Bio-adaptive closed-loop system for detection of Cardiac Arrhythmias

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Research conducted under the supervision of Prof. Nicholas S. Peters, Imperial College London

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Abstract

We present an AI-based, real-time adaptive music therapy framework that dynamically generates and adjusts music based on physiological signals and EEG-derived emotional states. By analyzing Galvanic Skin Response (GSR), Heart Rate Variability (HRV), and EEG frequency bands (delta, theta, alpha, beta, gamma), our system fine-tunes musical properties such as tempo, brightness, and complexity using the MusicGen model. The system simulates human-like musical intuition and responsiveness through deep learning models trained on biosignal data. We demonstrate three progressively refined implementations of the therapy system, each improving accuracy, personalization, and adaptability. The framework holds potential in emotion regulation, stress relief, and adjunctive cardiac therapies.

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1. Introduction

Music, as a universal medium, has long been studied for its psychological and physiological effects. Listening to music can influence emotional state, heart rate, stress levels, and cognitive performance. Traditional music therapy, however, is mostly non-personalized and manually administered. In this research, we bridge that gap using real-time biometric feedback to generate therapeutic music that adapts moment-by-moment to a user's physiological and mental state.

This project integrates:

- **EEG** for real-time brain activity monitoring.
- **GSR** for sympathetic nervous system arousal.
- **HRV** for assessing parasympathetic tone.
- **AI-generated music** using Meta's MusicGen.
- **Deep learning** to predict EEG emotional valence and drive feedback loops.

2. Motivation

There is a growing global burden of **stress, anxiety, and emotional dysregulation**, exacerbated by modern lifestyle factors such as chronic workload, digital fatigue, and social isolation. These psychological stressors are not only mental health concerns but have significant **physiological consequences**, particularly in **cardiac patients**. Clinical studies have consistently shown that emotional states like fear, anger, and anxiety can **precipitate arrhythmic episodes**, elevate blood pressure, and disturb autonomic balance. This has led researchers to recognize the heart-brain axis as a critical domain for intervention.

Within this context, **non-invasive, real-time interventions** that can modulate emotional state are of urgent interest. Music therapy has emerged as one such promising solution due to its accessibility, low cost, and effectiveness in emotional regulation. However, traditional music therapy is **static and non-personalized**, relying on predefined playlists or therapist-selected tracks, which may not reflect the real-time mental and physiological state of the individual.

This project seeks to bridge that gap by designing an **adaptive music generation system** that can sense and respond to the user's internal state through **biosignals such as EEG, GSR, and HRV**. The system dynamically tunes musical parameters (like tempo, brightness, and complexity) in real time to elicit desirable emotional and physiological responses. This represents a leap toward **personalized, responsive, and AI-driven music therapy**.

Under the guidance of **Prof. Nicholas S. Peters**, a world leader in cardiac electrophysiology and neural-cardiac interactions at Imperial College London, this research aligns with emerging paradigms that treat **emotional homeostasis as a vital component of cardiac health**. By leveraging modern AI models and biosignal processing, we aim to contribute to a future where **digital therapeutics can augment traditional medicine** through intelligent, non-pharmacological interventions.

3. Background: EEG Bands and Their Implications

The EEG signal is divided into several frequency bands, each associated with specific cognitive and emotional states:

Band	Frequency	Associated State	Therapeutic Implication
Delta	0.5–4 Hz	Deep sleep, unconsciousness	Lower tempo, ambient tones
Theta	4–8 Hz	Meditation, drowsiness	Slow, rhythmic, repetitive motifs

Alpha	8–13 Hz	Relaxation, calm alertness	Moderate tempo, smoother tones, **lower complexity**
Beta	13–30 Hz	Active thinking, anxiety	Upbeat tempo, sharper transitions, **higher complexity**
Gamma	30–100 Hz	Cognitive processing, attention	Complex textures, **high brightness**, richer harmonics

The EEG predictor model extracts band-level intensities, which inform music customization.

In our system:

- **Alpha dominance** → Suggests **soothing music** (simple structures, slow-to-mid tempo).
- **Beta dominance** → Indicates **focused or anxious states**, suggesting **stimulating but harmonious music**.
- **High Gamma** → Signals **high processing**; can be modulated with **bright, ambient layers**.
- **Low Theta/Delta** → Avoid overly sedative music to maintain wakefulness.

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4. Methodology

4.1 Data Sources

- **EEG Dataset**: Muse headband-based EEG recordings from 2 individuals in 3 emotional states (positive, neutral, negative).
- **Biosignals**: GSR and HRV simulated for testing with statistical ranges.
- **SAM Ratings**: Used to label valence of EEG trials.

4.2 System Architecture

Each version builds upon the prior:

Version 1: Basic Adaptive Therapy System

- Predicts 5-band EEG values from raw audio via CNN.
- Uses GSR/HRV feedback to modulate music tempo, brightness, and complexity.
- Utilizes static descriptors for music generation.

Version 2: CNN-LSTM Hybrid

- Enhances EEG prediction using temporal sequence modeling.
- Improved EEG band resolution and musical personalization.

Version 3: Fully Integrated Therapy with Dataset Training

- Trains model on actual EEG data (valence prediction).
- Logs sessions and visualizes trends.
- Includes end-to-end closed-loop from EEG to music and back.

4.3 Control Mapping Summary

Input	**Mapped to**	**Effect on Music**
Alpha ↑	Complexity ↓, Tempo ↓	Soothing, minimal structure
Beta ↑	Complexity ↑	Energetic, possibly rhythmic/motivic
Gamma ↑	Brightness ↑	Ethereal, wide-spectrum harmonics
HRV ↓	Complexity ↓	Simpler musical layers
GSR ↑	Brightness ↓	Darker, warmer timbres

Descriptors such as "`Piano in C major, 85 BPM, Brightness 0.3, Simple structure`" are sent to MusicGen.

4.4 Physiological Feedback and Control Parameters

In addition to EEG, we incorporate biometric signals:

- **Heart Rate Variability (HRV):** Lower HRV often reflects stress. Used to modulate **complexity** and indirectly **tempo**.
- **Galvanic Skin Response (GSR):** Indicates sympathetic nervous activity. Higher GSR lowers **brightness** (to calm arousal).

The music is generated via descriptors like:

"Piano in C major, 85 BPM, brightness 0.3, simple structure"

These parameters are computed using a weighted function of EEG and bio-signals.

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5. Implementation Highlights

- **EEG Predictor**: Trained CNN and CNN-LSTM models using Mel spectrogram input from audio.
- **Biofeedback Processing**: Real-time calculation of HRV and normalized GSR.
- **Music Generation**: Facebook's MusicGen model used to generate waveforms from text prompts.

- **Logging & Visualization**: Tracks valence, descriptors, and session data.

5.1 System Versions

Version	EEG Input	Music Control	Dataset Used	Description
v1	Audio → EEG Bands	Tempo Only	Synthetic Bio Data	Basic prototype with CNN + MusicGen
v2	Audio → EEG Bands	Tempo + Brightness + Complexity	Synthetic Bio Data	Adds CNN-LSTM and richer feedback
v3	Real EEG → Valence	Tempo + Descriptor	GameEmo Dataset	Trained predictor, session logger, EEG trend analysis

5.2 Dataset and Preprocessing

GameEmo Dataset (v3)

- EEG: 32 channels, 5000-sample window.
- Labels: Valence from SAM Ratings.
- Preprocessing: Standardization, truncation, channel selection.

Training Pipeline

- Model: CNN for feature extraction, regression head for valence prediction.
- Loss: MSE
- Optimizer: Adam

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6. Results

Each implementation was validated through:

- Visual inspection of EEG prediction consistency.
- Adjustment curves over time for tempo and complexity.
- Human interpretability of generated music matching bio-state.
- Using matplotlib, we visualize the valence predictions over time across therapy sessions.

Sample Outputs:

“Generated music with adjustments :{'tempo': 88, 'brightness': 0.2, 'complexity': 0.9}
Relaxing piano, 90 BPM, brightness 0.20, complex structure”

“Music descriptor: Piano in C major, 88 BPM, brightness 0.20, simple structure EEG Prediction (Valence): 0.67
Session logged to: therapy_log.json”

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7. Applications

• **Clinical Therapy**: Adaptive music as a **non-invasive adjunct to cardiac care**, especially for managing **arrhythmias, heart rate variability (HRV) abnormalities**, and emotional triggers in cardiac patients.

• **Mental Health Support**: Personalized soundscapes for **anxiety reduction**, **depression management**, and **mood stabilization**, tailored to an individual’s bio-signals.

• **Neurofeedback & Biofeedback Training**: Real-time **EEG-informed feedback loops** for cognitive training, stress resilience, emotional awareness, and improving **attention regulation**.

• **Rehabilitation Programs**: Integrated into **post-stroke**, **post-MI (myocardial infarction)**, or **chronic illness rehabilitation**, where emotional regulation is key to recovery.

• **Sleep Therapy**: Customized ambient music based on alpha and delta wave patterns to **facilitate sleep induction and improve sleep quality**.

• **Cognitive Performance Enhancement**: Music guided by **EEG beta and gamma activity** to enhance **focus**, **creativity**, and **memory recall** in work or learning environments.

• **Human-Computer Interaction (HCI)**: Embedded in **emotion-aware interfaces**, where systems respond to user states in real time (e.g., virtual reality, gaming, adaptive learning platforms).

• **Wellness and Preventive Health**: Daily emotional hygiene via passive monitoring of stress markers like GSR and HRV to provide **music as intervention** before psychological thresholds are crossed.

• **Elderly and Dementia Care**: Use in memory care environments where music, tailored to emotional and cognitive states, supports **engagement, reminiscence, and agitation reduction**.

• **Autism Spectrum and Sensory Processing Disorders**: Sensory-friendly and emotionally adaptive sound environments that respond to physiological signals, aiding in **sensory integration and emotional grounding**.

8. Discussion

This framework showcases how **bio-signal informed music generation** can be effectively implemented using modern AI tools. While early versions used simulated data, the final implementation demonstrates feasibility with real EEG inputs.

Challenges:

- Dataset size and diversity.
- EEG inter-subject variability.
- Mapping EEG/music features in a personalized way.

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9. Limitations and Future Work

- Limited EEG data restricts generalizability.
- Current MusicGen model is not fine-tuned for emotion.
- Future work will explore:
  - Reinforcement learning for reward-based music generation.
  - Multi-modal emotion detection (video, text, speech).
  - Deployment on edge devices or wearables.

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10. Conclusion

Our work presents an innovative, multi-modal, AI-based music therapy system that adapts to users' cognitive and emotional states. By merging EEG frequency interpretation, physiological feedback, and real-time AI-generated music, the system offers a powerful tool for personalized emotional regulation and therapeutic intervention.

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