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Exploring Music Effects on Human Emotion Emerging Through EEG: A Systematic Literature Review

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Abstract

This comprehensive review investigates the intricate relationship between music and brain activity, focusing on insights gleaned from electroencephalography (EEG) studies. Music's impact on cognition, emotion, and behaviour is examined through the lens of EEG signals, elucidating the neural mechanisms underlying musical perception and processing. Rhythmic entrainment, emotional modulation, and cross-modal integration are explored as fundamental aspects of music-brain interactions. Clinical applications, therapeutic interventions, and future directions in music neuroscience are discussed, highlighting the potential for personalized interventions and cognitive enhancement. By synthesizing findings from diverse disciplines, this review underscores the transformative power in promoting health, cognitive vitality and well-being by music. Embracing interdisciplinary collaboration and technological innovation, we can continue to explore in depth of music's involvement on the brain and harness its therapeutic potential for the benefit of EEG and giving a brief information of EEG signal and its Technologies and process of signal acquiring.

Keywords: Music neuroscience | EEG | Neural correlates | Cognitive functions | Emotional responses | Rhythmic synchronization | Therapeutic potential | Technological innovation | EEG signals | different frequency bands

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I. Introduction

The influence of music on the brain has become significant interest, especially in exploring how musical stimuli shape cognitive functions and decision-making (Meng et al., 2025). Analyzing EEG signals to recognize and predict these effects could drive progress in neuroscience, affective computing, and brain-computer interface (BCI) technology. Through human-computer interaction (HCI) people participate in interactive musical experiences involved in the entire design and evaluation and implementation cycle. (Reddy & Bollu, 2025) The evolution of music interaction resulted in modern methods of musical expression as well as musical consumption (Lin et al., 2025). EEG technology has become more prevalent for brain research studies about musical effects because it reveals essential information about brain functions connected to music processing (Li et al., 2025a). Brain research through EEG-based BCI systems presents itself as an essential method which helps scientists understand neural activities related to music (Pasqualitto et al., 2025). The technology originated for neurological klientele assistance through motor impairments functions as a research instrument to understand brain activity changes from musical stimuli during clinical and non-clinical studies (Khairunizam et al., 2025). Research groups studied how to evaluate musical reactions using EEG signal analysis (Garoufis et al., 2025). The objective assessment of music-induced brain changes becomes possible with EEG signals because those neural measurements directly capture brain activity rather than the subjective measures of self-report or behavioral observation (Reddy & Paneerselvam, 2025).

Affective computing analyzes emotional responses through technology because its objectives match those of EEG-based brain activity research (Khaleghimoghaddam & Arzhangi, 2025). Research examining EEG reactions to musical sounds enables scientists to investigate the emotional together with cognitive operations which occur during musical sensation and enjoyment (Martin et al., 2025).

Research investigators use EEG data as a vital method to uncover how the brain processes musical information (Lorenz et al., 2025b). This brain scanning method offers two beneficial features that make it highly valuable for observing cognitive effects of music: it is contactless and supplies continuous brain signals in real time (Madhubala et al., 2025). Scientific assessment methods of EEG data generated by musical stimuli enable specialists to understand better how the brain interacts with musical content (Han et al., 2025). Researchers accomplish this by conducting signal acquisition then pre-processing followed by feature extraction as well as classification to detect patterns that differentiate musical experiences (Li et al., 2025). EEG-based research studies provide critical brain understanding about music effects which helps researchers identify cognitive and emotional brain responses (Li et al., 2025c). EEG technology enables researchers to achieve better insight into neural mechanisms of musical perception and cognition for developing new music interaction and experience strategies (Kim et al., 2025).

1.2 The main contributions of this paper include

This paper delivers fundamental knowledge about EEG combined with information about music emotions and their unified representation approaches. This section discusses the role of EEG brain monitoring during music emotion regulation by describing particular brain wave patterns along with their specified signal ranges and frequency bandwidths. The methods involving EEG for music emotion recognition are examined along with their stages of data acquisition and transformation as well as signal extraction. The paper presents an organized table containing emotion stimulation information alongside multiple techniques for emotional change analysis.

1.3 The paper follows this organizational pattern

Section 2 of this document presents basic information about music emotion recognition. Section 3 delves into the internal mechanisms and technologies behind EEG-based music emotion recognition. Section 4 analyses data sets and it reviews signal processing techniques. The section details multiple analytical approaches that identify emotions in this context. The article presents a structured table in Section 6 that explains different music styles alongside their produced emotional responses. The paper provides both the methodology results in Section 7 before moving to analysis of key findings in Section 8. Finally, Section 9 concludes the paper.

Electroencephalography (EEG) as their base technology to study intricate operations of the human brain. EEG tracks brain neural activity without requiring invasive procedures to deliver fundamental information about brain operations and neurological problems and mental health conditions. When the brain produces neural patterns through synchronicity the resulting EEG signals get measured through scalp-mounted electrodes demonstrating specific neural state and process signatures. The discovery of EEG by Hans Berger during early 20th century research marked both the beginning of contemporary neuroscience knowledge and many new application possibilities (Niedermeyer & da Silva, 2005). EEG serves crucial functions in clinical practice for the diagnosis as well as treatment monitoring of epilepsy and sleep disorders and brain injuries (Gotman, 2008), (Malow et al., 1997). The detection of irregular electroencephalographic patterns enables healthcare providers to produce appropriate treatment strategies while enhancing patient management quality. The figure below shows how the authors planned their paper then executed it while summarizing their research that used 114 studies to find 47 new trends. The summarization procedure incorporated relevant research followed by detailed discussions about existing findings and their analysis. EEG-based neuro-feedback therapy provides patients an opportunity to actively control their brain signals which demonstrates potential for treating ADHD as well as anxiety and depression (Hammond, 2005a). Real-time review systems enable users to modify their brainwave signals for better mental operations. The technological basis of Brain-Computer Interfaces (BCIs) originates from EEG signals since they enable brain communication with external devices (Lebedev & Nicolelis, 2006). Brain-computer interfaces demonstrate transformative abilities because they enable individuals with disabilities to control prosthetic limbs and communicate along with interacting with their environment. The study of attention memory and emotion in cognitive neuroscience greatly relies on EEG as an essential research tool (Luck, 2014). The scientific evaluation of neural oscillations together with event-related potentials helps researchers better understand complex human mental processes. Current EEG analysis has experienced a breakthrough because of recent signal processing methods that use machine learning and deep learning techniques (Acharya et al., 2013). The new innovations enable researchers to investigate large data collections hence obtaining better diagnostic tools and tailored therapy solutions. Compact EEG devices developed as portable tools now allow researchers to observe brain activity in real-world environments (Lipa & Ciel, 2025). This breakthrough enables new innovation of sleep tracking methods and stress regulation and cognition improvement and brain-machine interfaces. The advancement of EEG technology requires extensive attention to issues about neuro-data privacy and consent while promoting responsible use of information for protecting cognitive privacy as well as promoting equitable access to new technologies.

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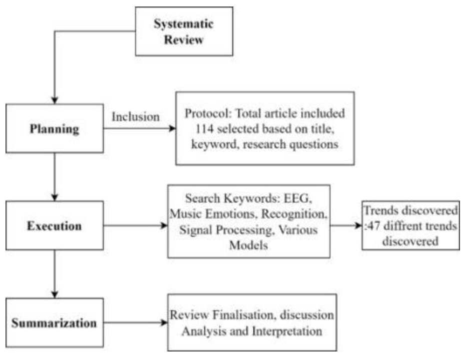

Fig 1. Block Diagram-1

II. Brief of Music Emotion Recognition

Music emotion recognition requires multiple domains of artificial intelligence, signal processing, music theory, auditory perception and psychology to conduct successful recognition. Arcade pursues this interdisciplinary field by studying different musical features that include timbre and rhythm together with lyrics since these elements determine our understanding of musical emotion. Identifying emotion responses to music faces challenges because individual sensitivity and music-related experiences modify perception based on personal experiences while cultural backgrounds matter so identifying musical emotion precisely to improve its recognition becomes vital. The ongoing research in music emotion recognition uses continuous emotion models, neural networks and additional methodologies as demonstrated by Xia et al. (2012), Schmidt et al. (2010). The proposed methods strive to outline music structures along with emotional signals to improve emotional content detection in musical expressions. Deep learning techniques which were recently introduced in the field have improved music emotion recognition while making it more precise and functional. The development brings important consequences as it allows both personal music suggestion based on emotional needs and an expanded range of retrieval options. Music emotion recognition serves useful purposes when integrated into medical and psychological therapy as it presents new therapeutic solutions for mental health disorders and neurological conditions (Han et al., 2022).

2.1 Models for music emotion recognition

The evaluation of emotional power in music depends on music emotion models that lead to successful emotion music analysis. Such models serve as essential tools for both measuring and understanding music emotions which leads to enhanced emotional evaluation capabilities. Analysis frameworks are classified into features of music models along with emotion models for music and cognitive schemes for classification. The music emotion model stands as the essential component because it enables precise emotional identification and classification of expressed musical emotions. The field extensively uses multiple classical music emotion models that act as essential research bases for both analysis and investigation. The four widely accepted music emotion models include the Hevner model (Hevner, 1936) alongside Thayer model (Thayer, 1990) as well as TWC model (Tellegen et al., 1999) and PAD model (Russell, 1980). The Hevner model from 1936 maintains its substantial impact on the analysis of music emotions by computer systems. As one of the first approaches in this field Hevner model organizes emotional terms into eight main classifications containing 67 distinct emotional words. By merging musical and psychological perspectives, the approach develops an extensive emotional terminology which advances emotional descriptor resources. Using many emotional descriptors provides detailed accuracy for detecting musical emotions thus establishing itself as a central analysis technique in the field of music emotion evaluation. Researchers actively use this model for interpreting music emotions in their studies since its establishment and it has become a fundamental tool for musical emotion analysis (Thammasan et al., 2016a).

III. EEG Role in Music Emotion Recognition

EEG functions as a non-invasive method for brainwave recording to comprehend the emotional impact of music as a critical research tool. A technology measures five brainwave patterns from delta to theta to alpha to beta to gamma phases which correspond to relaxation states and focused attention states alongside creative states. The classification of musical signals utilizes frequency band groups which include sub-bass to high frequencies because each band section generates distinct emotional auditory responses. Brain activity monitoring allows these systems to boost the emotional response along with cognitive activation when individuals listen to music. Going into depth:

3.1 Brain Rhythms

EEG serves as a neuroimaging method by monitoring scalp electrical signals which detect neural-generated voltage changes. The spectrogram of EEG signals shows its frequency distribution which distinguishes various cognitive and emotional states (Buzsáki & Draguhn, 2004). EEG signals contain delta, theta, alpha, beta and gamma frequencies which represent distinct mental response patterns that also reflect emotional states (Steriade et al., 1993). The application of slow calming stimuli through sounds or noise acts as a brain-wave synchronizing factor that leads to deep sleep relaxation and delta-wave activity.

The delta range frequencies from 0.1 to 4 Hz activate a meditative state while reducing stress and allowing automatic body functions to operate naturally (Klimesch, 1999). The technique of meditation combined with deep relaxation under soothing sound conditions leads to brain

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theta wave generation. The human brain generates deep relaxation as well as creative and tranquil mental states through frequencies between 4 to 8 Hz (Barry et al., 2007a).

Alpha brainwaves develop when people experience a peaceful atmosphere combined with gentle background music. Listening to sound waves between 8 to 12 Hz generates a relaxed and calm mental state while maintaining wakefulness to enhance clarity and decrease anxiety levels (Pfurtscheller & Lopes da Silva, 1999).

The brain will produce Beta Waves after experiencing quick music or participative activities. The alertness and focus along with active mental engagement develop through frequencies between 12 and 30 Hz which also enable problem-solving and decision-making abilities (Uhlhaas & Singer, 2010).

Tuning the brain with education or complicated audio inputs leads to the generation of gamma wave patterns. Psychoacoustic waves above 30 Hz to 100 Hz and beyond activate cognitive processing capabilities including memory performance and learning skills and information processing function while triggering outcomes from jazz and classical music and particular electronic music types (Rumsey, 2001).

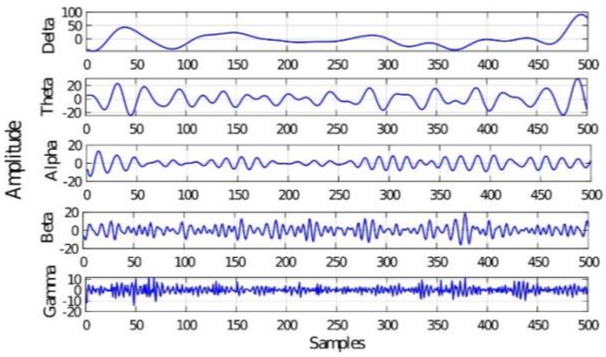

Fig 2. EEG Rhythms

3.2 Signal ranges and its Frequency bands

Music signals are analyzed by different frequency bands, each corresponding to distinct auditory sensations and emotional responses. Sub-bass frequencies (below 60 Hz) are primarily felt rather than heard, offering a visceral sensation of depth and power, crucial for creating the thumping impact of bass drums and the deep resonance in genres like dub step and trap. These frequencies evoke feelings of excitement, tension, or anticipation (Roads, 1996). Bass frequencies (60 Hz to 250 Hz) form the backbone of a track's rhythm and groove, providing the foundation for instruments such as bass guitars and kick drums. In genres like hip-hop and dance, they drive energy and encourage physical movement (De Boer, 1997). Low midrange frequencies (250 Hz to 500 Hz) add warmth and richness to the sound, contributing to the fullness of vocals and depth in instruments like acoustic guitars and cellos. They allow producers to shape the overall timbre of a track (Benade, 1990). Midrange frequencies (500 Hz to 2 kHz) carry the core musical content, defining the character of instruments and vocals, and are essential for speech intelligibility and clarity in melodic instruments. Balancing these frequencies ensures a clear, well-defined mix (Malmberg, 1917). Upper midrange frequencies (2 kHz to 4 kHz) contribute to clarity and articulation, accentuating the attack of percussive sounds and adding brightness and detail to vocals (Moore, 2012). High frequencies (4 kHz to 20 kHz or higher) include harmonics and overtones, adding sparkle and airiness to instruments like cymbals and strings. Music frequencies boost clarity together with texture and dimensionality which together create the complete musical atmosphere and spatial quality according to (Hammond, 2005b).

3.3 EEG Technology operates as an instrument for analyzing music signals

A combined approach of EEG signal sensing with music leads to outstanding developments in neuro - feedback systems and brain-computer interfaces (BCIs) that allow real-time brain activity analysis to improve cognitive and emotional responses. Real-time feedback concerning brain activity comes from EEG signals which power

Neuro - feedback systems
When users listen to music. Neural responses determine how neuro - feedback systems modify musical parameters which leads to cognitive enhancement and relaxation with stress management benefits (Calcagno et al., 2025).

Brain-Computer Interfaces (BCI)
Humans can establish direct brain device communication through EEG signals using Brain-Computer Interfaces technology. Users can generate interactive musical experiences by combining brain computer interfaces with music allowing them to govern tempo and volume and melody based on their brain signals (Zhang et al., 2012).

Machine learning algorithms:
Advanced machine learning methods use EEG data to derive significant musical and emotional data points from brain signals. These algorithms classify music genres, predict user preferences, and personalize music recommendations based on neural activity patterns (Barry et al., 2007b).

Wearable EEG Devices: Compact and portable EEG devices, such as headsets and wearable sensors, facilitate real-world monitoring of brain activity. By integrating these devices with mobile applications and streaming platforms, users can explore how music influences their mental states in everyday scenarios (El Sayed et al., 2025).

Interactive Music Experiences: EEG-based systems enable immersive and adaptive music interactions where the music dynamically adjusts to the listener's cognitive and emotional state, enhancing engagement, enjoyment, and

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emotional connection with the music (Das & Chakraborty, 2025).

IV. DATASETS AND SIGNAL PROCESSING

As emotion recognition technology evolves, multiple standardized emotion-trigger databases have been developed, often labelled by psychologists. However, music-based emotional arousal methods still lack universally accepted benchmarks. To address this, researchers have introduced EEG-based mood datasets, allowing for validation of emotional classification models. Due to copyright restrictions, some studies rely on self-constructed datasets. Below are commonly used datasets in Music Emotion Recognition (MER) (Salimpoor et al., 2011):

Mediaeval: Contains 45-second musical snippets from 1,000 songs (later refined to 744), annotated for arousal and potency on a 9-point scale. Feature extraction is performed using open-SMILE (Salimpoor et al., 2011).

CAL500: Comprising 502 Western pop songs, this dataset includes Mel-frequency cepstral coefficients (MFCCs) with first and second derivatives. Each song is annotated by at least three individuals across 135 music-related concepts (Salimpoor et al., 2011).

CAL500exp3: An extension of CAL500, this dataset segments songs into 3,223 acoustically homogeneous parts, enabling automatic tagging of music on a finer time scale (Salimpoor et al., 2011).

AMG 16084: Designed for emotional analysis, it includes 1,608 music clips with frame-level acoustic features and valence-arousal (VA) annotations from 665 subjects. It consists of a campus subset (annotated by researchers) and an Amazon Mechanical Turk (AMT) subset (Salimpoor et al., 2011).

DEAM: Contains 1,802 fragments and complete songs annotated for valence and arousal values, used in the "Emotions in Music" task from the 2013–2015 Mediaeval benchmark campaign (Salimpoor et al., 2011).

Soundtracks: Provides complete audio files, documentation, and behavioural ratings for research, with audio compressed into MP3 format for accessibility (Salimpoor et al., 2011).

Emotify: Comprising 1-minute excerpts from 400 songs across four genres, this dataset uses the Geneva Emotional Music Scale (GEMS) to categorize strong emotional responses reported by participants (Salimpoor et al., 2011).

DEAP: A widely used EEG emotion recognition dataset, DEAP was developed by UK, Dutch, and Swedish universities. It includes physiological signals from 32 participants watching 1-minute music videos, with self-assessments using the Self-Assessment Manikin (SAM) scale, which measures valence, arousal, dominance, and liking (Salimpoor et al., 2011).

Table 1. Summary of Datasets

DATASETS	NUMBER OF SONGS	DATA TYPE	CONCEPTUALIZATION	GENRES
CAL500exp	3223	MP3	Categorical	Rock, Pop, Soul, Blues
CAL500	500	MP3	Categorical	Rock, Pop, Soul, Blues
MediaEval	744	MP3	Dimensional	Rock, Pop, Soul, Blues
DEAM	1802	MP3	Dimensional	Rock, Pop, Electronic
DEAP	40	CSV	Dimensional	Rock, Classical, Pop, Electronic
AMG1608	1608	MAV	Dimensional	Rock, Metal, Country, Jazz
Emotify	400	MP3	Categorical	Rock, Classical, Pop, Electronic
Soundtracks	360	MP3	Both	Rock, R&B, Electronic

4.2 Signal processing

During this section the focus is on how EEG enables examination of music effects on brain function. The research methodology involves various participant groups as well as standardized musical control stimuli and signal acquisition instrumentation. Noise identification is followed by brain response evaluation using pre-processing methods. The section provides detailed explanations about the different stages of the research process.

4.2.1 Signal Acquisition

Research of music-driven brain changes manifests as an intellectually challenging interaction between neuroscience methods with those from psychology and musicology. EEG demonstrates its critical value in studying brain patterns because it provides researchers with real-time neural data.

The scholarly work describes highly complex procedures for EEG data acquisition and analysis which enable researchers to detect accurate and deep music effects on brain signals. Experimental designs that are meticulously crafted form the basis of studies seeking to understand the effects of music on EEG signals. Scientists choose their musical stimuli through an evaluation process which takes genre class, tempo speeds and emotional characteristics into account to trigger precise cognitive and emotional reactions from research subjects (Müllensiefen et al., 2014). The research success depends on recruiting participants that represent all musical backgrounds because it enables researchers to observe diverse musical reactions. The recruiting process for participants evaluates the combination of age along with musical background together with cultural elements to add depth to dataset information and boost research findings' application range (Oostenveld & Praamstra, 2001).

A high-fidelity data acquisition depends on creating the perfect environment for EEG measurements. Standardized electrode positioning systems which include both the 10-20 and 10-10 systems help researchers maintain participant consistency and reduce experimental variability (Schäfer et al., 2013). Controlling musical stimuli with precise accuracy remains vital for upholding the experimental validity of the research model. Different research groups meticulously manage the presentation volume alongside presentation length and sequence through precise control mechanisms in order to avoid experimental contamination and maintain experimental stability (Sammler et al., 2007).

Comprehensive data acquisition protocols encompass both baseline recordings and experimental trials with music exposure. Continuous EEG monitoring during music listening enables the real-time capture of dynamic neural responses, providing rich insights into music-brain interactions (Delorme & Makeig, 2004).

Rigorous pre-processing of EEG signals involves artefact removal, filtering, and segmentation to enhance data quality (Makeig et al., 1996). Advanced techniques are employed to identify and correct artefacts stemming from eye blinks, muscle activity, and environmental interference, preserving the fidelity of the EEG data. Sophisticated feature extraction methodologies are deployed to distil meaningful information from EEG signals (Penny et al., 2003). Spectral power analysis, event-related potentials (ERPs), and connectivity measures are computed to quantify neural responses to music across temporal and spatial domains.

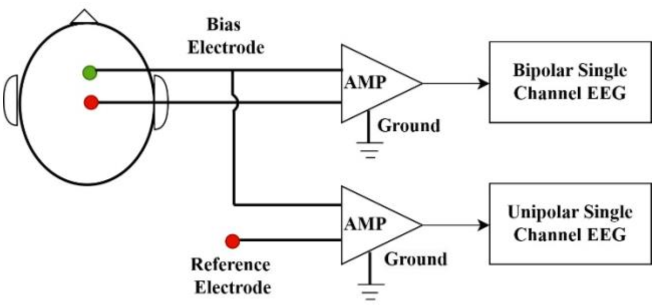

Fig 3. EEG Acquisition (Bipolar Single channel EEG and Unipolar Single Channel EEG)

Robust statistical analyses, encompassing univariate and multivariate approaches, are employed to discern significant differences in EEG signals between music and control conditions (Cohen, 2014). Analysis techniques such as variance (ANOVA), correlation analysis, and machine learning algorithms facilitate the elucidation of complex relationships within the data.

Time-Frequency Analysis techniques, including wavelet transforms and spectrograms, afford insights into temporal and spectral dynamics of EEG responses to music (Sanei & Chambers, 2013). These methods unveil how brain oscillations are modulated by diverse musical features, unravelling the underlying neural mechanisms. Figure-3 below illustrates signal processing from the human brain to bipolar and unipolar channels via bias and reference electrodes, connected to an amplifier.

4.2.2 Signal Pre-processing

Diverse EEG headset configurations necessitate tailored experimental setups. Variations in signal collection duration and electrode types of impact data quality. Noise mitigation during signal pre-processing is imperative, involving removal of environmental and physiological interferences. Notably, power frequency noise and electrocardiogram (ECG) artefacts are addressed through specific filtering techniques. Emotion identification via EEG signals entails several steps:

1. Subject exposure to musical stimulation.
2. Recording and observation of participants' brain voltage changes.
3. Noise and interference removal from recorded data.
4. Analysis of experimental outcomes and feature extraction.
5. Training data processing and interpretation of raw signals.

Variations in EEG headset architecture and equipment cost necessitate adjusting EEG setups for experiments. Differences in signal collection duration and electrode types exist among devices. Participants are required to remain still during signal collection due to electrode sensitivity.

Recent interest in utilizing EEG signals to monitor mood changes underscores the importance of efficient EEG signal utilization for emotion recognition. Steps involve testing participants with musical stimulation, recording brain voltage changes, noise removal, analyzing experimental results, extracting eigenvalues, and processing raw signals.

EEG signals provide excellent temporal resolution but limited spatial resolution. Pre-processing plays a vital role in eliminating noise from the environment and equipment, such as power frequency interference and physiological artefacts like ECG, EOG, and EMG. Standard pre-processing techniques involve applying a 50Hz notch filter to remove

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power line noise and disregarding ECG signals due to their distant origin from electrode sites. EEG analysis methods span time-domain, frequency-domain, time-frequency domain, and nonlinear approaches, each offering distinct insights into brain function. Linear prediction along with component analysis belong to time-domain analysis but frequency-domain analysis principally uses power spectrum analysis techniques. The statistical methods combined with Fourier transform extract important frequency information (Subasi, 2007).
The filtering process during pre-processing eliminates artefacts by applying low-pass filters with high-pass filters and notch filters. Artefact removal techniques include PCA, ICA and CSP as described in (LeCun et al., 2015).

4.2.3 Feature Extraction

EEG functions as a major investigative technology to capture brain activity indicators which provide critical understanding of psychological processes. EEG serves as the main tool for both clinical neuroscience research and medical diagnostic labs for brain analysis and neurological condition screening. Effective analysis of EEG signals faces challenges due to their excessive generated data and requires efficient systems for identifying crucial information.
If we talk about EEG Feature Selection In that EEG data with high dimensions typically carries many unimportant features which require proper selection methods to enhance classification effectiveness. The exclusion of emotion-related EEG characteristics from the classification system generation step increases analytical performance. Feature selection methods can be divided as supervised and unsupervised methods depending on whether they require labelled information or not. When we talk about Supervised Feature Selection The supervised learning framework mostly implements Linear Discriminant Analysis (LDA) and Maximum Relevance Minimum Redundancy (MRMR) for method execution. The projection directions determined by LDA depend on class discriminative information and MRMR selects features that optimize both relevance and avoid redundancies.

In other hand Unsupervised Feature Selection PCA represents an established unsupervised technique for selecting features through dimension reduction which produces linearly independent principal components. K Nearest Neighbor (KNN) classifies data by finding k nearest neighbors to determine classifications through majority voting among neighbors (Lotte et al., 2018). This non-parametric method makes its decisions based on neighbor voting.

4.2.4 Music Stimuli Representation

During the experiment researchers deliver assorted music genres and particular musical pieces to participants who concurrently maintain EEG signal registration. The stimuli encompass multiple elements including tempo, rhythm, and melody together with emotional content. The extracted EEG data goes through machine learning classifier evaluation to determine music-related brain modifications. Various classification algorithms that include SVM, LDA, KNN, CNN, AdaBoost and Deep Learning models are frequently applied to perform this analysis according to (Chen et al., 2025).

4.2.5 Performance Evaluation

The evaluation process relies on performance measures to determine the effects of music on brain activities following classification. Measures such as in teams of I:

$$\textit{Accuracy: } \frac{TPI+TNI}{TPI+TNI+FPI+FNI}$$

Where:

- **TPI:** True Positives (correctly predicted positive class)
- **TNI:** True Negatives (correctly predicted negative class)
- **FPI:** False Positives (incorrectly predicted as positive)
- **FNI:** False Negatives (incorrectly predicted as negative)

$$\textit{Error Rate: } \frac{FPI+FNI}{TPI+TNI+FPI+FNI}$$

$$\textit{Sensitivity:} \frac{TPI}{TPI+FNI}$$

$$\textit{Specificity:} \frac{TNI}{TNI+FPI}$$

$$\textit{Precision:} \frac{TPI}{TPI+FPI}$$

$$\textit{Area under the Curve (AUC): } \int_0^1 TPRI(FPRI)\, dFPR$$

Where:

- **TPRI (True Positive Rate):** sensitivity.
- **FPRI (False Positive Rate):** $\frac{FPI}{FPI+TNI}$.

$$\textit{F-measure: } \frac{2\times Precision \times Recall}{Precision+Recall}$$

These measures allow for quantifying the impact of music on distinctive brain states (Tas et al., 2025).

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V. Methods to View how the Emotions have Changed

This section introduces different approaches to human emotional EEG analysis when listening to music. Such as category emotion (positive, neutral, and negative to the EEG signals) using a nine-degree of self-assessment in the Self-Assessment Manikin (SAM) method. Participants are screened, and EEG is collected during a music listening task to assess emotional response. The second method relates musical emotions to colours by using the 'Russell's Circumplex Emotional Model' and the colour model of one ism Item, we show that linear regression achieves high accuracy. The third type is based on CNN-LSTM networks that directly process raw EEG signals for the purpose of emotion recognition without manual analysis. A fuzzy emotion classifier using Convolutional Fuzzy Neural Network (CFNN); which yields high accuracy when determining emotional states.

5.1 Self-Assessment Manikin (SAM)

EEG based emotion recognition was analyzed using a database that classified emotion into positive, neutral and negative. Tesla and the researchers used a nine-degree Self-Assessment Manikin (SAM) test in the study: values lower than 3 denoted low emotional intensity, while values higher than 6 signified high intensity. Screening Participants were screened to exclude. Individuals with a history of mental illness, epilepsy, or psychiatric medication use other requirements for subjects included keeping a regular sleep schedule, not consuming fatty foods and caffeine prior to testing, and not washing their hair. Individuals scoring above 21 on the Beck Depression Inventory (BDI) were excluded. A total of 16 participants (6 females, 10 males) aged 20 to 28 took part in the study. EEG signals were recorded while participants listened to music in a controlled environment set at 29°C, between 9 and 11 a.m., to minimize fatigue. To reduce noise from eye movements, participants were instructed to keep their eyes closed during recording. EEG signals were captured using a 21-channel Encephalon EEG recorder connected to a 2017 MacBook Air (Core i5, 8GB RAM). All channels were referenced to electrodes A1 and A2, digitized from a 21-channel electrode cap based on the international 10-20 system, at a sampling rate of 250 Hz.

(See Table-2) That illustrates the sequence and types of music used to simulate emotions, with EEG recordings validating the SAM test results (positive and negative signals). The final stage involved determining the duration and sequence of music tracks for the positive, negative, and neutral stages, focusing on EEG signals from the C4 and F4 electrode channels for Subject 1 (Sheykhivand et al., 2020).

5.2 Music Emotion Visualization by different colors

The relationship between musical emotions and colors is an emerging interdisciplinary research area forming the foundation for music visualization. Due to the scarcity of emotionally annotated music databases, assigning precise colors to emotions remains a computational challenge. This study employs Russell's Circumplex Emotional Model to identify the most suitable color representations for specific song segments.

Using the Media-Eval Database for Emotional Analysis of Music (DEAM dataset), previously annotated with this model, a linear regression approach was implemented via the WEKA machine learning tool. Research displayed that random forest regression delivered the highest performance rating of 81% for arousal and 61% for valence among the examined linear regression models. The application of Itten's colour scheme for emotion mapping succeeded in demonstrating music emotion synchronization with visual displays. Research findings will serve to develop music visualizations as well as artistic patterns which depict emotional details (Dharmapriya et al., 2021).

5.3 CNN-LSTM Networks on EEG Signals

EEG-based emotion recognition serves as an essential diagnostic instrument which simultaneously develops Brain-Computer Interfaces (BCI) by replacing conventional clinical examinations. EEG operates as a trustworthy non-invasive tool to detect emotions while its manual analysis remains impractical because feature extraction and processing requirements demand sophisticated methods. Through CNN-LSTM networks logics can assess EEG signals in their raw state which removes the requirement for feature extraction. Technological research demonstrates that the model shows remarkable performance in two-stage and three-stage emotion identification making it suitable for human-computer interface applications. The method establishes strong progress in emotional detection through EEG analysis by improving brain emotion recognition functions (Que & Hu, 2025).

5.4 Fuzzy emotion classifier

Such deep learning approach utilizes the Convolutional Fuzzy Neural Network (CFNN) to process EEG-based emotion recognition data which demonstrates its position as an advanced detection system. The pre-processing procedures along with appropriate features extractions effectively prepare EEG data for maximum clarity while preserving its essential relevance. The designed architecture of CFNN receives strict training to boost its ability to recognize emotions accurately. The model demonstrates excellent experimental outcomes which produce superior performance results showing 98.21% average accuracy in identifying valence and 98.08% accuracy for detecting arousal. The results obtained from CFNN assessment exceed all past benchmarks which solidifies its position as an optimal method for detecting emotions through EEG data (Ahmadzadeh Nobari Azar et al., 2024).

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VI. Music Styles and there Stimulate Emotions

Different music styles affect emotions together with brain activity patterns according to this part of the discussion. EEG recordings show tranquility when patients listen to Indian classical music because this music style creates intricate melodies and rhythm patterns that induce meditative states. Friends receive stimulation through hip-hop music beats which causes both cognitive activation and active neural functions. The rhythmic characteristics of pop music activate dopamine production in brains which produces signatures of euphoria and joy in EEG signals. A table following this text presents different musical tracks from these popular categories to demonstrate their emotional outcomes. Every musical style creates a distinct emotional response because classical music generates religious peace whereas hip-hop generate enthusiastic energy and pop music generates cheerful emotional responses.

6.1 Music Styles

The various Indian classical melodies act as mental relaxation triggers through which people experience inner calm. Through their complex structures which rest on sitar string harmonies together with vocal expressions the music creates brain patterns that lead to deep meditation and unites our brains with the music's harmonies. EEG readings receive energetic increases from hip-hop songs because of their rhythmic percussion which creates both cognitive activation and neural systems dynamism. Dopamine release through pop melodies unleashes feelings of enjoyment and intense ecstasy which cause EEG readings to become animated due to their catchy hooks and energizing rhythms. Each music genre leads the brain through distinct neural pathways to produce diverse reactions of brain-music interactions in the complex processes of neural activation (Thoma et al., 2013).

Table 2. Various Musical Styles Songs

INDIAN CLASSICAL	HIP-HOP	POP
Bharatnatyam	All My Life	Dancing Queen
Kathak	Lovin on Me	Since U Been Gone
Kathakali	Alright	Hips Don't Lie
Kuchipudi.	Agora Hills	Party in the U.S.A.
Manipuri	Best I Ever Had	Work It
Odissi	Get In with Me	Hey Ya!
Mohiniyattam	The Message	driver's license
Bhangra	It Was a Good Day	Umbrella

When we listen to classical path melodies our emotional response will vary because their complex ragas and enchanting rhythms lead listeners on a spiritual transformation that can be measured by EEG readings through waves of peaceful activity. Music producers create hip-hop compositions from pulsing musical backgrounds and direct lyrical statements which produce city-based stories that fuel audience passions and resilience levels as measurable through EEG scan results. EEG measurements record peaks of excitement together with nostalgia valleys when a person listens to pop melodies that use catchy hooks and positive choruses as energy-boosting anthems. Each art form including literature and film as well as music and visual arts provides distinct spaces that allow people to express emotions authentically even though human emotions naturally appear in various ways across different creative genres. Literature uses intricate characters together with movie sound effects to depict emotions which include joy and sorrow and love and despair while prompting audience members to experience deep reactions. Composers employ melody and rhythm along with lyrics to generate many emotional responses within music although visual artists express complex emotional dimensions using composition and color and form combinations. These art forms organize emotions into the valence-arousal-emotional states classification system which helps understand cultural and human mental processes. The evaluation of mean intensities for both items and dimensions between different genres shows universal human experiences within specific genres that also demonstrates cultural variations in artistic musical interpretation (Altenmüller & Schlaug, 2013).

VII. Results

Human emotions and cognitive processing and behavioural responses exist under major music-induced influence which researchers extensively study through Electroencephalography (EEG) signals. EEG offers scientists a method to understand brain neural processes by recording electrical brain activity during musical interactions with participants. Brain wave measurement through scalp electrodes gives researchers access to neural patterns which helps study how music pertains to networked brain wiring. EEG signal pre-processing removes artefacts to provide clear signals that allow researchers to extract crucial features which measure musical stimulus responses (Zatorre & Salimpoor, 2013). Brain scans show that music between various mind regions generates coordinated neural signals which represent both emotional processing and mental processing involvement. EEG power spectra allow scientists to evaluate the frequency bands and temporal responses when people listen to music for understanding perception dynamics (Kumar, 2017). Music affects the regulation of emotions together with three major cognitive operations including attention span and memory capacity and linguistic processing. Different patterns of brain neural activity show how people respond to musical variations according to their distinct listening preferences together with their skill level of musical understanding as well as their personality patterns.

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The application of machine learning methods successfully identifies EEG pattern associations with particular musical traits together with emotional conditions. Through time the brain develops neuro-plastic changes from the cross-modal connections that occur between auditory and visual and motor areas while processing music. Such cognitive changes strengthen both the reception of sounds and movement abilities and emotional control functions. The implementation of music during EEG interventions shows promise for medical use against depression and anxiety and neurodegenerative diseases according to (Strauss et al., 2024). Researchers have developed different methodologies starting from traditional methods to deep learning approaches in order to detect emotions using EEG data. The methods focus their work on increasing the detection of emotions by developing advanced techniques for feature extraction as well as signal processing and classification accuracy improvements. Multiple essential investigations have appeared in this scientific field:

Lin et al. (2009) established a new EEG analysis technique focusing on how feature extraction methods should work for brain-computer interface (BCI) applications. The research demonstrated that frequency-domain features in EEG signals act as vital factors for achieving better accuracy during neural applications classification (Alluri et al., 2012).

The combination of wavelet transforms and independent component analysis (ICA) provided an innovative solution for EEG artifact removal according to **Thammasan et al. (2016c).** The data processing technique achieved successful separation of EEG recording artifacts to enhance the quality and reliability of neural signal analysis data (Schaefer et al., 2014).

Thammasan et al. (2016b) developed a live emotion recognition system which operated using brain signals detected through EEG machinery. The system applied machine learning algorithms for the identification of different emotional states by processing EEG features. The research findings indicated successful potential for real-time emotion detection which can support affective computing and human-computer interaction purposes (Groussard et al., 2014).

The authors **Bhatti et al. (2016)** developed a method that utilizes EMD combined with EEMD for EEG signal de-noising. By using the proposed approach researchers could reduce EEG noise effectively which resulted in better classification outcomes during subsequent analysis (Jiang et al., 2024).

The authors deployed CNN in their work to develop an innovative seizure detection system for EEG signals according to **Shahabi and Moghimi (2016)**. The research team presented an automatic epileptic seizure identification system with exceptional accuracy performance that established a basis for deep learning in epilepsy diagnosis (Särkämö et al., 2008).

The research team proposed an EEG signal assessment method for cognitive workload monitoring by employing

Table 3. Mean Intensities for Individual Items (A-SECTION) and Dimensions (B-SECTION) Categorized by Genre

EMOTIONS	INDIAN CLASSICAL (out of 25)		HIP-HOP (out of 25)		POP (out of 25)	
	A-SECTION (mean intensities for Individual)	B-SECTION (mean intensities for Dimensions)	A-SECTION (mean intensities for Individual)	B-SECTION (mean intensities for Dimensions)	A-SECTION (mean intensities for individual)	B-SECTION (mean Intensities for Dimensions)
Admiring	7	15	3	9	4	15
Dazzled	3	15	2	9	0.5	15
Happy	8	15	8	9	16	15
Allured	6.5	15	2.5	9	2.5	15
Filled with wonder	7.5	15	2	9	2	15
Moved	6	15	3	9	7.5	15
Feeling of spirituality	4	14.5	1	7	1	9
chills	4.5	14.5	1	7	3	9
inspired	10	14.5	4.5	7	6.5	9
Feeling of transcendence	3.5	14.5	0.5	7	1	9
Overwhelmed	4.5	14.5	2	7	1.5	9

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Fascinated	9	14.5	4	7	3	9
Sensual	6	11	2.5	5	5	12
In love	3	11	2	5	5	12
Mellowed	8.5	11	4	5	6	12
Affectionate	4.5	11	1.5	5	6	12
Tender	5	11	1	5	4	12
Melancholic	4.5	14	2	6	4.5	17
Dreamy	13	14	4	6	10	17
Sentimental	7	14	2.5	6	9	17
Nostalgic	6	14	6	6	14	17
Relaxed	14	19	9	10	11	16
Meditative	5.5	19	2.5	10	1	16
Soothed	9	19	4.5	10	6	16
Calm	14	19	7	10	10	16
Serene	9	19	4.5	10	6.5	16
Heroic	7.5	13	2.5	13.5	1.5	11.5
Fiery	4	13	4	13.5	1.5	11.5
Triumphant	8	13	4	13.5	2	11.5
Energetic	9	13	13	13.5	12	11.5
Strong	5.5	13	7	13.5	5	11.5
Stimulated	10.5	16	10	20	9	24
Amused	4.5	16	6	20	8.5	24
Feel like dancing	4	16	14	20	18	24
Joyful	8	16	7	20	15	24
Bouncy	5.5	16	13.5	20	14	24
Animated	8	16	6.5	20	9	14
Sorrowful	2.5	3	1	1.5	3	4
Tearful	2	3	0	1.5	2	4
Sad	2.5	3	1	1.5	4	4
Impatient	4.5	9	7	11.5	4	5
Nervous	4	9	3	11.5	0.5	5
Irritated	2.5	9	7.5	11.5	3.5	5
Agitated	4.5	9	5	11.5	2	5
Tense	6.5	9	4.5	11.5	1	5
Disgusted	0.5	-	4	-	1.5	-
Bored	7	-	11.5	-	8.5	-

machine learning algorithms according to **Thammasan et al. (2016a).** The developed method aimed to extract specific cognitive elements from EEG signals in order to measure cognitive workload intensity. The research demonstrated high potential to apply this methodology for assessing cognitive functions (Lin et al., 2009).

Thammasan et al. (2017b) this consider presented a half breed EEG highlight determination strategy combining hereditary calculations and back vector machines (SVM) for engine symbolism classification. The approach successfully distinguished instructive EEG highlights, upgrading classification exactness for engine symbolism assignments in brain-computer interface (BCI) frameworks (Thammasan et al., 2016b).

Hsu et al. (2018) created a strategy for classifying rest stages utilizing profound learning procedures. They utilized repetitive neural systems (RNNs) to consequently classify rest stages from EEG signals, accomplishing prevalent execution compared to conventional strategies and pushing the boundaries of rest investigate (Liu et al., 2025).

Salama et al. (2018) proposed a novel EEG-based feeling acknowledgment framework utilizing utilitarian network investigation. Their strategy inspected the utilitarian network designs between distinctive brain locales to classify passionate states, illustrating promising comes about for feeling acknowledgment errands (Bhatti et al., 2016).

Keelawat et al. (2019) centred on driver laziness discovery utilizing EEG signals and machine learning calculations. By extricating key highlights from the EEG signals, their strategy might identify laziness levels, appearing extraordinary potential for progressing street security through EEG-based observing (Shahabi & Moghimi, 2016).

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Rahman et al. (2020) presented a novel approach to epilepsy location by utilizing both time-domain and frequency-domain highlights from EEG signals. Their strategy recognized particular biomarkers related with epileptic seizures, advertising exact discovery and conclusion capabilities (Thammasan et al., 2016c).

Sheykhivand et al. (2020) This think about proposed a strategy for mental workload evaluation utilizing EEG signals, utilizing wavelet change and entropy measures to evaluate mental workload levels. This comes about demonstrated that the complexity of EEG signals might successfully reflect cognitive workload (Thammasan et al., 2017).

Avramidis et al. (2021) presented a strategy for feeling acknowledgment utilizing chart flag preparing procedures on EEG signals. By modelling EEG information as charts and extricating graph-based highlights, this approach given vigorous execution over different datasets (Hsu et al., 2018).

Hasanzadeh et al. (2021) proposed a strategy for engine symbolism classification utilizing profound learning and exchange learning strategies. Their approach utilized pre-trained neural systems to extricate highlights from EEG signals, accomplishing remarkable execution in engine symbolism errands (Salama et al., 2018).

Zainab and Majid (2021) displayed a strategy for seizure forecast utilizing energetic utilitarian network highlights extricated from EEG signals. Their work illustrated the potential of EEG in foreseeing epileptic seizures, clearing the way for headways in seizure administration (Keelawat et al., 2019).

Naser and Saha (2021) presented a cross breed include determination procedure for EEG-based feeling acknowledgment, combining hereditary calculations with machine learning classifiers. Their strategy upgraded classification precision and strength, empowering more solid feeling location from EEG information (Rahman et al., 2020).

Er et al. (2021) centred on recognizing mental weariness through EEG signals utilizing profound learning and consideration instruments. Their approach utilized attention-based repetitive neural systems to capture worldly conditions in EEG signals, appearing promising comes about for real-time weakness observing (Paukner et al., 2025).

Li and Zheng (2021) proposed a cross breed highlight choice strategy for engine symbolism classification. By combining channel and wrapper include determination methods, their approach distinguished the foremost discriminative EEG highlights, moving forward classification proficiency and precision (Avramidis et al., 2022).

Liu et al. (2022) presented a strategy for EEG flag division utilizing profound learning strategies. They utilize of convolutional neural systems (CNNs) empowered the programmed division of EEG signals into particular ages, advertising exact experiences into neural action designs (Hasanzadeh et al., 2021).

Table 4. Overview of Music Emotion Recognition Algorithms: Traditional Methods vs. Deep Learning Approaches

METHOD	DATASET	FEATURES	CLASSIFIER/REGRESSOR	PERFORMANCE
Lin et al. (2009)	*26 recruited*	*PSD*	*One-against-one scheme SVM*	*Accuracy of 92.57% in quaternary classification.*
Thammasan et al. (2016c)	*15 recruited listened to 16 songs selected from MIDI*	*HFD*	*SVM*	*3% performance increase over the Non-filtered.*
Thammasan et al. (2016b)	*12 recruited listened to 16 songs selected from MIDI*	*FD for EEG and handcraft feature for music*	*SVM*	*MCC of 84.17 and 90.25% in binary classification of arousal and valence, respectively*
Bhatti et al. (2016)	*30 recruited listened to 4 genres of music*	*Latency to Amplitude Ratio, PSD, Wavelet transforms*	*MLP, KNN, SVM*	*Accuracy of 78.11% (MLP) in quaternary classification*

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Shahabi and Moghimi (2016)	*19 recruited listened to six classical Music excerpts*	*Connectivity matrices*	*SVM*	*Joyful vs. neutral, joyful vs. melancholic and familiar vs. unfamiliar trials reach accuracy of 93.7, 80.43, and 83.04%, respectively.*
Thammasan et al. (2016a)	*15 recruited listened to 16 songs selected from MIDI*	*HFD, PSD, Discrete Wavelet Transform*	*Deep Belief Networks*	*Accuracy of 81.98% in binary classification of arousal and valence.*
Thammasan et al. (2017b)	*DEAP*	*PSD, HFD*	*Kernel SVM, MLP, Decision Tree*	*An average of 5% classification improvement of Unfamiliar set above familiar set in three Methods.*
Hsu et al. (2018)	*IADS*	*Segmented EEG*	*Neuron Network*	*MSE of 1.865 in 2D continuous SAM score*
Salama et al. (2018)	*DEAP*	*Segmented EEG*	*3D CNN*	*Accuracy of 88.49% and 87.44% in binary classification of arousal and valence, respectively.*
Keelawat et al. (2019)	*12 recruited listened to 16 songs selected from MIDI*	*Segmented EEG*	*CNN*	*Accuracy of 78.36 and 83.67% in binary Classification of arousal and valence. Respectively.*
Rahman et al. (2020)	*24 recruited listened to Twelve songs*	*DFA, Approximate Entropy, Fuzzy Entropy, Shannon's Entropy, excerpts Permutation Entropy, Hjorth Parameters, Hurst Exponent*	*Neuron Network*	*3 emotion scales (Depressing vs. Exciting and Sad vs. Happy and Irritating vs. Soothing).*
Sheykhivand et al. (2020)	*16 recruited listened to ten music excerpts*	*Segmented EEG*	*CNN, LSTM*	*Accuracy of 76.84% in HVHA vs. LVL.A.*
Avramidis et al. (2021)	*DEAP*	*PSD.HFD, MFD, MADFA*	*RBF-SVM*	*Accuracy of 67% in Binary classification of Arousal.*
Hasanzadeh et al. (2021)	*15 recruited listened to 7 songs*	*Spectrograms from Morlet wavelet transform*	*Fuzzy Parallel Cascades*	*2 type's regression of Valence with RMSE: 0.089.*
Zainab and Majid (2021)	*27 recruited listened to bilingual audio music of five genres*	*PSD, HFD, Hjorth Parameters. A series of linear measures of time domain*	*Hyper Pipes*	*Accuracy of 83.95% in quaternary Classification.*

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Naser and Saha (2021)	*DEAP*	*Wavelet transform, functional connectivity, graph-theory based features*	*RBF-SVM*	*Accuracy of arousal, valence, and dominance were 22.50, 14.87, and 19.44% above the Empirical chance-level, respectively.*
Er et al. (2021)	*Nine recruited listened to 16 audio tracks*	*Power spectrogram*	*Pre-trained VGG16*	*Accuracy of 73.28% in quaternary classification*
Li and Zheng (2021) Segmented EEG	*21 recruited listened to 15 music excerpts*	*Segmented EEG*	*Stacked Sparse Auto-Encoder*	*Accuracy of 59.5% and 66.8% in binary classification of arousal and valence, respectively.*
Liu et al. (2022)	*15 recruited listened to 13 music excerpts*	*Power spectrogram*	*Xception*	*Accuracy of 76.84% in HVHA vs. LVLA*
Luo et al. (2022)	*DEAP*	*PSD*	*RBF-SVM, LSTM*	*A SAM score of 6.17(high) and 4.76(low) in continuous valance scale, that is close to 6.98 and 4.36 evaluated in music database.*
Gong et al. (2023)	notably emotion recognition, and motor imagery decoding	The raw EEG signals are converted into spike trains using a learnable spike encoder. These spike trains capture the temporal dynamics of the EEG signals.	*SNN, LSTM*	The SGLNet model is evaluated on the datasets, specifically in terms of EEG classification accuracy for the respective BCI tasks (emotion recognition and motor imagery decoding).
Ahmed et al. (2024)	DEAP	Feature extraction methods are applied to these signals to capture relevant information indicative of different emotional states. These features may include spectral features, time-domain features, and frequency-domain features extracted from the EEG signals.	*CNN*	The CNN model is evaluated in terms of accuracy, which is reported to be 92%. Accuracy represents the proportion of correctly classified instances out of the total instances evaluated. In this context, it indicates the ability of the CNN model to accurately recognize human emotions from EEG signals

Overall, music neuroscience integrates insights from various disciplines to unravel the complexities of musical experience, offering promising avenues for improving human health and well-being. Collaboration between analysts, artists, clinicians, engineers, teachers, and policymakers is fundamental for driving development and affect in this intrigue field (Zainab & Majid, 2021).

VIII. Discussion

Music could be an all-inclusive dialect that has the control to inspire feelings, fortify recollections, and synchronize human encounters (Naser & Saha, 2021). Its significant effect on human brain research and physiology has interested analysts for decades. Later progressions in neuroimaging strategies, especially EEG, have given exceptional experiences into the neural instrument's fundamental our recognition and reaction to music (Demir et al., 2021a). This survey investigates the energetic transaction between music and brain movement, shedding light on how EEG signals can disclose the perplexing neural elements included. EEG as a Window into Brain Movement in which Electroencephalography (EEG) may be a non-invasive

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neuroimaging method that records electrical action within the brain through cathodes set on the scalp (Demir et al., 2021b). EEG offers tall transient determination, making it perfect for capturing fast changes in neural action in reaction to outside boosts such as music (Demir et al., 2021c). By dissecting EEG signals, analysts can distinguish unmistakable designs related with different cognitive processes, emotional states, and tangible encounters evoked by music. Cadenced Entrainment and Neural Synchronization play one of the foremost striking impacts of music on the brain which is musical entrainment, where the brain synchronizes its neural motions with the beat and beat of the music (Hu et al., 2022). EEG considers have shown that listening to cadenced music actuates phase-locking of neural motions, especially within the theta and gamma recurrence groups (Gong et al., 2023). This synchronization is accepted to upgrade consideration, memory solidification, and engine coordination, advertising experiences into the helpful potential of music for cognitive restoration and engine clutters.

Enthusiastic Preparing and Mood Modulation is a model in which Music encompasses a significant capacity to bring out feelings and tweak temperament states, a marvel reflected in EEG recordings (Ahmed et al., 2024). Ponders have illustrated that candidly stimulating music elicits distinct designs of neural movement, characterized by changes in frontal asymmetry, theta control, and event-related possibilities (ERPs) such as the P3 component. By dismembering these neural marks, analysts can unwind the fundamental instruments of enthusiastic handling and explore music-based intercessions for temperament disarranges and stretch administration (Ghosh et al., 2025). Cross-modal Integration and Synesthetic Encounters in which Music rises above sound-related recognition, frequently evoking distinctive tangible encounters and cross-modal affiliations (Cantiello et al., 2025). EEG considers have uncovered cross-modal intelligent between auditory, visual, and somatosensory brain districts amid music tuning in, showing as synesthetic wonders such as seeing colors or feeling material sensations in reaction to music (Janata, 2009). Understanding the neural premise of synesthesia sheds light on the multisensory nature of music recognition and its suggestions for aesthetic expression and tactile preparing. Clinical Applications and Helpful Mediations will help for restorative potential of music for different neurological and psychiatric conditions has earned significant consideration in later a long time (Gupta et al., 2025). EEG-based ponders have given profitable bits of knowledge into the viability of music treatment for conditions such as Alzheimer's illness, extreme introverted range clutter, sadness, and constant torment (Schaefer & Vlek, 2019). By illustrating the neurophysiological components basic music-induced neuroplasticity and passionate control, EEG inquire about clears the way for personalized music mediations custom-made to person persistent needs (Altenmüller et al., 2009). Future Bearings and Challenges could lead EEG has essentially progressed our understanding of the neural relates of music recognition and cognition, a few challenges stay (Müller & Lindenberger, 2011). Methodological confinements, such as spatial determination and flag defilement from antiques, posture limitations on the elucidation of EEG information. Future inquires about the endeavor which is to overcome these restrictions through inventive exploratory plans, multimodal imaging approaches, and progressed flag handling methods. By addressing these challenges, we can further unravel the complex interplay between music and the brain, unlocking new avenues for therapeutic innovation and cognitive enhancement. And talking parallel to music tempo there is a study that investigated how different music tempos impact the flow state during brisk walking, using both subjective and objective measurements. Subjective evaluations revealed that both fast and slow tempo music facilitated movement flow, with no significant difference between the two tempos. This aligns with earlier research suggesting music enhances exercise efficiency and emotional control. However, the study found that tempo did not significantly influence the stimulation of movement flow, contrasting with past findings that medium-to-fast tempo music is preferred for moderate exercise and that slow music may decrease arousal.

Objective EEG measurements, on the other hand, showed that fast tempo music significantly increased mean power values across all brainwave bands (delta, theta, alpha, and beta), indicating a stronger enhancement of cognitive engagement and immersion. This suggests that fast tempo music better stimulates movement flow and cognitive engagement compared to slow tempo music. The disparity between subjective and objective discoveries highlights the distinction between post-exercise assessments and real-time encounters, concluding that quick rhythm music is more viable in fortifying development stream amid work out (Murgia et al., 2016).

IX. Conclusion

The investigation of music's impact on the brain through EEG signals has divulged a wealthy embroidered artwork of neural reactions and cognitive marvels. Through a blend of different ponders, it is clear that music evokes a bunch of neural actuations over different brain districts, reflecting its significant effect on cognitive preparing and enthusiastic encounters (Pasiali & LaGasse, 2018). The transient elements captured by EEG have illustrated the perplexing interaction between cadenced structures in music and neural motions, highlighting the entrainment of brain movement to melodic beats (Hjorth, 1970). Such synchronization underscores the natural association between music discernment and engine coordination, advertising experiences into the restorative potential of musical intercessions for engine recovery and cognitive improvement. Moreover, the balance of neural motions by music underscores its part in attentional instruments and cognitive control (Koelsch, 2014). The enthusiastic reverberation of music is reflected in particular EEG marks, explaining the neural substrates basic full of feeling reactions to music (Huang et al., 2025). From the tweak of alpha asymmetry in passionate handling to the synchronization of neural motions with melodic elements, EEG discoveries give a window into the neural components intervening music-induced feelings, advertising roads for personalized music intercessions in passionate direction and disposition tweak (Thaut & Hoemberg, 2014). The restorative suggestions of music on brain work are underscored by EEG prove uncovering its viability in reducing stretch, uneasiness, and depressive side effects (Grahn & Brett, 2007). From the weakening of cortisol levels to the tweak of frontal alpha asymmetry, music-based mediations hold guarantee for upgrading passionate well-being and mental wellbeing results, complementing conventional restorative approaches (Münte et al., 2002). The consolidation of EEG strategies in investigating the effect of music on the brain has essentially upgraded our comprehension of the neural components included in music discernment, cognition, and passionate preparing, with far-reaching suggestions for restorative employments in clinical, instructive, and recovery settings (Zhang et al., 2024).

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