Journal of Emerging Computer Technologies
Research Article
Received: *2021-10-22* | ***Reviewing:*** *2021-10-22* & *2022-01-07*| ***Accepted:*** *2022-01-07* | ***Online:*** *2022-01-08* | ***Issue Date:*** *2021-12-31*

Overview of Techniques and Methods for Stress Recognition

Natasa Koceska
Faculty of Computer Science,
University of Goce Delchev, "Krste Misirkov" 10-A,
Shtip, North Macedonia
natasa.koceska@ugd.edu.mk
0000-0002-3392-8871

Saso Koceski
Faculty of Computer Science,
University of Goce Delchev, "Krste Misirkov" 10-A,
Shtip, North Macedonia
saso.koceski@ugd.edu.mk
0000-0002-5513-1898

***Abstract*— Stress has become a significant cause of many diseases in modern society, such as high blood pressure, atherosclerosis, heart disease, obesity, diabetes, insomnia etc. Moreover, the Covid-19 pandemic negatively affects people's mental health, increasing depression and anxiety. This raised the question of whether automatic stress detection and recognition systems can be developed and used in everyday life. In this review study, we will examine the recent works on stress recognition systems by reviewing the techniques and methods used. Only studies involving human participants were taken into consideration, as no such analysis has been made so far. By providing a comprehensive review of the state-of-the-art, we would like to encourage other researchers to take active participation in the field of stress research as well as to explore the benefits and opportunities offered by stress recognition systems.**

***Keywords*— Stress recognition, stress detection, physiological, behavioural, multimodal, machine learning**

I. Introduction

Stress can be defined as any type of change that causes physical, emotional, or psychological strain. When you experience changes or challenges (stressors), your body produces physical and mental responses. These stress responses help your body adjust to new situations. 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.

Stress can be positive ("eustress"), keeping us alert, motivated and ready to avoid danger. This positive stress can improve the performance in everyday situations (e.g.: during a stage performance, during job presentation, during school exams, winning a race etc.). Stress becomes a problem (negative stress - "distress") when stressors continue without relief or relaxation between challenges. As a result, the person becomes overworked and creates stress-related tension, which affects their lifestyle.

Human body is well equipped to handle stress in small doses, but when that stress becomes long-term or chronic, it can have serious effects on the body. Evidence indicate that severe or prolonged (chronic) stress resulted in increased risk for physical and mental disorders, which is called stress-related disease. Stress is the common risk factor of 75%–90% diseases, including cardiovascular diseases, metabolic diseases, psychotic and neurodegenerative disorders, cancer etc. Thus, it is necessary to manage mental stress before it causes negative impacts on people. For the proper management, it should be beneficial to recognize whether individuals become stressed or not whenever they stand in the middle of stressful episodes. In addition, detecting and recognizing stress play a particularly important role in certain work environments.

Much progress has been done in the last years towards the development of an automatic stress recognition systems. Various approaches exist that involve the use of physiological signals (heart rate variability, hormone levels, electrocardiogram, etc.), behavioural responses (keystroke and mouse dynamics, posture, mobile phone usage, etc.), contextual events (place, time, ambient factors), and multi-modal techniques (combination of multiple type of data).

This work reviews and brings together the recent works carried out in the last 5 years, in the field of stress recognition. The stressors, techniques, results, advantages, limitations, and issues for each study are highlighted and expected to provide a path for future research studies.

II. Methodology

The approach adopted in this review firstly performs search through two databases: Science Direct and IEEE Xplore, with the search keywords: "stress recognition" OR "stress detection". Relevant papers were considered only papers published in last 5 (from 2016 till the end of 2020). This was considered appropriate due to the rapid technology development in this field.

The result of the query was a set of over 200 articles from both databases. After careful analysis (titles and abstracts of all papers were reviewed in order to retain only the relevant ones), and duplicate removal, 73 research papers from journals, conferences or early access articles, were selected for further reading. These articles were divided into two groups: articles where stress recognition is made using data from the existing databases, and articles where stress detection and classification is performed using the human participants.

After identifying the main modalities involved in the current state of stress recognition, it was decided in this review study to analyze only the second group of articles (with user participation), as no such analysis has been made so far. Thirty research papers were identified and included in the final analyses. Each one of the selected papers was fully read and specific information were extracted. The collected information is summarized in Table I.

III. Reporting the results

Selected papers were divided into two major groups: studies where stress recognition was done using physiological signals and studies where behavioural signals are used for stress recognition.

TABLE I. SUMMARY OF SELECTED PAPERS

Ref. Num	Parameters measured	Hardware (sensors) used during the measurement	Measuring environment	Stress induction	Algorithm	Results (accuracy)	Advantage/Disadvantage	Limitations
[1]	Heart rate , skin temperature, galvanic skin response of the hand, oxygen saturation, and breath-flow rate	E-Health V2 (Cooking Hacks, Spain) shield and the Arduino Uno board	Academic environment-laboratory settings	Neutral task, non-stress task (listening to instrumental music), and a stress task (time-constrained arithmetic task)	Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest and Logistic Regression (LogR)	Two class stress: KNN - 95.98% anxiety: SVM - 98.89%	/	Only one type of stress task was tested
[2]	EEG	Wearable EEG sensor (Emotiv EPOC+)	3 construction sites	Job site stressors: working hazards and tiredness	k-Nearest Neighbors (k-NN); Gaussian Discriminant Analysis (GDA); Support Vector Machine (SVM)	80.32% - Gaussian SVM	Need of applying multi-subjects/tasks learning algorithms, which optimize classifier parameters for different tasks and subjects (on contrary of static ones applied)	/
[3]	Thermal images	FLIR SC7600 thermal IR imager (infrared camera), chest strap heart monitor (Garmin) and a finger probe (Miroxi) to measure HR	Laboratory settings	Heavy running, Trier Social Stress Test	Eulerian magnification-canonical correlation analysis (EM-CCA) Back propagation (BP) neural network	90%	More efficient and accurate thermal imaging tracking algorithm is required. Relationship between amplification intervals and different types of stress should be further refined, here it is based on blind source analysis	/
[4]	EMG, ECG	ECG v.12 Bayamed, Datalog Biometrics (EMG), SX230 surface electrode (EMG) and Skintact F-55 electrode (ECG)	Laboratory settings	Mental arithmetic, Stroop color-word test	SVM with RBF kernel	Two, three and four levels classification 100%, 97.6%, and 96.2%,	/	Lack of evaluation in real-world applications - recording EMG signals in an uncontrolled environment is challenging
[5]	Electrodermal activity (EDA), Electrocardiography (ECG), Electromyography (EMG), Reaction Time (RT)	BIOPAC System, Two LEDs (for RT measurement)	Laboratory settings	Visual stressor (Stroop test) and auditory stressor	SVM	Visual stressor – over 83.3% Auditory stressor – over 71.4%	/	/
[6]	EEG	Wired-EEG Wearable EEG device- Emotiv EPOC+	Dataset for Emotion Analysis Using Physiological Signals (DEAP) 3 construction site	Music, videos job sites stressors	OMTL-Covariance, OMTL-LogDet, OMTL-Vonneumann	OMTL-VonNeumann 71.14% - DEAP dataset 77.61% - construction site dataset	Near real-time stress recognition, reduce workers' injuries, accidents, and errors	/
[7]	ECG, EDA, respiration	Zephyr BioModule, Empatica E4, LG Watch Style	Laboratory settings-experimental room	socio-evaluative stressor and a cognitive stressor	Naïve Bayes, LibSVM, IBk, Multi-ClassClassifier, JRip, and Random Forest Neural network	three class - 78.7% two class – 98.3%	/	/
[8]	EEG	EEG reusable electrodes from supplier BIOKIT	Laboratory settings	Stroop color-word test	SVM	72.3%	/	/
[9]	ECG (Heart rate), PPG (Pulse rate), skin temperature and 3-axial acceleration	Toshiba Silmee Bar Type wearable sensor, Silmee W20/W212 wristband sensor	Office environment	/	k-Nearest Neighbour (k-NN), Decision Tree (DT) and Bagged Ensembles of Decision Trees (BE-DT)	Average accuracy of 70.60% for personalized approach and BE-DT	/	Larger study is required to confirm the significance of the results
[10]	EEG	Emotiv Epoc neuroheadset	Laboratory settings	Stroop colour-word test and mental arithmetic test	SVM	75%	/	/
[11]	ECG, EDA	Three-lead ECG sensor, two-lead EDA sensor attached on the BITalino - wearable sensor platform	Real life settings – relaxing periods and exam periods	Written exam and oral exam	SVM, Linear Discriminant Analysis, Ensemble, kNN, Decision Tree J4.8	91% with SVM	/	/
[12]	Face images, facial landmarks	General camera	Laboratory settings	Predefined experimental scenario	Deep neural network	64.63%	/	/
[13]	ECG, EDA, RSP (respiration), BVP (blood volume pulse), and SKT (skin temperature)	Shimmer3 ECG Unit and the Empatica E4 wristband	Laboratory settings	Four horror clips and a cognitive test	k-Nearest Neighbors (kNN) Decision Tree (DT) Random Forest (RF)	84.13%	/	/
[14]	HRV (extracted from ECG)	Three bipolar silver-chloride electrode pads	Laboratory settings	Trier social stress test	Fuzzy ARTMAP (FAM) neural network	Ensemble FAMs 80.57%	Processing salivary samples to derive the alpha-amylase and the cortisol as objective indicators of stress is a long and laborious process	/
[15]	Spatiotemporal behaviour of the head (i.e. head motion and head pose patterns)	High performance color camera – for video recording	Laboratory settings	Social Exposure, Emotional Recall, Stressful images/ Stroop Color Word Task, Stressful videos	K-nearest neighbours (K-nn), Generalized Likelihood Ratio (GLR), Support Vector Machines (SVM)	For social exposure K-nn =98.6 % GLR =97.9 % SVM =97.2 %	/	/
[16]	(ECG, PPG)-HRV	Wristband PPG device, Polar h10	Laboratory settings	Mental arithmetic	Random forest	5 min ECG-97.94%, 5 min PPG-98.48%	Consumer-grade wrist-based PPG sensor is used, which is affordable, convenient, and with reason- able accuracy as consumer ECG sensors	/

[17]	ECG-HRV	Two Ag/AgCl electrodes were placed in symmetric position of the chest	Laboratory settings	Social exposure, recall of a stressful event, cognitive load, watching of stressful videos	1-dimensional Deep Wide Convolutional Neural Network	89.9%	/	/
[18]	Handwriting and drawing	INTUOS WACOM series 4 digitizing tablet and a writing device- Intuos Inkpen	Laboratory settings	/	Random forest and SVM	Random Forest-60.2% SVM - 55 %	Providing a handwriting/ drawing database to the scientific community for further testing.	Involved a specific class of subjects (students) - does not allow for a generalization of the identified features
[19]	ECG signal (Heart Rate), Galvanic Skin Response and Respiration Rate	Pasco sensors	Laboratory settings - Multiplex 7D Cinema	Not specified	Artificial Neural Network – feedforward network	Accuracy-99% Sensitivity-98%	/	/
[20]	EEG	14-channel Emotiv device	Laboratory settings – flight scenario	Training program	LDA, 1-NN, SVM, Naïve Bayes	3 emotions with SVM 72.22% 4 workload levels with SVM 74.23%	/	/
[21]	Handwriting and signature	Pressure sensitive tablet called Wacom Intuos Pro – large (19”x12.5”) and a writing device called Intuos Inkpen (Wacom Art Pen - KP701E2)	Laboratory settings	Video, time constrains for task performance	K-Nearest Neighbor (k-NN), JRIP and Random Forest	three class classification 55% - 58% for the handwriting 45% - 50% for the signature biometrics	Offline and online handwriting and signature biometric database with a wide range of ground truths (emotional status labels – happy, sad and stress) in addition to the identity labels	/
[22]	Body parts movements (Head, Shoulder, Elbow, Palm), Galvanic Skin Response (GSR) (fatigue, stress), Heart Rate (HR) (fatigue and stress), Skin Conductance Response (SCR) (fatigue)	Kinect sensor for movements of each subject, GSR and ECG sensors	Laboratory settings – indoor environment	Customized version of the Stroop Colour Word test	Fuzzy Inference Systems (FIS)	/	/	/
[23]	EDA	BioNeuro multichannel biofeedback instrument (Thought Technology, Canada)	Laboratory settings	Movie clips and images (International Affective Picture System (IAPS))	Particle swarm optimization (PSO)-k-nearest neighbor’s algorithm (kNNs)	79.83±5.67%	/	/
[24]	ECG signal -heart rate, respiration, temperature and Skin Conductance	4 sensors with a NeXus-10 MKII, motion capture system VICON	Outdoor environment (controlled)	Disturbance command sent to the UAV	ANFIS (Adaptive neuro fuzzy inference system) model	/	/	/
[25]	Blood Volume Pulse, Galvanic Skin Response and Skin Temperature	eHealth sensor- left arms, palms and fingers	Laboratory settings	International Affective Picture System (IAPS)	decision tree (J48) and IBK classifiers	J48=98.63% IBK=97.4%	/	/
[26]	Combination of behavior data (body movement and hand movement) and weather conditions	Web-camera	Office settings	/	K-Nearest Neighbors (k-NN) Support Vector Machine (SVM) Decision Tree (D-Tree)	SVM algorithms generic model – 83% personalized model – 91%	/	/
[27]	EEG signal	MindWave Mobile sensor attached on forehead	Laboratory settings	Music	Deep back-propagation network	80.13%	/	/
[28]	Thermal data from five facial regions, electrodermal activity (EDA)	InfrREC R300SR-S high resolution infrared video camera, Empatica E3 electrodermal activity (EDA) sensor, modified version of MyKeepon robot	Laboratory settings	Two interactive sessions with a robot and three sets of video clips	Principal component analysis (PCA), logistic regression and a support vector machine (SVM)	77.5%	/	The sample size is small and results may not be representative of the larger population. The order of elicitation method might influence the classification results.
[29]	Human facial expressions associated with visual discomfort	Linear polarized stereoscopic display (Redrover SDM-400®), high definition camcorder (SONY HDR-XR350®)	Laboratory settings	Excessive screen disparities of stereoscopic three-dimensional (S3D) contents- 8 video sequences	binary SVM classifier with a RBF kernel	81.42%	Novel facial expression database regarding the visual discomfort	/
[30]	Interaction details (pressure, speed, duration, key type)	Android based custom keyboard	In-the-wild	/	LSTM (Long Short-Term Memory) encoder + multitask learning (MTL) based deep neural network (DNN)	84%	MTL is used to train the model using all users data vs relying only on personal data Automatic representation learning	/

A. Stress Recognition Based On Physiological Signals

a) *EEG (Electroencephalogram) signal* - is a neuro signal which is generated due to various electrical activities in the brain, and is measured using electrodes placed on the scalp. Several types of electrical activities correspond to different states of the brain, e.g., Alpha waves 7.5–13Hz, Beta waves 15–20Hz, Gamma waves 38–higher Hz, Delta waves 0.5–4Hz and Theta waves 4–7.5Hz. These signals can be captured and processed to get the useful information. The presence of stress can be identified by the changes of EEG Alpha and Beta power. 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. A number of papers used EEG as for stress recognition.

The authors in [2] propose a procedure to automatically recognize workers' stress in construction sites using EEG signals. EEG signals were obtained from 11 male workers working on three construction sites. Workers were exposed on 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 when working on construction sites. 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, 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 (where wired EEG devices were used and the subjects were engaged in minimal body movement).

EEG-based stress recognition framework that takes into account subject’s brainwave patterns to train the stress recognition classifier and continuously update it, based on new input signals in near real-time is proposed in [6]. The proposed framework applies different Online Multi-Task Learning (OMTL) algorithms to recognize individuals’ stress in near real time. The proposed framework was applied on the EEG collected in two environments. The first EEG dataset was collected in a controlled lab environment from 32 subjects using a wired-EEG (DEAP dataset). The second dataset was collected at in the field using a wearable EEG device, from 7 healthy workers on three real construction sites, while facing various stressors (working at the top of a ladder in a confined space). The OMTL-VonNeuman method resulted in the best prediction accuracy on both datasets (71.14% on the first and 77.61% on second dataset) among all tested algorithms (two class classification).

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 (aged 20 to 35 years) are collected. Validation of algorithm is carried out using Stroop Color Word Test (SCWT) as the stressor to induce various stress levels. Measure of stress is taken by means of questionnaires method. Discrete Wavelet Transform (DWT) is used for pre-processing and SVM is used as the classifier. Average accuracy for subject independent model is about 72.3%.

In [10] a framework for stress recognition based on power band features from EEG signals and relative difference of beta and alpha power as feature is proposed. A total of 10 subjects (9 male and 1 female.) participated in dataset acquisition experiment. All the subjects were healthy, at the age of 20 to 35 years. For stress elicitation SCWT and mental arithmetic test were utilized. With SVM as classifier, three-levels of stress can be recognized with an accuracy of 75%. For two-level stress analysis, accuracy of 88% and 96% are achieved for SCWT test and mental arithmetic test respectively.

EEG based human factors evaluation tools allows workload, emotion and stress recognition during the air traffic control operators’ task performance with high temporal resolution [20]. 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. Training program was interrupted after 15, 60 and 120 minutes. SVM was used for three class emotion classification with achieved accuracy of 72.22% and for four class workload level classification with obtained accuracy of 74.23%.

In [27] a system which 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 the music. The system used this data to predict the test 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.

b) *ECG (Electrocardiogram)* - one of the most prominent signals for discriminating stress is the heart activity, as the Autonomous Nervous System (ANS) directly affects the heart rate. ECG is a standard heart rhythm measurement that track electrical impulses during the contraction and relaxation of the heart. For a standard threepoint ECG, three electrodes are placed on the subject’s torso, measuring the depolarisation and repolarisation of the heart tissue during each heartbeat. Sampling rates of ECG devices range up to 1024 Hz. ECG is frequently used to extract information about Heart Rate (HR) and Heart Rate Variability (HRV).

The authors in [7] propose a stress state classification method by considering not only users’ subjective evaluations but also temporal changes of stress responses in short periods. Dataset was obtained with measurement of ECG, Electrodermal activity (EDA) and respiration (RSP) signals from 40 subjects, 17 females and 23 males.

Dataset acquisition was performed in laboratory settings, where the stress induction was achieved by socio-evaluative stressor (interview in English) and a cognitive stressor (cross out alphabet “e”s in a document). 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-Class Classifier, JRip, and Random Forest Neural), as well as the implemented neural network algorithm based on the labeled data, were trained and tested for stress recognition. The achieved classification accuracy with neural network models are 78.7% for three class scenario and 98.3% for 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.

Features of the ECG and EDA signals were used as input for different classification methods (SVM, Linear Discriminant Analysis, Ensemble, kNN, Decision Tree J4.8) in [11]. Students, wearing sensors, were monitored in real life settings (during exams), in order to recognize the experienced stress levels. An experimental study was conducted with 10 students (4 male and 6 female, 19-26 years old), with no major health issues. 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 [13] the physiological signals: ECG, EDA, RSP (respiration), BVP (blood volume pulse), and SKT (skin temperature) are acquired for stress recognition. Participants in the experiments included 30 subjects in the range of 25 to 35 years. Stress was elicited by four horror clips and a cognitive test (i.e., an arithmetic task - final stage of the Trier Social Stress Test) at the end. The horror clips have been selected from the Emotional Movie Database (EMDB). The experiments were conducted to induce two main states: no-stress and stress. Decision Tree (DT), k-Nearest Neighbors (kNN) and Random Forest (RF) were employed for dataset classification. The proposed multi-modal machine-learning algorithm, based on the random forest 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 an average accuracy of 83.33%.

ECG was used for stress recognition in articles [4] and [5] as well. In article [4] it was used together with EMG signal, and in article [5] it was combined with EDA, Electromyography (EMG) and Reaction Time (RT). These two articles will be analyzed in details in the following sections.

c) *Heart rate* - is the speed of the heartbeat measured by the number of contractions of the heart per unit of time, typically beats per minute (bpm). The heart rate can vary according to the body's physical needs, including the need to absorb oxygen and excrete carbon dioxide. It is usually equal or close to the pulse measured at any peripheral point. Activities that can provoke change include physical exercise, anxiety, stress, illness, ingesting drugs etc.

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 analyzed. 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). Four classifiers (SVM), k-NN, Random Forest and Logistic Regression) were compared to find the physiological feature subset that provides the best accuracy to identify states of stress and anxiety. Stress was identified with an accuracy greater than 90% (Kappa = 0.84) using the k-Nearest Neighbors 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 data from the galvanic skin response signal and three physiological features. Maximum achieved accuracy for two class stress recognition was 95.98% obtained with k-NN (5 signals, 13 features), while for anxiety recognition 98.89% was obtained with SVM (3 signals, 6 features).

Heart rate, respiration rate, foot galvanic skin response and hand galvanic skin response were used for stress recognition task in [19]. Artificial Neural Network (ANN) was trained using data from Physionet database as well as data collected from other researchers. Developed neural network was validated with 77 samples. Samples were obtained from subjects in 7D cinemas. Output data was classified into two output classes: stress and no stress. The achieved accuracy with the proposed method was 99% and sensitivity was 98%.

The article [24] presents a prototype that monitors the physiological conditions of the pilot in order to recognize the altered states that have occurred. If the system recognizes the certain stress condition, the system overrides the pilot's commands, which under altered (stress) states may be erroneous. Thus, the system takes over the command of the plane UAV (Unmanned Aerial Vehicle) in order to perform a safe routine flight such as landing or flying back to a safe location. This test was performed with 13 subjects, once per person. ECG signal-heart rate, respiration, temperature and skin conductance were collected in dataset acquisition phase. The experiments were conducted outdoor, introducing stress with disturbance command sent to the UAV. For the test with the ANFIS (Adaptive Neuro Fuzzy InferenceSystem) model, 3 different types of models (Grid Partitioning, Subtractive Grouping, and fuzzy c-means) were used, from which the fuzzy c-means showed best results in the prediction of values.

In [9] heart rate, PPG (Pulse rate), skin temperature and 3-axial acceleration were used for automatic stress recognition. In this paper the dataset was acquired in office environment from 4 users without stress induction methods. The participants were observed 11 working days, resulting in 44 segments per user. In total, 352 hours of physiological data was collected. An advanced multi-classification model of 8 distinct moods and 5 levels of intensity, operating on 2-hour time windows is proposed. k-NN, Decision Tree (DT) and Bagged Ensembles of Decision Trees (BE-DT) algorithms were employed 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. Average accuracy of 70.60% for personalized approach and BE-DT was achieved.

Heart rate was used for stress recognition in [22] as well. Here it was combined with behavioural signals: Galvanic Skin Response (GSR), and Skin Conductance Response (SCR). This paper will be analyzed in details in the following section.

d) *Heart Rate Variability (HRV)* - is also a common measure of human stress state, as it reveals the balance between the sympathetic and parasympathetic nervous system. When the sympathetic nervous system is triggered, and the parasympathetic system is suppressed, which is called fight-or-flight reaction, epinephrine and nor-epinephrine hormones are secreted. This process evokes the increase of blood pressure (BP), heart rate (HR), muscle tension, skin conductance, and the decrease of HRV. When parasympathetic system is activated and sympathetic system is suppressed, which is called relax and digest process, the opposite physiological response as that of fight-or-flight process will be triggered. Generally, HRV features are generated from the successive R-R intervals of ECG.

Authors in [14] measured the salivary alpha-amylase and cortisol as objective measures of stress. These data were then correlated with the HRV features using fuzzy ARTMAP (FAM) neural network. A total of 176 ECG recordings and 264 salivary samples were obtained from 22 subjects while performing Trier Social Stress Test. 17 male and 5 females subjects, with an average age of 21 years, participated in this research. The ensemble of FAMs is used for predicting stress responses of salivary alpha-amylase or cortisol using heart rate measurements as the input. Using alpha-amylase as the stress indicator, the ensemble was able to classify stress from heart rate features with 75% accuracy, and 80% accuracy when cortisol was used.

HRV extracted from PPG and ECG signals is used for stress recognition in [16]. The experiment was performed with six healthy participants (ages 21-40 years), 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 stress state detection within subjects is 98% and the Leave-One-Participant-Out F1 score reaches 80% with Random Forest algorithm. The results demonstrate that 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 [17] proposes 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 study's experimental phases. 24 participants (7 women and 17 men) participated in this study. In order to investigate the effects of stress conditions, stress experiment that included social exposure, recall of a stressful event, cognitive load, and watching of stressful videos, was designed and developed,

e) *Blood Volume Pulse (BVP)* - is the measure of the volume of blood that passes over a PPG sensor with each pulse. Photoplethysmography (PPG) is the low-cost optical technique to measure BVP. It uses the absorption of light by blood. After light is emitted from a light source, different amounts of blood in the volume will absorb different amount of light. In this manner, blood volume can be measured.

In [25] a system for recognizing several emotional states like 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal', 'No-Idea', 'Positive' and 'Negative' based on BVP, GSR and Skin Temperature is proposed. Dataset is obtained from 24 participants; each experiment took from 11 to 12 minutes; the sample rate of all physiological sensors were 650 Hz. Emotion elicitation was performed with International Affective Picture System (IAPS). Decision tree (J48) and IBk classifiers were utilized for dataset classification. The results indicate that the system has an accuracy rate of approximately 97% with IBk and 98% with J48.

BVP together with ECG, EDA, respiration and skin temperature, was already used to identify stress in the article [13].

f) *The Electrodermal Activity (EDA)* - is defined as a change in the electrical properties of a person's skin, caused by an interaction between environmental events and the individual's psychological state. EDA is commonly measured at locations with a high density of sweat glands, e.g. palm/finger or feet, by means of two electrodes placed on the skin surface, next to each other, while applying a weak electrical current between them. The minimal sampling rate to decompose the EDA signal into skin conductance level and skin conductance response contributions is around 30 Hz.

In [5] EDA, ECG and Electromyography (EMG) as well as Reaction Time (RT) are recorded for the purpose of stress recognition. 22 students, divided in two groups, participated in the study. The first group of 10 male students participated into the experiment of visual stressor (Stroop test) while the second group of 12 female students participated in the experiment of auditory stressor. Using physiological signals as well as RT, a classifier based on the SVM was developed. The strategy of recognition using the decision fusion is presented in this paper. The recognition is achieved by fusing the classification results of physiological signals and RT with the voting method. For 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 [23] the authors utilized movie clips and images from International Affective Picture System (IAPS) to evoke emotion in athletes. The experimental paradigm designed for emotion induction effectively aroused four common emotions: calmness, sadness, fear, and happiness. Ten subjects, 6 males and 4 females, participated in the experiments. The indoor temperature was controlled at around 20°C. In this way, 86 samples of EDA data were determined for the four emotions. To improve recognition accuracy, the captured emotions were subjected to 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. The proposed method achieved recognition accuracy of 79.83±5.67% with PSO – kNNs algorithm.

Stress recognition based on EDA was also employed in other papers that were subject of analysis [1, 7, 11, 19, 24, 25].

g) *Electromyogram (EMG)* - measures muscle action potentials by placing electrodes on selected muscles. Facial and Trapezius muscles are regions of interests for measuring muscle activity. The mean, median, standard deviation, RMS, peak loads and gaps per minute are the features that are used commonly.

In [4] both EMG and ECG signals were acquired simultaneously from 34 healthy students (23 females and 11 males, aged 20-37 years). Mental arithmetic, SCWT, under time pressure, and stressful environment were employed to induce stress in the laboratory. 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. These were obtained from the distinct combination of feature selection and machine learning algorithms-SVM with RBF kernel. It was found that EMG signal of the right trapezius muscle recognizes stress better than other muscles.

EMG signal combined with EDA, ECG and Reaction Time was also utilized for stress detection in article [5] (presented in previous section).

h) *Skin temperature* - the average body temperature of an individual is around 36°C-37°C. Stress effects result in changes in body temperature. 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 analyzed in the previous sections.

i) *Respiration (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. Commonly a chest belt (Respiratory Inductive Plethysmograph - RIP), which is either worn thoracically or abdominally, is utilized to measure the respiration pattern directly.

Respiration rate or breath-flow rate or breathing rate is combined with other physiological signals in articles [1], [7], [13], [19] and [24] to build stress recognition systems. All these papers are already presented in the above sections.

j) *Thermal Images* – because stressed persons suffer from temperature changes, stress states can also be recognized from thermal images, taken with 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 (55% male and 45% female) participated in the experimental trials. Stress was induced with heavy running, and Trier Social Stress Test (public speaking in the form of an interview, mental arithmetic, and recognition memory task). Classification algorithm based on signal amplification and correlation analysis called Eulerian magnification-canonical correlation analysis is proposed. This signal amplification algorithm expands the signals of ES and PS in different frequency domains. 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, it was achieved an accuracy rate of 90%.

In [28], 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. Localized changes in the face are analyzed in order to assess whether the thermal or electrodermal responses to emotions, evoked by traditional video techniques and by robots, are similar. Finally, 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%.

B. Stress Recognition Based On Behavioral Signals

a) *Body gestures and movements* - body language refers to the nonverbal signals that we use to communicate. According to experts, these nonverbal signals make up a huge part of daily communication. From our facial expressions to our body movements, the things we don't say can still convey volumes of information. Persons under stress show various changes in behavior as well as changes in body movement or body gestures, like: jaw clenching, arm movements, self-touching, finger rubbing, posture change etc.

Features related to head movements and pose were computationally estimated and analyzed in [15]. Towards this direction, facial landmarks were fitted using Active Appearance Models (AAM). The population of this study were 24 participants (7 women, 17 men) with age 47.3±9.3 years. The participants were exposed on Social Exposure, Emotional Recall, Stressful images/ SCWT, and Stressful videos. Data recordings belong to Semeoticons Reference Dataset for Stress Assessment SRDSA’15. Results indicate that specific stress conditions increase head mobility and mobility velocity, in both translational and rotational features. For dataset classification k-NN, Generalized Likelihood Ratio (GLR), and SVM were utilized. The highest classification accuracy (for 2 class scenario) was obtained during social exposure which includes the interview task: k-NN =98.6 %, GLR =97.9 %, and SVM =97.2 %.

In [22] 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 SCR. 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 SCWT. The average of GSR and HR, as well as the frequency of SCR occurrences were calculated for each interval. 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), 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. It should be mentioned that 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%.

Well-being recognition system where a deep learning technique is adopted to provide a non-invasive monitoring system in an office setting is proposed in [26]. The experiment was conducted on two human subjects in office environment without stress induction. The monitoring process lasted for a total of 60 days. The system extracted behaviour data (body movement and hand movement) using the trained body and hand detector based on a Faster Region-based Convolutional Neural Network (Faster R-CNN). The classification of the well-being level was performed with three features from two surveys, which covered both stress and mood. The employed classifiers were k-NN, SVM with linear kernel function and Gaussian kernel function, and Decision Tree (D-Tree). The achieved accuracy with SVM (binary classification problem) was 83% on generic model and 91% on a personalized model.

b) *Facial expressions* - stress and emotional states have a correlation with facial expressions, and thus can be recognized from them.

In [12] a method for recognizing stress by extracting high-dimensional features from face images acquired by a general camera is proposed. Fifty subjects took part in the experiment, with predefined scenario. The total number of collected images was 242,730 divided in 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 is 64.63%. Shortcut mapping and bottleneck architecture are used to optimize neural network structure. It is found that facial landmarks are better at perceiving stress because they allow us to better understand eye, mouth, and head movements.

The authors of the paper [29] 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 (S3D) 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 (21 males and 8 females). 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 binary SVM classifier with a RBF kernel).

c) *Handwriting and drawing* - provides opportunities for personal characteristics estimation, particularly, emotional state. These 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 paper [18] the first publicly available database which relates emotional states to handwriting and drawing, 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 data acquisition process the subjects were performing seven different writing or drawing tasks: drawing predefined objects/lines, writing in printed/cursive letters. Records consist in pen positions, on-paper and in-air, time stamp, pressure, pen azimuth, and altitude. Although the depression recognition systems have the best overall accuracies, they are the worst in ROC (Receiver operating characteristic) space. Stress recognition with Random forest based on drawing and writing features achieved 60.2% accuracy, while stress recognition with SVM obtained 55% accuracy.

In [21] a system for stress recognition based on handwriting and signature biometrics is proposed. The database 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, since on-line systems generally perform better than their off-line counterparts. k-NN, JRIP and Random Forest were utilized as classification algorithms in three class scenario (happy, sad and stress). Considering handwriting and signature biometrics, the best prediction accuracy is achieved using a Random Forest classifier with accuracy between 55% - 58% for the handwriting and 45% - 50% for the signature biometrics.

d) *Keystroke dynamics* – various subjects have different keyboard writing speed and style. The muscles of the stressed individual contract much more than regular, which affects the pressing of the keyboard. Thus the Keystroke dynamic can be use as a valid behaviour data for stress detection.

In [30] stress recognition method that utilizes keystroke interaction details (pressure, speed, duration and key type) is presented. The classification dataset was acquired during 3-week in-the-wild study involving 24 participants (20 male and 4 female). A custom keyboard capable of tracing users' interaction pattern during text entry was used. Interaction details like touch speed, error rate, pressure and self-reported emotions (happy, sad, stressed, and relaxed) were collected during the study. The analysis on 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 (AUCROC) of 84% with LSTM (Long Short-Term Memory) encoder combined with multitask learning (MTL) based deep neural network (DNN).

IV. Discussion and conclusion

The aim of this review was to provide an overview of 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. From 30 analyzed articles in this review study, systems for stress recognition based on physiological signals are proposed in 22 articles; the other 8 papers use behavioral signals. From the physiological signals only EEG was used independently, the other signals were used in combination with other signals. Most widely used signal is ECG and its derivatives: heart rate and heart rate variability;

For classification of the acquired datasets the following machine learning algorithms were used: k-Nearest Neighbours, SVM –Support Vector Machine, Random Forest, JRIP, GDA - Gaussian Discriminant Analysis, IBk classifier, LR – Logistic Regression. In a number of stress/emotion recognition methods neuro fuzzy logic is presented: deep learning model, ANFIS (adaptive network-based fuzzy inference system), fuzzy ARTMAP (FAM), deep wide Convolutional Neural Network (CNN), LSTM (Long Short-Term Memory) encoder combined with multitask learning (MTL) based deep neural network (DNN).

The proposed stress recognition techniques are tested on different datasets. Different number of participants took place in the different experiments. The duration of time series as well as the number of collected images varies depending on the scenario. Further, the classification problems are not unified: the number of classes varies from 2 to 8. Thus, it is very difficult to conclude which machine learning technique or neuro fuzzy system is most suitable for stress detection. For three class scenarios, classification accuracy goes over 70%, for two class scenario the obtained classification accuracy can be over 95%, in some articles even 99%. The authors report SVM as most successful machine learning technique for stress recognition.

For further research in the corresponding field it will be challenging to employ, more intensively, some up to date neural network architectures, like deep convolutional neural networks. Additional boosting of classification accuracy in those systems can be obtained by usage of ensembles of CNN with voting method.

REFERENCES

[1] Rodríguez-Arce, J., Lara-Flores, L., Portillo-Rodríguez, O., & Martínez-Méndez, R. (2020). Towards an anxiety and stress recognition system for academic environments based on physiological features. Computer methods and programs in biomedicine, 190, 105408.

[2] Jebelli, H., Hwang, S., & Lee, S. (2018). EEG-based workers' stress recognition at construction sites. Automation in Construction, 93, 315-324.

[3] Hong, K., Liu, G., Chen, W., & Hong, S. (2018). Classification of the emotional stress and physical stress using signal magnification and canonical correlation analysis. Pattern Recognition, 77, 140-149.

[4] Pourmohammadi, S., & Maleki, A. (2020). Stress detection using ECG and EMG signals: A comprehensive study. Computer methods and programs in biomedicine, 193, 105482.

[5] Zhang, B., Morère, Y., Sieler, L., Langlet, C., Bolmont, B., & Bourhis, G. (2017). Reaction time and physiological signals for stress recognition. Biomedical Signal Processing and Control, 38, 100-107.

[6] Jebelli, H., Khalili, M. M., & Lee, S. (2018). 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, 23(5), 1928-1939.

[7] Moon, J., Lee, J., Cheon, D., Lee, M., & Lee, K. (2019, November). Stress Recognition with State Classification Considering Temporal Variation of Stress Responses. In 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 2852-2859). IEEE.

[8] Gaikwad, P., & Paithane, A. N. (2017, July). Novel approach for stress recognition using EEG signal by SVM classifier. In 2017 International Conference on Computing Methodologies and Communication (ICCMC) (pp. 967-971). IEEE.

[9] Zenonos, A., Khan, A., Kalogridis, G., Vatsikas, S., Lewis, T., & Sooriyabandara, M. (2016, March). HealthyOffice: Mood recognition at work using smartphones and wearable sensors. In 2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops) (pp. 1-6). IEEE.

[10] Jun, G., & Smitha, K. G. (2016, October). EEG based stress level identification. In 2016 IEEE international conference on systems, man, and cybernetics (SMC) (pp. 003270-003274). IEEE.

[11] Hasanbasic, A., Spahic, M., Bosnjic, D., Mesic, V., & Jahic, O. (2019, March). Recognition of stress levels among students with wearable sensors. In 2019 18th International Symposium INFOTEH-JAHORINA (INFOTEH) (pp. 1-4). IEEE.

[12] Jeon, T., Bae, H., Lee, Y., Jang, S., & Lee, S. (2020, January). Stress Recognition using Face Images and Facial Landmarks. In 2020 International Conference on Electronics, Information, and Communication (ICEIC) (pp. 1-3). IEEE.

[13] Montesinos, V., Dell'Agnola, F., Arza, A., Aminifar, A., & Atienza, D. (2019, July). Multi-modal acute stress recognition using off-the-shelf wearable devices. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 2196-2201). IEEE.

[14] Liew, W. S., Seera, M., Loo, C. K., Lim, E., & Kubota, N. (2015). Classifying stress from heart rate variability using salivary biomarkers as reference. IEEE transactions on neural networks and learning systems, 27(10), 2035-2046.

[15] Giannakakis, G., Manousos, D., Chaniotakis, V., & Tsiknakis, M. (2018, March). Evaluation of head pose features for stress detection and classification. In 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI) (pp. 406-409). IEEE.

[16] Chen, C., Li, C., Tsai, C. W., & Deng, X. (2019, May). Evaluation of mental stress and heart rate variability derived from wrist-based photoplethysmography. In 2019 IEEE Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS) (pp. 65-68). IEEE.

[17] Giannakakis, G., Trivizakis, E., Tsiknakis, M., & Marias, K. (2019, September). A novel multi-kernel 1D convolutional neural network for stress recognition from ECG. In 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW) (pp. 1-4). IEEE.

[18] Likforman-Sulem, L., Esposito, A., Faundez-Zanuy, M., Clémençon, S., & Cordasco, G. (2017). EMOTHAW: A novel database for emotional state recognition from handwriting and drawing. IEEE Transactions on Human-Machine Systems, 47(2), 273-284.

[19] Alić, B., Sejdinović, D., Gurbeta, L., & Badnjevic, A. (2016, June). Classification of stress recognition using artificial neural network. In 2016 5th Mediterranean Conference on Embedded Computing (MECO) (pp. 297-300). IEEE.

[20] Liu, Y., Lan, Z., Traspsilawati, F., Sourina, O., Chen, C. H., & Müller-Wittig, W. (2019, October). EEG-based Human Factors Evaluation of Air Traffic Control Operators (ATCOs) for Optimal Training. In 2019 International Conference on Cyberworlds (CW) (pp. 253-260). IEEE.

[21] Ayzeren, Y. B., Erbilek, M., & Çelebi, E. (2019). Emotional state prediction from online handwriting and signature biometrics. IEEE Access, 7, 164759-164774.

[22] Drosou, A., Giakoumis, D., & Tzovaras, D. (2017, June). Affective state aware biometric recognition. In 2017 International conference on engineering, technology and innovation (ICE/ITMC) (pp. 601-610). IEEE..

[23] Liu, Y., & Jiang, C. (2019). Recognition of shooter's emotions under stress based on affective computing. IEEE Access, 7, 62338-62343.

[24] Corichi, E. Z., Carranza, J. M., Garca, C. A. R., & Pineda, L. V. (2017, October). Real-time prediction of altered states in Drone pilots using physiological signals. In 2017 Workshop on Research, Education and Development of Unmanned Aerial Systems (RED-UAS) (pp. 246-251). IEEE.

[25] Khan, A. M., & Lawo, M. (2016, September). Developing a system for recognizing the emotional states using physiological devices. In 2016 12th International Conference on Intelligent Environments (IE) (pp. 48-53). IEEE.

[26] Lawanot, W., Inoue, M., Yokemura, T., Mongkolnam, P., & Nukoolkit, C. (2019, January). Daily stress and mood recognition system using deep learning and fuzzy clustering for promoting better well-being. In 2019 IEEE International Conference on Consumer Electronics (ICCE) (pp. 1-6). IEEE.

[27] Liao, C. Y., Chen, R. C., & Tai, S. K. (2018, April). Emotion stress detection using EEG signal and deep learning technologies. In 2018 IEEE International Conference on Applied System Invention (ICASI) (pp. 90-93). IEEE.

[28] Boccanfuso, L., Wang, Q., Leite, I., Li, B., Torres, C., Chen, L., ... & Shic, F. (2016, August). A thermal emotion classifier for improved human-robot interaction. In 2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN) (pp. 718-723). IEEE.

[29] Lee, S. I., Lee, S. H., Plataniotis, K. N., & Ro, Y. M. (2016). Experimental investigation of facial expressions associated with visual discomfort: feasibility study toward an objective measurement of visual discomfort based on facial expression. Journal of Display Technology, 12(12), 1785-1797..

[30] Ghosh, S., Goenka, S., Ganguly, N., Mitra, B., & De, P. (2019, September). Representation Learning for Emotion Recognition from Smartphone Keyboard Interactions. In 2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII) (pp. 704-710). IEEE.