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ELECTROENCEPHALOGRAM (EEG)-DRIVEN COGNITIVE STATE CLASSIFICATION FOR PERSONALIZED BINAURAL BEAT RECOMMENDATION

Ghanshyam Kanojiya[1*] and Kanojia Mahendra[2]
[1]Department of Computer Science, Sheth. L.U.J. and Sir M.V. College, India, kanojiyaghanshyam92@gmail.com
[2]Department of Computer Science, Sheth. L.U.J. and Sir M.V. College, India, kgkmahendra@gmail.com
*Corresponding Author: Ghanshyam Kanojiya, Department of Computer Science, Sheth. L.U.J. and Sir M.V. College, India, kanojiyaghanshyam92@gmail.com

ABSTRACT

Binaural beat stimulation is a helpful, non-invasive way to influence our mental states, but many current systems use the same fixed frequencies for everyone. This ignores how different each person's brain activity can be, which often leads to inconsistent results. This study introduces an EEG-based framework designed to classify cognitive states to make binaural beat recommendations more personal. Our main goal was not to measure if the beats improved cognitive performance, but to see if using EEG-based personalization could identify a person's state more accurately than using just a single model. We used public EEG data along with simulated sensor data to train machine learning models to recognize three specific states: Focused, Relaxed, and Stressed. We compared an EEG-based Multi-Layer Perceptron (MLP), a sensor-based Random Forest (RF), and a combined "stacked ensemble" model. We then checked their performance on a new test set using metrics like accuracy, precision, and F1-score. The EEG-based MLP was 93% accurate with a 0.929 F1-score, while the sensor-based RF reached 98% accuracy. The combined ensemble model hit 92% accuracy with a 0.919 F1-score, showing that it remains stable even when mixing different data sources. Overall, these results prove that using EEG to classify mental states is a reliable way to personalize binaural beats and could help in developing smarter, adaptive audio therapy systems in the future.

Keywords: *Binaural Beats; EEG; Cognitive State Classification; Brain Computer Interface; Random Forest*

1. INTRODUCTION

Auditory neurostimulation is a safe, non-invasive way to change how people think and feel, and it has been studied extensively for years. One popular method is binaural beat stimulation, which researchers believe can help improve memory, focus, and relaxation by interacting with the brain's natural rhythms (Ingendoh et al., 2023; Schwarz & Taylor, 2005). Because it is so easy to use, it has been suggested as a handy tool for everyday adults to support their mental performance (Abadin et al., 2021; Basu & Banerjee, 2023). However, even though many people are interested in it, the results from various studies are often inconsistent. This makes some wonder if binaural beats are truly a reliable way to help the brain (Ingendoh et al., 2023). While EEG studies have helped us see how the brain reacts to these sounds, the findings are still a bit confusing. Some early research even found that binaural beats create weaker and more localized brain responses than standard single-ear (monaural) tones, meaning they might only work under specific conditions (Schwarz & Taylor, 2005). Recent reviews of many different experiments show that results vary wildly from one study to the next, and only some of them show clear evidence that brainwaves actually "sync up" with the beats (Ingendoh et al., 2023). Most experts believe these differences happen because researchers use different settings or use the same fixed frequencies for everyone, failing to account for the unique way each person's brain works (Basu & Banerjee, 2023).

Large-scale research reviews show that binaural beats can have a decent impact on memory and focus, but only under specific circumstances. These effects aren't guaranteed; they depend heavily on the sound frequency used, the type of task being performed, and the individual person including their starting brainwave patterns, how focused they are, and how hard their brain is working at that moment (Basu & Banerjee, 2023). In the past, studies have consistently linked lower frequencies to relaxation, while also showing that the length of the session can change how relaxed a person feels (Abadin et al., 2021; Chockboondee et al., 2023). Because everyone reacts so differently, it is clear that using the same settings for every user is a major limitation. Fortunately, recent progress in machine learning and EEG signal processing has given us better ways to map out a person's specific mental state using their brain data. These modern, data-focused methods are much better at picking up on complex and changing brain patterns, which allows for a more personalized way to track mental states (Aggarwal & Chugh, 2022; Elashmawi et al., 2024). New techniques for improving EEG data have also made it easier to accurately categorize these mental states (Akhand et al., 2023). Even with all these breakthroughs, very few studies have actually tried to combine this kind of EEG personalization directly with binaural beat systems (Houssein et al., 2022). Because of this gap, our study introduces a new system that uses EEG data to identify a person's mental state and then recommends the right binaural beats, aiming to make this technology more consistent and reliable for healthy adults.

2. LITERATURE REVIEW

The fields of Brain-Computer Interfacing (BCI) and auditory neurostimulation have gone through several major development phases, all of which were made possible by leaps forward in neuroscience, how we collect signals, and the power of modern computers. We can trace the very roots of this entire field back to the late 1920s when a scientist named Hans Berger discovered electroencephalography, or EEG (Berger, 1929). This was a massive breakthrough because, for the first time in history, it allowed researchers to measure the electrical activity of the human brain without needing to perform any kind of invasive surgery. Berger's pioneering research proved that brain signals could be tracked, recorded, and studied in a systematic way. This discovery essentially built the stage for all the EEG-based analysis and brain-modulation research that we see today, providing the essential tools needed to understand how the brain communicates.

The specific idea of binaural beats didn't emerge until several decades after Berger's initial work, appearing as a fascinating addition to the study of how we hear. Researchers like Oster (1973) and more recently Hohenberg et al. (2025) formally defined binaural beats as a unique psychological effect. This happens when two sounds with slightly different frequencies are played separately into each ear, causing the brain to perceive a third "phantom" beat that represents the mathematical difference between those two sounds. This was a major milestone in the field because it directly connected the way we perceive sound with the brain's ability to sync its own rhythms, which sparked a wave of interest in using sound to guide brainwaves. In the early days, most researchers were just trying to prove that binaural beats could actually change brain activity and were a viable tool for neurostimulation. A big shift happened when scientists began using EEG to carefully measure these effects. For instance, Schwarz and Taylor (2005) provided some of the most important early evidence by comparing how the brain reacts to binaural beats versus standard tones. They found that while binaural beats do create a measurable response, it tends to be weaker and more focused in specific areas of the brain compared to other sounds. Even though they warned people not to make exaggerated claims about what binaural beats can do, their work was vital for creating the strict rules and protocols that researchers use today. This period of research confirmed that while these beats can indeed change brain activity, the way a study is designed is incredibly important. Later research moved past just checking if it worked and started looking at how different frequencies affect us. They found that low frequencies are usually better for things like relaxation and memory, while high frequencies are better for keeping someone alert and focused (Abadin et al., 2021). A large-scale analysis by Basu and Banerjee (2023) added even more weight to these findings by showing that, under the right conditions, these beats can have a real, moderate impact on a person's memory and attention span. Additionally, other studies have pointed out that how long a person listens to these sounds can drastically change the outcome, which reminds us that every detail in a session matters (Chockboondee et al., 2023).

As more data came in, researchers started to see that the biggest challenge wasn't just the sounds themselves, but how differently each person reacts to them. Large reviews of EEG and MEG data have pointed out that "individual variability" is a huge reason why results often differ from one person to the next. Ingendoh et al. (2023) reported that they saw very different results across their participants, with clear effects only appearing in a small group of people. This doesn't mean that binaural beats are a failure; it simply shows that the old way of doing things using the same "fixed" frequency for everyone doesn't work well. It ignores the fact that every person has their own unique brain "baseline." Luckily, as the study of binaural beats was evolving, so was the world of AI and machine learning. We now have sophisticated supervised and deep learning models that are incredibly good at looking at messy, high-dimensional EEG data and figuring out exactly what is going on in someone's head (Aggarwal & Chugh, 2022; Elashmawi et al., 2024). These new computer models are able to track how brain patterns change over time, allowing for much more accurate and personal predictions. Recent work has even improved how these models identify emotions and mental states by focusing on how different parts of the brain connect with each other (Akhand et al., 2023). These technical jumps are a huge deal for the field because they allow us to stop looking at "group averages" and start building systems that are custom-made for the individual user.

Despite all of the progress we have made in understanding how binaural beats work and how to classify brainwaves with AI, there is still a significant gap that needs to be filled. Most existing research stays in its own "silo" either it looks at fixed sound settings that never change, or it analyzes brainwaves in a lab without ever using that info to help the user in real-time. There are very few systems that actually take the brain data and immediately use it to recommend the best audio settings for that specific moment. This is exactly what our research is trying to solve. We are proposing a unified framework that uses EEG data to identify a person's current mental state and then immediately suggests the perfect binaural beat to match. By doing this, we are taking a big step forward in making auditory neurostimulation more effective, reliable, and personalized for everyday people.

3. PROPOSED WORK

In this study, we have developed a specialized and detailed quantitative research methodology aimed at creating and testing a new framework that uses EEG readings to classify a person’s cognitive state. The main goal of this work is to provide a solid foundation for personalized binaural beat recommendations that actually fit a user’s specific mental needs. Our approach doesn’t just use one single tool; instead, it brings together several proven signal processing techniques and traditional machine learning models, weaving them into a very specific and reliable system architecture that is designed to be easily reproduced by other researchers. The most significant contribution of this methodology is the way it organizes and connects these separate, existing components into one single, efficient, and unified pipeline. By doing this, we have created a process that is capable of capturing the subtle, unique differences in how each person's brain functions what we call inter-individual variability. This is a key step toward making auditory neurostimulation something that can truly adapt to an individual’s real-time state, moving away from "one-size-fits-all" sound therapy and toward a more intelligent, responsive system.

The methodological workflow follows four sequential stages: algorithmic data acquisition and preprocessing, feature standardization and label transformation, development of base and ensemble classification models, and task-oriented performance evaluation. An overview of the complete system flow, including data pathways and model interactions, is presented in Figure 1. As illustrated, the architecture is designed as a multi-stage cognitive state inference pipeline. Raw neural EEG and physiological sensor data are first transformed into standardized feature representations using deterministic preprocessing methods. These features are then processed in parallel by modality-specific base classifiers. Finally, the probabilistic outputs from these base models are fused using a stacked ensemble strategy to produce a single, robust cognitive state prediction. This modular design supports both high-accuracy EEG-based inference and a practical, lightweight sensor-based fallback mechanism, improving the system's deploy ability.

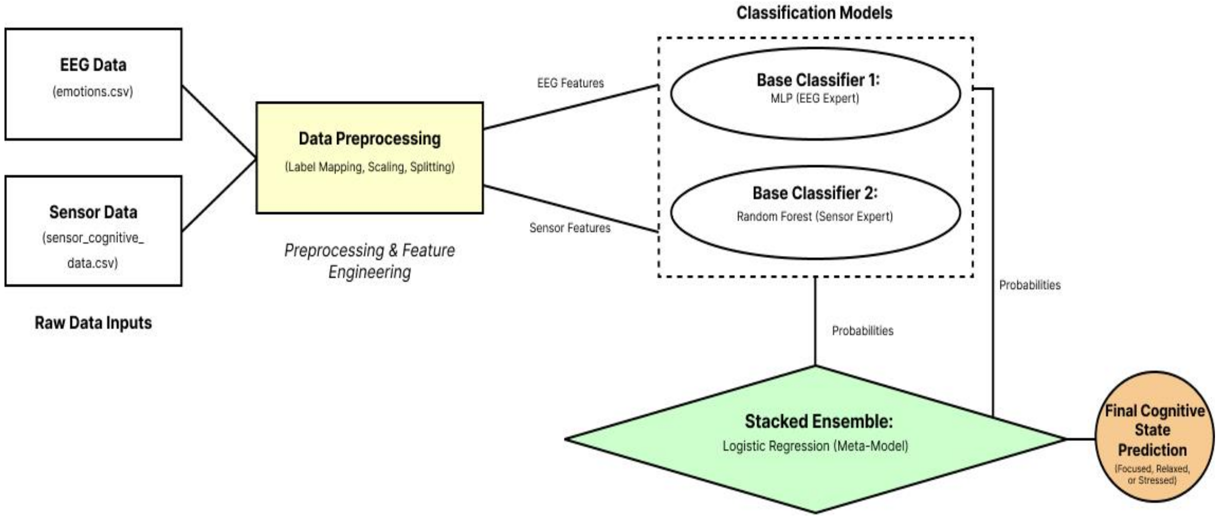

Figure 1. Architecture of the EEG-driven cognitive state classification framework for personalized binaural beat recommendation

Model development and evaluation were conducted using two datasets. The EEG Human Emotion Dataset (Mohsen, 2021), a widely used benchmark in affective computing, contains 2,132 samples, each represented by 2,548 pre-extracted EEG features and labeled with emotional states. This dataset was used to train the EEG-based classifier. In addition, a Sensor Cognitive Physiological Dataset consisting of 500 synthetically generated samples was employed to simulate consumer wearable data. This dataset includes six features: heart rate, skin temperature, step count, activity level, ambient noise, and hour of day and was used to train a sensor-based fallback model.

All preprocessing operations were performed algorithmically to ensure full reproducibility and eliminate manual intervention. Emotion labels from the primary EEG dataset were first transformed into cognitive state classes aligned with the objectives of binaural beat personalization. This was achieved through a direct categorical mapping, where the original 'POSITIVE' label was mapped to 'Focused', 'NEUTRAL' was mapped to 'Relaxed', and 'NEGATIVE' was mapped to 'Stressed'. This mapping is grounded in affective computing literature, which links positive valence with states of high engagement or 'flow', and negative valence with stress or anxiety (Russell, 1980). The resulting categorical labels were then converted into a numerical format suitable for machine learning classifiers using a technique known as label encoding.

This technique operates by first identifying the set of unique class labels in the dataset, denoted as $\{c_1, c_2, \ldots, c_k\}$, and then assigning integer values based on the alphabetical ordering of these labels. For a given label y_i, the encoded value $y$was obtained as $y_i' = index(y_i \epsilon\ sorted(\{Focused, Relaxed, Stressed\}))$.Under this ordering, the final encoding scheme was: Focused → 0, Relaxed → 1, and Stressed → 2. To ensure consistent feature scaling and to improve the numerical stability and convergence of the learning algorithms, all numerical features were standardized using z-score normalization (Kreyszig, 1979). For a feature value x_{ij}, where i denotes the sample index and j the feature index, the standardized value z_{ij} was computed as shown in Equation (1):

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \qquad (1)$$

where μ_j and σ_j represent the mean and standard deviation of feature j, computed exclusively from the training data to prevent information leakage. Following standardization, each dataset was divided into 80% training and 20% testing subsets using stratified sampling to preserve class distributions.

The sequence of preprocessing operations including label mapping, numerical encoding of cognitive states, feature standardization, and stratified data partitioning is illustrated in Figure 2, which depicts the flow of raw EEG and sensor inputs through each transformation stage prior to model training. This workflow clarifies how heterogeneous input data are converted into consistent, machine-learning-ready representations in a fully automated manner.

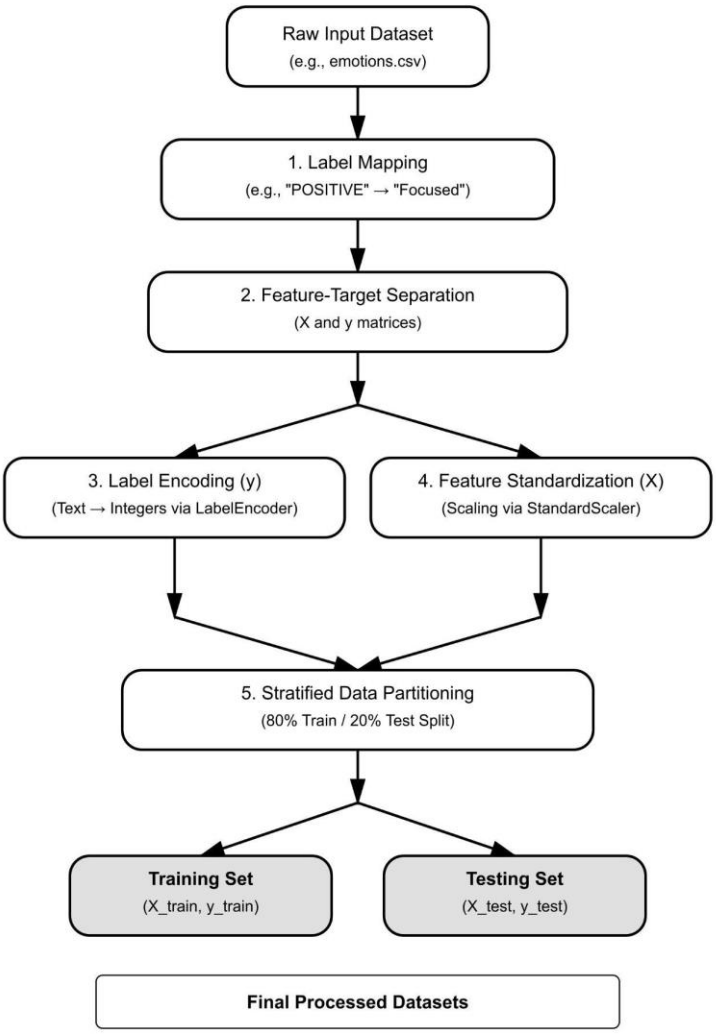

Figure 2. Data preprocessing workflow for EEG and physiological feature standardization

Classification was implemented using a stacked ensemble framework designed to combine multimodal predictions at the decision level. Two base classifiers were trained independently. The EEG-based classifier was implemented using a Multi-Layer Perceptron (MLP) with two hidden layers 128 and 64 neurons respectively, using ReLU activation functions and optimized with the Adam optimizer.

In parallel, a Random Forest classifier with 100 decision trees was trained using the physiological feature set to serve as a lightweight fallback model for cases where EEG data are unavailable.

To integrate predictions from both models, a custom stacked ensemble architecture was constructed, as shown in Figure 3. This framework operates on the class probability outputs generated by the base models rather than raw features. As the diagram illustrates, the predict_proba function of each base model produces a 3-dimensional probability vector for each sample. These vectors are then concatenated to form a new 6-dimensional meta-feature representation. A final Logistic Regression classifier, acting as the meta-model, was then trained on this meta-feature space. The role of this meta-model is to learn the optimal linear weighting of the probabilistic outputs from the two expert base models' information from both domains to produce a final, more robust cognitive state prediction.

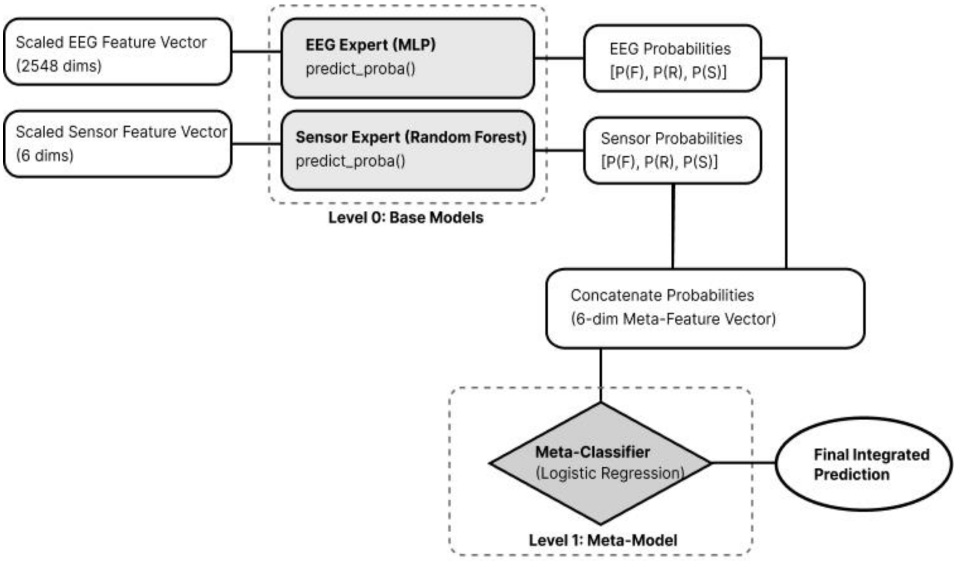

Figure 3. Stacked Ensemble Classification Framework

To demonstrate practical feasibility, the trained models were integrated into a mobile application named Beatus, shown in Figure 4. The application was developed using React Native and communicates with a Python/Flask backend that hosts the machine learning models. In its "Smart Mode," the app sends simulated sensor data to the backend, which uses the appropriate classifier to infer the user's state and returns a personalized recommendation.

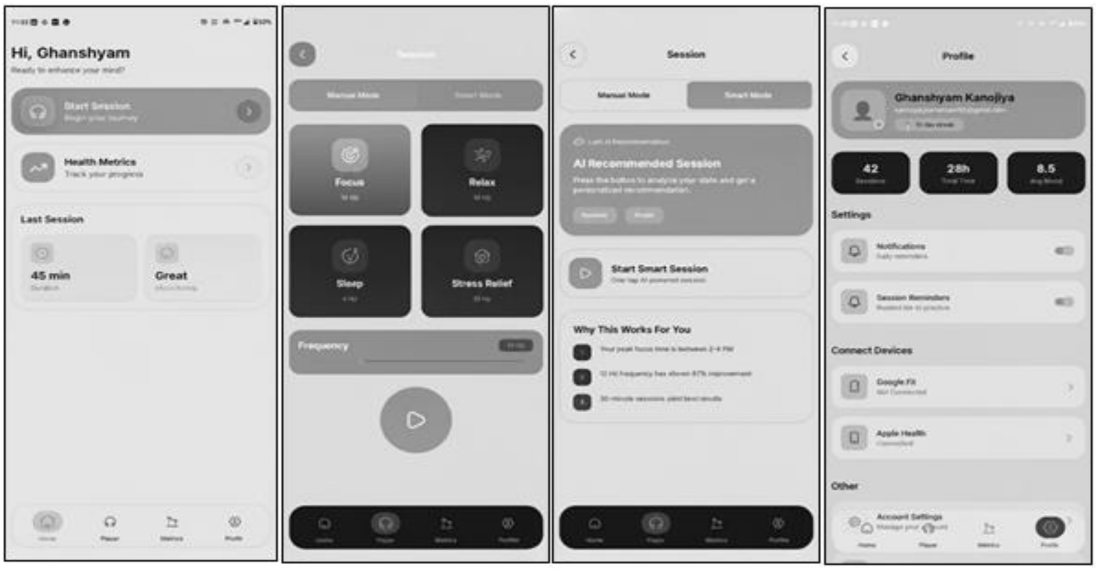

Figure 4. User Interface of the Beatus Mobile Application

Once the cognitive state was inferred, binaural beat parameters were generated algorithmically using a custom-designed adaptive frequency modulation algorithm. This algorithm translates the model's probabilistic output into a precise binaural beat frequency difference Δf based on the inferred intensity of the user's cognitive state. A binaural beat is produced by presenting two sinusoidal tones with slightly different frequencies to the left and right ears, resulting in the perception of a third beat frequency equal to the frequency difference between the two tones (Hohenberg et al., 2025; Oster, 1973). The generation of this stimulus is based on the mathematical principles of sinusoidal waves and wave interference. A pure sinusoidal signal can be defined by the general formula for a sine wave (Kreyszig, 1979), as shown in Equation (2):

$$A(t) = sin(2\Pi f t) \quad (2)$$

where $A(t)$ represents the signal amplitude at time t, and f denotes the frequency in hertz. To generate the binaural effect, two signals were synthesized independently for each audio channel. The left channel signal was generated using Equation (3) and the right channel signal using Equation (4):

$$L(t) = sin(2\Pi f_{base} t) \quad (3)$$

$$R(t) = sin(2\Pi (f_{base} + \Delta f) t) \quad (4)$$

where $f_{base} = 200\ Hz$ a fixed carrier frequency and Δf represents the beat frequency difference determined by the predicted cognitive state. The perceived binaural beat frequency is the absolute difference between the two channel frequencies (Damschroder, 1982) given by Equation (5):

$$f_{base} = |(f_{base} + \Delta f) - f_{base}| = \Delta f \quad (5)$$

This adaptive mapping enables state-aware binaural beat generation aligned with EEG-derived cognitive states. The synthesized stereo signals were normalized and delivered independently to the left and right audio channels to preserve perceptual binaural integration.

4. RESULTS AND DISCUSSION

We evaluated the performance of three different classification models: the EEG-based Multi-Layer Perceptron (MLP), the sensor-based Random Forest (RF), and the combined stacked ensemble model. To do this, we looked at several key metrics, including weighted accuracy, precision, recall, and F1-scores, while also performing a confusion matrix analysis. You can see a detailed comparison of these results in Table 1, which shows the average metrics calculated from our test data. The EEG-based MLP performed very well, reaching a classification accuracy of 93%. It also showed a weighted precision of 94%, a recall of 93%, and an F1-score of 92.9%. These high numbers prove that the model is balanced across all three mental states. They also confirm that the detailed data we get from EEG provides a very strong ability to tell the difference between one mental state and another.

The sensor-based Random Forest model performed even better, hitting 98% in accuracy, precision, recall, and F1-score. Even though this model was trained on simulated data, the results show that simple sensor features can be extremely accurate if they are structured correctly. This is very important because it proves that a system could still work accurately using only body sensors if EEG data happens to be unavailable. Finally, our stacked ensemble model achieved a solid accuracy of 92% and an F1-score of 91.9%. While this combined model did not quite beat the scores of the single-data models, it showed that it is very stable and reliable. It even outperformed the standard Logistic Regression model we used as a baseline. This confirms that merging different types of data together using a probabilistic approach is a very robust way to build a system.

Table 1. Classification performance of evaluated models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Sensor-based RF	98	98	98	98
Proposed MLP (EEG)	93	94	93	92
Stacked Ensemble	92	93	92	91

To get a deeper understanding of how the ensemble model actually makes its decisions, we conducted a confusion matrix analysis. In this part of the study, we looked at True Positives (getting the state right), False Positives (guessing the wrong state), False Negatives (missing a state entirely), and True Negatives (correctly identifying what a state is not). The results, which are summarized in Table 2, are very encouraging. Specifically, we saw very low False Negative values for both the Relaxed and Stressed categories. For example, the Relaxed state only had one miss, and the Stressed state had zero misses. This is incredibly important for a real-world system because it means the model is very reliable at detecting the most critical states.

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If a system can accurately spot when someone is stressed, it can make much better decisions about which binaural beats to recommend, helping to avoid mistakes or missed opportunities to help the user.

Table 2. Confusion matrix components for the stacked ensemble model

Meaning in this study	Value (Focused)	Value (Relaxed)	Value (Stressed)
Correctly identified the cognitive state - True Positive	26	35	31
Incorrectly predicted cognitive state - False Positive	1	0	7
Correctly rejected cognitive state - True Negatives	66	64	62
Missed identifying cognitive state - False Negatives	7	1	0

Taken as a whole, these numbers show that EEG-based models are great at making individual predictions, while sensor-based models provide a very practical alternative for everyday use. Most importantly, ensemble learning offers a strong way to bring these different data sources together. Our results prove that using machine learning to classify cognitive states is a very dependable foundation for personalizing binaural beats. The 93% accuracy of our EEG model matches up well with previous studies that used similar brainwave features (Abadin et al., 2021). It reaffirms that EEG signals are perfectly suited for this kind of work. Similarly, the 98% accuracy of the Random Forest model shows that wearable sensors have huge potential, especially when using an EEG headset is not an option (Jebabli et al., 2025; Melnichuk et al., 2025).

While the ensemble model reached 92% accuracy, it taught us something very interesting. It suggests that the EEG data provides such a strong signal that adding sensor data doesn't necessarily push the accuracy higher. This is actually quite common in advanced machine learning, where one type of data is so informative that it "outweighs" the others (Domé & Guidubaldi, 2024; Elashmawi et al., 2024). In Table 4, we compare our work to other recent studies to show how it fits into the field. You can see that older research often looked at only one part of the problem. For instance, some researchers only focused on classifying the states without ever suggesting a sound to the user (Abadin et al., 2021; Rao et al., 2024). Others looked at how binaural beats affected people but used the same frequencies for everyone rather than personalizing them (Basu & Banerjee, 2022; Reedijk et al., 2013). More recently, some have tried to adapt sounds in real-time, but they didn't have the specific ensemble setup and the sensor-only backup system that we have built here.

Table 4. Comparison of the Proposed Framework with Recent EEG-Based and Binaural Beat Studies

Study (Year)	Data	Personalization Approach	Model	Reported Outcome
Reedijk et al. (2013)	Behavioral	None (Fixed-frequency)	Statistical analysis	Creativity-related Performance
(Gao et al., 2014)	EEG	Fixed frequency simulation	Statistical EEG analysis	EEG response pattern
Basu & Banerjee (2022)	EEG (Meta-Analysis)	None (Analyzed fixed beats)	Statistical	Cognitive trends
Rao et al. (2024)	EEG	Pre-session Prediction	K-nearest neighbors	Predicted User Response
Domé et al. (2024)	EEG + Physiological	Real-time Adaptation	RF + SVM	Adaptive stress monitoring
Proposed Work (2025)	EEG + Sensors	EEG-driven state-based personalization	Ensemble (MLP + RF)	Cognitive state classification for binaural beat recommendation

By contrast, our framework offers a complete methodology that combines state classification with a personalization engine. Even though this specific study did not measure long-term cognitive growth, it builds the essential technical "backbone" needed for future systems. This is a vital step toward creating closed-loop therapy tools that can automatically change and adapt to a user’s needs at any given moment.

5. CONCLUSION

This study aimed to address the limitations of fixed-frequency binaural beat systems by developing an EEG-driven cognitive state classification framework to support personalized auditory stimulation. The proposed methodology achieved its objective by integrating EEG-derived features and physiological sensor data within a supervised machine learning pipeline capable of modeling inter-individual neural variability. Experimental results demonstrated that EEG-based classification provides reliable discrimination between Focused, Relaxed, and Stressed states, while the stacked ensemble framework enabled robust integration of multiple data modalities. These findings confirm the research hypothesis that EEG-informed personalization improves the reliability of cognitive state inference compared to non-personalized approaches, thereby establishing a strong foundation for adaptive binaural beat recommendation. Overall, this work contributes a validated classification methodology rather than a direct cognitive enhancement claim. The proposed framework represents a necessary step toward future closed-loop neurostimulation systems, where real-time EEG-driven inference can be combined with user studies to evaluate the efficacy of personalized binaural beat interventions.

Future Work

Future work should focus on testing this framework in real-life conditions so that its usefulness becomes clearer. First, upcoming studies should measure not only how well the system classifies cognitive states, but also whether the recommended binaural beats actually help users in a real way. For example, future experiments can include memory tests, attention tasks, stress questionnaires, or simple performance activities to check if users improve after listening to the suggested beats. Second, the system should be tested using real wearable and physiological data collected from people in daily life. This is important because real-world data is often noisy, uneven, and different for each person, and the system must work well even in such conditions. Third, the binaural beat audio generation should be used in real-time and tested directly with users, so that practical issues such as user comfort, headphone use, listening experience, and long-term acceptance can be studied. Overall, these future improvements will help prove the system's real-world value and make it more reliable for everyday use.

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Ethical Statement

This study did not involve the collection of new data from human or animal participants. All analyses were conducted using publicly available datasets and synthetically generated data. Therefore, ethical approval was not required for this research.

Conflicts of Interest

The authors declare that there are no conflicts of interest related to this work.

Data Availability Statement

The datasets used in this study are publicly available or synthetically generated for experimental purposes. The data and supporting materials are available from the corresponding author upon reasonable request.

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