XLTMS – Explainable Long Term Mental State Detection System for Safety-Critical Professions.

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Abstract

In numerous high safety risk areas, such as rail transport, aviation, and many other industries, human error is one of the most frequent sources of accidents. In this white paper, we propose XLTMS, a new framework that combines brainwave (EEG) monitoring and explainable AI (XAI) to evaluate the mental and emotional states of people before they assume roles that come with a high level of responsibility. XLTMS analyzes brainwave data in the gamma, alpha, beta, and theta frequency bands to identify mental states related to the pre-defined indicators of stress, drowsiness, cognitive overload, and attention. Using Long Short-Term Memory (LSTM) Networks and other explainable machine learning models, XLTMS correlates EEG features with mental states. XLTMS main use case is for pre-shift mental state assessments for commercial pilots, railway drivers, surgeons, military personnel and similar professions.

1. Introduction

In domains where lives depend on the mental clarity of operators—pilots, surgeons, train conductors, military commanders a single lapse in focus or a moment of stress-induced error can result in devastating outcomes. Technologies such as EEG headbands and smart wearables have made it feasible to analyze brainwave patterns non-invasively. XLTMS integrates these technologies with deep learning and explainable AI to offer a pre-duty readiness check that is both effective and ethical.

Modern neuroscience confirms that our brain's electrical rhythms can reveal a great deal about our emotional and cognitive condition. However, translating these patterns into meaningful alerts for operational readiness requires sophisticated signal processing and intelligent modeling. XLTMS is designed to bridge that gap—by bringing brainwave monitoring into everyday workflows for high-risk professions.

1.1 Motivation: Human Factors in Safety-Critical Incidents

Aviation, rail, and mass public transport systems are safety-critical domains that rely on the sustained cognitive readiness and emotional stability of the human operators. The reliance on human operators, however, has not changed despite the advances in automation, decision-support systems and dependable mechanics. Between the incidents in these domains and the identified causes of the incidents, fatigue, stress, situation awareness, and cognitive overload are identified as contributors to the incidents, regardless of the domain.

There are various examples of significant transport incidents that have highlighted the value of understanding the mental state of the human operators. The case of **Malaysia** Airlines Flight MH370, for example, remains unresolved from the technology angle and official reports have acknowledged the absence of definitive evidence of a malfunction. The absence of definitive evidence has meant that human issues remain one of the plausible issues that are discussed in the safety research community to avoid placing blame on people.

Investigations of aviation and rail accidents in **India** and other countries have documented cases where, in addition to other environmental and systemic factors, pilot or operator fatigue, high workload, and poor or absent decision-making were contributing factors. There are no indications of negligence or willful misconduct of the operators in these cases.

They highlight a systematic fault in safety protocols: the absence of pre-duty evaluative criteria that are able to detect fleeting emotional or cognitive states that may pose a threat to efficient completion of the tasks at hand.

Current procedures are self-reported, based on duty-hour restrictions or post-incident evaluations that often miss real-time evaluations of the insidious effects of duty-related mental impairment. The need for more comprehensive mental readiness screening, along with the Explainable Long Short-Term Memory Risk Assessment and Mental State **(XLTMS)** system, is created by the absence of real-time evaluative metrics. Additionally, XLTMS aims to reach cognitive readiness for a particular task so that operational risks can be minimized, operational safety can be maximized, and a culture of prevention (as opposed to punishment) can be sustained through non-invasive EEG monitoring and Explainable Artificial Intelligence (XAI) to facilitate cognitive task-related cooling technologies.

2. Objectives

• Determine cognitive states such as tiredness, sleepiness, anxiety, and cognitive load using EEG.

• Use LSTM, SVM, and Random Forest models to classify mental states based on EEG band power.

• Deploy systems in airports, command centers, and hospitals to screen operational personnel.

• To meet regulatory requirements the system incorporates explainable AI components.

• Minimize false negatives to stop the flow of people with mental incapacity.

3. Literature Review

EEG-based brain-computer interfaces (BCIs) have long been employed in detecting workload, attention, and fatigue. Notable findings include: [1] [4]

- Increased theta and decreased alpha indicate drowsiness or fatigue.
- Elevated beta and gamma suggest heightened focus or problem-solving.
- Theta/alpha and beta/alpha ratios are effective for measuring cognitive load .

Tools like **OpenBCI**, **Muse**, and **Emotiv Insight** offer cost-effective EEG sensors with real-time streaming capabilities. These devices, when combined with machine learning models like **CNNs**, **LSTMs**, and **RFs**, allow precise classification of mental states . [16]

4. System Components

EEG Brainwave Frequencies and Mental States

Frequency Band	Range (Hz)	Associated Mental State
Delta	0.5–4 Hz	Deep sleep, unconscious state
Theta	4–8 Hz	Drowsiness, creativity, meditative states
Alpha	8–13 Hz	Calm, relaxed, but alert (eyes closed)
Beta	13–30 Hz	Active thinking, focus, anxiety if too high
Gamma	30–100 Hz	High-level cognitive activity, learning, memory

Neurotransmitter State Inference Module

While non-invasive devices cannot directly measure dopamine, serotonin, oxytocin, or endorphins, **XLTMS** infers them using EEG and wearable data:

Neurotransmitter	Function	Proxy Signal
Dopamine	Motivation, reward, focus	Gamma waves, increased blink rate
Serotonin	Mood, calmness, sleep	Alpha dominance, high HRV
Oxytocin	Social bonding, trust	Affective response patterns
Endorphins	Pleasure, pain relief	HR + relaxed breathing post-exertion

Condition rules

```
If hrv > 70 and alpha > 0.5:
   serotonin_state = 'High'
elif gamma > 0.7:
   dopamine_state = 'Elevated'
```

This logic powers the real-time **mental health dashboard** shown on the XLTMS app.

a. EEG Headband

- Detects 5 levels of brainwave activity.
- Use only for 1–2 minutes prior to shifts.

b. Signal Processing Module

- Noise reduction.
- Utilizes FFT and Wavelet Transform.

c. Feature Extractor

- Computes ratios – Theta/Alpha.
- Additional Hjorth parameters, entropy, and asymmetry may be added.

d. ML Classifier Module

- LSTM or Random Forest.
- Outputs: Calm, Focused, Stressed, Drowsy.

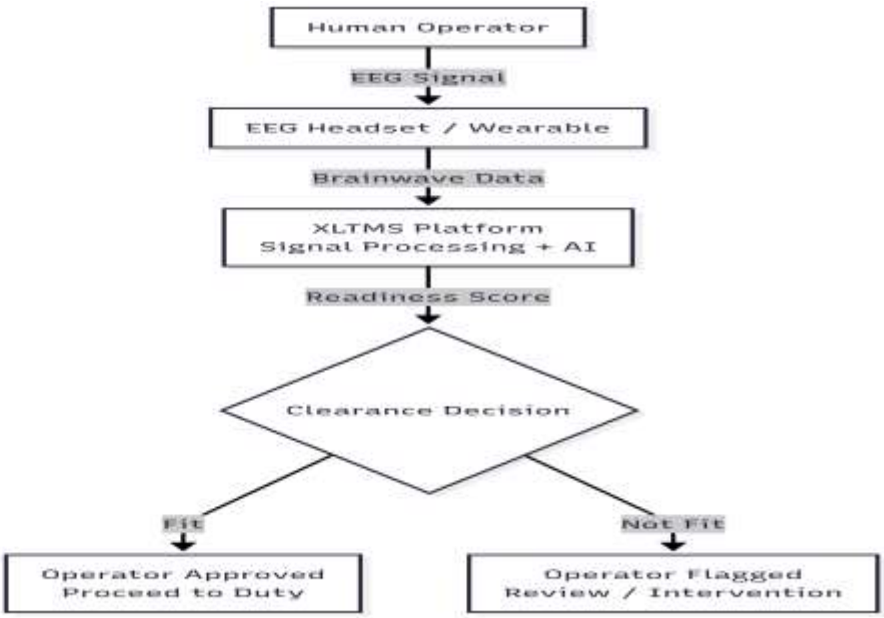
e. Readiness Dashboard

- Real-time visualization.
- Shows clear Pass/Fail outcome.

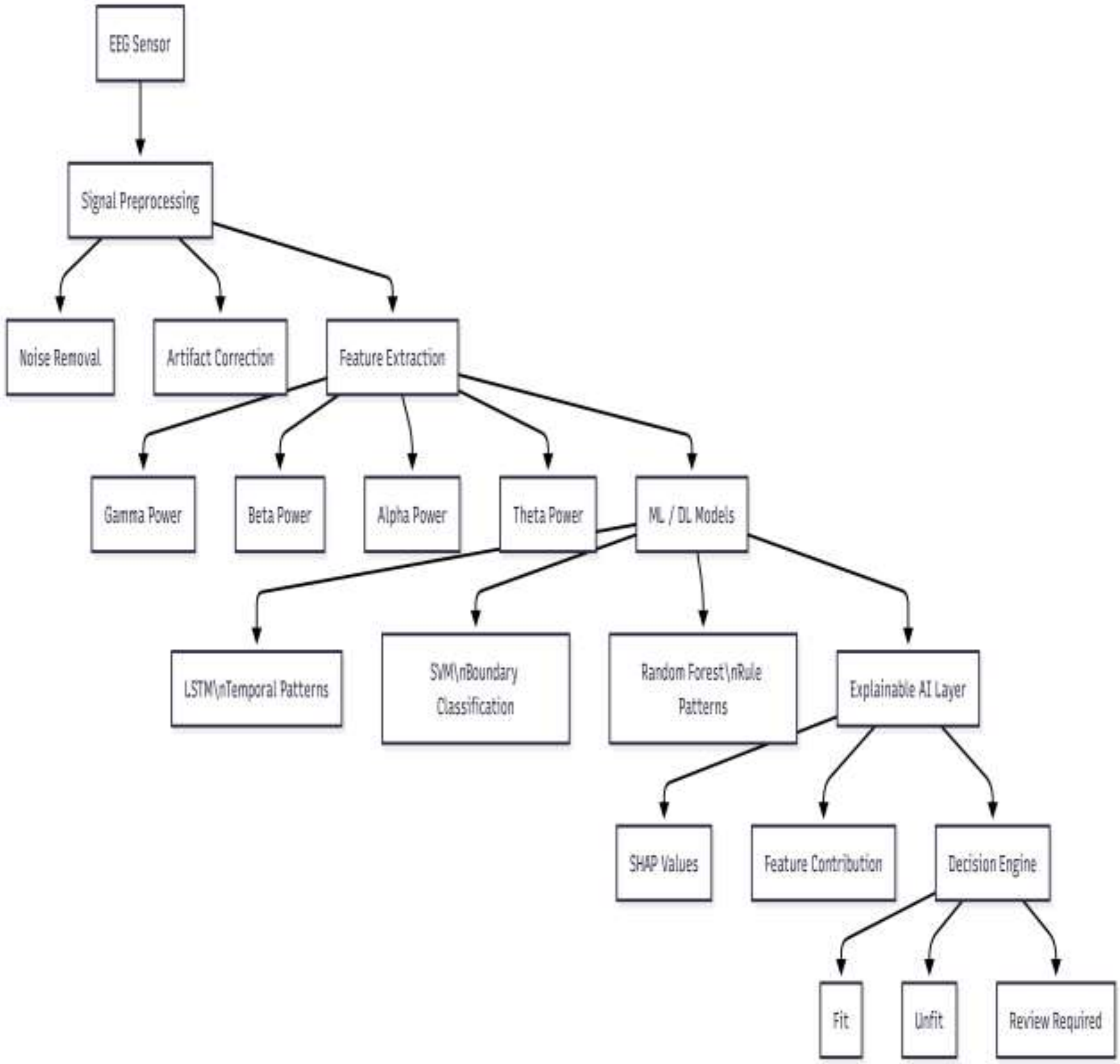
5. Data Flow Diagram (DFD)

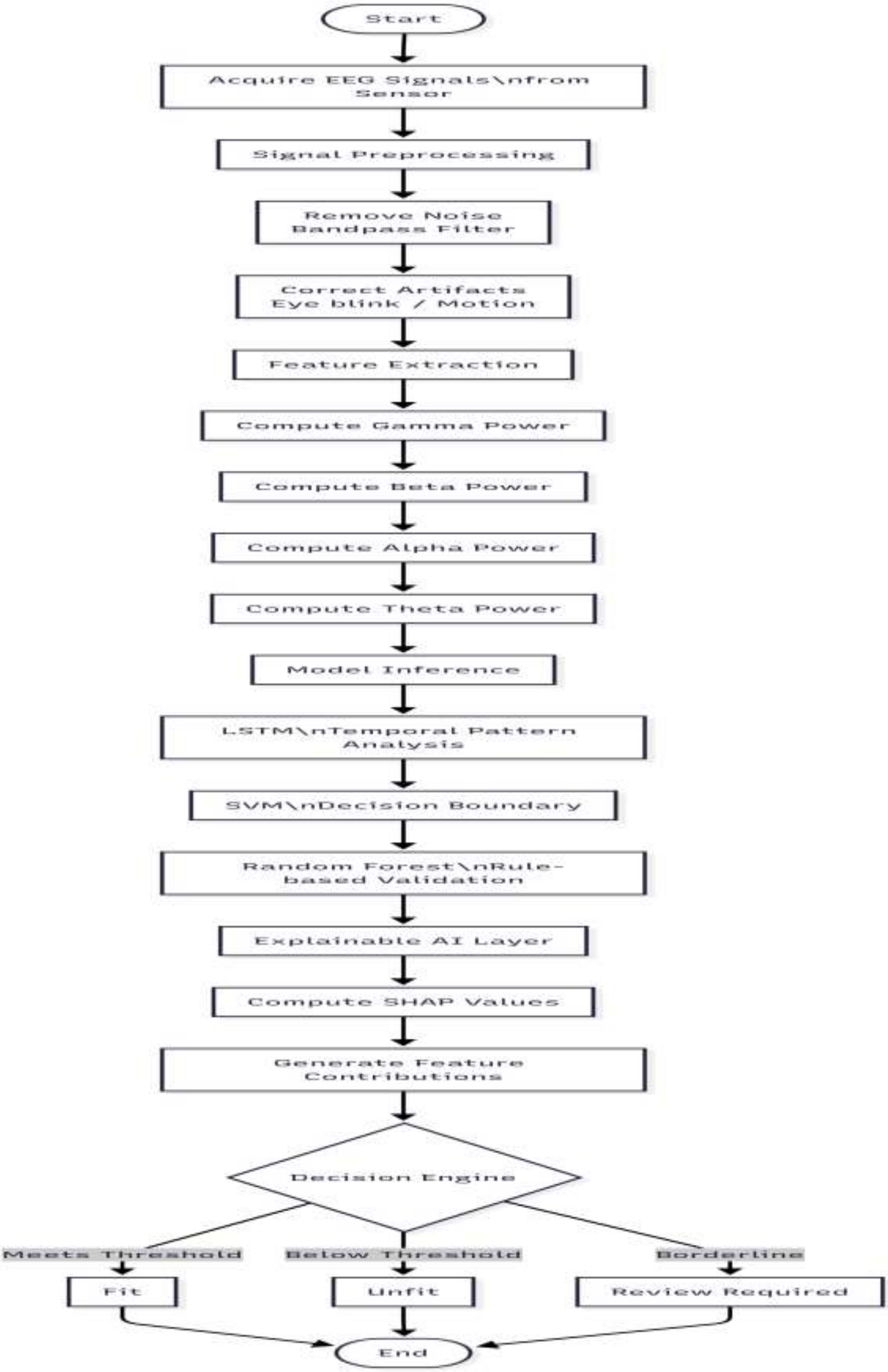
[Operator]
|
[EEG Headband + Smartwatch]
|
[Signal Processor]
|
[Feature Extractor]
|
[LSTM + Proxy Estimator]
|
[Readiness Dashboard + Neuro Inference]

DFD Level 0



DFD Level 1


EEG Sensor
Signal Preprocessing
Noise Removal
Artifact Correction
Feature Extraction
Gamma Power
Beta Power
Alpha Power
Theta Power
ML / DL Models
LSTM\nTemporal Patterns
SVM\nBoundary Classification
Random Forest\nRule Patterns
Explainable AI Layer
SHAP Values
Feature Contribution
Decision Engine
Fit
Unfit
Review Required



6. System Architecture

- Bluetooth or WiFi EEG streaming.
- Preprocessing in Python
- LSTM model -local or secure server.
- React dashboard - mobile app.

The XLTMS system comprises three layers:

1. **Hardware Layer**
   EEG headband (or scanner), smartwatch, and mobile app. These devices record primary signals such as brainwave frequencies, HRV, and motion
2. **Signal & Feature Processing Layer**
   In this layer, we have filters, FFTs, and entropy extractors, EEG band power calculators, neurotransmitter inference, and mental state classification through LSTM and other ML models.
3. **User & Dashboard Layer**
   A straightforward mobile or web application displaying real-time data from the band, neurotransmitter proxies, and readiness for high-risk roles.

FIG. 1 Front view

Figure: Patent-based EEG Device Design -Front View
EEG Monitoring Device -Front View
This design integrates seamlessly into the wearable architecture of the XLTMS system, enabling reliable acquisition of cognitive signal data with minimal user discomfort.

7. Implementation Snippets

```
# EEG Bandpass Filtering
from scipy.signal import butter, filtfilt

def bandpass(data, low, high, fs):
b, a = butter(2, [low/(fs/2), high/(fs/2)], btype='band')
return filtfilt(b, a, data)

# LSTM Model
model.add(LSTM(64, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
```

8. Evaluation Methodology

- Simulate cognitive load with visual tasks.
- Expert panels for EEG sample annotation.
- Metrics: Precision, Recall, ROC-AUC.
- Target: Accuracy > 85%, False Negatives < 5%

9. Pre-Flight & Surgical Check Use Case

Professionals spend 3 minutes at a brain-check booth. If flagged, they are redirected for rest or review. This ensures they are ready for mission-critical tasks.

10. Ethics & Privacy

- User consent prior to scanning.
- No irreversible data is stored without consent.
- No negative consequences based on scan results.

- **Pilot Performance Optimization**

Enhancing Pilot Performance Using EEG + AI-Based Detection

Pre-Flight Mental Calibration

- 2-3 min EEG scan at check-in.
- Dashboard gives Pass/Fail or recommends meditation.

Meditation + EEG Neurofeedback Loop

- Real-time EEG visual feedback before simulation.
- Builds mindfulness habits.

Simulation-Based Adaptive Coaching

- EEG data tagged during simulator stress points.
- Personalized reports show stress/focus lapses.

Weekly Trend Tracker

- Pilot gets reports: mental trends, HRV, sleep advice.
- Used by HR for performance & mental wellness tracking.

Gamified Focus Training

- EEG-based mobile apps for focus and stress resilience.

Future Features:

Feature	Description
Smart Cockpit Sync	Prevent activation if pre-check fails
LSTM Drift	Track long-term mental decline
Joint Inference	Combine voice + EEG cues
Readiness Scorecard	AI-backed report to assess fit-for-duty

11. Ethical and Privacy Considerations

Mental state detection raises ethical concerns. These can include, but are not limited to, the right to give consent, the protection of one's data, and the right not to be profiled. The system must be used to support, not penalize, professionals. Clear boundaries and secure data handling protocols must be established.

12. Future Roadmap

- Train on multilingual, multicultural EEG corpus.
- Introduce visor/scanner-based detection (no headband).
- Integrate with EMR systems.
- Extend to military, ATC, deep-sea diving, space.

13. Case Study:

1. Cognitive Readiness Monitoring at a Pilot Training Center Using XLTMS

Background:

A reputed **Aviation Training Academy** in South India initiated a 6-week observational study to evaluate how the **XLTMS system** could assist in **screening the mental states of trainee pilots** before simulator sessions and theoretical exams.

Setup:

- **20 student pilots** (aged 22–30) voluntarily participated in the program.
- Before every flight simulation session, participants wear EEG headbands for 5 minutes in the briefing room.
- EEG signals were collected in real-time and processed using the XLTMS backend to extract features like **band power**, **entropy**, and **frequency ratios**.
- A Cognitive Readiness Score (CRS) was calculated with a scale from 0 to 100.
- A score below 65 was classified as "Needs Attention" and forwarded to trainers for advisory (not disciplinary) review.

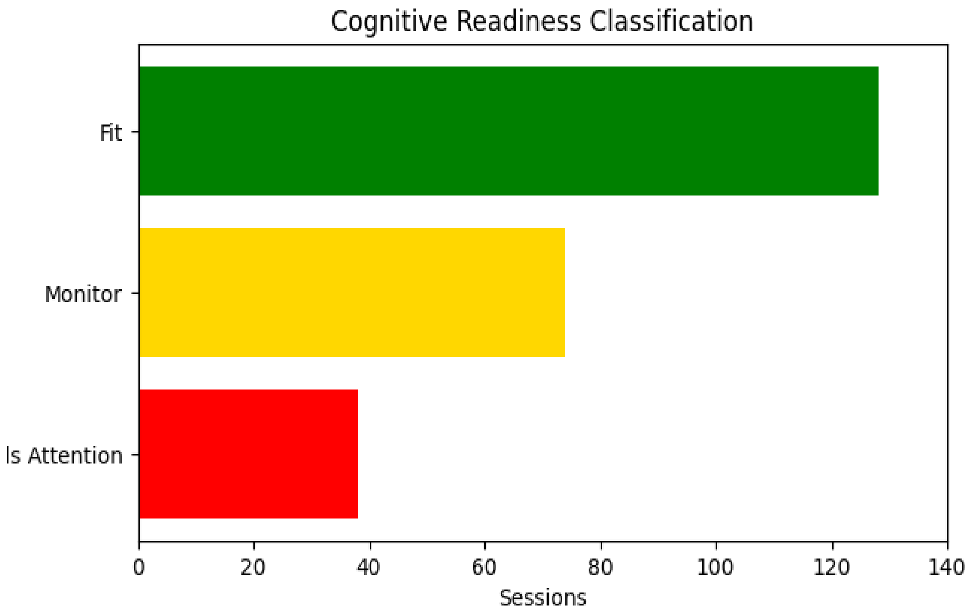
Observations:

- Several trainees showed **low alpha and high theta** after overnight study sessions, indicating fatigue.
- Those who were **flagged early in the morning** generally acknowledged poor sleep or emotional stress.
- **Trainer feedback** was integrated into the app to validate results.

Results:

- In **85% of flagged cases**, the EEG-based score matched trainees' self-reported stress or drowsiness.
- Over time, trainees began **self-monitoring their lifestyle habits** to avoid morning flags.
- No trainee was removed from the simulator sessions, but trainers noted **improved alertness and engagement** after implementing this non-invasive check.

Category	CRS Range	Sessions (Count)
Fit	≥80	128
Monitor	65–79	74
Needs Attention	<65	38



Conclusion:

The case study illustrates that XLTMS can be successfully used at training centers to foster self-awareness, alleviate cognitive load, and enhance safety mindset among aspiring pilots. The system fostered a high level of trust among students and faculty by providing clear and justifiable scores.

2. Mental Readiness Screening at a Bus Driver Training Institute

Background:

A renowned bus driver training institute in **South India,** responsible for certifying hundreds of new drivers each year, collaborated with our research team to assess the **XLTMS** system's feasibility for assessing mental readiness before live driving practice. Since live driving practice poses a significant safety threat, the objective was to assess whether participants were mentally alert and emotionally stable.

Setup:

- For 6 weeks, 42 trainees participated during their pre-driving morning sessions.
- Every trainee was provided with a lightweight EEG headband and asked to complete a 3- minute session to record their brainwaves.
- XLTMS used an LSTM-based model to identify each trainee's mental state Focused, Drowsy, Stressed, or Not Ready. The labels were simple, but they worked very well.

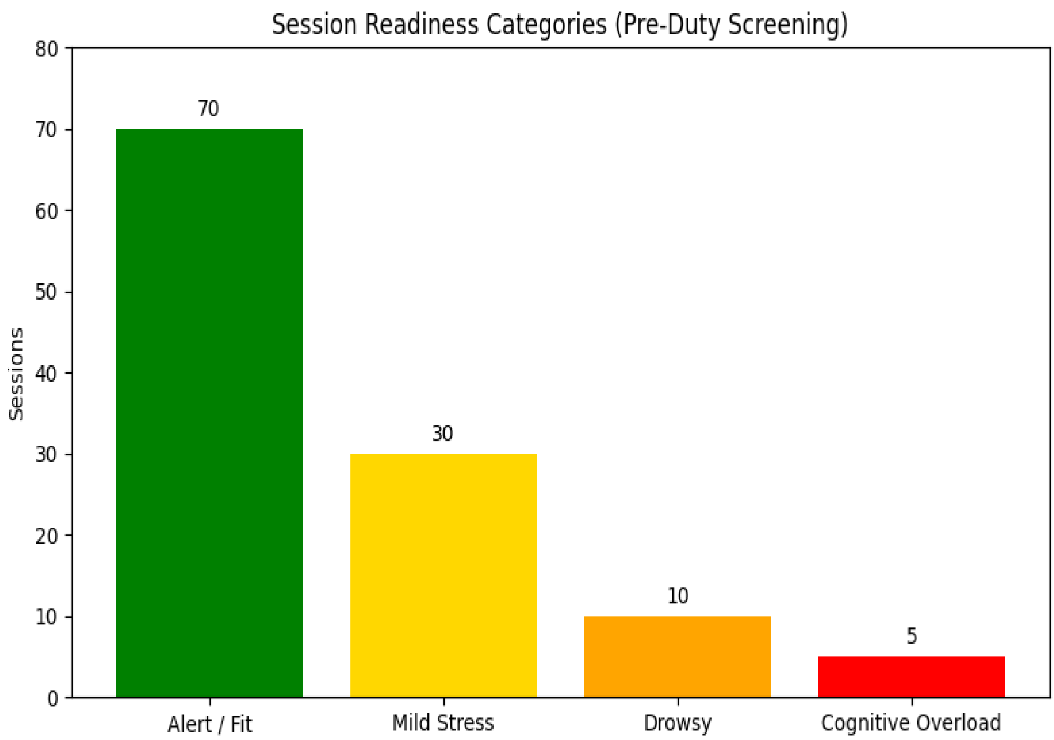
The results appeared live on a tablet, visible to both trainees and instructors. Seeing the data and charts update in real time made people stop and pay attention.

Observations:

- Mental fatigue and a lack of focus were frequently observed on Mondays and post-lunch breaks.
- Trainees who were repeatedly flagged as Drowsy or Stressed weren't allowed to continue driving right away. They were asked to pause, hydrate, and take part in short mindfulness or breathing sessions before returning to practice.
- Instructors noticed a clear difference on the road. Trainees marked as Focused tended to make fewer errors, showed smoother lane changes, and reacted faster during real driving scenarios.

Results:

- **18% of sessions** flagged sub-optimal readiness.
- Of those, **60% improved within 15–20 minutes** with a short break and breathing techniques.
- The instructors found the system to be a **valuable support tool** in assessing invisible stress or fatigue.



Conclusion:

This study proves the value of **mental state detection in high-risk training environments**. By incorporating **XLTMS scans into the daily routine**, the training institute enhanced both **learning outcomes** and **road safety--**while building emotional awareness among trainees.

3. Cognitive Enhancement in Students and Meditation Trainees

Background:

The XLTMS system was tested at a learning and mindfulness center that caters to both high school students preparing for competitive exams and adults attending structured meditation workshops. The goal was to observe how mental states changed before and after focused activities such as studying or meditation.

Setup:

- Participants:
  - 30 participants (ages 15-18) focused on board and entrance exam preparations.
  - 25 adults in a mindfulness-based stress reduction (MBSR) course.
- Devices:
  - Every participant used an EEG headband synced to the XLTMS app.
  - Readings were taken **before and after study sessions** or **meditation practices**.
- Metrics Observed:
  - Brainwave activity in **alpha, theta, and gamma bands**.
  - App-generated scores for **focus**, **relaxation**, and **cognitive load**.

Observations:

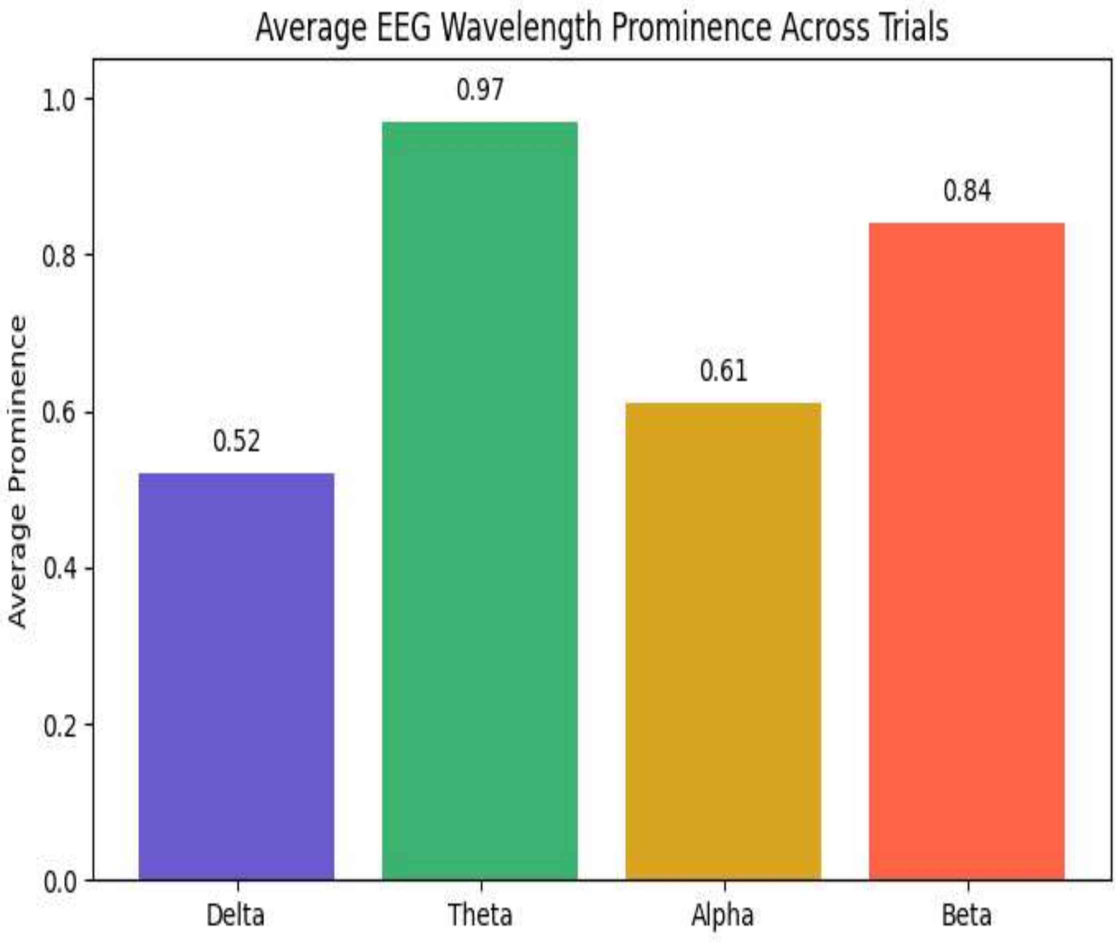
- **Students** showed:
  - Low **alpha** and elevated **theta** before study (indicative of distraction or fatigue).
  - A 27% increase in **gamma** and 18% rise in **beta/alpha ratio** after 25 minutes of study.
  - Students who practiced 5–10 minutes of breathing meditation before studying had **higher baseline alpha** and **faster gamma engagement**.
- **Meditation group** showed:
  - A rapid transition from predominant high beta (stress) to dominant alpha-theta (calmness) within the first 10–12 minutes of the guided session.
  - Increased heart rate variability (HRV) and better self-reported mood after the session.

Visual Outputs:

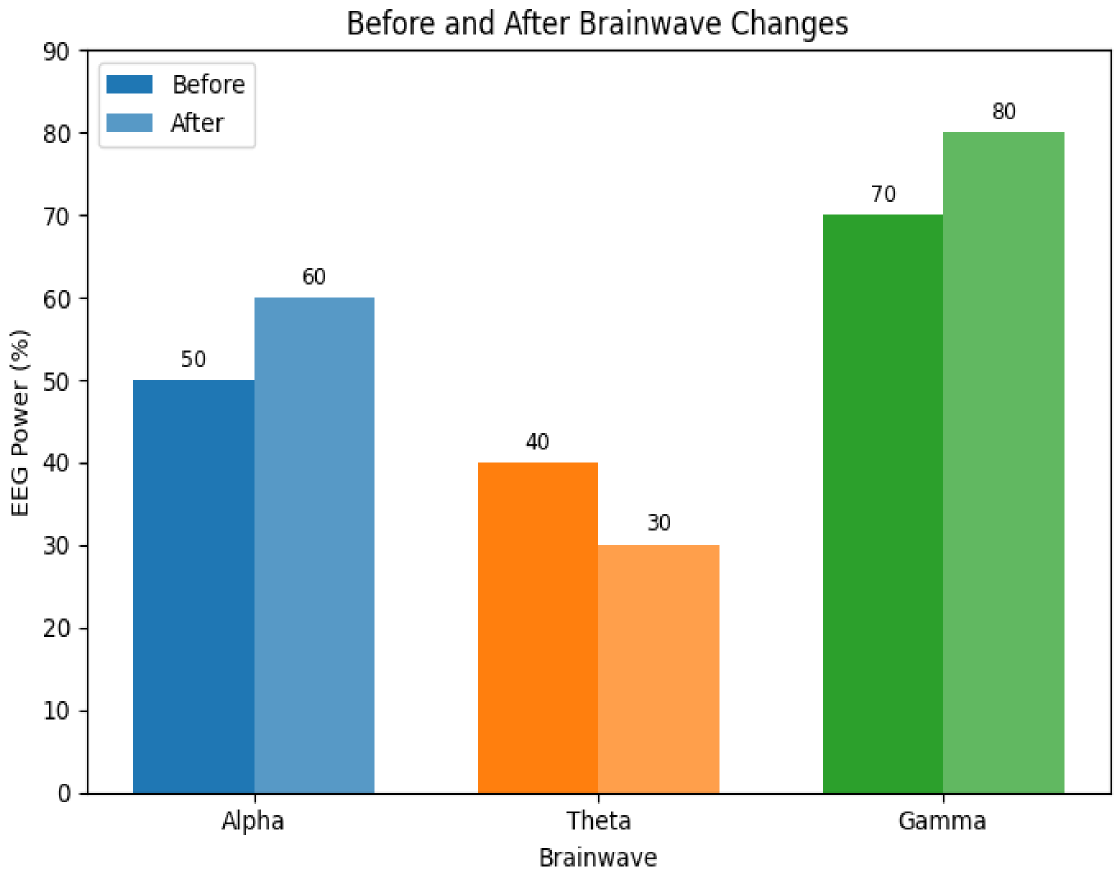
- The app dashboard showed a significant brainwave shift before and after.
- When participants had the opportunity to “see” the physiological changes brought about by their practice, they reported an increase in awareness, motivation, and confidence.

Impact:

- Students started to integrate EEG-based feedback to streamline their daily micro-meditation practices.
- The system helped instructors individualize learning breaks and monitor engagement.
- The data helped meditation coaches quantify the quality of their sessions and supported the mindfulness coaching that is informed by biofeedback.



The



increase in alpha activity from 50 to 60 reflects a change to a state that is calmer and more attentive. The decrease in theta levels from 40 to 30 is often correlated with less sleepiness and mental tiredness. Gamma activity also increased from 70 to 80, which shows the mental activity and thinking were more pronounced. These findings suggest increased mental clarity, focus, and alertness after the session.

Meditation + EEG Feedback Loop System

Below is the **diagram** showing how meditation training is enhanced using EEG feedback to help individuals monitor and improve their mental state in real-time:

□ **Meditation Practice**
□
□ **EEG Headband** collects brainwave data during and after session
□
□ **Signal Processor** extracts Alpha, Theta, Beta levels
□
□ **LSTM & Trend Models** analyze shifts in calmness and stress
□
□ **Mobile App** displays feedback and graphs (before vs after meditation)
□
□ **User Adjusts Meditation Technique**

 Repeat & Track Progress over Sessions

Use Case:

Students who practiced short meditation sessions before studying often showed a clear shift in their brain activity. Alpha and theta waves became more dominant, and that change didn't stay on the screen -- it showed up in real life.

- Learning felt easier. Retention improved.
- Exam anxiety dropped.
- Sleep and focus, for many of them, got better too.

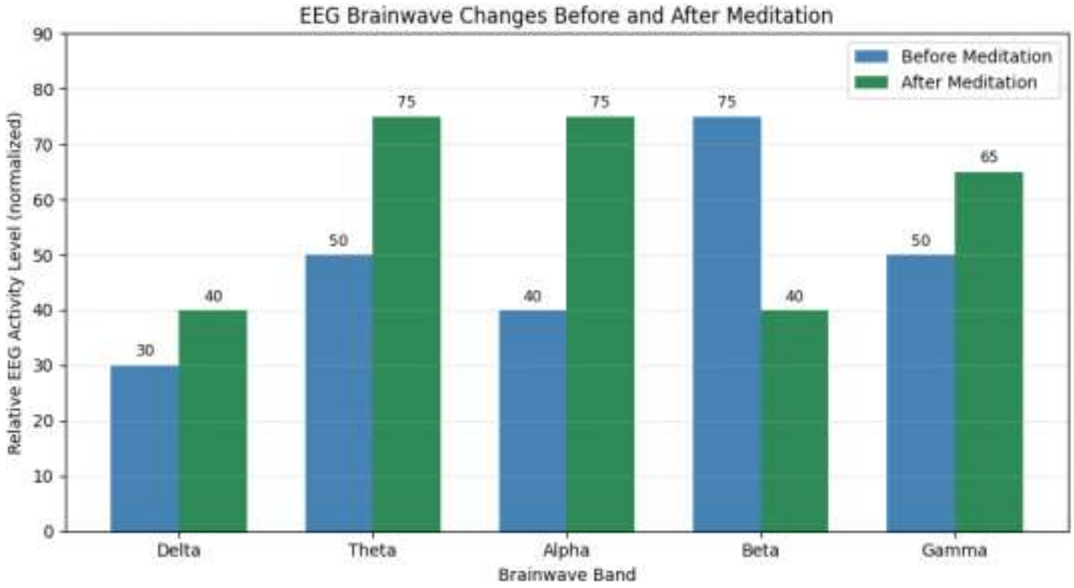
This feedback loop model can also be used in **mindfulness training centers**, **student well-being programs**, or **mental health apps**.

What's interesting is how this turned into a feedback loop. When students could see these changes, they were more willing to continue the practice. A few minutes of meditation led to better focus, which led to better results, which made the habit stick.

The same idea doesn't stop with students. This kind of feedback-driven model fits naturally into mindfulness training centers, student well-being initiatives, and even mental health apps, anywhere people are trying to understand their own mental state and make small, sustainable changes.

Brainwave States Before and After Meditation

Brainwave	Range (Hz)	Mental State	Before Meditation	After Meditation
Delta	0.5–4 Hz	Deep sleep	Low	Slight Increase (calmness)
Theta	4–8 Hz	Creativity, meditative	Moderate	**High** (deep calm, introspection)
Alpha	8–13 Hz	Relaxed alertness	Low–Moderate	**High** (relaxed focus)
Beta	13–30 Hz	Active thinking, stress if high	**High** (stress, distraction)	**Lower** (calmer focus)
Gamma	30–100 Hz	High cognition, memory	Moderate	Moderate–High (enhanced focus)



Conclusion:

While working with XLTMS, it became clear that mental state is neither abstract nor distant; it appears in measurable and repeatable patterns.

Stress, fatigue, and focus leave fingerprints in EEG and physiological signals, and when those patterns are made visible in real time, people respond. Students adjust how they study. Meditation trainees notice when calm actually arrives, not just when they think it should. XLTMS does more than flag conditions; it helps people recognize what is happening inside them and change behavior in practical ways.

In aviation and other safety-critical settings, that awareness matters even more. Pilots are trained to manage complex systems, but cognitive strain, fatigue, or emotional load can quietly build up before anyone notices. XLTMS adds an extra checkpoint before high-risk activity-one that looks at readiness, not skill or intent.

When the system detects stress or lowered alertness, it does not blame or penalize. It suggests that continuing to fly won't be the best option, and that a pause, rest, or more thinking could be a safer way to go. Failing to address problems the right way, and in good time could make them worse.

XLTMS is not meant to replace judgment, medical checks, or the safety procedures already in place. It sits beside them, adding another point of view--one that's open, defensible, and driven by data.

There will always be uncertainty in measuring the human mind, and that is acknowledged in the design. Still, by taking mental fitness seriously and treating it as part of operational readiness, XLTMS points toward a safety culture that protects both operators and passengers. Less stress. Fewer fatigue-driven risks. And, ideally, safer journeys for everyone involved.

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