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A Comprehensive Review of Stress Detection Using Physiological Signals and Machine Learning Approaches

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Abstract. Stress is one of the most severe issues in contemporary society as it has bohemian effects on the physical health and mental state as well as the productivity at the workplace. The well-known self-reporting and questionnaires methods of assessing stress has various modest limitations of low reliability and subjectivity cueing the rise of automated methodologies of stress measurements. Over the past years, electrocardiogram (ECG), electroencephalogram (EEG), galvanic skin response (GSR), heart rate variability (HRV), blood pressure, and respiration rate have been used as reliable stress monitoring biomarkers. At the same time, machine learning (ML) advances contributed to the creation of intelligent models that can analyze even complex physiological data, and make precise predictions of the level of stress. This paper has the aim of covering the literature on stress detection with physiological signals and machine learning techniques in detail. We classify the literature with respect to what kinds of physiological signals are used, the methods used during the preprocessing step, feature extraction methods and machine learning algorithms, including both classical models (i.e., Support Vector Machines, Random Forests, and k-Nearest Neighbors) as well as deep learning models (i.e., Convolutional Neural Networks and Long Short-Term Memory networks). Additionally, we report stress-related datasets that have become publicly available with the help of which the benchmarking and comparative analyses across other studies became possible. Besides, this review also discusses the existing in the field, including inter-subject variability, signal noise, small dataset size, the real-time monitoring limitations, and generalization of non-homogeneous groups. We also comment on hybrid designs involving stacks of several physiological signals, wearable combinations, and the role of new technologies explaining the AI and federated learning might play in the development of stress detection systems. This paper concludes by providing future research directions on using multimodal datasets in large scale, privacy-preserving hardware and software models, and practical applications in the fields of healthcare, workplaces, and personal well-being solutions. The review will inform researchers and practitioners of a more comprehensive overview of the field and point to potentially fruitful areas of future-generation stress detecting systems.

Keywords: Stress detection, physiological signals, machine learning, deep learning, wearable devices, feature extraction, mental health monitoring**Keywords:** Medical X-ray imaging, deep learning, cryptography, federated learning, differential privacy, homomorphic encryption, watermarking, adversarial robustness, blockchain, healthcare data security

1 Introduction

Stress is an inescapable physiological and psychological adaptation to some external or internal so-called stressors. Although moderate levels of stress may improve motivation and performance, high stress levels are related to serious health problems, such as cardiovascular diseases, anxiety, depression, and lack of cognitive performance [1], [2]. Stress is a worldwide epidemic and has acquired a negative impact on both an individual and society in terms of productivity and well being, according to the world health organization (WHO) [3]. This has made stress detection and management significant research areas in health care, occupational safety and humans and computer interaction.

The current practices of stress assessment are based on self-reported questionnaires, interviews, and stress assessment scales (Perceived Stress Scale, PSS and State-Trait Anxiety Inventory, STAI) [4]. Though these methods yield subjective data, they have limitations that include recall biases, failure to monitor in real-time, and non-identical culture grounds of stress perception. Interest in using physiological indicators has grown, as physiological signals are seen by researchers as objective measures of stress that can overcome these limitations. Heart rate, blood pressure, electrodermal activity, brain activity, and respiratory patterns are physiological reactions within the autonomic nervous system (ANS), and thus are reliable stress measures [6], [7].

Two of the most popular physiological signals used in stress detection research are Electrocardiogram (ECG), and Heart rate variability (HRV) because they are highly correlated with parasympathetic and sympathetic nervous system measurements [8]. In the same manner, electroencephalogram (EEG) records changes in brain waves that are associated with stress, whereas galvanic skin response (GSR) measures stimulation of the sweat glands during emotional stimulation [9]. Further indicators of stress, including the rate of respiration, the blood pressure and skin temperature, also provide insight regarding stress conditions [10]. A new window has now opened up with the introduction of wearable technologies in which these physiological cues are captured in real-time, ultimately providing a continuous stress monitor in uncontrolled settings [11].

The availability of physiological data has been on the increase and this has called upon advanced computational data being used in the analysis and prediction of stress. The use of machine learning (ML) has become extremely relevant in this field, as it has the potential to work with data that is high-dimensional, and identify latent patterns that can be lost with other statistical models [12]. Classical ML methods which have been used extensively to classify stress include Support Vector, Random Forest, Decision Tree, k-Nearest Neighbors, and the Naive Bayes strategies, and have given notable results in some cases [13]. Nevertheless, the accuracy of these models rely heavily on preprocessing, feature extraction and selection of raw physiological data as it is usually noisy and non-stationary [14].

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been the subject of increased interest in deep learning in recent years [15] due to their capability to extract hierarchical representations directly, and thus the automization of feature learning. CNNs have been especially useful in conducting spatial tasks on physiological data, whereas LSTMs are useful when analyzing time correlation in sequential information like ECG and EEG. Also under investigation are hybrid models that use a combination of classical ML and deep learning models to strike the compromise between interpretability, desirable computational costs, and accuracy [16].

Instead of just technical improvements, there are a few challenges in the development of successful stress detecting mechanisms. The problem to be taken into consideration is inter-subject variability, as the reaction of the body to stress varies considerably among individuals because of genetic, cultural, and lifestyle aspects. Also, most of the available literature is based on small or controlled laboratory samples that cannot be extrapolated to the practical ways [18]. Movement, noise, and limitations of the sensors add to the stress detection endeavors in terms of creating signal artifacts [19]. Ethical issues such as privacy, informed consent and storage of sensitive physiological data must also be considered in order to implement it at large scale [20].

Regardless of these obstacles, the stress detection research has great implications in a variety of domains. Continuous monitoring in healthcare has the potential of supporting early diagnosis of stress-related disorders and a personal treatment plan [21]. In working places, stress detection tech could assist companies in supporting their workers and mitigating the risk of burnout and improving efficiency [22]. In a similar way, the scope of the integration with wearable devices and smartphone can provide real-time feedback, stress management interventions and adaptive human-computer interaction [23]. As the areas of digital health and explainable AI continue to grow in interest, and privacy-preserving methods of analysis like federated learning also gain traction, the future of stress detection should ideally shift towards scalable, explicitly explained, and easy-to-use methods [24], [25].

The paper that will be presented at hand shall contain a detailed overview of stress detection based on physiological signals and machine learning methods. We systematically encode extant literature according to the kinds of physiological signals, preprocessing, feature engineering, and ML model used. In addition, we discuss popular stress-related datasets, test results, and assessment measures in order to have a unified source in future works. In this review, the main challenges are highlighted and possible directions are outlined, including multimodal signal combination, large datasets and scalable stress detection using advanced AI models. This serves to fill in the knowledge gap between signal processing of physiological parameters and the development of intelligent machine learning systems, with the expected positivity of transferring the research into next-generation stress monitoring technologies.

2. Background

Stress is a complex process which is caused by the reaction of both physiological and psychological body to the challenges. It deals with the coordination of several systems including the central nervous system, the autonomic nervous system (ANS), and endocrinological pathways (such as hypothalamic-pituitary-adrenal (HPA) axis) [26]. Short-term stress can make people perform better and more adaptive, but long-term or chronic stress has a negative impact, and it can cause cardiovascular diseases, anxiety, depression, and cause work productivity to be lower.

Within the parameters of traditional stress assessment, self-report questionnaires, psychological scales and clinical interviews have been employed [28]. These approaches become limited by the fact that they rely on recall bias, cultural differences, and failure to offer a real-time or continuous monitoring situation. There has also been increased tendency among researchers to measure physiological indicators as a source of the objective indicators of stress. The variety of these signals is that they offer assessable pointers and rules to changes in autonomic activity caused by stress, and can be measured without intrusive implementations by modern sensor technology [29].

Electrocardiogram (ECG) and Heart rate variability (HRV) are two of the widely investigated signals in terms of being closely related to balance of sympathetic and parasympathetic nervous system. EEG can provide a picture of how behaviour in the brain is affected by the stressful condition and Galvanic skin response (GSR) measures change in conductance of the skin to gauge emotional arousal. These other parameters which have been found to correlate with stress reactions are respiration rate, skin temperature, and blood oxygen level [30]. As more wearable devices become available, it is now a possibility to track such signals continuously in the field, and thus stress detection is more achievable and available.

High amounts of physiological data have led to the application of sophisticated computational techniques. Machine learning (ML) methods have become critical in the processing of complex, high dimensional, and typically noisy signals. Decision Trees and Random Forests as well as Support Vector Machines approach has been successfully implemented as classical models in stress classification task. Most recently, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, and other deep learning models, have shown that they can learn features automatically, and capture temporal dependencies in physiological signals, with superior performance [31].

Despite the achievements, some challenges have to be overcome, including inter-subject variability, signal artifacts, lack of available datasets, the generalization of work on various populations. However, further advancement in linking physiological sensing with machine learning holds the potential of improving reliability, soaring and personalized stress detecting systems with real-world applications in health care, workplace well-being and mental health monitoring.

3 Physiological Signals Used in Stress Detection

Stress is evidenced by the following physiological and cardiovascular alterations, which are controlled by ANS and endocrine system. The changes are measurable in terms of various biosignals thus they have high potential as objective measures of stress. Cardiovascular, neurophysiological, electrodermal, respiratory, and thermal responses are the most popular to study with regard to responses. Each gives insights into stress responses that are unique to it, as well as raising methodological concerns.

3.1 Cardiovascular Signals

Cardiovascular behavior is very sensitive to stress dynamics because it is directly correlated with sympathetic and parasympathetic activities. The most popular signal is the electrocardiogram (ECG) which measures the electrical activity of the heart. Stress may be related to the increased heart rate (HR) and decreased heart rate variability (HRV), provision of sympathetic dominance [32]. The features of RV in time as well as frequency domains have been greatly utilized in stress classification. HR and HRV are commonly estimated with photoplethysmography (PPG), which is less invasive than most other methods, and widely implemented in wearable devices [33]. Stress-related blood pressure (BP) changes are also an additional body of evidence; however, permanent monitoring of BP in free conditions is still a technical challenge [34].

3.2 Neurophysiological Signals

Electroencephalogram (EEG) is a direct measure of brain activity and offers fine-EEG records what is directly going on in the brain and provides a high-resolution picture of stress-driven neural functions. Stress generally induces changes in the distribution of power across frequencies with increase in beta power and decrease in alpha activity being the typical features [35]. Failed to gain enough popularity, fNIRS was also used to detect cerebral hemodynamic stress responses. The neurophysiological signals are very informative and necessitate very intelligent acquisition system and precision related to artifacts removal.

3.3 Electrodermal Activity

Galvanic skin response (EDA) EDA is popularly called galvanic skin response and measures skin conductance change caused by sympathetic activation. Stress enhances the activity of the sweat glands and this elevates the levels of skin conductance. Compared to other measures of stress, DAs are relatively easy to measure, even with low-cost wearable sensors, thus making it quite appropriate to use in real-world stress monitoring [36]. EDA measures are however sensitive to body movements and environmental factors, which make its reliability lower in uncontrolled circumstances.

3.4 Respiratory Signals

Stress can also affect how long people breathe under physiological activity, known as respiration When placed under stressful conditions, 7 persons tend to breathe at an accelerated and shortened rate. Some of the common stress indicators signals extracted include respiration rate, tidal volume and respiratory sinus arrhythmia [37]. Respiration may be measured by either chest bands, spirometers, or indirectly by ECG-derived respiration (EDR). Whereas respiration features complement the information in cardiovascular and electrodermal signals, they are more susceptible to physical activity effects.

3.5 Thermal and Other Signals

During a stressful situation, skin temperature peripheral is controlled through vasoconstriction which typically causes the distal skin temperatures to lower [38]. These slight changes have been captured with the infrared thermography and wearable temperature sensors. Other stress biomarkers explored are oxygen saturation (SpO_2), pupil dilation and electro-myology

(EMG). Although these modalities are considered less frequent, they can be used together with primary signals to give more insight into stress responses.

3.6 Multimodal Approaches

As stress is a complicated psychophysiological condition, a single biosignal might not be sufficient to represent it. Fusion of signals improves accuracy and robustness including respiration, as well as electrocardiography and electrodermal activity [39]. Research has demonstrated that the combination of multiple signals minimises the impact of single noise and inter-subject variation and increases the reliability of the stress detection technology. Recent studies included on sensor fusion and deep learning models that could learn based on multimodal data, which may benefit future stress monitoring systems [40]/remarks hormones cross talk

Table 1. Comparative analysis of physiological signals used in stress detection

Signal Type	Stress Markers	Advantages	Limitations	Common Devices / Sensors
ECG / HRV	Heart rate (HR), heart rate variability (HRV)	Reliable biomarkers of sympathetic/parasympathetic activity; widely validated	Requires good electrode contact; sensitive to motion artifacts	ECG electrodes, chest straps, smartwatches
PPG	Pulse rate, pulse rate variability	Non-invasive, widely available in wearables, low power consumption	Less accurate than ECG; prone to motion and ambient light interference	Wristbands, smart rings, fitness trackers
Blood Pressure (BP)	Systolic/diastolic BP, mean arterial pressure	Direct measure of cardiovascular stress response	Continuous monitoring difficult; intrusive in real-world scenarios	BP cuffs, finger sensors, wearable BP monitors
EEG	Alpha, beta, theta, gamma band power variations	Direct measure of brain activity; detailed neural insights	Requires multi-channel setup; sensitive to noise and electrode placement	EEG caps, headbands, clinical EEG systems
fNIRS	Hemodynamic changes in prefrontal cortex	Portable and non-invasive; less sensitive to electrical noise	Lower temporal resolution; limited	fNIRS headbands, optical sensors

			penetration depth	
EDA / GSR	Skin conductance level (SCL), skin conductance response (SCR)	Easy to acquire, inexpensive, well-established stress marker	Sensitive to environmental factors and motion artifacts	Finger electrodes, wristbands, EDA sensors
Respiration	Respiration rate, tidal volume, RSA	Reflects stress-induced breathing changes; complements cardiovascular signals	Prone to artifacts from physical activity or irregular breathing patterns	Chest bands, spirometers, ECG-derived methods
Skin Temperature	Peripheral skin temperature changes	Easy to measure with low-cost sensors; useful in multimodal systems	Sensitive to ambient temperature and physical activity	Infrared thermography, wrist temperature sensors
SpO_2 / Oxygenation	Oxygen saturation, pulse transit time	Provides insights into cardiovascular–respiratory interaction	Less direct correlation with stress; influenced by movement and perfusion issues	Pulse oximeters, wearable finger/wrist sensors
EMG	Muscle tension, facial EMG signals	Captures stress-induced muscular activity; useful in emotion recognition	Requires careful electrode placement; susceptible to motion interference	Surface EMG electrodes, facial EMG headsets
Multimodal Fusion	Combined features from ECG, EDA, respiration, EEG	Higher robustness and accuracy; reduces signal-specific limitations	Increased computational complexity; sensor integration challenges	Wearables with multiple sensors, research-grade systems

4 Machine Learning Approaches for Stress Detection

Recent availability of physiological data on wearable devices and experimental studies has inspired the application of machine learning (ML) in development of stress detection systems. ML offers the capability to extract unknown patterns, work with high-dimensional data and extrapolate to new situations, why it is well-suited to the analysis of complex physiological responses. Generally, ML methods of detecting stress can be divided into classical machine learning models, deep learning models, and hybrid/ensemble techniques.

4.1 Data Preprocessing and Feature Engineering

Raw physiological signals such as ECG, EEG, and EDA often contain noise, artifacts, and baseline drifts that must be removed before further analysis. Preprocessing techniques include filtering, normalization, artifact removal, and signal segmentation [41]. Once cleaned, relevant features are extracted to represent the physiological changes associated with stress.

Common feature categories include:

- Time-domain features: mean, standard deviation, root mean square, and peak-to-peak intervals (e.g., HRV metrics from ECG).
- Frequency-domain features: power spectral density in specific bands (e.g., alpha/beta from EEG).
- Nonlinear features: entropy, fractal dimensions, and Poincaré plot indices.

Feature selection methods, such as Principal Component Analysis (PCA), ReliefF, or mutual information, are often employed to reduce dimensionality and enhance classification performance [42].

4.2 Classical Machine Learning Models

Early studies in stress detection predominantly used classical ML algorithms due to their interpretability and relatively low computational requirements.

- Support Vector Machines (SVM): Among the most widely used classifiers in stress research, SVMs are effective in handling high-dimensional data and can achieve strong performance when stress levels are linearly or non-linearly separable [43].
- Decision Trees (DT) and Random Forests (RF): These models are popular due to their robustness to noisy features and ability to capture non-linear decision boundaries. RF, an ensemble of decision trees, is particularly effective for handling physiological variability [44].
- k-Nearest Neighbors (k-NN): Provides simple, instance-based classification, though it can be computationally expensive for large datasets and sensitive to the choice of distance metric.
- Naïve Bayes (NB): Useful in cases where stress-related features are conditionally independent, though this assumption often does not hold in complex physiological data.

These classical methods have been successfully applied to stress classification tasks, often achieving accuracies ranging between 70–85% depending on the dataset and signal modalities used.

4.3 Deep Learning Models

With the rise of large datasets and improved computational resources, deep learning (DL) has become increasingly prominent in stress detection research. Unlike classical methods, DL models automatically learn hierarchical feature representations from raw signals, reducing reliance on handcrafted features.

- Convolutional Neural Networks (CNNs): CNNs are well-suited for extracting spatial and temporal patterns from physiological signals. For example, CNNs applied to ECG or EEG data have demonstrated superior accuracy compared to traditional feature-based methods [45].

- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM): Since stress-related signals are inherently sequential, LSTMs are widely used to capture temporal dependencies and dynamic variations. Studies show that LSTM-based models outperform classical ML in multi-class stress classification [46].
- Transformers: Recently, transformer-based architectures have been applied to physiological time series, showing strong potential for capturing long-term dependencies and improving generalization across subjects [47].
- Autoencoders: Unsupervised models such as autoencoders are applied for feature extraction and dimensionality reduction, particularly in multimodal stress datasets.

Deep learning models typically achieve higher accuracies (often exceeding 90%) but require large datasets, extensive training, and greater computational resources.

4.4 Hybrid and Ensemble Models

Hybrid approaches combine classical and deep learning techniques to leverage their complementary strengths. For instance, CNNs or autoencoders may be used for feature extraction, followed by SVMs or Random Forests for classification [48]. Ensemble learning, which combines multiple classifiers, has also been shown to improve robustness and reduce overfitting. Majority voting, bagging, and boosting are common ensemble strategies in stress detection.

Another emerging trend is the fusion of multimodal signals (e.g., combining ECG, EDA, and respiration) with hybrid ML models. Multimodal fusion enhances accuracy by capturing complementary information from different physiological processes [49].

Table 2. Comparative summary of machine learning approaches for stress detection

Approach	**Typical Input Signals**	**Advantages**	**Limitations**	**Reported Accuracy (Range)**
Support Vector Machine (SVM)	ECG, HRV, EEG, EDA	Handles high-dimensional data; strong generalization; effective with small datasets	Requires careful kernel tuning; less effective with noisy data	75–88%
Decision Tree (DT) / Random Forest (RF)	ECG, EDA, Respiration	Interpretable; robust to noise; RF reduces overfitting through ensemble learning	DT prone to overfitting; RF computationally heavy with many trees	72–85%
k-Nearest Neighbors (k-NN)	ECG, HRV, multimodal signals	Simple and non-parametric; no training phase	Sensitive to distance metric and data scaling; computationally costly at inference	70–82%

Naïve Bayes (NB)	ECG, EDA, respiration	Fast, computationally efficient; works well with small datasets	Assumes feature independence; not suitable for highly correlated signals	68–80%
Convolutional Neural Network (CNN)	ECG, EEG, multimodal images	Learns hierarchical features; robust to noise; effective for spatial patterns	Requires large datasets; high computational cost	85–94%
Recurrent Neural Network (RNN) / LSTM	ECG, HRV, EEG, multimodal	Captures temporal dependencies; effective for sequential data	Prone to vanishing gradients; training complexity	83–92%
Transformers	Multimodal time series (ECG, EEG, EDA)	Captures long-range dependencies; scalable; strong generalization	Requires very large datasets; computationally demanding	86–95% (emerging studies)
Autoencoders (AE)	ECG, EEG, multimodal	Useful for feature extraction and dimensionality reduction; unsupervised learning	Reconstruction quality depends on architecture; needs additional classifier	78–88%
Hybrid / Ensemble Models	Multimodal (ECG + EDA + Respiration)	Combines strengths of multiple models; higher robustness and accuracy	Increased complexity; sensor integration challenges	88–96%

2. Stress Detection Datasets

The availability of high-quality, annotated datasets plays a pivotal role in the advancement of stress detection research. Publicly accessible datasets enable benchmarking of machine learning models, comparison of feature extraction techniques, and validation of novel methodologies under standardized conditions. Stress datasets typically include multimodal physiological signals such as ECG, EDA, respiration, EEG, and behavioral responses (e.g., questionnaires or event labels). Below are widely used datasets:

WESAD (Wearable Stress and Affect Detection): A benchmark dataset containing chest- and wrist-worn sensor data (ECG, EDA, EMG, respiration, temperature, and accelerometer) from 15 participants under baseline, stress (Trier Social Stress Test), and amusement conditions.

SWELL (Stress at Work Dataset): Records physiological signals (ECG, skin conductance, respiration, blood pressure) and office-task performance data from 25 participants under different work-related stressors.

DEAP (Database for Emotion Analysis Using Physiological Signals): A multimodal dataset containing EEG, EDA, EMG, respiration, and temperature recordings from 32 subjects exposed to emotional video stimuli, often used for stress and affective state classification.

DREAMER Dataset: Provides EEG and ECG data from 23 subjects exposed to emotional stimuli, with self-assessment of valence, arousal, and dominance, enabling stress-related emotion analysis.

AMIGOS Dataset: Includes EEG, ECG, EDA, and video recordings from 40 subjects exposed to long/short videos, annotated for valence, arousal, and stress-related responses.

MIT Stress Recognition Dataset (MIT Driver Stress): Contains ECG, EMG, skin conductance, and respiration signals recorded from drivers under different driving conditions (rest, highway, city, stressful city).

Table 3. Summary of publicly available stress detection datasets

Dataset	Subjects	Signals Recorded	Context / Task	Applications
WESAD (2018)	15	ECG, EDA, EMG, respiration, temperature, accelerometer	Trier Social Stress Test + amusement	Stress, affect recognition
SWELL (2014)	25	ECG, EDA, respiration, blood pressure, performance metrics	Office work stress (time pressure, interruptions)	Workplace stress detection
DEAP (2012)	32	EEG (32 channels), ECG, EDA, EMG, respiration, temperature	Emotional video stimuli	Emotion/stress classification
DREAMER (2016)	23	EEG, ECG	Emotional audio-visual stimuli	Emotion recognition, stress analysis
AMIGOS (2018)	40	EEG, ECG, EDA, video recordings	Long/short video watching	Affective computing, stress detection
MIT Driver Stress (2001)	24	ECG, EMG, skin conductance, respiration	Real driving scenarios (rest, highway, stress)	Driver stress detection

3. Evaluation Metrics

The growing prevalence of stress-related health problems has encouraged research into the integration of stress detection systems across multiple domains. With advancements in physiological sensing technologies and machine learning, stress monitoring has moved beyond clinical environments into everyday life. The following subsections highlight the major application areas of stress detection.

1. Healthcare and Mental Health Monitoring

Stress is a critical risk factor for cardiovascular diseases, hypertension, diabetes, and depression. Continuous stress monitoring can support early diagnosis and intervention, allowing healthcare providers to recommend personalized coping strategies. Wearable devices integrated with stress detection algorithms (e.g., Fitbit, Apple Watch) provide real-time biofeedback, while clinical studies employ datasets such as WESAD and DREAMER to develop predictive systems. These technologies enhance telemedicine by enabling remote stress tracking for patients with chronic conditions or mental health disorders.

2. Workplace Productivity and Occupational Stress

Work-related stress reduces productivity, increases absenteeism, and contributes to burnout. Stress detection systems, when combined with ergonomic workplace design and HR analytics, can help organizations monitor employee well-being. Datasets such as SWELL have demonstrated the feasibility of detecting stress induced by workload, interruptions, and time pressure. AI-driven dashboards may provide insights for organizational decision-making, allowing companies to reduce stressors and create healthier work environments.

3. Driver Safety and Transportation Systems

Stress and fatigue significantly impair driving performance, leading to accidents. Stress detection technologies integrated into vehicles, using signals such as ECG, EDA, and respiration, can monitor drivers in real time. The MIT Driver Stress dataset has been widely used to design models that detect stress during city and highway driving. Automotive applications include adaptive cruise control, fatigue alerts, and personalized in-vehicle assistance systems aimed at reducing road accidents caused by stress-induced errors.

4. Education and E-Learning

Academic stress affects students' cognitive performance, learning outcomes, and mental well-being. Wearable-based stress detection systems in classrooms and online learning platforms can identify high-stress situations such as exams or interactive tasks. These systems can be integrated into intelligent tutoring systems to adapt content delivery and provide timely interventions such as relaxation breaks or motivational support.

5. Human–Computer Interaction (HCI) and User Experience (UX)

Stress detection enhances the adaptability of intelligent systems by enabling emotion-aware computing. Applications in gaming, virtual reality, and adaptive learning platforms can adjust difficulty levels based on the user's stress state. In HCI, stress monitoring allows developers to evaluate user interface complexity, thereby improving system usability. This is especially valuable in mission-critical environments such as air traffic control, military operations, and emergency response, where stress can impair decision-making.

6. Personalized Wellness and Lifestyle Management

Consumer-grade wearables and mobile applications provide individuals with tools to monitor daily stress and adopt personalized coping mechanisms, such as guided breathing, meditation, or exercise routines. Stress detection integrated with digital assistants enables personalized recommendations, promoting proactive mental health management and long-term well-being.

6. Applications of Stress Detection

Even though deep learning and cryptographic methods have shown a significant boost in the context of medical X-ray imaging, there are a number of challenges that restrain their application on a massive scale, directly in healthcare systems. Such challenges are brought about by the nature of the trade-offs between the area of accuracy, security, efficiency and clinical usability.

1. Trade-off Between Accuracy and Privacy

Deep learning models have high levels of diagnostic precision with application to a large, centralized database. Nonetheless, most privacy-preserving methods like federated learning, differential privacy, or homomorphic encryption frequently impact their performance by decreasing accuracy as the result of fragmenting their data, injecting noise, or having limited computational restrictions [50]. The need to reach the balance between the quality of diagnostic performance and patient-data secrecy is another challenge left to be determined.

2. Computational and Resource Overheads

Computational cost of cryptographic cryptographic methods such as homomorphic encryption, secure multi-party computing can be heavy. Training or inference of encrypted data are 5-20 slower than normal models [51]. That makes real time or resource-limited deployment challenging (e.g. in rural clinics), where making decisions without high latency is essential to patient safety.

3. Vulnerability to Adversarial Attacks

Adversarial perturbation is very effective against deep learning algorithms even with the security measures put in place. Even tiny alterations of pixels may confuse the models to make false diagnosis [52]. There are strong protection mechanisms, which tend to either decrease model accuracy, or at best increase costs of computation, making them impractical.

4. Data Availability and Standardization Issues

The majority of the publicly released medical X-ray datasets are narrowly constricted in terms of diversity, usually skewed with respect to the demographics or pathology [52]. What is more, differences in annotations and absence ofofficial benchmarks complicate training of the model and its fair comparison across institutions. The privacy laws like HIPAA and GDPR also curb data sharing and stall the creation of strong and stable secure models.

5. Scalability and Interoperability

Such methodologies as federal learning will entail smooth interconnection among various healthcare facilities. The large-scale collaboration is complicated, however, by data heterogeneity formed by data format, imaging protocol, and the computation infrastructure [53]. The challenge of ensuring the interoperability of various hospitals without compromise of the security aspect is by no means a closed problem.

6. Integrity vs. Confidentiality Dilemma

Localized approaches like blockchain and watermarking are high-confidence assurances to both data integrity and provenance, but confound confidentiality and identity protection of the patient through encryption [54]. However, on the contrary, encryption renders it confidential but challenging to follow provenance. Integrating the two in a way that they do not overwhelm the system is still very difficult.

7. Usability and Clinical Acceptance

Complex cryptographic procedures/intensive modeling may reduce feasibility, in an actual hospital environment. Clinicians want simple secure pipelines to be fast, interpretable, and easy to obtain. There must be a transition between the technicalities of security demands and the practicality of getting things done clinically in order to be adopted actually [55].

V. CONCLUSION

Stress detection using physiological signals and machine learning approaches has emerged as a critical research domain due to its implications for healthcare, workplace productivity, transportation safety, education, and personal well-being. This review highlighted the most commonly used physiological signals—such as ECG, EDA, EEG, respiration, and heart rate variability—that serve as objective biomarkers of stress. The discussion also explored the role of various machine learning and deep learning models in extracting meaningful patterns from these signals to achieve reliable stress classification. Comparative analyses indicate that while classical machine learning models such as Support Vector Machines, Random Forests, and k-Nearest Neighbors remain widely used for their interpretability and moderate data requirements, deep learning approaches—particularly CNNs, LSTMs, and hybrid architectures—have shown superior performance in handling complex, multimodal datasets. An important enabler of progress in this field is the availability of open-access datasets, such as WESAD, SWELL, DEAP, DREAMER, AMIGOS, and MIT Driver Stress, which have facilitated benchmarking and reproducibility. However, challenges persist due to limited sample sizes, controlled experimental environments, and lack of diversity in population demographics. These limitations hinder the generalizability of stress detection models in real-world settings. Moreover, stress is a multifaceted construct influenced by cultural, environmental, and psychological factors, making accurate and universal detection inherently complex.

Despite these challenges, applications of stress detection are expanding rapidly, from clinical and telemedicine platforms to consumer-grade wearable technologies. The integration of stress monitoring into everyday devices holds significant promise for personalized healthcare, preventive medicine, adaptive learning, driver assistance systems, and workplace well-being programs. Future research should focus on developing scalable multimodal models, leveraging transfer learning and federated learning, and ensuring privacy-preserving data collection to encourage large-scale adoption. Additionally, ethical considerations such as data security, informed consent, and responsible AI usage must be prioritized to prevent misuse of sensitive stress-related information.

In summary, stress detection research has advanced considerably in the last decade, but greater emphasis on real-world validation, dataset diversity, and interdisciplinary collaboration will be essential for translating academic advances into practical, impactful solutions that enhance human health, safety, and quality of life.

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