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Advances in Wearable Sensor-Based Machine Learning for Mental Stress Detection: Techniques, Challenges, and Future Directions

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Abstract: *Mental stress is a prevalent health issue that substantially impacts productivity, quality of life, and general well-being. Real-time stress detection and management have become possible because of the rapid advancements in machine learning and wearable sensor technology. This paper explores these emerging technologies and their application to mental stress detection, providing insights into the underlying factors influencing stress responses. We examine stress's physiological and psychological factors, highlighting critical biomarkers like heart rate variability (HRV) and electrodermal activity (EDA), which can be reliably captured through wearable sensors like ECG and PPG. Our analysis covers the essential detailing of the capabilities of various wearable sensors, data transfer and signal processing technologies, and data handling techniques that transform raw signals into meaningful stress indicators. Additionally, we delve into ML approaches for stress detection, comparing traditional algorithms with advanced models capable of recognizing complicated stress patterns from multimodal data. Furthermore, we address key challenges such as sensor quality, data diversity, and individual health variability that influence the robustness and accuracy of stress monitoring systems. This work underscores the potential of wearable sensor data and ML to present precise, proactive stress management solutions that could transform mental health monitoring and enhance intervention strategies.*

Keywords: *Mental Stress Detection, Wearable Sensors, Machine Learning, Wearable Health Monitoring, Health Monitoring Systems*

1. INTRODUCTION

Mental health (MH) issues are widespread, with the WHO reporting 970 million people affected in 2019 [1]. The COVID-19 pandemic worsened the situation, increasing anxiety and depression rates by 25% in 2020 [2]. Improving mental health worldwide is the goal of the Comprehensive Mental Health Action Plan 2013–2030, targeting a 50% increase in service coverage and 80% of countries integrating mental health into primary care by 2030 [3]. Mental stress has become a significant issue in modern society that affects millions of people globally with a range of physical and psychological health concerns. The increasing majority of stress-related disorders, compounded by exterior forces such as work demands, personal challenges, and societal expectations, has made it critical to develop effective and scalable methods for evaluating mental stress. Traditional methods of stress assessment, like self-reports and clinical evaluations, can be subjective and frequently fail to capture the real-time nature of stress reactions [4]. Therefore, innovative approaches are required to monitor stress continuously and objectively, presenting timely interventions.

Wearable sensor technology has revolutionized measuring and tracking mental stress [5]. Wearable sensors are gaining popularity for their simplicity and usefulness in stress-monitoring applications. These devices are non-intrusive, comfortable, and do not need complex medical procedures, making them suitable for various environments, including daily life, hobbies, and work. Smartwatches, wristbands, rings, and eyeglasses conveniently monitor stress-related biosignals. While some devices, such as chest straps and patches, may be less comfortable, they remain helpful for stress detection. Smartwatches, in particular, have seen substantial advancements in recent years. Beyond telling time, modern smartwatches incorporate various features, including internet connectivity, wellness applications, and sensors capable of measuring heart rate, body temperature, blood oxygen levels, and blood pressure. These sensors, ingrained in everyday wearable devices, permit the continuous collection of physiological signals such as heart rate variability (HRV), electrodermal activity (EDA), respiration rate, skin temperature, and electromyography (EMG) [6]. The body's autonomic nervous system is closely connected to these signals, which offer essential information on how a person's body responds to stress. Changes in breathing rate, for instance, can indicate tension or anxiety, whereas variations in HRV and EDA are frequently linked to elevated stress levels [7]. New avenues for stress detection have been made available by the capacity to quantify these physiological responses in real-time, enabling ongoing mental health monitoring outside the clinical environment [8]. Many of these measurements are certified by the U.S. Food and Drug Administration (FDA), ensuring high accuracy.

Mental stress detection employing wearable sensors, improved by machine learning (ML), deep learning (DL), and other modelling techniques, presents a comprehensive approach to real-time monitoring and classification of stress. Once data is collected, various AI techniques are processed and analyzed. Integrating machine learning (ML) with wearable sensor technology has hugely extended the field of mental stress evaluation [9]. ML algorithms can process and analyze massive amounts of physiological data, enabling the extraction of meaningful patterns and features from these complex signals. ML models can produce precise, real-time stress predictions through feature extraction, data transformation, and fusion [10]. ML models like Support Vector Machines (SVM), Random Forests and K-Nearest Neighbors (KNN) are commonly applied for classification tasks, where features like HRV, GSR, and heart rate are extracted to determine the minor level. In contrast, DL models, including Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks for time-series data, can handle more complex patterns, offering improved accuracy in detecting stress over time. Other models, such as Decision Trees, Gradient Boosting Machines (GBMs), and XGBoost, can also capture non-linear relationships between sensor data and stress levels. This combination of sensors and AI models provides a practical, continuous solution for monitoring and predicting mental stress, facilitating early intervention and personalized stress management strategies. Figure 1 represents the overall taxonomy of the mental health issues.

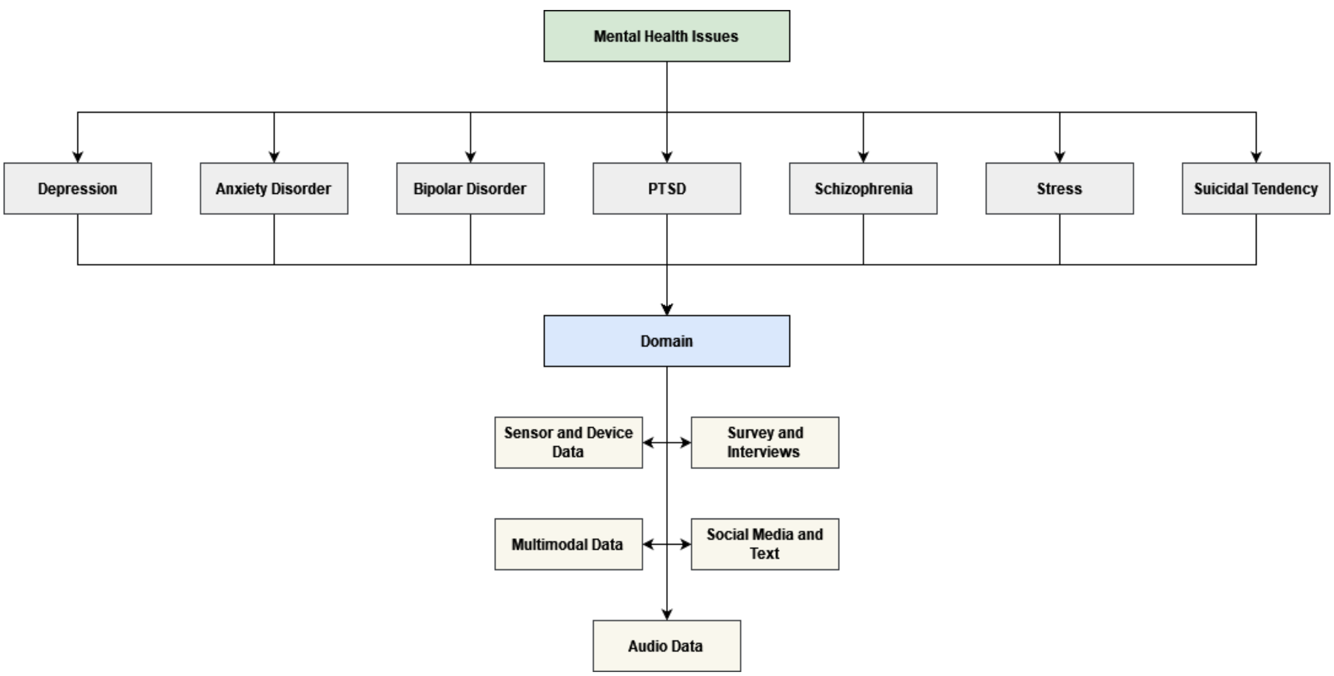

FIGURE 1. Taxonomy of mental health issues

This paper offers a comprehensive overview of wearable sensor-based approaches for detecting mental stress using machine learning techniques. Our contributions span several vital areas. We provide a detailed analysis of stress biomarkers, including heart rate variability (HRV) and electrodermal activity (EDA), which are pivotal in quantifying stress levels also present an in-depth review of wearable sensors, including bio-potential, inertial, and acoustic sensors, examining their capabilities in collecting real-time stress-related data. This analysis is an exploration of data transfer technologies, both wireless and wired, that provide efficient sensor data transmission. This holistic review highlights challenges, advancements, and future research opportunities in wearable sensor-based stress detection.

2. LITERATURE REVIEW

Abd et al. [11] proposed an ML-based approach for stress detection utilizing wearable sensors with the SWEET dataset, which has data from 240 subjects and includes four ML models: K-Nearest Neighbors (KNN), Support Vector Classification (SVC), DT, Random Forest (RF), and XGBoost. The research examined multiple classification scenarios, including two binary and two multi-class classifications, with and without applying SMOTE. The outcomes presented that the RF model outperformed others in binary classification without SMOTE, performing an accuracy of 98.29% and an F1-score of 97.89%. XGBoost revealed the highest performance for three-level classification with SMOTE, performing accuracy and an F1-score of 98.98%.

Al-Alim et al. [12] suggested an ML-based method for wearable sensor stress detection using the SWEET dataset, which was gathered from 240 participants using skin conductance (SC), skin temperature (ST), and electrocardiography (ECG). KNN, Support Vector Classification (SVC), DT, and RF are the four ML models tested on this dataset. Four distinct data scenarios were used to train and evaluate the models. According to the data, the KNN model had the highest accuracy, at 98%.

Gedam et al. [13] explored the detection of mental stress using wearable physiological sensors, both individually and in combination, along with DL techniques, specifically proposed Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) classifiers. The physiological signals examined include ECG, GSR, and ST, which present insights into autonomic nervous system regulation, emotional arousal, and peripheral blood flow changes induced by stress. The highest accuracy was 97.51% for LSTM with RFE.

Geetha et al. [14] proposed an enhanced Multilayer Perceptron (MLP) model developed to process medical datasets with a comprehensive feature analysis, enhancing stress level prediction accuracy. The enhanced MLP model aids in the swift and accurate diagnosis of stress, ultimately leading to better patient outcomes. The model experienced several evaluations, performing exceptional performance metrics: 99% accuracy, 98.6% precision, 99% recall, and 99.5% F1 score. These results corresponded against several leading ML algorithms across various stress levels, including Adaboost, RF, Gradient Boosting, and DT.

Bajpai et al. [15] evaluated the performance of KNN models for classifying the WESAD dataset. F. D. Martino et al. [16] proposed a method that combines ensemble learners with recurrent neural networks (RNNs) for stress detection. They utilized the Leave-One-Subject-Out (LOSO) cross-validation scheme to assess the generalization capabilities of each model in predicting individual stress scores. C. P. Hsieh et al. [17] underscored the significance of choosing dominant features based on their relevance to the classifier and correlation with other features, employing the XGBoost algorithm for classification.

Similarly, N. Rashid et al. [18] introduced the SELF-CARE (Selective Sensor Fusion for Stress Detection) method, designed to handle variations in sensing conditions, often referred to as the "noise context." The study used wrist- and chest-based wearable sensors to evaluate SELF-CARE, achieving accuracy rates of 86.34% and 86.19%, respectively, for a 3-class stress classification task and 94.12% and 93.68% for a 2-class classification problem. In [19], the performance of six classifiers was assessed on the WESAD dataset, with the random forest (RF) classifier showing the highest performance. Sensor placement also played a significant role, with chest-worn sensors outperforming wrist-worn sensors, achieving accuracies of 97.15% and 95.54%, respectively. Lastly, S. Ghosh et al. [20] proposed a novel method for detecting mental stress using ECG and GSR signals, addressing dataset imbalance with the adaptive synthetic minority oversampling (ADASYN) technique. A multi-class random forest (RF) classifier was employed, achieving an impressive overall accuracy of 97.08% on the WESAD dataset. Table 1 presents the existing methodologies for stress detection.

TABLE 1. Overview of existing ML-based studies on stress detection

Ref	Feature Selection	Classifier	Accuracy	Key Findings
11	SMOTE	KNN, SVC, DT, RF, XGBoost	RF: 98.29%	RF outperformed other models in binary classification without SMOTE, while XGBoost achieved the highest accuracy for multi-class classification with SMOTE.
12	-	KNN, SVC, DT, RF	KNN: 98%	KNN achieved the highest accuracy in classifying stress levels using the SWEET dataset.
13	Recursive Feature Elimination (RFE)	RNN, LSTM	LSTM with RFE: 97.51%	LSTM achieved the highest accuracy (97.51%) with RFE for stress detection, outperforming RNN.
14	-	Multilayer Perceptron (MLP)	99%	The MLP model demonstrated exceptional performance, with 99% accuracy and other high metrics, outperforming Adaboost, RF, Gradient Boosting, and DT.
15	-	KNN	90%	Examine KNN models using different cross-validation (cv) techniques and parameters. It reaches its highest accuracy when k=5 and cv=20.
16	-	Ensemble learners and RNNs, Leave-One-Subject-Out CV	-	It uses ensemble learners and RNNs through LOSO cross-validation.
17	RFE	XGBoost	F1-score-92.38% chest 89.92% wrist	XGBoost emphasizes the selection of dominating features according to correlation and significance.
18	-	Decision Tree (DT), Random Forest (RF), AdaBoost (AB), Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN)	94.12%	The SELF-CARE method performed better for 2-class classification, with wrist-based sensors slightly outperforming chest-based sensors in some tasks.
19	-	RF	wrist-worn: 95.54% chest-worn: 97.1%	RF classifier performed better with chest-worn sensors for stress detection in the WESAD dataset.
20	Extremely randomized tree (ERT)	RF	97.08%	Used ADASYN for addressing dataset imbalance, achieving an overall accuracy of 97.08% using RF for stress detection in the WESAD dataset.

3. ASPECTS CONNECTED TO STRESS

A. Biological Signal Measurements

Detecting stress in real time by employing biosignals from wearable devices is challenging, mainly outside medical environments. Technological advances in wearables have made out-of-lab stress detection increasingly viable. The autonomic nervous system (ANS) regulates different bodily functions, all of which are stress-affected [21]. Figure 2 depicts the different wearable biosignal devices for stress detection and analysis

1. Heart Rate (HR) [22]: HR expansions under stress as the body needs more oxygen. Heart rate variability (HRV) refers to fluctuations between heartbeats, showing stress responses. Methods like ECG and photoplethysmography (PPG) can estimate HR and HRV.
2. Temperature: Wearable sensors typically measure skin temperature, which may reveal acute stress.
3. Blood Oxygen Saturation: SpO2 levels are computed to detect hypoxia and stress.
4. Blood Pressure (BP): BP can increase under stress, though it is impacted by physical activity. Wearable devices may evaluate BP using methods like ballistocardiography and photoplethysmography.
5. Brain Activity: The brain regulates the ANS through the hypothalamus. Wearable devices that estimate brain activity, such as through near-infrared spectroscopy, can detect stress-related changes.

B. Physical Secretions - Biomarkers

The ANS and the hypothalamic-pituitary-adrenal (HPA) axis control stress responses through hormones. Sensors now detect biomarkers created by the HPA axis in bodily fluids, assisting in stress detection. These biomarkers include cortisol, glucose, prolactin, and alpha-amylase.

1. Sweat: Sweat contains lactate, cortisol, and glucose biomarkers. Wearable sensors for sweat monitoring are becoming increasingly popular in health and sports.
2. Tears: Contains cortisol, glucose, and proteins. Wearable lenses can observe biomarkers in tears, which is helpful for stress detection.
3. Saliva: Includes stress biomarkers like alpha-amylase and cortisol. While wearable sensors are being designed, ongoing usage remains impractical.
4. Urine: Urine is utilized to diagnose diseases and measure glucose. Wearable devices for glucose detection in urine are available.
5. Interstitial Fluid (ISF): This fluid contains biomarkers like glucose and cortisol. Minimal-invasive wearable sensors are emerging to monitor ISF biomarkers.

C. Physiological and Behavioral Indicators

Numerous physiological and behavioral indicators observed through wearable technologies provide helpful insights into stress levels. These indicators contain bodily movements, speech characteristics, posture, and hand tremors, each contributing to an exhaustive understanding of stress.

1. Body Movements: Modern wearable devices like 3D accelerometers and gyroscopes are essential for tracking body movements and assessing stress. These devices can detect activities such as walking and running and identify physical tremors frequently associated with social anxiety. Stress advances heart, blood, and breathing rates, leading to muscle tension that may cause shaking or tremors.
2. Speech: Speech production affects several body systems, including the lungs, vocal cords, and brain. Stress can significantly impact speech patterns, influencing tone, flow, volume, and pitch. Speaking, particularly aloud, activates the autonomic nervous system, and differences in speech characteristics, such as faster speech or an altered tone, can indicate stress.
3. Body Posture: Stress can generate changes in body posture, such as slouching or tensing. Conversely, poor posture can cause additional stress and physical discomfort.
4. Hand Tremor: Another indication of stress is hand tremors, which can be brought on by anxiety, Parkinson's disease, exhaustion, or too much caffeine. Wearable technology with gyroscopes and accelerometers can detect and track hand tremors, providing early warning indicators for hypoglycemia or tremors brought on by stress.

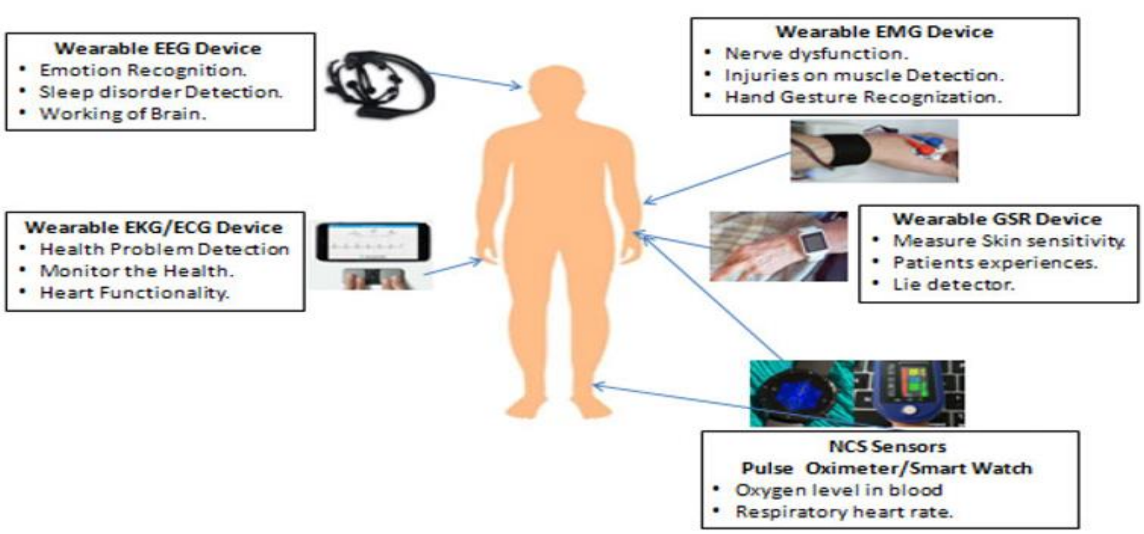

FIGURE 2. Various wearable biosignal devices for stress detection and analysis

4. MATERIALS AND METHODS

A. Search Strategy

We comprehensively searched renowned databases selected for coverage in clinical and computing sciences. Our search concentrated on studies from recent years' publications using ML techniques for mental health (MH) disorder detection. We employed a structured query integrating relevant keywords and terms, including mental health, AI, ML, detection, and wearable devices. The cutoff year of 2015 was chosen to include recent, relevant progress in the field.

B. Inclusion and Exclusion Criteria

Studies were included if they fulfilled the following criteria:

- Collected data passively using wearable devices.
- Applied ML algorithms to detect MH disorders.
- Published in English from 2015 onwards.
- Only the journal and conference articles are included
- Full-text obtainability in digital databases

Studies were excluded if they:

- Focused on other algorithms or did not employ ML algorithms.
- Duplicate articles are available in multiple academic databases
- Used specialized equipment or clinical data.
- Remove duplicate entries across multiple databases and non-research materials such as reviews, book chapters, magazine articles, theses, and interview-based articles.

C. Wearable Sensors

Wearable sensor technologies are increasingly critical in maternal and fetal health monitoring. Table 2 illustrates wearable devices used for stress detection purposes and these devices generate two types of data:

Raw Data: The original, unprocessed data from sensors, such as ECG or PPG signals, captured in real-time.

Shaped Data: Processed and organized, generally visualized or structured for more straightforward interpretation and analysis.

1. **Bio-Potential Sensors** [23]**:** Bio-potential sensors are crucial for detecting biological signals through electrical interactions. Fundamental types include ECG, EEG, and EHG sensors. These sensors convert biological activity into electrical signals, often enhanced by nanomaterials for better sensitivity. Their miniaturization has improved their practicality for noninvasive, real-time health monitoring in clinical and home settings.
   - **ECG** [24]**:** Measures heart electrical activity. Recent wearable devices like the Apple Watch allow for continuous heart health monitoring, though challenges like signal quality and power consumption persist.
   - **EEG:** This recorder records brain electrical activity and is crucial in neurophysiology. Advances in fetal EEG (EEG) technology now enable better monitoring of fetal brain activity, overcoming previous issues like signal interference from maternal movements.
   - **EHG:** Monitors uterine electrical activity, offering a noninvasive alternative to traditional methods for assessing uterine contractions. This provides significant benefits for labor monitoring.

2. **Inertial and Pressure Sensors:** Inertial sensors (accelerometers and gyroscopes) detect body movements, while pressure sensors measure variations in pressure. Together, these sensors monitor maternal physical activity, fetal movements, and uterine contractions, aiding in detecting complications like preterm labour. The recent focus has been on enhancing their sensitivity and flexibility for integration into wearable devices.

3. **Electrodermal Activity (EDA) Sensors** [25]: EDA sensors measure skin conductance, which increases with stress or emotional arousal. These sensors are particularly valuable in tracking maternal stress levels during pregnancy, providing insights into emotional well-being and autonomic nervous system activity.

4. **Acoustic Sensors** [26]**:** Acoustic sensors, particularly fetal phonocardiography (fPCG), detect fetal heart sounds, offering a noninvasive, cost-effective method for monitoring fetal well-being. Ongoing advancements in sensor design and signal processing are improving the accuracy and reliability of fetal heart rate tracking.

These sensor technologies are shaping the future of maternal and fetal health monitoring, enabling real-time, noninvasive tracking that enhances care and improves outcomes.

D. Data Transfer and Signal Technologies

Data transfer in wearable devices and sensors can be categorized into wireless and wired.

1. Wireless Technologies

Wireless technologies have seen quick development and are selected based on specific application needs:

- **Wi-Fi:** Provides medium to extensive coverage, excellent networking, and strong security.
- **Bluetooth:** Commonly used for low-power applications with a small to medium coverage range.
- **ANT+:** Short-range data transfer for applications like fitness trackers with smaller data volumes.
- **Cellular Technology (2G, 3 G, 4G, 5G):** This technology offers broad coverage, with 5G providing faster speeds and lower latency, though it is limited in certain areas.
- **NFC and RFID:** Enable short-range (NFC: 5 cm; RFID: up to 100 m) communication for payments and access control applications.

2. Wired Technologies

Wired technologies are stable and reliable, typically used when data volume and speed demands are lower:

- **USB Cables**: Commonly used for connecting devices for data transfer.
- **Electrodes and Cables**: Transfer raw signals from the body to wearable devices for analysis and processing.

Wireless methods are gaining popularity due to their flexibility, while wired options remain vital for stability and accuracy in specific applications.

TABLE 2. Wearable devices used for stress detection purposes

Device	Description	Body Location	Measurements
AutoSense [27]	AutoSense is a wearable wireless sensor for the assessment of psychological stress.	Chest band	ECG, GSR, Skin Temperature
Biobeat [28]	Monitoring for vital signs	Wrist, chest	HR, HRV, Skin Temperature, Blood Pressure, ECG
E4 Empatica – EmbracePlus [29]	Smartwatch for continuous health monitoring	Wrist	EDA, HR, HRV, Accelerometer, Gyroscope
Fitbit Sense – 2 [30]	A stress, wellness, and sleep management watch	Wrist	Blood Oxygen tracking, heart rate tracking, EDA
GraphWear [31]	Wearable glucose monitor	Wrist, abnomen	Glucose measurement
Imec ECG Necklace [32]	Wearable ECG	Neck, chest	ECG holter monitoring, HRV
O2Ring [33]	Oxygen Monitor	Hand Finger	Tracking oxygen level and heart rate

E. Data Processing

Data processing is a crucial step in preparing wearable sensor data for ML, as it provides that the data is accurate, consistent, and optimized for model training. Stress detection often involves handling complex physiological data from heart rate monitors, electrodermal activity (EDA) sensors, and accelerometers, which can produce high-frequency, multi-channel signals. Properly processed data enhances model performance by reducing noise and improving feature representation. Below is a comprehensive look at the main steps involved in data processing for stress detection applications.

- **Data Cleaning and Noise Reduction:** Wearable sensor data can be noisy due to sensor placement, movement artefacts, or environmental conditions. Cleaning this data enhances signal quality, leading to better model training and more accurate stress detection.
- **Segmentation and Labeling:** Segmentation splits the continuous sensor data into smaller, manageable time windows for model training, such as 1-second or 5-second intervals. This approach is essential in capturing stress patterns that may evolve gradually or suddenly over time.
- **Feature Extraction and Selection:** Feature extraction transforms raw sensor data into meaningful attributes that machine learning algorithms can interpret. Commonly extracted features for stress detection include Time-Domain Features, Frequency-Domain Features, Dimensionality Reduction
- **Normalization and Scaling:** Data normalization and scaling are essential for bringing different sensor measurements onto a standard scale, especially when using algorithms sensitive to data magnitudes, like SVM or KNN.
- **Data Augmentation:** Data augmentation techniques help address the common issue of limited or imbalanced datasets in stress detection by artificially increasing the training data. Methods include:
- **Feature Engineering for Real-Time Processing:** Real-time stress detection on wearable devices requires optimized data processing techniques to ensure low latency and efficient resource use.

By carefully executing each step of cleaning, segmenting, feature extraction, normalization, and, if necessary, augmentation, researchers and developers can create robust, real-time stress detection models that can operate on wearable devices.

5. MACHINE LEARNING TECHNIQUES FOR STRESS DETECTION

ML has dramatically extended the ability to analyze and interpret wearable sensor data for stress detection. With sensors capturing real-time physiological responses, ML techniques can process this complicated data to identify mental stress patterns. Below is an in-depth overview of some ML techniques used in stress detection, including their unique advantages and use cases in handling various physiological indicators. Figure 3 displays an explainable ML approach for mental stress detection.

1. **Supervised Learning Algorithms:** Supervised learning algorithms are widely used for stress detection, as they require labelled data to train models on specific outputs, such as classifying stress into different levels (e.g., high, moderate, low). Essential supervised methods include:

- **Support Vector Machines (SVM):** SVMs are particularly effective in binary or multi-class classification problems where stress levels must be categorized [34]. SVMs work by finding the optimal boundary, or hyperplane, that best separates data into classes. In stress detection, they help distinguish between stressed and non-stressed states based on sensor data features like heart rate variability or skin conductance.
- **Decision Trees and Random Forests:** Decision trees are simple, interpretable models that classify data by creating a series of decision points based on features (e.g., heart rate thresholds, EDA spikes). Random Forests, which are ensembles of multiple decision trees, improve the robustness and accuracy of predictions. This approach is particularly suitable for wearable sensor data because it can handle varied physiological inputs and reduce the risk of overfitting.
- **K-Nearest Neighbors (KNN):** KNN is another effective algorithm for stress classification [35]. It assigns a class to new data points based on the “k” nearest neighbors in the feature space. This method works well in applications where the relationship between stress indicators and outcomes is non-linear, though it can be computationally demanding for larger datasets.

2. **Deep Learning Techniques:** DL models, especially neural networks, are valuable in stress detection because they can capture complex patterns and interactions within high-dimensional data. Since stress signals can be intricate and time-dependent, DL offers advanced ways to analyze these nuanced physiological responses.

- **Convolutional Neural Networks (CNNs):** Although CNNs are most commonly associated with image data, they are also applied to physiological data from wearables [36]. CNNs use multiple layers of filters to detect patterns within the sensor data. For instance, CNNs can process ECG data and detect subtle changes in heart rhythm that may indicate stress. They excel at identifying spatial patterns and can be adapted to work on multi-channel sensor data, where each channel represents a different physiological measure.
- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM):** RNNs, particularly LSTMs, are well-suited for sequential data, such as time-series data from wearable sensors [37]. Since stress responses evolve, LSTMs effectively capture these temporal dynamics, allowing for more accurate stress

detection. By maintaining a memory of previous inputs, LSTMs can analyze how stress indicators change over seconds or minutes, making them especially useful for real-time applications.

- **Hybrid CNN-LSTM Models**: Hybrid models combine CNNs and LSTMs to leverage spatial and temporal features from wearable sensor data [38]. In such models, CNN layers extract features from the raw data, which are then processed by LSTM layers to account for temporal dependencies. This approach is particularly advantageous for stress detection as it captures the immediate physiological responses and their evolution over time.

3. **Unsupervised Learning Techniques**: Unsupervised learning is helpful when labelled data is limited or unavailable, which is often the case in stress detection. These techniques identify hidden patterns and group data without predefined categories, making them useful for exploratory analysis and anomaly detection in stress monitoring.
   - **Clustering Algorithms:** Clustering algorithms like K-means and hierarchical clustering can segment sensor data into groups based on similarity [39]. For stress detection, clustering can identify patterns corresponding to distinct stress levels or behavioural states without requiring labelled data. For example, data clusters with similar physiological responses may represent a high-stress group, while others could correspond to relaxed states.
   - **Principal Component Analysis (PCA)**: PCA is a dimensionality reduction technique that identifies the most informative features in a dataset [40]. Since wearable sensors can produce large volumes of data, PCA is beneficial for reducing complexity and enhancing model training and inference times. For stress detection, PCA can reveal which physiological measures contribute most to stress, such as heart rate variability or EDA changes.

4. **Ensemble Learning Techniques:** Ensemble learning methods combine multiple algorithms to improve prediction accuracy and robustness, addressing the variability of physiological stress data.
   - **XGBoost (Extreme Gradient Boosting):** XGBoost is an efficient ensemble algorithm known for its speed and accuracy. It uses a series of decision trees and continuously improves performance by correcting errors in previous trees. For stress detection, XGBoost can handle complex interactions between physiological measures, leading to more reliable classifications across diverse data.
   - **Voting and Stacking Ensembles:** These methods combine predictions from multiple models (e.g., SVM, Random Forest, CNN) to achieve consensus or a weighted average. Voting ensembles are beneficial in situations where a single algorithm may struggle to generalize across all cases, while stacking ensembles use a meta-model to synthesize predictions from base models, offering enhanced flexibility in stress prediction.

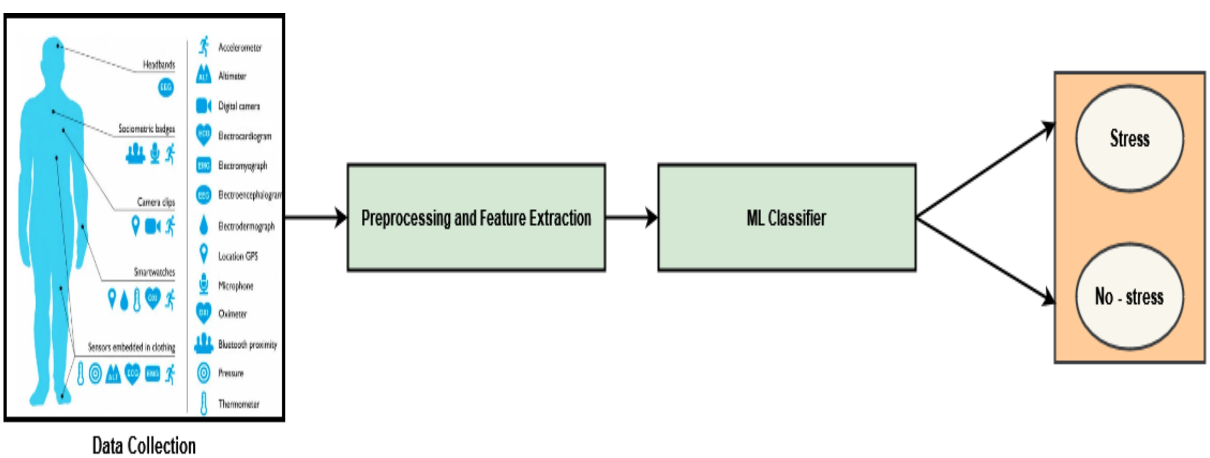

FIGURE 3. An explainable machine learning approach for mental stress detection

Evaluating ML models in stress detection involves using specific metrics such as accuracy, precision, recall, and F1 score. This is particularly important when dealing with imbalanced datasets, as stress episodes may be less frequent than non-stressful periods.

6. CHALLENGES AND FUTURE SCOPE

Predicting and detecting mental stress faces several crucial challenges, from data quality and methodology to sensor limitations. This section examines the key obstacles in this field and potential directions to guide future researchers.

1. **Impact of Individual Health and Mood Variability:** The ANS highly impacts HRV, an essential measure in stress detection. This dependency makes HRV sensitive to individual differences in mood and health factors, such as blood sugar, hormonal balance, and blood pressure. Accounting for baseline mood and physical health status during data collection could improve the accuracy and generalizability of stress detection systems.
2. **Controlled Environments and Dataset Bias:** Most stress prediction datasets are collected under controlled laboratory circumstances, lacking real-world applicability. Extending data collection to more natural settings, such as workplaces or daily commuting environments, would enhance model robustness. Additionally, these datasets frequently skew towards male participants, affecting model performance for female data. Balanced datasets are essential for more inclusive and accurate stress prediction.
3. **Scarcity of Large Benchmark Datasets:** Many studies depend on proprietary datasets, which are not widely available or standardized. Publicly available datasets are often small and lack diversity, limiting the generalizability of results. Establishing comprehensive benchmark datasets would support comparative studies and increase performance evaluation across different AI models in stress detection.
4. **Sensor Quality and Multimodal Data Collectio**n: The quality of sensors such as ECG, EMG, and GSR is vital in accurate HRV-based stress prediction. Incorporating high-quality, multimodal sensors to capture diverse physiological signals can generate more robust datasets, allowing for more reliable stress detection models.
5. **Real-Time Stress Monitoring:** Real-time stress monitoring stays an underexplored area, yet it retains promise for preventing productivity loss, health deterioration, and other negative impacts of chronic stress. Future studies should prioritize developing trustworthy real-time monitoring systems that provide timely interventions to alleviate stress.
6. **Hybrid Model Architectures:** While numerous ML and DL approaches are applied in stress detection, hybrid models combining multiple techniques are rare. Exploring hybrid architectures could generate more accurate and adaptable stress detection solutions.
7. **Expanded HRV Feature Exploration:** Current studies typically lean on a limited set of HRV features for stress prediction. Incorporating additional time-domain, frequency-domain, and statistical features could improve model effectiveness and increase datasets.

Inconsistent Evaluation Metrics: Various evaluation metrics across studies make comparing and benchmarking stress detection models challenging. Developing standardized, widely accepted evaluation criteria could facilitate comparison and improve the transparency of model performance in this field.

7. CONCLUSION

The detection and prediction of mental stress through wearable sensor data and ML define a transformative approach to health monitoring. By incorporating advanced sensors and sophisticated data analysis techniques, researchers discover new dimensions in real-time stress assessment, presenting profound implications for personalized health management. However, challenges remain, particularly in data quality, individual variability, and limitations in current datasets. Addressing these challenges through various data collection environments, including multimodal sensors, and exploring hybrid models will be important in advancing this field. As we move toward more inclusive, real-time stress monitoring systems, the potential for impactful applications in daily life is vast, from enhancing workplace productivity to improving mental well-being. Future research on developing benchmark datasets, refining sensor technology, and standardizing evaluation metrics will be essential to ensure these systems are accurate, reliable, and widely applicable.

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