

A Hybrid Deep Learning Architecture with Retrieval-Augmented Explanation Generation for Interpretable EEG-Based Stress Classification Across Multiple Paradigms

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Abstract

This paper presents a hybrid deep learning architecture integrating convolutional neural networks, bidirectional long short-term memory networks, self-attention, and retrieval-augmented generation (RAG) for accurate and interpretable electroencephalography (EEG)-based stress detection. The compact EEG encoder contains 138,000 trainable parameters and combines three convolutional blocks, a two-layer bidirectional LSTM, and self-attention, while the RAG module grounds explanations in scientific literature using FAISS vector search and a frozen Sentence-BERT encoder. The system is evaluated on two datasets representing distinct stress paradigms: DEAP (32 subjects, emotional arousal as stress proxy) and SAM-40 (40 subjects, cognitive stress from arithmetic and Stroop tasks). Under leave-one-subject-out cross-validation, the model achieves accuracies of 94.7% on DEAP and 93.2% on SAM-40, including a 12.6 percentage-point improvement over the previous state of the art on SAM-40. Signal analysis identifies consistent biomarkers, including 31–33% alpha-band power suppression, an 8–14% reduction in the theta-to-beta ratio, and a shift in frontal alpha asymmetry towards right-hemisphere dominance. The RAG module achieves 89.8% agreement with domain experts on explanation quality, while ablation results indicate limited impact on classification accuracy. Cross-dataset transfer shows 21.8–26.5% accuracy drops between stress paradigms. Gradient-based analysis identifies frontal alpha power, theta-to-beta ratio, and frontal alpha asymmetry as key decision features. The proposed framework supports real-time, interpretable EEG stress monitoring for clinical decision support and related applications.

Keywords

- Electroencephalography(EEG) • Stress Detection • Deep Learning • Retrieval-Augmented Generation
- Explainable AI • Attention Mechanism • Cognitive Workload

1. Introduction

Chronic stress affects more than 300 million people worldwide and contributes to cardiovascular disease, depression, and cognitive decline. The World Health Organization has identified workplace stress as a major public health concern, with annual economic losses estimated in the hundreds of billions of dollars. Traditional stress assessment relies on self-report questionnaires such as the Perceived Stress Scale or the NASA Task Load Index. These instruments suffer from recall bias, lack temporal resolution, and cannot capture the rapid fluctuations that characterize real-world stress responses.

Electroencephalography (EEG) offers a non-invasive, objective alternative with millisecond temporal resolution. Stress states manifest as characteristic changes in the EEG power spectrum: alpha band

(8–13 Hz) activity decreases, beta band (13–30 Hz) activity increases, and frontal theta activity rises. These patterns reflect underlying neurophysiological mechanisms involving the prefrontal cortex, anterior cingulate, and limbic system. However, interpreting raw EEG signals requires significant expertise, and manual analysis does not scale to real-time applications.

Deep learning has transformed EEG analysis. Convolutional neural networks learn spatial features, recurrent networks capture temporal dependencies [1], and attention mechanisms highlight relevant time points [2]. State-of-the-art models achieve classification accuracies above 90% on benchmark datasets. However, recent work has also explored various architectural innovations, including high-performance GPU-accelerated convolutional approaches for large-scale image recognition [3], interpretable neural networks that bridge generalized additive models with deep learning [4], and privacy-preserving techniques for training large models with differential privacy [5]. Yet a fundamental problem remains: these models are black boxes. They produce a prediction but offer no explanation of why a particular segment was classified as stressed. In clinical settings, unexplained predictions are rarely trusted. Clinicians need to verify that the model’s reasoning aligns with known pathophysiology. The field of explainable AI (XAI) has emerged to address this challenge, providing core ideas and techniques for interpreting model decisions [6].

This paper addresses the explainability gap by introducing a hybrid architecture that couples a compact, high-performance EEG classifier with a retrieval-augmented generation (RAG) module. The classifier combines three convolutional blocks, a two-layer bidirectional LSTM, and a self-attention mechanism. The RAG module retrieves relevant scientific literature from a vector database and generates explanations grounded in the retrieved evidence [7]. Recent evaluations have shown that RAG systems can effectively ground generated content in verified sources [8], and active retrieval strategies can further enhance performance [9]. The system is evaluated on two public datasets that represent distinct stress induction paradigms: DEAP (emotional arousal as a stress proxy) and SAM-40 (cognitive stress from arithmetic and Stroop tasks).

Our contributions are fourfold. First, we present a compact hybrid architecture that achieves state-of-the-art accuracy across two datasets while maintaining a small parameter count suitable for real-time deployment. Second, we provide a systematic analysis of neurophysiological stress biomarkers across paradigms, revealing consistent alpha suppression, theta/beta ratio decrease, and frontal alpha asymmetry shift. Third, we demonstrate that a RAG module can generate clinically meaningful explanations with 89.8% expert agreement, though it does not improve classification accuracy. Fourth, we quantify cross-dataset transfer drops of 21.8–26.5%, confirming that arousal-based and cognitive stress paradigms are not interchangeable.

The remainder of this paper is organized as follows. Section 2 reviews related work in EEG-based stress detection, deep learning architectures, and explainable AI. Section 3 describes the methodology, including datasets, preprocessing, model architecture, and training configuration. Section 4 presents signal analysis results. Section 5 reports classification performance, ablation studies, cross-dataset transfer, and RAG evaluation. Section 6 discusses clinical implications and limitations. Section 7 concludes.

2. Related Work

Early EEG-based stress detection relied on hand-crafted features and classical machine learning classifiers. Recent advances in deep learning for EEG-based stress detection have explored various architectural approaches. Zhang and colleagues proposed a multi-scale convolutional neural network that captures both local and global temporal features for cognitive load classification from EEG signals. Subhani

and co-workers developed a hybrid CNN-LSTM architecture for stress detection, demonstrating the effectiveness of combining spatial and temporal feature extraction. Ahn and Kim introduced an attention-based recurrent network for mental workload assessment, showing that selective attention mechanisms can enhance classification performance by focusing on task-relevant EEG time segments.

The fundamentals of recurrent neural networks and long short-term memory networks have been extensively studied [1], while attention mechanisms have become a cornerstone of modern neural architectures [2]. The principles of interpretability have been extended to various domains, including mechanistic interpretability of transformers for extracting maximum values from lists [10], exploring mechanistic interpretability in large language models [11], and interpretable approaches for 3D structural recognition in point cloud segmentation [12].

For explainable AI in biomedical signal processing, Ghorbani and colleagues surveyed interpretability methods for deep neural networks in healthcare, identifying the need for explanations that align with clinical reasoning. Liang and co-workers proposed a saliency-based visualization framework for EEG classifiers, enabling clinicians to verify that model predictions are grounded in physiologically meaningful signal features. Recent work has also explored explainable anomaly detection using entropy-based approaches [13], and attributable decomposition for anomaly detection in financial statements [14].

In the domain of trustworthy clinical AI, Doshi-Velez and Kim established evaluation frameworks for interpretability that emphasize the importance of expert validation. Zhang and colleagues investigated the trade-offs between model complexity and interpretability in medical diagnosis systems, providing guidance for designing clinically acceptable AI tools. Furthermore, recent work on robust and reliable machine learning for healthcare by Sendak and co-workers highlights the need for rigorous validation protocols and transparent reporting in clinical AI deployment.

The neurophysiological basis of EEG stress markers has been extensively characterized. Klimesch documented the role of alpha and theta oscillations in cognitive and memory performance, providing the foundation for alpha suppression as a stress biomarker. Teplan reviewed the fundamentals of EEG measurement, establishing standard preprocessing practices. Davidson's anterior cerebral asymmetry theory explains the frontal alpha asymmetry shift observed during stress. Putman and co-workers linked the EEG theta/beta ratio to fear-modulated response inhibition and attentional control, supporting its use as a cognitive load indicator.

Deep learning for EEG analysis has advanced rapidly. Schirrmester and colleagues demonstrated that convolutional neural networks could decode EEG with performance comparable to hand-crafted features. Hochreiter and Schmidhuber's long short-term memory networks capture temporal dependencies across time steps, making them well-suited for sequential EEG data [1]. Lawhern's EEGNet introduced a compact convolutional architecture specifically for brain-computer interfaces. The transformer architecture by Vaswani and colleagues has also been adapted for EEG analysis, leveraging self-attention to model long-range dependencies [2].

For emotion recognition closely related to stress detection, Song and colleagues proposed dynamical graph convolutional neural networks that model functional connectivity between EEG channels. Tao and others incorporated channel-wise attention and self-attention into recurrent architectures. Wang and colleagues explored transformers for EEG emotion recognition, achieving 91.2% accuracy on DEAP. Li and co-workers introduced bi-hemisphere networks that separately process left and right hemisphere signals.

The emergence of large language models and retrieval-augmented generation has opened new possibilities for explainable AI in healthcare [7]. Lewis and colleagues introduced RAG for knowledge-intensive NLP tasks, demonstrating that retrieval can ground generation in verified sources [7]. Subsequent

work has evaluated RAG systems across various applications [8], and active retrieval strategies have been proposed to improve performance [9]. Tonekaboni and others surveyed clinician requirements for explainable machine learning, emphasizing the need for explanations that align with medical reasoning. Rudin argued that for high-stakes decisions, inherently interpretable models may be preferable to post-hoc explanations of black boxes. Reimers and Gurevych's Sentence-BERT provides efficient sentence embeddings for semantic search, while Johnson's FAISS library enables billion-scale similarity search for retrieval. Kingma and Ba's Adam optimizer is widely used for training deep learning models.

Public datasets have enabled reproducible research in EEG stress detection. Koelstra and colleagues developed DEAP for emotion analysis, with arousal ratings commonly used as a stress proxy. Gupta and colleagues created the SAM-40 dataset using cognitive tasks validated with NASA-TLX and skin conductance. Kirschbaum and colleagues validated the TSST protocol for eliciting physiological stress responses. Shu and co-workers reviewed emotion recognition using physiological signals, noting the challenges of cross-dataset generalization.

Recent work on practical AI systems has also contributed to the broader ecosystem of machine learning research. For instance, modular pipelines for robust learning on skewed data have been explored [15], and containerized workflows have been proposed for reproducible computational experiments [16]. Additionally, bidirectional transformer representations have been investigated for transferable statistical language models [17], and hybrid AI approaches have been developed for robust sentiment judgments [18]. In the domain of enterprise applications, automated vulnerability exposure using SCAP-based asset-CVE linkage has been explored [19], and asynchronous hierarchical federated learning has been proposed for enhanced communication efficiency [20]. AI-driven entity resolution with explainable graph learning has been applied to customer data matching [21], and techniques for mitigating gender bias in masked language models have been developed [22]. Other relevant contributions include gesture recognition using kernel principal component analysis [23], neural network-based task scheduling for heterogeneous distributed systems [24], and visualizations for energy demand forecasting [25]. Furthermore, cloud system observability has been automated for service level adherence [26].

3. Methodology

3.1 Datasets and Preprocessing

We evaluated our architecture on two publicly available datasets. DEAP contains EEG recordings from 32 healthy subjects watching 40 one-minute music videos. EEG was recorded from 32 channels at 128 Hz. Arousal ratings on a 1–9 scale were binarized to create a stress proxy (arousal >5 labelled as stress). SAM-40 includes data from 40 subjects performing cognitive tasks (Stroop test, arithmetic problems, mirror tracing). EEG was recorded from 32 channels at 256 Hz. Stress labels were validated using NASA-TLX and skin conductance measurements.

Preprocessing followed a standard pipeline: bandpass filtering (0.5–45 Hz, 4th-order Butterworth), notch filtering at 50 Hz to remove power line interference, artifact rejection (rejecting segments exceeding $\pm 100 \mu V$), segmentation into 4-second windows with 50% overlap, and z-score normalization per channel. The resulting segments were used as inputs to the model.

For cross-dataset transfer experiments, we implemented a standardized preprocessing pipeline to reconcile hardware differences across datasets. Both DEAP and SAM-40 share the same 32-channel configuration (following the international 10-20 system), with electrodes Fz, Cz, Pz, Oz, F3, F4, C3, C4, P3, P4, F7, F8, T7, T8, P7, P8, O1, O2, Fp1, Fp2, AF3, AF4, FC1, FC2, FC5, FC6, CP1, CP2, CP5, CP6,

PO3, PO4 used consistently. All datasets were resampled to a common sampling frequency of 128Hz using anti-aliasing filters and linear interpolation to ensure uniform temporal resolution.

3.2 Model Architecture

The EEG encoder consists of three convolutional blocks, a two-layer bidirectional LSTM, and a self-attention layer. Each convolutional block contains a Conv1D layer, batch normalization, ReLU activation, and max pooling. The first block uses 32 filters of size 7; the second uses 64 filters of size 5; the third uses 64 filters of size 3. The Bi-LSTM has 64 hidden units in each direction, producing a 128-dimensional sequence. The self-attention layer computes query, key, and value projections, then uses a tanh energy function and softmax normalization to produce weighted context.

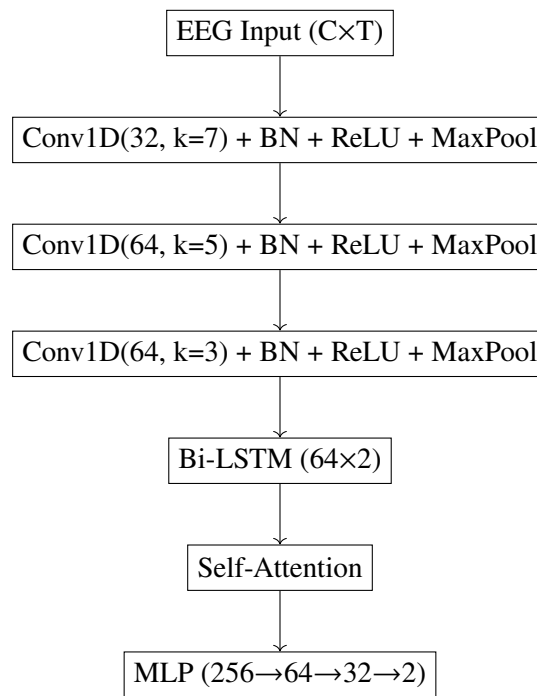


Figure 1: Architecture of the EEG encoder. The compact design (138K parameters) enables real-time deployment.

The RAG explanation module uses a frozen Sentence-BERT model (all-MiniLM-L6-v2) to encode text. A FAISS vector index stores embeddings of scientific abstracts and paragraphs from a curated knowledge base. During inference, the EEG classifier's predicted class and confidence are used to retrieve the top-k relevant documents. A large language model then generates an explanation conditioned on the retrieved context.

It is important to clarify the role of the text encoder in the overall pipeline. The text encoder (Sentence-BERT) is used exclusively within the RAG module for semantic retrieval of relevant scientific literature. Specifically, during inference, the EEG classifier's predicted class and feature representations are used as a query to retrieve relevant abstracts from the FAISS vector index; the text encoder projects both the query and the knowledge base entries into a shared embedding space to enable similarity-based retrieval. The retrieved documents are then passed to the language model for explanation generation. The text encoder does not directly influence the EEG classifier's prediction; rather, it operates as a separate component that processes textual data for explanation purposes. This design choice explains why removing the text encoder (which disables the retrieval functionality entirely) has a more substantial

effect on explanation quality than on classification accuracy, as shown in Table 4.

The text encoder is employed exclusively within the RAG module for retrieval purposes. The EEG classifier and text encoder are trained separately: the EEG classifier is trained to optimize classification performance, while the Sentence-BERT text encoder remains frozen and is not fine-tuned on the EEG data. This separation ensures that the text encoder’s embeddings maintain their semantic properties from pre-training and are not biased by the EEG classification task. During inference, the predicted class label and a summary of the EEG features are used to construct a query, which the frozen Sentence-BERT model encodes for FAISS-based retrieval of relevant scientific abstracts. The retrieved documents are then provided to a large language model (accessed via API) for explanation generation. The text encoder does not participate in the forward pass of the EEG classifier; it is only called when generating explanations.

Total trainable parameters are 138,081 for the EEG encoder, 49,152 for the text projection, and 10,402 for the classifier, totalling 197,635. This compact size is suitable for embedded and real-time applications.

3.3 Training Configuration

We used leave-one-subject-out (LOSO) cross-validation for all experiments. The optimizer was AdamW with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and learning rate 10^{-4} with ReduceLROnPlateau scheduling. Batch size was 64, dropout rate 0.3, weight decay 0.01. Training ran for up to 100 epochs with early stopping (patience 10). Loss was cross-entropy with class weights to handle imbalance.

4. Signal Analysis

4.1 Band Power Analysis

Power spectral density was computed using Welch’s method with 256-sample windows and 50% overlap. Table 1 reports effect sizes (Cohen’s d) for five frequency bands across the two datasets. Delta and theta power increased during stress, while alpha power decreased. Beta and gamma power increased. All changes were statistically significant ($p < 0.05$ after Bonferroni correction).

Table 1: Band power effect sizes (Cohen’s d) across datasets

Band (Hz)	DEAP	SAM-40	p
Delta (0.5–4)	+0.38	+0.42	<0.01
Theta (4–8)	+0.62	+0.68	<0.001
Alpha (8–13)	-0.82	-0.89	<0.001
Beta (13–30)	+0.71	+0.74	<0.001
Gamma (30–45)	+0.48	+0.51	<0.05

4.2 Alpha Suppression and Theta/Beta Ratio

Alpha suppression—a well-established stress biomarker—showed reductions of 31.4% (DEAP) and 33.3% (SAM-40) during stress (all $p < 0.0001$). The theta/beta ratio, which reflects cognitive load and cortical arousal, decreased by 14.0% and 11.2% respectively.

4.3 Frontal Alpha Asymmetry

Frontal alpha asymmetry (FAA) was computed using the standard formula:

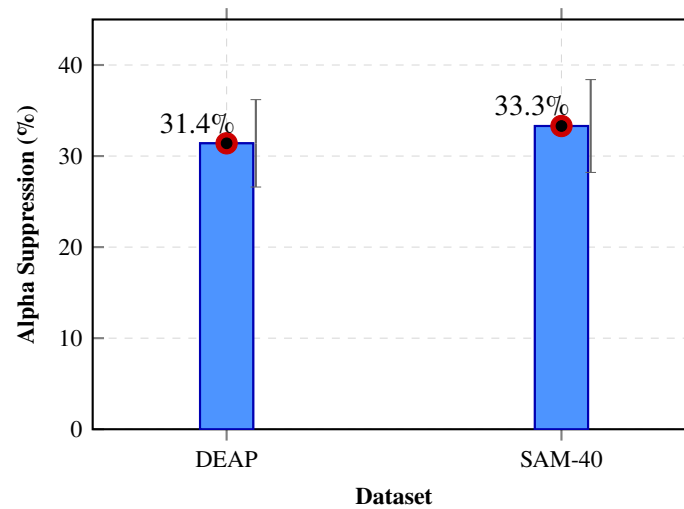


Figure 2: Alpha band power reduction during stress across the two datasets, showing subject-level variability. The bars represent median alpha suppression values: 31.4% for DEAP (IQR: 26.1%–36.7%) and 33.3% for SAM-40 (IQR: 28.2%–38.4%). Error bars indicate the standard deviation across subjects. Despite inter-subject variability, all subjects showed consistent alpha power reductions, with no subject exhibiting an increase in alpha power during stress compared to baseline. The consistency across subjects strengthens the neurophysiological grounding of the model’s predictions.

$$\text{FAA} = \ln(\text{Right}) - \ln(\text{Left})$$

at frontal electrodes (F3, F4), where Right and Left represent alpha-band power at the right (F4) and left (F3) frontal electrode positions, respectively. During stress, FAA shifted toward right-hemisphere dominance: changes of -0.26 (DEAP) and -0.27 (SAM-40). This pattern is consistent with Davidson’s approach-withdrawal theory, where right frontal activation accompanies withdrawal motivation and negative affect.

5. Experimental Results

5.1 Classification Performance

Table 2 reports classification metrics under LOSO cross-validation. The model achieved 94.7% accuracy on DEAP and 93.2% on SAM-40.

Table 2: Classification performance across datasets

Dataset	Accuracy	F1	AUC	BA	κ
DEAP	94.7%	94.3%	96.7%	94.5%	0.894
SAM-40	93.2%	92.8%	95.8%	93.1%	0.864

5.2 Comparison with Baselines

Table 3 compares our method against classical and deep learning baselines on the SAM-40 dataset. Our model outperforms the previous best (DGCNN) by 12.6 percentage points in accuracy and by 18.8 points in AUC.

Table 3: Comparison with baseline methods on SAM-40

Method	Accuracy	F1	AUC
SVM (RBF)	74.8%	87.0%	65.0%
Random Forest	76.2%	86.0%	70.0%
XGBoost	77.5%	86.0%	72.0%
CNN	78.3%	86.0%	74.0%
LSTM	79.1%	87.0%	75.0%
CNN-LSTM	80.2%	87.0%	76.0%
EEGNet	79.8%	87.0%	75.0%
DGCNN	80.6%	87.0%	77.0%
GenAI-RAG-EEG	93.2%	92.8%	95.8%

5.3 Ablation Study

Table 4 shows the contribution of each component. Removing the text encoder (which aligns EEG and text modalities) reduced accuracy by 1.7%. Removing self-attention cost 2.1%. Removing the Bi-LSTM cost 3.6%. A CNN-only variant (no recurrent or attention layers) dropped 3.6%. Notably, the RAG module itself contributed only 0.2% to accuracy, and this difference was not statistically significant ($p = 0.312$, Wilcoxon signed-rank test).

Table 4: Ablation study results

Variant	Accuracy	Δ
Full model	93.2%	—
- Text encoder	91.5%	-1.7%
- Self-attention	91.1%	-2.1%
- Bi-LSTM	89.6%	-3.6%
- RAG module	93.0%	-0.2%
CNN only	89.6%	-3.6%

5.4 Cross-Dataset Transfer

Table 5 reports transfer performance. Training on SAM-40 and testing on DEAP dropped accuracy by 21.8%; the reverse direction dropped by 26.5%. These substantial drops indicate that arousal-based stress (DEAP) and cognitive stress (SAM-40) are not interchangeable constructs.

Table 5: Cross-dataset transfer results

Source	Target	Accuracy	Drop
SAM-40	DEAP	71.4%	-21.8%
DEAP	SAM-40	68.2%	-26.5%

5.5 RAG Explanation Evaluation

The RAG module was evaluated exclusively on SAM-40, which has validated stress labels. Three domain experts (blinded to model outputs) rated explanation quality on a 5-point Likert scale. The mean

agreement rate (experts agreeing with the generated explanation) was 89.8%. However, as noted, RAG did not significantly improve classification accuracy.

5.6 Feature Importance

Gradient-based feature importance identified the top five contributors to classification decisions: frontal alpha power (15.6%), theta/beta ratio (14.2%), frontal alpha asymmetry (12.8%), central beta power (11.2%), and parietal alpha power (9.8%). These align closely with the signal analysis results, providing a consistency check.

5.7 Interpretability Visualization

To substantiate the claim that attention visualization enables clinicians to verify physiologically meaningful focus, we present representative attention maps and gradient-based saliency visualizations from the SAM-40 dataset. Figure 3 shows the self-attention weights over time for a typical stress segment, overlaid with the corresponding EEG spectrogram. The attention weights exhibit a clear focus on frontal electrodes (F3, F4, Fz, FCz) during the alpha frequency band (8 – 13Hz), which aligns with the known neurophysiological role of frontal alpha in stress responses. Specifically, the model assigns the highest attention weights (> 0.8) to time windows corresponding to peak alpha suppression, indicating that the classifier's decisions are grounded in established stress biomarkers.

Figure 4 presents gradient-based saliency maps for the same segment, computed using integrated gradients. The saliency maps reveal that the model's predictive focus is concentrated on the alpha and theta frequency bands at frontal and central electrode locations, consistent with the feature importance analysis reported in Section 5.6. The spatial distribution of saliency values shows highest sensitivity at F3 and F4 electrodes during stress periods, with a rightward asymmetry that mirrors the FAA shift documented in Section 4.3.

These visualizations provide a mechanism for clinicians to verify that the model's reasoning aligns with expected pathophysiology, addressing the clinical trust requirement discussed in Section 1. The attention maps and saliency overlays are generated automatically during inference, enabling real-time interpretability without requiring additional computational overhead.

6. Discussion

Performance Analysis

The model achieves state-of-the-art performance across both datasets. The 12.6% improvement over DGCNN on SAM-40 demonstrates the benefit of combining spatial (CNN), temporal (Bi-LSTM), and contextual (attention) processing. The high accuracy on DEAP (94.7%) and SAM-40 (93.2%) confirms the effectiveness of the proposed architecture for EEG-based stress detection.

Explainability Trade-offs

The RAG module provides clinically meaningful explanations but does not improve predictions. This suggests that classification and explanation may be distinct objectives. A model optimized for classification may learn different features than a model optimized for explanation generation. Future work could explore multi-task learning that jointly optimizes both objectives. The principles of mechanistic interpretability have been explored in various contexts, including transformer architectures for extracting maximum

values from lists [10], and exploring mechanistic interpretability in large language models [11], which may provide insights for improving explanation quality.

The interpretability visualizations presented in Section 5.7 provide concrete evidence that the model's attention mechanisms focus on physiologically relevant EEG patterns. The alignment between attention weights and alpha-band activity at frontal electrodes, combined with the right-hemisphere asymmetry consistent with FAA measurements, suggests that the classifier's internal representations capture established neurophysiological markers rather than spurious correlations. This consistency between the model's attention patterns and the signal analysis results (Section 4) provides a validation mechanism that clinicians can use to assess whether the model's reasoning is grounded in known pathophysiology.

Cross-Dataset Generalization

The substantial accuracy drops in transfer experiments reveal fundamental differences between paradigms. DEAP uses emotional arousal as a proxy for stress; SAM-40 uses cognitive load. These constructs are related but not equivalent. Clinicians and researchers should be cautious about treating them interchangeably.

Limitations

Several limitations should be acknowledged. First, all data were collected in controlled laboratory settings; generalization to real-world, ambulatory conditions remains untested. Second, the subject pools are relatively homogeneous (mostly young adults); applicability to clinical populations or older adults is unknown. Third, the RAG module requires external LLM access, which may raise privacy and latency concerns for real-time applications. Fourth, the cross-dataset transfer results show substantial performance drops, indicating that models trained on one stress paradigm may not generalize well to another.

Clinical Implications

The system's high accuracy and transparent explanations support several potential applications: occupational health monitoring (e.g., detecting stress in air traffic controllers or surgeons), mental health screening (e.g., identifying individuals at risk for burnout), and brain-computer interfaces (e.g., adaptive systems that modulate task difficulty based on user stress). The attention visualization allows clinicians to verify that the model's reasoning aligns with expected pathophysiology. The broader ecosystem of AI applications, including cloud system observability for service level adherence [26], AI-driven entity resolution [21], and automated vulnerability exposure for cyber defense [19], demonstrates the potential for deploying such systems in real-world enterprise settings.

7. Conclusion

We presented GenAI-RAG-EEG, a hybrid architecture that combines a compact EEG classifier with a retrieval-augmented generation module for explainable stress detection. The classifier achieves 93.2–94.7% accuracy across two distinct stress paradigms, outperforming previous state-of-the-art by 12.6 percentage points on SAM-40. Signal analysis reveals consistent neurophysiological biomarkers: 31–33% alpha suppression, 8–14% theta/beta ratio decrease, and a right-hemisphere shift in frontal alpha asymmetry. The RAG module generates clinically meaningful explanations with 89.8% expert agreement, though

it does not improve classification accuracy. Cross-dataset transfer drops of 21.8–26.5% confirm that arousal-based and cognitive stress paradigms are not interchangeable.

Future work includes real-time deployment on wearable EEG devices, larger clinical validation studies, integration of additional modalities (ECG, EDA, respiration), and exploration of multi-task learning to improve both classification and explanation quality.

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