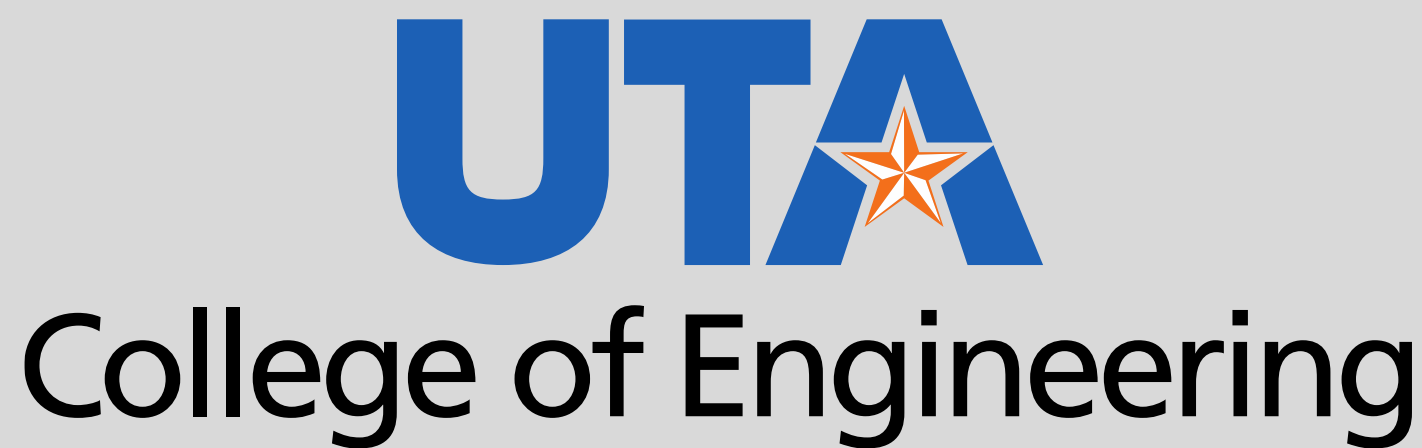


Machine Learning on EEG for Cognitive Monitoring in AR/MR Experiences



IMSE REU

Thomas Diaz, Prithvi Nair, Shabharish Iyer
Dr. Aera LeBoulluec



Executive Summary

Advances in Augmented Reality (AR) and Mixed Reality (MR) offer new insight into user cognition, yet real-time assessment of cognitive states remains challenging. This study integrates electroencephalography (EEG) with machine learning to monitor and decode cognitive processes during AR/MR tasks. EEG data from engineering students at the **University of Texas at Arlington** engaged in immersive activities are analyzed to identify neural patterns linked to attention, workload, and engagement, enabling classification of cognitive states and prediction of performance. The findings provide real-time insight into students’ cognitive states during high-stress situations, such as final exams, and advance EEG-based cognitive monitoring for intelligent, user-aware AR/MR systems.

Background

Growing mental-health and academic pressures in higher education highlight the need for early-detection systems that identify students at risk. Self-report surveys capture socioeconomic and lifestyle factors but are limited by bias and underreporting, especially for stressors like financial strain, heavy workloads, trauma, poor sleep, and stimulant use. EEG offers an objective complement by measuring neural activity linked to stress, attention, and cognitive load. Deep-learning models using EEG spectral features can classify stress with accuracies near 90% (Hafeez & Shakil, 2024), and EEG-based stress markers correlate with lower academic performance (González Díez et al., 2026). EEG also shows strong sensitivity for detecting anxiety and depression when paired with behavioral data (Zhao et al., 2025). Combining EEG with self-report instruments creates a dual-channel screening framework that captures both real-time neurophysiology and longer-term contextual risks. This multimodal approach reduces false negatives, improves early-intervention precision, and supports timely academic accommodations and mental-health services. Overall, EEG-enhanced screening offers a promising, ethical strategy for identifying vulnerable students earlier and strengthening institutional support systems.

Experimental Setup

Data Source:

- Data were collected from 41 engineering students at UTA using a survey and an EEG-based cognitive test.
- Each record includes 30 predictors describing personal background, lifestyle habits, and self-reported stress.
- The dependent variable is EEG performance accuracy, enabling analysis of how individual factors relate to cognitive outcomes.

Data Pre-processing:

- Encoding: 19 predictors with text values required encoding to convert to numerical values.
- Scaling: Scaling was applied to ensure that the model is not affected by a broad range of feature values.
- Multicollinearity Check: Large sets of predictors often exhibit high correlation, necessitating a multicollinearity assessment.



Figure 1. Participant with EEG Headset

Experimental Test Plan

Modeling Approach

Given the continuous nature of the dependent variable, we selected three regression techniques: Multiple Linear Regression with Stepwise Selection, Random Forest Regression, and k-Nearest Neighbors (kNN).

Stepwise Selection:

- Optimize parsimony and prevent overfitting.
- Handle multicollinearity to reduce model noise.
- Automate feature selection, identifying the most significant predictors.

Random Forest Regression:

- Exceptional Robustness to Overfitting
- Handles Non-Linearity and High Dimensionality
- Built-in Feature Importance

kNN Regression:

- Simple and Intuitive Implementation
- Highly Adaptive to Complex Patterns
- No Assumptions About Data Distribution

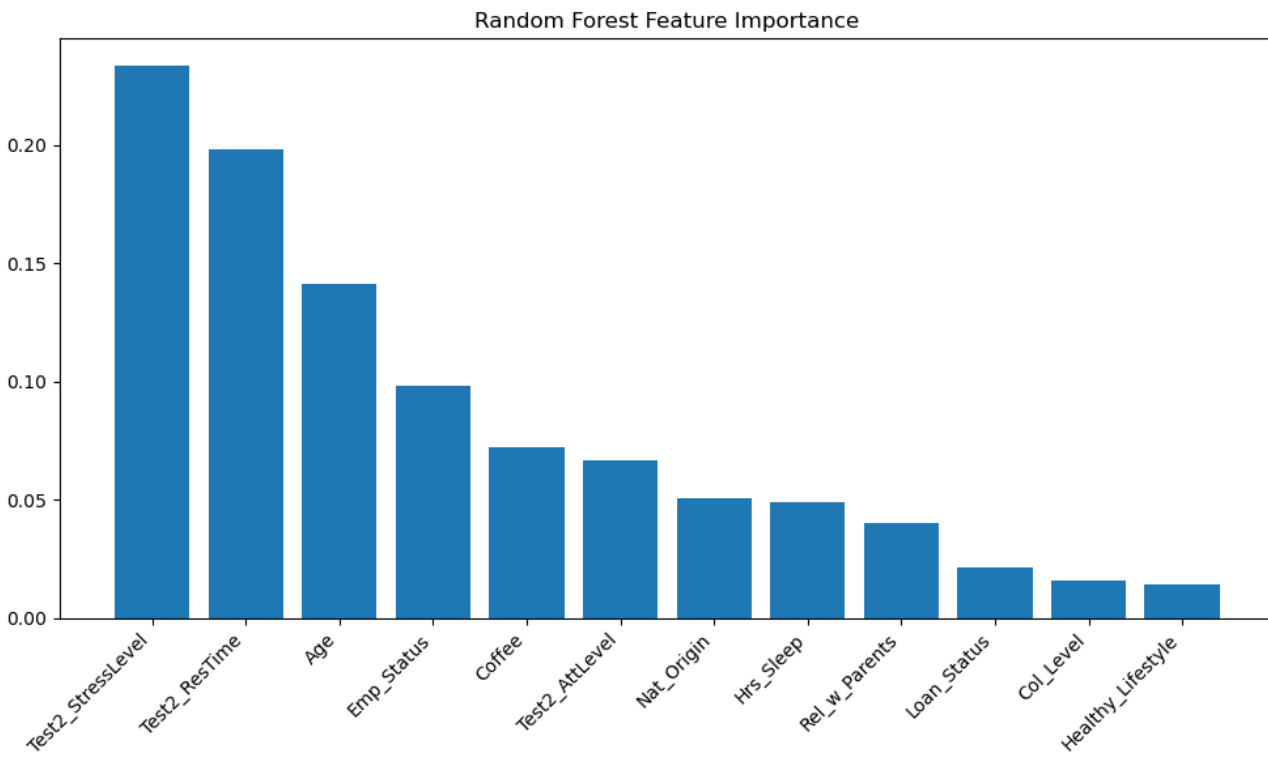


Figure 2. Random Forest Feature Importance

Experimental Results

Final Model:

$$Test2_{Accuracy} = 8.05 - 7.28 * (Test2_{StressLevel}) + 11.23 * (Employee_Status) + 6.36 * (Loan_Status) + 5.21 * (Hours_Sleep) + 14.76 * (College_Level) + 9.08 * (Relationship\ with\ Parents) - 5.80 * (Coffee) - 0.11 * (Test2_{ResponseTime}) + 7.22 * (National_Origin) + 5.72 * (Healthy_Lifestyle) + 2.62 * Test2_{AttentionLevel}$$

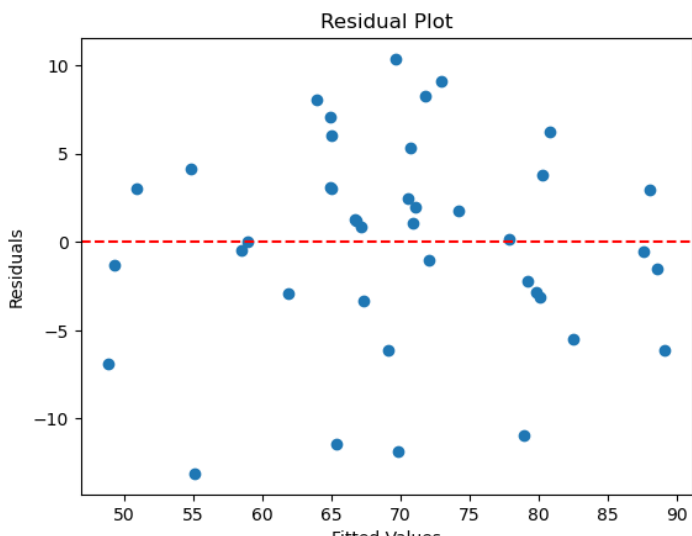


Figure 3. Residual Plot

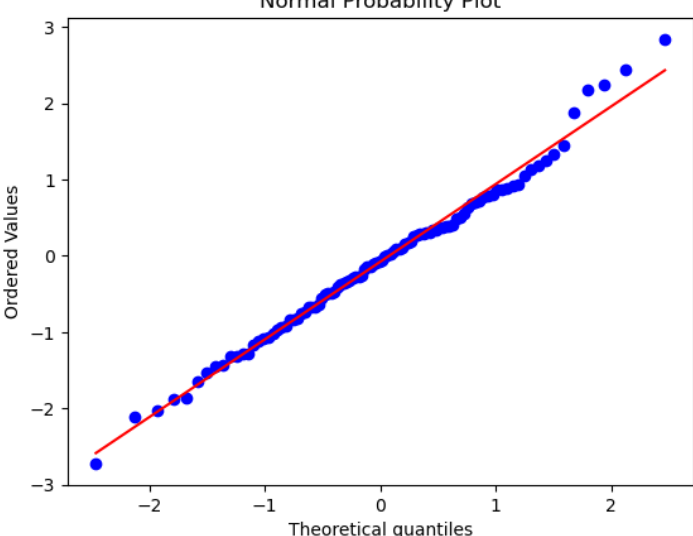


Figure 4. Normal Probability Plot

	Stepwise Regression	KNN (K=3)	Random Forest
R-squared	0.854	0.748	0.750
MSE	4.321	6.122	6.103
MAE	4.891	11.690	8.231

Table 1. Comparison of Three Models

Conclusions

Conclusion

- As illustrated in Plot 3, the requirements for homoscedasticity and linearity are satisfied, with no significant outliers observed. Furthermore, Plot 4 confirms the normality of residuals, validating the stepwise selection approach as an effective modeling strategy.
- Result in Table 1 indicate that the Stepwise regression outperformed KNN and Random Forest, yielding the highest accuracy. This superior performance is attributed to the continuous nature of the dependent variable, for which linear regression techniques are inherently optimized.

Highlights and Further Research

- This study contributes to engineering education, cognitive modeling, and stress research by highlighting how non-academic factors influence students’ cognitive performance.
- The results can inform student-support initiatives and help educators and program designers develop interventions that enhance students’ cognitive readiness and overall academic success.

References

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