

AI-based Stress Monitoring Using Heart Rate Variability: A Survey

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ABSTRACT: Stress is both a physiological and psychological response to external or internal stimuli that disrupt homeostasis. Prolonged exposure to stress can result in negative health consequences, including cardiovascular disease, anxiety, depression, and a weakened immune system. Heart Rate Variability (HRV)—the variation in the time intervals between heartbeats—is a well-recognized biomarker for autonomic nervous system (ANS) activity, particularly in reflecting the balance between sympathetic and parasympathetic responses. Recent advancements in Artificial Intelligence (AI) have enabled the development of robust, non-invasive stress monitoring systems based on HRV data. AI models can identify complex patterns within HRV signals to accurately classify and predict stress levels in real time. This manuscript discusses various AI techniques, including machine learning, deep learning, and the integration of wearable technology, and their roles in stress detection and management. Additionally, ethical considerations—such as data privacy, informed consent, and inclusivity—are highlighted to ensure the responsible implementation of these technologies.

Index Terms:- AI, HRV, Linear Features, Non-linear Features, Stress.

I. INTRODUCTION

In today's fast-paced world, stress has become an essential part of daily life, arising from personal, environmental, professional, and other factors. It is both a physiological and psychological response to external or internal stimuli that upset homeostasis [1]. In response, the human body activates a fight-or-flight mechanism to deal with these stressful situations. While stress can sometimes be beneficial without causing harm, it can also lead to negative effects on both physical and mental health. Stress can be short-term or long-term, with prolonged exposure leading to various health issues, such as cardiovascular problems, strokes, depression, and a weakened immune system.

Stress levels can be assessed through subjective methods like questionnaires and interviews [2], though these may be less accurate than physiological markers. Objective methods, including electrocardiograms (ECG), heart rate variability (HRV), respiration, skin temperature, electrodermal activity (EDA), and electromyography (EMG) etc. show promise in detecting stress by using physiological measures as biomarkers [3]. The ECG records heart activity through electrical signals, while HRV measures the variation in time between heartbeats [4]. This metric is closely linked to the autonomic nervous system (ANS) and is useful for detecting changes in stress levels. Research shows that lower HRV is associated with higher stress, whereas higher HRV indicates relaxation and emotional resilience. Therefore, HRV is a well-known biomarker for ANS activity, especially in reflecting the balance between sympathetic and parasympathetic responses[5].

Recent advancements in Artificial Intelligence (AI) have facilitated the development of robust, non-invasive stress monitoring systems based on HRV data [6]. AI models can identify complex patterns within HRV signals, allowing for accurate classification and real-time prediction of stress levels. With improvements in AI techniques, including machine learning, deep learning, and the integration of wearable technology, the accuracy and efficiency of HRV-based mental health monitoring systems have significantly enhanced.

This manuscript aims to explore how integrating AI and HRV monitoring can transform mental health support, addressing related challenges and providing practical recommendations for implementation. The following sections will detail HRV as an indicator of mental stress, review AI techniques for stress monitoring, discuss ethical considerations, limitations, and challenges, outline future directions, and conclude with a summary of findings.

II. HEART RATE VARIABILITY AS A MENTAL STRESS INDICATOR

Heart Rate Variability (HRV) is a measure of the variation in time intervals between consecutive heartbeats, known as R-R intervals or NN intervals. Unlike a static heart rate, HRV evaluates the subtle fluctuations regulated by the autonomic nervous system (ANS), reflecting the balance between the Sympathetic Nervous System (SNS) often associated with the fight or flight response, which accelerates heart rate and decreases HRV and the Parasympathetic Nervous System (PNS) linked to rest and digest, which slows heart rate and increases HRV as shown in Figure 1. Typically, lower HRV is associated with stress, whereas higher HRV indicates relaxation and resilience.

A key advantage of HRV lies in its ability to provide continuous, objective insights into mental health, complementing traditional self-reported measures. Its non-invasive nature makes it advantageous for applications in personal health, sports, and the management of cardiac arrhythmias, among others [7]. This section offers a concise overview of HRV extraction from ECG signals, its various features, and its role as an indicator of mental stress.

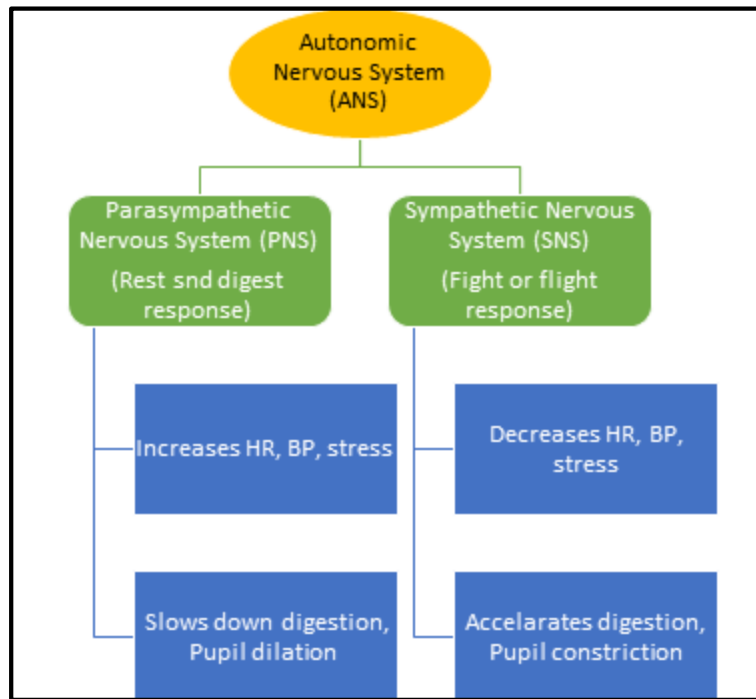


Figure 1: Autonomic nervous system (ANS)

2.1 HRV Extraction from ECG Signal

Heart rate variability (HRV) can be extracted from both ECG (electrocardiogram) and PPG (photoplethysmogram) signals, with ECG-based HRV generally considered more accurate. A typical ECG signal as shown in Figure 2 displays a sequence of P-QRS-T waves, which are recorded on specialized ECG graph paper divided into gridlike boxes. Each small box measures 1 mm², and the paper typically moves at a speed of 25 mm/sec, meaning each horizontal unit corresponds to 0.04 seconds. Groups of five boxes are marked with a heavy line, indicating that each 5 mm unit horizontally represents 0.2 seconds. Thus, the ECG can be viewed as a moving graph where time is represented horizontally, with divisions of 0.04 and 0.2 seconds.

On the vertical axis, the ECG graph measures the voltages, or amplitudes, of the ECG waves. The electrocardiograph is standardized so that a 1 mV signal results in a 10-mm amplitude deflection (1 mV = 10 mm), and the sensitivity can often be adjusted to half or double the usual levels.

The RR interval, which is measured between two successive R waves, indicates the length of the cardiac cycle and serves as an essential measure of the ventricular rate. It is crucial for ECG interpretation and plays a vital role in identifying various types of arrhythmias and studying HRV. Variability in consecutive RR intervals is referred to as the HRV signal as shown in Figure 3.

To extract RR intervals from the ECG signal, a clean ECG signal is necessary. Numerous denoising methods are available in the literature for this purpose [8]. Afterward, the widely used Pan-Tompkins algorithm [9] can be employed to extract RR intervals. The resulting HRV signal can then be visualised by plotting the RR intervals on a time axis, as illustrated in Figures 4-6 representing a normal individual, a heart failure patient, and a patient affected by sudden cardiac death (SCD), which were sourced from the Physionet database (<https://archive.physionet.org/physiobank/database>).

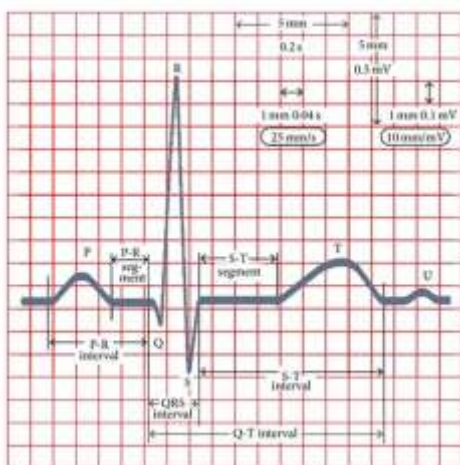


Figure 2: ECG signal

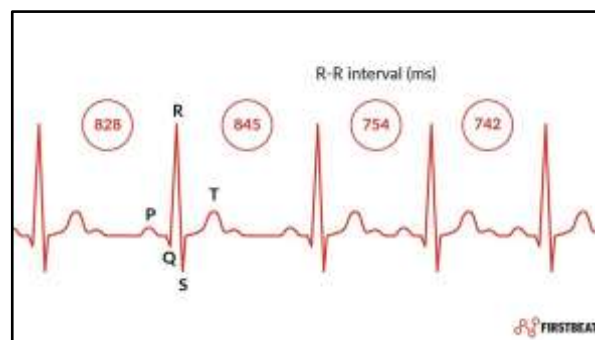


Figure 3: ECG signal showing RR intervals (Picture courtesy, <https://www.firstbeat.com/en/blog/what-is-heart-rate-variability-hrv/>)

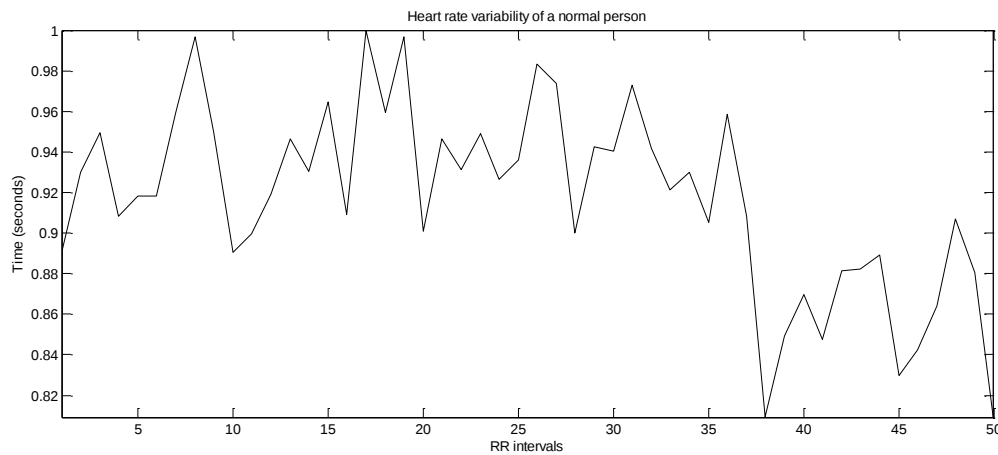


Figure 4: HRV of a healthy person

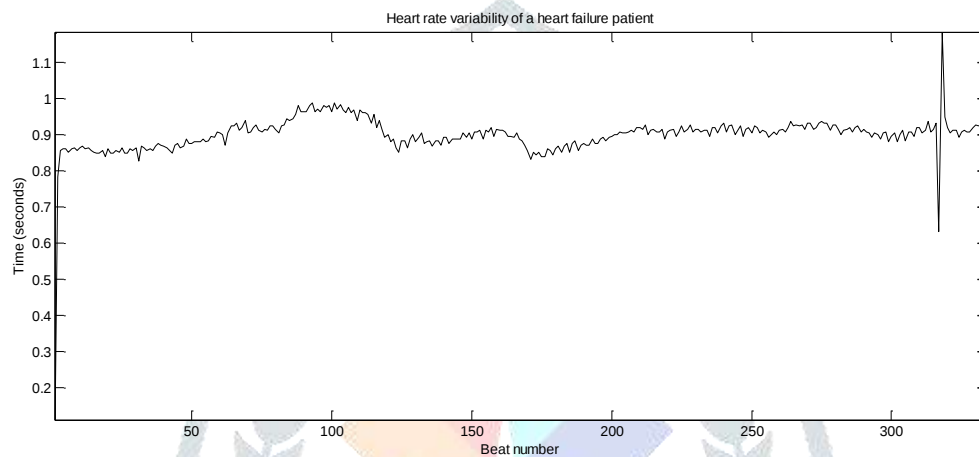


Figure 5: HRV of a heart failure patient

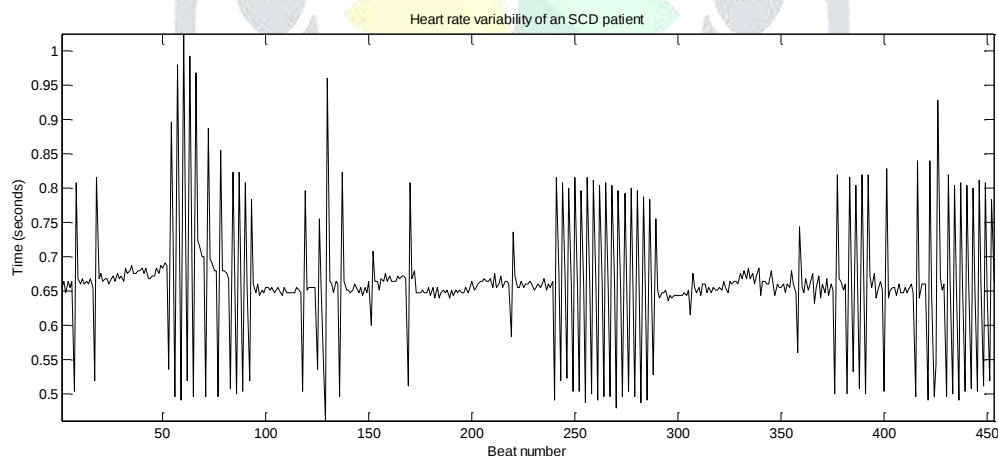


Figure 6: HRV of an SCD patient

2.2 Measures of HRV

The electrocardiogram (ECG) is the gold standard for analyzing heart rate variability (HRV), as it captures the heart's electrical activity to measure the intervals between R-wave peaks, known as RR intervals. This data is essential for accurately quantifying HRV through various methods, which can be categorized into time domain, frequency domain, time-frequency domain, geometric, and non-linear analyses.

In the time domain, HRV features are derived from three types of statistical measures: direct measurements from RR intervals, measurements from the differences between RR intervals, and measurements based on heart rate. Specific features and their computational formulas are typically detailed in Tables 1-3 [4], [5], [10].

Frequency domain analysis can be executed using techniques such as periodogram, parametric, or non-parametric power spectrum estimation. These methods allow for the extraction of HRV features, which are displayed in Table 4, summarising results from parametric techniques like Welch power spectrum estimation or the Burg method [4].

Time-frequency analysis serves as a signal processing technique that investigates signals changing over time by simultaneously assessing their time and frequency characteristics [11]. This kind of analysis is particularly beneficial for signals with time-varying spectral content, including both audio and biological data. For HRV, techniques like the short-time Fourier transform, wavelet transform, modified Wigner-ville distribution, and Hilbert-Huang transform can be employed in this analysis.

Geometric measures of HRV comprise the histogram, the HRV triangular index (HRVTi), and its modifications, as well as the triangular interpolation of the normal RR interval histogram (TiNN) [4]. The histogram helps assess the relationship between the total detected RR intervals and their variations. The triangular HRV index views the major peak of the histogram as a triangle, with its baseline width representing RR interval variability, its height indicating the most common duration of RR intervals, and its area reflecting the cumulative number of RR intervals used for construction. This index serves as a broad estimate of overall HRV.

Additionally, non-linear metrics of HRV can be extracted using methods such as sample entropy, approximate entropy, Poincaré plot, recurrence plot, and detrended fluctuation analysis [12], [13]. These approaches provide valuable insights into the complexity and predictability of heart rhythm patterns.

Table 1: Time domain features directly measured from RR intervals

Sr. No.	Statistical Feature	Equation	Description
1	Max RR	$\max(RR(i))$	Maximum of RR interval
2	Min RR	$\min(RR(i))$	Minimum of RR interval
3	Mean RR	$\frac{1}{N} \sum_{i=1}^N RR_i$	Mean of RR interval
4	Median RR	$\begin{cases} \left(\frac{N+1}{2}\right)^{th} \text{ term; } & \text{if } N \text{ is odd} \\ \left(\frac{N}{2}\right)^{th} \text{ term; } & \text{if } N \text{ is even} \end{cases}$	Median of RR interval
5	SDRR	$\sqrt{\frac{1}{N} \sum (RR(i) - \text{Mean } RR)^2}$	Standard deviation of RR interval
6	Mean RR/ SDRR	$\frac{\frac{1}{N} \sum_{i=1}^N RR_i}{\sqrt{\frac{1}{N} \sum (RR(i) - \text{Mean } RR)^2}}$	Ratio of the meanRR and SDRR
7	SDRR _i	$\frac{1}{N} \sum_{i=1}^{N-1} SDRR_{ind}$	Mean of the standard deviation of all NN intervals for all 1 minute segments of long term (5 min) signal

Table 2: Time domain features measured from difference of RR intervals

Sr. No.	Statistical Feature	Equation	Description
1	RMSSD	$\sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2}$	The square root of the mean squared difference between adjacent RR intervals
2	NN50	$\sum_{i=1}^N \{ RR_{i+1} - RR_i > 50ms \}$	Number of NN intervals which differs by 50 ms in the entire analysis segment
3	pNN50	$\frac{[(RR(i+1) - RR(i)) > 50ms]}{[total(RR(diff))]}$	NN50 divided by total number of all NN interval in selected segment

Table 3: Time domain variables measured from the heart rate

Sr. No.	Statistical Feature	Equation	Description
1	Mean HR	$\frac{1}{N} \sum_{i=1}^N HR_i$	Mean of heart rate
2	sdHR	$\sqrt{\frac{1}{N} \sum (meanHR(i) - meanHR_{all})^2}$	Standard deviation of heart rate
3	meanHR/ sdHR	$\frac{\frac{1}{N} \sum_{i=1}^N HR_i}{\sqrt{\frac{1}{N} \sum (meanHR(i) - meanHR_{all})^2}}$	Ratio of the mean heart rate and standard deviation of the heart rate

Table 4: Frequency domain features of HRV

Sr. No.	Statistical Feature	Units	Description
1	Abs VLF	ms^2	Absolute power in very low frequency band of 0.003-0.04 Hz
2	Abs LF	ms^2	Absolute power in low frequency band of 0.04-0.15 Hz
3	LF norm	%	Normalized LF band power $[(absLF/Total\ Power - absVLF) * 100]$
4	Abs HF	ms^2	Absolute power in high frequency band of 0.15-0.4 Hz
5	HF norm	%	Normalized HF band power $[(absHF/Total\ Power - absVLF) * 100]$
6	Total Power	ms^2	Total power of RR intervals (absVLF + absLF + absHF)
7	perVLF	%	% absolute power in very low frequency band $(absVLF/Total\ Power * 100)$
8	perLF	%	% absolute power in low frequency band $(absLF/Total\ Power * 100)$
9	perHF	%	% absolute power in high frequency band $(absHF/Total\ Power * 100)$
10	LF/HF	dimensionless	Ratio (LF norm/ HF norm)
11	Peak VLF	Hz	Very low peak frequency
12	Peak LF	Hz	Low peak frequency
13	Peak HF	Hz	High peak frequency

2.3 HRV and Mental Stress

Heart rate variability indicates autonomic nervous system activity associated with emotions [14]. Therefore, it is an important measure for detecting mental stress, highlighting the connection between the ANS and mental states. The ANS has two main parts: the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS), as depicted in Figure 1. The SNS activates during stressful events, triggering a fight-or-flight response, while the PNS supports recovery through rest and digestion. Keeping this balance is crucial because higher SNS activity during stress leads to lower HRV, indicating a stronger stress response.

Increases in stress are associated with decreases in the RR interval, and psychological stress is significantly associated with an increase in the LF/HF ratio also confirmed by the study reported in [1]. Most studies showed HRV variables changing in response to stress induced by various methods, with low parasympathetic activity being the most frequently reported factor. Mental stress leads to an increase in predictability, RR interval regularity, and reduced complexity reflecting a change toward more stable and periodic HR behaviour under stress [1].

A recent study [15] presents a method that utilizes HRV analysis, guided by respiration, to identify emotional states by redefining the high-frequency (HF) band. This approach was first tested with simulated HRV signals and subsequently applied to differentiate among five emotional states in a video-induced elicitation database. The results indicated that the strongest correlation between HRV and respiration spectra effectively distinguished joy from relaxation, joy from various negative valence emotions, and fear from sadness. Another study [12] investigates how stress, especially from university exams, impacts heart rate variability (HRV). It uses nonlinear HRV features to create an automated stress detection system. Exam-related stress lowers heart rate complexity. Techniques like the Poincaré Plot and Approximate Entropy help identify stress. The developed classifier achieves 90% accuracy in detecting stress.

In practical terms, a reduction in HRV is typically associated with stress, anxiety, and difficulties in emotional regulation [1]. Various measures as indicated above in Tables 1-4 help assess HRV. Time-domain features, such as SDNN (standard deviation of normal-to-normal intervals), reflect overall HRV, while RMSSD (root mean square of successive differences) indicates parasympathetic activity. In frequency-domain analysis, Low Frequency (LF) waves relate to both sympathetic and parasympathetic activity, whereas High Frequency (HF) waves are primarily associated with the parasympathetic (vagal) response. A higher LF/HF ratio indicates sympathetic dominance, suggesting stress. Acute stress events may lead to temporary decreases in RMSSD and HF power, alongside an increased LF/HF ratio. Chronic stress, however, results in a sustained reduction in overall HRV (measured by SDNN) [5].

Therefore, HRV is a non-invasive, effective way to gauge mental stress and is commonly used in areas like personal health, workplace wellness, and clinical psychology. However, it should be interpreted alongside other physiological markers, such as EEG and cortisol levels, for a complete assessment. Wearable devices like smart-watches are increasingly used to track HRV and monitor stress [3]. Additionally, biofeedback therapy can help individuals improve their stress resilience through HRV training. Mindfulness practices facilitate adaptive psychological functioning, with evidence from correlational, clinical, and experimental studies [2]. Training in mindfulness may bring about positive psychological effects, from increased well-being to improved behavior regulation.

However, when using HRV as an indicator of mental stress, several limitations, as mentioned below, must be considered.

- Individual variability in baseline HRV due to factors like age, fitness, and health.
- Confounding factors, including physical activity, sleep, caffeine consumption, and medications, which can influence HRV.
- The distinction between short-term and long-term stress, where acute stressors may create temporary decreases in HRV, while chronic stress can lead to enduring low HRV levels.

III. AI APPLICATIONS IN STRESS DETECTION USING HRV

As stated above, HRV is a key indicator of autonomic nervous system (ANS) function and overall cardiovascular health [4]. Machine learning (ML) and deep learning (DL) techniques are widely used for processing HRV data to classify stress levels and predict mental health states. The primarily used models include the classification and regression algorithms which are used to predict acute or low-levels stress and anxiety. Support vector machines (SVMs) are widely utilised for the classification of stress and anxiety due to their robustness in both classification and regression tasks, particularly when dealing with high-dimensional and nonlinear data. The paper [16] investigates stress level detection in drivers through heart rate variability (HRV) analysis from ECG signals using data from 16 subjects in the DRIVEDB database. The approach includes ECG preprocessing, QRS detection, and HRV derivation. Feature extraction covers time, frequency, non-linear, and time-frequency domains using Wavelet and STFT methods. Classification techniques employed are K Nearest Neighbor (KNN), radial basis function (RBF), and Support Vector Machine (SVM). The findings indicate that stress detection can be predicted with 83% accuracy using the SVM-RBF classifier.

The authors of the study [17] aim to evaluate the effectiveness of features extracted through discrete wavelet transform (DWT) from heart rate variability (HRV), which are selected using a genetic algorithm (GA) and classified with SVM. They analyzed 53 electrocardiograms (ECGs) from the MIT/BIH arrhythmia database, including cases of ventricular fibrillation (VF), atrial fibrillation (AF), and normal sinus rhythm (NSR). The classification process achieved an impressive accuracy of 97.14%, with 97.54% sensitivity, 96.9% specificity, and 97.64% precision.

A method for continuous detection of stressful events using data from a wrist device has been developed [18], employing three machine-learning components: a laboratory stress detector, an activity recognizer, and a context-based stress detector. This approach achieved 92% accuracy over 55 days of real-life data. Data was collected through a standardized stress-inducing laboratory experiment and from five participants wearing the wrist device in everyday situations. Participants completed four Short STAI-Y anxiety questionnaires and logged stress events through Ecological Momentary Assessment (EMA) prompts, which included the event's start time, duration, and a stress level rating from 1 to 5. The base stress detector was built from laboratory data, while the context-based detector used predictions from the base classifier to improve accuracy. A total of 63 features were extracted from blood volume pulse rate (BVP), heart rate, skin temperature, and galvanic skin response (GSR) signals. The activity recognizer classified user activities, which informed the context-based stress detection. The system classified each 20-minute period as stressful or non-stressful, with training conducted using a Support Vector Machine (SVM). Performance tests revealed that the method distinguished between stressful and non-stressful events with 92% accuracy. Participants showed variability in outcomes, with one having many false negatives and another displaying many false positives. Overall, this commercial wrist device integrates multiple sensors to enhance real-life stress detection, demonstrating its practical applicability.

The research article [19] discusses stress detection achieved through the analysis of heart rate variability (HRV) using an ECG-based chest strap device. The optimal feature set comprises eight features derived from both time and frequency domain analysis, resulting in a classification accuracy of 79.17% when using the k-nearest neighbors (kNN) algorithm and 79.2% with a backpropagation neural network (BPNN). Among these, kNN is favoured for mobile applications due to its swift processing time and straightforward implementation, particularly with k set to 3, which yields the highest accuracy.

This study [20] introduces new features based on dominant frequencies from intrinsic mode functions after applying bivariate empirical mode decomposition to short ECGs. The performance was assessed against traditional HRV analysis and instantaneous frequency distributions. KNN classification of emotions in valence and arousal achieved average accuracies of 55.8% and 59.7%, respectively, outperforming standard HRV analysis and other methods.

The study by Philip Schmidt et al. [21] engaged 15 participants and utilized a chest-worn RespiBAN Professional alongside a wrist-worn Empatica E4 to gather physiological and movement data. The protocol was designed to elicit three emotional states: neutral, stress, and amusement, achieved through a 20-minute baseline period, exposure to humorous videos, and the Trier Social Stress Test (TSST), followed by meditation sessions to facilitate relaxation. Each participant completed five self-reports, which included questionnaires such as PANAS, STAI, and SSSQ, as well as Self-Assessment Manikins (SAM) to generate labels within the valence-arousal space. Data analysis encompassed preprocessing, segmenting the data using a sliding window approach, and feature extraction (statistical and frequency-domain) from various signals, including electrocardiogram (ECG), respiration (RESP), 3-axis accelerometer (ACC), blood volume pulse (BVP), electrodermal activity (EDA), skin temperature (TEMP), and electromyogram (EMG). Classification was performed using five machine learning algorithms: Decision Tree (DT), Random Forest (RF), AdaBoost (AB), Linear Discriminant Analysis (LDA), and k-Nearest Neighbor (kNN). The evaluation focused on accuracy and F1-score, employing a leave-one-subject-out (LOSO) cross-validation method. The self-reports confirmed the effectiveness of the protocol: the amusement condition had a minimal effect, whereas

the stress condition notably influenced all questionnaires, indicating increased engagement and worry during the TSST. Ensemble methods (RF and AB) and LDA achieved comparable classification scores of up to 80% for the three emotional classes and 93% for binary classification, while kNN exhibited the poorest performance. Moreover, features derived solely from motion yielded lower classification accuracy compared to those from physiological data, with the highest results obtained by integrating all chest-based physiological signals.

A recent study has been proposed utilizing convolutional neural network (CNN) to detect acute stress in real-time from heart rate signals [6]. The research compares traditional heart rate variability (HRV) methods to a CNN approach to determine which is more effective at identifying stress during mental tasks. CNN achieved a lower detection error rate (17.3%) using only 10 seconds of ECG data. It outperformed six conventional HRV techniques, particularly by reducing false positive stress detections. This method enables quick and accurate stress monitoring, which could assist in everyday stress management.

From the above discussion, it is clear that AI models have significantly enhanced the capabilities of stress detection systems. The most commonly used AI based machine learning (ML) and deep learning (DL) techniques include SVM, k-NN, DT, RF, and CNN. Further research is needed to explore how accuracy can be improved by using other innovative AI techniques and combining these algorithms.

IV. ETHICAL CONSIDERATIONS

The integration of AI-based HRV monitoring raises ethical and practical concerns that need to be addressed. Some important issues are listed below:

- **Privacy:** The collection of heart rate variability data can reveal sensitive information about an individual's health and emotional state. Ensuring this data is handled with confidentiality and only used for its intended purpose is crucial.
- **Data Security:** Protecting the data from breaches and unauthorized access is essential. Organizations must implement robust security measures to safeguard the information collected through HRV monitoring.
- **Informed Consent:** Users should be fully informed about how their data will be used, who will have access to it, and the implications of sharing their biometric information before they consent to participate.
- **Bias in AI Algorithms:** There is a risk that AI algorithms could inherit biases present in their training data, leading to unfair treatment of certain groups. Continuous evaluation and correction of these biases are necessary to ensure equitable outcomes.
- **Mental Health Implications:** The interpretation of HRV data may impact users' mental health. Misinterpretation of results or overemphasis on HRV readings could lead to unnecessary anxiety or stress.
- **Dependence on Technology:** Overreliance on AI-driven HRV monitoring might lead individuals to neglect traditional methods of self-care and mental health management, fostering a dependency on digital assessments.
- **Accessibility:** There may be disparities in access to AI-based HRV monitoring tools, which could widen existing health inequalities among different socioeconomic groups.
- **Regulatory Compliance:** Adhering to regulations and standards, such as HIPAA in the United States, is crucial to ensure ethical use and protect individuals' rights.
- **Clinical Integration:** Determining how AI-based HRV monitoring fits into existing clinical practices and ensuring that healthcare professionals are trained to interpret and use this data effectively is essential.

These concerns must be thoughtfully managed to harness the benefits of AI in HRV monitoring while protecting individuals' rights and well-being.

V. CHALLENGES AND LIMITATIONS

Despite its potential, AI-based stress detection using HRV faces several challenges as mentioned below:

- **Data Quality and Noise:** Wearable sensors can introduce motion artifacts, which can lead to inaccurate HRV measurements.
- **Inter-individual Variability:** Stress responses and HRV baselines differ significantly across individuals, requiring the development of personalized models to enhance accuracy.
- **Lack of Standardization:** Variations in experimental protocols, datasets, and the methods of stress labeling can limit the generalizability of findings.
- **Ethical and Privacy Concerns:** Continuous physiological monitoring raises important questions regarding data security and the need for informed consent.

VI. FUTURE DIRECTIONS

AI-based stress detection using HRV offers a promising pathway for unobtrusive, real-time mental health monitoring. While current models show high potential, future efforts must focus on multimodal fusion, enhancing personalisation, robustness, and ethical implementation, as outlined below:

- **Multimodal Fusion:** Integrating heart rate variability (HRV) with other physiological signals, such as skin conductance, respiration, and EEG, can significantly enhance the robustness of stress detection methods.
- **Personalized AI Models:** By incorporating individual baseline HRV and unique stress response profiles, we can increase the accuracy of predictive models for stress.
- **Edge AI:** Implementing lightweight AI models on wearable devices enables real-time and offline stress detection, making it more accessible for users.
- **Explainable AI (XAI):** This approach prioritizes transparency and trustworthiness, which is especially important in healthcare settings where decisions significantly impact patient outcomes.

VII.CONCLUSION

HRV is a non-invasive, effective way to measure mental stress and is commonly used in areas like personal health, workplace wellness, and clinical psychology. The integration of AI with HRV monitoring offers a transformative approach to stress detection. Connecting wearable devices and health platforms could revolutionize proactive stress management and support well-being on a large scale. By extracting various HRV features such as time-domain, frequency-domain, time-frequency, and non-linear measures and combining them with machine learning and deep learning techniques such as SVMs, k-NN, RF, CNNs, and others, researchers have achieved high accuracy in stress classification. Wearable technology enables real-time, non-invasive monitoring, providing continuous insights into physiological responses to stress. Explainable AI further enhances transparency, ensuring that stress detection models remain interpretable and trustworthy. However, challenges still exist, including ethical issues related to data privacy, informed consent, and algorithmic bias. Addressing these concerns is essential for responsible implementation and widespread adoption. Future research should aim to improve AI models for higher accuracy, incorporate multi-modal data like EEG, respiration, sleep patterns, and activity levels, and develop scalable, affordable solutions for broader access. AI-driven HRV analysis can support proactive mental health care, reduce burnout, and help create a healthier learning environment that promotes well-being and performance.

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