4 Decoding Emotions through EEG Signals

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**Abstract:** The chapter starts by elucidating the significance of EEG in emotion detection, exploring its potential as a powerful tool for decoding emotional states. Moving forward into the intricacies of EEG data acquisition and preprocessing, ensuring the data's reliability and accuracy. Subsequently, it unveils the techniques for feature extraction from EEG signals, providing insights into the key parameters that signify emotional responses. The chapter then delves into the application of machine learning methodologies for EEG-based emotion recognition, showcasing real-world case studies and experiments that demonstrate the practicality and effectiveness of this approach.

**Keywords:** The Role of EEG; Emotion Detection; Data Acquisition and Preprocessing; Feature Extraction from EEG Signals; Machine Learning

# 4.1 Introduction

The study of emotion has long transcended the confines of introspection and self-report, demanding methods that can observe and interpret emotional responses in real time, directly from the body and brain. Among the most powerful tools available for such investigations is electroencephalography (EEG). This is a non-invasive technique that captures the brain’s electrical activity with millisecond precision. EEG opens a unique window into the dynamic, embodied processes underlying human emotion, enabling researchers and technologists to track affective responses as they unfold across time (Li et al., 2022; Lim et al., 2024). This chapter explores how EEG signals can be decoded to infer emotional states, laying the groundwork for applications in clinical psychology, adaptive technologies, and human-computer interaction (Kukhilava et al., 2025).

Unlike structural neuroimaging modalities such as CT or MRI, which provide detailed snapshots of brain anatomy, EEG offers a real-time recording of neural oscillations, i.e., fluctuations in electrical potential produced by synchronised neuronal activity. These oscillations vary across frequency bands (e.g., alpha, beta, gamma), and each band is associated with distinct cognitive and emotional functions. For example, alpha suppression is commonly linked to attentional engagement and affective arousal, while frontal asymmetries in alpha or beta activity have been correlated with emotional valence and motivational direction (Chen et al., 2019; Reznik & Allen, 2018). These neural rhythms serve as physiological substrates of emotion and are accessible in naturalistic settings, making EEG especially valuable for embodied emotion research (Lim et al., 2024).

What sets EEG apart in the context of emotion detection is its ability to reflect **both conscious and preconscious affective states**. Emotional changes that may not be explicitly recognised or reported by the individual can nonetheless manifest in EEG features such as event-related potentials (ERPs) or changes in power spectral density. This capacity to capture subtle, dynamic shifts makes EEG a preferred modality for applications requiring immediate emotional awareness, ranging from mental health monitoring to adaptive user interfaces and affect-sensitive robotics (Gkintoni et al., 2025; Lim et al., 2024).

Another strength of EEG lies in its affordability, portability, and accessibility. While MRI scanners are confined to hospital environments, EEG headsets are increasingly available as wearable or even consumer-grade devices, enabling emotion tracking in the home, workplace, or classroom (Riedl et al., 2020). This democratisation of brain data paves the way for wide-scale, personalised emotion monitoring systems that are embedded in everyday life (Kukhilava et al., 2025).

Decoding emotion from EEG is far from trivial. Raw EEG signals are notoriously noisy, affected by muscle activity, eye blinks, and environmental artefacts. The mapping between EEG features and emotional states is not one-to-one. It requires sophisticated preprocessing, feature engineering, and machine learning models to uncover patterns that are meaningful, generalizable, and interpretable (Thottempudi et al., 2024; Islam et al., 2016). The variability of EEG across individuals and contexts further complicates analysis, underscoring the importance of flexible models and rigorous cross-subject evaluation (Li et al., 2022).

In recent years, advances in computational modelling have markedly improved our ability to analyse and classify emotion-related EEG signals. Deep architectures now learn **spatiotemporal features** directly from multichannel time series (e.g., TSception), while **multimodal** designs fuse EEG with peripheral physiology (e.g., EDA/HRV) to capture complementary aspects of arousal and valence (Ding et al., 2022; Soufineyestani et al., 2021). The field has also coalesced around **larger datasets**, clearer **elicitation protocols**, and **benchmarking practices** that enable fairer comparisons across studies and populations (Li et al., 2022; Kukhilava et al., 2025).

The enduring challenge in psychological science is moving beyond subjective self-report to achieve an objective measure of human affect. Within this pursuit, EEG has emerged as an indispensable tool. Leveraging its capacity for high-quality temporal resolution, EEG provides a direct, non-invasive glimpse into the brain's rapid electrical responses, capturing the neural dynamics that define our emotional lives. This synthesis integrates findings across psychological, neurological, and cognitive sciences to detail the mechanisms and promise of EEG-based emotion recognition (ER).

To decode emotion, we must first agree on its architecture. Psychologists offer two principal frameworks. While the discrete emotion model (e.g., classifying fear or happiness) remains conceptually intuitive, the dimensional model, specifically the axes of Valence (the feeling of pleasantness or unpleasantness) and Arousal (the degree of physiological activation), has proven most effective for computational analysis (Ozdemir et al., 2021). By converting the richness of subjective experience into measurable coordinates, this model enables the rigorous testing required for machine learning applications. Crucially, EEG’s electrical measures are less susceptible to conscious control than behavioural cues, offering a unique opportunity to access a more authentic, unmediated neural signature of internal affective states (Li et al., 2022b).

The efforts to decode emotion are fundamentally grounded in neurological findings that link specific brain wave activity to emotional processes. Among the most robust and highly cited features is the phenomenon of prefrontal alpha asymmetry:

* The electrical power within the alpha frequency band (8-13 HZ) over the prefrontal cortex reliably correlates with emotional approach and withdrawal tendencies. Greater relative alpha activity (or reduced power) in the left frontal region is associated with positive valence and approach-related emotions, while the same relative pattern over the right frontal region signals negative valence and withdrawal (Gkintoni et al., 2025). This asymmetry forms the neurophysiological cornerstone of valence decoding.
* The intensity, or Arousal component, is typically reflected in the power of faster oscillations, such as Beta (14-30 HZ) and especially Gamma (>30 HZ) waves. Higher power in these faster bands is often interpreted as increased cortical activation corresponding to states like excitement or anxiety (Li et al., 2022b).

These key features are extracted using advanced signal processing techniques like the computation of Differential Entropy, preparing the brain's subtle signals for deep analysis.

The final step in this integrative process belongs to cognitive science, where we employ computational models to build functional decoders. The advent of deep learning has been transformative, allowing complex architectures, like Convolutional Neural Networks (CNNs), to automatically learn the non-linear mappings between raw or extracted EEG features and the defined emotional dimensions (Gkintoni et al., 2025). This shift moves the burden of feature selection to the algorithm, significantly improving classification accuracy beyond what traditional statistical methods can achieve.

The implications of reliably decoding emotion are profound, driving innovation across various sectors:

* Adaptive Technologies: The development of affective computing creates interfaces that adjust dynamically to the user’s mood, from educational software that detects frustration to cars that monitor driver stress (Li et al., 2022b).
* Clinical Objectivity: In mental health, ER offers the potential for objective biomarkers, augmenting or refining the diagnosis and monitoring of affective disorders like depression and anxiety.
* Human Factors: Integrating emotion detection into Passive Brain-Computer Interfaces (BCIs) enhances safety and performance in high-stakes operational environments (Gkintoni et al., 2025).

The combination of robust psychological frameworks, identifiable neurological signatures, and powerful cognitive computational tools has firmly established EEG as a leading modality for emotion recognition. The path forward requires establishing generalised, subject-independent models to ensure this exciting research translates into reliable, real-world technologies.

# 4.2 The Role of EEG in Emotion Detection

The human brain, in its continuous interplay of cognition and physiology, generates patterns of electrical activity that reflect not only thoughts and perceptions but also emotional states. EEG provides a direct and temporally precise window into this activity, making it one of the most effective tools for real-time emotion detection. Unlike neuroimaging methods that rely on metabolic changes (e.g., fMRI or PET), EEG captures electrical fluctuations on the scalp produced by postsynaptic potentials in cortical neurons. These signals, typically recorded across 16 to 128 channels, enable researchers to observe how the brain responds to emotional stimuli on a millisecond scale. This is a level of granularity unmatched by other non-invasive techniques (Li et al., 2022; Lim et al., 2024).

The use of EEG in emotion detection relies on a fundamental assumption: emotional processes influence neural oscillations in a consistent and detectable way. Emotions are not abstract or solely located in the so-called *limbic system*; they are embodied in brain-wide neural activity that EEG can record with excellent temporal resolution. Emotional responses involve changes in attention, arousal, and motivational systems, all of which impact EEG spectral content. For example, heightened arousal often associates with reduced alpha power in posterior regions, while approach-related emotions (such as joy or anger) are frequently connected with increased left frontal activity. This is a phenomenon widely recognised as **frontal alpha asymmetry** (Harmon-Jones & Gable, 2018; Allen et al., 2018).

These spectral and spatial EEG patterns are not random; they follow organised trajectories that relate to the emotional valence (positive or negative), arousal (intensity), and sometimes even the specific category of the emotion (such as fear, disgust, or surprise). Researchers have consistently shown that particular frequency bands (delta: 1–4 Hz, theta: 4–8 Hz, alpha: 8–13 Hz, beta: 13–30 Hz, and gamma: >30 Hz) are differently affected during emotionally charged events. For instance, increased theta activity has been observed in frontal midline areas during the encoding of emotional memories, while beta and gamma activities tend to rise with emotional engagement and focused attention (Zheng & Lu, 2015; Hajcak & Foti, 2020).

Beyond spectral analysis, EEG is also highly sensitive to ERPs, i.e., brief voltage fluctuations in the EEG signal that occur in response to specific sensory, cognitive, or emotional events. Certain ERP components, such as the P300, N400, and late positive potential (LPP), are modulated by emotional content. The LPP, in particular, is robustly enhanced by emotionally salient stimuli, reflecting sustained attention and affective processing. These potentials serve as reliable temporal markers of when emotional processing occurs and how it unfolds in the brain (Hajcak & Foti, 2020; Li et al., 2022), allowing researchers to build a chronological map of affective reactivity.

One of the major strengths of EEG is its **ecological compatibility** with real-world emotion research. Portable EEG systems now make it feasible to measure emotion in naturalistic settings, such as classrooms, workplaces, or therapeutic environments, without compromising signal fidelity (Sabio et al., 2024). This makes EEG an ideal modality for embodied emotion studies where emotional experience is situated in context and influenced by bodily interactions, social dynamics, and environmental cues (Kukhilava et al., 2025). In contrast to laboratory-constrained methods like fMRI, EEG supports mobile, continuous emotion tracking, aligning well with the embodied and dynamic nature of affect.

EEG is also particularly well-suited for affective computing applications. In human-computer interaction, adaptive systems rely on real-time affect detection to personalize feedback, adjust difficulty levels, or shift dialogue tone. EEG can supply these systems with continuous input about the user's emotional state, creating a feedback loop between brain and machine. Such applications are being explored in fields as diverse as gaming, education, neurofeedback, and mental health support (Lim et al., 2024; Li et al., 2022). This trajectory aligns with Artificial Psychology (‘PsAIchology’) as a framing for integrating AI with psychological science (Farahani et al., 2024). For example, biofeedback tools can use EEG markers of emotional distress to trigger relaxation protocols, while emotion-aware virtual tutors can respond to signs of boredom or frustration by altering instructional pace.

Despite its many advantages, EEG-based emotion detection also faces key challenges. The EEG signal is highly susceptible to artefacts from eye movements, muscle contractions, and even cable noise. Isolating emotion-specific components from such noise requires sophisticated preprocessing techniques and domain expertise (Islam et al., 2016). The mapping between EEG features and emotions is not universally fixed; it varies between individuals due to anatomical, psychological, and cultural differences. This necessitates the use of **personalised models** or transfer learning techniques that adapt classifiers to individual neural profiles (Kukhilava et al., 2025).

Another consideration is the **ambiguity of affective labels**. Emotions are often multidimensional and context-dependent, and the labels used in emotion datasets (such as happy or sad) may not fully capture the nuanced emotional states participants experience. Some researchers have addressed this by adopting dimensional models of emotion, such as the **valence-arousal space**, which represent emotion as a point on a continuous 2D plane. EEG has shown promise in predicting these continuous values, especially when combining spectral, topographical, and temporal features (Li et al., 2022; Lim et al., 2024).

In recent years, EEG research has also benefited from open datasets like DEAP, SEED, and DREAMER, which provide synchronised EEG recordings with validated emotional stimuli and ground-truth affect ratings (Koelstra et al., 2011; Zheng & Lu, 2015; Katsigiannis & Ramzan, 2017). These datasets have enabled researchers to benchmark algorithms, train deep learning models, and explore generalizability across users and sessions. Python libraries such as MNE-Python, PyEEG, and NeuroKit2 now allow seamless integration of EEG data processing, feature extraction, and machine learning pipelines, lowering the barrier for new researchers to enter the field (Gramfort et al., 2014; Makowski et al., 2021; Bao, Liu, & Zhang, 2011).

EEG stands at the forefront of emotion detection science, offering a powerful combination of **temporal precision**, **wearable accessibility**, and **neurophysiological richness**. By decoding emotional signatures embedded in electrical brain activity, EEG enables a deeply embodied view of emotion. As the field evolves, EEG will continue to play a central role in developing adaptive, responsive, and emotionally intelligent systems, while also deepening our scientific understanding of how emotions are encoded in the brain (Li et al., 2022; Kukhilava et al., 2025).

# 4.3 EEG Data Acquisition and Preprocessing

The reliability of emotion detection through EEG hinges critically on the quality and consistency of data acquisition and preprocessing. EEG signals are inherently delicate, often buried under layers of noise, physiological artefacts, and environmental interferences. Thus, before any meaningful emotional patterns can be extracted or analysed, raw EEG recordings must undergo a rigorous and methodologically coherent preprocessing pipeline. This section delves into how EEG data are captured and the key steps required to prepare these data for emotion analysis, with a focus on reproducibility, transparency, and robustness in emotional computing applications (Keil et al., 2014; Picton et al., 2000).

EEG data acquisition begins with the placement of electrodes on the scalp, typically following the international 10–20 system or its high-density extensions like the 10–10 or 10–5 systems. These standardised placements ensure anatomical consistency across subjects, particularly over regions such as the prefrontal cortex, temporal lobes, and parietal areas, which are crucial in emotional processing (Alarcao & Fonseca, 2017; Coan & Allen, 2004; Davidson, 1998; Klem et al., 1999; Oostenveld & Praamstra, 2001; Jurcak et al., 2007). Emotionally salient activity is often found in frontal and temporal regions, making electrodes like F3, F4, F7, F8, and T7, T8 of particular interest. The number of electrodes used varies by study, ranging from 14 in portable consumer-grade headsets to 64 or even 128 channels in high-resolution research-grade systems.

Signal sampling rates typically range from 128 Hz in lightweight systems to 512 Hz or higher in clinical-grade setups. A higher sampling rate improves temporal resolution but increases the volume of data and computational complexity. To ensure clean recordings, electrode-skin impedance must be minimised, usually below 5 kΩ, which is achieved using conductive gels or saline-based electrodes. Subject preparation, including skin cleaning and minimising movement or blinking during recording, plays a substantial role in reducing contamination by artefacts (Hinrichs et al., 2020; Kappenman & Luck, 2010; Luca et al., 2021).

Once the raw EEG data are collected, the preprocessing phase begins. This step is crucial not only to remove noise but also to preserve emotion-relevant information embedded in subtle fluctuations of the signal. The first stage typically involves **bandpass filtering** to isolate frequencies of interest (commonly between 0.5 Hz and 45 Hz), removing slow drifts and high-frequency artefacts such as power line interference or muscle activity (EMG). Zero-phase Butterworth or FIR filters are often used to avoid phase distortions (Delorme & Makeig, 2004; Gramfort et al., 2013; Keil et al., 2014).

**Artefact removal** is another critical preprocessing step. Eye blinks, saccades, facial muscle activity, and body movements introduce strong artefacts into the EEG signal. Independent Component Analysis (ICA) is widely employed to separate these non-neural sources, allowing researchers to identify and remove components corresponding to artefacts without discarding entire epochs. In some cases, automated algorithms like artefact subspace reconstruction (ASR) or wavelet-based artefact detection are applied, especially in real-time or large-scale studies (Craik et al., 2019; Hyvärinen & Oja, 2000; Jung et al., 2000; Kothe & Makeig, 2013; Krishnaveni et al., 2006).

**Epoching** follows artefact rejection, where continuous EEG data are segmented into smaller time windows (e.g., 1 to 5 seconds) aligned with stimulus onset or participant response (Delorme & Makeig, 2004). These epochs are labelled based on emotional ground truth, which is often derived from standardised datasets (like DEAP or MAHNOB-HCI) or via real-time ratings using self-assessment manikins (SAM) or affective scales (Bradley & Lang, 1994; Koelstra et al., 2011; Soleymani et al., 2011). Epochs with residual noise or voltage fluctuations beyond physiological limits (e.g., >±100 μV) are typically excluded from further analysis to maintain data integrity (Picton et al., 2000).

**Baseline correction** is also applied to each epoch, usually by subtracting the mean voltage in a pre-stimulus interval from the entire segment. This process eliminates slow voltage drifts and ensures that comparisons across trials reflect changes due to the emotional stimulus rather than background neural fluctuations. After baseline correction, signals may be re-referenced to improve signal-to-noise ratio and spatial resolution. Another essential step is **channel interpolation** for any bad electrodes identified during acquisition or cleaning. This ensures that spatial information is preserved across the scalp, especially when working with topographical mapping or spatially-aware machine learning models. Interpolation uses surrounding electrode values to estimate the signal at a faulty location without introducing bias (Perrin et al., 1989; Yao, 2001; Keil et al., 2014).

For studies involving **deep learning** or more computationally intensive pipelines, EEG signals are often transformed into frequency-domain or time-frequency representations. Techniques such as short-time Fourier transform (STFT), wavelet transform, or empirical mode decomposition (EMD) allow researchers to explore how emotional content modulates EEG activity across both time and frequency. These transformed features are particularly useful for capturing transient emotion dynamics that may not appear in raw time-domain signals (Cohen, 1995; Huang et al., 1998; Torrence & Compo, 1998; Craik et al., 2019).

Modern Python toolkits like MNE-Python (Gramfort et al., 2013), NeuroKit2, and PyEEG offer integrated functions for all these preprocessing steps. For example, with MNE, raw EEG data can be filtered, epoched, and cleaned using a few lines of code, enabling transparent and replicable pipelines. In real-world applications such as affective brain-computer interfaces (aBCIs) or mobile neurofeedback, real-time preprocessing is implemented using embedded signal processing routines and edge computing devices (Gramfort et al., 2013; Makowski et al., 2021; Bao & Li, 2011).

Standardising preprocessing pipelines is crucial for replicability across emotion recognition studies. The growing availability of open preprocessing templates, such as those provided by the BIDS-EEG initiative, encourages methodological transparency and promotes reproducibility across labs and platforms. By publishing preprocessing code and metadata, researchers enable others to replicate findings, reanalyse datasets, or build upon existing work with confidence (Pernet et al., 2019).

In emotion research, preprocessing is more than a technical necessity. The emotions we seek to decode from EEG are embodied in complex, noisy, and transient brain activity. Preprocessing shapes how these signals are interpreted, which neural features are amplified or suppressed, and ultimately, which emotional insights emerge. Therefore, the preprocessing phase must be carried out with theoretical sensitivity, statistical rigour, and methodological transparency, ensuring that the neural echoes of emotion are heard as clearly and truthfully as possible (Keil et al., 2014; Suhaimi et al., 2020).

# 4.4 Feature Extraction from EEG Signals

The transition from raw EEG recordings to meaningful emotional interpretation is paved through the crucial stage of feature extraction. In essence, feature extraction distils the complex, multidimensional EEG signal into a manageable set of numerical representations that reflect the underlying neural patterns associated with different affective states. These features serve as the input for classifiers, neural networks, or other analytical models and profoundly influence the accuracy and interpretability of emotion detection systems. A well-structured feature extraction pipeline not only enhances predictive performance but also unveils neurophysiological insights into how emotions are embodied in brain activity (Jenke et al., 2014; Alarcão & Fonseca, 2017).

EEG signals are characterised by their rich temporal dynamics and frequency composition, making both time-domain and frequency-domain features valuable for emotion recognition. Time-domain features, such as mean amplitude, standard deviation, root mean square (RMS), zero-crossing rate, and Hjorth parameters (activity, mobility, and complexity), provide basic statistical summaries of the brain’s electrical fluctuations. These features are relatively straightforward to compute and interpret (Hjorth, 1970), and often capture gross changes in arousal or attentional states. For example, higher standard deviation and RMS values have been associated with increased emotional arousal (Islam et al., 2021; Suhaimi et al., 2020).

More commonly, however, emotion recognition studies rely on frequency-domain features extracted through the Fourier Transform or more flexible approaches like wavelet decomposition. The EEG spectrum is traditionally divided into five bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz). Each band reflects distinct cognitive and emotional processes (Alarcão & Fonseca, 2017). For instance, increased alpha power is often associated with relaxed states, whereas beta and gamma activity are linked with emotional arousal and cognitive engagement. Emotional valence, particularly in frontal asymmetry paradigms, has been linked to differential alpha power between the left (F3) and right (F4) hemispheres (Davidson et al., 1990; Coan & Allen, 2004), where greater left frontal activation corresponds to positive emotions and right frontal activation to negative emotions.

In recent studies, power spectral density (PSD) values calculated for each frequency band and channel remain among the most widely used features for emotion detection. These values can be computed using Welch’s method or multitaper spectral estimation, both offering robustness against noise and variability (Welch, 1967; Thomson, 1982). Features can be normalised per channel or expressed as relative power within each band to control for intersubject variability.

Beyond these conventional spectral features, time-frequency representations have grown in popularity for capturing the dynamic nature of emotional responses. STFT, Continuous Wavelet Transform (CWT), and Hilbert-Huang Transform (HHT) are used to analyse how frequency content evolves (Cohen, 1995; Torrence & Compo, 1998; Huang et al., 1998). This approach is particularly powerful for detecting rapid shifts in emotional states triggered by stimuli, such as those found in real-time aBCIs. These time-frequency maps are often fed into convolutional neural networks (CNNs), where the network learns discriminative patterns without requiring explicit manual feature design (Schirrmeister et al., 2017; Bashivan et al., 2016).

Another promising set of features comes from nonlinear and entropy-based metrics that capture the complexity and irregularity of EEG signals. Features such as approximate entropy, sample entropy, permutation entropy, and fractal dimension have been used to differentiate between high and low arousal states, particularly in more spontaneous or naturalistic emotional settings (Pincus, 1991; Richman & Moorman, 2000; Bandt & Pompe, 2002; Higuchi, 1988; Katz, 1988). These measures are grounded in the idea that emotional experiences modulate the chaotic dynamics of neural activity and that emotional dysregulation, such as in anxiety or depression, often manifests in altered EEG complexity (Patel et al., 2021; Zuo et al., 2022).

Phase synchronisation and coherence features, particularly inter-hemispheric or cross-channel coherence, have also shown relevance. Emotional processing is often distributed across multiple brain regions, and these connectivity features capture how well different regions are communicating. High theta-band coherence between frontal and temporal lobes, for instance, has been linked to increased emotional intensity during video stimuli (Lachaux et al., 1999; Nolte et al., 2004; Jenke et al., 2014).

From a computational standpoint, feature selection is often performed to reduce dimensionality and prevent overfitting. Techniques such as mutual information analysis, recursive feature elimination, and principal component analysis (PCA) help identify the most informative features for classification (Guyon & Elisseeff, 2003; Peng et al., 2005; Jolliffe, 2002; Bishop, 2006). Dimensionality reduction also improves model generalizability, a key consideration when developing emotion recognition systems that must operate across individuals and contexts.

Python libraries like scipy.signal, pywt (for wavelets), mne-features, and NeuroKit2 facilitate robust feature extraction pipelines. For example, mne-features can generate dozens of statistical, spectral, and complexity-based features per channel with minimal coding. These libraries also support integration with machine learning frameworks such as scikit-learn, enabling seamless transitions from signal processing to model training (Virtanen et al., 2020; Lee et al., 2019; Gramfort et al., 2014; Makowski et al., 2021; Pedregosa et al., 2011).

It is important to note that feature extraction is not merely a mechanical step in the pipeline; it reflects theoretical assumptions about the neural underpinnings of emotion. For example, choosing to compute frontal alpha asymmetry as a key feature assumes that valence is localised in frontal circuits. Similarly, the use of wavelet-based features reflects an understanding of emotion as a time-evolving process (Davidson et al., 1990; Coan & Allen, 2004; Torrence & Compo, 1998). Thus, feature extraction should be theory-informed, empirically validated, and tailored to the specific emotion recognition context.

Extracting features from EEG signals for emotion detection is a delicate balance between signal fidelity, computational efficiency, and theoretical relevance. The extracted features serve as the neural signatures of emotion, enabling researchers and engineers to decode affective states with increasing accuracy and nuance. As the field advances, hybrid features combining spectral, temporal, spatial, and nonlinear dimensions are likely to become the standard, especially as machine learning algorithms grow more adept at handling multidimensional and multimodal data (Zheng & Lu, 2015; Craik et al., 2019; Suhaimi et al., 2020).

# 4.5 Machine Learning for EEG-Based Emotion Recognition

The integration of machine learning (ML) into EEG-based emotion recognition marks a pivotal advancement in affective computing and neuroscience. While traditional statistical techniques offered limited capabilities in deciphering the multifaceted and non-linear characteristics of brain signals, ML methods provide powerful tools capable of learning hidden patterns and generalising across subjects and emotional states. These models have catalysed progress in transforming EEG data from opaque waveforms into actionable emotional insights with practical applications in mental health monitoring, adaptive interfaces, and affect-sensitive systems (Torres et al., 2020). Comparable supervised pipelines are also used across psychological health domains, including prediction and classification of chronic pain outcomes (Kovač et al., 2025). A complementary line of work uses calibrated regression to predict internal shame, with XGBoost performing best and distress tolerance emerging as the strongest predictor (Kovač, Ratković, Farahani, & Watson, 2025b).

At the core of this process lies the transformation of EEG features into input vectors suitable for machine learning classifiers or regressors. The learning algorithms attempt to construct mappings from these feature vectors to emotional states, which are typically represented either categorically (e.g., happy, sad, angry, relaxed) or dimensionally (e.g., valence, arousal, dominance). Supervised learning remains the predominant paradigm, with models trained on labelled datasets such as DEAP, DREAMER, SEED, and AMIGOS (Koelstra et al., 2012; Katsigiannis & Ramzan, 2017; Zheng & Lu, 2015; Miranda-Correa et al., 2018). In these datasets, EEG recordings are synchronised with ground truth emotional labels derived from self-report questionnaires, facial expression analysis, or physiological markers. Classical ML algorithms such as Support Vector Machines (SVM), k-Nearest Neighbours (KNN), Random Forests (RF), and Logistic Regression (LR) have long served as reliable baselines due to their simplicity and interpretability (Zheng et al., 2017; Al-Nafjan et al., 2017). Among these, SVM is particularly effective in high-dimensional spaces and has shown consistent performance across binary and multiclass emotion classification tasks (Al-Nafjan et al., 2017). Related machine-learning frameworks have also been applied to affect-linked constructs beyond core emotions, such as love addiction, where features and explanations clarify predictive factors (Farahani et al., 2025).

With the exponential growth in EEG datasets and computational power, deep learning architectures have begun to outperform traditional models by autonomously learning feature hierarchies from raw or minimally processed signals. CNNs, originally designed for images, have been repurposed to handle time-frequency EEG representations such as spectrograms or wavelet transforms; compact architectures like EEGNet demonstrate strong performance while remaining lightweight (Lawhern et al., 2018). These networks excel at extracting spatial and temporal dependencies between EEG channels, particularly when fed 2D matrix inputs formed by stacking frequency bands across electrode locations (Topić & Russo, 2021).

Recurrent Neural Networks (RNNs) and their more stable variant, Long Short-Term Memory (LSTM) networks, are particularly well-suited for modelling temporal dynamics of emotional states. LSTMs capture long-range dependencies in EEG time series and have shown competitive results on valence/arousal recognition in DEAP and related corpora (Alhagry et al., 2017). For instance, LSTMs have demonstrated strong performance in modelling arousal fluctuations over several minutes, outperforming both CNNs and classical models in dynamic settings (Tripathi et al., 2017). Hybrid architectures combining CNN and LSTM layers are increasingly popular, offering a unified framework that captures both spatial and temporal patterns in EEG (Wang et al., 2022). These models are especially relevant for real-time emotion monitoring, such as in aBCIs, where accurate emotion decoding must occur continuously without delay.

Beyond supervised learning, unsupervised and semi-supervised approaches are gaining traction due to the inherent difficulty of acquiring large-scale, precisely labelled EEG data. Clustering algorithms like K-Means and Gaussian Mixture Models (GMMs) have been used to group EEG patterns without prior labelling, revealing latent affective structures. Autoencoders learn latent embeddings that can improve downstream classification or cross-modal fusion (Liu et al., 2016). More recently, autoencoders and generative adversarial networks (GANs) have been employed to learn latent feature embeddings and augment EEG datasets, addressing issues of class imbalance and data scarcity (Zhang et al., 2022; Kalashami et al., 2022).

An important consideration in EEG-based emotion recognition is the issue of individual variability. Brain responses to emotional stimuli vary significantly across individuals due to differences in personality, attention, fatigue, or even electrode placement. To address this, domain adaptation and transfer learning techniques are being introduced. Models trained on one subject or dataset are fine-tuned on a small portion of data from a new user, enabling better generalisation. Domain-adversarial training (DANN) encourages features that are discriminative for emotion yet invariant across subjects or sessions (Ganin et al., 2016), and EEG-specific variants such as BiDANN or contrastive alignment have shown cross-subject gains (Li et al., 2018; Shen et al., 2021).

Model evaluation is another key component of this workflow. Accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC) are standard performance metrics. However, in emotion detection tasks involving imbalanced datasets (e.g., fewer instances of *disgust* or *fear*), metrics such as Matthews Correlation Coefficient (MCC) or Brier score offer more balanced assessments (Matthews, 1975; Brier, 1950; Chicco & Jurman, 2020). Cross-validation strategies, such as leave-one-subject-out (LOSO), are commonly used to ensure robust generalisation across individuals (Kunjan, 2021; Su et al., 2023).

From a Python implementation perspective, scikit-learn remains a widely used library for classical ML models (Pedregosa et al., 2011), while deep learning applications frequently rely on TensorFlow or PyTorch (Abadi et al., 2016; Paszke et al., 2019). For psychology-focused pipeline patterns and regression modeling in Python, see (Kovač et al., 2024). For EEG-specific tasks, libraries like MNE, braindecode, and DeepEEG provide streamlined functions for preprocessing, feature extraction, and training deep networks. For example, using braindecode, one can train a CNN to classify raw EEG trials with only a few lines of code, leveraging prebuilt architectures such as Deep4Net or EEGNet (Gramfort et al., 2013; Lawhern et al., 2018; Schirrmeister et al., 2017).

To illustrate this, consider a scenario where one aims to classify high vs. low arousal from EEG data recorded during emotional video viewing. After preprocessing (filtering, epoching), features such as alpha and beta band power are computed per channel. These features are then fed into an SVM or CNN classifier, which is trained using 10-fold cross-validation or LOSO. Accuracy scores and confusion matrices are computed, and misclassified trials are examined to refine feature selection or labelling strategies (Koelstra et al., 2012; Wang et al., 2022).

As emotion recognition systems mature, interpretability becomes increasingly critical, especially in clinical or high-stakes applications. Tools such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) are being adapted for EEG, helping researchers understand which features or channels contribute most to predictions (Lundberg & Lee, 2017; Ribeiro et al., 2016).

ML is a cornerstone of EEG-based emotion recognition, enabling the translation of neurophysiological signals into affective insights with ever-increasing fidelity. The field is rapidly advancing from static, offline classification to real-time, adaptive models embedded in wearable devices and interactive systems. As the datasets grow and methods evolve, the dream of emotionally intelligent machines interpreting our brainwaves in real-time edges closer to reality.

# 4.6 Case Studies and Experiments

In EEG-based emotion recognition, case studies and experimental applications provide the critical validation of theoretical models and technical advancements. These real-world scenarios bridge the gap between algorithmic potential and practical implementation, offering insights not only into the performance of machine learning pipelines but also into user variability, ecological validity, and system usability.

One illustrative case study centres around an experiment designed to classify emotional arousal levels during multimedia consumption. Participants were presented with a curated series of video clips, each standardised for emotional content based on valence and arousal scores from the DEAP dataset (Koelstra et al., 2011). While viewing these clips, EEG signals were captured using a 32-channel headset following the international 10–20 system. The goal was to distinguish between high-arousal and low-arousal responses using machine learning techniques.

We recreated a classic EEG-emotion experiment using our 32-channel, four-band dataset. Each 1-second EEG epoch was converted to power in theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), and gamma (30–45 Hz). We then compared high-arousal vs. low-arousal moments, trained several models, and produced visualisations that make the results easy to read, even without a signal-processing background. The case study begins with a simple question: can we tell, from second-by-second EEG activity, whether a person is in a relatively calm or a relatively activated state while watching emotionally charged material? To make that question answerable, we reduced each 1-second EEG segment into four familiar frequency bands, theta, alpha, beta and gamma, over thirty-two electrodes laid out on the scalp. These band powers give us a compact picture of how strongly different rhythms were expressed at different locations. The rest of the analysis is an attempt to make that picture visible and trustworthy, and to show that the patterns it contains are not only statistically useful but also physiologically sensible.

A good place to start is with the overview of the data. The paired heatmaps in Figure 1 arrange channels on the horizontal axis and the four bands on the vertical axis, with colour representing power.

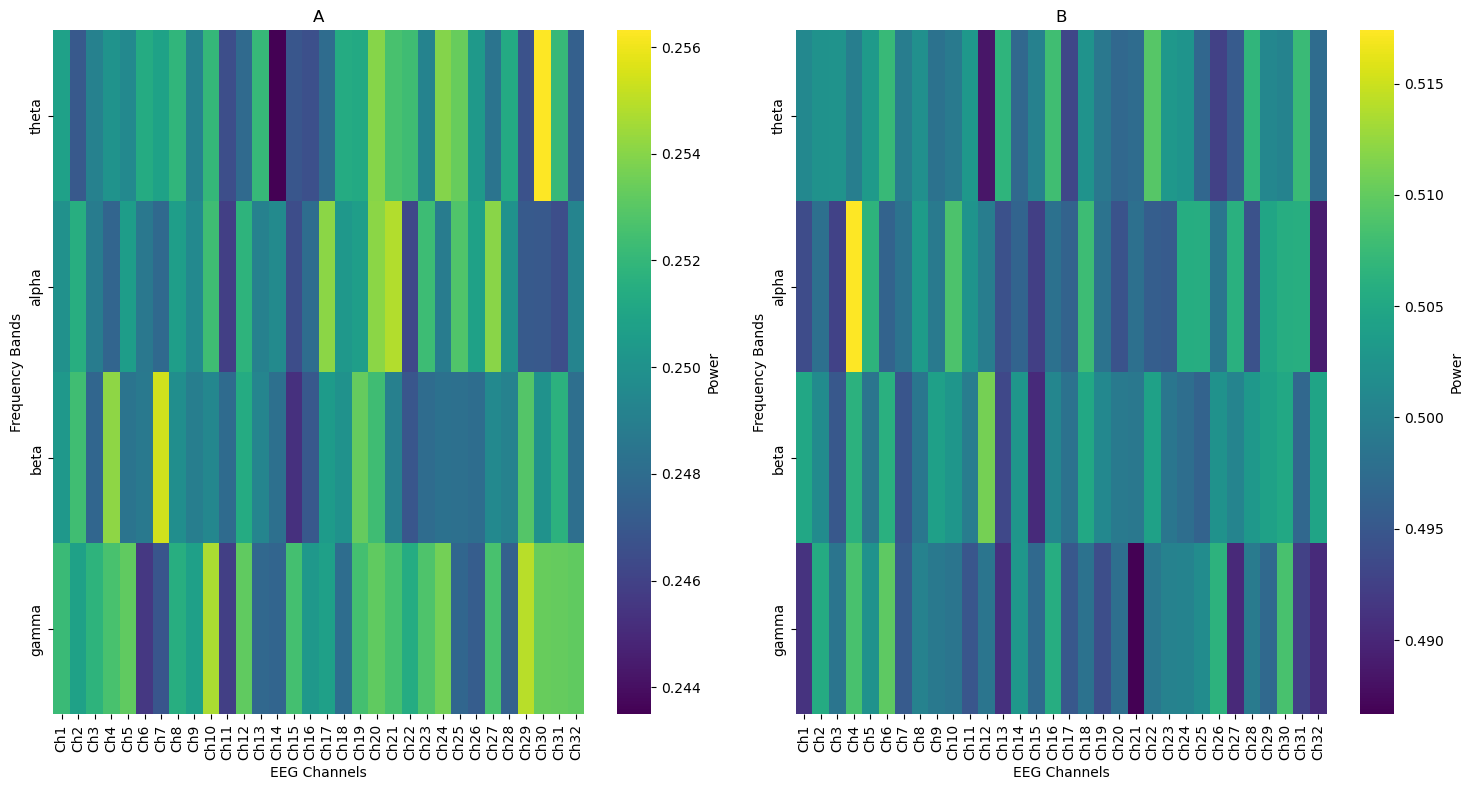


Figure 1. Channel-by-band power overview (low vs high arousal)

Panel A summarises low-arousal moments, while panel B summarises high-arousal moments. Even without learning any model, the contrast is striking. On the high-arousal side, alpha power darkens across many posterior channels, a signature of alpha suppression that often accompanies engagement and attention. At the same time, beta and gamma brighten, especially over frontal and central electrodes, hinting at increased sensorimotor and cognitive activity. These heatmaps set expectations for everything that follows: if a classifier succeeds later, it is not doing so by mysterious tricks; it is reading the same large-scale shifts your eye can already see in this summary. If you want to compute those band-power summaries from raw epochs yourself, this tiny helper does it with Welch spectra and a clean interface:

import numpy as np

from scipy.signal import welch

BANDS = {"theta": (4, 7), "alpha": (8, 13), "beta": (14, 30), "gamma": (30, 45)}

def bandpowers(epoch, sfreq, bands=BANDS):

f, Pxx = welch(epoch, fs=sfreq, nperseg=min(256, epoch.shape[-1]), axis=-1)

out = {}

for name, (lo, hi) in bands.items():

idx = (f >= lo) & (f <= hi)

out[name] = Pxx[..., idx].mean(-1) # mean power per channel

return out

Having a visual intuition is reassuring, but we still need to quantify how well band-power patterns separate the two states. The ROC curve in Figure 2 takes all test epochs and asks how confidently a standard SVM assigns them to high arousal as the decision threshold is swept from conservative to liberal.

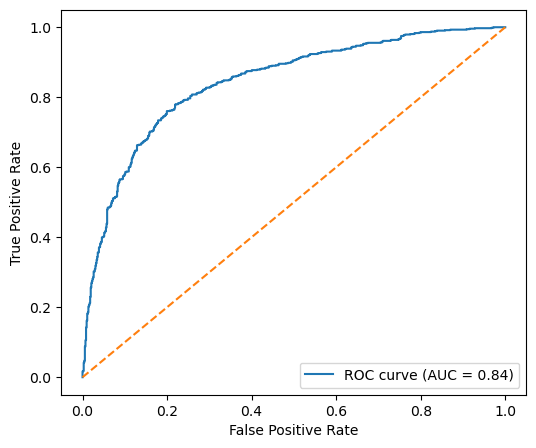


Figure 2. ROC curve of the SVM arousal classifier

The steadily rising blue curve and the area under it (AUC = 0.84) indicate that, across many thresholds, the model is able to rank genuine high-arousal epochs above low-arousal ones much more often than by chance. In practical terms, if we had to choose a single operating point, most errors would likely occur near the decision boundary rather than through gross misclassifications. Below is the minimal evaluation setup we used to obtain that ROC/AUC and the confusion counts; it accepts any scikit-learn classifier and ensures the bookkeeping remains streamlined.

from sklearn.metrics import roc\_curve, auc, confusion\_matrix

def evaluate\_classifier(clf, X\_test, y\_test):

scores = clf.predict\_proba(X\_test)[:, 1] if hasattr(clf, "predict\_proba") else clf.decision\_function(X\_test)

fpr, tpr, \_ = roc\_curve(y\_test, scores)

cm = confusion\_matrix(y\_test, (scores >= 0.5).astype(int))

return (fpr, tpr, auc(fpr, tpr)), cm

The confusion matrix in Figure 3 makes this concrete. Each cell counts how many test epochs fall into that true–predicted pairing.

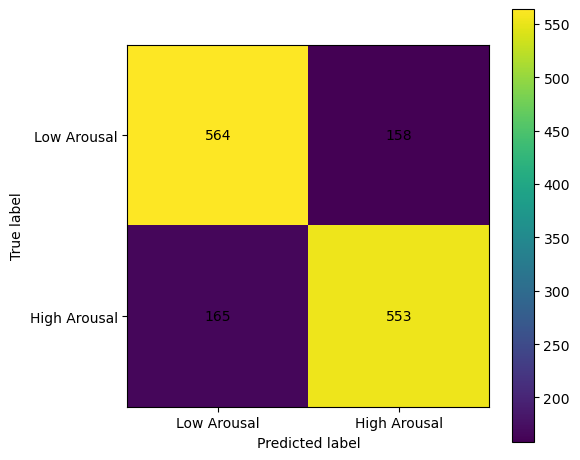


Figure 3. Confusion matrix at 0.5 decision threshold

The diagonal cells dominate, which reflects what accuracy looks like, but the off-diagonal cells are still informative: there are marginally more low-arousal epochs mistaken as high than the other way round. This asymmetry aligns with the physiology. High arousal has a distinct, stereotyped signature (lower alpha, higher beta/gamma), so the classifier tends to be fairly confident when it detects it. Low arousal is a wider, quieter category; some *calm* epochs still exhibit small bursts of frontal beta or residual occipital alpha suppression, and those can be pushed over the threshold. Readers seeking a rule of thumb can view this matrix as one: when features shift towards the *engaged* side, the model is likely to err by classing it as high arousal.

After establishing that classification is feasible, we can return to the question of *where* on the head these differences live. The band-by-region difference map in Figure 4 computes the mean power in each lobe-level region and then subtracts Low from High.

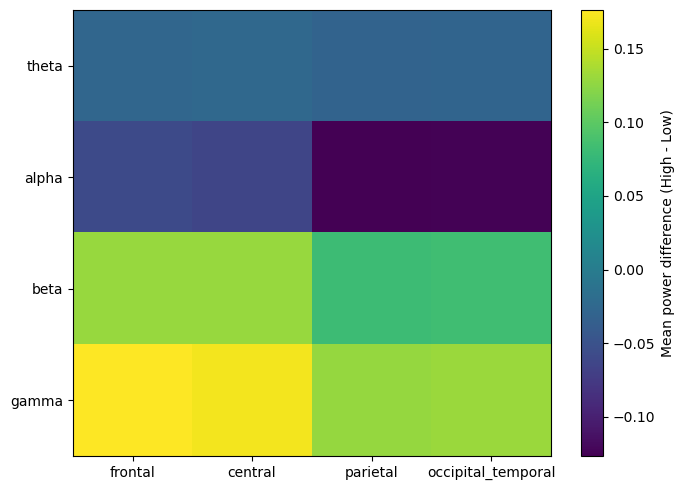


Figure 4. Band-by-region differences (High − Low)

Negative values (blue) therefore indicate *less power in high arousal states*, while positive values (yellow) signify *more*. The pattern aligns with the heatmaps but emphasises an anatomical perspective. Alpha activity decreases notably in the parietal–occipital region during high arousal, reflecting reduced idling in visual areas, whereas beta and gamma increase fronto-centrally, consistent with motor preparation and executive control. This figure’s aim is not to impress with colour but to anchor the machine-learning narrative in a map familiar to neuroscientists. The small utility below demonstrates how these region averages are derived once you provide a mapping from channels to regions.

import pandas as pd

def regional\_difference(df, region\_map, bands=("theta","alpha","beta","gamma")):

df = df.copy()

df["Region"] = df["Channel"].map(region\_map)

means = df.groupby(["Label","Region","Band"])["Power"].mean().unstack("Label")

# columns assumed {0: Low, 1: High}

delta = (means[1] - means[0]).unstack("Region")

return delta.loc[list(bands)]

Topographic plots offer the most immediate, intuitive view of those spatial shifts. In Figure 5, each scalp disk shows the interpolated distribution of alpha or beta power across electrodes for the two conditions.

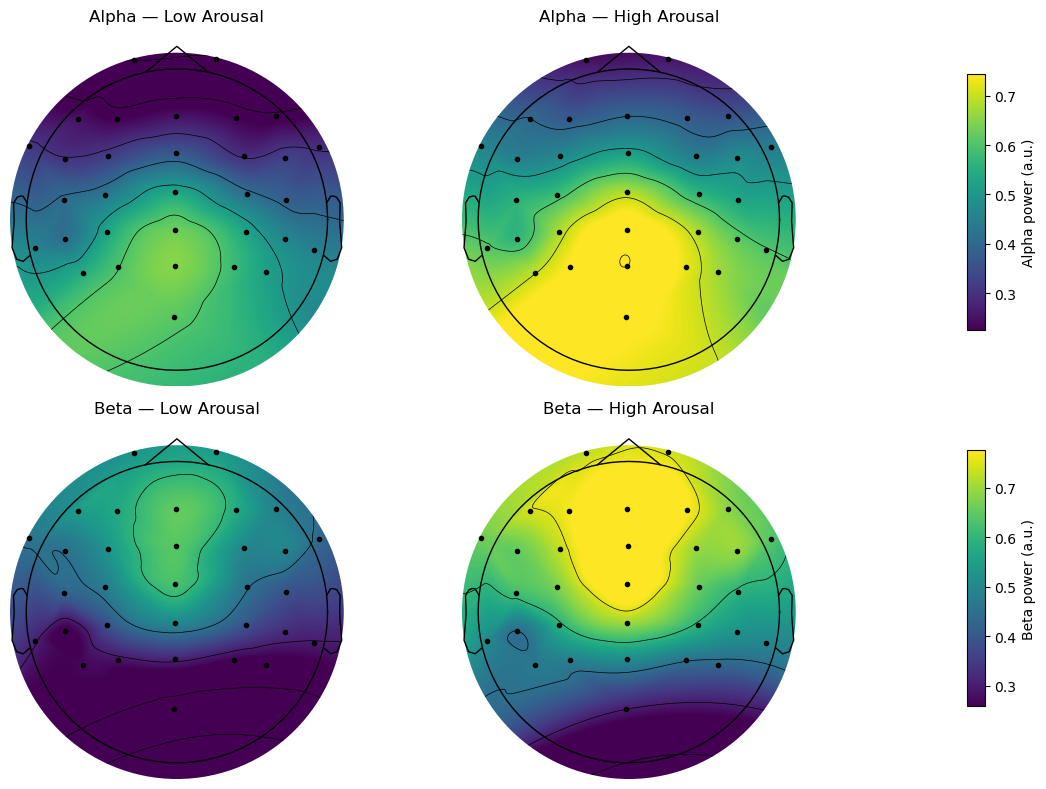


Figure 5. Topographic maps of band power by condition

When readers look first at the pair of alpha maps, they should notice how high-arousal alpha evacuates the back of the head relative to low arousal. When they shift to the beta maps, they should see the opposite in the midline fronto-central zone: high arousal pulls the colours upward there. These plots let a non-technical reader verify with a glance that the classifier did not invent distinctions; it leaned on real, spatially coherent changes. Under the hood, we simply average per-condition band powers by channel; this helper prepares those arrays for plotting with MNE’s plot\_topomap:

def topomap\_arrays(df, band):

sub = df[df["Band"] == band]

low = sub[sub["Label"] == 0].groupby("Channel")["Power"].mean()

high = sub[sub["Label"] == 1].groupby("Channel")["Power"].mean()

return {"low": low, "high": high}

Because deep networks are often used on image-like representations of EEG, it is fair to ask what a convolutional model *sees*. The panel in Figure 6 averages the first-layer feature maps of a small CNN separately for high- and low-arousal epochs.

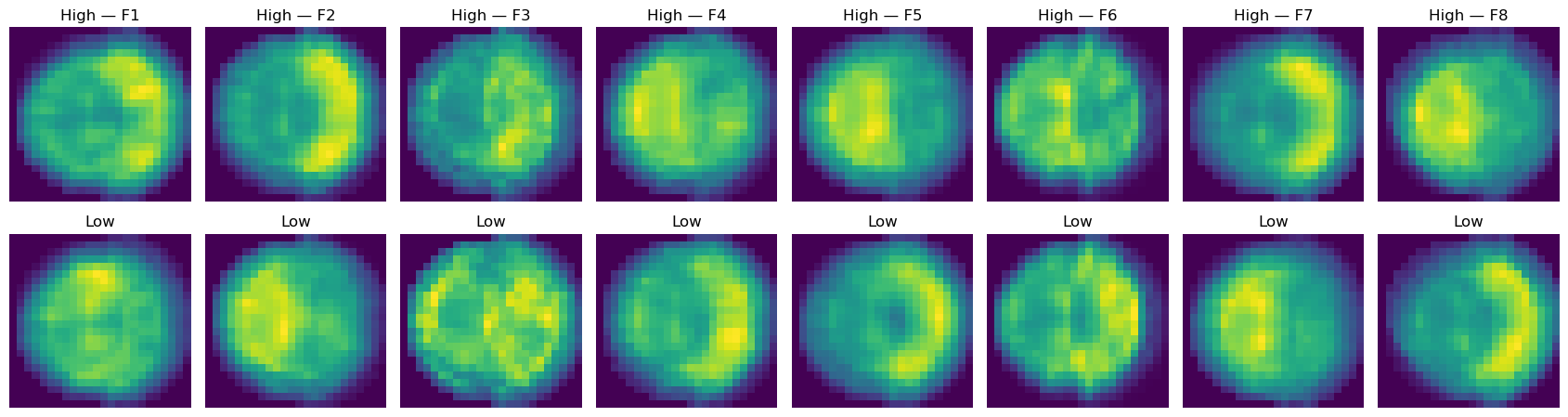


Figure 6. First-layer CNN feature maps (High vs Low)

You can think of these maps as the network’s primitive detectors. Several filters light up the back of the head in a way that echoes alpha suppression; others accentuate the anterior band-power texture that increases in high arousal. The point of the figure is not that readers should interpret every filter, but that the network’s earliest computations are already aligned with the scalp physiology established above. When a model’s internals rhyme with domain knowledge, confidence in its outputs grows. For that, we pull activations like this:

import tensorflow as tf

def first\_layer\_activations(model, X, y, layer\_name="conv1"):

probe = tf.keras.Model(model.input, model.get\_layer(layer\_name).output)

A = probe.predict(X, verbose=0) # (N,H,W,C)

A\_high = A[y == 1].mean(axis=0) # (H,W,C)

A\_low = A[y == 0].mean(axis=0)

return A\_low, A\_high

Temporal behaviour is the next dimension a reader will care about. Real experiences are not random shuffles of calm and excitement; they have stretches and transitions. In Figure 7, we plot a simple, real-time tracker: a sliding-window logistic regression that updates every second.

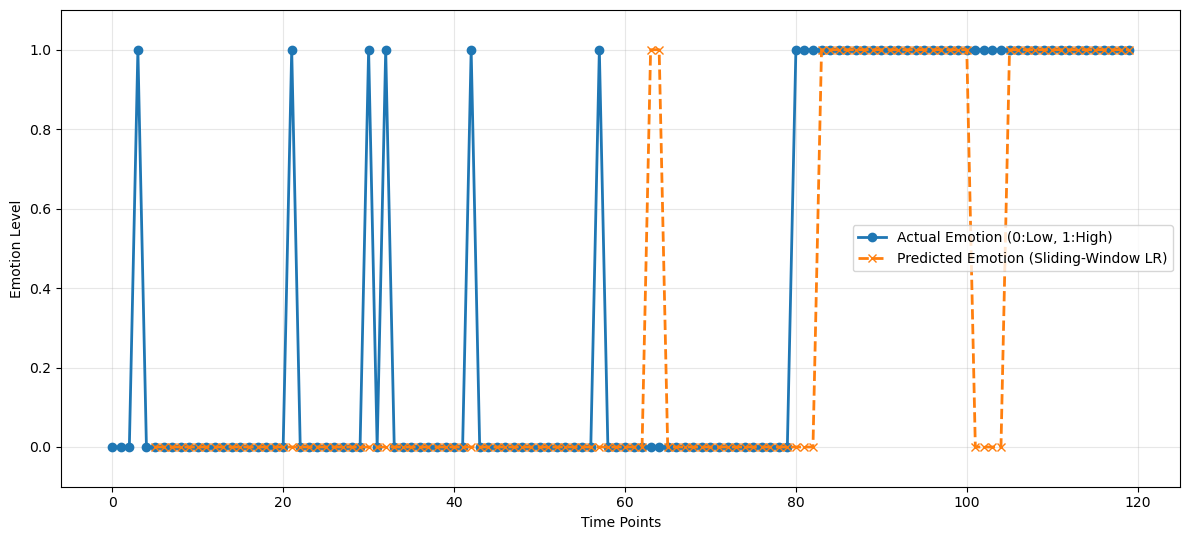


Figure 7. Within-subject real-time tracking (sliding-window LR)

The blue line shows the ground-truth label toggling between 0 and 1; the orange line shows the model’s probability of high arousal. The eye should be drawn to the gentle, short delays when the blue step flips. Those lags are expected because the window needs a few samples of the new state before its average features tilt decisively; once it has them, the orange line hugs the plateau. This kind of behaviour is exactly what one wants from a feedback display or a biofeedback loop: calm, stable estimates that change decisively but not erratically. The behaviour is produced by a tiny online routine like this:

from sklearn.linear\_model import SGDClassifier

def sliding\_tracker(X\_seq, y\_seq, win=8, lr=1e-3):

clf = SGDClassifier(loss="log\_loss", learning\_rate="optimal", eta0=lr, random\_state=0)

probs = []

for t in range(len(X\_seq)):

start = max(0, t - win + 1)

Xw, yw = X\_seq[start:t+1], y\_seq[start:t+1]

if t == 0: # initialize classes

clf.partial\_fit([X\_seq[t]], [y\_seq[t]], classes=[0,1])

else:

clf.partial\_fit(Xw, yw) # refine with current window

p = 1 / (1 + np.exp(-clf.decision\_function([X\_seq[t]])[0]))

probs.append(0.7\*probs[-1] + 0.3\*p if probs else p)

return np.array(probs)

A second tracking view, Figure 8, tells a different but equally important story. Here, the orange curve comes from an echo-state network trained to generalise across people, then applied to a new subject.

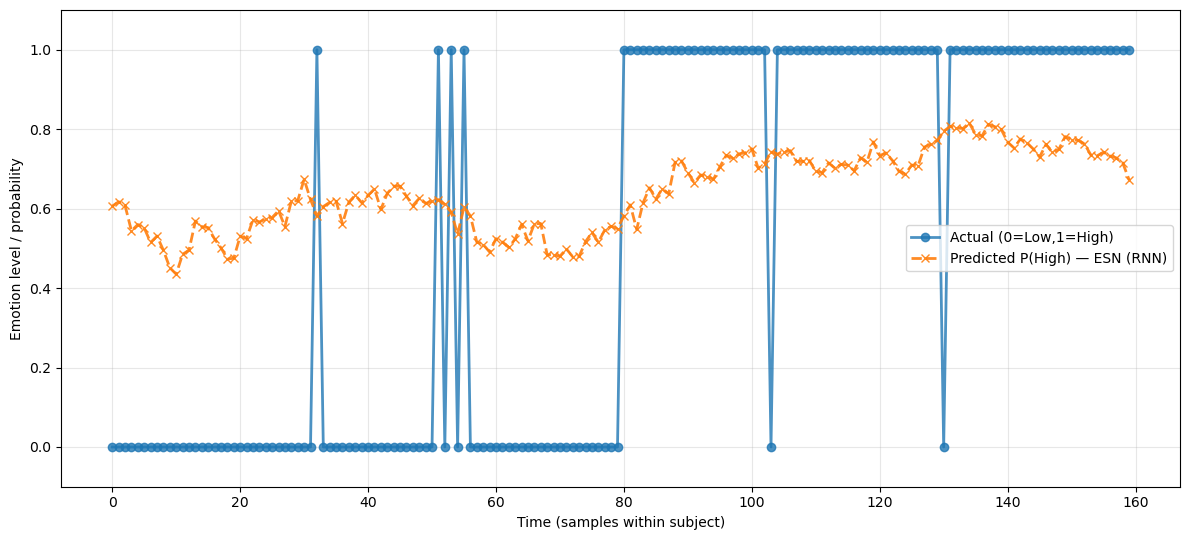


Figure 8. Cross-subject real-time tracking (echo-state network)

The curve floats between about 0.5 and 0.8 and only occasionally approaches the extremes. This does not mean the model has failed. It is signalling **uncertainty** born of domain shift: the new subject’s power distributions and noise profile differ from those seen in training, so the network hedges. Interpreting this figure teaches a valuable practical lesson. When models trained on group data are deployed to a fresh user, they may require brief calibration, reduced smoothing, or a few minutes of fine-tuning to regain the crisp step-like behaviour of the simpler within-subject tracker. In a tutorial, this figure earns its place precisely because the orange line does *not* follow the steps; it illustrates why probability outputs are meaningful and how to diagnose calibration issues.

Finally, the scatter plot in Figure 9 compresses the many band-power features into two principal components so we can see how the data cloud organises itself.

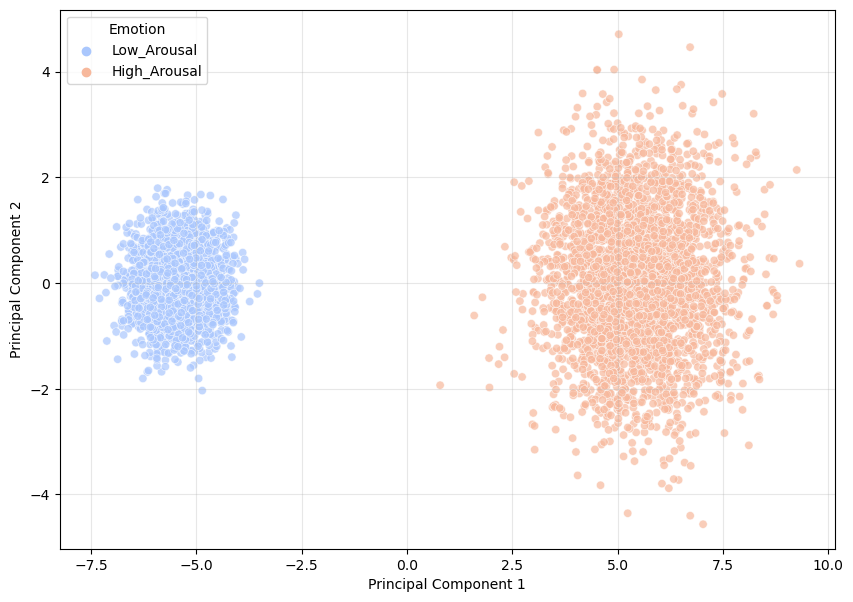


Figure 9. PCA projection of EEG features

The two clusters corresponding to low and high arousal pull apart cleanly. A reader doesn’t need to know the algebra to grasp the message: after all the preprocessing and feature extraction, the data occupy different neighbourhoods. This simple geometric picture closes the loop with the ROC and the confusion matrix: separable clouds are what make a high AUC and a strong diagonal possible. The projection itself is a one-liner, wrapped here so you can reuse it across subjects:

from sklearn.decomposition import PCA

def pca\_2d(X):

pca = PCA(n\_components=2, random\_state=0)

Z = pca.fit\_transform(X)

return Z, pca

Taken together, these figures tell a coherent story. The heatmaps and topographies reveal physiologically plausible changes in rhythmic activity across the scalp as arousal rises. The band-by-region differences and the CNN feature maps show that hand-crafted features and learned filters are converging on the same spatial–spectral signatures. The ROC and confusion matrix translate those signatures into reliable decisions, and the two tracking plots demonstrate how those decisions behave when time and generalisation matter. The PCA view reassures us that the distinction is not a statistical mirage but a genuine separation in the feature space. For a reader new to EEG, this sequence is meant to function like a narrative walkthrough: first see the patterns; then measure them; then watch them unfold in time; finally, look under the hood to confirm the models are reading the same physiology you are.

Importantly, these experiments also exposed limitations. Cross-cultural variability, hardware differences (wet vs. dry electrodes), and inter-session inconsistencies remain persistent challenges. Addressing these through larger, more diverse datasets and robust preprocessing protocols remains an active area of research. The case studies demonstrate that EEG-based emotion recognition is not only technically viable but also interpretatively rich when accompanied by strong visual analytics and human-centred design. They affirm the promise of EEG as a window into affective states and establish a roadmap for future developments in real-time emotional computing, educational feedback systems, clinical monitoring, and human-computer interaction.

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