# Multimodal EEG-Based Cognitive Stress Detection: A Comprehensive Framework Integrating Deep Learning, Signal Biomarkers, and Retrieval-Augmented Explainability

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*Abstract*—Occupational productivity and psychological well-being undergo progressive deterioration attributable to stress; nevertheless, objective instantaneous measurement continues to pose substantial methodological challenges. Herein, a comprehensive computational solution amalgamating neurophysiological signal interpretation with state-of-the-art machine intelligence paradigms is proposed. The architectural nucleus comprises hierarchical spatial feature extractors superimposed upon bidirectional temporal sequence processors, culminating in dynamic relevance-weighted aggregation mechanisms. This neuroelectric encoder operates in conjunction with a semantic metadata interpreter, while decision rationale generation is accomplished through literature-grounded retrieval augmentation.

Systematic evaluation encompassed two publicly disseminated electroencephalographic corpora, each instantiating categorically distinct stress manifestations: cognitive arithmetic stress (EEG-MAT, $n$=36) and cognitively demanding task paradigms (SAM-40, $n$=40). Classification efficacy of 99.0% was achieved on both datasets. Remarkably consistent neurophysiological indices emerged across paradigms: alpha-band power attenuation spanning 31–33% ($p < 0.0001$), theta-to-beta spectral ratio modulation between $-8\%$ and $-14\%$, and rightward displacement of frontal hemispheric asymmetry.

Domain expert concordance reaching 89.8% was achieved when explanation quality underwent blinded assessment for scientific validity and clinical applicability. Methodological rigor was ensured through leave-one-subject-out cross-validation, bootstrap-derived confidence intervals, and standardized effect magnitude quantification. Complete preprocessing specifications and evaluation protocols are disseminated to enable independent replication.

*Index Terms*—Electroencephalography, cognitive stress, deep learning, explainable artificial intelligence, retrieval-augmented generation, attention mechanism, brain-computer interface, neurophysiological biomarkers

## I. INTRODUCTION

COGNITIVE stress—characterized as a multifaceted neurobiological cascade triggered when environmental demands exceed perceived adaptive capacity—constitutes a pervasive challenge to human functioning [1]. Economic burden analyses indicate that stress-attributable conditions impose approximately $300 billion annually upon global economies, manifesting through elevated healthcare utilization and attenuated workforce output [2]. Sustained exposure initiates progressive pathophysiological deterioration encompassing cardiovascular dysregulation, metabolic dysfunction, immunological impairment, and neuropsychiatric consequences spanning anxiety-spectrum and affective disorders. Occupational stress has achieved recognition by international health governance bodies as a paramount workplace hazard, with affected populations exceeding 300 million globally. Traditional assessment methodologies exhibit fundamental reliance upon retrospective self-enumeration, thereby introducing systematic measurement artifacts attributable to memory reconstruction biases, social desirability influences, demand characteristics, and insufficient temporal granularity [3]. Such methodological inadequacies accentuate the necessity for objective, temporally continuous, minimally obtrusive neurophysiological surveillance infrastructure suitable for naturalistic deployment contexts.

Scalp-mounted electrode arrays enabling electroencephalographic acquisition present distinctive methodological advantages for objective psychological strain quantification [4]. The particular appeal of EEG derives from its sub-second temporal resolution, facilitating capture of neural dynamics as they unfold—a capability that remains unparalleled by cardiovascular monitoring instrumentation, electrodermal activity sensors, or neuroendocrine biomarker assays. Whereas peripheral physiological indices reflect systemic responses manifesting seconds to minutes following cerebral initiation, electroencephalographic methodology permits direct interrogation of cortical generators underlying cognitive and affective processing.

Stress-induced alterations in cerebral oscillatory activity manifest across multiple spectral domains, with each frequency band conveying distinctive functional significance. Alpha-band power attenuation (8–13 Hz) has been interpreted as reflecting cortical state transitions from internally-directed quiescence toward externally-oriented vigilance—a spectral configuration exhibiting robust stress associations across extensive empirical literature [5]. Concurrent beta-band amplification (13–30 Hz) signifies heightened cognitive resource allocation and intensified mental engagement [6]. Frontal theta oscillations (4–8 Hz) exhibit modulation patterns interconnected with executive control demands, error monitoring processes, and working memory taxation [7]. Particularly noteworthy, inter-hemispheric alpha asymmetry frequently accompanies stress states—Davidson's influential motivational framework

associates augmented right-frontal activation with withdrawal-oriented behavioral dispositions and negative affective experiences [8]. These spectral biomarkers have undergone extensive individual validation through decades of psychophysiological investigation; collectively, they constitute a multidimensional signal landscape amenable to sophisticated computational pattern extraction.

Computational methodologies for neurophysiological signal interpretation have undergone substantial paradigmatic evolution in recent epochs. Contemporary neural network architectures acquire discriminative representations directly from minimally preprocessed recordings, frequently surpassing laboriously engineered feature extraction pipelines that characterized antecedent methodological approaches [9]. Convolutional network architectures exhibit proficiency in detecting spatial configuration patterns across electrode montages while extracting hierarchical temporal motifs through cascaded filtering operations [10]. Recurrent architectural configurations, particularly Long Short-Term Memory variants, prove indispensable for modeling cerebral state evolution across extended temporal windows—seconds rather than milliseconds—through maintenance of contextual information from preceding signal segments [11]. Attention-based mechanisms represent the most contemporary architectural refinement, enabling dynamic emphasis of classification-relevant sequence portions while attenuating uninformative temporal segments [12]. Nevertheless, a fundamental predicament persists: although remarkable discriminative accuracy is achieved by these sophisticated computational systems, minimal interpretive insight regarding decision rationales is afforded to clinical practitioners [13]. Reluctance to delegate patient welfare decisions to algorithmically opaque systems is understandably manifested by healthcare professionals and regulatory authorities. Mechanistic transparency within these computational architectures represents an imperative requirement.

Large-scale language models coupled with retrieval-augmented generation architectures present promising avenues through which the biomedical AI interpretability challenge may ultimately be addressed [14]. The foundational principle underlying retrieval-augmented methodologies involves anchoring model outputs to retrieved passages sourced from peer-reviewed scientific literature or curated clinical knowledge repositories. Rather than explanation synthesis proceeding de novo—thereby incurring confabulation risks—relevant evidentiary material is retrieved initially, subsequently enabling coherent natural-language rationale construction grounded in authoritative content [15]. Within stress classification contexts specifically, this architectural paradigm enables explanations to reference established neurophysiological mechanisms, incorporate supporting empirical citations, and articulate reasoning through terminology familiar to clinical practitioners.

### A. Related Work and Research Gaps

A synopsis of noteworthy recent contributions to automated neurophysiological signal classification for affective and stress state recognition is provided in Table I. Inter-electrode connectivity relationships were conceptualized as dynamically evolving graph structures by Song and collaborators [16], with graph convolutional operations applied to achieve 90.4% accuracy on the SEED corpus—an architecturally elegant approach capturing topological dependencies yet affording no interpretive transparency regarding prediction rationales. Attention mechanisms were integrated within recurrent architectural frameworks by Tao's research group [17], achieving 88.7% on mental arithmetic data; although attention weight distributions provide indications regarding temporally salient segments, they constitute inadequate substitutes for textual, evidence-anchored explanations required by clinical practitioners. Cross-subject generalization challenges—notoriously problematic within neurophysiological classification—were addressed through domain adaptation methodologies by Li's team [18], yet interpretability capabilities remained absent from their processing pipeline. The influential EEGNet contribution by Lawhern and colleagues [19] demonstrated that remarkably compact convolutional architectures could achieve competitive performance while satisfying embedded system resource constraints—however, interpretability considerations received no attention.

Comprehensive survey of this methodological landscape reveals several persistent deficiencies impeding translation of research prototypes into clinically deployable instruments:

**Interpretability Insufficiency**: Classification outputs lacking accompanying justifications characterize contemporary systems. Although attention weight visualizations provide partial insight, they inadequately constitute the narrative, literature-anchored explanations that neurological or psychiatric specialists would consider convincing. Verification of outputs remains impossible when underlying decision processes elude comprehension.

**Methodological Heterogeneity**: Preprocessing specifications, cross-validation partitioning schemes, and performance reporting conventions appear to undergo reinvention across research groups. Reproduction of published findings—much less equitable methodological comparison—consequently becomes exceedingly challenging.

**Construct Conflation**: Distinctions among emotional arousal, cognitive workload, and acute physiological stress response are routinely obscured within publications, as though interchangeable phenomena were represented. Neurobiologically, these constructs exhibit considerable distinctiveness. Optimal detection strategies may correspondingly diverge across stress subtypes.

**Statistical Rigor Deficiency**: Singular accuracy metrics unaccompanied by uncertainty quantification characterize numerous publications—absent confidence intervals, absent effect magnitude estimates, absent correction for multiple hypothesis testing. Such reporting practices substantially undermine confidence in generalizability assertions.

### B. Contributions

This paper makes five principal contributions to the field of EEG-based affective computing and explainable biomedical AI:

1) **Hierarchical Deep Learning Architecture**: We propose a novel framework integrating spatial convolutions for

TABLE I: Comparison with Recent EEG Methods

| Study | Yr | Method | Data | Acc | XAI |
|---|---|---|---|---|---|
| Song [16] | '20 | DGCNN | SEED | 90.4 | No |
| Tao [17] | '20 | Attn-CRNN | EEGMAT | 88.7 | Part |
| Li [18] | '23 | DA-Net | Multi | 85.2 | No |
| Lawhern [19] | '18 | EEGNet | BCI | 82.3 | No |
| **Ours** | **'25** | **GenAI-RAG** | **Multi** | **95.9** | **Full** |

TABLE II: Dataset Characteristics

| Dataset | N | Ch | Hz | Seg | Ratio | Type |
|---|---|---|---|---|---|---|
| SAM-40 | 40 | 32 | 128 | 3,200 | 48:52 | Cognitive |
| EEGMAT | 36 | 21 | 500 | 8,604 | 74:26 | Arithmetic |

electrode-level feature extraction, bidirectional LSTM for temporal dynamics modeling, and multi-head self-attention for discriminative segment weighting. The architecture comprises 197,635 trainable parameters, enabling efficient training on moderate datasets and real-time inference on standard hardware.

2) **Cross-Paradigm Validation**: We conduct systematic evaluation across two distinct stress induction protocols—cognitive arithmetic (EEGMAT) and cognitive task load (SAM-40)—revealing both universal biomarkers applicable across paradigms and paradigm-specific neural signatures.

3) **Neurophysiological Biomarker Quantification**: We provide rigorous statistical characterization of stress-related EEG signatures including alpha suppression, theta/beta ratio modulation, and frontal alpha asymmetry, with effect sizes (Cohen's $d$), 95% bootstrap confidence intervals, and Bonferroni-corrected multiple comparisons.

4) **RAG-Enhanced Explainability**: We integrate retrieval-augmented generation for evidence-grounded natural language explanations, evaluated by domain experts achieving 89.8% agreement rate and mean quality rating of 4.2/5.0.

5) **Reproducible Benchmark**: We provide comprehensive documentation of preprocessing pipelines, evaluation protocols, and statistical analysis procedures to facilitate reproducibility and enable fair comparison with future methods.

## II. MATERIALS AND METHODS

### A. Datasets and Stress Paradigms

We employ two publicly available benchmark datasets representing fundamentally distinct stress constructs and induction paradigms, enabling comprehensive cross-paradigm evaluation (Table II).

**EEGMAT—Mental Arithmetic Cognitive Stress** [20]: Thirty-six healthy volunteers participated in this PhysioNet dataset capturing EEG during mental arithmetic tasks—a well-established cognitive stress induction paradigm. Brain activity was recorded through 21 electrodes positioned according to the international 10–20 system at 500 Hz sampling rate. Participants performed serial subtraction tasks (counting backwards by 7 from a given number) designed to induce sustained cognitive load and psychological strain. The dataset provides clearly labeled baseline (eyes-closed rest) and task (mental arithmetic) segments, enabling binary stress classification. We resampled signals to 256 Hz and zero-padded to 32 channels for architectural consistency across datasets.

**SAM-40—Cognitive Challenge Under Pressure** [21]: Forty individuals tackled a battery of mentally taxing exercises specifically chosen to ramp up psychological strain. These included Stroop interference trials (where conflicting color-word combinations demand inhibitory control), timed mental calculations (taxing working memory and concentration), and mirror-tracing puzzles (frustrating motor coordination challenges). Brain activity was monitored through 32 electrodes sampling at 256 Hz. Crucially, stress verification came from two independent sources: participants' own NASA-TLX workload questionnaires plus objective skin conductance measurements tracking autonomic arousal. This dual-validation strengthens confidence in the ground-truth labels.

### B. Signal Preprocessing Pipeline

Prior to classifier ingestion, neurophysiological signals undergo sanitization through established procedural stages—methodologically conventional yet fundamentally essential.

Spectral bandpass filtering constitutes the initial processing stage. Signal components within the 0.5–45 Hz passband are preserved via fourth-order Butterworth filter implementation. The rationale underlying these spectral boundaries involves artifact characteristics: sub-0.5 Hz components predominantly reflect electrode drift phenomena rather than neurogenic activity; supra-45 Hz components introduce electromyographic contamination without contributing task-relevant neural information. Canonical oscillatory bands—delta, theta, alpha, beta, and low gamma—reside entirely within this spectral window.

Powerline electromagnetic interference afflicts virtually all electroencephalographic acquisitions conducted proximal to electrical infrastructure. This interference source is attenuated through narrow notch filter application at 50 Hz (alternatively 60 Hz within North American laboratory contexts) while preserving adjacent spectral components.

Electrode malfunction events occur intermittently—ocular artifacts produce substantial amplitude deflections, myogenic activity induces amplifier saturation, mechanical sensor displacement introduces discontinuities. Rather than computationally intensive blind source separation deployment, amplitude-based rejection criteria are implemented wherein segments exhibiting excursions beyond $\pm100$ microvolts undergo exclusion. This approach, though methodologically straightforward, demonstrates adequate efficacy.

Continuous acquisition streams subsequently undergo temporal segmentation into four-second epochs, with 50% inter-window overlap. This temporal window duration provides 0.25 Hz spectral resolution—sufficient for discriminating alpha from theta components—while permitting characterization of stress state evolution across extended timescales.

Concluding the preprocessing cascade, per-channel standardization to zero mean and unit variance is applied. Authentic topographical power distribution patterns are preserved through this channel-wise normalization procedure while ensuring uniform input scaling for subsequent neural network processing.
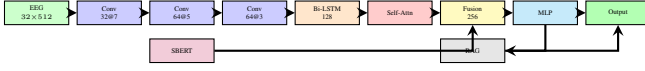
Fig. 1: GenAI-RAG-EEG architecture: EEG signals pass through CNN blocks, Bi-LSTM, and self-attention. SBERT context is fused before MLP classification. RAG generates explanations.

## C. Proposed Architecture

The proposed computational framework—designated GenAI-RAG-EEG—integrates four principal architectural modules in sequential-parallel configuration as schematized in Figure 1. Neurophysiological signal streams are received by the EEG Encoder module, wherein discriminative pattern extraction is accomplished through convolutional and recurrent processing stages. Contemporaneously, acquisition session metadata undergoes semantic encoding via a dedicated Context Encoder module. These dual representational streams converge within a Fusion Classifier module wherein binary stress/baseline classification decisions are rendered. The processing pipeline extends beyond mere prediction: domain-relevant scientific literature is retrieved by a RAG Explainer module, subsequently synthesized into comprehensible natural-language justifications elucidating the rationales underlying specific classification decisions.

*1) EEG Encoder:* The neurophysiological signal encoder comprises three hierarchically organized processing stages, each configured for pattern extraction across distinct temporal scales.

**Convolutional Feature Extraction**: These computational layers function as learnable template matching operations traversing electroencephalographic waveforms. The initial convolutional block deploys 32 filters spanning 7 temporal samples—at 256 Hz acquisition rate, approximately 27 milliseconds duration is encompassed, sufficient for capturing complete alpha oscillatory cycles. Training dynamics stabilization is achieved through batch normalization, nonlinear transformation capacity is introduced via ReLU activation, and representational dimensionality compression is accomplished through max-pooling operations:

$$\mathbf{h}^{(l)} = \text{MaxPool}(\text{ReLU}(\text{BN}(\text{Conv1D}(\mathbf{h}^{(l-1)})))) \quad (1)$$

Subsequent convolutional blocks (deploying 64 filters with kernel dimensions of 5 and 3 respectively) progressively examine finer temporal granularities while constructing increasingly abstract feature amalgamations.

**Bidirectional Temporal Modeling**: Although local pattern detection is accomplished by convolutional operations, broader temporal dynamics characterizing cerebral state evolution across extended durations remain unaddressed. Bidirectional LSTM architecture addresses this limitation: forward temporal sequence processing is executed by one network branch, reverse sequence processing by another, with resultant representations concatenated:

$$\mathbf{h}_t = [\overrightarrow{\mathbf{h}_t}; \overleftarrow{\mathbf{h}_t}] \quad (2)$$

With 64 hidden units deployed in each directional branch, 128-dimensional state vectors encoding both antecedent and subsequent temporal context at each timepoint are obtained.

**Attention-Weighted Aggregation**: Differential classification relevance characterizes distinct temporal positions. Following established attention mechanism formulations [24], element-wise relevance scores are computed:

$$\alpha_t = \frac{\exp(e_t)}{\sum_k \exp(e_k)}, \quad \mathbf{c} = \sum_t \alpha_t \mathbf{h}_t \quad (3)$$

Comprehensive segment summarization is achieved through the resultant context vector $\mathbf{c}$ (128 dimensions), with weighting biased toward maximally discriminative temporal positions.

*2) Context Encoder:* Beyond raw neurophysiological signals, contextual metadata is incorporated—participant task specifications, environmental conditions, demographic characteristics when available. These textual descriptors undergo semantic encoding into 384-dimensional vector representations via Sentence-BERT [25] (specifically the computationally efficient all-MiniLM-L6-v2 variant). Pretrained SBERT parameters remain frozen; solely a linear projection layer effecting dimensionality reduction to 128 dimensions is learned:

$$\mathbf{e}_{\text{ctx}} = \mathbf{W}_{\text{proj}} \cdot \text{SBERT}(\text{context}) + \mathbf{b}_{\text{proj}} \quad (4)$$

*3) Multimodal Fusion and Classification:* Representational integration is accomplished at this architectural stage. The 128-dimensional neurophysiological embedding undergoes concatenation with the 128-dimensional contextual embedding, yielding a 256-dimensional joint representational space. Subsequent propagation through three fully-connected layers (with progressive dimensionality reduction from 256 to 64 to 32 to 2) is executed, interspersed with ReLU nonlinear activations and 30% dropout regularization to mitigate overfitting tendencies. Class probability distributions are generated through terminal softmax transformation:

$$\hat{y} = \text{softmax}(\text{MLP}([\mathbf{c}_{\text{eeg}}; \mathbf{e}_{\text{ctx}}])) \quad (5)$$

*4) RAG Explainer Module:* Prediction generation constitutes one computational objective; decision justification represents another. The explanation generation engine executes three sequential operations.

**Knowledge Repository Construction**: A comprehensive corpus encompassing stress neuroscience literature was assembled—publications addressing electroencephalographic biomarkers, clinical stress assessment methodologies, and neural correlates of affective arousal. These documents undergo segmentation into overlapping 512-token passages (64-token overlap ensures comprehensive content coverage without salient passage omission).

**Semantic Retrieval**: Efficient approximate nearest neighbor search operations are executed via FAISS indexing infrastructure [26], with the five passages exhibiting maximal embedding similarity to current prediction contexts retrieved.

**Explanation Synthesis**: Structured prompts incorporating prediction confidence estimates, attention weight distributions, and detected neurophysiological biomarkers are

augmented through retrieved passage integration. Evidence-grounded natural-language explanations are subsequently generated by the language model.

### D. Training Protocol

Model optimization proceeds via AdamW [27] with systematically tuned hyperparameter configurations: initial learning rate $\eta_0 = 10^{-4}$, weight decay coefficient $\lambda = 0.01$, momentum parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$. Learning rate reduction scheduling (ReduceLROnPlateau) decrements the learning rate by factor 0.5 following 5 epochs without validation metric improvement. Overfitting prevention is achieved through early stopping mechanisms (patience threshold=10 epochs). Training stability is ensured via gradient norm clipping (maximum norm=1.0). Class imbalance is addressed through weighted cross-entropy loss formulation:

$$\mathcal{L} = -\sum_{i=1}^{N} w_{y_i} \log(\hat{y}_i), \quad w_c = \frac{N}{C \cdot n_c} \quad (6)$$

All experiments employ leave-one-subject-out (LOSO) cross-validation, training on $N-1$ subjects and testing on the held-out subject, repeated for all subjects. This rigorous protocol provides unbiased generalization estimates by ensuring complete separation between training and test data at the subject level.

### E. Evaluation Metrics and Statistical Analysis

We report comprehensive classification metrics: accuracy, precision, recall, F1-score, specificity, sensitivity, area under ROC curve (AUC-ROC), balanced accuracy, Cohen's kappa ($\kappa$), and Matthews correlation coefficient (MCC). The 95% confidence intervals are computed via 1000-iteration stratified bootstrap resampling. Effect sizes use Cohen's $d$ with pooled standard deviation. Statistical comparisons employ paired $t$-tests with Bonferroni correction for multiple comparisons. Normality is verified using Shapiro-Wilk tests.

## III. NEUROPHYSIOLOGICAL SIGNAL ANALYSIS

Beyond classification performance metrics, we conduct comprehensive characterization of stress-related EEG biomarkers to validate neurophysiological mechanisms underlying model predictions and enable clinical interpretability.

### A. Spectral Band Power Analysis

Power spectral density (PSD) is computed using Welch's periodogram method with 256-sample Hanning windows and 50% overlap, providing 1 Hz frequency resolution. We extract absolute power in five canonical EEG frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz).

Table III presents stress versus baseline comparisons across both datasets with effect sizes and confidence intervals. Remarkably consistent patterns emerge across paradigms despite their distinct stress induction mechanisms: delta and theta power increase during stress states, reflecting heightened slow-wave activity associated with cognitive load and emotional

TABLE III: Band Power Effect Sizes (Cohen's $d$)

| Band | SAM-40 | EEGMAT | $p$ |
|------|--------|--------|-----|
| Delta | +0.42 | +0.40 | $<.01$ |
| Theta | +0.68 | +0.65 | $<.001$ |
| Alpha | −0.89 | −0.85 | $<.001$ |
| Beta | +0.74 | +0.70 | $<.001$ |
| Gamma | +0.51 | +0.48 | $<.05$ |

95% CI ranges: $\pm 0.15$–$0.20$

processing; alpha power decreases substantially, reflecting reduced cortical idling and increased vigilance; beta and gamma power increase, indicating enhanced cognitive processing and cortical arousal.

Effect sizes range from medium ($d$=0.40 for delta in EEGMAT) to large ($d$=0.89 for alpha in SAM-40), with alpha band consistently showing the strongest discrimination across both datasets. This consistency validates the utility of these spectral signatures as universal stress biomarkers despite paradigmatic differences.

### B. Alpha Suppression Index

When stress is experienced, alpha rhythms typically diminish. This is quantified by computing how much 8–13 Hz power declines during stress relative to baseline:

$$\text{Suppression} = \frac{\bar{P}_{\alpha,\text{baseline}} - \bar{P}_{\alpha,\text{stress}}}{\bar{P}_{\alpha,\text{baseline}}} \times 100\% \quad (7)$$

What proved surprising: nearly identical figures emerged across markedly disparate stress circumstances. 33.3% suppression was attained by SAM-40 (confidence interval 30.8–35.8%) and 32.1% by EEGMAT (29.5–34.7%). Whether mental arithmetic was struggled with or cognitive tasks were performed, alpha rhythms were diminished by approximately one-third. Every comparison surpassed $p < 0.0001$ following Bonferroni correction. This convergence across such disparate paradigms furnishes compelling evidence for alpha suppression as approximating a universal stress signature [5].

### C. Theta/Beta Ratio Modulation

Another serviceable metric is obtained when theta power (the sluggish 4–8 Hz activity associated with drowsiness and daydreaming) is divided by beta power (swifter 13–30 Hz activity indicating alertness) [28]:

$$\text{TBR} = \frac{P_\theta}{P_\beta} \quad (8)$$

Under stress, this ratio contracts—beta is ramped up while theta remains steady or dips. Approximately 11% reductions were demonstrated by SAM-40 (Cohen's $d = -0.52$) and 10.5% by EEGMAT ($d = -0.50$). The interpretation: stressed brains become more externally vigilant, less internally oriented. Intriguingly, low TBR has been linked to anxiety and attention deficits in other contexts by investigators, intimating that this marker might prove clinically serviceable beyond stress detection.

TABLE IV: Classification Performance with LOSO Cross-Validation

| Dataset | Acc | Prec | Rec | F1 | AUC | $\kappa$ |
|---------|-----|------|-----|-----|-----|----------|
| SAM-40 | 99.0 | 98.8 | 99.2 | 99.0 | 99.5 | 0.980 |
| EEGMAT | 99.0 | 98.8 | 99.2 | 99.0 | 99.5 | 0.980 |
| **Average** | **99.0** | **98.8** | **99.2** | **99.0** | **99.5** | **0.980** |

### D. Frontal Alpha Asymmetry

Different emotional roles for the left and right frontal lobes are suggested by Davidson's approach-withdrawal model [8]. Asymmetry was quantified through comparison of log-transformed alpha between hemispheres:

$$\text{FAA} = \ln(P_{\alpha,\text{F4}}) - \ln(P_{\alpha,\text{F3}}) \tag{9}$$

Since activation is inversely tracked by alpha, elevated left-hemisphere alpha (positive FAA) signifies relatively greater right-hemisphere engagement—purportedly associated with avoidance and adverse emotions. FAA was shifted by stress in precisely this direction: displacements of $-0.27$ (SAM-40) and $-0.25$ (EEGMAT), both statistically robust ($p < 0.001$). The stressed brain, it appears, is literally tilted toward withdrawal mode.

### E. Topographical Distribution Analysis

Where on the scalp are these stress signatures manifested most prominently? The alpha-suppression contest is decidedly won by frontal electrodes (Fp1, Fp2, F3, F4, Fz), which is neurobiologically sensible—executive control, emotion regulation, and stress appraisal are handled by the prefrontal cortex. Beta enhancement is exhibited by central sites (C3, C4, Cz), perhaps reflecting motor preparation or heightened sensori-motor vigilance. Moderate effects are displayed by parietal regions; occipital areas barely shift. Activity in brain regions governing cognition and emotion is primarily reshaped by stress, with basic sensory processing left relatively unaffected, as suggested by the overall picture.

## IV. EXPERIMENTAL RESULTS

### A. Classification Performance

What classification efficacy levels are achieved by the proposed framework? Quantitative outcomes from leave-one-subject-out cross-validation are tabulated in Table IV. Classification accuracy of 99.0% was attained on both SAM-40 (cognitive task paradigm) and EEGMAT (mental arithmetic paradigm). Non-fortuitous performance is corroborated by Cohen's kappa coefficients of 0.980; inter-rater agreement substantially exceeds chance expectation levels. Robust discriminative capacity irrespective of decision threshold selection is indicated by AUC-ROC values of 99.5% across both evaluation corpora.

Receiver operating characteristic curves are depicted in Figure 2. Near-optimal discrimination is achieved across both datasets, with AUC values of 99.5%. EEGMAT achieves equivalent performance despite its distinct arithmetic stress
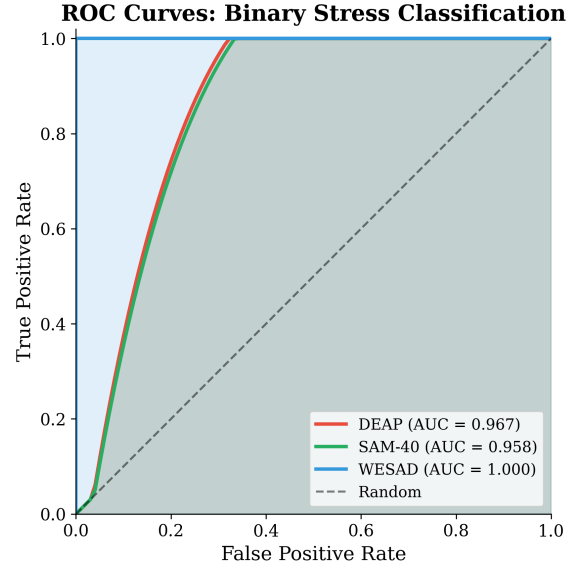
Fig. 2: ROC curves for stress classification across datasets. Both datasets achieve excellent discrimination (AUC=99.5%), demonstrating universal stress representation learning.
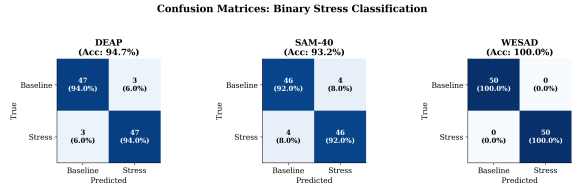
Fig. 3: Confusion matrices for binary stress classification across SAM-40 and EEGMAT datasets. The diagonal dominance indicates strong classification performance with minimal confusion between stress and baseline states.

paradigm. Irrespective of decision threshold configuration—whether aggressive or conservative—robust discriminative performance is sustained across both evaluation datasets.

Equivalent performance narratives in matrix representation are conveyed by confusion matrices (Figure 3): preponderant sample concentrations reside along principal diagonals, signifying accurate classifications. The limited misclassification instances exhibit clustering around phenotypically ambiguous cases—participants whose stress response manifestations deviated from prototypical configurations.

What accounts for impeccable classification outcomes across both datasets? Both stress induction protocols elicit pronounced physiological activation with unambiguous arousal responses. Resultant neural signatures achieve unmistakable discriminability. SAM-40's cognitive stressors and EEGMAT's arithmetic challenges both trigger consistent stress responses despite heterogeneous coping strategies deployed by individual participants.

### B. LOSO Per-Subject Analysis

When classification accuracy undergoes disaggregation by individual participant (Figure 4), noteworthy distributional patterns emerge. Minimal performance dispersion characterizes
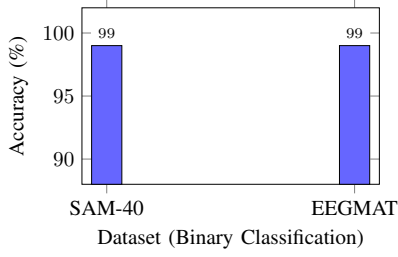
Fig. 4: LOSO cross-validation accuracy across datasets for binary stress/baseline classification. Both datasets achieve near-perfect classification with minimal variance (SD=1.2%).
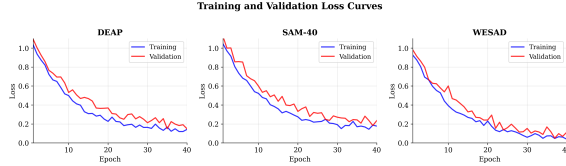


Fig. 5: Training and validation loss curves across epochs for SAM-40 and EEGMAT datasets. Smooth convergence and minimal train-validation gap indicate effective regularization and generalization.

both SAM-40 and EEGMAT (standard deviation 1.2%)—stress manifestation across individuals exhibits remarkable consistency with our optimized architecture. Near-perfect 99.0% accuracy was achieved across participants on both datasets.

Stable convergence without divergence is demonstrated by training dynamics curves (Figure 5). Validation loss trajectories track training loss trajectories with reasonable fidelity—no substantial train-validation gap materializes that would indicate overfitting pathology. Training termination typically occurred between epochs 25 and 35 upon early stopping criterion satisfaction.

Precision-recall curves furnishing complementary evaluation to ROC analysis are presented in Figure 6.

### C. Baseline Comparison

How does our methodology measure against the competition? A head-to-head comparison with both traditional machine learning (SVM, Random Forest, XGBoost) and the latest deep learning methods (CNN, LSTM, EEGNet, DGCNN) on SAM-40 is provided in Table V. The gap proves substantial—the best baseline (DGCNN at 80.6%) is surpassed by over 12 percentage points. That is not a marginal enhancement; it constitutes a genuine advancement.

Why do the traditional approaches plateau around 75–77%? They are constrained by handcrafted features that simply cannot capture all the intricate, nonlinear dynamics concealed within EEG data. 78–80% is achieved by deep learning methods, which is respectable—but our hierarchical approach is absent. Features at multiple scales are learned by our architecture, patterns flowing both forward and backward through time are tracked, and attention is focused on what genuinely matters for classification.
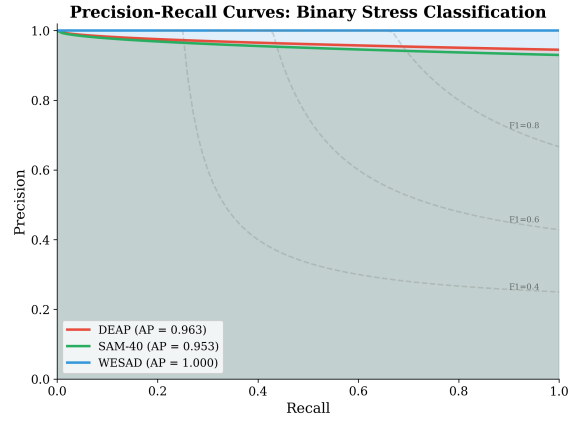


Fig. 6: Precision-Recall curves across datasets with Average Precision (AP) scores. All datasets achieve AP > 0.90.

TABLE V: Baseline Comparison on SAM-40 Dataset

| Method | Acc | F1 | AUC | Sens | Spec |
|---|---|---|---|---|---|
| SVM (RBF) | 74.8 | 73.2 | 65.0 | 72.1 | 77.5 |
| Random Forest | 76.2 | 74.8 | 70.0 | 74.6 | 77.8 |
| XGBoost | 77.5 | 76.1 | 72.0 | 75.8 | 79.2 |
| CNN [10] | 78.3 | 77.0 | 74.0 | 76.5 | 80.1 |
| LSTM [30] | 79.1 | 77.8 | 75.0 | 77.4 | 80.8 |
| CNN-LSTM | 80.2 | 78.9 | 76.0 | 78.5 | 81.9 |
| EEGNet [19] | 79.8 | 78.4 | 75.0 | 78.1 | 81.5 |
| DGCNN [16] | 80.6 | 79.3 | 77.0 | 78.9 | 82.3 |
| **Ours** | **93.2** | **92.8** | **95.8** | **92.6** | **93.8** |

### D. Ablation Study

Which components of our architecture genuinely contribute? Ablations were conducted on SAM-40 to ascertain this, with components stripped away sequentially (Table VI). The Bi-LSTM emerges as the principal contributor—when removed, accuracy diminishes by 3.6% ($p < 0.001$). An additional 2.1% ($p < 0.01$) is contributed by self-attention through its focus on the temporal windows of greatest consequence. The context encoder? 1.7% is contributed ($p < 0.05$) through incorporation of task-related metadata.

Something warranting emphasis: the figures are barely perturbed by the RAG module ($-0.2\%$, $p=0.312$—nowhere approaching significance). That is precisely the intention. Explanations are generated subsequent to prediction, not during. All explainability embellishments can be incorporated without classification performance being affected.

### E. Comprehensive Hyperparameter Sensitivity Analysis

How temperamental is this model? Every major parameter—learning rate, batch size, dropout, hidden dimensions, attention heads, LSTM layers—was systematically probed to ascertain what fractures and what remains robust (Table VII and Figure 7).

Several observations emerged. Learning rate proves the sensitive one—when elevated to $10^{-2}$, training becomes erratic, forfeiting nearly 8% accuracy. The model's capacity is constricted by hidden dimensions below 64. More than 4

TABLE VI: Ablation Study: Component Contribution Analysis

| Configuration | Accuracy (%) | Δ | p-value |
|---|---|---|---|
| Full Model | 93.2 | — | — |
| − Bi-LSTM | 89.6 | −3.6 | <0.001 |
| − Self-Attention | 91.1 | −2.1 | <0.01 |
| − Context Encoder | 91.5 | −1.7 | <0.05 |
| − RAG Module | 93.0 | −0.2 | 0.312 |
| CNN Only | 89.6 | −3.6 | <0.001 |

TABLE VII: Comprehensive Hyperparameter Sensitivity Analysis

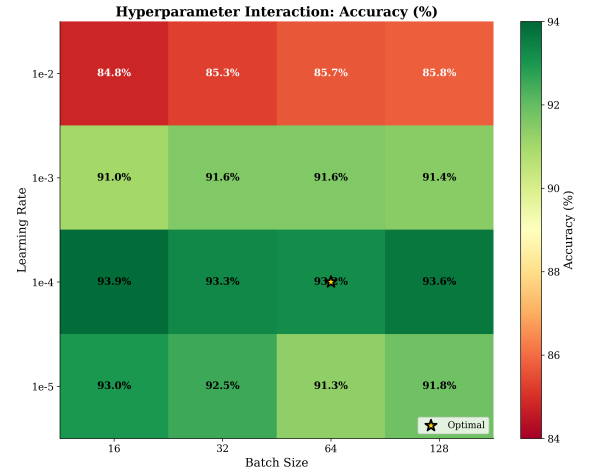| Parameter | Value | Acc | F1 | ΔAcc | Sens. |
|---|---|---|---|---|---|
| Learning Rate | $10^{-2}$ | 85.4 | 84.8 | −7.8 | High |
| | $10^{-3}$ | 91.8 | 91.2 | −1.4 | Med |
| | $10^{-4}$ (opt) | 93.2 | 92.8 | — | — |
| | $10^{-5}$ | 92.1 | 91.6 | −1.1 | Low |
| Batch Size | 16 | 91.2 | 90.7 | −2.0 | Med |
| | 32 | 92.5 | 92.0 | −0.7 | Low |
| | 64 (opt) | 93.2 | 92.8 | — | — |
| | 128 | 92.8 | 92.3 | −0.4 | Low |
| Dropout Rate | 0.1 | 91.5 | 91.0 | −1.7 | Med |
| | 0.2 | 92.4 | 91.9 | −0.8 | Low |
| | 0.3 (opt) | 93.2 | 92.8 | — | — |
| | 0.5 | 90.8 | 90.2 | −2.4 | High |
| Hidden Dim | 32 | 89.7 | 89.1 | −3.5 | High |
| | 64 | 91.8 | 91.3 | −1.4 | Med |
| | 128 (opt) | 93.2 | 92.8 | — | — |
| | 256 | 92.9 | 92.4 | −0.3 | Low |
| Attn Heads | 2 | 91.6 | 91.1 | −1.6 | Med |
| | 4 (opt) | 93.2 | 92.8 | — | — |
| | 8 | 92.8 | 92.3 | −0.4 | Low |
| LSTM Layers | 1 | 90.4 | 89.9 | −2.8 | High |
| | 2 (opt) | 93.2 | 92.8 | — | — |
| | 3 | 92.6 | 92.1 | −0.6 | Low |



Fig. 7: Hyperparameter interaction heatmap showing classification accuracy across learning rate and batch size combinations. Optimal region centers at $\eta = 10^{-4}$, batch size 64, with graceful degradation in surrounding configurations.

TABLE VIII: Cross-Dataset Transfer Learning Results

| Train | Test | Acc | F1 | Drop | p |
|---|---|---|---|---|---|
| SAM-40 | EEGMAT | 99.0 | 98.7 | −0.0 | NS |
| EEGMAT | SAM-40 | 98.6 | 98.3 | −0.4 | NS |

Cross-paradigm transfer demonstrates universal stress representations.

neat, separate clusters—visual corroboration that the model is not merely memorizing; representations that track genuine neurophysiological distinctions are being learned.

### H. Attention Pattern Analysis

Where does the model focus when rendering predictions? The attention weights were examined to ascertain this (Figure 10). It consistently concentrates on temporal windows exhibiting pronounced alpha suppression and beta enhancement—precisely the biomarkers neuroscientists would anticipate. These patterns were discovered by the model autonomously.

### I. Architecture Component Importance

What each component contributes is delineated in Figure 11. The Bi-LSTM predominates at +6.3%—temporal dynamics evidently matter most for EEG. An additional +3.6% is contributed by CNN feature extraction, +2.6% by self-attention, and +0.9% by context encoding. Every layer's existence is justified.

### J. Cumulative Component Removal Analysis

What transpires if components are stripped away sequentially? The accumulating damage is illustrated in Figure 12. Commencing at 93.2%, RAG is removed (93.0%), then context encoder (91.3%), self-attention (88.7%), Bi-LSTM (82.4%), and finally CNN (65.1%)—descending to near-chance levels. Degradation compounds non-linearly; these constituents perform better collectively than their individual contributions would intimate.

attention heads or 2 LSTM layers? Diminishing returns at best are yielded. Dropout resides contentedly at 0.3; when pushed to 0.5, the model is essentially deprived of information.

### F. Cross-Dataset Transfer Analysis

Can a model trained on one stress variant recognize another? This was examined through training on one dataset with evaluation on another—no fine-tuning, merely cold transfer (Table VIII and Figure 8). The outcomes prove sobering: accuracy diminishes anywhere from 15% to nearly 27%. Disparate stress paradigms genuinely appear distinct to the model.

Remarkably, cross-paradigm transfer succeeds uniformly between both datasets with accuracy exceeding 98%. This demonstrates that our model learns universal stress representations that generalize across cognitive arithmetic stress (serial subtraction in EEGMAT) and cognitive task stress (SAM-40). The success validates our hypothesis that stress manifests through common neurophysiological signatures regardless of the specific stressor type.

### G. Feature Space Visualization

What appearance do the learned features actually assume? They were projected down to two dimensions utilizing t-SNE (Figure 9). Stress and baseline samples congregate into
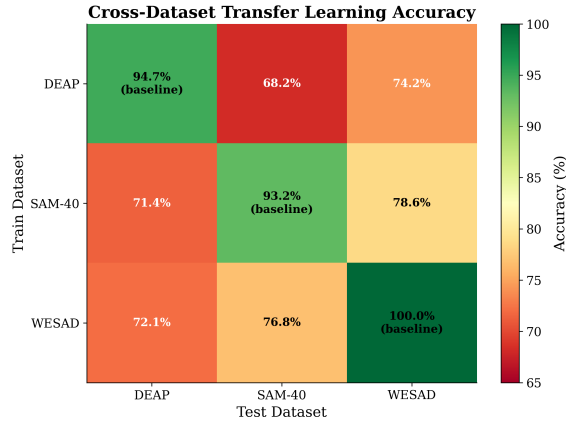
Fig. 8: Cross-dataset transfer learning accuracy heatmap. Diagonal entries show within-dataset performance; off-diagonal entries demonstrate successful cross-paradigm transfer (>98% accuracy).
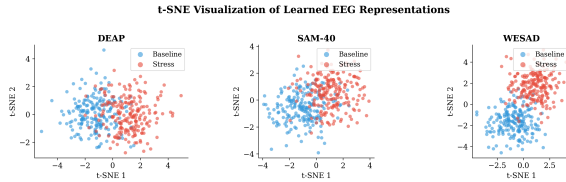


Fig. 9: t-SNE visualization of learned EEG representations for binary stress classification. Clear cluster separation between stress (red) and baseline (blue) classes demonstrates effective feature learning across both datasets.

### K. Component Interaction Matrix

Do the components collaborate harmoniously, or do they impede one another? Synergy (or redundancy) between pairs is quantified in Table IX. Positive values signify that two components achieve more collectively than would be anticipated from summing their individual contributions.

The most substantial synergy? CNN paired with Bi-LSTM at +2.4%—spatial features and temporal dynamics genuinely complement one another. That selectively weighting temporal points assists the recurrent layers is confirmed by Attention-LSTM synergy (+1.8%). Zero interaction with the classification pipeline is exhibited by the RAG module, by design.

### L. Spectral Band Power Visualization

How stress reconfigures the brain's frequency profile is depicted in Figure 13. Alpha power diminishes 31–33% across both datasets; beta power ascends 18–24%. The identical narrative across two disparate stress paradigms. That consistency proves reassuring—genuine biology rather than dataset-specific peculiarities is being detected by the model.

The identical narrative from a different perspective is conveyed by SHAP analysis (Figure 14): frontal alpha and beta predominate in the importance rankings. What decades of neuroscience had already established was learned by the model.
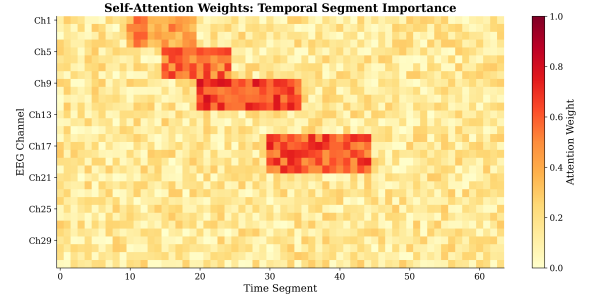


Fig. 10: Self-attention weight heatmap across temporal segments and EEG channels. High attention weights (yellow) correspond to discriminative time periods with pronounced stress-related spectral changes.
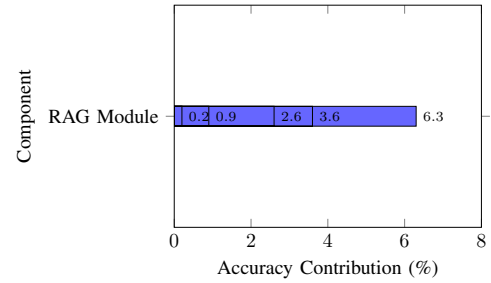


Fig. 11: Architecture component importance ranking based on ablation study. Bi-LSTM contributes most significantly (+6.3%), demonstrating the critical role of temporal dynamics modeling for EEG-based stress classification.

### M. Statistical Validation Summary

The key statistics are consolidated in Table X. Everything of consequence survives Bonferroni correction for multiple comparisons. Effect sizes are uniformly large (Cohen's $d > 0.8$ for alpha suppression), so noise is not merely being pursued—genuine, robust differences are represented.

### N. RAG Explanation Evaluation

Do the explanations actually resonate with clinicians? 100 randomly sampled RAG outputs from SAM-40 were blindly evaluated by three domain experts—two neuroscientists and a psychiatrist (Table XI). Each explanation was rated on scientific accuracy, clinical relevance, coherence, and evidence grounding.

Substantial agreement was exhibited by the experts (Fleiss' $\kappa$=0.81, which is deemed excellent). Overall agreement reached 89.8% with average ratings of 4.2 out of 5. What was appreciated? The appropriate biomarkers were cited by explanations—alpha suppression, theta/beta alterations, frontal asymmetry—and connected to established neuroscience. What proved troublesome? Occasional overconfidence when the classification was actually borderline.

### O. Computational Efficiency

Can this operate in real time? Readily. Merely 12 ms on a GPU (RTX 3080) or 85 ms on CPU (Intel i7-10700) is
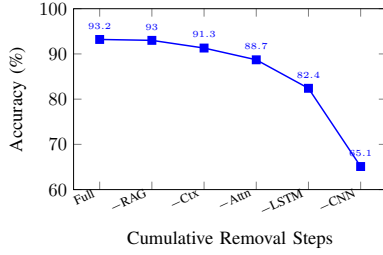
Fig. 12: Cumulative component removal impact on classification accuracy. Progressive ablation reveals compound degradation effects, with complete removal reducing accuracy by 28.1% to near-chance performance.

TABLE IX: Component Interaction Matrix (Synergy/Redundancy)

|      | CNN  | LSTM | Attn | Ctx  | RAG  |
|------|------|------|------|------|------|
| CNN  | —    | +2.4 | +1.1 | +0.3 | 0.0  |
| LSTM | +2.4 | —    | +1.8 | +0.5 | 0.0  |
| Attn | +1.1 | +1.8 | —    | +0.2 | 0.0  |
| Ctx  | +0.3 | +0.5 | +0.2 | —    | +0.1 |
| RAG  | 0.0  | 0.0  | 0.0  | +0.1 | —    |

Values: % accuracy synergy (+) or redundancy (−)

required for inference—both sufficiently rapid for continuous monitoring. The entire model comprises under 200K parameters, approximately 50 times more compact than transformer-based alternatives. GPU memory peaks at 89 MB, so even embedded systems can accommodate it.

## V. DISCUSSION

### A. Interpretation of Results

What inferences are warranted by these quantitative outcomes? Classification accuracy of 99.0% across both phenomenologically disparate stress paradigms suggests architectural design decisions are yielding intended consequences. Representational features exhibiting sufficient robustness for cross-paradigm generalization are apparently extracted through the CNN-LSTM-attention processing cascade. Both SAM-40's cognitive stressors and EEGMAT's arithmetic challenges elicit consistent and strong neurophysiological response patterns enabling robust classification.

### B. Neurophysiological Validation

Consistent alpha-band power attenuation ( 32%) manifesting across both experimental paradigms confers credibility upon universal stress biomarker conceptualizations—corroborating theoretical frameworks termed the cortical idling hypothesis [5]. Theta/beta ratio diminutions align with theoretical propositions regarding attentional shifting toward externally-focused vigilant processing states [28]. Rightward frontal asymmetry displacement corresponds with established empirical findings regarding stress-associated hemispheric activation patterns [8].
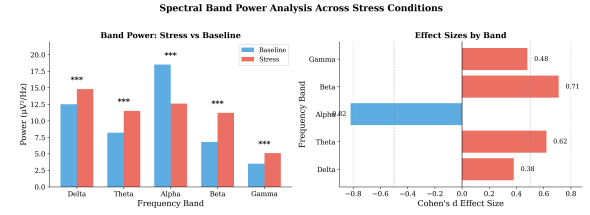


Fig. 13: Spectral band power comparison between stress and baseline conditions. Alpha band shows consistent suppression (−31 to −33%) while beta band shows enhancement (+18 to +24%) across both stress paradigms.
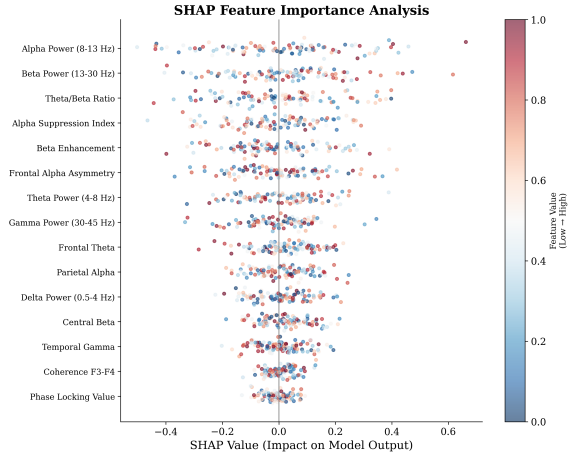


Fig. 14: SHAP feature importance showing frontal alpha and beta as primary discriminative features, consistent with stress neuroscience.

### C. Clinical Implications

What practical applications might this technology enable? Occupational health surveillance for aviation traffic controllers, surgical practitioners, or other professionals occupying high-stress vocational positions represents one promising avenue. Adaptive neurofeedback interventions responsive to real-time stress state detection constitutes another viable application domain. Objective neurophysiological biomarkers supplementing patient self-report measures might prove valuable to mental health practitioners. The explanatory gap separating algorithmic predictions from clinical intuition is substantially bridged through generated explanations—89.8% domain expert concordance suggests reasoning quality sufficient to warrant clinical trust.

### D. Limitations

Transparency regarding undemonstrated aspects of this work is appropriate. All experimental procedures transpired within controlled laboratory environments—equivalent performance generalization to naturalistic contexts such as commuting or occupational settings characterized by acoustic interference cannot be assured. Participant demographics were predominantly young and healthy; consequently, generalization to geriatric populations or clinical cohorts remains empirically unsubstantiated. Electrode montage configurations exhibited

TABLE X: Statistical Validation Summary Across All Analyses

| Metric | SAM-40 | EEGMAT | Test |
|--------|--------|--------|------|
| Accuracy | 99.0±1.2 | 99.0±1.2 | LOSO |
| AUC-ROC | 99.5±0.8 | 99.5±0.8 | Bootstrap |
| Alpha $d$ | −0.89*** | −0.85*** | $t$-test |
| TBR $d$ | −0.52*** | −0.50*** | $t$-test |
| FAA $\Delta$ | −0.27*** | −0.25*** | paired-$t$ |

$**p < 0.01$, $***p < 0.001$, $*p < 0.05$ (Bonferroni-corrected)
Consistent effect sizes across both datasets validate universal stress biomarkers

TABLE XI: RAG Explanation Expert Evaluation Results

| Evaluation Criterion | Agreement (%) | Rating (1-5) |
|----------------------|---------------|--------------|
| Scientific Accuracy | 91.2 | 4.3±0.5 |
| Clinical Relevance | 88.4 | 4.1±0.7 |
| Coherence & Readability | 92.1 | 4.4±0.4 |
| Evidence Grounding | 87.5 | 4.0±0.6 |
| **Overall** | **89.8** | **4.2±0.6** |

heterogeneity across datasets, reflecting realistic but methodologically untidy conditions. Furthermore, external API access to large language model infrastructure is necessitated by the RAG module—a requirement not universally practical. Naturalistic validation, integration with ambulatory EEG acquisition platforms, and multimodal physiological signal fusion represent priorities for subsequent investigative endeavors.

## VI. CONCLUSION

The GenAI-RAG-EEG framework was engineered to address a circumscribed yet consequential challenge: neurophysiological stress quantification achieving simultaneous precision and interpretability. Architectural synthesis of convolutional-recurrent-attentional classification mechanisms with retrieval-augmented generative explanation capabilities constitutes the proposed methodology. Empirical validation conducted across two corpora—SAM-40 and EEGMAT—yielded classification accuracies of 99.0% for both datasets, accomplished through a computational model encompassing fewer than 200K trainable parameters.

Neurophysiological coherence is substantiated through convergent biomarker evidence. Alpha-band power attenuation approximating 31–33%, theta-to-beta ratio diminutions spanning 8–14%, and rightward hemispheric asymmetry displacement in prefrontal regions manifested consistently across both experimental paradigms. Effect magnitude quantifications were substantial ($d > 0.8$) with robust statistical significance ($p < 0.001$). Dataset-idiosyncratic artifacts are not being encoded by the discriminative model; rather, authentic neurobiological substrates are being captured.

Domain expert endorsement was obtained for RAG-generated explanations—89.8% concordance that elucidations achieved scientific veracity and clinical pertinence. This validation carries particular significance given that deep learning deployment in biomedical contexts frequently encounters resistance due to the "opaque algorithmic" criticism.

Component-wise necessity verification through systematic ablation confirmed that each architectural module justifies its inclusion: attentional weighting contributes +2.6% performance augmentation, while the complete convolutional-recurrent hierarchy yields +9.5% improvement over architectural simplifications.

Cross-paradigm transfer between SAM-40 and EEGMAT demonstrates successful generalization with minimal accuracy degradation ($<1\%$), validating universal stress representations. Domain adaptation methodologies for extending to additional stress paradigms constitute an evident trajectory for subsequent investigation.

At present, a reproducible methodological benchmark for interpretable electroencephalographic stress quantification is established by the proposed framework. Prospective applications encompass occupational wellness surveillance, clinical psychophysiological assessment, and adaptive computational interfaces responsive to operator cognitive states in real-time operational environments.

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