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Stress Detection with Machine Learning Using Multimodal Physiological Data

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Abstract: Stress is a common part of everyday life that most people have to deal with on various occasions. However, having long-term stress, or a high degree of stress, will hinder our safety and disrupt our normal lives. Detecting mental stress earlier can prevent many health problems associated with stress. When a person gets stressed, there are notable shifts in various bio-signals like thermal, electrical, impedance, acoustic, optical, etc., by using such bio-signals stress levels can be identified. This paper proposes different machine learning and deep learning techniques for stress detection on individuals using multimodal dataset recorded from wearable physiological and motion sensors, which can prevent a person from various stress related health problems. The researchers looked at data from sensors that track things like- movement, heart rate-, breathing, and sweat. They gathered this data while people were feeling amused, neutral, or stressed. The goal is to see if they could use machine learning to figure out someone's emotional state based on the sensor readings.

Keywords – Photoplethysmography, Stressors, Accelerometer, Dichotomous, Sudomotor Nerve Activity, Convex Optimization

I. INTRODUCTION:

According to S. Palmer [17],"Stress is a rather complex psychological and behavioural state that can often be defined as an individual's perception of an imbalance in his or her vital points that places greater demands on him/her than he/she can thus meet." Stress leads to mental as well as biological problems including abnormal cardiac activities This is because stress has different effects on an individual's general well-being, which may subsequently imply other signs like losing appetite or excessive sweating Mental disorder results to a varying degree of awareness and stunned when faced with death or any other extreme situation. rhythmic and depression. According to the American Institute of Stress, [14] 80% of workers feel stress on the job and nearly half say they need help in learning how to manage stress and 42% say their co-workers need such help. According to Health and Safety Executive (HSE), work-related stress, depression or anxiety accounted for 44% of all work-related ill health cases and 54% of all working days lost due to ill health in 2018/19. Research conducted on both humans and animals suggests that stress can actually have an impact on the immune system, increasing the likelihood of developing cancer. Given these findings and the effects stress can have on our health, it's important to have a reliable system in place that can detect signs of stress. This way, we can find ways to alleviate stress through personalized interventions or, if necessary, medications.

Traditionally, experts in psychology and physiology have used questionnaires to assess an individual's stress levels. However, this approach comes with a lot of uncertainty and isn't always reliable, as it relies solely on the person's responses. Understandably, some people may feel hesitant or anxious about answering these questionnaires.

Numerous studies have been conducted to identify and measure stress based on a person's physical indicators. Stress can arise from various psychological factors, such as persistent worries about job security or looming work deadlines. These stressful situations can trigger a release of stress hormones, leading to noticeable physiological changes like a racing heart, quickened breath, tense muscles, and even a few beads of sweat. These physical changes are part of the body's "fight-or-flight" response. As these changes occur, the affected individuals emit corresponding bio-signals, which can be measured to detect stress levels. To achieve automatic stress detection, researchers have utilized a range of physical sensors.

The goal of this project is to automatically detect an individual's stress levels by analyzing their physiological data during stressful situations. By doing so, we can monitor stress levels and take preventative measures against stress-related illnesses. To achieve this, we employ a range of machine learning and deep learning techniques to identify whether a person is feeling stressed, unstressed, normal, amused, or stressed. To reach our objective, we follow a sequence of steps. First, we familiarize ourselves with the structure and format of the publicly available WESAD dataset. Then, we clean and transform the data to make it suitable for constructing machine learning and deep learning classification models. Finally, we explore and build different classification models, comparing their effectiveness.

II. RELATED WORK:

In recent years, there have been efforts to automate the prediction and detection of stress using machine learning models. These models are trained using physiological responses to stress and emotional stimuli. One notable contribution in this field is the WESAD dataset, introduced by Philip Schmidt et al. [1], which aims to facilitate wearable affect and stress detection. This dataset is publicly available for researchers to utilize.

To collect the data, Schmidt and his team selected 15 individuals and recorded various physiological measurements using wearable devices. These measurements included three-axis acceleration, electrocardiogram, blood volume pulse, body temperature, respiration, electromyogram, and electrodermal activity. They placed the RespiBAN Professional device on the chest and the Empatica E4 device on the wrist. The participants were exposed to different stress conditions such as baseline, amusement, stress, and meditation. Schmidt and his team then compared the performance of five machine learning algorithms for stress state detection: K-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA), Random Forest (RF), Decision Tree (DT), and AdaBoost (AB). They achieved classification accuracies of up to 80.34% and 93.12% for three-class (amusement vs. baseline vs. stress) and binary (stress vs. non-stress) classification problems, respectively. By utilizing common features and classical machine learning methods, Schmidt and his team were able to achieve these impressive results. This research contributes to the advancement of stress detection and paves the way for future developments in the field.

Jacqueline Wijsman et al. [7] have developed the use of wearable sensors for the purpose of monitoring physiological signs in relation to mental stress. They would measure the ECG, skin conductance, respiration, and EMG of the participants, and any number of physiological features would be calculated from those measurements. Hence, to do the further analysis; 9 features from this 19 features were selected by critically studying correlations and normalizing these features values and finally reducing them to 7 features by using Principal component analysis. This was achieved because these features were applied together and different types of classifiers such as Linear Bayes Normal Classifier, Quadratic Bayes Normal Classifier, K-Nearest Neighbors Classifier, and Fisher's Least Square Linear Classifier. As a result, 80% accuracy between stress and nonstress conditions was achieved. This experiment, in a way, is approximating what we have done before. Albeit the number of participants used and the features extracted differ. They had applied three different sources of stress in their study and tested their results against those of other articles on stress classification that used only on stress type.

A novel multimodal dataset developed by Saskia Koldijk, et al. [6] named SWELL Knowledge Work (SWELL-KW) is used in research on stress levels and user model development. This dataset was collected using 25 people performing ordinary knowledge works like writing, reading, searching, etc. and by manipulating the working conditions using two stressors: time restraint and email constant interruptions. In the recorded data, we are to notice information on the posture and expressions of the body, computer logging, skin conductance, and heart rate, among others. The dataset was provided in raw and preprocessed forms with acquired features for everyone. Behavior of work and affect assessment was based on the questionnaires that have been verified to assess task load, mental effort, etc.

In this study, the benchmarks are performed without using machine learning techniques. At the same time, it has done one of the most useful things to the literature; it has created a new stress-related dataset. The BioNomadix model BN-PPGED, a portable device produced by Biopac, was used to pursue the measurement of physiological responses in the same study [4]. The subject wore the equipment like a wristband just on the non- dominant hand with two electrodes situated on the two fingers measuring the signals PPG and EDA. Moreover, the power spectral density and the HRV signal were also obtained using the Acqknowledge software. The Support Vector Machine (SVM) was applied to the classification of a person as stressed or not stressed, which gave us 82% accuracy marks. Addressing the employees report on stress at work, Saskia Koldijk, et al. [3] developed automatic classifiers to examine the relation between working conditions and mental stress related conditions from sensor data: body gestures, facial expression, retracing computer log and recording of body indexes (ECG and skin conductance).

They concluded that a specialized model outperformed or was characterized by the same level of competency or better than the general model in nearly all cases when users of a similar subset were subgrouped, and models were trained separately on each subset. The most important source that differentiates a work stressor from non-stress work condition is the information of movement which is crucial from the point of modalities. Performance will be further improved by an extra infusion of data on the person's facial expressions. They actually reached an accuracy of 90% implementing SVM classifier. Along with the body language, the facial cues also are the essential factors that can characterize the stress. Furthermore, Giannakakisa, G. et al. [8] employed this framework to capture feelings of stress/anxiety by analyzing facial gestures in video clips.

Among them were cameras, data on mouth activity and events, photoplethysmographic monitoring of the heart rate, and head parameters. Participants had to occupy positions separated by 50 cm from each other utilizing cameras integrated monitors. With their frontal visages visible, the latter were also responsible for providing responses and expressions cooperating the main actors. Techniques of classification such as Generalized Likelihood Ratio, Naive Bayes classifier, K-nearest neighbors, AdaBoost classifier, and Support Vector Machines were made use of and evaluated. The results of the exposure process used the Adaboost classifier, which had achieved the highest results with an accuracy of 91. 68%. Hugo Ibay obtained a high specificity of 100% and a low sensitivity of 75%. In a different study, Md Fahim Rizwan, et al. [5] used ECG feature for the stress condition classification. Due to the ECG feature extraction techniques that utilize common portable clinical recorders, placing the ECG recording in front of hands became simple. In this study, ECG was the primary candidate. There is no need for design of respiratory signal detection sensor system again since the respiratory signal can be gotten from ECG by using the EDR technique, which is easier.

Respiration monitoring from ECG-derived Respiration (ECG-derived Respiration (ECGiRP)), in this context, making ECG to get a bigger edge. Feature Selection: making use of SVM for the RR interval, QT interval and EDR using SVM. Through the adoption of this technique, the accuracy almost of 98 predictor is being achieved. Among these, 60% was implemented by them. However, there is no means for fail-proof observation. A single signal (i. e. ECG) was observed and other shared signals by the body (preferably) were not taken into account.

Another observational work to measure workers stress level was conducted by Enrique Garcia-Ceja, et al. [2] they applied smartphones integrated accelerometer sensor data in order to pick the activity which corresponds stress level of the subjects. However since this sensor carries little of the privacy concerns present in the location, audio, and video sensors it is selected for privacy reasons. The other factor tempts to adopt this sensor because it is convenient for getting installed in smaller wearable devices (fitness trackers) by means of its low power consumption. A 30 had to be selected from a group of two organizations; however, they were given smartphones. The similar users and user-specific models had an accuracy of 60% and 71% respectively using only accelerometer data from a smartphone which could not preclude stress detection due to being the least reliable data model. The traditional machine learning algorithms were used to classify stress such as Random Forest attained 83% accuracy on a binary class (“No stress” vs. “Stress”) problem [9] using a tracking data from a tracker belonging to a health monitoring system commercially. Elizabeth Andre and Jonghwa Kim [10] got users listening to songs that comprised of 4 in order to decide about their emotional arousal, with them reaching a recognition accuracy of 70% using EMCD (emotion-specific multilevel dichotomous classification- EDMC), which is empathic. A research paper [11] that Kurt Plarre and his colleagues has published shows that there was a possibility for volunteers to have not zero (0), low (1), moderate (2) or high (3) stress levels in a day and they did this by giving them questions like How tense were you which they responded with 'Yes'(YES) or No(no)wearing sensor-based sensors on their bodies provided an accuracy of about 90% for binary classification.

III. EXISTING SYSTEM:

An existing system for stress detection with machine learning utilizing multimodal physiological data typically encompasses several key components. Initially, the system involves data acquisition from various sensors and sources, such as electrocardiography (ECG) for heart rate variability, electrodermal activity (EDA) for skin conductance, photoplethysmography (PPG) for blood volume changes, accelerometers for motion detection, audio recordings for voice analysis, and environmental sensors for contextual data. Ensuring synchronization and proper labeling of this data with ground truth stress levels is crucial. Following data acquisition, preprocessing steps are employed to clean the data from noise and artifacts, segment it into appropriate time windows, and normalize or standardize it for consistency across modalities. Feature extraction then takes place, where relevant features are derived from each modality, including statistical measures, frequency-domain features, time-domain features, and nonlinear features, possibly employing feature selection techniques to focus on the most informative ones.

Subsequently, machine learning models are developed, selecting algorithms such as Support Vector Machines (SVM), Random Forests, Gradient Boosting Machines (GBM), or deep learning models like Convolutional Neural Networks or Recurrent Neural Networks. These models are trained using the extracted features and ground truth labels, exploring ensemble methods or hybrid models to effectively combine information from multiple modalities, and hyperparameters are fine-tuned using cross-validation techniques for optimized performance. The trained models are then evaluated using metrics like accuracy, precision, recall, F1-score, and area under the ROC curve, employing techniques such as k-fold cross-validation for generalization assessment and significance testing for performance comparison. Finally, the system is integrated and deployed into a user-friendly interface or application capable of real-time data streaming and inference, with provisions for model updating and retraining to accommodate evolving stress detection needs.

In addition to the core components outlined above, an existing system for stress detection with machine learning using multimodal physiological data may involve further intricacies and considerations.

- Data acquisition might involve selecting appropriate sensor types and deployment strategies tailored to the target population and context of use. For instance, wearable sensors could be chosen for continuous monitoring in everyday settings, while stationary sensors may be suitable for controlled laboratory experiments. Calibration procedures might also be implemented to ensure data accuracy and consistency across different devices and individuals. Moreover, the system may include mechanisms for data encryption and privacy protection, especially when dealing with sensitive physiological information.

- Preprocessing techniques could encompass advanced signal processing methods, such as filtering, artifact removal algorithms, and feature normalization approaches tailored to the characteristics of each modality. Additionally, efforts might be made to address challenges related to data imbalance, outliers, and non-stationarity inherent in physiological signals. Techniques like data augmentation could be employed to enhance the robustness and generalization capability of the models, particularly when faced with limited annotated data.

- Feature extraction could delve deeper into domain-specific knowledge to derive meaningful features that capture physiological correlates of stress across different modalities. For example, in voice analysis, features related to prosody, intonation, and speech rate could be extracted to capture emotional states. Similarly, in ECG signals, features derived from heart rate variability analysis could provide insights into autonomic nervous system activity. Feature fusion techniques might be explored to effectively integrate information from diverse modalities, potentially leveraging domain adaptation methods to mitigate domain shifts between training and deployment environments.

- Model development could involve not only selecting appropriate algorithms but also customizing them to account for the temporal dynamics and interplay between different physiological signals. For instance, recurrent neural networks (RNNs) or attention mechanisms might be employed to model temporal dependencies in time-series data. Additionally, domain adaptation techniques could be utilized to enhance model generalization across different populations or contexts, particularly in scenarios where labeled data from the target domain is limited. Model evaluation might extend beyond traditional performance metrics to include user-centric evaluation criteria, such as user satisfaction, usability, and interpretability of the system's outputs. Human-in-the-loop approaches could be adopted to incorporate expert feedback and refine the system iteratively. Furthermore, efforts might be made to assess the impact of the system on user well-being and behavior, potentially through longitudinal studies or real-world deployment trials.

- Integration and deployment could involve considerations such as system scalability, interoperability with existing infrastructures (e.g., electronic health records), and compliance with regulatory requirements (e.g., data privacy regulations). Continuous monitoring and maintenance mechanisms might be established to ensure the system's reliability and effectiveness over time, including techniques for model retraining and adaptation to evolving user needs and preferences. Additionally, user education and training programs might be developed to facilitate adoption and acceptance of the system by end-users, including both individuals seeking stress management support and healthcare professionals utilizing the system in clinical settings.

IV. PROPOSED SYSTEM:

A proposed system for stress detection with machine learning using multimodal physiological data entails a comprehensive approach spanning several interconnected stages. Firstly, data acquisition involves strategically selecting sensors and deployment methods tailored to the target population and context, ensuring data integrity and privacy protection measures are in place. Preprocessing steps encompass advanced signal processing techniques to clean, segment, and normalize the data, addressing challenges like noise, artifacts, and non-stationarity inherent in physiological signals. Feature extraction strategies delve deep into domain-specific knowledge to derive meaningful features capturing various aspects of stress across different modalities, employing fusion techniques to integrate information effectively.

Model development entails selecting and customizing machine learning algorithms to account for temporal dynamics and interplay between physiological signals, with a focus on enhancing generalization capability and adaptability to diverse populations and environments. Model evaluation extends beyond traditional metrics to include user-centric criteria, incorporating expert feedback and assessing real-world impact on user well-being and behavior. Integration and deployment considerations revolve around scalability, interoperability, and regulatory compliance, with continuous monitoring and maintenance mechanisms ensuring system reliability and effectiveness over time. User education and training programs facilitate adoption and acceptance, fostering a holistic approach to stress management and support.

In the data acquisition phase, the proposed system will not only focus on selecting appropriate sensors but also emphasize the importance of data quality and reliability. Wearable sensors such as smartwatches, fitness trackers, and biometric patches will be chosen for their non-invasive nature and ability to continuously monitor physiological signals in real-world settings. Non-wearable sensors, including stationary devices and environmental sensors, may complement the data collection process, providing contextual information about the user's surroundings. Rigorous calibration and validation procedures will be implemented to ensure the accuracy and consistency of the collected data across different devices and individuals. Additionally, efforts will be made to address potential sources of bias or confounding factors, such as demographic variability and sensor placement differences. Privacy concerns will be paramount, with stringent measures in place to safeguard sensitive health information, including data encryption, anonymization techniques, and adherence to data protection regulations like GDPR and HIPAA.

In the preprocessing phase, sophisticated signal processing techniques will be employed to enhance the quality of the collected physiological data. Noise reduction algorithms, artifact removal techniques, and signal denoising methods will be applied to mitigate interference from environmental factors and motion artifacts. Advanced feature extraction algorithms will be utilized to derive informative features from the raw data, encompassing statistical measures, spectral analysis, and time-frequency domain representations. Furthermore, dimensionality reduction techniques, such as principal component analysis (PCA) and independent component analysis (ICA), may be employed to extract the most relevant features while reducing computational complexity. Data augmentation strategies, including synthetic data generation and data resampling, will be explored to increase the diversity of the training dataset and improve the robustness of the machine learning models. Overall, the preprocessing phase will focus on transforming raw physiological data into a standardized format suitable for subsequent analysis and modelling.

V. METHODOLOGY:

WESAD is the dataset which is used as this research examines it. This dataset which was made publicly available by Attila Reiss, Philip Schmidt et al. in 2018 was the first of its kind and the data set featured 4k faces [1]. The collected data is multimodal, which comprises chest-worn data through RespiBAN Professional and wrist-worn data through Empatica E4 in 15 subjects. Some of the subjects were introduced into various protocols – preparation, baseline conditions, amusement, stress, meditation, recovery, etc.; and their physiological responses and stimuli were monitored. [1], on the other hand, gives readers the details about sensors set, sensor positioning, and the procedure employed to obtain this data set which data are collected during different protocol of the subject. Besides, the RespiBAN was designed for the measurement of Accelerometer, EMG, ECG, TEMP, EDA, and additionally, all the signals were sampled at 700 Hz. The E4 was setup to measure BVP, EDA, Accelerometer, and TEMP at 64 Hz, 4 Hz, 4 Hz, and 32 Hz,The dataset is organized by the naming scheme, in which each subject has a separate filed (SX, where X is subject's ID number).

A sliding window of 1s window was used to divide the signals obtained from all sensors. The modality information from the WESAD dataset was used for feature extraction. These extracted features are filled in Table I. These features are the subset of all. To identify and describe some aspects described in [1]. The computation of statistical parameters (e. g. , standard deviation, mean, minimum, and maximum values) was done as separate outputs for each axis (i. e. , x, y, z) and as the total absolute magnitude computed for all axes (3D). The mean, standard deviation, minimum, and maximum value of the statistical features of raw ECG, BVP, RESP, and TEMP signals were calculated on raw ECG, BVP, RESP, and TEMP signals. However, the peak frequency of the BVP and amplification of the signal δT EMP are utilized as feature vectors. RAW EDA signal was passed through and order of 5 Hz which was a low pass filter. Statival features like standard deviation, mean, minimum, and maximum value were computed [1].

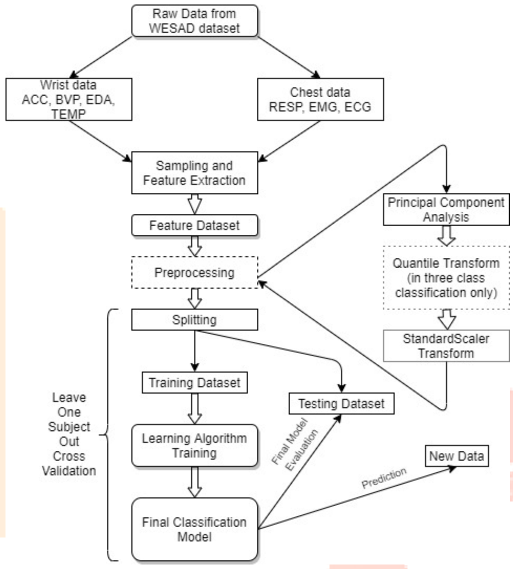

Fig. 1. Schematic flow diagram of Stress Detection Methodology.

To calculate the statistical features mentioned above, let us define Wi = {x1, x2, . . . , xn} as a window of raw data where x1, x2, etc. are n data points/measured signal of a 1 second window. The suggested works to determine the statistical measurement such as mean, standard deviation, min and max for a particular window frame by using mathematical expressions given as (1), (2), (3), and (4). Moreover, the EDA signal is made up of phasic and tonic (the tonic being the SCL) parts, so they were differentiated. Having done that, the EDA and SCR algorithms were separated, and the same features were computed. Besides, due to the non-autonomous sparse SMNA driven phasic component, cvxEDA algorithm was applied to extract the same features as EDA. Thus the DC component of the raw EMG signal was eliminated through the first order 5 Hz high pass filter.

Next, important statistical features such as standard deviation, mean, minimum, maximum and peak frequency value were computed. Among the machine learning models (Random Forest, Decision Tree, AdaBoost, k-Nearest Neighbour, Linear Discriminant Analysis and Kernel Support Vector Machine), the deep learning artificial neural network (ANN) was also performed and their performance was compared. The feature vectors, defined supra, are pre-processed to match the requirements of the classifiers. There are two classifications of learning-three class and binary classification. Three class classification is given as classifying a person as within a affected, normal, or stressed state; and, binary classification is defined as splitting a person into either within a stressed or an unstressed condition. The stress detection scheme is shown in Fig. 1 where the flow diagram is shown.

Therefore, we considered three-class classification problem that could be solved by means of both machine learning and deep learning algorithms. Initially, PCA (Principal Component Analysis) was performed with the number of components equal to 20 and with full svd solver. Using a transformation technique, which is the Quartile-to-Z value, which transforms the features to follow uniform or normal distribution, the transform method was used to account for data generation. Consequently, as regards a given feature, this process is the opposite of filing signs which leads to the most frequent values spreading and minimizes the impact of outliers. A last preprocessing operation performed is known as Standard Scalar, which is used to remove the mean from the data and scale up to unit variance. For binary classification problem, two methods used are Principal Component Analysis based on the number of components as 20, which used a full svd solver. Thereafter, the data standard scalar preprocessing which was also visualised with Figure 1 was applied. This research study is implemented using the respective libraries namely sci-kit learn for supervised machine learning models by Python classifiers and Keras for deep learning by the neural network library.

VI. RESULTS AND DISCUSSION:

It is important to note that the model is dedicated to two classification tasks that are dependent on the current states of an individual for the stress detection. First, a three-class classification task was defined: function not amusement. Second, the amusement and baseline states were combined to non-stress class, and a binary classification task was defined. The chart below reveals that explored classifiers performed to a certain extent for both classifications as shown in Table II.

When all the features listed above are exploited and their behavior compared, then the DT classifier shows low accuracy in both three-class problem and binary classification. After loading all the features and classifying with machine learning algorithms as we discussed above, the accuracy reached to 81. 65%, as high as up to 93. 20% in respect to the three-class and two-classes problems, respectively. Additionally, with deep learning classifier's simple artificial neural network, our accuracy has been revealed to be about 84. 32% and even go up to 95. By using binary and three-class, we have achieved 21% and 21% accuracy in the case of these two problems, respectively. As highlighted by table 2, the DT outperformed all the machine learning models, SVM with kernel gave the overall best results among all the machine learning classifiers, and ANN came out overall on top among all the classifiers. These true cases are better than those which were studied by Philip Schmidt et al. [1], having detected 80. 26% of the three-tier, and 89%. 7. 2% on the binary classification tasks.

VII. CONCLUSION:

The research work has seen the structure of the publicly available WESAD dataset, cleaned and transformed data to a set of math to implement machine learning and deep learning classifier methods, has performed some exploration and finally construct classification models and compare them. Data acquisition is executed by numerous physiologic modalities such as three-axial accelerometer (ACC), respiration (RESP), electrodermal activity (EDA), electrocardiogram (ECG), body temperature (TEMP), electromyogram (EMG) and blood volume pulse (BVP), which are not present in any other existing dataset, hence, its accuracy technique of quantifying stress is more valid. Such a model has reached the level of accuracy that is 84%. 21% up on three-class and a binary classifi-cation tasks. In this case, the inaccuracy of such findings is likely because of the reduction in the subjects being researched. But, our findings show that there is generalization, since the use of LOSO as a criterion for evaluation is done.

Also, further research can entail exploring who are the respondents in a dataset and taking their self-reports into account, which were obtained through a survey with several questionnaires. The kinds of devices such as facial clues, logging information, audio/video recordings, FITBIT data etc. which are individually utilized in different areas of study can be combined with physiological data and can be put together while a new dataset is introduced. That dataset can be adapted with much better precision for stress detection as it will involve almost all features required for producing stress in human beings.

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