A Multimodal Intelligent Framework for Real-Time Stress Detection and Personalized Mental Health Assessment Using EEG, Facial Expression Analysis, and Machine Learning

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Abstract:
Stress has become a major factor affecting human health and daily life, making timely detection and management essential for maintaining well-being. This paper presents a web-based intelligent system developed to identify stress levels using multiple data sources. The proposed platform collects Electroencephalogram (EEG) parameters entered by the user, captures facial expressions through a webcam, and evaluates responses to structured questionnaire-based questions. These inputs are processed using machine learning and computer vision techniques to determine the user's stress level, which is categorized as low, medium, or high. After classification, the system generates a personalized report and provides suitable precautionary suggestions such as relaxation methods, breathing exercises, and motivational guidance to help users manage stress effectively. The platform also enables users to monitor their condition through recorded results, supporting better awareness and long-term stress management. The overall objective of the system is to offer an accessible and user-friendly solution that integrates multiple indicators to improve the accuracy of stress detection and promote mental health care.

Key Words: Stress Detection, EEG Parameters, Facial Expression Analysis, Machine Learning, Mental Health, Personalized Recommendations.

INTRODUCTION

In recent years, stress has become one of the most common challenges affecting individuals due to increasing academic pressure, professional demands, and lifestyle changes. Prolonged exposure to stress can negatively influence both mental and physical health, leading to issues such as anxiety, reduced productivity, and emotional instability. However, many people remain unaware of their stress levels until noticeable symptoms appear, which makes early detection and proper management extremely important. Traditional stress assessment methods often rely on self-reporting or single-parameter analysis, which may not always provide accurate or reliable results.

To address these limitations, an intelligent and interactive solution is required that can evaluate stress using multiple indicators and provide meaningful feedback to users. The proposed system introduces a web-based platform that combines physiological data, facial expression analysis, and psychological assessment to determine an individual's stress level. The system begins with a secure user login process, followed by the entry of EEG report parameters that reflect brain activity related to stress conditions. In addition, the platform uses a webcam to monitor facial expressions while the user answers structured questionnaire-based questions designed to evaluate emotional and cognitive responses. The collected information is analysed using machine

learning and computer vision techniques to classify stress into three categories: low, medium, or high. After identifying the stress level, the system generates a personalized report and provides appropriate precautionary suggestions to help users manage their condition effectively. These suggestions may include relaxation techniques, breathing exercises, or motivational guidance aimed at improving emotional well-being.
By integrating multiple sources of information into a single platform, the proposed system provides a more comprehensive understanding of stress compared to conventional approaches. The solution is designed to be user-friendly, accessible, and supportive of long-term stress awareness, enabling individuals to monitor their condition and take preventive measures for maintaining better mental health.

LITERATURE SURVEY

Several research studies have explored different approaches for detecting and analysing stress using physiological signals, behavioural patterns, and machine learning techniques. These methods aim to improve the accuracy of stress identification and provide reliable mental health monitoring solutions.
Al-Shargie et al. proposed a method for mental stress assessment by combining Electroencephalogram (EEG) signals with functional Near-Infrared Spectroscopy (fNIRS). EEG captures electrical brain activity, while fNIRS measures variations in blood oxygen levels associated with cognitive workload and stress conditions. By integrating these two physiological signals, the system achieved improved accuracy compared to single-signal approaches. The study demonstrated that multimodal physiological analysis can provide objective and non-invasive stress evaluation.
Lu et al. introduced a stress detection technique based on speech characteristics and machine learning algorithms. The research analysed vocal features such as pitch, tone, speaking rate, and intensity to identify patterns associated with emotional stress. Machine learning models were trained to classify stress conditions from speech data, enabling real-time monitoring without the need for physical sensors. This approach highlighted the feasibility of contactless stress assessment using behavioural indicators.
Ko et al. presented a deep learning-based framework for recognizing stress through facial expressions. The study focused on identifying subtle facial movements, including eye activity, muscle tension, and micro-expressions, which often reflect emotional states. By applying convolutional neural networks, the system achieved reliable classification of stress levels from visual data. The research emphasized the advantages of non-intrusive monitoring methods for human–computer interaction and mental health applications.
Zhang et al. proposed a multimodal deep learning model that integrates multiple sources of information, such as physiological signals and facial features, to improve stress detection performance. The fusion of diverse data types allowed the system to capture complex stress patterns more effectively than single-modal systems. The study concluded that combining different modalities significantly enhances reliability and robustness in stress recognition systems.
From the reviewed literature, it is evident that multimodal approaches provide better accuracy and reliability compared to traditional single-factor methods. However, there is still a need for user-friendly platforms that integrate multiple data sources into a unified system capable of delivering personalized feedback. The proposed system addresses this gap by combining EEG parameters, facial expression analysis, and questionnaire-based evaluation within an accessible web-based environment

METHODOLOGY

The proposed system is designed as a web-based platform that detects and manages stress by analysing multiple types of user data, including physiological parameters, facial expressions, and questionnaire responses. The methodology follows a structured workflow that integrates data collection, processing, analysis, and personalized recommendation generation to provide an accurate assessment of an individual’s stress condition.

The process begins with user authentication, where individuals create an account and securely log into the system. After successful login, users are required to provide key parameters obtained from their Electroencephalogram (EEG) reports. These parameters represent brain activity patterns that are associated with mental states and stress conditions. Once the EEG data is entered, the system activates the device camera to capture facial expressions in real time while the user responds to a set of multiple-choice questions designed to evaluate emotional and psychological factors related to stress.

The collected information from EEG inputs, facial expression data, and questionnaire responses is then processed using machine learning and computer vision techniques. Facial regions are detected and analysed to extract important visual features, while the EEG parameters and questionnaire responses are evaluated to identify patterns related to stress levels. By combining multiple data sources, the system improves the reliability of prediction compared to single-input approaches. The stress condition is classified into three categories: low, medium, or high.

After determining the stress level, the system generates a personalized report that includes the analysis results along with suitable precautionary suggestions. These recommendations may include relaxation methods, breathing exercises, or motivational guidance aimed at helping users reduce stress and improve their mental well-being. The system also stores user results to allow individuals to review previous assessments and observe changes in their condition over time.

Overall, the methodology integrates multimodal data acquisition, intelligent analysis, and personalized feedback within a unified platform, providing an effective solution for stress detection and management while maintaining ease of use and accessibility.

OBJECTIVE

1. To collect and analyse Electroencephalogram (EEG) report parameters that indicate brain activity related to stress conditions.
2. To capture and interpret facial expressions through camera-based monitoring in order to recognize emotional indicators associated with stress.
3. To evaluate user responses to structured questionnaire-based questions for assessing psychological and cognitive factors influencing stress.
4. To integrate physiological data, facial features, and behavioural responses to improve the accuracy of stress level classification.
5. To categorize the detected stress condition into predefined levels such as low, medium, and high.

PROBLEM DEFINATIONS

In today’s fast-paced environment, stress has become a common issue affecting both mental and physical health. Many individuals experience stress due to academic workload, professional responsibilities, and personal challenges, but they often lack awareness about their actual stress levels or effective ways to manage them. Existing stress detection methods are limited because they typically rely on a single factor such as self-assessment, physiological signals, or behavioral observation, which may not provide accurate or comprehensive results. Additionally, most available systems do not offer interactive features or personalized guidance for stress management. Therefore, there is a need for an integrated solution that can analyze multiple indicators of stress and provide reliable detection along with appropriate recommendations for improving mental well-being.

SYSTEM ARCHITECTURE

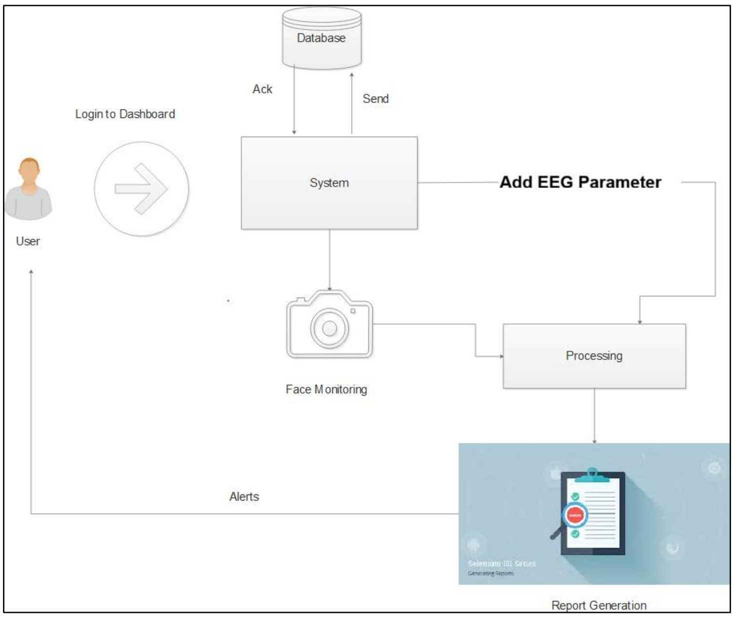


Fig: System Architecture

The system architecture illustrates the workflow of the stress detection platform and the interaction between different components. The process begins when the user logs into the system through the dashboard. After authentication, the user enters EEG parameters into the platform, which are stored and managed through the connected database. The database communicates with the main system by sending and receiving data whenever required. Once the EEG data is provided, the system activates the face monitoring module, which captures the user's facial expressions using the device camera. Both the EEG inputs and facial data are forwarded to the processing unit, where machine learning and analysis techniques are applied to evaluate the user's stress condition.

After processing is completed, the system generates a report that includes the detected stress level and appropriate suggestions. The results are then displayed to the user in the form of alerts and recommendations. This architecture ensures smooth data flow from input collection to analysis and final report generation within a unified platform.

FUCTIONAL REQUIREMENTS

1. **User Authentication:** The system should allow users to register and securely log in to access the platform features.
2. **Data Input Management:** Users should be able to enter EEG report parameters and provide responses to questionnaire-based questions for stress analysis.
3. **Facial Expression Monitoring:** The system should capture and analyse facial expressions through the device camera to detect emotional indicators.
4. **Stress Level Detection:** The platform should process the collected data using machine learning techniques to classify stress levels as low, medium, or high.
5. **Report and Recommendation Generation:** The system should generate a personalized report and provide appropriate suggestions for stress management based on the detected level.

NON FUCTIONAL REQUIREMENTS

1. **Performance:**

The system should analyse user data efficiently and display results within a short time to ensure a smooth user experience.

2. **Usability:**

The interface should be simple, interactive, and easy to use for individuals with different levels of technical knowledge.

3. **Reliability:**

The system should provide consistent and accurate stress detection results whenever it is used.

4. **Security:**

User information, including EEG data and analysis results, should be stored securely to maintain privacy and confidentiality.

5. **Scalability:**

The platform should be capable of handling multiple users and increasing data volume without affecting performance.

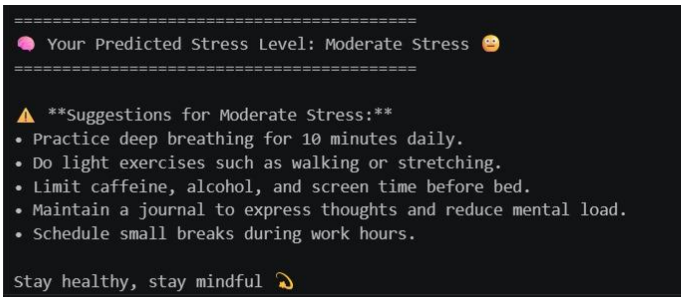
RESULTS

```
Final Model Accuracy: 86.67%

Classification Report:
              precision    recall  f1-score   support

       Angry       0.95      0.90      0.92        20
        Calm       0.85      0.85      0.85        20
       Happy       0.78      0.90      0.84        20
     Relaxed       0.79      0.75      0.77        20
         Sad       0.95      0.95      0.95        20
    Stressed       0.89      0.85      0.87        20

    accuracy                           0.87       120
   macro avg       0.87      0.87      0.87       120
weighted avg       0.87      0.87      0.87       120
```

This screen shows the result of a stress prediction from an EEG-based system. It clearly states that your predicted stress level is "Moderate Stress" with a slightly concerned emoji. Below this, there is a list of helpful suggestions to manage the moderate stress. These include practicing deep breathing for 10 minutes every day, doing light exercises like walking or stretching, limiting caffeine, alcohol, and screen time before bed, maintaining a journal to express thoughts, and scheduling small breaks during work hours. At the bottom, it ends with a positive message: "Stay healthy, stay mindful" along with a yoga hand emoji.

```
EEG Mood Prediction System (Final Version)
Please enter EEG feature values (range: 0.1 - 1.0):


===================================
Predicted Mood: Angry
===================================
```

This image displays the performance report of the machine learning model used in the system. It mentions that the final model accuracy is 86.67%. A detailed classification report follows, showing how well the model can identify six different moods: Angry, Calm, Happy, Relaxed, Sad, and Stressed. Each mood has scores for precision, recall, and f1-score, along with the number of test samples (20 for each). The model performs particularly well on "Sad" and "Angry" moods, while "Happy" and "Relaxed" have slightly lower scores. Overall, the average accuracy across all moods is around 87%, which is considered quite good for such a system.



This is the main user interface of the "EEG Mood Prediction System (Final Version)". It asks the user to enter EEG feature values, which should be numbers between 0.1 and 1.0. These values come from brain signal data. After processing the input, the system displays the predicted mood. In this case, the predicted mood is clearly shown as "Angry" with a lightbulb emoji, indicating the system's conclusion based on the provided brain features.

These three images together demonstrate a complete flow of an AI-powered mood detection tool that uses brain signals (EEG) to predict emotions and stress levels, provides accuracy details, and offers practical advice for better mental well-being.

CONCLUSION

The proposed system provides an efficient method for detecting and managing stress by combining EEG parameters, facial expression analysis, and questionnaire responses. Using machine learning techniques, the platform classifies stress levels and generates personalized suggestions to help users improve their mental well-being. The system also allows users to track their results over time, promoting better awareness of their stress condition. Overall, the project demonstrates a practical and accessible approach for supporting stress detection and management using intelligent technologies.

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