

Advances in EEG-Based Neural Mechanism Analysis and Decoding Methods for Pain

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ABSTRACT

Objective pain assessment remains challenging, particularly in patients with limited capacity for self-report. Electroencephalography (EEG), with its high temporal resolution, non-invasiveness, and clinical accessibility, has become an important tool for investigating pain-related neural dynamics and developing objective pain decoding models. This review summarizes recent advances in EEG-based pain decoding, focusing on neural oscillatory mechanisms, signal processing strategies, and machine learning (ML) and deep learning (DL) approaches. Current evidence indicates that acute pain is mainly associated with stimulus-evoked oscillatory responses, especially gamma-band activity related to pain intensity, whereas chronic pain is characterized by altered resting-state rhythms, abnormal low-frequency activity, and reorganization of large-scale brain networks. Traditional ML methods offer interpretability and are suitable for small-sample studies but rely heavily on handcrafted features. In contrast, DL models can automatically learn complex spatiotemporal representations and generally achieve higher decoding performance, although their generalizability and interpretability remain limited. Key challenges include signal artifacts, inter-individual variability, inconsistent experimental paradigms, and a lack of standardized public datasets. Future studies should emphasize multimodal fusion, transfer learning, explainable artificial intelligence, standardized validation, and clinical translation toward real-time and personalized pain monitoring.

KEYWORDS

EEG, pain decoding, machine learning, deep learning, neural oscillations, brain-computer interface(BCI)

1 Introduction

Pain is an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage and is one of the most common clinical symptoms^[1]. Pain assessment has traditionally relied on subjective self-report measures, such as the visual analog scale (VAS) and numeric rating scale. However, these methods have clear limitations in patients with disorders of consciousness, infants, and individuals with cognitive impairment, and they cannot fully capture the dynamic neural processing of pain^[2]. Therefore, identifying neurophysiological biomarkers that objectively reflect pain perception and developing reliable models for pain recognition and quantification have become central challenges in pain neuroscience and translational medicine.

Brain-computer interface (BCI) systems establish direct communication between the brain and external devices by converting neural activity into computer-interpretable control commands or state outputs. BCI systems have shown considerable potential in motor rehabilitation, cognitive-state monitoring, and computer-aided diagnosis of mental disorders^[3].

This principle is also applicable to objective pain detection: real-time acquisition and pattern recognition of brain signals may enable automatic identification of pain presence, intensity, and potentially pain source or quality^[4]. Owing to its high temporal resolution, non-invasiveness, and cost-effectiveness, Electroencephalography (EEG) is well suited for capturing the dynamic processes of pain and is currently the most widely used signal modality in pain-related BCI research^[5].

The integration of machine learning (ML) and deep learning (DL) into EEG analysis has substantially advanced the conversion of neural signals into objective evidence for pain assessment. Pain-related information is often embedded in high-dimensional, nonlinear EEG signals with substantial inter-individual variability, making stable extraction difficult using conventional manual analysis^[6]. ML models learn data-driven patterns and generate predictions without explicit rule-based programming^[7]. To date, support vector machine (SVM), random forest (RF), and K-nearest neighbor (KNN) have shown robust performance in experimental pain classification. In contrast, DL constructs multilayer neural networks that automatically extract hierarchical representations from raw or transformed EEG signals, substantially reducing the need

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for handcrafted feature engineering. Convolutional neural network (CNN), recurrent neural network (RNN), and graph neural network (GNN), among other architectures, enable models to capture local temporal dynamics, global network topology, and cross-trial evolution in pain-related neural activity, thereby improving pain-intensity prediction and pain-type differentiation^[8].

Fig. 1 presents the classification framework for EEG-based pain decoding research. Rather than providing a simple juxtaposition of related topics, the framework follows a logical chain from theoretical foundations and decoding methods to technical challenges and future directions, reflecting the trajectory from mechanistic understanding to methodological implementation and translational development. The top-level node defines the scope of the topic. The four first-level branches correspond to core issues at different levels: the theoretical foundation layer explains why pain-related information can be represented in EEG and includes both the neural mechanisms of pain and EEG signal characteristics; the decoding method layer addresses how pain-related information is extracted and recognized through preprocessing, feature extraction, and ML/DL methods; the technical challenge layer summarizes data- and signal-level bottlenecks that limit stable generalization and clinical translation; and the future direction layer proposes research pathways aimed at clinical translation

and algorithmic innovation. The hierarchical relationships indicate inclusion, refinement, and conceptual support rather than parallel classification alone, and they also reflect a progressive relationship in which technical bottlenecks feed back to guide future research.

This review systematically examines progress in EEG-based decoding of pain states across four core dimensions. First, it summarizes the neural mechanisms of pain and the EEG-based representations that provide a theoretical basis for decoding. Second, it reviews EEG-based pain decoding studies that use ML and DL methods. Third, it compares the advantages and limitations of these methodological categories across different contexts. Finally, it discusses current technical bottlenecks and future development directions. By critically evaluating published peer-reviewed studies, this review identifies current trends, knowledge gaps, methodological challenges, and opportunities for future investigation.

The remainder of this review is organized as follows. Section 2 reviews the theoretical foundations relevant to EEG-based pain decoding. Section 3 describes the methodology used for literature retrieval and study selection. Section 4 reviews the studies on pain assessment systems. Section 5 presents the results and discussion. Section 6 discusses future research directions. Section 7 summarizes the major conclusions.

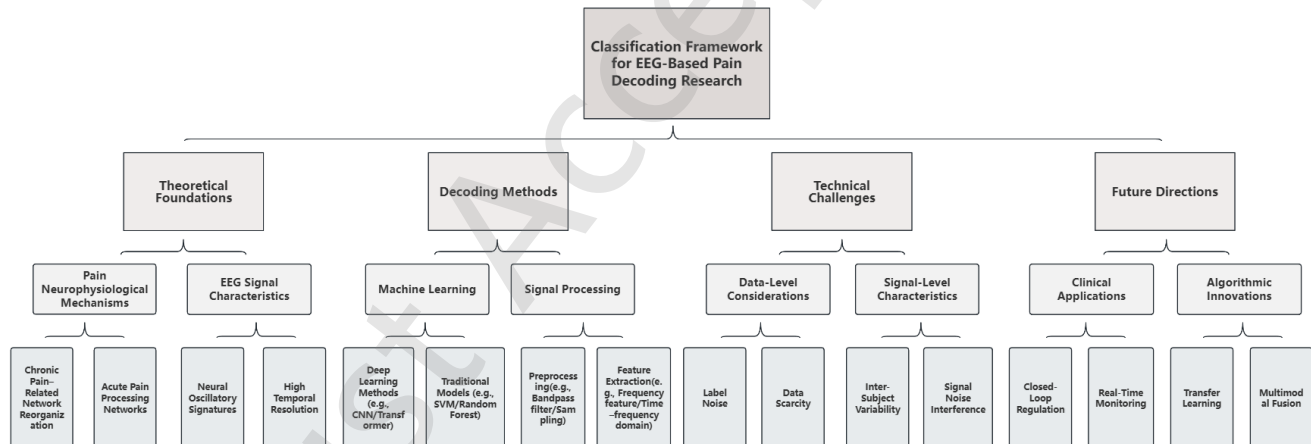


Fig. 1 Classification Framework of EEG-Based Pain Decoding Research

2 Theoretical Foundations

This section outlines the theoretical foundations of the review, focusing on BCI systems, the neural mechanisms of pain, and key EEG signal characteristics. A clear understanding of BCI systems is necessary for interpreting the goals and significance of EEG-based pain decoding. Moreover, the feasibility of pain decoding depends on both knowledge of how pain information is encoded and transmitted in the central nervous system and an understanding of EEG properties that determine which temporal and spatial patterns of neural activity can be extracted. Accordingly, this section discusses the theoretical basis of pain decoding from these three perspectives.

2.1 Overview of BCI Systems

A BCI is a system that establishes a direct communication pathway between the brain and an external device. Instead of relying on peripheral nerves and muscles, it acquires and decodes signals generated by the central nervous system and converts them into commands that can be recognized by a computer or external device^[3]. The primary goal of BCI systems is to provide an information exchange and control channel independent of conventional motor output, offering broad application prospects in medical rehabilitation, neuromodulation, and human-computer interaction.

Based on signal acquisition method and invasiveness, BCI systems can be classified into three categories^[9]. (1) Non-invasive BCI systems record neural activity from the scalp using EEG, functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG), and related modalities. These

approaches are safe, portable, and non-invasive, but they provide relatively limited spatial resolution. (2) Semi-invasive BCI systems place sensors beneath the skull, such as in the epidural or subarachnoid space, as in electrocorticography (ECoG). This approach provides a higher signal-to-noise ratio and better spatial precision than scalp EEG but requires surgical implantation. (3) Invasive BCI systems implant microelectrode arrays directly into the cerebral cortex to record single-neuron activity or local field potentials. Although this approach provides the highest signal quality, it is also the most invasive and is mainly used for neural prosthesis control in patients with severe motor impairments. In pain decoding research, EEG has become the most commonly used signal source because it is non-invasive, temporally precise, relatively inexpensive, and widely accessible^[10, 11].

Fig. 2 illustrates five consecutive signal-processing stages in a typical BCI system^[12]:

(1) Signal acquisition: EEG signals are recorded using scalp electrodes. Appropriate sampling rates and spatial montages should be selected to ensure sufficient time-frequency precision and spatial coverage for subsequent analysis.

(2) Preprocessing: The quality of raw EEG signals is enhanced through techniques such as band-pass/band-stop filtering, amplitude scaling, artifact removal, signal segmentation,

and baseline correction.

(3) Feature extraction: Quantitative indicators that characterize brain states are extracted from the preprocessed signals. Commonly used features include temporal statistics, power spectral density (PSD), time-frequency representations, non-linear dynamics, and functional connectivity. Feature quality directly constrains subsequent classification performance.

(4) Classification: Extracted feature vectors are mapped onto discrete intention or state categories. Commonly used classifiers include ML models such as SVM, RF, and KNN, as well as DL models such as CNN and Transformer.

(5) Application interface: The classification results are translated into control commands for external devices or user feedback. In the context of pain decoding, the output can be a real-time display of pain status, an alarm signal, or a trigger for closed-loop neuromodulation^[10].

These five stages constitute the fundamental framework of a BCI system. Importantly, they are tightly coupled: preprocessing quality affects the reliability of feature extraction, feature quality constrains classifier performance, and the intended application scenario determines acceptable latency and precision. In EEG-based pain decoding research, this framework has been widely adopted, and the following sections review the specific methods used at each stage.

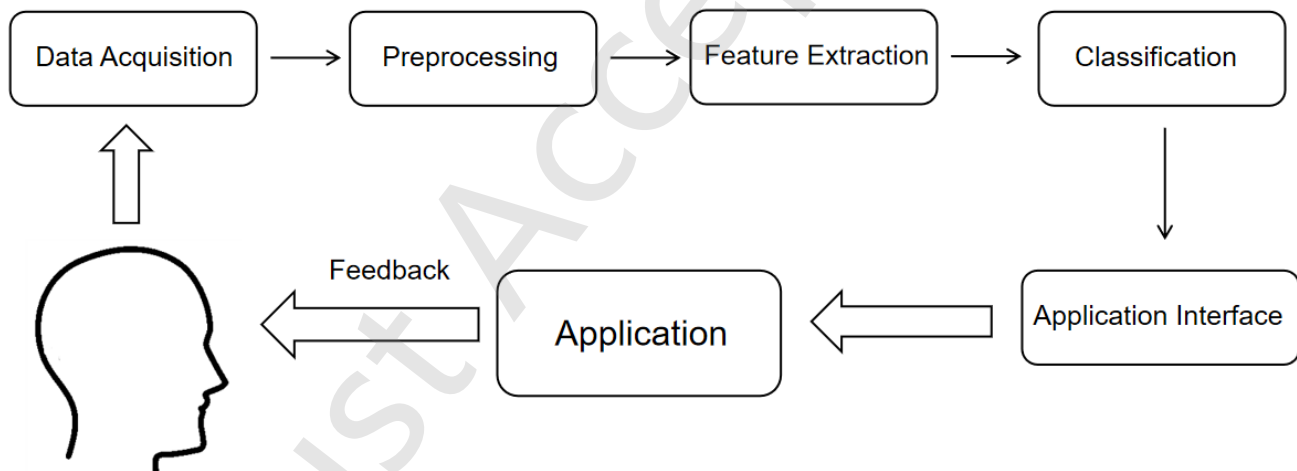


Fig. 2 Signal processing pipeline in a typical EEG-based pain decoding BCI system

2.2 Neural Mechanisms of Pain

Pain does not arise from the activity of a single brain region; rather, it is a complex experience encoded by the coordinated activity of multiple widely distributed brain areas. Based on differences in duration, etiology, and pathophysiological mechanisms, pain is commonly classified into acute pain and chronic pain, which share common pathways but also exhibit fundamentally distinct neural mechanisms.

Acute Pain

Acute pain is an immediate protective response to actual or potential tissue damage, and its neural processing follows a hierarchical transmission and integration pathway from the periphery to the central nervous system. Nociceptive signals are initiated by peripheral nociceptors (such as A δ and C

fibers), relayed through the dorsal horn, and then transmitted via ascending pathways—including the spinothalamic and spinoreticular tracts—to the thalamus, from which they project to the primary and secondary somatosensory cortices, the insula, the anterior cingulate cortex, and the prefrontal cortex, among other regions^[13]. This distributed neural network is often referred to as the “pain matrix,” with each node subserving distinct functional roles: the somatosensory cortices are primarily responsible for the sensory-discriminative dimension of pain (encoding stimulus location, intensity, and quality); the insula and anterior cingulate cortex contribute to the affective-motivational dimension and salience detection; and the prefrontal cortex mediates cognitive appraisal and top-down modulation of pain^[14].

In the temporal domain, acute pain processing is a highly dynamic multistage process. The cascade from nociceptive

signal transmission to cortical network engagement unfolds on a sub-second timescale^[15]. After reaching the cortex, nociceptive information undergoes early sensory encoding, salience detection, cognitive appraisal, and affective integration, with these stages separated by only tens to hundreds of milliseconds. Among time-locked event-related potentials (ERPs) evoked by nociceptive stimuli, the N1 component (approximately 100-150 ms) reflects early sensory processing and automatic salience detection, the N2 component (approximately 200-250 ms) is associated with orienting and resource allocation by the salience network, and the P2 component (approximately 300-400 ms) involves cognitive evaluation and contextual integration of painful stimuli^[16]. The high temporal resolution of EEG makes it possible to demonstrate that nociceptive input engages sensorimotor, cingulate-attentional, and amygdala-affective regions and that multiple networks are subsequently recruited during the transition to conscious pain perception. This phasic and coordinated multi-network pattern provides a neurophysiological basis for extracting pain-specific information from the temporal dynamics of EEG signals.

Chronic Pain

Unlike the protective function of acute pain, chronic pain typically persists beyond the normal tissue healing period (generally more than three months). It no longer serves the physiological purpose of signaling tissue damage but is instead regarded as a distinct disease state in its own right. The core mechanisms of chronic pain involve central sensitization, dysfunction of descending inhibitory systems, and reorganization at the brain network level^[17, 18].

Central sensitization refers to a persistent increase in the excitability of nociceptive pathways within the central nervous system, characterized by reduced response thresholds to stimuli, increased response amplitudes, and expanded receptive fields. This process involves molecular mechanisms such as N-methyl-D-aspartate receptor activation, glial cell activation, and pro-inflammatory cytokine release, leading to long-term potentiation of synaptic efficacy at both spinal and cortical levels^[19, 20]. At the cortical level, patients with chronic pain often exhibit reorganization of somatosensory cortical representations and changes in gray matter density in regions such as the insula and anterior cingulate cortex.

From a large-scale brain network perspective, chronic pain is closely associated with aberrant interactions among the default mode, salience, and central executive networks. Deficient deactivation of the default mode network may cause patients to allocate persistent attentional resources to internal pain sensations, whereas hyperactivation of the salience network may assign excessive priority to pain-related signals. Long-term abnormal coupling among these networks is considered a neural basis for pain chronification and spontaneous pain. Importantly, the neural representations of chronic pain do not completely overlap with those of acute experimental pain in terms of spatiotemporal patterns, creating a mechanistic barrier to directly generalizing decoders trained on experimental pain models to clinical chronic pain.

It is worth noting that recent theoretical frameworks have moved beyond the traditional “pain matrix” perspective, offering novel explanatory pathways for understanding the neural mechanisms of pain. Models such as predictive coding

and active inference conceptualize pain as an active inference process over nociceptive sensory input and its uncertainty, emphasizing that the pain experience arises from the continuously updated balance between top-down prior expectations and bottom-up prediction errors^[21, 22, 23]. From this perspective, EEG oscillatory features can be reinterpreted: high-frequency gamma oscillations are thought to predominantly encode prediction error signals elicited by unexpected nociceptive input, whereas alpha/beta oscillations are considered neural carriers of prior expectations and their precision weighting, modulating and suppressing the transmission of nociceptive information^[24, 25, 26]. In a recent human EEG study, Strube et al. showed that alpha to beta band activity tracks expectations of stimulus intensity, while gamma band activity reflects prediction errors, providing direct empirical support for this framework in pain processing^[27]. Integrating these emerging theoretical accounts into EEG-based pain research helps to move beyond a purely locational description of the “pain matrix” toward a more mechanistic understanding of how distinct frequency bands and large-scale networks contribute to acute and chronic pain, thereby laying a theoretical foundation for building biologically interpretable pain decoding models^[22, 23, 26, 28, 29].

2.3 Characteristics of EEG Signals

EEG records the synchronous postsynaptic potentials of cortical pyramidal neurons through scalp electrodes, providing a unique source of information for pain decoding. Understanding the basic characteristics of EEG signals is therefore essential for designing effective decoding strategies.

Neural Oscillatory Signatures

Neural rhythmic oscillations are a core characteristic of EEG signals and provide an important window into understanding brain functional states and information processing mechanisms. These oscillations reflect the degree of synchronization of neuronal populations across various spatial and temporal scales and are functionally implicated in sensory processing, attentional regulation, memory integration, and information transmission. In pain research, oscillatory activity spanning from low-frequency delta to high-frequency gamma oscillations has been identified as candidate neural signatures for encoding pain:

Delta oscillations (0.5-4 Hz) are the lowest-frequency and highest-amplitude rhythmic components of the EEG signal. In the awake state, delta oscillations are closely linked to synaptic plasticity and endogenous pain modulation. Both animal experiments and human EEG studies have demonstrated that peripheral noxious stimulation can induce phase resetting of cortical delta oscillations, a phenomenon thought to reflect synchronous reorganization of large-scale cortical networks following the arrival of nociceptive information^[5]. In patients with chronic neuropathic pain, delta power in thalamic and cortical regions is abnormally enhanced and correlates with the persistence of spontaneous pain^[30]. Furthermore, the coupling between delta oscillations and peripheral physiological indices, such as skin conductance responses, is altered under pain conditions, suggesting that rhythmic activity in the delta band may encode the affective arousal dimension of pain^[31].

Theta oscillations (4-7 Hz) serve as an interface between sensory information integration and cognitive modulation during pain processing. Acute noxious stimulation can elicit enhanced frontal midline theta power, typically originating from the anterior cingulate cortex and medial prefrontal cortex, reflecting pain-triggered salience detection and orienting responses^[30]. This theta response can be observed within a sub-second time window after noxious stimulation and constitutes an important spectral feature of the late components of pain-related event-related potentials. At the level of cross-frequency coupling, theta-gamma phase-amplitude coupling is regarded as a core framework for coordinating local processing with global network communication; in acute experimental pain, the strength of gamma amplitude modulation by theta phase can predict subjective pain ratings^[32]. In chronic pain, elevated baseline frontal theta power is considered an electrophysiological marker of pain-related attentional bias and repetitive rumination, and is associated with cognitive factors such as pain catastrophizing^[33]. Moreover, abnormally enhanced theta-gamma coupling is also observed across various chronic pain conditions, reflecting an imbalance between bottom-up information transmission and top-down regulation^[32].

Alpha oscillations (8-13 Hz) have long been considered to reflect the state of cortical excitation-inhibition balance. Under acute noxious stimulation, a pronounced alpha event-related desynchronization can be elicited in the somatosensory cortex, signaling the release of the relevant cortical regions from inhibition and their transition into an active processing mode^[34]. However, the specificity of alpha desynchronization for pain encoding has been debated, because non-noxious stimuli of equal intensity can also evoke similar responses. Recent studies suggest that pain-specific information may be encoded more in the spatiotemporal topological features of alpha desynchronization than in power changes alone. Under chronic pain conditions, resting-state alpha oscillations display a pattern distinctly different from acute responses: mainly characterized by a slowing of the alpha peak frequency and an abnormal increase in spontaneous power. This pattern is regarded as a marker of dysregulated thalamocortical rhythm, and its severity correlates with clinical pain intensity^[30]. Notably, abnormal baseline alpha activity is also a potential electrophysiological indicator for predicting the transition from acute to chronic pain, suggesting that alpha oscillations play a special role in the acute-to-chronic pain transformation chain.

Beta oscillations (14-29 Hz) are involved in maintaining the stability of the current motor state and sensory expectations within the sensorimotor system. Acute noxious stimulation can evoke a biphasic beta power response in the sensorimotor cortex: early beta desynchronization reflects the interruption of the ongoing motor plan or sensory anticipation, while the subsequent beta synchronization represents the process of the sensorimotor system returning to its baseline state. The duration and amplitude of both components can, to some extent, index the intensity and salience of the stimulus^[35]. In chronic pain, the directional changes of resting-state and task-related beta oscillations differ from the acute evoked responses. Patients often exhibit altered baseline beta power in sensorimotor regions and attenuated beta desynchronization during motor imagery, which may reflect the persistent inhibitory effect of pain on the motor system and dysfunction of GABAergic inhibitory circuits^[36]. This characteristic of

beta oscillations makes it a promising candidate marker for distinguishing central adaptive changes between the acute and chronic phases of pain.

Gamma oscillations (30-100 Hz) arise from the rapid disinhibitory drive of pyramidal cells by local inhibitory interneuron networks and are widely recognized as the frequency band most intimately linked to pain intensity encoding. In acute experiments, noxious stimuli can elicit enhanced gamma power in the sensorimotor, prefrontal, and insular cortices, with the amplitude showing a positive dose-response relationship with subjective pain ratings. This represents a key electrophysiological stage in the amplification and integration of nociceptive information within thalamo-cortical loops and local cortical networks, and it is capable of simultaneously reflecting both the sensory-discriminative and affective-motivational dimensions of pain^[37]. In chronic pain, resting-state gamma power is often higher than in healthy controls, yet its linear relationship with pain intensity is less stable than in acute experiments, possibly due to the combined influence of long-term central sensitization and compensatory inhibition^[38]. Moreover, the selectivity of gamma oscillations for pain decoding has long been challenged because their activity is also modulated by attentional load and stimulus novelty; integrating multi-band combinations with fine-grained spatiotemporal pattern analysis can help enhance their discriminative validity as pain biomarkers^[5].

In summary, oscillatory activity across the full frequency range from delta to gamma contributes in distinct ways to the transient encoding of acute pain and the maintenance of persistent states in chronic pain. Neural oscillations in acute pain primarily manifest as evoked responses-either phase-locked or non-phase-locked-emphasizing sensory input, salience detection, and intensity encoding, whereas chronic pain is characterized more by shifts in baseline rhythms, reconfiguration of inter-regional coupling, and functional reorganization at the network level. Understanding these commonalities and distinctions provides the electrophysiological theoretical basis for leveraging neural oscillatory features to construct high-performance pain decoding models that generalize across states.

High Temporal Resolution

EEG non-invasively records the synchronous electrical activity of postsynaptic potentials of cortical pyramidal neurons via scalp electrodes. With a sampling rate typically reaching 250-1000 Hz or even higher, it allows changes in neural activity to be captured on the order of milliseconds^[39]. This property endows EEG with unparalleled temporal precision among neuroimaging techniques and constitutes one of the fundamental reasons why it has become the tool of choice for pain decoding research. EEG can reveal millisecond-level patterns of local brain network activity, and inter-regional correlations can reflect functional connectivity. Although scalp EEG has limited spatial resolution and insufficient sensitivity to signals from deep brain structures, its high temporal resolution enables researchers to precisely track the temporal dynamics of neural activity, a capability that is difficult to achieve with other neuroimaging modalities^[39].

In contrast, functional magnetic resonance imaging (fMRI), despite its excellent millimeter-level spatial resolution,

relies on the blood oxygen level-dependent (BOLD) signal, which reflects metabolic and hemodynamic changes induced by neural activity. The time constant of this hemodynamic response function is on the order of seconds, far too slow to resolve the rapidly evolving sequence of neural events during pain processing^[40]. Positron emission tomography (PET) is similarly constrained by a temporal resolution on the order of seconds to minutes. The high temporal resolution of EEG makes it more sensitive to recording the complex interplay among different brain functional processes over millisecond time intervals^[41]. The combination of EEG and fMRI exploits their complementary strengths: the high temporal resolution of EEG is used to track the precise time course of responses evoked by noxious stimuli, while fMRI is used to localize the fine-grained spatial coordinates of the brain regions generating these responses^[40]. It is precisely this millisecond-level temporal precision that makes EEG a natural fit with the temporal dynamics of pain processing^[42].

In the practice of pain decoding, the value of high temporal resolution manifests at multiple levels. First, it enables researchers to precisely extract stimulus-locked evoked potential components from continuous EEG signals. The different peak latencies and amplitudes of these components have been shown to effectively differentiate between pain and non-pain states and, to some extent, encode stimulus intensity information^[43]. Second, the high temporal resolution makes it possible to perform fine-grained time-frequency analysis of non-phase-locked oscillatory activity. Researchers can extract dynamic information about power changes in various frequency bands and cross-frequency coupling from specific time windows, capturing the cascading responses of oscillatory activity across different frequency bands on a sub-second timescale. For example, as described earlier, gamma-band power enhancement is often accompanied by sequential changes in alpha and beta power-a temporal relationship that can only be fully revealed with high temporal resolution. Third, in real-time pain monitoring and closed-loop BCI applications, high temporal resolution translates to low detection latency, allowing the system to recognize and respond to pain at its early stages-a capability that is critical for clinical scenarios such as postoperative analgesia regulation and chronic pain early warning. By virtue of its high temporal resolution, non-invasiveness, convenience, and relatively low cost, EEG has been recognized as one of the most promising tools for establishing objective biomarkers of chronic pain and related neural processes^[30].

3 Research Methods

A comprehensive search was conducted across multiple databases, including Web of Science, Scopus, PubMed, and Google Scholar, covering multiple disciplines such as biomedical science, engineering technology, and clinical research, to ensure the breadth and interdisciplinarity of the literature retrieval. The search focused on peer-reviewed papers indexed by the Institute for Scientific Information (ISI) to guarantee the rigor and reliability of the sources.

The search spanned the period from 2019 to 2026, aiming to capture the latest trends and methodologies in EEG-based pain decoding. The initial search query was organized

around three main groups of keywords. The first group centered on the context of pain, including pain-related terms (e. g., "pain," "acute pain," "chronic pain," "nociception," "pain perception") and assessment actions (e. g., "detection," "assessment," "identification," "classification," "monitoring," "decoding," "recognition"). The second group focused on technical methods, encompassing "machine learning," "deep learning," "artificial intelligence," and "neural network," to capture the broad range of computational approaches applied to pain assessment. The third group targeted the types of data used in the studies, specifically including "EEG," "electroencephalography," "brain signal," "physiological signal," "biomedical signal," "neural oscillation," "brain activity," and "neurophysiological marker," to ensure the inclusion of articles employing physiological data for pain assessment.

For this literature review, we established specific inclusion and exclusion criteria to guide study selection. The inclusion criteria were as follows: (1) studies published between 2019 and 2026 to ensure timeliness; (2) studies focusing on acute pain or chronic pain; (3) studies using ML models or DL techniques to decode pain; (4) studies using EEG signals to decode pain; and (5) original research articles from peer-reviewed journals or conferences. Exclusion criteria were applied to filter out certain types of articles and maintain the focus and relevance of the review. The exclusion criteria were: (1) articles that primarily used image/facial, medical imaging, audio, or video processing techniques for pain assessment; (2) studies focusing on emotion recognition; and (3) articles that incorporated images or videos as part of their multimodal pain assessment approach. After screening, 30 articles met the selection criteria.

4 Literature Review

This section reviews representative studies on EEG-based pain decoding, with emphasis on two major methodological pathways: traditional ML and DL. Traditional ML studies generally rely on handcrafted features, such as band power, time-frequency characteristics, nonlinear dynamics, functional connectivity, and quantitative EEG, followed by classifiers including SVM, RF and KNN. These approaches are relatively interpretable and suitable for small-sample studies, but their performance is strongly affected by feature design and parameter selection. In contrast, DL methods can automatically learn discriminative representations from raw EEG signals, time-frequency maps, topographic images, or connectivity matrices, showing advantages in complex spatiotemporal feature extraction and pain-state classification. Accordingly, this section summarizes recent ML- and DL-based studies to compare their datasets, pain types, EEG features, decoding methods, and classification performance, thereby clarifying the current methodological progress and remaining limitations in EEG-based pain decoding.

4.1 EEG-Based Pain Decoding Using Traditional ML

Traditional ML offers an earlier and relatively interpretable technical pathway for EEG-based pain detection. Such methods are typically built upon signal preprocessing and handcrafted feature extraction, transforming high-dimensional EEG signals into feature vectors learnable by classifiers through

the construction of spectral, time-frequency, nonlinear dynamics, brain network topological, or quantitative EEG features. Compared with DL, traditional ML models generally impose lower requirements on sample size, making them suitable for early exploratory studies and small-sample clinical data analysis; however, their performance heavily depends on the quality of feature engineering, the definition of pain labels, and the configuration of classifier hyperparameters. Representative research progress is summarized in Table 1, illustrating the main application pathways of traditional ML in EEG-based pain decoding.

In an experimental cold pain study, Alazrai et al.^[44, 45] provided an early exploration of the potential of quadratic time-frequency distributions for feature extraction from cold pain EEG. They recorded EEG signals from 24 healthy participants under sustained cold pain stimulation and employed the Wigner-Ville distribution (WVD) and the Choi-Williams distribution (CWD) to characterize the non-stationary, time-varying features of pain-induced EEG. On this basis, 12 time-frequency features quantifying energy distribution were extracted, and an SVM with a radial basis function (RBF) kernel was used for binary pain classification. The results showed that the model with WVD-based features achieved an accuracy of 83.4% in distinguishing "no pain" from "pain"; when CWD, which better suppresses cross-term interference, was adopted, the classification accuracy further improved to 89.24%. This study demonstrates that time-frequency representations tailored to the non-stationary nature of pain EEG can substantially enhance the discriminative power of traditional classifiers.

Following the line of frequency-domain feature research under the cold pressor test paradigm, Bonotis et al.^[46] further validated the feasibility of using portable, low-cost EEG devices for automated pain intensity assessment. They recorded EEG signals from 22 healthy volunteers during a cold pressor test using a 14-channel Emotiv headset, extracted whole-band relative power features, and employed an ensemble learning method based on RF for pain intensity classification. Despite an imbalanced distribution of subjective pain ratings, the model achieved a decoding accuracy of 72.7% in a five-level pain intensity multi-class task. This study suggests that low-cost EEG devices combined with ensemble learning algorithms have potential for clinical dissemination, although multi-level pain recognition remains constrained by signal quality and class imbalance.

In another multi-level pain recognition study also based on the cold pressor test, Afrasiabi et al.^[47] focused on the role of the alpha band in distinguishing pain intensities. They recorded 34-channel EEG signals from 44 healthy participants across five pain states, and after denoising, extracted 12 statistical distribution features from the alpha band. Subsequently, a Bayesian-optimized SVM (BSVM) was proposed for feature selection and classification. The results showed that this hybrid model achieved an accuracy of 93.33% in the five-level pain intensity classification task, and an accuracy of 99.8% in the binary task of distinguishing "no pain" from "pain." These findings further corroborate the critical role of the alpha band in pain state recognition and demonstrate that feature selection and parameter optimization can significantly boost the performance of conventional SVM models.

Beyond band power features, Modares-Haghighi et al.^[52]

shifted their focus to EEG functional connectivity graph features, aiming to quantify pain severity from a brain network perspective. They recorded 29-channel EEG signals from 23 healthy participants experiencing five levels of pain induced by the cold pressor test, and concentrated on alpha band activity. Partial directed coherence (PDC) was employed to construct directed graphs of brain functional connectivity, from which graph-theoretic features such as degree and betweenness were extracted. Subsequently, sequential floating forward selection (SFFS) was used to identify the most discriminative features, which were then fed into a bio-inspired decision tree classifier based on multi-layer SVM. The results showed that this method achieved an accuracy of 86.84% in the five-level pain intensity classification task and 92.14% in the binary classification of "no pain" versus "pain." This study demonstrates that pain is reflected not only in local band power changes but also in altered inter-regional information flow and network topology.

Nezam et al.^[53] further combined band-wise brain topographic features with nonlinear features and proposed a novel EEG signal processing and classification strategy for the quantitative assessment of three-level and five-level pain intensity. They recruited 24 healthy participants, recorded EEG signals under the cold pressor test paradigm, and removed artifacts via independent component analysis (ICA). Alpha and delta band topographic features were extracted and combined with other nonlinear EEG features to enrich the feature representation. In the classification stage, a decision tree structure was built, and at each node, sequential forward selection (SFS) and a KNN classifier were jointly applied for discrimination. The results showed that this strategy achieved an accuracy of 83.19% in three-level pain intensity classification, but dropped to 62.13% in the more challenging five-level classification. These findings suggest that with finer pain gradations, label subjectivity and inter-individual variability exert a more pronounced impact on the performance of traditional classifiers.

Tavasoli et al.^[56] supplemented the pain detection perspective beyond traditional spectral and network features from the perspective of nonlinear dynamics. They recruited 10 healthy participants, recorded multi-channel EEG signals under a cold pressor test paradigm that induced phasic pain, and focused on extracting 13 nonlinear dynamic features based on recurrence quantification analysis (RQA) from the Fz, Cz, and Pz channels. Subsequently, a rough neural network classifier tuned on this dataset was employed to distinguish "rest" from "pain" states. The results showed that the model ultimately achieved a decoding accuracy of 95.25%, indicating that nonlinear dynamic features can capture pain-processing-related differences from complex neural activity and provide a valuable feature complement for pain state detection in small samples.

Beyond the cold pressor test, Sai et al.^[54] applied EEG-based pain decoding to the more clinically relevant assessment of uterine contraction pain during the first stage of labor. They collected 16-channel EEG data from 10 parturients in the first stage of labor and used cardiotocography (CTG) tracings to objectively label uterine contraction pain states versus baseline resting states. After denoising the signals with wavelet multiresolution analysis (WMA) and ICA, the study extracted relative band power, statistical features, and nonlinear features, and applied principal component analysis (PCA) to reduce dimensionality and mitigate the risk of overfitting

Table 1 Recent studies using ML techniques for EEG-based pain detection

Reference	Year	EEG dataset	Bands	Pain type	ML method	Accuracy
[47]	2021	44 subjects through cold stimulation	Alpha	Acute	SVM	93.33% (five-class); 99.8% (binary)
[44]	2019	24 subjects through cold stimulation	Delta, Theta, Alpha, Beta, Gamma	Acute	SVM	83.4% (binary)
[45]	2019	24 subjects through cold stimulation	Delta, Theta, Alpha, Beta, Gamma	Acute	SVM	89.24% (binary)
[46]	2019	22 subjects through cold stimulation	Delta, Theta, Alpha, Beta, Gamma	Acute	RF	72.7% (five-class)
[48]	2021	23 subjects who underwent total hip replacement	Delta, Theta, Alpha, Beta, Gamma	Chronic	SVM	79.6% (four-class)
[49]	2021	26 amputee subjects	Delta, Theta, Alpha, Beta, Gamma	Chronic	SVM	93.7% (binary)
[50]	2024	35 healthy subjects and 151 subjects with chronic pain	Delta, Theta, Alpha, Beta, Gamma	Chronic	Elastic Net	79.6% (binary)
[51]	2023	40 subjects through pneumatic pressure stimulation	Theta, Alpha, Beta, Gamma	Acute	RF	73.18% (binary)
[52]	2021	23 subjects through cold stimulation	Alpha	Acute	SVM	86.84% (five-class); 92.14% (binary)
[53]	2018	24 subjects through cold stimulation	Delta, Alpha	Acute	DT + SVM	83% (three-class); 62% (five-class)
[54]	2019	10 women in the first stage of labor	Delta, Theta, Alpha, Beta	Acute	SVM	84% (binary)
[55]	2024	36 subjects with chronic neuropathic pain	Theta, Alpha, Beta, Gamma	Chronic	KNN	99.72% (three-class)
[56]	2025	10 subjects through cold stimulation	Delta, Theta, Alpha, Beta, Gamma	Acute	Rough neural network	95.25% (binary)
[57]	2021	35 subjects with chronic neuropathic pain	Delta, Theta, Alpha, Beta, Gamma	Chronic	SVM	96% (three-class)
[58]	2023	28 subjects with spinal cord injury	Theta, Alpha, Beta	Chronic	SVM	76% (binary)
[59]	2025	13 healthy subjects and 36 subjects with chronic neuropathic pain	Delta, Theta, Alpha, Beta, Gamma	Chronic	SVM	97-99% (binary)

caused by high-dimensional features. Ultimately, 68 of the most discriminative features were selected and fed into an RBF-SVM for training. The results showed that the model achieved a maximum accuracy of 84.0% in the binary classification of "rest" versus "pain," indicating the potential of EEG as a biomarker for objective assessment of labor pain.

Mari et al.^[51] further focused on model generalizability and conducted the first ML study with external validation for EEG-based pain intensity classification. They applied pneumatic pressure stimuli of high and low intensities to the nail bed and collected data in two independent experiments: Experiment 1 ($n=25$, where n denotes the number of participants) was used for training and internal cross-validation, while Experiment 2 ($n=15$) served as an independent external validation set. Single-trial event-related desynchronization (ERD) time-frequency features distributed over frontal, central, and parietal regions were extracted, and multiple ML models were compared. The best-performing RF model achieved an accuracy of 73.18% in cross-validation, 68.32% in external validation using the same stimulus parameters, and still maintained an accuracy of 60.42% in a second external validation with entirely new stimulus parameters. The study emphasized that reporting only internal cross-validation results is insufficient to demonstrate the clinical applicability of a model, and that external validation should become an essential standard in pain decoding research.

In a movement-related clinical pain scenario, Kimura et al.^[48] attempted to objectively assess hip pain levels during walking. They recorded EEG signals from 23 patients after total hip arthroplasty during a 5-minute walking task using a single-electrode portable EEG device positioned at Fp1. The average power spectrum within the 1-35 Hz range was extracted as a quantitative EEG (qEEG) feature, and an SVM with a radial basis function (RBF) kernel was used for evaluation. The method achieved an accuracy of 79.6% in a multi-class task that detected pain and further subdivided it into four intensity levels. This study demonstrates the practical value of lightweight EEG devices in dynamic clinical settings, while also indicating that the limited spatial information provided by single-channel EEG may constrain the comprehensive capture of pain-related neural representations.

As the research focus has expanded from experimental acute pain to chronic pain, Lendaro et al.^[49] explored the clinical potential of EEG in detecting phantom limb pain (PLP) after amputation. The study collected EEG data from 26 amputees during eyes-closed resting state, including individuals with and without PLP. The common spatial pattern (CSP) algorithm was applied to decompose the EEG signals, and the average power features of four components were extracted. Six classifiers, including linear discriminant analysis (LDA), RF, and SVM, were then compared. Under leave-one-out cross-validation (LOOCV), the support vector classifier (SVC) achieved the best performance in the binary classification of the presence versus absence of PLP, with an accuracy of 93.7%. This study suggests that stable neural representations associated with PLP may exist in resting-state EEG.

Lovelace et al.^[50] further developed an ML classification algorithm to detect the presence of chronic pain using EEG data in a larger chronic pain cohort. The study enrolled 186 participants, including 35 pain-free healthy controls and 151 chronic pain patients with diverse etiologies. Resting-state EEG

was recorded for 15 minutes with a 19-channel wireless system while participants kept their eyes closed. After rigorous artifact removal, over 6,000 qEEG features-including band power, connectivity, and asymmetry measures-were extracted, and the Elastic Net algorithm was used to handle high dimensionality and multicollinearity. The resulting classifier achieved an accuracy of 79.6% in the binary classification of "pain" versus "no pain," with a sensitivity of 82.2% and a specificity of 66.7%. This study highlights the advantage of regularized models in screening high-dimensional EEG features, while also illustrating that the heterogeneity of chronic pain can substantially increase classification difficulty.

For chronic neuropathic pain (NP) severity identification, Zolezzi et al.^[57] sought to classify pain levels by fusing linear and nonlinear EEG features. They recruited 35 patients with chronic NP and recorded 10-minute EEG data under eyes-closed and eyes-open resting states. Based on the Brief Pain Inventory (BPI), subjective pain was categorized as low, moderate, or high. Absolute band power across classical frequency bands in five brain regions and approximate entropy for each channel were extracted to construct a high-dimensional feature vector. An SVM with a quadratic kernel was then used for feature selection and multi-class training. The method achieved 96% accuracy in distinguishing low, moderate, and high clinical pain severity, indicating that combining linear spectral features with nonlinear complexity measures can improve chronic pain severity classification.

Tasci et al.^[55] introduced more sophisticated automated feature engineering strategies for the same chronic NP classification problem. The study used 22-channel resting-state EEG data from 36 patients with chronic NP and categorized pain severity into three levels: low, moderate, and high. In the feature extraction stage, a dynamic self-organizing feature extraction function called the "Black-White Hole Pattern" (BWHPat) was proposed, and combined with tunable Q-factor wavelet transform (TQWT) and conventional statistical methods to extract multi-level texture and spatial statistical features. Subsequently, iterative neighborhood component analysis (INCA) was employed to select the most informative features, and a KNN classifier was used for classification. The results showed that this hybrid model achieved a decoding accuracy of 99.72% in distinguishing low, moderate, and high pain intensities. This study demonstrates that automated feature extraction can yield extremely high performance in small-sample chronic pain classification, but its generalizability still requires further validation with external data.

Sofia Bobby et al.^[58] focused on decoding central neuropathic pain (CNP), which poses substantial clinical challenges. The study collected clinical EEG data from 28 patients with spinal cord injury. After extracting CSP and band-energy features, the authors addressed the training burden of high-dimensional features and concept drift in patient EEG by designing a weighted incremental-decremental support vector machine (WIDSVM) based on the quantum chaotic butterfly optimization algorithm (QCBOA). The model achieved a success rate of approximately 76% in identifying whether patients developed CNP and performed relatively well in statistical tests across different local brain regions. This study suggests that concept drift and inter-individual variability are important issues in CNP decoding after spinal cord injury.

Adebisi et al.^[59] investigated potential neural mechanisms

of chronic NP from a brain functional-network perspective and achieved automated detection. The study used a dataset comprising 36 patients with NP of varying severity and 13 pain-free controls. EEG was recorded for 5 minutes under both eyes-closed and eyes-open resting states. Weighted phase lag index (wPLI) was used to assess phase connectivity while mitigating volume-conduction effects, and orthogonal minimum spanning tree (OMST) analysis was applied to construct optimal brain functional networks. In addition, the minimum dominating set (MDSet) was introduced to identify key nodes controlling network dynamics, and persistent homology was used to extract multiscale topological features. These features were input into an SVM classifier. In the binary classification of patients with NP versus controls, the model achieved an accuracy of 97%, reaching 99% in selected frequency bands. These findings indicate that topological data analysis and brain-network features provide additional representational dimensions for mechanistic interpretation and classification of chronic pain.

Overall, traditional ML studies have established a relatively well-defined technical trajectory in EEG-based pain decoding: ranging from early band power and time-frequency features, through nonlinear dynamics, functional connectivity, and brain network topological features, to high-dimensional qEEG features and regularized models. The strengths of these approaches lie in their amenability to small-sample data, relatively interpretable feature meanings, and the ability to provide interpretive clues for screening pain-related EEG biomarkers. Their limitations include a heavy reliance on handcrafted feature engineering, parameter selection, and experimental paradigms, as well as unstable generalization performance across subjects, tasks, and centers. Consequently, subsequent research has increasingly shifted toward DL methods that can automatically learn high-dimensional representations.

4.2 EEG-Based Pain Decoding Using DL

Unlike traditional ML, which relies on handcrafted features, DL can learn discriminative representations directly from raw EEG signals, time-frequency maps, topographic images, or multimodal features through multi-layer nonlinear architectures. In recent years, CNN, Transformer, artificial neural network (ANN), and other models have been widely applied to classify pain presence, pain intensity levels, pain types, and pain etiologies. DL models typically achieve higher classification performance, particularly excelling in spatiotemporal feature fusion, cross-band information integration, and modeling complex clinical scenarios. At the same time, however, their training often requires relatively large sample sizes, they offer weaker model interpretability, and there is a risk that performance may be overestimated due to data augmentation or random partitioning strategies. The relevant research progress is summarized in Table 2, illustrating the major advances of DL in EEG-based pain decoding.

Yu et al.^[60] applied a CNN system to sustained cold pain EEG classification early on, proposing a Diverse Frequency Band-based Convolutional Neural Networks (DFB-ConvNets) framework to objectively identify different levels of cold pressor pain. The study recruited 32 healthy participants, induced cold pain via the cold pressor test, and recorded 32-channel EEG signals. After preprocessing, signals from five frequency bands-

delta, theta, alpha, beta, and gamma-were extracted separately, and independent convolutional branches were set up for each band. Each branch automatically learned temporal features from the corresponding band, and the deep multi-band features were then concatenated and fed into a fully connected network for three-class pain classification. A data cropping strategy was adopted to augment samples, and 10-fold stratified cross-validation was used to evaluate model performance. The results showed that when alpha, beta, and gamma bands were jointly input, DFB-ConvNets achieved the best performance with an average accuracy of 97.37%, significantly outperforming traditional classifiers such as SVM, LDA, and KNN. This study demonstrates that the deep fusion of complementary multi-band information can substantially improve the recognition of cold pain states.

Elsayed et al.^[61] also focused on cold pressor pain intensity recognition, but their study placed greater emphasis on the use of low-cost EEG devices and data augmentation strategies. They recruited 30 healthy participants, induced pain using a cold pressor test, and collected EEG data with an 8-channel OpenBCI device. Pain states were categorized into four levels-no pain, low pain, moderate pain, and high pain-and a Pain Index Matrix was proposed as the feature representation, combining band power and time-related features as model input. To address the issue of limited sample size, random noise and a variational autoencoder (VAE) were further employed for data augmentation, and an ANN was then used for four-class classification training. The results showed that this method achieved an accuracy of 94.83% in the four-level pain classification task. The study found that as pain intensity increased, alpha power decreased and gamma activity increased in somatosensory-related areas, suggesting that band power changes may reflect pain intensity-related neuromodulatory processes.

Wang et al.^[62] addressed the problems of low signal-to-noise ratio in laser-evoked pain EEG and the reliance of traditional features on prior knowledge by proposing an autoencoder (AE)-based method for predicting pain perception from high-density evoked EEG. The study recruited 29 healthy participants, applied laser stimuli of four energy levels to the left hand dorsum to induce pain, and recorded 62-channel EEG signals. Preprocessing included 1-30 Hz filtering, ICA-based ocular artifact removal, and downsampling to 250 Hz. Subsequently, an EEGNet-based convolutional AE was constructed to encode high-dimensional EEG data into a low-dimensional feature vector, which was then used by classifiers such as SVM, LDA, and KNN to discriminate high versus low pain. Leave-one-subject-out cross-validation showed that with an encoding dimension of 64, a logistic regression classifier achieved an accuracy of 74.6%, significantly outperforming prior features based on N2 amplitude and dimensionality reduction methods such as PCA and MDS. This study indicates that unsupervised deep feature compression can facilitate the extraction of pain-related latent representations from high-density evoked EEG.

To further preserve the spatial topology of EEG, Wu et al.^[63] proposed a deep Attentive-Recurrent-Convolutional Neural Network (ARCNN) for learning joint spatial-spectral-temporal representations in pain intensity assessment. They recruited 24 healthy right-handed subjects, induced sustained pain using the cold pressor test, and recorded 32-channel

EEG signals. After preprocessing, 5-second EEG samples were segmented into ten 0.5-second frames; delta, alpha, and beta band power was extracted for each frame and interpolated to generate 32×32 three-channel EEG image sequences. The ARCNN employed a CNN to extract spatial features, a bidirectional long short-term memory (BiLSTM) network to model temporal dynamics, and an attention mechanism to focus on critical periods. In leave-one-subject-out cross-subject four-class classification, the model achieved an accuracy of 92.14%, significantly outperforming traditional ML and other DL baselines. This study demonstrates that transforming EEG into image sequences that retain spatial topology can enhance cross-subject pain intensity recognition.

In decoding laser-evoked pain intensity, Aktaş et al.^[64] further explored the combination of time-frequency representations and convolutional networks. The study enrolled 50 healthy participants, analyzed their EEG signals during motor tasks while receiving laser stimuli at low, medium, and high pain levels, and focused on parietal electrodes such as CPz, Pz, P1, and P2. The short-time Fourier transform (STFT) was used to convert EEG signals into time-frequency representations, which were then fed into a one-dimensional convolutional neural network (1D-CNN) for pain intensity classification. To assess cross-subject generalizability, a leave-one-subject-out (LOSO) cross-validation strategy was adopted. The results showed that in the binary classification of low versus high pain, the model achieved a mean accuracy of $95.85\% \pm 5.06\%$, with a sensitivity of 93.60%, specificity of 98.10%, and precision of 98.12%. Moreover, DeepSHAP explanations revealed that high pain states were primarily associated with 14-15 Hz beta activity, whereas low pain states relied more on 11-12 Hz alpha activity, suggesting that alpha/beta rhythms may serve as important EEG markers for discriminating pain intensities.

Reyes-Galaviz et al.^[65] also used the Tiemann laser-evoked pain EEG public dataset, but their study focused on comparing the impact of different pain label definitions on DL decoding performance. Using EEG data from 51 healthy participants, they set the task as low versus high pain classification, constructed time-frequency features via Morlet wavelet transform, and employed a Pre-LN Transformer for pain intensity classification. Unlike most studies that define pain labels solely based on physical stimulus intensity, this study compared the classification performance of two labeling approaches: one based on laser stimulus intensity and the other on reaction time. Under LOSO cross-validation, the model with reaction time-based labels achieved a mean balanced accuracy of $64\% \pm 9\%$, whereas the model with laser intensity-based labels achieved only $54\% \pm 6\%$. These findings indicate that stimulus intensity does not necessarily equate to subjective pain experience, and that incorporating behavioral indicators such as reaction time may help establish a more reliable pain EEG labeling system.

Beyond time-frequency features, Han et al.^[68] explored the feasibility of EEG-based pain recognition under thermal pain conditions from the perspective of brain functional connectivity. The study recruited 36 healthy participants, recorded EEG data under four states-thermal pain, warmth, eyes-open resting, and eyes-closed resting-and focused on alpha-band phase synchronization features. The phase-locking connectivity index, inter-site phase clustering (ISPC), was computed between different electrodes, and the connectivity

relationships among 32 representative electrodes were constructed as a two-dimensional connectivity matrix, which was then fed into a two-dimensional convolutional neural network (2D-CNN) for classification. The results showed that under pooled across-subject training and testing conditions, the model achieved an average accuracy of 96.26%, with a classification accuracy of 94.16% for thermal pain versus eyes-open resting. However, under leave-one-subject-out (LOSO) cross-validation, the average accuracy dropped to 63.69%, and the accuracy for thermal pain versus eyes-open resting was only 61.01%. These findings indicate that functional-connectivity-based CNN models perform well under within-subject or mixed-sample conditions, but cross-subject generalization remains a core challenge for EEG-based pain decoding.

Rezzouk et al.^[70] further systematically evaluated the cross-individual generalization ability of multiple ML and DL models for EEG-based pain perception recognition by comparing model performance. The study recruited 108 healthy participants, who received painful thermal stimuli and aversive auditory stimuli, respectively, while 64-channel EEG signals were recorded. The study compared traditional ML methods such as CSP+SVM, minimum distance to mean (MDM), and tangent space logistic regression (TSLR), as well as DL models including Deep4Net, ShallowFBCSPNet, EEG-Netv4, EEGConformer, and GGN. In within-subject scenarios, TSLR achieved an accuracy of 98.64%; however, under LOSO scenarios, the accuracies of all models decreased significantly, with traditional classifiers dropping below 57%, while among the DL models, Deep4Net achieved an accuracy of 86.06%. This study suggests that DL models, particularly those capable of representing spatial structure and inter-regional relationships, may be better suited for extracting stable cross-individual EEG features of pain.

Fu et al.^[67] extended DL-based pain decoding to the scenario of clinical pain assessment in children, proposing the STPA-Net model that combines CNN and Transformer. The study collected 21-channel EEG data from 33 pediatric patients during arterial puncture, recording neural activity under real clinical pain stimuli, and formulated the task as binary classification of pain versus non-pain. Methodologically, on the one hand, 15 types of handcrafted EEG features were extracted and organized into a three-dimensional feature matrix; on the other hand, the preprocessed raw EEG signals were fed into a CNN to extract local spatial features, followed by a Transformer encoder to capture long-range temporal dependencies. Subject-independent 10-fold cross-validation was used to evaluate model performance. The results showed that STPA-Net achieved an accuracy of $87.83\% \pm 8.08\%$ in the pediatric pain recognition task. This study demonstrates the application potential of DL models in detecting pain during real clinical procedures.

Chen et al.^[66] focused on pain-state recognition in patients with chronic back pain and used DL to automatically extract chronic pain-related EEG representations. The study recruited 10 patients with chronic back pain, induced pain responses using motor and video stimulation, and recorded 32-channel EEG data. Five-second EEG segments were used as input, and a multilayer CNN was constructed to distinguish pain from non-pain states. Leave-one-subject-out cross-validation (LOSOCV) was used to evaluate generalization to unseen subjects. The model achieved an area under the

Table 2 Recent studies using DL techniques for EEG-based pain detection

Reference	Year	EEG dataset	Bands	Pain type	DL method	Accuracy
[64]	2026	50 subjects through laser stimulation	Delta, Theta, Alpha, Beta	Acute	CNN	95.85%(binary)
[66]	2022	10 subjects with chronic back pain through motor stimulation and video stimulation	Delta, Theta, Alpha, Beta, Gamma	Chronic	CNN	AUC 0.83(binary based on motor stimulation); AUC 0.81(binary based on video stimulation)
[61]	2020	30 subjects through cold stimulation	Delta, Theta, Alpha, Beta, Gamma	Acute	ANN	94.83%(four-class)
[67]	2024	33 child subjects during arterial puncture	Delta, Theta, Alpha, Beta, Gamma	Acute	CNN+Transformer	87.83%(binary)
[68]	2022	36 subjects in four conditions: hot pain, warm heat, resting with eyes open, and resting with eyes closed	Alpha	Acute	CNN	96.26%(binary)
[69]	2025	101 chronic pain subjects and 88 healthy subjects	Delta, Theta, Alpha, Beta, Gamma	Chronic	Transformer	97.59% (binary); 83.48% (four-class)
[65]	2025	51 subjects based on laser stimulation and response time	Delta, Theta, Alpha, Beta	Acute	Transformer	54% (binary based on reaction-time); 54%(binary based on laser stimulation)
[70]	2025	108 subjects through thermal stimulation and aversive auditory stimulation	Delta, Theta, Alpha, Beta, Gamma	Acute	CNN	86.06%(binary)
[62]	2020	29 subjects through laser stimulation	Delta, Theta, Alpha, Beta	Acute	CNN	74.6%(four-class)
[63]	2022	24 right-handed subjects through cold stimulation	Delta, Alpha, Beta	Acute	CNN	92.14%(four-class)
[60]	2020	32 subjects through cold stimulation	Delta, Theta, Alpha, Beta, Gamma	Acute	CNN	97.37% (three-class)
[71]	2025	36 subjects with chronic neuropathic pain	Delta, Theta, Alpha, Beta, Gamma	Chronic	CNN	99%(six-class)
[72]	2025	17 healthy subjects and 42 subjects with back pain	Delta, Theta, Alpha, Beta	Chronic	CNN	98.95%(four-class)
[73]	2023	42 subjects through pinching and pressing stimulation	Delta, Theta, Alpha, Beta	Acute	CNN	99.12%(binary)

receiver operating characteristic curve (AUC) of 0.83 ± 0.09 under motor stimulation and an AUC of 0.81 ± 0.15 under video stimulation. These findings indicate that CNNs can automatically capture chronic pain EEG representations across induction paradigms, although the small sample size limits the robustness of the conclusions.

Qiu et al.^[69] further extended chronic pain EEG decoding from binary classification to pain type and pain intensity recognition, proposing a multi-scale frequency-domain Transformer model, MFDFormer. Based on the BFCP chronic pain public dataset, the study included 189 subjects-101 chronic pain patients and 88 healthy controls-and used 65-channel resting-state EEG data for modeling. MFDFormer captures EEG representations at different temporal scales through a multi-scale feature extraction module, and jointly models spatial-frequency and temporal-frequency dependencies using a frequency-domain MetaFormer encoder. Leave-one-subject-out cross-validation was employed to assess cross-subject generalization. The results showed that MFDFormer achieved an accuracy of 97.59% in the pain versus non-pain binary classification task, 96.02% in the pain type classification task, and 83.48% in the four-class pain intensity classification task. This study demonstrates that multi-scale time-frequency feature fusion and frequency-domain dependency modeling hold considerable potential for chronic pain EEG decoding.

Şentürk^[71] addressed chronic NP etiology classification by proposing an EEG decoding framework that combines a deep AE and a Hybrid Mamba classifier. The study included 36 patients with chronic NP and recorded 24-channel scalp EEG signals. EEG signals were first subjected to 0.5-45 Hz band-pass filtering, ICA-based artifact removal, 2-second epoch segmentation, and normalization, with the Synthetic Minority Oversampling Technique (SMOTE) used to balance the classes. A 1D convolution-based deep AE compressed each EEG epoch into a 64-dimensional latent feature vector, which was then fed into a Hybrid Mamba model combining Mamba operations and multi-head attention mechanisms for six-class classification. The model achieved 99% accuracy in CNP etiology classification. This study demonstrates the potential of state-space models and attention mechanisms for identifying complex chronic pain etiologies, although the high performance requires validation in larger samples and external datasets.

De et al.^[73] proposed an EEG-based pain detection framework that combines a stacked AE, a Chebyshev polynomial LSTM, and an attention mechanism to identify pain states induced by pinch stimulation. The study recruited 42 healthy participants and recorded EEG signals under pain and no-pain conditions using 20 EEG electrodes. The stacked AE was first utilized to extract deep features from raw EEG, after which the Chebyshev polynomial LSTM was employed to model the temporal dynamics of the EEG, and an attention mechanism was introduced to enhance the weighting of critical features. Model performance was evaluated using 10-fold cross-validation and a training/validation/test set split. The results showed that the model achieved an overall accuracy of 99.12% in the binary classification of pain versus no-pain. This study suggests that combining AEs with temporal networks can effectively improve pain detection performance; however, the high accuracy obtained under random partitioning conditions still requires further verification through rigorous cross-subject

validation.

De et al.^[72] further developed a multimodal DL framework, GLEAM, for chronic low back pain intensity assessment. The study recruited 17 healthy participants and 42 patients with low back pain and simultaneously recorded 19-channel EEG and surface electromyography (sEMG) signals from the lumbar multifidus muscle during standing forward flexion and standing backward extension. Pain intensity was categorized into four classes: no pain, mild, moderate, and intolerable. The model integrated a denoising generative adversarial network, a CNN, a self-attention module, and an enhanced long short-term memory network (ETLSTM), enabling joint use of EEG and sEMG features for pain-intensity recognition. GLEAM achieved an average accuracy of 98.95% in the four-class task. This study demonstrates that multimodal physiological signal fusion and deep denoising can improve chronic low back pain intensity recognition and provides a methodological reference for pain monitoring in real-world movement scenarios.

Overall, DL research has propelled EEG-based pain decoding from shallow classification reliant on handcrafted features toward end-to-end or semi-end-to-end automatic representation learning. Prior studies have demonstrated that multi-band convolution, time-frequency map modeling, brain topographic image sequences, AE latent representations, Transformer-based long-range dependency modeling, and multimodal fusion can all substantially improve pain classification performance. Nevertheless, DL models still face challenges such as overfitting on small-sample pain EEG data, insufficient interpretability, and unstable external generalization. In particular, the performance of some models drops markedly under cross-subject validation, indicating that inter-individual variability remains a critical bottleneck that must be addressed before clinical translation.

Considering both approaches together, traditional ML is better suited for exploring interpretable EEG features and establishing baseline models on small samples, whereas DL has greater advantages in automatic extraction of complex features, fusion of multi-source information, and modeling high-dimensional nonlinear relationships. Future research should seek complementarity between the two: on the one hand, preserving the neurophysiological interpretative value of traditional feature engineering; on the other, leveraging DL models to enhance generalization across scenarios, subjects, and pain types. Only with the joint support of standardized datasets, rigorous external validation, and interpretable mechanism analysis can EEG-based pain decoding progressively advance from laboratory algorithm verification toward clinical assisted assessment.

5 Results and Analysis

5.1 EEG Signal Types

Effective representation and extraction of EEG features is a critical prerequisite for identifying pain states. This review integrates existing research findings and categorizes EEG features according to the frequency bands analyzed. Table 3 summarizes the distribution of different frequency band combinations used in pain decoding studies. As can be seen from the table, full-band analysis is the most prevalent approach, constituting the predominant paradigm in existing

studies. A total of 16 studies covered all five clinical frequency bands: delta, theta, alpha, beta, and gamma. This trend indicates that researchers generally favor constructing multi-dimensional, full-band feature spaces to capture the complex neural responses elicited by pain, with the aim of achieving higher decoding sensitivity.

In terms of specific band combinations, the strategy of combining four frequency bands is the second most common choice, accounting for eight studies. Among these, the combination of delta, theta, alpha, and beta bands is the most widely used (six studies). This may reflect a greater emphasis in pain EEG analysis on the perceptual and affective information carried by low- and mid-frequency bands, while the exclusion of gamma oscillations could be related to high-frequency noise filtering or the neurophysiological characteristics of particular pain types. In contrast, the more refined combination strategies involving three or two frequency bands are relatively rare, indicating that there is still room for a deeper exploration of

frequency-band interactions in current research.

Notably, single-band analysis accounts for the lowest proportion of all the surveyed studies, with only three studies relying solely on the alpha band. This differs from traditional pain EEG research paradigms and suggests that classical markers based purely on the alpha band may no longer be sufficient to meet current demands for high-precision decoding, and that research trends are progressively moving toward multi-band fusion.

In summary, feature extraction strategies in current pain EEG research have undergone a large-scale shift from early single-band (e. g., alpha) analysis toward comprehensive network analysis spanning full-band or four-band approaches. This evolution not only reflects improvements in computational capacity but also reveals that pain, as a multidimensional experience involving sensory, affective, and cognitive components, requires a richer set of neural oscillatory spectral features for comprehensive characterization.

Table 3 Pain detection studies sorted by EEG type

EEG Type	Number of Bands	EEG Band	Number of Studies	References
Rhythms	1 band	Alpha	3	[47], [52], [68]
	2 bands	Delta and Alpha	1	[53]
	3 bands	Delta, Alpha, and Beta	1	[63]
		Theta, Alpha, and Beta	1	[58]
	4 bands	Delta, Theta, Alpha, and Beta	6	[54], [64], [65], [62], [73], [72]
		Theta, Alpha, Beta, and Gamma	2	[51], [55]
	5 bands	Delta, Theta, Alpha, Beta, and Gamma	16	[44], [45], [46], [48], [49], [50], [56], [57], [59], [66], [61], [67], [69], [70], [60], [71]

Table 4 Pain detection studies sorted by pain type

Pain types	Main stimulation paradigms	Number of Studies	References
Acute pain	Cold pressor test	10	[47], [44], [45], [46], [52], [53], [56], [63], [61], [60]
	Thermal stimulation	2	[68], [70]
	Laser stimulation	3	[65], [64], [62]
	Pneumatic pressure stimulation	1	[51]
	Uterine contraction pain	1	[54]
	Arterial puncture	1	[67]
	Mechanical pressure stimulation	1	[73]
Chronic pain	Resting-state EEG recording	7	[49], [50], [55], [57], [71], [69], [59]
	Motor stimulation	4	[48], [66], [58], [72]
	Video stimulation	1	[66]

5.2 Pain Types

The pain types in the included studies can be divided into two major categories—acute pain and chronic pain—each employing different experimental stimulation paradigms. Table 4 summarizes the distribution of different pain types and their main stimulation paradigms. The statistical results show

that the cold pressor test is the most mainstream experimental paradigm for inducing acute pain, with ten studies adopting this paradigm. This indicates that cold stimulation, as a non-invasive, controllable method capable of reliably eliciting moderate-intensity nociception, occupies a central position in the exploration of the physiological mechanisms of acute

pain. In addition, laser stimulation, thermal stimulation, and mechanical/pneumatic pressure stimulation are also widely used to induce acute pain. Among these, laser stimulation uses radiant heat pulses to selectively activate cutaneous A δ and C fibers, producing purely nociceptive input with virtually no tactile confound. The N1 and N2-P2 components of laser-evoked potentials (LEPs) possess clear pain specificity and have been used to construct neural indices of pain discrimination. The advantages of laser stimulation include precise targeting of the stimulation site and accurate time-locking, making it suitable for event-related potential analysis. However, the equipment is expensive, there is a risk of skin burns, and the pain intensity produced by a single stimulus is relatively low, necessitating repeated averaging across trials. Thermal stimulation, by contrast, typically uses contact thermodes, allowing the temperature to be precisely controlled near the tolerance threshold. Compared with the cold pressor test, the intensity of thermal stimulation is easier to standardize, but the slower rate of temperature rise means the evoked pain is less acute than that produced by laser stimulation.

Unlike acute pain, which is induced by external stimuli, chronic pain research markedly favors resting-state EEG recordings. This trend reveals a shift in the core logic of chronic pain research from a "stimulus-response" causal analysis to the investigation of trait-like abnormalities in the brain's intrinsic functional networks. Nevertheless, to establish objective quantitative metrics, some studies have supplemented resting-state recordings with motor-related evoked paradigms, among which motor stimulation is the most widely used, followed by video-evoked paradigms, which are typically employed to study the neural basis of empathic pain or anticipatory pain. Such paradigms are closer to real-life scenarios, but the signals are confounded by substantial motion artifacts and visual evoked potentials, imposing higher demands on preprocessing.

In summary, acute pain research predominantly adopts external noxious stimulation paradigms, with the cold pressor test being the most prevalent due to its low cost and ease of implementation, while laser stimulation serves as the gold standard for investigating pain-specific neural markers because of its selective activation of nociceptive pathways. Chronic pain research, in contrast, relies primarily on resting-state EEG, supplemented by task-state paradigms to simulate real-life situations. Future research should focus on the essential differences in neural representations between acute and chronic pain, and, wherever possible, incorporate data from clinical

chronic pain patients during model training to enhance the clinical relevance of the decoders.

5.3 Signal Processing

Table 5 summarizes the signal-processing methods used for EEG-based pain detection and their frequency of use. Signal filtering and resampling constitute the core of EEG preprocessing. Band-pass filtering, the most common approach, isolates pain-related neural oscillatory bands while removing ultra-low-frequency baseline drift and high-frequency electromyographic (EMG) noise. However, steep filter orders may induce spectral leakage or distort transient evoked potentials such as ERPs. Resampling was used as a routine step in 11 studies; it harmonizes temporal data acquired from different devices and reduces computational cost, provided that anti-aliasing low-pass filtering is applied beforehand to prevent high-frequency aliasing artifacts.

In terms of artifact removal, ICA predominates because of its powerful blind source separation capability. The greatest advantage of this method lies in its ability to successfully isolate and remove complex mixed physiological artifacts (e. g., eye blinks, electrocardiographic activity) while preserving uncontaminated brain-derived components. However, its limitations are also pronounced: it relies heavily on the researcher's subjective visual inspection, and the separated noise components can easily carry along critical neural signals, leading to irreversible loss of meaningful information. In comparison, other denoising techniques, such as artifact subspace reconstruction (ASR), possess strong automation potential when handling non-stationary motion artifacts, but typically depend on a standard segment of reference data for calibration. Parametric methods such as adaptive artifact removal (AAR), although computationally efficient and well-suited for online real-time processing, often face considerable challenges in adaptively tracking model parameters when confronted with highly non-stationary pain-evoked signals.

In summary, the current processing pipeline in pain EEG research generally follows the mainstream paradigm of "rigorous band-pass filtering + standardized resampling + ICA-based artifact removal." This strategy essentially represents an engineering trade-off between "maximally preserving neural features" and "minimizing the risk of information loss." Future research trends are likely to converge toward hybrid processing frameworks that offer higher degrees of automation while better preserving signal integrity.

Table 5 Signal processing approaches used in EEG-based pain detection

Method	Number of Studies	References
Band-pass filtering	15	[59], [47], [44], [45], [48], [49], [50], [51], [52], [53], [56], [73], [66], [61], [67]
High-pass filtering	2	[58], [57]
Notch filtering	9	[47], [49], [50], [51], [52], [53], [58], [56], [66]
Resampling	11	[59], [44], [45], [46], [49], [51], [58], [73], [61], [67], [69]
Baseline correction	1	[46]
Artifact removal by ICA	6	[47], [53], [57], [73], [66], [69]
Artifact removal by ASR	2	[47], [57]
Artifact removal by PCA	2	[51], [58]
Artifact removal by AAR	2	[44], [45]

5.4 Feature Extraction

Feature extraction is a core component of BCI systems, and its quality directly constrains subsequent classification performance. Table 6 summarizes the feature-extraction methods used for EEG-based pain detection and their frequency of use. Spectral features are the most widely adopted approach, with 10 studies relying on metrics such as PSD, entropy, and band power. These features have clear physical interpretations because they quantify the energy distribution and complexity of neural oscillations across frequency bands and are compatible with conventional ML classifiers. However, their relatively low dimensionality may limit their ability to capture dynamic brain-network changes and nonlinear pain-related signatures.

In terms of specific technical implementation pathways, time-frequency analysis has been adopted by three studies and wavelet transform by four. The advantage of time-frequency analysis lies in its ability to handle non-stationary signals, effectively capturing the dynamic evolution of EEG rhythms during pain induction through an extended joint time-frequency distribution (e. g., the short-time Fourier transform, STFT, or wavelet transform). However, its limitations include susceptibility to cross-term interference (e. g., the window function constraints of STFT) and the inherent difficulty in achieving a perfect balance between temporal and frequency resolution. The wavelet transform, because of its multi-resolution analysis capability, offers greater flexibility in extracting transient or abrupt pain-related features, but the choice of basis functions is often somewhat subjective and empirically driven, and it imposes relatively high computational demands.

In addition, statistical features and functional connectivity have been adopted by four and three studies, respectively. The former characterize the static statistical properties of the

signal through measures such as the mean, variance, and fractal dimension, while the latter aims to reveal synergistic mechanisms between different brain regions. Although statistical features are computationally simple, they rely excessively on local signal properties and lack consideration of global network organization. Functional connectivity features, while capable of probing the neural circuitry mechanisms of pain, are highly susceptible to the effects of volume conduction and the choice of reference electrodes. In contrast, deep learning features and the common spatial pattern (CSP) each account for two studies, respectively, representing data-driven cutting-edge directions. Deep learning features do not require manually predefined features and possess powerful automatic representation learning capabilities; however, their black-box nature leads to poor model interpretability and a heavy dependence on large-scale, high-quality labeled data. CSP is specifically designed for paradigms such as motor imagery, extracting spatial filtering features by maximizing the variance between two classes of signals, but its generalization ability may be limited in complex multi-class pain classification tasks.

In summary, the feature extraction techniques in current pain EEG research are undergoing a transition from a stage dominated by shallow, physically defined features to one that places equal emphasis on deep data-driven and network-based features. A single feature extraction method invariably possesses inherent limitations in representing the complex experience of pain. Future research trends are likely to focus on constructing hybrid models that integrate features from multiple domains, aiming to overcome the representational bottleneck of a single dimension and achieve both precise quantification of pain intensity and in-depth elucidation of the underlying neural mechanisms.

Table 6 Feature extraction approaches used in EEG-based pain detection

Method	Number of Studies	References
Frequency features (PSD, entropy, band power)	10	[46], [73], [61], [67], [48], [50], [51], [53], [54], [57]
Time-frequency features	3	[44], [45], [51]
Wavelet transform	4	[59], [73], [58], [55]
Statistical features (mean, variance, skewness, fractal dimension, entropy, etc.)	4	[47], [53], [54], [55]
Functional connectivity	3	[59], [50], [52]
Deep learning-derived features	2	[66], [69]
Common spatial pattern (CSP)	2	[49], [58]

5.5 Types of Decoding Techniques

Current EEG-based pain decoding research primarily employs two major categories of algorithms: ML and DL. Table 7 summarizes the strengths and limitations of each approach. The selection of algorithms in existing studies exhibits a high degree of diversity. Statistical results indicate that a wide range of methods, from traditional ML to cutting-edge deep neural networks, are extensively applied, reflecting an ongoing search

for an optimal balance between feature suitability and model generalization capability in pain decoding tasks.

In traditional ML studies, SVM accounts for the largest proportion of the literature and is the most common baseline model. Its main advantage is the maximum-margin classification principle, which performs robustly on high-dimensional sparse spectral features such as PSD and phase-locking value (PLV), particularly in small-sample EEG datasets. However,

SVM performance depends strongly on kernel selection and penalty-parameter tuning, and its shallow architecture limits its ability to capture deep spatiotemporal EEG dynamics. KNN and RF are also used as complementary approaches. KNN is intuitive and effective for nonlinearly distributed data but is memory- and computation-intensive and sensitive to noise. RF reduces the overfitting risk of a single decision tree and provides feature-importance estimates, although it may still be affected by the curse of dimensionality in extremely high-dimensional feature spaces. A few studies have also used Elastic Net, a regression-based classification method; decision tree (DT), an interpretable rule-partitioning model; and rough neural network models, which integrate rough set theory with neural-network learning to handle data uncertainty. These methods remain relatively isolated explorations.

The introduction of DL marks a transition toward end-to-end automatic extraction of high-dimensional pain-related features. CNN is effective for spatial feature extraction because local receptive fields and weight sharing can capture the

topological structure of EEG topographic maps. However, standard CNNs are constrained by local receptive fields and may be limited in modeling long-range temporal dependencies. Transformer models use self-attention to overcome the recursive limitations of sequence modeling and show potential for parallel computation and long-range dependency modeling. Nevertheless, their large parameter counts impose high computational requirements, and model performance may be unstable when training data are limited.

Overall, SVM and RF are reliable choices when datasets are small and features have been carefully engineered, whereas CNN and Transformer models are better suited to end-to-end learning when sufficient data are available. Adequate regularization, data augmentation, and cross-subject validation are essential to prevent overfitting and inflated performance estimates. Future research should emphasize fair comparisons across methods using standardized public datasets and should explore lightweight models suitable for real-time clinical deployment.

Table 7 Classification approaches used in EEG-based pain detection

Decoding category	Subcategory	Advantages	Limitations	References
Machine learning	SVM	Effective for high-dimensional and nonlinear data.	Sensitive to kernel and parameters; low interpretability.	[47], [44], [45], [48], [49], [52], [54], [57], [58], [59], [53]
	KNN	Simple and effective for clear decision boundaries.	Computationally costly and sensitive to distance metrics.	[55]
	RF	Stable performance and supports feature importance analysis.	Limited interpretability and may overfit small datasets.	[46], [51]
	Elastic Net	Sparse, interpretable, and reduces overfitting.	Limited ability to model nonlinear relationships.	[50]
	Decision tree (DT)	Highly interpretable and easy to implement.	Sensitive to noise and prone to poor generalization.	[53]
	Rough neural network	Combines rough sets with nonlinear learning ability.	Complex structure with limited interpretability.	[56]
Deep learning	CNN	Strong spatial feature extraction from EEG data.	Limited long-range temporal modeling and generalization.	[64], [66], [68], [70], [62], [63], [71], [73], [67]
	Transformer	Captures long-range dependencies and supports feature fusion.	Requires large datasets and high computational cost.	[67], [69], [65]
	ANN	Simple structure, fast training, and easy implementation.	Weak feature learning and limited generalization.	[61]

5.6 Public Datasets and Reproducibility

Public EEG-pain datasets are essential for benchmarking and ensuring reproducibility, yet they differ substantially in design and target populations. The BioVid Heat Pain Database (BVDB) is one of the most widely used benchmarks, containing recordings from about 90 healthy participants undergoing four individualized levels of heat stimulation with simultaneous multimodal signals (EEG, ECG, EDA, EMG, facial video, behavioral ratings), which makes it ideal for acute pain detection and multi-level intensity classification, though its controlled laboratory setting and healthy sample limit ecological validity for chronic pain^[74, 75]. High-density EEG datasets based on laser-evoked pain (e.g., the dataset by Gross et al.) provide relatively “pure” nociceptive input and fine-grained single-trial ratings, and are well suited for studying laser-evoked potentials and time-frequency markers of pain perception, but they are also restricted to acute experimental paradigms and require specialized equipment^[76, 77]. In contrast, publicly shared resting-state EEG datasets from chronic pain patients (e.g., the OSF dataset) capture real-world clinical heterogeneity and include rich clinical scales, making them valuable for diagnostic

and prognostic modeling, though they often lack standardized evoked tasks and trial-level labels, which constrains supervised intensity decoding^[78].

Reproducibility across these datasets is hampered by major differences in pain type (thermal, laser, cold pressor, chronic spontaneous pain), recording setups (channel count, reference montage), and sample sizes, leading to large performance discrepancies and poor cross-dataset transfer: models that achieve high accuracies on a single acute pain dataset often show markedly reduced performance on heterogeneous chronic pain cohorts^[74, 76, 78]. Validation strategies are far from standardized; many studies report only within-subject or random k-fold cross-validation, which tends to overestimate performance, whereas more stringent leave-one-subject-out or external validation typically reduces accuracy by 10–30 percentage points^[51]. Preprocessing pipelines (filter bands, artifact removal methods such as ICA or ASR, rereferencing schemes) and feature extraction procedures are highly variable and sometimes insufficiently documented, making exact replication difficult; even when using the same public dataset and model, changes in preprocessing alone can lead to non-trivial

performance shifts^[79, 80].

To improve reproducibility and clinical relevance, future work should evaluate methods on multiple representative public datasets (e.g., combining BVDB or laser-evoked data for acute experimental pain with chronic pain resting-state EEG for clinical scenarios) and consistently report both within-subject and cross-subject (and, where possible, external) validation results^[74, 76, 78, 51]. Adopting standardized data formats such as BIDS-EEG and providing detailed, ideally open-source, descriptions of preprocessing and modeling pipelines will greatly facilitate independent verification and method comparison^[79, 80]. Finally, the community would benefit from converging on a set of common benchmark tasks (binary pain vs no-pain detection, multi-level intensity classification, continuous pain regression) and evaluation metrics, with strict safeguards against data leakage (nested cross-validation, non-overlapping time windows, subject-wise splits)^[10]. Such coordinated efforts around public datasets and transparent workflows are essential for moving from isolated high accuracies on single datasets toward robust, reproducible, and clinically meaningful EEG-based pain decoding.

6 Future Research Directions

Although EEG has shown considerable potential for pain-state decoding, several technical challenges remain. Signal noise is a primary issue because EEG signals are weak and susceptible to contamination by EMG activity, ocular movements, and other artifacts; conventional preprocessing methods often cannot fully remove their influence on feature extraction. Inter-individual variability is also prominent because neural representations of pain differ substantially across subjects, limiting model generalizability. In addition, high-quality pain EEG data remain scarce, especially long-term monitoring data from patients with chronic pain, restricting the performance gains of data-driven DL approaches. Together, these challenges mean that the accuracy and stability of existing decoding models remain insufficient for routine clinical use.

A key direction for future work is to clarify whether current EEG-based pain decoders capture pain-specific neural signatures or predominantly reflect broader processes such as arousal, attention, and stimulus salience. Many commonly used EEG markers are sensitive to these general factors: alpha oscillations do not differentiate between painful thermal stimulation and equally unpleasant non-painful auditory stimuli^[81]; gamma-band responses increase with stimulus intensity for both painful and non-painful tactile inputs^[82]; and nociceptive ERPs are strongly modulated by stimulus salience and anticipation^[83]. Therefore, high classification accuracies in typical acute pain paradigms may largely reflect the decoding of arousal or salience rather than pain itself.

To address this, future studies should incorporate explicit control conditions—such as non-painful but equally salient or unpleasant stimuli—to test whether decoding performance persists when pain is absent but arousal is matched. Additionally, designs that dissociate anticipation from actual nociceptive input and, where feasible, multimodal approaches (e.g., combining EEG with autonomic or fMRI measures) would help isolate pain-specific neural representations from general arousal and attention networks^[83]. Only models that

remain robust under such stringent controls can be considered truly pain-specific and clinically useful.

Future research should address these bottlenecks through multimodal fusion and adaptive algorithm design. Integrating neuroimaging modalities such as fNIRS and fMRI can compensate for the limited spatial resolution of EEG and improve decoding robustness through cross-modal feature complementarity. Personalized transfer learning represents an effective strategy for addressing inter-individual variability, for example through meta-learning or domain-adaptation methods. At the data level, generative adversarial networks (GANs) may alleviate data scarcity by synthesizing physiologically plausible EEG signals for training-sample augmentation.

These technological advances should ultimately support clinical translation. Portable dry-electrode EEG devices could facilitate the transition of pain monitoring from laboratory settings to bedside applications, while edge computing may enable real-time pain assessment. Because pain is a multidimensional experience, future models should integrate physiological signals with psychological and behavioral indicators to construct a more comprehensive decoding framework. Clinical acceptability also requires model interpretability: clinicians need to understand why a model assigns a specific pain state rather than merely receiving a predicted label. Therefore, in addition to intrinsic interpretation methods such as attention mechanisms, post-hoc explanation techniques, including Shapley additive explanations (SHAP) values and gradient-based saliency mapping, should be systematically introduced. These methods can attribute model decisions to critical EEG frequency bands, channels, and spatiotemporal segments, thereby providing verifiable neurophysiological evidence for predictions and facilitating the discovery of objective neural markers of pain.

In the long term, progress in this field will require standardized research paradigms, including unified pain-induction protocols, standardized EEG feature-extraction procedures, and open shared databases. Interdisciplinary collaboration among neuroscientists, clinicians, and algorithm engineers is equally critical. As BCI systems mature, closed-loop neuromodulation may become a promising long-term direction, enabling real-time decoding of pain states followed by timely intervention. Progress in these directions could help shift pain management from empirical judgment toward precision medicine.

7 Conclusion

The objective assessment of pain has long been a major challenge in clinical diagnosis and treatment, particularly for patients who have difficulty communicating subjective experiences. EEG, with its millisecond-level temporal resolution, non-invasiveness, and broad accessibility, provides an effective window for analyzing the dynamics of pain-related neural activity and offers a methodological foundation for pain-state recognition and quantitative evaluation.

This review systematically summarized research on EEG-based neural mechanism analysis and pain decoding, covering pain-related neural representations, signal-processing pipelines, feature-extraction methods, and ML and DL models. The findings indicate that pain is not generated by a single

brain region; rather, it is a complex process involving coordinated activity across multiple brain regions and networks. Oscillations across different frequency bands, time-frequency dynamics, and EEG-derived brain-network features all provide important information for pain recognition.

From the perspective of decoding performance, traditional ML methods remain practical and interpretable under small-sample conditions and are suitable for exploring pain-related EEG features and establishing baseline models. In contrast, DL methods can learn complex nonlinear spatiotemporal patterns more effectively and show advantages in multi-band fusion, long-range dependency modeling, and complex task recognition. Although DL methods generally achieve higher classification performance, their effectiveness depends on data scale, label quality, and model architecture, and their interpretability remains limited.

Nevertheless, current research still faces signal noise, pronounced inter-individual variability, limited data scale, inconsistent experimental paradigms, and insufficient cross-subject generalization, all of which constrain model stability and clinical translatability. Future studies should strengthen standardized dataset construction, promote multimodal information fusion and individualized adaptive modeling, and incorporate interpretable algorithms to improve model trustworthiness. Real-time monitoring and clinically oriented closed-loop intervention will also be important pathways for translating EEG-based pain decoding from experimental research into practical application.

In summary, EEG-based pain decoding provides technical support for objective pain assessment and contributes to a deeper understanding of the neural mechanisms of pain. Although current methods still have limitations in accuracy, generalizability, and clinical applicability, continued advances in algorithmic innovation, data standardization, and interdisciplinary collaboration may enable more intelligent pain assessment and precision pain management.

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