performed by using self-report questionnaires or by being interviewed by a psychologist. Therefore, automatic stress detection topics do not include this class. The second way to detect stress is by evaluating physiological signals. Various signals can be used, such as Electrocardiogram (ECG), Electroencephalogram (EEG), Electro-Dermal Activity (EDA), Blood Pressure (BP), Skin Temperature (ST), Electromyogram (EMG), Respiration (RSP), Blood Volume Pulse (BVP), etc. Stress can also be recognized from behavioural changes. Behavioural responses consist of keystroke and mouse dynamics, posture, facial expressions, speech, mobile phone usage, walking pattern, as well as text linguistics. Another way of recognizing stress is from contextual information that consists of calendar events and location. The place, the time, and the ambient factors where the subject is may affect the stress response, thus, measuring these parameters could help inferring the subjects' stress levels. The multi-modal techniques used a combination of multiple type of data for stress recognition. The multimodal nature of stress forced the researchers to combine different information in order to detect and measure human stress.

3.1 Stress recognition based on physiological signals

3.1.1 EEG

The electroencephalogram (EEG) is used to measure brain activity by placing a series of electrodes onto the scalp of the subject. EEG signals can be divided into four main frequency bands: Alpha, Beta, Delta, and Theta. The presence of stress can be identified by the changes of EEG Alpha and Beta signals. Alpha activities are a sign of a calm and balanced state of mind and decrease in stressful states. Beta activity correlates with emotional and cognitive processes and increases with stress.

Many researchers use EEG signals for stress detection. The authors in [2] used EEG signals obtained from 11 male workers working on three construction sites. Workers were exposed to two job site stressors: working hazards (working at the top of a ladder and working in a confined space) and tiredness (continuous work without taking a break time). Workers' salivary cortisol that is frequently used as a biomarker of psychological stress, was also collected to label low or high-stress levels. Different classification algorithms were employed: k-Nearest Neighbours (k-NN); Gaussian Discriminant Analysis (GDA); Support Vector Machine (SVM) with different similarity functions (linear, Gaussian, cubic, and quadratic). The results showed that the fixed windowing approach and the Gaussian Support Vector Machine (SVM) yielded the highest classification accuracy of 80.32% for two class classification, which is very promising, given the similar accuracy of stress recognition in clinical domains.

In [6] the authors proposed a framework that applies different Online Multi-Task Learning (OMTL) algorithms to recognize individuals' stress in near real time. The proposed framework was applied on the EEG signals collected in two environments: controlled lab environment (where 32 subjects were using a wired-EEG) and in the field environment (7 healthy workers were wearing an EEG device, while working on three real construction sites and facing with various stressors). Among all tested algorithms, the OMTL-VonNeuman method resulted in the best prediction accuracy on both datasets (71.14% on the first and 77.61% on second dataset).

A system designed to classify three levels of stress: low, moderate, and high stress, by means of EEG signal, is presented in [8]. A total of 132 signals from 12 subjects were collected. The validation of algorithm was carried out using the Stroop colour-word test, as the stressor, to induce various stress levels. The measure of stress is taken by means of the questionnaire's method. The Discrete Wavelet Transform (DWT) is used for pre-processing while the SVM is used as a classifier. Stress levels of the person under test are seen on screen using a graph. The average accuracy for the subject independent model is about 72.3%.

In [9], the band power features extracted from the EEG signal are used to understand human stress based on the emotional response of the users. The multitasking framework is utilized to evoke the subjective emotional stress response (three question panels that include a Stroop-colour word question, an arithmetic question, and a memory question are displayed at any given time). A total of 7 subjects (4 male and 3 female, aged 20 to 22 years) participated in this experiment. Using the SVM technique that effectively differentiates good and bad stress from the relaxed state of mind, an average recognition accuracy of 77.53% is obtained in the three-level stress classification.

EEG based human factors evaluation tools allow workload, emotion, and stress recognition during the air traffic control operators' task performance with high temporal resolution [17]. Twelve air traffic control operators (ACTOs) participated in the two-hour training session on the novel air traffic control three-dimensional radar display. EEG is used to monitor the brain states of the ATCOs while they are learning to use the 2D+3D display. The training program was interrupted after 15 minutes, 60 minutes, and 120 minutes. SVM was used for the three-class emotion classification with an accuracy of 72.22% and for the four-class workload level classification with an accuracy of 74.23%.

In [22], a system that could collect multi-users' brainwaves at the same time is developed. The system's dataset consists of brainwaves from 7 test subjects. Each test subject has 10 minutes of brainwaves inducted by listening to music. The system used this data to predict the subjects' mental state from their emitting brainwaves for each class, 1 (attention) and 0 (meditation). The achieved classification accuracy is 80.13%. The system classification method is a deep learning model with fully connected layers.

3.1.2 ECG

The electrocardiogram (ECG) is employed to measure the electrical activity produced by the heart via electrodes placed on various parts of the body. ECG is frequently used to extract information about Heart Rate (HR) and Heart Rate Variability (HRV).

In [7] authors propose a stress state classification method by considering not only users' subjective evaluations, but also temporal changes of stress responses in short periods. The dataset was obtained with measurements of ECG, EDA and RSP signals from 40 subjects, 17 females and 23 males. The dataset acquisition was performed in laboratory settings, where stress induction was achieved by a socio-evaluative stressor and a cognitive stressor. Both the evaluation scores and the cortisol levels are utilized to classify labels of the collected data. Then, 6 machine learning algorithms (Naïve Bayes, LibSVM, IBk classifier, Multi-ClassClassifier, JRip, and Random Forest Neural), as well as the implemented neural network algorithm based on the labelled data, were trained and tested for stress recognition. The achieved classification accuracy with neural network models is 78.7% for a three-class scenario and 98.3% for a two-class scenario. Binary stress recognition with the proposed classification method improves the recognition accuracy by up to 31.6% as compared to those with conventional techniques.

The features of the ECG and EDA signals were used as input for different classification methods (SVM, Linear Discriminant Analysis, Ensemble, k-NN, Decision Tree J4.8) in [10]. The students wearing sensors were monitored in real life settings (during exams) in order to recognize the experienced stress levels. The results revealed a recognition accuracy between 86-91% (the best classification results are achieved with SVM) for three classes, including relax state, written exam, and oral exam.

In [12] the physiological signals: ECG, EDA, RSP, BVP (blood volume pulse), and SKT (skin temperature) were measured in 30 subjects who participated in the experiments. Stress was elicited by four horror clips and a cognitive test at the end. The experiments were conducted to induce two main states: no-stress and stress. Decision Tree (DT), k-Nearest Neighbors (k-NN) and Random Forest (RF) were employed for dataset classification. The proposed multi-modal machine-learning algorithm, based on the RF algorithm, was able to distinguish between the relaxing task and the intense cognitive task with an accuracy of 84.13%, on average. Moreover, the proposed multi-modal machine-learning algorithm also distinguishes between two different emotion states with 83.33% of accuracy on average.

3.1.3 Heart rate

HR is defined as the number of heart beats per minute. Worldwide scientific research has shown that heart rate increases during stressful times.

In [1] a test with 21 students was conducted and 21 physiological features of five signals (heart rate, skin temperature, galvanic skin response of the hand, oxygen saturation, and breath-flow rate) were analysed. The stress induction protocol consisted of a neutral task, a non-stress task (listening to instrumental music), and a stress task (time-constrained arithmetic task). Stress was identified with an accuracy greater than 90% (Kappa = 0.84) using the k-NN classifier, using data from heart rate, skin temperature and oximetry signals and four physiological features. The identification of anxiety was achieved with an accuracy greater than 95% (Kappa = 0.90) using the SVM classifier with the data from the Galvanic Skin Response (GSR) signal and three physiological features. The maximum achieved accuracy for two class stress recognition was 95.98%, obtained with k-NN (5 signals, 13 features), and for anxiety recognition it was 98.89%, obtained with SVM (3 signals, 6 features).

Heart rate, PPG (Pulse rate), skin temperature and 3-axial acceleration were used for automatic stress recognition in [23]. The dataset was acquired in the office environment from 4 users without stress induction methods. In total, 352 hours of physiological data were collected. k-NN, Decision Tree (DT) and Bagged Ensembles of Decision Trees (BE-DT) are the employed algorithms for data classification. The most predictable mood, in terms of classification accuracy of the personalized model, is Anger followed by Sadness, Happiness, Stress, Tiredness, Boredom, and the least is Calmness. The average accuracy of 70.60% for personalized approach and BE-DT was achieved.

3.1.4 Heart rate variability

Heart rate variability (HRV) is the physiological phenomenon of variation in the time interval between heartbeats. It is measured by the variation in the beat-to-beat interval. HRV is probably the most commonly used trait in stress detection, as it is considered a non-invasive biomarker of health.

The HRV extracted from PPG and ECG signals is utilized for stress recognition in [14]. The experiment was performed with six healthy participants performing mental arithmetic. The result shows that ten HRV parameters have significant differences between stress and non-stress states. Furthermore, the 10-fold accuracy of the stress state detection within subjects is 98% and the Leave-One-Participant-Out F1 score reaches 80% with the RF algorithm. The results demonstrate that the wrist-based PPG can provide HRV measurements that enable the recognition of mental stress as accurately as ECG, even for a short three-minute temporal window.

Authors in [15] propose a 1-dimensional Deep Wide Convolutional Neural Network with 6-fold cross-validation for stress recognition, based on HRV signal. The proposed methodology outperforms single kernel networks achieving classification accuracy up to 99.1%, better overall performance (avg. F1score 88.1%, avg. accuracy 89.8%), and more consistent behaviour across the study’s experimental phases.

3.1.5 PPG

The Photoplethysmography (PPG) consists of measuring blood volume in skin capillary beds in the finger, relying on the capability of blood for absorbing light. The advantage of PPG is that it is cheap and convenient and is a promising alternative to ECG. Blood Volume Pulse (BVP) is the measure of the volume of blood that passes over a PPG sensor with each pulse.

In [21], a system for recognizing several emotional states like 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal', 'No-Idea', 'Positive' and 'Negative' based on BVP, Galvanic Skin Response and Skin Temperature is proposed. The dataset is obtained from 24 participants. Emotion elicitation was performed with International Affective Picture System (IAPS). The results indicate that the system has an accuracy rate of approximately 97% with IBk classifiers and 98% with the decision tree (J48).

PPG signals have also been used for stress recognition in articles [14] and [23]. In [14] HRV was extracted from PPG signals, while in [23] pulse rate was extracted for stress recognition. Both papers are presented in detail in the previous section.

3.1.6 EDA

The Electrodermal Activity (EDA) is defined as a change in the electrical properties of a person's skin, caused by an interaction between the environmental events and the individual's psychological state. EDA is one of the best real-time correlates of stress. It can be measured with placing two electrodes on the skin surface, next to each other, while applying a weak electrical current between them.

In [5], EDA, ECG and EMG as well as Reaction Time (RT) were recorded for the purpose of stress recognition. Twenty-two students, divided in two groups, participated in the study. The first group of ten male students participated in the experiment of the visual stressor (Stroop test), while the second group of twelve female students participated in the experiment of the auditory stressor. Using physiological signals as well as RT, a classifier based on SVM was developed. The recognition is achieved by fusing the classification results of physiological signals and RT with the voting method, and a further improvement of recognition accuracy is observed. For the two-class classification problem visual stressor gave over 83.3% accuracy (up to 100% for different subjects), and auditory stressor gave over 71.4% (up to 100% for different subjects).

In [20] the authors utilized movie clips and images from the International Affective Picture System (IAPS) to evoke emotion in athletes. 86 samples of EDA data, gathered form 10 subjects, were determined for the four emotions: calmness, sadness, fear, and happiness. To improve recognition accuracy, the captured emotions were subjected to the baseline removal and particle swarm optimization (PSO) feature. The emotional model for the athletes was set up based on the emotional probability space of the Markov Chain (MC). The proposed method achieved recognition accuracy of 79.83±5.67% with particle swarm optimization k-NN algorithm.

Stress recognition based on EDA was also employed in other papers that were analysed previously [1, 7, 13, 19, 24].

3.1.7 EMG

An Electromyogram (EMG) measures the electrical activity of the muscles by using electrodes placed over the muscle of interest. As it is known that stress elevates muscle tone, many researchers have used EMG for measuring stress.

In [4], both EMG and ECG signals were acquired simultaneously from 34 healthy students. Mental arithmetic, Stroop colour-word test, under time pressure, and stressful environment were employed to induce stress in the laboratory. A well-trained SVM classifier was employed as a detection model to map the stress to two, three and four different levels. The accuracies of stress recognition in two, three and four levels were 100%, 97.6%, and 96.2%, respectively. It was found that the EMG signal of the right trapezius muscle recognizes stress better than other muscles.

3.1.8 Skin temperature

The temperature of the body is also used to detect the stress rate of a person. The average body temperature of an individual is around 36°C-37°C. Stressful situations result in consistent temperature changes. Acute stress triggers peripheral vasoconstriction, causing a rapid, short-term drop in skin temperature in homeotherms.

Skin temperature, in combination with other physiological signals, has been used in many studies [1, 12, 21, 23]. All these articles have already been analysed in the previous sections.

3.1.9 Respiration

Respiration Rate (RR), also known as ventilation rate or ventilation frequency, is the number of breaths (inhalation-exhalation cycles) taken within a set amount of time (typically 60 seconds). Human respiration rate is measured when a person is at rest and involves counting the number of breaths for one minute by counting how many times the chest rises.

Respiration rate or breath-flow rate or breathing rate is combined with other physiological signals in articles [1], [7] and [12] to build stress/emotion recognition systems. All these papers are already presented in the above sections.

3.1.10 Thermal Images

Because stressed persons suffer from temperature changes, stress states can also be recognized by thermal images, taken with an infrared camera. This signal acquisition method is unobtrusive, and thus interesting for development of stress recognition systems.

In [3], authors are focused on the establishment of a set of non-contact imaging-based classifications for Emotional Stress (ES) and Physical Stress (PS). A total of 60 healthy volunteers with different skin colours (Caucasians, Indians, Chinese, Malaysians, and South Africans) and different genders participated in the experimental trials. Stress was induced with heavy running, and the Trier Social Stress Test (public speaking in the form of an interview, mental arithmetic, and recognition memory task). In this study, a classification algorithm based on signal amplification and correlation analysis called Eulerian magnification-canonical correlation analysis is proposed. Sparse coding and canonical correlation analysis then fuse the original signal and its amplified features. The extracted entropy features are used to train the correlation weight between ES and PS, which formulates stress classifications. With the new classification method, based on Back Propagation (BP) neural network, an accuracy rate of 90% was achieved.

In [24], the efficacy of using a far infrared (FIR) camera for detecting robot-elicited affective response compared to video-elicited affective response by tracking thermal changes in five areas of the face, is evaluated. Ten healthy adults participated in the study for a duration of approximately 30 minutes. The principal component analysis is performed to reduce the dimensionality of data and to evaluate the performance using machine learning techniques (SVM 2-state emotion classifier) for classifying thermal data by emotion state, resulting in a thermal classifier with a performance accuracy of 77.5%.

3.2 Stress recognition based on behavioural signals

3.2.1 Body gestures and movements

Body language refers to the nonverbal signals that we use to communicate. Persons under stress show various changes in behaviour as well as changes in body movement or body gestures, such as: jaw clenching, arm movements, self-touching, finger rubbing, posture change etc.

Features related to head movements and pose were computationally estimated and analysed in [13]. The subjects participating in this experiment were exposed to Social Exposure, Emotional Recall, Stressful images/Stroop Color Word Task, and Stressful videos. The results indicate that specific stress conditions increase head mobility and mobility velocity, in both translational and rotational features. For the dataset classification k-NN, the Generalized Likelihood Ratio (GLR), and SVM were utilized. The highest classification accuracy (for a 2-class scenario) was obtained during the social exposure which includes the interview task: k-NN =98.6 %, GLR =97.9 %, and SVM =97.2 %.

In [19] authors propose a framework for recognition of stress and fatigue based on affective and corporal indicators: body parts movements (Head, Shoulder, Elbow, Palm), GSR, HR, and EDA. The framework has been experimentally validated on a dataset of 25 subjects. The dataset consists of 1064 intervals of 20 sec. each for both GSR and HR recordings. Stress was evoked with customized version of the Stroop Colour Word test. The inference system takes the values of the GSR and HR features as input and based on a set of appropriate fuzzy rules (Fuzzy Inference Systems-FIS), it calculates an estimation regarding the subject's stress level, encoded in the range [0, 1]. At the authentication stage, each movement is compared to the corresponding template signatures via the HMM classification algorithm, and the returned probability is held as the matching score. The proposed framework decreases the FAR (False Acceptance Rate) and FRR (False Rejection Rate) in the equal error rate-EER point from 7.8% to less than 3.2%.

3.2.2 Facial expressions

Stress and emotional states have a correlation with facial expressions, and thus can be recognized from them.

In [11], a method for recognizing stress by extracting high-dimensional features from face images acquired by a general camera is proposed. The total number of collected images (from 50 subjects) was 242,730 divided into three classes – no stress, weak stress, and strong stress. In the proposed deep neural network, the face images and face landmarks detected earlier are inputted to output stress recognition results. The achieved classification accuracy was 64.63%.

In [25], the authors investigate human facial expressions associated with visual discomfort, from a face captured by a camera. The visual discomfort was induced by excessive screen disparities of stereoscopic three-dimensional contents - 8 video sequences (10 second length and about 300 frames per video). The acquired database contained approximately 230 face videos (696,000 frames) from 29 adult participants. The relevance scores (confidence values) between the facial expressions caused by the visual discomfort and the six emotional facial expressions (“stressed”, “fear”, “happiness”, “sadness”, “surprise” and “neutral”) were measured. As a result, it is observed that the emotional facial expression of “stressed” (i.e., anger or disgust) highly correlated with visual discomfort (Pearson correlation coefficient: 0.91). Based on this observation, a simple and practical discomfort measurement method (+1 for the class “Discomfort” and -1 for the class “Comfort”) was designed and its feasibility was successfully verified (classification accuracy of 81.42% achieved with the binary SVM classifier with an RBF kernel).

3.2.3 Handwriting and drawing

Handwriting, drawing, and signature biometrics provides opportunities for personal characteristics estimation, particularly emotional state. Biometrics can be represented in two ways: off-line and on-line. The input of the off-line systems is an image of a written text; the image is pre-processed by grey scaling, removing noise, and segmenting characters and words. On the other hand, on-line systems take the input through an electronic pen used during the handwriting/drawing/signature process.

In [16], the first publicly available database which relates emotional states to handwriting and drawing, the so called EMOTHAW (EMOTion recognition from HAndWriting and draWing) is presented. This database includes samples of 129 participants whose emotional states, namely anxiety, depression, and stress, are assessed by the Depression–Anxiety–Stress Scales (DASS) questionnaire. During the data acquisition process, the subjects performed seven different writing or drawing tasks. Stress recognition with Random forest based on drawing and writing features achieved 60.2% accuracy, while stress recognition with SVM obtained 55% accuracy.

In [18], a system for stress recognition based on handwriting and signature biometrics is proposed. The database was comprised of a total of 134 participants with 804 handwriting and 8040 signature biometric samples. The participants performed 2 text-dependent and 2 text-independent tasks. Video and time constrain were applied during task performance. This study focuses on the online features collecting path and time dependent features. k-NN, JRIP and Random Forest were utilized as classification algorithms in a three-class scenario (happy, sad and stress). The best prediction accuracy is achieved using a Random Forest classifier with accuracies approximately between 55% - 58% for the handwriting and 45% - 50% for the signature biometrics.

3.2.4 Keystroke dynamics

Keyboard usage dynamic is important behavioural data for stress detection. Various subjects have different keyboard writing speeds and styles. The muscles of the stressed individual contract much more than regular, which affects the pressing of the keyboard.

In [26], the stress recognition method that utilizes keystroke interaction details (pressure, speed, duration, key type) is presented. The classification dataset was acquired during a 3-week in-the-wild study involving 24 participants. A custom keyboard capable of tracing users’ interaction patterns during text entry was used. Interaction details such as touch speed, error rate, pressure, and self-reported emotions (happy, sad, stressed, and relaxed) were collected during the study. The analysis of the collected dataset reveals that the representation learned from the interaction pattern has an average correlation of 0.901 within the same emotion and 0.811 between different emotions. As a result, the representation is effective in distinguishing different emotions with an average accuracy of 84% with the LSTM (Long Short-Term Memory) encoder combined with multitask learning based deep neural network.

4. **Discussion and conclusion**

The aim of this review was to provide an overview of the stress recognition systems, along with the techniques and methods used. Although different modalities can be used to recognize stress, the most dominant method for recognizing stress is physiological signals. This does not mean that behavioural and contextual information do not have the potential to correctly detect stress, but there is still much work to do in this area. The results also suggest that ECG, especially using HRV features, and EDA are the most accurate physiological signals for recognizing stress.

For classification of the acquired datasets, the following machine learning algorithms were used: k-NN, SVM, RF, JRIP, GDA, IBk classifier and Logistic Regression. In a number of stress/emotion recognition methods neuro fuzzy logic is presented: deep learning model, ANFIS, fuzzy ARTMAP, deep wide CNN, LSTM encoder combined with multitask learning based deep neural network. The proposed stress recognition techniques are tested on different datasets, obtained during experiments with human participants. Different number of participants took place in different experiments, with different duration time. Thus, it is very difficult to conclude which machine learning technique or neuro fuzzy system is most suitable for stress detection. The authors report SVM as the most successful machine learning technique for stress recognition, as it is the most widely used.

Despite the impressive progress made in recent years in the field of stress recognition, the systems mentioned above are still under research and not available for customers. We hope that this review paper will help future researchers to choose the best techniques and methods for achieving their goal of stress detection and recognition.

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