Mental Stress Detection In Real Time Using Wearable Sensors And Machine Learning

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Abstract: When we encounter difficult or taxing circumstances, or stressors, our bodies and minds go into a hyperarousal state, commonly known as stress. Chronic illnesses including anxiety, depression, and cardiovascular disease can develop in people who are exposed to various stressors for an extended period of time, particularly when these stressors happen at the same time. In order to avoid these long-term impacts, it is essential to recognise stress early on, and continuous monitoring provides a viable option. One possibility for personal stress monitoring is the use of wearable devices that can gather data continuously and in real-time, allowing users to keep tabs on their stress levels as the day progresses. This study provides an extensive analysis of several approaches to stress detection that make use of wearable sensors in conjunction with machine learning methodologies. Wearable sensors including electrocardiograms (ECGs), electroencephalograms (EEGs), and photoplethysmography (PPGs) are reviewed, along with the many settings when stress is tracked, such as while driving, learning, or working. Various stress detection approaches were examined in this review, with an emphasis on the stressors, procedures, outcomes, benefits, drawbacks, and difficulties encountered by each research. The area of stress monitoring is anticipated to benefit from these findings in the future. In addition, the study suggests a multimodal stress detection system that combines various kinds of wearable sensors with deep learning algorithms. This could be a great step towards better real-time stress detection that is both accurate and adaptive, which would be great for mental health management and healthcare prevention.

1. INTRODUCTION

Stress is an inevitable part of human life, arising from various environmental, social, and psychological factors. It is a psycho-physiological state triggered by challenging events, known as stressors, which can significantly impact mental and physical health. While short-term stress can

sometimes enhance performance and alertness, prolonged exposure to stressors can lead to severe health complications such as anxiety, depression, and cardiovascular diseases. Therefore, early detection and management of stress are crucial to preventing long-term adverse effects and promoting overall well-being.

With advancements in technology, wearable sensors have emerged as an effective solution for real-time stress monitoring. These devices enable continuous data collection, allowing individuals to track their stress levels throughout the day. Various wearable sensors, including Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), are widely used to measure physiological signals associated with stress. The integration of these sensors with machine learning techniques has further enhanced stress detection accuracy, making it possible to develop intelligent systems capable of recognizing stress patterns in real time.

Recent research has focused on leveraging machine learning models to analyze physiological data and classify stress levels based on different activities and environments, such as workplaces, educational settings, and driving scenarios. These studies provide valuable insights into stress detection methodologies, highlighting their advantages, limitations, and challenges. To improve the reliability and accuracy of stress detection, a multimodal approach combining multiple sensor data with deep learning techniques has been proposed. This method enhances stress recognition by utilizing diverse physiological inputs, making it a promising solution for effective mental health monitoring and personalized stress management.

2. LITERATURE SURVEY

2.1 A Review of Eeg Sensors used for Data Acquisition

https://www.researchgate.net/publication/308259085_A_Review_of_Eeg_Sensors_used_for_Data_Acquisition

ABSTRACT: Electroencephalography is a method that uses sensors to record the brain's electric fields, which change in strength over time. The coordinated actions of the brain's

billions of neurones produce these fields. The exact measurement of these fields from the scalp is made possible by sensors that use several techniques that have been developed over the years. One of these ways is relying on direct and low-resistance contact between the sensor and the scalp. With the development of more sophisticated EEG monitoring equipment, its applications have expanded into the entertainment and leisure industries. Methods for obtaining an electroencephalogram (EEG) signal using a variety of sensors, including wireless EEG systems, wet electrodes, and dry electrodes, are covered in detail in this article.

2.2 Support vector machine for classification of stress subjects using EEG signals:

https://ieeexplore.ieee.org/abstract/document/7086243

ABSTRACT: When people are under stress, their brain electrical activity might deviate from what is considered normal. Electroencephalograms can detect this shift in brain function. Using support vector machines (SVMs), this research aims to categorise stress individuals according to their EEG signals. Residents of Pusat Darul Wardah, a refuge institution for problematic women, provided the data used to depict stress subjects. Power Spectral Density and Energy Spectral Density are calculated from the EEG Alpha band data using SVM. The RBF kernel function achieved a classification rate of 83.33% for ESD data when 5-fold cross validation was applied.

2.3 An Effective Mental Stress State Detection and Evaluation System Using Minimum Number of Frontal Brain Electrodes:

https://pmc.ncbi.nlm.nih.gov/articles/PMC7278014/

ABSTRACT: People are currently dealing with mental stress, which is a frequent societal problem. Stress lowers human performance in everyday tasks and might cause serious health problems. In order to assess the efficacy of instruction, enhance learning, and lessen the likelihood of mistakes caused by stressed-out employees, stress detection

is crucial in the business and academic sectors. Preventing disease and health problems, improving education quality, and enhancing industrial safety all depend on early identification of mental stress utilising ML approaches. When we're under emotional stress, our brains are particularly vulnerable. This is why we provide an ML system that analyses 36 subjects' electroencephalogram (EEG) signals. A good mental stress detection (MSD) system must be able to extract relevant characteristics. As a result, five ML classifiers are trained on this framework's hybrid feature-set in order to distinguish between stress and non-stress situations, as well as to categorise stress levels. In order to create an effective, efficient, and dependable MSD system with fewer electrodes, the suggested MSD scheme studies the placement of electrodes on several scalp locations and chooses the site with the most influence on the system's accuracy. Also, in order to minimise the complexity of the model, we use principal component analysis to reduce the characteristics retrieved from these electrodes. We use a sequential forward technique to analyse the ideal number of principle components. More importantly for stress assessment and detection, it determines the minimal number of electrodes that need be installed at the spot. The suggested system is evaluated by comparing its findings to those of existing feature extraction methods found in the literature. Additionally, they are contrasted with documented state-of-the-art methods for stress detection. In this study, the highest accuracies for detecting stress and non-stress states using only two frontal brain electrodes and for evaluating stress levels using three frontal electrodes were 99.9% (sd = 0.015) and 99.26% (sd = 0.08), respectively. With sensitivity of 99.9(0.064), specificity of 99.94(0.02), precision of 99.94(0.06), and a diagnostics odd ratio (DOR) of $\geq$ 100 for stress and non-stress detection and evaluation, respectively, the results demonstrate the reliability of the proposed system. This demonstrates that the suggested framework performs well and has applications in the areas of medicine, education, and industry for the identification and assessment of stress. Using only two frontal electrodes, the proposed system was able to achieve an accuracy of 98.48% (sd = 1.12), sensitivity of 97.78% (sd = 1.84), specificity of 97.75% (sd = 2.05), precision of 99.26% (sd = 0.67), and a DOR of 100

or higher. These results validate the system's efficiency and reliability in stress and non-stress prediction on new patients.

2.4 CogniMeter: EEG-based Emotion, Mental Workload and Stress Visual Monitoring:

https://ieeexplore.ieee.org/abstract/document/7398407

ABSTRACT: Real-time EEG (Electroencephalogram)-based user's emotion, mental workload and stress monitoring is a new direction in research and development of human-machine interfaces. It has attracted recently more attention from the research community and industry as wireless portable EEG devices became easily available on the market. EEG-based technology has been applied in anesthesiology, psychology, serious games or even in marketing. In this work, we describe available real-time algorithms of emotion recognition, mental workload, and stress recognition from EEG and propose a novel interface Cogni Meter for the user's mental state visual monitoring. The system can be used in real time to assess human current emotions, levels of mental workload and stress. Currently, it is applied to monitor the user's emotional state, mental workload and stress in simulation scenarios or used as a tool to assess the subject's mental state in human factor study experiments.

2.5 EEG based stress level identification

https://ieeexplore.ieee.org/document/7844738

ABSTRACT: This paper investigates detection of patterns in brain waves while induced with mental stress. Electroencephalogram (EEG) is the most commonly used brain signal acquisition method as it is simple, economical and portable. An automatic EEG based stress recognition system is designed and implemented in this study with two effective stressors to induce different levels of mental stress. The Stroop colour-word test and mental arithmetic test are used as stressors to induce low level and high level of stress respectively, and their relevant C# applications are developed in Microsoft Visual Studio to interface with

Emotiv Epoc device. Power band features from EEG signals are analyzed and using the relative difference of beta and alpha power as feature along with Support Vector Machine as classifier, three-levels of stress can be recognized with an accuracy of 75%. For two-level stress analysis, accuracy of 88% and 96% are achieved for Stroop colour-word test and mental arithmetic test respectively.

3. METHODOLOGY

i) Proposed Work:

To enhance the accuracy and reliability of stress detection, a multimodal system integrating multiple wearable sensors with deep learning techniques is proposed. This system combines data from Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG) sensors to capture diverse physiological responses to stress. By leveraging advanced machine learning algorithms, the system can analyze real-time data and classify stress levels with higher precision. Deep learning models are employed to extract meaningful patterns from sensor inputs, improving the adaptability and efficiency of stress detection. The proposed approach aims to provide continuous, real-time monitoring, enabling early intervention and personalized stress management. Additionally, addressing challenges like data privacy, device comfort, and accuracy under varying conditions will be crucial for the system's widespread adoption and effectiveness in real-world applications.

ii) System Architecture:

The proposed system consists of multiple layers that work together to detect stress in real-time using wearable sensors and machine learning techniques. Wearable sensors such as ECG, EEG, and PPG collect physiological signals, which are then preprocessed to remove noise and extract relevant features like heart rate variability, brain activity, and blood flow patterns. These features are analyzed using deep learning models like CNN and LSTM to classify stress levels into low, moderate, or high. The system provides real-time monitoring through a user-friendly interface, offering personalized feedback and stress management

recommendations. Additionally, the integration of multimodal sensor data improves detection accuracy, while real-time alerts help users take timely action to reduce stress. This adaptive approach enhances the system's effectiveness in continuous mental health monitoring and early intervention.
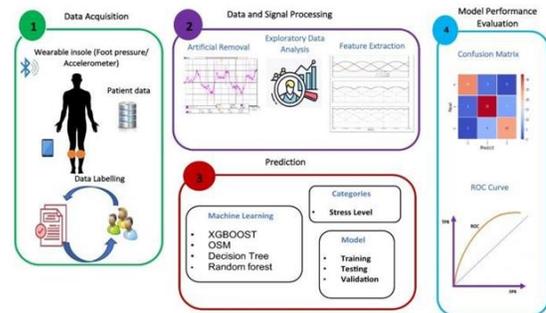

Fig 1 Proposed architecture

iii) Modules:

a) Data Collection Module

This module is responsible for gathering real-time physiological data from wearable sensors.

- **Wearable Devices**: Various wearable sensors are utilized to capture physiological signals associated with stress. These sensors can be embedded in devices like smartwatches, fitness bands, or specialized wearable patches.

  o **Heart Rate Monitor (HRM)**: Measures heart rate and heart rate variability (HRV), which can indicate stress levels. An increase in heart rate or variability patterns often correlates with stress responses.

  o **Electrodermal Activity (EDA) Sensors**: Measure skin conductance, which is influenced by changes in sweat gland activity. Stress can lead to increased skin conductance.

  o **Temperature Sensors**: Monitor skin or body temperature. Stress can lead to fluctuations in temperature due to changes in blood flow. o

Accelerometers: Detect changes in movement or activity. Increased movement, such as fidgeting or restlessness, can be a sign of stress.

- **Data Acquisition**: The sensor data is continuously collected and transmitted in real-time. The wearable device often stores the data temporarily and sends it to a processing unit (e.g., mobile app, cloud server).

b) Data Preprocessing Module

Raw sensor data often includes noise, missing values, or other issues that need to be addressed before analysis. This module cleans and transforms the data into a usable format for machine learning models.

- **Noise Removal**: Signals from wearable sensors can be noisy due to various factors like body movement or external interference. Filtering techniques like low-pass or high-pass filters, or wavelet transforms, can remove unwanted noise.

- **Normalization**: Physiological signals, such as heart rate, vary widely among individuals. Data normalization scales these signals into a common range (e.g., between 0 and 1) to ensure consistency and better performance of machine learning models.

- **Feature Extraction**: Key features are extracted from raw sensor signals, such as:

  o **Heart Rate Variability (HRV)**: Metrics like the standard deviation of heart rate intervals or the root mean square of successive differences.

  o **EDA Features**: Measures like skin conductance level (SCL) and skin conductance response (SCR).

  o **Activity Level**: Derived from accelerometer data, indicating movement patterns and intensity.

  o **Time-Domain and Frequency-Domain Features:** These features help understand the variability and trends in signals over time, such as spectral analysis of heart rate or skin conductance. Output: Cleaned and extracted features, ready for analysis by machine learning algorithms.

c) Feature Selection/Dimensionality Reduction Module

This module ensures that only the most relevant features are used for model training, reducing noise and computational complexity.

- **Feature Selection**: Using techniques such as mutual information or recursive feature elimination (RFE), irrelevant or redundant features are eliminated.

- **Dimensionality Reduction:** Methods like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) can reduce the number of features while preserving the most important variance in the data. Goal: To reduce overfitting and improve model performance by focusing on the most predictive features.

d) Machine Learning Model Module

This module is at the core of the system, where machine learning algorithms analyze the preprocessed sensor data and classify the user's stress levels. The model is trained on labeled datasets and continuously improves as new data is added.

- Supervised Learning: The model is trained using a labeled dataset, where the input data (sensor features) is paired with corresponding stress labels (e.g., low, moderate, high stress).

- Real-Time Prediction: The model is deployed to perform predictions on real-time data. When new sensor data is received, the model classifies the current stress level and provides feedback.

- Model Evaluation: The model is evaluated based on various metrics such as accuracy, precision, recall, F1-score, and confusion matrices to assess its performance in detecting stress.

e) Feedback and User Interaction Module

This module is responsible for providing users with real-time feedback based on the system's stress predictions.

- **Stress Level Notification**: If the system detects a high stress level, it can trigger visual, auditory, or haptic feedback (e.g., vibration on the wearable device). The feedback could be delivered through the wearable itself, a connected mobile app, or a web platform.

- **Personalized Recommendations**: Based on the stress level, the system may offer tailored suggestions for relaxation or stress management (e.g., "Take a 5-minute break," "Try breathing exercises," or "Walk for 10 minutes").

- **Intervention Triggers**: The system could activate intervention protocols such as guided meditation, breathing exercises, or mindfulness reminders through the user interface (mobile app, smart device, etc.).

User Experience Considerations: Feedback must be delivered in a non-intrusive manner to avoid increasing user stress. The UI should be intuitive and allow users to track their stress patterns over time.

f) Data Storage and Cloud Integration Module

This module ensures that the collected data is securely stored and can be accessed for analysis or further action.

- **Cloud Storage**: The collected data (sensor readings, stress predictions, and feedback logs) is uploaded to a secure cloud server for long-term storage.

- **Data Synchronization**: The system needs to ensure that data from wearable devices is synced in realtime or periodically with cloud-based services, enabling continuous monitoring.

- **Data Privacy and Security**: Encryption techniques (e.g., SSL/TLS) ensure that all transmitted data is secure. Access control and user authentication mechanisms are put in place to protect sensitive health information.

g) Personalization and Adaptation Module

Over time, the system can learn from each user's stress patterns and adapt its behavior for better accuracy and relevance.

- **User Profiles**: A profile is created for each user based on their physiological signals and stress responses. This profile stores baseline stress levels and personalized feedback preferences.

- **Continuous Learning**: The model continuously adapts and improves by learning from new data, either through user feedback or additional training datasets.

Customizable Alerts: Users can personalize the thresholds for when they want to be notified about highstress levels (e.g., set a more sensitive threshold for stress detection).

h) Evaluation and Monitoring Module

This module provides insight into the system's performance and allows for real-time monitoring of the system's effectiveness.

- **Performance Metrics**: The module tracks performance indicators, such as accuracy, prediction speed, and user satisfaction. Metrics like false positives or false negatives are monitored to ensure model reliability.

- Health and Stress Trends: It provides users with visualizations of their stress patterns over time, helping them identify recurring stress triggers and improve their coping strategies.

- Clinical Validation: This module is useful for validating the system in clinical or professional settings by comparing its

predictions with expert evaluations or standardized psychological assessments.

iv) Algorithms:

a) **Convolutional Neural Network (CNN):**

- Extracts spatial features from sensor data.
- Helps in identifying stress patterns from ECG, EEG, and PPG signals.

b) **Long Short-Term Memory (LSTM):**

- Captures temporal dependencies in physiological signals.
- Suitable for analyzing time-series data like heart rate and brain activity.

c) **Support Vector Machine (SVM):**

- Classifies stress levels based on extracted features.
- Works well with high-dimensional physiological data.

d) **Random Forest (RF):**

- Enhances classification accuracy by using multiple decision trees.
- Robust against overfitting and noise in sensor data.

e) **K-Nearest Neighbors (KNN):**

- Compares new sensor readings with existing patterns.
- Helps in quick classification of stress levels.

4. EXPERIMENTAL RESULTS

	X	Y	Z	EDA	HR	TEMP	id	datetime	label
0	-13.0	-61.0	5.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.000000000	2.0
1	-20.0	-69.0	-3.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.031249920	2.0
2	-31.0	-78.0	-15.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.062500096	2.0
3	-47.0	-65.0	-38.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.093750016	2.0
4	-67.0	-57.0	-53.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.124999936	2.0
...	...	...	...	...	...	...	...	...	...
11509046	-16.0	-56.0	24.0	3.386070	88.37	33.77	F5	2020-07-23 17:28:59.875000064	2.0
11509047	-8.0	-50.0	27.0	3.386070	88.37	33.77	F5	2020-07-23 17:28:59.906249984	2.0
11509048	-28.0	-36.0	28.0	3.386070	88.37	33.77	F5	2020-07-23 17:28:59.937499904	2.0
11509049	-29.0	-29.0	30.0	3.386070	88.37	33.77	F5	2020-07-23 17:28:59.968750080	2.0
11509050	-22.0	-24.0	29.0	3.374543	88.33	33.75	F5	2020-07-23 17:29:00.000000000	2.0

Fig 2 dataset

	Model	Accuracy
0	LGBMClassifier	0.843198
1	XGBClassifier	0.867347

```
f, axe = plt.subplots(1,1, figsize=(8,1))

predict.sort_values(by=['Accuracy'], ascending=False, inplace=True)

sns.barplot(x='Accuracy', y='Model', data = predict, ax = axe)
axe.set_xlabel('Accuracy(Eval)', size=15)
axe.set_ylabel('Model', size=15)
axe.set_xlim(0,1.0)
plt.show()
```

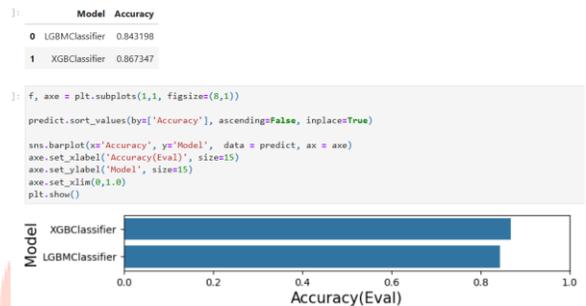Fig 3 accuracy graph

5. CONCLUSION

The proposed real-time mental stress detection system leverages wearable sensors and machine learning techniques to enhance stress monitoring accuracy. By integrating multimodal physiological data from ECG, EEG, and PPG sensors with deep learning models like CNN and LSTM, the system provides reliable stress classification in real-time. The inclusion of advanced algorithms ensures improved detection, enabling timely intervention and personalized stress management. This approach contributes to mental health monitoring by offering a user-friendly and effective solution for early stress detection, ultimately promoting well-being and preventing long-term health complications.

6. FUTURE SCOPE

The proposed stress detection system can be further enhanced by integrating more advanced wearable sensors, such as skin temperature and respiration rate sensors, to improve detection accuracy. The use of federated learning

can address privacy concerns by enabling decentralized stress analysis without sharing raw data. Additionally, real-time stress prediction models using AI can provide proactive stress management recommendations. The system can also be expanded to support integration with smart healthcare platforms, mental health applications, and IoT-based smart environments for a more personalized and adaptive stress monitoring experience.

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