Neuro-AI: Hybrid Model for Cognitive Enhancements

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***Abstract*—Modern academic and workplace environments demand sustained attention and rapid learning, yet prolonged screen exposure, multitasking, and stress degrade focus and memory. This paper proposes *Neuro-AI*, a hybrid model that combines neurophysiological signal processing with machine intelligence to infer cognitive states (*high focus*, *low focus*, *cognitive fatigue*) and deliver *personalized micro-interventions* (e.g., paced breathing, micro-breaks, memory drills, focus priming). The pipeline integrates lightweight EEG preprocessing, bandpower/ratio feature engineering, supervised classification, and an adaptive recommendation layer exposed via a minimal user interface. We outline system design, current prototype status, and an evaluation plan; placeholders are included for results to be inserted after the next experiment cycle.**

***Index Terms*—EEG, cognitive load, attention, mental fatigue, recommendation, hybrid AI, Neuro-AI**

I. Introduction

Cognitive performance underpins learning, problem solving, and productivity. Reports of reduced attention spans, memory overload, and fatigue are common among students and knowledge workers. While timers and to-do tools aid scheduling, they do not *sense* cognitive state. Non-invasive electroencephalography (EEG) offers a window into neural dynamics linked to attention and workload. However, raw EEG is noisy and hard to interpret without algorithmic support.

Neuro-AI targets *closed-loop cognitive support*: (i) estimate cognitive state from EEG features using efficient ML; (ii) translate predictions into small, timely actions that fit study/work routines; (iii) learn what works per user over time. This work describes our design choices, current progress, and next steps toward a practical assistant for sustained focus.

II. Related Work

EEG and cognitive markers. Alpha (8–13 Hz) is associated with relaxed wakefulness; beta (13–30 Hz) increases with goal-directed focus; theta (4–8 Hz) relates to working memory engagement. Ratios such as α/β and θ/β have been linked to attention dynamics and mental effort. Prior studies leverage bandpower features and power spectral density (PSD) for workload estimation.

Classifiers for mental-state decoding. Traditional models—SVM, Logistic Regression, Random Forest—perform competitively on compact feature sets. Deep approaches (CNNs on spectrograms/topomaps; RNN/LSTM for temporal context) capture richer structure but require more data and compute. Despite promising accuracy, many works remain offline or end at state estimation.

From estimation to intervention. Fewer systems map state estimates to *actionable* support (break scheduling, breathing, task switching). Personalization and adherence feedback loops are underexplored. Our contribution focuses on an *integrated* pipeline that couples state estimation with a lightweight recommendation engine and real-time UI, designed for commodity EEG.

III. System Methodology / Proposed Model

Fig. 1 (placeholder) outlines the end-to-end pipeline.

A. EEG Acquisition

Phase 1: public datasets (for rapid iteration). Phase 2: controlled data collection during short study tasks (reading, recall, coding) under consent. Metadata include task type, duration, subjective effort, and self-reported focus.

B. Preprocessing

Band-pass filtering (1–45 Hz) and notch filtering (50/60 Hz) reduce noise. We segment into overlapping epochs (2–4 s) and apply simple artifact handling (blink/muscle thresholds) with per-channel z-normalization to stabilize features.

C. Feature Extraction

We compute per-epoch bandpowers for $\delta, \theta, \alpha, \beta, \gamma$; ratios α/β (relaxation vs. alertness) and θ/β (effort/fatigue); and basic time-domain descriptors (variance, Hjorth parameters). For deep variants, we consider short-time Fourier spectrograms.

Fig. 1. Pipeline placeholder: EEG → Preprocess → Features → Classifier → Recommendation → UI/Feedback.

D. State Classification

Lightweight models (SVM-RBF, Logistic Regression, Random Forest) and a compact CNN are evaluated to predict *High Focus*, *Low Focus*, and *Cognitive Fatigue*. We use stratified k-fold validation, probability calibration for a *Cognitive Score*, and class-imbalance handling.

E. Recommendation Engine

We map states to micro-interventions feasible during study/work: 60 s paced breathing; 3–5 min micro-break (posture+eye relaxation); quick memory exercise; optional focus music. A simple bandit-style updater records adherence and quick ratings to adapt choices.

F. User Interface

A minimal UI (e.g., Streamlit/React) shows the Cognitive Score gauge, trendlines, and the current recommendation with a one-click "helped?" button. A small API surfaces state and suggested action.

IV. Implementation (Current & Planned)

A. Implemented

- Data layer: filtering, epoching, artifact thresholds, feature computation.
- Modeling: SVM/RF baselines with nested CV; probability-based Cognitive Score.
- UI prototype: live gauge, last 10 min trend, action card, feedback capture.

B. Planned (Near-Term)

- **Real-time device integration:** connect a commodity EEG and stream epochs.
- **Personalization:** contextual bandit to adapt interventions per user/time/task.
- **Ablations:** feature importance, window sizes, channel subsets, model families.
- **Evaluation:** subject-independent vs. subject-dependent performance; macro-F1; AUROC; adherence metrics.

Fig. 2. Placeholder: confusion matrix / ROC curves for best model.

Fig. 3. Placeholder: UI screenshot (Cognitive Score gauge + recommendation card).

C. Planned (Mid-Term)

- **On-device inference:** quantized models for laptops/phones.
- **Task-aware support:** integrate timers and calendar context.
- **Longitudinal tracking:** weekly summaries; trends in focus windows and fatigue risk.

V. Experimental Plan and Placeholders

We will evaluate on train/val/test splits with no temporal leakage. Metrics: accuracy, macro-F1, per-class precision/recall, AUROC. For recommendations: adherence rate and short-term task improvements.

VI. Conclusion and Future Work

We presented **Neuro-AI**, a practical hybrid for cognitive enhancements that links EEG-based state estimation to actionable micro-interventions. The modular design supports offline analysis and near real-time demos on commodity hardware. Next steps include real-time streaming, personalization via bandits, on-device inference, and longitudinal studies to quantify sustained gains in attention and learning outcomes.

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