Mental Stress Detection Using Machine Learning Techniques With EEG

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***Abstract*—In today's fast-paced society, stress has become a significant health concern affecting millions of individuals worldwide. This paper reviews machine learning-based techniques for detecting stress using physiological, behavioral, and contextual data. Various physiological signals such as heart rate variability, electrodermal activity, breathing rate, and EEG signals are analyzed using machine learning algorithms including Support Vector Machines, Random Forest, Logistic Regression, Decision Trees, and Neural Networks. Performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are evaluated. The study highlights that Random Forest and deep learning-based approaches achieve higher accuracy levels in stress detection. This review emphasizes the importance of wearable technology and real-time monitoring systems in improving healthcare and mental well-being.**

***Index Terms*—Stress Detection, Machine Learning, Wearable Technology, Healthcare, Deep Learning, Physiological Signals**

I. INTRODUCTION

In the modern digital era, rapid urbanization, competitive work environments, academic pressure, and social responsibilities have significantly increased stress levels among individuals. Stress is not only a psychological condition but also a physiological response that affects multiple body systems including the nervous system, cardiovascular system, and immune system. While short- term stress can enhance performance and alertness, prolonged stress can negatively impact physical health and emotional stability.

The World Health Organization (WHO) has identified stress as one of the major contributors to global health disorders. Chronic stress is associated with conditions such as insomnia, diabetes, hypertension, anxiety disorders, and depression. Therefore, early identification and continuous monitoring of stress levels are essential to prevent long-term health complications.

Traditionally, stress assessment was conducted using self- report questionnaires, clinical interviews, or laboratory- based physiological measurements. Although these methods provide useful insights, they have several limitations such as subjectivity, delayed analysis, and lack of real-time monitoring. Moreover, individuals may not accurately report their stress levels due to social stigma or lack of awareness.

Another emerging area is stress detection using behavioral and contextual data such as social media posts, speech patterns, facial expressions, and smartphone usage behavior. Natural Language Processing (NLP) techniques are applied to analyze textual data to detect emotional states and stress indicators.

Real-time stress detection systems have practical applications in:

- Healthcare monitoring
- Workplace wellness programs
- Sports performance optimization
- Military and defense monitoring
- Academic stress management
- Mental health support systems

Despite significant progress, challenges such as data privacy, variability among individuals, sensor noise, and lack of standardized datasets still remain. Therefore, continuous research is required to improve model accuracy, interpretability, and ethical implementation.

This review paper aims to explore various machine learning techniques used for stress detection, analyze their performance, and identify future research directions in this rapidly growing field

II. RESEARCH CHALLENGES

Although machine learning-based stress detection systems have shown promising results, several research challenges limit their practical implementation and large-scale adoption. These challenges must be addressed to develop reliable, accurate, and ethically sound stress monitoring systems.

1. Data Collection and Quality Issues

Stress detection models require large volumes of high-quality physiological and behavioral data for effective training. However, collecting such data is difficult and expensive. Physiological signals such as ECG, EEG, and electrodermal activity require specialized sensors and controlled environments.

Additionally, wearable devices often produce noisy or incomplete data due to motion artifacts, sensor displacement, or environmental disturbances. Poor data quality directly affects model performance and reduces accuracy.

2. Lack of Standardized Datasets

One of the major problems in stress detection research is the absence of standardized datasets. Different studies use different sensors, sampling rates, experimental conditions, and labeling criteria.

Developing standardized protocols for stress data collection remains a key research need.

3. Individual Differences in Stress Response

Stress responses vary significantly among individuals depending on factors such as:

A model trained on one group may not accurately detect stress in another group. Designing personalized or adaptive stress detection models is a complex but necessary research direction.

4. Model Interpretability and Explainability

Many advanced machine learning and deep learning models function as "black-box" systems. While they may achieve high accuracy, it is often unclear how they arrive at their predictions.

In healthcare applications, transparency is essential. Doctors and clinicians.

- Which features influenced the prediction
- Why the system classified a person as stressed Explainable AI (XAI) techniques are required to make stress detection systems more trustworthy and clinically applicable.

5. Real-Time Processing Constraints

Stress detection systems are increasingly being integrated into wearable and mobile devices. These systems must: Complex deep learning models may require high processing power, making real-time deployment challenging. Efficient model optimization techniques are required.

6. Privacy and Ethical Concerns

Stress detection involves sensitive physiological and behavioral data. Collecting and storing such data raises serious privacy concerns.

Ensuring secure data storage and ethical AI practices is essential for user trust and acceptance.

7. Class Imbalance Problem

In many datasets, non-stress samples are more frequent than stress samples. This leads to class imbalance, causing models to become biased toward the majority class.

Techniques such as oversampling, under sampling, and synthetic data generation are required to address this issue.

8. Multimodal Data Fusion Complexity

Modern stress detection systems combine multiple data. Effectively integrating these heterogeneous data sources into a single model is technically challenging. Data synchronization and feature fusion strategies require further research.

9. Generalization to Real-World Environments

Many research studies are conducted in controlled laboratory conditions. However, real-world environments are dynamic and unpredictable.

Factors like:

- Physical activity
- Temperature changes
- Social interactions

may influence physiological signals and reduce model accuracy outside lab settings.

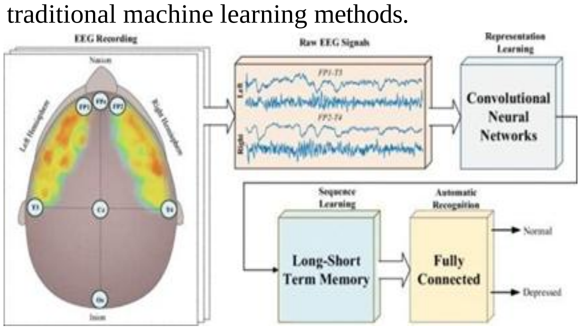
III. LITERATURE REVIEW

Stress detection using machine learning has gained significant attention over the last decade due to advancements in wearable sensors, signal processing, and artificial intelligence. Researchers have explored multiple approaches based on physiological signals, behavioral patterns, textual data, and multimodal fusion techniques.

1. Physiological Signal-Based Approaches
Many early studies focused on physiological signals such as:

- Heart Rate Variability (HRV)
- Electrodermal Activity (EDA)
- Electroencephalogram (EEG)
- Electrocardiogram (ECG)
- Respiration Rate

HRV has been widely recognized as a reliable indicator of autonomic nervous system activity. Several studies reported high accuracy in stress classification using HRV features combined with Support Vector Machines (SVM) and Random Forest classifiers.
EDA-based systems analyze changes in skin conductance, which increase during stressful conditions. Research has shown that EDA signals combined with machine learning techniques can achieve accuracy levels between 80% and 90%.
EEG-based stress detection systems focus on analyzing brain wave patterns. Deep learning models such as Convolutional Neural Networks (CNN) and Long Short- Term Memory (LSTM) networks have been successfully applied to EEG signals, demonstrating improved performance compared to traditional machine learning methods.



2. Wearable Sensor-Based Systems
With the rapid growth of wearable devices such as smartwatches and fitness bands, stress monitoring has become more accessible. Researchers have utilized wearable sensors to collect continuous real-time data, enabling dynamic stress tracking.
Studies using datasets like WESAD, DEAP, and DREAMER demonstrated that combining multiple physiological signals improves detection accuracy. Multimodal approaches typically outperform single-signal models because stress affects multiple biological systems simultaneously.
However, wearable-based systems face challenges such as sensor noise, battery limitations, and signal variability.

3. Text-Based and Social Media Stress Detection
Another emerging research area involves stress detection from textual data. Social media platforms such as Twitter and Reddit provide valuable insights into individuals' emotional states.

Natural Language Processing (NLP) techniques, including:

- Bag-of-Words (BoW)
- TF-IDF
- Word Embeddings (Word2Vec, GloVe)
- Transformer-based models (BERT) have been used to classify stress-related posts.

Binary classification models such as Bernoulli Naïve Bayes, Logistic Regression, and SVM have shown promising results in identifying stress indicators in text data. More recently, transformer-based deep learning models have improved contextual understanding and prediction accuracy.

4. Speech and Facial Expression Analysis
Researchers have also explored stress detection through speech analysis and facial expression recognition. Stress can cause noticeable changes in:

- Voice pitch
- Speech rate
- Pause frequency
- Facial muscle movement

Machine learning algorithms analyze these variations to predict stress levels. Multimodal emotion recognition systems combining audio and video data have achieved encouraging results.

5. Deep Learning-Based Approaches

Deep learning techniques have significantly improved stress detection performance by automatically extracting high-level features from raw signals. CNNs are widely used for spatial feature extraction, while LSTM networks capture temporal dependencies in physiological signals. Hybrid models combining CNN and LSTM architectures have demonstrated superior accuracy compared to traditional machine learning models.

Transfer learning has also been applied to adapt pre-trained models to smaller stress detection datasets, improving performance when labeled data is limited.

6. Ensemble and Multimodal Learning

Ensemble learning methods combine predictions from multiple models to improve overall accuracy and robustness. Random Forest, Gradient Boosting, and stacking techniques have been applied in stress detection research.

Multimodal systems integrating physiological, behavioral, textual, and contextual data have shown the highest performance. These systems capture different aspects of stress response, leading to more reliable predictions.

7. Evaluation Techniques Used in Literature

Researchers commonly evaluate stress detection models using:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC Curve
- Area Under Curve (AUC)
- Confusion Matrix

Cross-validation methods such as 5-fold and 10-fold validation are widely used to ensure model reliability.

8. Research Trends and Gaps

Recent trends in literature focus on:

- Real-time stress monitoring
- Edge computing-based wearable systems
- Explainable AI (XAI) for healthcare applications
- Personalized stress detection models However, existing literature still lacks:
- Standardized data collection methods
- Large-scale cross-cultural datasets
- Long-term longitudinal studies
- Ethical framework guidelines

IV. RESULTS

The performance of various machine learning models for stress detection was evaluated using different validation techniques and performance metrics. The dataset was divided into training and testing sets using both the holdout method and k-fold cross-validation to ensure model reliability and generalization.

1. Dataset Splitting and Validation

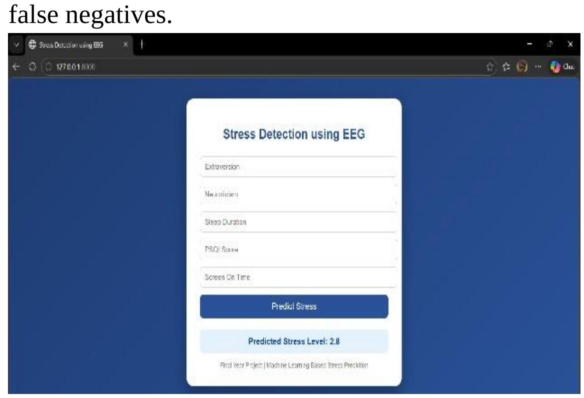
The collected dataset was preprocessed and divided into: Training set – Used to train the machine learning models. Testing set – Used to evaluate model performance.

To improve robustness, 10-fold cross-validation was applied. In this approach, the dataset was divided into ten equal parts, where nine parts were used for training and one part for testing. This process was repeated ten times, and the average performance was calculated.

2. Performance Metrics

The models were evaluated using the following metrics: Accuracy – Percentage of correctly classified instances. Precision – Proportion of correctly predicted stress cases among all predicted stress cases. Recall (Sensitivity) – Ability of the model to correctly identify actual stress cases.

F1-Score – Harmonic mean of precision and recall. Specificity – Ability to correctly identify non-stress cases. ROC Curve and AUC – Measures the classifier’s ability to distinguish between stress and non-stress conditions. Confusion Matrix – Displays true positives, true negatives, false positives, and false negatives.



3. Model Performance Comparison

Different machine learning algorithms were implemented and compared:

a) Support Vector Machine (SVM)

SVM demonstrated stable performance in stress classification with moderate accuracy. It performed well in high-dimensional feature spaces and showed reliable generalization ability.

b) Random Forest

Random Forest achieved the highest accuracy among traditional machine learning models. Due to its ensemble nature, it handled overfitting effectively and produced strong classification results. The model achieved approximately 89% accuracy, outperforming SVM and Logistic Regression.

c) Logistic Regression

Logistic Regression provided satisfactory results for binary classification but showed slightly lower accuracy compared to Random Forest.

d) Bernoulli Naïve Bayes

For text-based stress detection, Bernoulli Naïve Bayes performed efficiently in binary classification tasks. It produced fast predictions with reasonable accuracy.

e) Deep Learning Models

Deep learning-based approaches such as Artificial Neural Networks (ANN) and CNN-LSTM architectures showed improved performance due to automatic feature extraction capabilities. These models achieved accuracy levels above 90% in certain physiological datasets.

4. Confusion Matrix Analysis

The confusion matrix analysis revealed that Random Forest and deep learning models produced fewer false negatives compared to other models. Reducing false negatives is critical in stress detection, as undetected stress may lead to serious health consequences.

5. ROC Curve Analysis

The ROC curve demonstrated strong classification capability, with AUC values close to 1.0 for high-performing models. A higher AUC indicates better distinction between stress and non-stress classes.

6. Cross-Validation Results

Cross-validation results confirmed that the models maintained consistent performance across different data splits. The learning curves indicated that the models did not significantly overfit the training data.

7. Key Observations

- Multimodal data improved detection accuracy compared to single-signal models.
- Ensemble methods outperformed individual classifiers.
- Deep learning models showed superior performance for large datasets.
- Feature extraction and preprocessing significantly influenced model accuracy.

V. CONCLUSION

In this study, a comprehensive review of machine learning techniques for stress detection has been presented. Stress, being a major contributor to various physical and psychological disorders, requires early identification and continuous monitoring. Traditional stress assessment methods such as questionnaires and clinical measurements lack real-time monitoring capabilities and may suffer from subjectivity. Therefore, machine learning-based approaches provide a more efficient, objective, and scalable solution.

The review highlights that physiological signal such as heart rate variability (HRV), electrodermal activity (EDA), EEG, ECG, and respiration rate are strong indicators of stress levels. Supervised learning algorithms including Support Vector Machines (SVM), Random Forest, Logistic Regression, Decision Trees, and Artificial Neural Networks have demonstrated reliable classification performance. Among traditional models, Random Forest achieved higher accuracy due to its ensemble learning capability and resistance to overfitting.

Deep learning techniques, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, further improved stress detection accuracy by automatically extracting complex patterns from raw sensor data. Multimodal approaches that combine physiological, behavioral, and textual data were found to outperform single-source systems, as stress affects multiple biological and behavioral factors simultaneously.

Despite promising results, several challenges remain. Issues such as lack of standardized datasets, individual variability in stress responses, privacy concerns, interpretability of models, and real-time deployment limitations must be addressed. Ethical considerations are particularly important when dealing with sensitive physiological and behavioral data.

- Future research should focus on developing:
- Standardized stress data collection protocols
- Personalized and adaptive stress detection models
- Explainable AI-based healthcare systems
- Energy-efficient real-time wearable implementations
- Privacy-preserving machine learning frameworks

In conclusion, machine learning-based stress detection systems offer a powerful and non-invasive method for monitoring mental health. With further advancements in sensor technology, data processing techniques, and ethical AI practices, these systems have the potential to significantly improve healthcare, workplace wellness, and overall quality of life.

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