EEG-Based Stress Detection Using Deep Learning Techniques : A Survey

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***Abstract*—Distinguishing between simple physiological arousal and the maladaptive state of true stress is crucial. This harmful condition arises when environmental demands exceed an organism's coping capacity, impairing physiological recovery. Due to its widespread negative impact, early and accurate detection of maladaptive stress is vital for protecting personal, social, and economic wellbeing in today's fast-paced world. Electroencephalography (EEG), as a primary method for monitoring neural activity, has shown significant promise in identifying the distinct brain states associated with this stress. Modern deep learning architectures provide a powerful approach by automatically extracting meaningful patterns and hierarchical features from complex EEG data. This comprehensive survey offers researchers, practitioners, and technology enthusiasts a definitive overview of current advancements and highlights the future directions of EEG-based stress detection using deep learning.**

***Index Terms*—component, formatting, style, styling, insert.**

I. Introduction

Stress, a biological response to internal or external stimuli, plays a critical role in exacerbating numerous pathological conditions [?]. It is generally classified as acute (short-term) or chronic (long-term), with unresolved chronic stress leading to serious health consequences by impairing the immune system and disrupting neuroendocrine functions. This persistent state is associated with a broad spectrum of illnesses, including cardiovascular disorders, diabetes, mental health conditions such as depression, and structural brain changes that negatively affect cognition and memory [?]. Recognizing the profound impact of stress, research has shifted toward identifying objective physiological markers beyond subjective assessments. Common approaches monitor autonomic nervous system responses through peripheral signals like Heart Rate Variability (HRV) from Electrocardiography (ECG), Galvanic Skin Response (GSR), and skin temperature [?] [?] [?]. However, attention has increasingly turned to the brain's electrical activity as the origin of the stress response, positioning Electroencephalogram (EEG) signals as a valuable, non-invasive, real-time tool for assessing neural dynamics. Traditional machine learning (ML) methods, especially Support Vector Machines (SVMs), have shown promise in classifying stress states from EEG data. Yet, these methods often depend heavily on manual, time-intensive feature extraction. In contrast, deep learning (DL) architectures offer a robust alternative by automatically learning meaningful features from complex, high-dimensional EEG signals. Models such as Convolutional Neural Networks (CNNs) excel at capturing spatial patterns, while Long Short-Term Memory (LSTM) networks effectively model temporal dependencies. Hybrid CNN-LSTM models are increasingly demonstrating superior classification accuracy by integrating both spatial and temporal information. This survey aims to deliver a thorough review of EEG-based stress detection using advanced deep learning techniques, analyzing current methodologies and performance trends, identifying key challenges, and exploring promising directions for future research.

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II. BACKGROUND

A. Stress

Stress is a psychophysiological response of the human body to internal or external stressors, manifesting in physical, mental, or emotional forms. It is triggered when an individual perceives a situation as challenging, threatening, or demanding. Stressors may be biological, developmental, psychological, socio-cultural, or environmental, and even positive events can disrupt homeostasis, the body's internal balance. Stress is generally classified into two main categories: short-term (episodic) and long-term stress (chronic). Short-term stress arises from specific tasks or situations such as examinations, deadlines, or sudden pressures. Repeated exposure to such stressors may result in episodic stress, often linked to anxiety and hypertension [?]. Prolonged exposure leads to chronic stress, which can cause depression, psychological disorders, and severe physical illnesses. Chronic stress disrupts the nervous system, impairs functional capacity, and adversely affects daily life [?].

Assessing stress is difficult because people react differently to the same stressor, and the same individual may react differently at different times. Clinical and psychological tools such as the Perceived Stress Scale are used for evaluation, but these survey-based methods are better suited for long-term psychological conditions and may not capture real-time stress fluctuations [?]. In addition, physiological methods use bio-signals like ECG-based HRV, speech patterns, and galvanic skin response, all of which change with mental stress. More recently, EEG has gained attention as a non-invasive and reliable signal for detecting stress-related brain activity, making it a key focus in deep-learning-based stress detection research.

Today, stress has become a major public health concern, intensified by fast-paced lifestyles, heavy workloads, and increasing academic pressure on students. Prolonged or unmanaged stress is linked to serious consequences such as depression, cardiovascular disease, weakened immunity, violent behavior, and even suicidal tendencies. These risks highlight the growing need for early detection, continuous monitoring, and timely intervention. Establishing reliable and efficient stress-detection frameworks can greatly improve overall well-being by helping individuals manage stress more effectively. Such systems can contribute to better academic performance, enhanced workplace productivity, and more responsive medical care, making stress detection an essential component of modern health monitoring solutions.

B. Deep Learning Architectures for EEG Analysis

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C. An Introduction to Hyperbolic Geometry for Machine Learning

The vast majority of deep learning models operate in Euclidean space, the familiar geometry of flat surfaces. However, certain data types, particularly those with an underlying hierarchical or tree-like structure, can be embedded into Euclidean space only with significant distortion (Ganea et al., 2018). Hyperbolic geometry, a type of non-Euclidean geometry characterized by constant negative curvature, provides a compelling alternative. In hyperbolic space, the volume grows exponentially with the radius, mirroring the exponential growth of nodes in a tree. This property allows hierarchical structures to be embedded with much lower distortion, preserving their metric properties more faithfully (He et al., 2025). A common and convenient model for implementing hyperbolic geometry is the Poincaré ball model. This model represents an n-dimensional hyperbolic space as the interior of an n-dimensional unit ball, equipped with a specialized metric that causes distances to expand infinitely as they approach the boundary (Peng et al., 2022). To perform computations and build neural networks within this space, standard vector operations must be replaced with their hyperbolic equivalents, which are defined within the framework of Möbius gyrovector spaces. Key operations include:

- Möbius addition: A non-commutative and non-associative generalization of vector addition.
- Möbius scalar multiplication: A generalization of scalar-vector multiplication.

These principled generalizations, along with corresponding definitions for operations like matrix-vector multiplication, allow for the development of hyperbolic analogues of standard neural network layers (Ganea et al., 2018). By defining fully connected, recurrent, and other layers that operate entirely within the Poincaré ball, we can build deep learning models that are geometrically tailored to the intrinsic structure of hierarchical data, setting the stage for their application to complex EEG signals. counting.

III. A General Pipeline for EEG-Based Stress Detection

Research in EEG-based stress detection typically follows a standardized, end-to-end process, beginning with data collection and culminating in model evaluation. This systematic pipeline ensures that experiments are reproducible and provides a common framework for comparing the efficacy of different methodologies. The following sections describe the key stages of this process, from acquiring and cleaning the raw signals to deriving inputs for classification models

A. Data Acquisition and Public Datasets

The first step in any machine learning project is acquiring high-quality data. In the field of EEG-based emotion and stress recognition, a number of publicly available datasets have become benchmarks for evaluating new algorithms. These include:

- DEAP (Dataset for Emotion Analysis using Physiological signals)
- SEED and SEED-IV (SJTU Emotion EEG Dataset)
- DREAMER (Database for Emotion Recognition through EEG and ECG)

These datasets typically involve recording multi-channel EEG signals (e.g., 32 or 62 channels) from participants while they are exposed to stimuli designed to elicit specific emotional states, such as watching carefully selected music video clips (Li et al., 2023)

B. Signal Preprocessing and Artifact Removal

Raw EEG data is invariably contaminated by noise and artifacts from both physiological and environmental sources. Therefore, a critical preprocessing stage is required to clean the signals before any analysis can be performed. Key steps include:

Band-pass filtering: This is applied to isolate the frequency range of interest and remove unwanted noise. A common range used in emotion recognition studies is 4-45 Hz, which effectively removes low-frequency physiological artifacts (e.g., from breathing or heartbeats) and high-frequency environmental noise (e.g., 50/60 Hz power line interference) (Islam et al., 2021).

Artifact Removal: Specific techniques are used to remove artifacts caused by muscle movements (electromyography, EMG) and eye blinks (electrooculography, EOG). Independent Component Analysis (ICA) is a powerful method for separating these artifactual sources from the underlying brain signals (Katmah et al., 2021). Artifact Subspace

Reconstruction (ASR) is another technique that identifies and statistically interpolates high-variance signal components that exceed a certain threshold (Li et al., 2023).

Re-referencing: The recorded EEG potentials are relative. To standardize the signals and reduce common noise across channels, the data is often re-referenced. The Common Average Reference (CAR) method, which subtracts the average value of all electrodes from each individual electrode, is a widely recommended approach (Li et al., 2023)

C. Feature Extraction Methodologies

Once the EEG signals are preprocessed, the next step is to derive inputs suitable for a machine learning model. This is governed by one of two primary philosophies for feature handling, which are increasingly combined in hybrid approaches.

The traditional philosophy involves manually calculating a set of features from the signal, often based on domain knowledge. These "hand-crafted" features are designed to capture specific characteristics of the EEG signal across different domains.

Frequency-Domain Features: These describe the power distribution across different frequency bands

- Power Spectral Density (PSD): The average power of the signal in a specific frequency band (e.g., Alpha, Beta) (Islam et al., 2021).
- Differential Entropy (DE): A feature related to the complexity of the signal within a frequency band, often used in emotion recognition (Li et al., 2023)

Time-Frequency Domain Features: These capture how the frequency content of the signal changes over time

- Discrete Wavelet Transform (DWT): Decomposes the signal into different frequency sub-bands using a mother wavelet (e.g., 'db4'), providing both time and frequency information (Nirabi et al., 2021)
- oShort-Time Fourier Transform (STFT): Calculates the frequency spectrum over short, overlapping time windows (Li et al., 2023).

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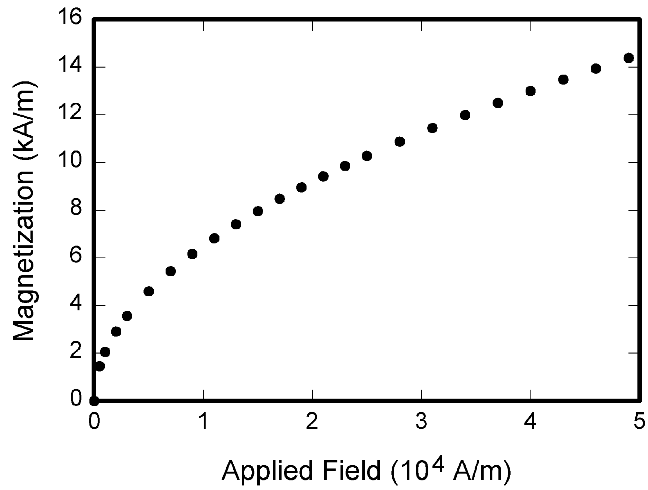

Fig. 1. Example of a figure caption.

ACKNOWLEDGMENT

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