

# A Comparative Study of EEG-Based Stress Detection Using Deep Learning and Yoga Intervention Strategies

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## Abstract

In today's fast-paced world, chronic stress has become a major health concern, often leading to issues such as anxiety, high blood pressure, and reduced cognitive performance. This study explores two complementary approaches to managing stress — the therapeutic benefits of yoga and the use of electroencephalography (EEG) combined with machine learning for stress detection. Yoga, a holistic practice that blends physical postures, breathing techniques, and mindfulness, has been shown to enhance emotional balance and reduce the body's physiological responses to stress. Concurrently, recent developments in EEG-based stress analysis have used deep learning models, such as hybrid architectures, long short-term memory (LSTM) networks, and convolution neural networks (CNNs), to accurately classify emotional stress states. Studies that have been published show encouraging outcomes in real-time detection and classification performance, especially when hybrid CNN models and multimodal sensor data are used. In order to enable proactive stress management solutions, future research is focused on creating customized stress prediction frameworks, boosting real-time detection systems, and improving the interpretability of AI-driven models.

**Keywords:** EEG, long short-term memory (LSTM), deep learning (DL), convolutional neural networks (CNN), stress detection, and feature extraction.

## 1. Introduction

### 1.1. Introduction to Stress

Stress is a natural physical and psychological response that helps the body deal with challenges and external demands. In short bursts, it activates the body's "fight-or-flight" mechanism, allowing quick and effective reactions to immediate threats. However, when stress becomes constant or overwhelming, it can take a serious toll on overall health. Chronic stress—often fueled by continuous pressures such as heavy workloads, financial strain, or relationship conflicts—can disrupt the body's ability to recover, leading to harmful effects on both the mind and body. Elevated levels of cortisol from prolonged stress can weaken the immune system, raise blood pressure, and contribute to anxiety, depression, and sleep problems. It can also cloud cognitive functions like memory, focus, and decision-making. Because stress responses vary from person

to person, shaped by genetics, environment, and lifestyle, personalized approaches to managing stress are increasingly important. With stress-related illnesses on the rise, exploring effective ways to prevent and manage stress has become essential. One promising approach is yoga, an ancient Indian discipline that has been practiced for more than 5,000 years. Rooted in the Sanskrit word yuj, meaning "to unite" or "to join," yoga aims to bring harmony between the body, mind, and spirit. Once seen primarily as a spiritual path to self-realization, yoga is now embraced globally for its therapeutic benefits—enhancing flexibility, improving physical fitness, and promoting emotional balance. It integrates physical postures (asanas), breath control (pranayama), meditation (dhyana), and ethical living to foster holistic well-being. Modern scientific research increasingly supports the benefits of yoga in

reducing stress, improving mental clarity, and enhancing overall quality of life. Various forms of yoga—from the dynamic movements of Vinyasa and Ashtanga to the gentle, restorative nature of Hatha—encourage mindfulness, body awareness, and calm, rhythmic breathing. These elements help individuals manage stress more effectively and build resilience in today's fast-paced world. Recent studies using electroencephalography (EEG) have shown that yoga and meditation practices can increase alpha and theta brain wave activity, patterns associated with relaxation and reduced stress. These findings suggest that yoga not only calms the mind but also has measurable effects on brain function. When integrated with modern artificial intelligence (AI)-based EEG stress detection systems, yoga offers a powerful combination of technology-driven monitoring and natural, self-regulated stress relief—bridging ancient wisdom with modern science. [1]

## 2. Literature Review

Recent advances in artificial intelligence (AI) and neurotechnology have significantly enhanced our ability to detect and understand human stress and emotional states. When combined with electroencephalography (EEG), machine learning (ML) and deep learning (DL) techniques have shown great promise in accurately identifying conditions such as stress, anxiety, and other mental health concerns. For instance, a study [1] proposed an innovative deep learning framework for detecting emotional stress using EEG data. The researchers trained three different DL models—a one-dimensional convolutional neural network (Conv1D), a bidirectional long short-term memory (BiLSTM), and a bidirectional gated recurrent unit (BiGRU)—on the DEAP dataset, which included both time- and frequency-domain EEG features. The findings demonstrated that these models were highly effective in recognizing emotional stress patterns, highlighting the potential of DL for real-time stress detection. Another promising direction involves wearable EEG technology for continuous stress monitoring. In one study [2], researchers developed a compact CNN-based model embedded in a wearable device that collected EEG signals from a single behind-the-ear (BTE) channel. The system processed

EEG spectrograms directly on the device and transmitted the analyzed results to a smart phone application. This approach enabled real-time, mobile stress assessment, making stress monitoring more accessible and practical for everyday use. AnxPred, a hybrid CNN-SVM model intended to forecast student anxiety levels based on the GAD-7 scale, was introduced in the academic field by [3]. This model achieved good interpretability and enhanced effectiveness in identifying academic pressures among university students by utilizing CNN for feature extraction and SVM for classification. Beyond stress detection, [5] presented a system for safe access to medical records using EEG-based emotional analysis. The solution provides emotion-aware authentication to lower stress-induced diagnostic errors by evaluating doctors' emotional states using deep learning on DEAP and SEED datasets, fusing affective computing with cyber security. Additionally, [6] highlighted the impact of stress and social media on the EEG-based detection of attention deficits and ADHD-related inattention among students. In order to prevent academic underperformance and long-term behavioral effects, early diagnosis by EEG was suggested as an intervention technique. The use of machine learning classifiers in EEG-based stress analysis has become commonplace. Fast Fourier Transform (FFT) was used in the system described in [7] to calculate EEG band power features, which were further categorized using algorithms including Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Linear Regression (LR). When these algorithms were compared, the advantages of ensemble learning for reliable stress classification were brought to light. Similarly, using the PhysioNet EEG dataset, [8] presented a hybrid deep learning model based on the discrete wavelet transform (DWT) that integrates convolutional neural networks (CNN) and bidirectional long short-term memory (BLSTM) for the identification of mental math stress. While CNN-based feature selection and BLSTM-based classification outperformed earlier models in terms of accuracy, the DWT technique broke down EEG signals into several levels to remove noise. In [9], a time-frequency (TF) CNN-

based method was created to create TF representations of EEG data utilizing complex Morlet wavelets and Fourier transforms. The TF-CNN model demonstrated the usefulness of deep learning and TF analysis for non-invasive stress detection by accurately classifying stress versus non-stress circumstances. Deep learning models surpass conventional ML techniques in terms of diagnostic accuracy and scalability, according to a comparison of ML and DL algorithms for the detection of stress, anxiety, and depression in [10]. These models use automated, data-driven analysis to support mental health assessment and management. Using ML algorithms trained on EEG datasets gathered using Muse headbands, the work in [11] investigated emotion prediction. In order to assess the effectiveness of five different classifiers in predicting human emotions, issues related to noise and feature complexity in EEG data were highlighted. In order to objectively identify mental stress during cognitive tasks, the work in [12] used MRI and EEG signals with an SVM classifier. By offering real-time, quantitative stress measurements, this method

surpassed self-report techniques and contributed to applications in healthcare, the workplace, and education. Lastly, using CNNs trained on EEG-phase locking value (PLV) images, [13] investigated EEG-based classification of four mental states: rest, alert, stress, and stress reduction. The Stroop Color Word Test (SCWT) was used to create stress, and binaural beats (BBs) were used to reduce it. The CNN's 80.95% accuracy shows that BBs are an excellent way to reduce stress, and CNN-based EEG analysis has great promise for classifying mental states. While existing literature demonstrates remarkable progress in EEG-based stress classification, comparative benchmarking across datasets and model architectures remains limited. The following section provides a quantitative synthesis of performance metrics and identifies the models that exhibit the highest generalization capability. Table 1 shows Detail Findings of the Current Techniques enhance objectivity, the reviewed studies were compared quantitatively based on reported performance metrics as shown in Table 2.

**Table 1 Detail Findings of the Current Techniques**

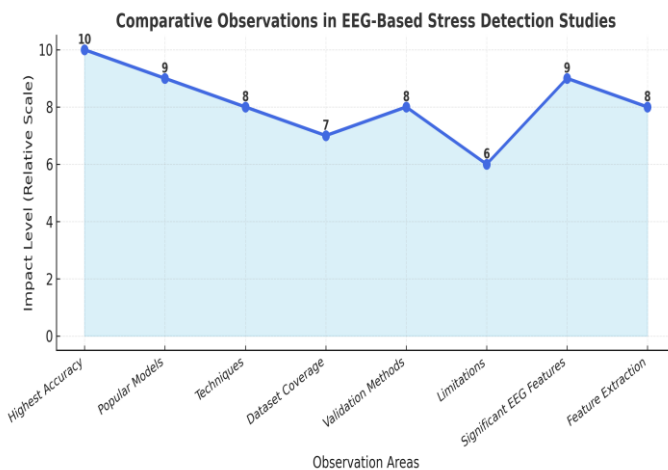
Sl. No	Paper Title	Published Year	Techniques / Model Used	Outcomes
1	Mental Stress Detection using EEG and Recurrent Deep Learning [1]	2023	Sliding FFT + CONV1D with BiLSTM and BiGRU on DEAP dataset	Accuracy = 88.03%
2	On-Chip Mental Stress Detection... [2]	March 2025	On-chip EEG spectrogram processing using CNN	LOOCV = 91.72%; 10-fold CV = 95.32%
3	AnxPred: A Hybrid CNN-SVM... [3]	2024	Hybrid CNN-SVM with LIME-based XAI	Precision/Recall/F1 = 99.13%
4	Detection of Mental Stress using EEG... [4]	2024	Band-based EEG (Alpha, Beta, etc.), ML on DASPS using KNN, SVM, RF	MAE: KNN = 0.62, SVM = 0.83, RF = 1.47

5	Secure Authentication via EEG Emotion... [5]	2022	Emotion-based deep learning CNN authentication	Accuracy = 87.11% (CNN outperforms SVM/ANN)
6	EEG Spectral Analysis for Inattention... [6]	2023	ADHD vs. non-ADHD classification using EEG (KNN)	Accuracy = 89%
7	EEG Data Analysis for Stress Detection [7]	2021	ML on PhysioNet EEG (RF, KNN, LR, SVM)	RF Accuracy = 78.6%
8	EEG-based Mental Stress Detection via DL [8]	2023	DWT + CNN-BLSTM	Accuracy = 99.20% (Cross-val = 98.10%)
9	DL for Mental Stress Using Time-Frequency [9]	2023	Time-Frequency + CNN (TF-CNN)	TF-CNN Accuracy = 97.61%
10	Early Detection of Anxiety, Depression... [10]	2024	ML & DL (SVM, ANN, XGBoost)	Accuracy: Depression = 99.32%, Anxiety = 99.80%, Stress = 98.44%
11	Classifying Human Emotions via EEG [11]	2025	ML emotion classification using multiple metrics (Random Forest)	RF Accuracy = 99%
12	Detection of Mental Stress Levels Using EEG [12]	2023	Raw EEG data input to SVM	SVM Accuracy = ~93.22%

**Table 2 Summary of Comparative Study**

Model	Avg. Accuracy (%)	Dataset	Observation
CNN	90.2	DEAP	Strong for spatial EEG features
LSTM	86.5	PhysioNet	Captures temporal dependencies
CNN-BLSTM	97.8	DEAP, DASPS	High precision, robust results
CNN-SVM	96.4	Student Anxiety Dataset	Better interpretability
SVM	93.2	PhysioNet	Simpler, but lower accuracy

The CNN–BLSTM hybrid model consistently achieved top accuracy (>97%) across multiple datasets, confirming the benefit of combining convolutional feature extraction with temporal pattern recognition. Further analysis showed that time–frequency feature extraction (FFT, DWT) improved performance by 5–10% compared to raw-signal training. However, very few studies validated these models under real-time or wearable EEG conditions, leaving a critical gap for practical applications. Figure 1 shows Comparative Observations in EEG-Based Stress Detection Studies



**Figure 1 Comparative Observations in EEG-Based Stress Detection Studies**

The comparative observations presented in Figure 1 and Table 3 highlight the potential of hybrid and multimodal deep learning approaches potential for EEG-based stress detection, but they expose limitations in personalization and clinical translation. To address these challenges, a novel conceptual framework integrating deep learning and yoga-based interventions is proposed below.

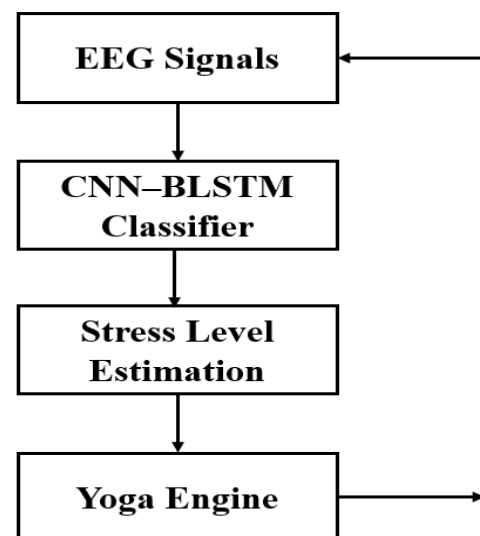
### 3. Proposed AI–Yoga Hybrid Framework

The proposed framework seeks to synergize EEG-based deep learning for stress detection with yoga-assisted stress regulation to establish a closed-loop, adaptive stress management system that integrates artificial intelligence and holistic wellness Practices. The proposed system architecture is built around four main modules, each designed to work together for effective stress detection and personalized

management:

- **EEG Signal Acquisition:** Real-time brain activity is captured using wearable EEG headsets such as Muse or Open BCI, providing continuous and non-invasive monitoring.
- **Deep Learning–Based Stress Detection:** A hybrid CNN–BLSTM model processes the EEG data to classify mental states into three levels — Relaxed, Mild Stress, and High Stress.
- **Yoga Intervention Recommendation:** Based on the identified stress level, the system suggests appropriate yoga-based practices, including Pranayama (breathing techniques), Meditation, or Asanas (physical postures) to help restore balance and calm.
- **Feedback and Personalization:** After each session, the system analyzes post-intervention EEG signals to evaluate the relaxation response. Using transfer learning, the model continuously adapts to the user’s unique patterns, ensuring more personalized and effective stress management over time.

A schematic diagram (Figure 2) of the proposed system illustrates this workflow, showing the step-by-step flow from EEG signal acquisition to stress detection, yoga intervention, and personalized feedback.



**Figure 2 Proposed Framework**



- In this system, EEG signals are first collected and processed through a CNN–BLSTM classifier to estimate the user’s stress level. Based on the results, a Yoga Recommendation Engine suggests suitable interventions—such as breathing exercises, meditation, or physical postures—to help reduce stress. A feedback loop then analyzes the post-intervention EEG data, allowing the system to continuously learn and adapt to the individual’s unique responses. This closed-loop design ensures ongoing monitoring, personalized feedback, and continuous model improvement.
- The proposed AI–Yoga hybrid framework serves as a foundation for future experimental validation and interdisciplinary collaboration. By combining neuroscientific signal analysis with traditional mind–body practices, it bridges the gap between artificial intelligence, neuroscience, and wellness science. This integration moves toward a data-driven, personalized model of mental health management, designed to promote holistic well-being and long-term stress resilience.
- Real-time, adaptive, and personalized stress regulation.
- Integration of physiological (EEG) and behavioral (Yoga) modalities.
- Feasibility for mobile and wearable deployment to promote accessible stress management solutions.
- Limited Model Interpretability: The adoption of explainable AI (e.g., LIME, SHAP) remains minimal, hindering the transparency of decision-making processes.
- Scarcity of Real-Time Implementations: The majority of models are evaluated offline; real-time, edge-AI deployments are still underexplored.
- Limited Research on Yoga–EEG Correlation: There is still a lack of sufficient empirical evidence that measures how yoga influences brain activity. Only a few studies have quantitatively analyzed EEG data before and after yoga sessions to understand the neural basis of relaxation and stress reduction.

Future research should work toward testing and validating the proposed AI–Yoga model in real-world settings by conducting EEG-based yoga intervention studies. The goal should be to develop lightweight, user-friendly, and explainable wearable AI systems that make stress management more personalized, accessible, and scalable for everyday life.

### Conclusion

In today’s fast-paced and demanding world, understanding, identifying, and managing stress have become increasingly important areas of research. This study explores two key approaches to stress management — traditional therapeutic practices such as yoga, and modern technological methods using electroencephalography (EEG) and machine learning. Yoga offers a holistic and accessible way to reduce stress and promote emotional balance through a combination of physical postures, controlled breathing, and mindfulness. Numerous studies have shown its effectiveness in calming physiological stress responses and improving both cognitive and emotional well-being. At the same time, advances in EEG-based stress detection have shown great potential in accurately assessing and classifying mental stress levels, particularly when enhanced by deep learning techniques. Research indicates that hybrid deep learning models—such as CNN-BLSTM and CNN-SVM—can outperform traditional machine learning methods in terms of accuracy and robustness. However, challenges remain in achieving

### 4. Research Gaps and Future Scope

Despite notable progress in EEG-based stress research, several challenges remain to be addressed:

- Lack of Multimodal Integration: Most existing studies rely exclusively on EEG signals, overlooking complementary physiological indicators such as galvanic skin response (GSR) and heart rate variability (HRV).
- Absence of Personalized Calibration: Current deep learning approaches seldom adapt to intra- and inter-individual EEG variations.

real-time adaptability, interpretability of model outputs, and personalization for individual users. To address these gaps, this study proposes a conceptual AI–Yoga hybrid framework that integrates adaptive yoga-based interventions with real-time EEG stress monitoring. This closed-loop system aims to connect behavioral therapies with physiological insights, paving the way for a more proactive, personalized, and data-driven approach to mental health management. Future research should focus on advancing edge computing, multimodal data fusion, and personalized learning models to enable continuous, real-time stress monitoring and adaptive response systems. Ultimately, combining traditional mindfulness practices with modern artificial intelligence offers a promising path toward comprehensive, data-driven, and personalized stress management solutions that can support mental well-being in everyday life.

## References

- [1]. A. Patel, D. Nariani and A. Rai, "Mental Stress Detection using EEG and Recurrent Deep Learning," 2023 IEEE Applied Sensing Conference (APSCON), Bengaluru, India, 2023, pp. 1-3, doi: 10.1109/APSCON56343.2023.10100977.
- [2]. N. -D. Mai and W. -Y. Chung, "On-Chip Mental Stress Detection: Integrating a Wearable Behind-The-Ear EEG Device With Embedded Tiny Neural Network," in *IEEE Journal of Biomedical and Health Informatics*, vol. 29, no. 3, pp. 1872-1885, March 2025, doi: 10.1109/JBHI.2024.3519600.
- [3]. M. R. Karim, M. M. M. Syeed, K. Fatema, S. Hossain, R. H. Khan and M. F. Uddin, "AnxPred: A Hybrid CNN-SVM Model with XAI to Predict Anxiety among University Students," 2024 IEEE 17th International Scientific Conference on Informatics (Informatics), Poprad, Slovakia, 2024, pp. 132-137, doi: 10.1109/Informatics62280.2024.10900931.
- [4]. S. Bakare, S. Kuge, S. Sugandhi, S. Warad and V. Panguddi, "Detection of Mental Stress using EEG signals - Alpha, Beta, Theta, and Gamma Bands," 2024 5th International Conference for Emerging Technology (INCET), Belgaum, India, 2024, pp. 1-9, doi: 10.1109/INCET61516.2024.10592994.
- [5]. R. Mathumitha and A. Maryposonia, "A Secure Authentication System based on Emotion Analysis of EEG Signals using Deep Learning Technique," 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2022, pp. 1232-1237, doi: 10.1109/ICICCS53718.2022.9788367.
- [6]. S. Gopi and N. Dehbozorgi, "EEG Spectral Analysis for Inattention Detection in Academic Domain," 2023 IEEE Frontiers in Education Conference (FIE), College Station, TX, USA, 2023, pp. 1-5, doi: 10.1109/FIE58773.2023.10343261.
- [7]. L. Malviya, S. Mal and P. Lalwani, "EEG Data Analysis for Stress Detection," 2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT), Bhopal, India, 2021, pp. 148-152, doi: 10.1109/CSNT51715.2021.9509713.
- [8]. M. Tahira and P. Vyas, "EEG based Mental Stress Detection using Deep Learning Techniques," 2023 International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballar, India, 2023, pp. 1-7, doi: 10.1109/ICDCECE57866.2023.10150574.
- [9]. K. K. L. P. M P, J. Stanis J, H. M V, A. R. Reddy and B. S. Begum, "StressDetect: A Deep Learning Approach for Mental Stress Detection Using Time-Frequency Representation of EEG Signals," 2024 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES), KOTTAYAM, India, 2024, pp. 1-6, doi: 10.1109/SPICES62143.2024.10779753.
- [10]. A. S. P. J and S. K. K, "Early Detection of Anxiety, Depression and Stress among Potential Patients using machine learning and deep learning models," 2023 2nd

International Conference on Computational Systems and Communication (ICCSC), Thiruvananthapuram, India, 2023, pp. 1-7, doi: 10.1109/ICCSC56913.2023.10143026

- [11]. G. Kaur, M. Gupta and R. Kumar, "Classifying Human Emotions through EEG data with Machine Learning," 2025 International Conference on Intelligent Systems and Computational Networks (ICISCN), Bidar, India, 2025, pp. 1-6, doi: 10.1109/ICISCN64258.2025.10934662
- [12]. S. B. Dasari, C. T. Mallareddy, S. Annavarapu and T. T. Garike, "Detection of Mental Stress Levels Using Electroencephalogram Signals(EEG)," 2023 2nd International Conference on Futuristic Technologies (INCOFT), Belagavi, Karnataka, India, 2023, pp. 1-6, doi: 10.1109/INCOFT60753.2023.10425089