Wrist-Based Electrodermal Activity Monitoring for Stress Detection

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With the most recent developments in wearable technology, the possibility of continually monitoring stress using various physiological factors has attracted much attention. By reducing the detrimental effects of chronic stress, early diagnosis of stress can enhance healthcare. Machine Learning (ML) models are trained for healthcare systems to track health status using adequate user data. Insufficient data is accessible.

Keywords: wearable sensor ; privacy ; federated learning ; stress detection

1. Introduction

Wearable technology has made significant strides in recent years. Humans can carry wearable devices such as smartwatches, spectacles, chest bands, and prosthetic implants [1]. In the larger area of the Internet of Medical Things (IoMT), wearable technology is simply one gadget. The IoMT comprises various medical tools and technologies that can collect and send data for medical use while connected. The IoMT also comprises ambient devices such as smart beds and detectors, implanted devices such as implantable cardiac and insulin pumps, and stationary devices such as hospital screens and imaging devices. Together, these gadgets gather and send information that can be used to track patient health, identify illnesses, and create specialized treatment regimens [2][3]. Accurate and persistent data analysis is possible with wearable technology, and this data can be utilized to track several elements of human health, such as stress levels. Wearable technology can help humans manage stress effectively by gathering data on irregular heartbeats, sleep habits, and physical activity [4].

Stress is a physical and physiological state that aggravates several serious illnesses, including diabetes, cardiovascular disease, and hypertension [5]. As reported by the British Health and Safety Executive, stress was the cause of 50% of all employment diseases in 2021–2022 (https://www.hse.gov.uk/statistics/causdis/, accessed on 23 January 2023). There exist two types of stress: Distress and Eustress. Distress is a harmful form of stress indicated by anxiety or a strong sensation of worry [6][7][8]. The consequences of distress are diminished performance and a fogginess of the mind. Further, eustress is a positive or beneficial form of stress that motivates us to achieve our goals, helps us to focus and concentrate, and keeps us alert and energized [9]. Furthermore, there are two categories of both Acute and Chronic. The main difference between acute and chronic eustress and distress is the duration and intensity of the stress and its impact on our health and well-being. Acute eustress is a short-term, positive stress that typically lasts for a short period. Acute distress is a short-term, negative stress typically lasting for a short period. Chronic eustress is a long-term, positive stress that typically lasts for a long period. Chronic distress is a long-term, negative stress that typically lasts for an extended period of time [10]. Severe or chronic illnesses might also lead to distress that is incredibly challenging for the body and brain to endure, ultimately resulting in depression and other problems with both physical and mental well-being [4][11][12]. Equally short-term and long-term occurrences are possible. Short-term stress might not always harm young and healthy individuals with an appropriate defense mechanism; however, if the traumatic situation is too frequent or severe, it may raise the chance of developing pathological conditions linked to anxiety and depression [13]. Acute periods of stress can precipitate a stroke or cardiac arrest, while long-term stress is recognized to raise the probability of life-threatening illnesses such as coronary artery disease, elevated cholesterol levels, diabetes, and adiposity [4].

In biomedical fields, self-reported questionnaires such as the Perceived Stress Scale (PSS) [14] are used to measure the psychological perception of stress and the State-Trait Anxiety Inventory (STAI) is used to measure responses to stress [15][16]. Further, there is evidence that stress-related anxiety can be detected through IMU sensors and video [17]. Following this strategy daily for regular inspection is not feasible because it requires time. Monitoring physiological responses to stress with sensors is another method for calculating stress levels [18][19][20]. The smartwatch is one of the best tools for stressful evaluations, particularly at work. Unlike certain wearables that are difficult to use and inconvenient to wear while working (such as chest-worn detectors, finger-placed galvanic skin response (GSR) sensors, etc.), the smartwatch is quite well recognized. It maintains a high level of social acceptability due to its widespread use in daily life [21]. The designed detectors of a smartwatch, such as an accelerometer, electrodermal activity, skin temperature, and blood volume pulse, can be employed for multimodal-based stress monitoring.

2. Wrist-Based Electrodermal Activity Monitoring for Stress Detection

2.1. Wearable Sensor-Based Techniques

With the most significant innovations in wearable technology, there is a substantial interest in continually monitoring stress using various physiological factors [22][23]. Ref. [24] addresses the connections between suffering and stress, how to measure them, and ways to identify them using wearable sensors and diagnostic implants. Numerous physiological signals, comprising pulse rate, neural activity, muscular activity, electrodermal action, breathing rate, blood volume pulse, and skin conductance, are structured to detect wearable sensors. The authors intend to discover a method for wearable health services systems to be employed in stress and pain assessment by analyzing the wearable sensors utilized in the healthcare system.

Ref. [25] examined which detector third-party producers have accessibility to and which ones are incorporated into the wearable technology that are now available in the marketplace. It investigates how the different study participants' diagnostic accuracy differs from one another and what impact bandwidth has on the detection rate. The publicly accessible WESAD dataset is the foundation for each experiment. The findings demonstrate that an electrodermal movement sensor signal is not required for consumer stress detection and that, provided the interval length is large enough, consumer smartwatches may be utilized to diagnose stress. It should also be emphasized that the study participants' detection rates vary considerably. The suggested system [26] classifies stress levels using multimodal data from the wearable Empatica E4 device on the wrist. The authors utilized four classification situations: stress, baseline, meditation, and amusement. The research used three classification techniques: Random Forest (RF), Logistic Regression (LR), and Decision Tree (DT). By measuring the effectiveness of the system, the researchers demonstrate that the approach can reliably identify the stress levels of 15 subjects with an accuracy of 88–99% using the RF.

Ref. [1] discussed ML objectives that have been studied in the context of wearable healthcare technology, the ML methods employed, the various modalities employed, and the relevant datasets. ML applications on wearable technology face various difficulties, including deployment options, energy usage, storage and memory requirements, functionality and user satisfaction, data availability and dependability, interaction, protection, and privacy concerns. These issues were discussed, along with the potential solutions that have been reported.

2.2. Machine and Deep Learning Techniques

The research provides various ML and DL algorithms for stress detection on persons utilizing heterogeneous datasets gathered through wearable metabolic and motion sensors to prevent a human from experiencing numerous stress-related health issues [27][28][29]. The WESAD dataset is employed in the ML and DL techniques. The accuracy for three-class (stress, amusement, and baseline) and binary (stress or non-stress) categories were compared using ML techniques. In addition, a feed-forward DL algorithm is introduced for these three-class and binary categories. The accuracy was reached for three-class and binary categorization issues using ML approaches up to 81.65% and 93.20%, respectively, while accuracy was obtained for these problems up to 84.32% and 95.21%, using DL [27].

In Ref. [30], the researchers strive to further emotion and sentiment evaluation to determine an individual's level of stress based on the remarks and posts that a person has published on social media platforms. The authors use ML algorithms and a DL model called BERT for classification tasks to do sentiment analysis on massive data of tweets. The results show that the trained model can identify the emotional status based on social connections, which are assessed using multiple indicators at the level of the micro and macro. Models have been refined to classify emotions into joy, sadness, neutrality, anger, and fear. The accuracy of the categorization ability in NLP backed by deep contextual language models such as BERT was 94%, according to the researchers. In Ref. [4], the authors provided a thorough review emphasizing stress recognition utilizing wearable sensors and applicable machine learning methods. The study examines the methods used to identify stress with sensing devices, including wearable sensors, Photoplethysmography (PPG), Electrocardiograms (ECG), and Electroencephalograms (EEG), as well as in different contexts, such as while driving, learning, and working.

For stress detection, Ref. [31] created two DNNs: a Multilayer Perceptron (MLP) neural network and a 1-dimensional (1D) Convolutional Neural Network (CNN). The DNN examined physiological data obtained from the wrist and chest-worn devices to complete two activities. In the first activity, networks distinguished among stressed and non-stressed states using binary classification for stress detection. The networks employed a three-class classification task in the second experiment to distinguish between stressed, baseline, and amused states. For binary and 3-class classification, the deep MLP-NN attained an average accuracy of 99.65% and 98.38%, correspondingly. For binary and 3-class classification, the deep CNN attained accuracy rates of 99.80% and 99.55%, respectively. Ref. [32] proposed the convolutional neural network multi-level deep neural network with hierarchical learning capabilities. The WESAD benchmark dataset for mental health is used to evaluate the model, which compares favorably to cutting-edge methods and has an exceptional performance accuracy of 87.7%. Ref. [33] used different ML algorithms. The Random Forest model fared better than other models for the classification of binary and three classes, with F1 scores of 83.34 and 65.73, respectively.

2.3. Federated Learning Techniques

In Ref. [34], the authors focused on implementing federated learning-based stress identification and comparing individual, centralized, and federated learning. The WESAD dataset was used for the experiment, and the classifier used was Logistic Regression (LR). The personalized learning technique performed better, with an average F1-measure and accuracy of 0.9998 and 0.9996, respectively. The findings of the experiment demonstrate that federated learning needs more individual and centralized accuracy. The researchers used federated learning in IoT-based wearable biomedical tracking devices to protect data privacy with positive outcomes. To track stress levels during various situations, Ref. [35] suggested federated learning to cardiac data information obtained using smart bands.

With the emergence of IoT technology, wearable devices are becoming popular for health monitoring and activities such as heart rate monitoring, medicine timing, pulse rate monitoring, sleep, walking, etc. [36][37][38][39]. ML models keep improving the performance of these devices without protecting the data. To address this issue, a framework FedHealth is proposed in Ref. [40] for wearable healthcare devices using federated learning. FedHealth uses federated learning for data aggregation and transfer learning for building models. FedHealth accuracy increased by 5.3% compared to other models while keeping data privacy.

In summary, different ML and DL techniques have been studied that provide techniques for predicting stress. However, they failed to provide encouraging results about greater accuracy and did not focus on securing data privacy. FL studies focused on overcoming the different healthcare issues and system privacy [40][41][42][43][44][45].

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