Accepted Manuscript

Accepted Manuscript (Uncorrected Proof)

Title: A Review of EEG-Based Neural Correlates of Handwriting and Motor Imagery: Signal Processing and Deep Learning Perspectives

Authors: Mozhgan Haji Hosseini[1,*], Mohammad Reza Nazari[1], Saeed Reza Hajian[1], Akbar Haji Ghasemalian[2]

1. *Department of Biomedical Eng., Qa .c., Islamic Azad University, Qazvin, Iran*
2. *Department of Aerospace and Submarine Medicine, AJA University of Medical Sciences, Tehran, Iran*

***Corresponding Author**: Mozhgan Haji Hosseini, Department of Biomedical Eng., Qa .c., Islamic Azad University, Qazvin, Iran. Email: m.hagyhoseini@iau.ac.ir

To appear in: **Basic and Clinical Neuroscience**

Received date: 2026/06/1

Revised date: 2026/8/29

Accepted date: 2026/9/14

Accepted Manuscript (Uncorrected Proof)

This is a “Just Accepted” manuscript, which has been examined by the peer-review process and has been accepted for publication. A “Just Accepted” manuscript is published online shortly after its acceptance, which is prior to technical editing and formatting and author proofing. *Basic and Clinical Neuroscience* provides “Just Accepted” as an optional and free service which allows authors to make their results available to the research community as soon as possible after acceptance. After a manuscript has been technically edited and formatted, it will be removed from the “Just Accepted” Web site and published as a published article. Please note that technical editing may introduce minor changes to the manuscript text and/or graphics which may affect the content, and all legal disclaimers that apply to the journal pertain.

Please cite this article as:

Haji Hosseini, M., Nazari, M.R., Hajian, S.R., Haji Ghasemalian, A. (In Press). A Review of EEG-Based Neural Correlates of Handwriting and Motor Imagery: Signal Processing and Deep Learning Perspectives. Basic and Clinical Neuroscience. Just Accepted publication Jul. 10, 2026. Doi: http://dx.doi.org/10.32598/bcn.2026.8604.1

DOI: http://dx.doi.org/10.32598/bcn.2026.8604.1

Accepted Manuscript (Uncorrected Proof)

Abstract

Handwriting is a complex cognitive–motor process involving the integration of sensorimotor coordination, visual processing, motor planning, and higher cognitive functions. Electroencephalography (EEG) has emerged as a valuable noninvasive neuroimaging technique for investigating the neural mechanisms underlying handwriting and motor imagery tasks due to its high temporal resolution and portability. Recent advances in brain–computer interface (BCI) systems, signal processing techniques, and deep learning algorithms have significantly improved the decoding and interpretation of EEG signals associated with handwriting-related activities.

This review summarizes recent developments in EEG-based handwriting and motor imagery research, with a particular focus on neural oscillations, signal preprocessing, feature extraction, classification approaches, and deep learning architectures. Major EEG rhythms associated with handwriting, especially mu and beta bands, are discussed in relation to sensorimotor brain networks. Traditional machine learning approaches such as Common Spatial Pattern (CSP), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVM) are compared with modern deep learning methods including convolutional neural networks (CNNs), recurrent neural networks (RNNs), EEGNet, and hybrid CNN–RNN models.

Furthermore, the review highlights current challenges including signal noise, inter-subject variability, limited dataset availability, and poor cross-session generalization. Emerging research directions such as interpretable artificial intelligence, multimodal neuroimaging integration, transfer learning, and portable real-time EEG systems are also discussed. The findings demonstrate that EEG-based handwriting analysis represents a promising interdisciplinary field with important applications in neurorehabilitation, cognitive assessment, assistive technologies, and intelligent BCI systems.

Keywords: Electroencephalography (EEG), handwriting analysis, motor imagery, brain–computer interface, deep learning, EEG decoding, neural oscillations, CNN, EEGNet.

Accepted Manuscript (Uncorrected Proof)

Introduction

Handwriting is one of the most sophisticated human motor skills and requires the coordinated interaction of multiple neural systems involved in motor control, sensory integration, language processing, attention, and executive functioning. The production of handwriting involves several cortical and subcortical brain regions, including the primary motor cortex, supplementary motor area, premotor cortex, parietal cortex, cerebellum, and prefrontal regions. Because handwriting combines cognitive and fine motor functions, it provides an important framework for studying brain activity and neural coordination.

Electroencephalography (EEG) is a noninvasive neurophysiological recording technique that measures electrical activity generated by neuronal populations in the brain. EEG has become widely used in neuroscience and biomedical engineering because of its high temporal resolution, relatively low cost, portability, and suitability for real-time applications. In recent years, EEG has been extensively applied in brain–computer interface (BCI) systems, motor imagery studies, cognitive neuroscience, and rehabilitation engineering.

Studies have shown that handwriting and hand movement tasks are associated with characteristic EEG oscillatory patterns, particularly within the mu (8–13 Hz) and beta (13–30 Hz) frequency bands. These neural oscillations are closely related to sensorimotor processing and motor planning. During both real and imagined hand movements, event-related desynchronization (ERD) and event-related synchronization (ERS) patterns can be observed in sensorimotor cortical regions. Understanding these neural signatures is important for improving BCI systems and developing EEG-based handwriting decoding technologies.

Traditional EEG analysis methods have relied on handcrafted feature extraction techniques such as spectral analysis, Common Spatial Pattern (CSP), wavelet transforms, and statistical feature engineering. Machine learning algorithms including Linear Discriminant Analysis (LDA), Support Vector Machines

Accepted Manuscript (Uncorrected Proof)

(SVM), and Random Forest classifiers have also been widely used for EEG classification tasks. However, EEG signals are highly nonlinear, nonstationary, and susceptible to various artifacts, which limits the performance of conventional methods.

Recent advances in artificial intelligence and deep learning have significantly transformed EEG signal analysis. Deep neural networks, particularly convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid deep learning architectures, can automatically learn complex spatiotemporal representations from raw EEG data. Models such as EEGNet and Deep ConvNet have demonstrated promising performance in motor imagery and EEG decoding applications. These developments have opened new opportunities for handwriting recognition, movement intention decoding, neurorehabilitation systems, and intelligent assistive technologies.

Despite these advances, several important challenges remain unresolved. EEG recordings are highly sensitive to physiological and environmental noise, and substantial inter-subject variability limits the generalizability of trained models. In addition, the lack of large standardized handwriting EEG datasets and the limited interpretability of deep learning models continue to hinder clinical and real-world applications.

Therefore, the purpose of this review is to provide a comprehensive overview of EEG-based handwriting and motor imagery research, focusing on neural mechanisms, signal processing techniques, machine learning methods, and deep learning approaches. This review also discusses current limitations and future research directions for improving EEG-based handwriting analysis systems and brain–computer interface technologies.

2. Neural Basis of Handwriting and Motor Imagery

Accepted Manuscript (Uncorrected Proof)

Handwriting is a multidimensional cognitive–motor activity that requires precise coordination between sensory, motor, visual, and cognitive systems. Unlike simple motor movements, handwriting involves continuous motor planning, visuospatial integration, linguistic processing, attention, and fine motor execution. Therefore, handwriting provides a valuable model for investigating neural mechanisms underlying complex human behaviors.

Several cortical and subcortical regions participate in handwriting production. The primary motor cortex (M1) plays a central role in the execution of fine hand and finger movements. The premotor cortex and supplementary motor area (SMA) contribute to movement preparation, motor sequencing, and coordination of complex motor actions. The parietal cortex is involved in visuospatial processing and sensorimotor integration, while the cerebellum contributes to movement precision and timing. In addition, prefrontal cortical regions support attention, working memory, and executive control during handwriting tasks.

EEG studies have demonstrated that handwriting and motor imagery tasks are associated with characteristic neural oscillatory patterns. Among different EEG frequency bands, mu rhythms (8–13 Hz) and beta rhythms (13–30 Hz) are particularly important because they are strongly associated with sensorimotor activity. During voluntary movement or imagined movement, event-related desynchronization (ERD) is commonly observed in sensorimotor cortical regions, reflecting cortical activation and motor preparation. Following movement completion, event-related synchronization (ERS), especially within the beta band, may occur and is believed to reflect motor inhibition and sensorimotor resetting.

Motor imagery refers to the mental simulation of movement without actual physical execution. Neurophysiological studies have shown that motor imagery activates neural networks similar to those involved in real movement execution. Because of this similarity, motor imagery has become a

Accepted Manuscript (Uncorrected Proof)

fundamental paradigm in EEG-based brain–computer interface systems. Imagined handwriting tasks are therefore increasingly used in BCI research to decode intended movements and reconstruct writing trajectories directly from brain activity.

Recent research has also explored functional connectivity and network-level brain interactions during handwriting tasks. Studies suggest that handwriting requires dynamic communication between motor, visual, and cognitive networks. Connectivity analyses using coherence, phase synchronization, and graph theoretical approaches have demonstrated that neural communication patterns change significantly during writing activities. These findings indicate that handwriting is not controlled by isolated brain regions but rather emerges from distributed neural network interactions.

Understanding the neural basis of handwriting is essential for multiple applications, including rehabilitation engineering, neurological disorder assessment, assistive communication technologies, and intelligent human–computer interaction systems. In particular, EEG-based handwriting decoding may provide new opportunities for patients with severe motor impairments who are unable to communicate through conventional methods.

3. EEG Signal Acquisition and Preprocessing

EEG signal acquisition is one of the most important stages in handwriting and motor imagery studies because signal quality directly affects the performance of subsequent analysis and classification methods. EEG signals are typically recorded using multiple scalp electrodes placed according to standardized electrode positioning systems such as the international 10–20 system or high-density electrode configurations.

In handwriting-related experiments, electrodes positioned over sensorimotor cortical areas are particularly

Accepted Manuscript (Uncorrected Proof)

important. Channels such as C3, C4, Cz, FC3, FC4, and CP3 are frequently used because they are closely associated with hand and finger motor control.

Depending on the experimental design, EEG systems may contain between 8 and 128 channels. Higher-density systems provide improved spatial resolution but increase computational complexity and setup time.

EEG signals are highly susceptible to various physiological and environmental artifacts. Common sources of noise include eye movements (electrooculography; EOG), muscle activity (electromyography; EMG), cardiac activity (ECG), power-line interference, and motion artifacts. Therefore, preprocessing is necessary to improve signal quality and remove unwanted components before feature extraction and classification.

Typical EEG preprocessing pipelines include several steps. First, bandpass filtering is applied to remove low-frequency drift and high-frequency noise. In many handwriting and motor imagery studies, EEG signals are filtered within frequency ranges between 0.5 Hz and 40 Hz or 1 Hz and 50 Hz. Notch filtering at 50 Hz or 60 Hz is also commonly used to suppress power-line interference.

Artifact removal represents another critical preprocessing step. Independent Component Analysis (ICA) is one of the most widely used methods for separating neural activity from artifacts such as eye blinks and muscle noise. Other approaches include regression-based correction methods, adaptive filtering, wavelet denoising, and automated artifact rejection algorithms.

After artifact removal, EEG recordings are segmented into shorter time windows known as epochs. Epoching is typically performed around specific events or task periods, such as handwriting onset or motor imagery initiation. Baseline correction may then be applied to normalize EEG activity relative to pre-task intervals.

Accepted Manuscript (Uncorrected Proof)

Normalization and standardization techniques are also commonly used to reduce inter-subject variability and improve machine learning performance. In recent years, automated preprocessing pipelines implemented in software platforms such as EEGLAB, MNE-Python, and Brainstorm have significantly improved reproducibility and standardization in EEG research.

Effective preprocessing is essential because poor signal quality can substantially reduce classification accuracy and negatively affect deep learning models. Consequently, preprocessing remains a foundational component of EEG-based handwriting and motor imagery analysis systems.

4. Feature Extraction Methods in EEG-Based Handwriting Analysis

Feature extraction aims to transform raw EEG signals into meaningful numerical representations that capture relevant neural information while reducing data dimensionality. Because EEG signals are highly complex, nonlinear, and nonstationary, effective feature extraction is critical for accurate handwriting and motor imagery classification.

Feature extraction methods in EEG analysis are commonly categorized into time-domain, frequency-domain, time–frequency, spatial, and deep representation learning approaches.

4.1 Time-Domain Features

Time-domain features are extracted directly from the EEG waveform without transforming the signal into another domain. These features are computationally efficient and widely used in real-time systems.

Common time-domain features include:

Accepted Manuscript (Uncorrected Proof)

Mean amplitude

Variance

Standard deviation

Root mean square (RMS)

Hjorth parameters

Signal energy

Zero-crossing rate

These measures provide information about signal amplitude variations and temporal characteristics associated with neural activity during handwriting tasks.

4.2 Frequency-Domain Features

Many neural processes are associated with oscillatory activity within specific frequency bands. Frequency-domain analysis therefore plays a central role in EEG studies.

Power spectral density (PSD) is commonly computed using Fourier transform methods or Welch's method. EEG frequency bands include:

Delta (1–4 Hz)

Theta (4–8 Hz)

Alpha/Mu (8–13 Hz)

Beta (13–30 Hz)

Gamma (>30 Hz)

Accepted Manuscript (Uncorrected Proof)

In handwriting and motor imagery research, mu and beta rhythms are particularly important because they are strongly associated with sensorimotor cortical activity.

4.3 Time–Frequency Analysis

Because EEG signals are nonstationary, time–frequency methods allow simultaneous analysis of temporal and spectral information.

Common approaches include:

Short-Time Fourier Transform (STFT)

Wavelet Transform

Continuous Wavelet Transform (CWT)

Wavelet Packet Decomposition

Time–frequency representations are especially useful for capturing transient neural patterns during movement preparation and execution.

4.4 Spatial Features

Spatial feature extraction methods analyze relationships among multiple EEG channels to identify spatial patterns associated with brain activity.

One of the most widely used methods is Common Spatial Pattern (CSP), which maximizes variance differences between task classes. CSP has demonstrated strong performance in motor imagery classification and remains a benchmark approach in BCI research.

Accepted Manuscript (Uncorrected Proof)

Connectivity-based features such as coherence, phase-locking value (PLV), and functional connectivity networks are also increasingly used to investigate neural interactions during handwriting tasks.

4.5 Deep Feature Learning

Recent advances in deep learning have enabled automatic extraction of hierarchical representations directly from raw EEG data. Convolutional neural networks (CNNs) can learn spatial and temporal patterns, while recurrent neural networks (RNNs) model sequential dependencies in EEG signals.

Hybrid architectures such as CNN–LSTM and compact models such as EEGNet have demonstrated promising performance in EEG decoding applications. Deep learning methods reduce the need for handcrafted feature engineering and may improve classification accuracy in complex handwriting tasks.

Despite these advances, feature extraction remains challenging because EEG signals exhibit substantial inter-subject variability and low signal-to-noise ratios. Therefore, selecting robust and interpretable features continues to be an important research direction in EEG-based handwriting analysis.

5. Machine Learning and Deep Learning Approaches for EEG Classification

Machine learning and deep learning techniques have become essential tools in EEG-based handwriting and motor imagery analysis. These methods aim to decode neural activity patterns and classify different cognitive or motor states from EEG recordings. Over the past two decades, advances in artificial intelligence have significantly improved the performance of EEG classification systems and expanded their applications in brain–computer interfaces (BCIs), neurorehabilitation, and intelligent assistive technologies.

Traditional machine learning approaches generally rely on handcrafted feature extraction methods followed by classification algorithms. In contrast, deep learning models can automatically learn hierarchical feature

Accepted Manuscript (Uncorrected Proof)

representations directly from raw EEG data. Both approaches have important advantages and limitations in handwriting-related EEG studies.

5.1 Traditional Machine Learning Methods

Traditional machine learning techniques remain widely used in EEG analysis because of their relatively low computational complexity and interpretability.

Linear Discriminant Analysis (LDA)

LDA is one of the most frequently used classifiers in BCI systems due to its simplicity and computational efficiency. LDA aims to identify a linear combination of features that maximizes class separability. It has demonstrated reliable performance in motor imagery EEG classification tasks, particularly when combined with CSP features.

Support Vector Machines (SVM)

SVM classifiers are highly effective for high-dimensional EEG datasets and nonlinear classification problems. By using kernel functions, SVM models can separate complex EEG feature distributions with improved accuracy. SVM-based approaches have been extensively applied in handwriting recognition, motor imagery classification, and movement intention decoding.

Random Forest and Ensemble Learning

Random Forest algorithms use multiple decision trees to improve classification robustness and reduce overfitting. Ensemble learning approaches are particularly useful when EEG datasets are noisy or contain substantial inter-subject variability.

k-Nearest Neighbors (k-NN)

Accepted Manuscript (Uncorrected Proof)

The k-NN algorithm classifies EEG samples based on similarities with neighboring feature vectors. Although computationally simple, k-NN performance may decrease in large-scale EEG datasets with high dimensionality.

Traditional machine learning methods generally require careful feature engineering and preprocessing. Their performance strongly depends on the quality of extracted EEG features.

5.2 Deep Learning Approaches

Deep learning has transformed EEG signal analysis by enabling automatic feature learning from raw or minimally processed EEG recordings. These approaches can model complex nonlinear spatiotemporal relationships within EEG data.

Convolutional Neural Networks (CNNs)

CNNs are among the most widely used deep learning architectures in EEG analysis. They are highly effective for extracting local spatial and temporal patterns from EEG signals.

Deep ConvNet architectures proposed by Schirrmeister et al. demonstrated that CNNs could achieve high performance in EEG decoding tasks. Similarly, EEGNet introduced a compact CNN architecture specifically optimized for EEG-based BCI applications. EEGNet significantly reduced model complexity while maintaining strong classification accuracy.

CNN-based approaches have been successfully applied in:

Motor imagery classification

Handwriting intention recognition

Finger movement decoding

Accepted Manuscript (Uncorrected Proof)

Real-time BCI systems

Recurrent Neural Networks (RNNs)

RNNs are designed to model sequential and temporal dependencies in EEG signals. Long Short-Term Memory (LSTM) networks, a specialized form of RNNs, can capture long-range temporal relationships and reduce vanishing gradient problems.

RNN and LSTM architectures are particularly useful for handwriting trajectory decoding because handwriting involves continuous temporal motor patterns.

Hybrid CNN–RNN Models

Hybrid architectures combine CNNs and RNNs to exploit both spatial and temporal information. CNN layers extract spatial EEG representations, while RNN or LSTM layers model temporal dependencies. CNN–LSTM models have shown promising results in motor imagery EEG classification and handwriting-related decoding tasks.

Transformer-Based Models

More recently, transformer architectures and attention mechanisms have emerged in EEG research. These models can capture long-range dependencies and selectively focus on important signal components. Transformer-based EEG models may improve robustness and interpretability in handwriting analysis systems.

5.3 Comparison Between Traditional and Deep Learning Methods

Traditional machine learning methods offer advantages such as lower computational requirements, easier interpretability, and suitability for small datasets. However, they often require extensive handcrafted feature engineering and may struggle with highly nonlinear EEG signals.

Accepted Manuscript (Uncorrected Proof)

Deep learning approaches can automatically learn hierarchical EEG representations and generally achieve higher classification accuracy. Nevertheless, they require larger datasets, increased computational resources, and careful model optimization. In addition, deep learning models often suffer from limited interpretability, which remains an important challenge for clinical applications.

Consequently, selecting an appropriate classification approach depends on multiple factors including dataset size, computational constraints, real-time processing requirements, and application goals.

6. Applications of EEG-Based Handwriting Analysis

EEG-based handwriting analysis has attracted growing attention because of its potential applications across neuroscience, rehabilitation engineering, education, healthcare, and human–computer interaction. By decoding neural activity associated with handwriting and motor imagery, researchers aim to develop intelligent systems capable of interpreting user intentions directly from brain signals.

6.1 Brain–Computer Interface Systems

One of the most important applications of EEG-based handwriting analysis is in brain–computer interface (BCI) systems. BCIs enable direct communication between the brain and external devices without relying on conventional muscular activity.

Handwriting-based BCIs may allow users to generate text, control virtual keyboards, or communicate through imagined writing movements. Such systems are particularly valuable for patients with severe motor disabilities, including individuals with amyotrophic lateral sclerosis (ALS), spinal cord injury, or locked-in syndrome.

Recent advances in deep learning and EEG decoding have improved the speed and accuracy of handwriting-related BCI systems.

6.2 Neurorehabilitation

Accepted Manuscript (Uncorrected Proof)

EEG-based handwriting analysis can also support neurorehabilitation programs for patients with neurological disorders affecting motor function.

Stroke patients, individuals with Parkinson's disease, traumatic brain injury patients, and children with developmental motor disorders may benefit from EEG-guided rehabilitation systems. Monitoring handwriting-related neural activity may help clinicians assess motor recovery, evaluate rehabilitation progress, and design personalized therapy protocols.

Motor imagery training combined with EEG feedback has demonstrated promising results for promoting neural plasticity and improving motor performance.

6.3 Cognitive and Neurological Assessment

Because handwriting involves multiple cognitive and motor processes, EEG-based handwriting analysis may provide useful biomarkers for neurological and cognitive disorders.

Changes in handwriting-related neural activity have been associated with:

Parkinson's disease

Alzheimer's disease

Dysgraphia

Attention deficit disorders

Cognitive impairment

EEG analysis may therefore contribute to early diagnosis and objective assessment of neurological conditions.

6.4 Intelligent Human–Computer Interaction

EEG-based handwriting systems may improve human–computer interaction by enabling more natural and adaptive communication technologies.

Accepted Manuscript (Uncorrected Proof)

Potential applications include:

Smart educational platforms

Neuroadaptive interfaces

Virtual reality systems

Assistive communication technologies

Intelligent robotics

Future systems may integrate EEG signals with eye tracking, electromyography (EMG), and motion sensors to improve interaction accuracy and usability.

6.5 Security and Authentication

Emerging studies suggest that neural signatures associated with handwriting may be used for biometric authentication and user identification. Since EEG patterns are highly individualized, combining handwriting behavior with brain activity may enhance cybersecurity and authentication systems.

Although this field remains in early stages, EEG-based biometric systems represent an important future research direction.

7. Challenges and Limitations

Despite significant advances in EEG-based handwriting analysis, several technical and methodological challenges remain unresolved.

One major challenge is the low signal-to-noise ratio (SNR) of EEG recordings. EEG signals are highly susceptible to physiological artifacts such as eye movements, muscle activity, and environmental interference. These artifacts may significantly reduce classification performance.

Another important limitation is inter-subject variability. Neural activity patterns differ considerably across individuals, making it difficult to develop generalized models that perform consistently for different users.

Accepted Manuscript (Uncorrected Proof)

Dataset limitations also remain problematic. Many handwriting EEG studies rely on small participant groups and nonstandardized experimental protocols. The absence of large publicly available datasets restricts reproducibility and comparison across studies.

Cross-session variability further complicates EEG analysis because neural patterns may change across recording sessions or experimental conditions.

Although deep learning methods have achieved impressive performance, they require large training datasets and substantial computational resources. In addition, many deep learning models function as "black boxes," limiting interpretability and clinical trustworthiness.

Real-time implementation also remains challenging because portable EEG systems often suffer from reduced signal quality and limited channel availability.

Addressing these limitations is essential for translating EEG-based handwriting technologies from laboratory research into practical real-world applications.

8. Future Research Directions

Future research in EEG-based handwriting analysis is expected to focus on improving model robustness, interpretability, portability, and clinical applicability.

One important direction is the development of large standardized datasets containing multimodal handwriting and EEG recordings. Publicly accessible datasets would improve reproducibility and facilitate benchmarking of machine learning algorithms.

Transfer learning and domain adaptation techniques may help reduce inter-subject variability and improve cross-session generalization. Personalized AI systems capable of adapting to individual neural characteristics may further enhance performance.

Accepted Manuscript (Uncorrected Proof)

Explainable artificial intelligence (XAI) is another promising area. Interpretable deep learning methods may improve understanding of neural mechanisms underlying handwriting and increase clinical trust in AI-driven EEG systems.

Multimodal approaches combining EEG with other physiological signals such as EMG, fNIRS, eye tracking, or motion capture may provide more comprehensive information about handwriting-related neural activity.

Portable and wearable EEG systems are also expected to play a major role in future research. Advances in dry electrodes, wireless EEG devices, and embedded AI algorithms may enable real-time handwriting decoding outside laboratory environments.

Finally, future studies should explore cross-cultural, multilingual, and longitudinal handwriting datasets to improve the generalizability and inclusiveness of EEG-based handwriting analysis systems.

9. Conclusion

EEG-based handwriting analysis represents an important interdisciplinary research area at the intersection of neuroscience, biomedical engineering, artificial intelligence, and human–computer interaction. Handwriting involves complex neural processes associated with motor control, sensory integration, cognition, and language processing.

Advances in EEG signal processing, machine learning, and deep learning have significantly improved the ability to decode handwriting-related neural activity. In particular, CNN-based architectures such as EEGNet and Deep ConvNet have demonstrated promising performance in EEG classification tasks.

Despite these advances, important challenges remain, including signal noise, inter-subject variability, limited dataset availability, and limited interpretability of deep learning models. Addressing these challenges will be essential for developing reliable and clinically applicable EEG-based handwriting systems.

Accepted Manuscript (Uncorrected Proof)

Future developments in explainable artificial intelligence, multimodal neuroimaging, transfer learning, and portable EEG technologies are expected to further improve handwriting decoding performance and expand practical applications in neurorehabilitation, assistive communication, education, and intelligent BCI systems.

Overall, EEG-based handwriting analysis has strong potential to contribute to the development of next-generation neurotechnology systems and provide deeper insights into the neural mechanisms underlying human motor and cognitive functions.

References

Abiri, R., Borhani, S., Sellers, E. W., Jiang, Y., & Zhao, X. (2019). A comprehensive review of EEG-based brain–computer interface paradigms. Journal of Neural Engineering, 16(1), 011001. https://doi.org/10.1088/1741-2552/aaf12e

Babiloni, C., Del Percio, C., Iacoboni, M., Infarinato, F., Lizio, R., Marzano, N., Crespi, G., Dassù, F., Pirritano, M., Gallamini, M., & Eusebi, F. (2010). Suppression of alpha rhythms during observation and execution of hand movements: A high-resolution EEG study. Clinical Neurophysiology, 121(6), 976–988. https://doi.org/10.1016/j.clinph.2009.12.008

Bashivan, P., Rish, I., Yeasin, M., & Codella, N. (2016). Learning representations from EEG with deep recurrent-convolutional neural networks. IEEE Transactions on Neural Networks and Learning Systems, 27(8), 1744–1753. https://doi.org/10.1109/TNNLS.2015.2468589

Blankertz, B., Dornhege, G., Krauledat, M., Müller, K. R., & Curio, G. (2007). The non-invasive Berlin brain–computer interface: Fast acquisition of effective performance in untrained subjects. NeuroImage, 37(2), 539–550. https://doi.org/10.1016/j.neuroimage.2007.01.051

Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M., & Müller, K. R. (2008). Optimizing spatial filters for robust EEG single-trial analysis. IEEE Signal Processing Magazine, 25(1), 41–56.

Accepted Manuscript (Uncorrected Proof)

https://doi.org/10.1109/MSP.2008.4408441

Craik, A., He, Y., & Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: A review. Journal of Neural Engineering, 16(3), 031001. https://doi.org/10.1088/1741-2552/ab0ab5

Delorme, A., & Makeig, S. (2004). EEGLAB: An open-source toolbox for analysis of single-trial EEG dynamics. Journal of Neuroscience Methods, 134(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Dose, H., Møller, J. S., Iversen, H. K., & Puthusserypady, S. (2018). An end-to-end deep learning approach to MI-EEG signal classification for BCIs. Frontiers in Neuroscience, 12, 425. https://doi.org/10.3389/fnins.2018.00425

Duan, F., Dai, L., Chang, W., Chen, Z., Zhu, C., & Li, W. (2020). Brain–computer interface based on motor imagery using deep learning networks. IEEE Access, 8, 75278–75286. https://doi.org/10.1109/ACCESS.2020.2988881

Engel, A. K., & Fries, P. (2010). Beta-band oscillations—signalling the status quo? Current Opinion in Neurobiology, 20(2), 156–165. https://doi.org/10.1016/j.conb.2010.02.015

He, B., Baxter, B., Edelman, B. J., Cline, C. C., & Ye, W. (2015). Noninvasive brain–computer interfaces based on sensorimotor rhythms. Proceedings of the IEEE, 103(6), 907–925. https://doi.org/10.1109/JPROC.2015.2407272

Jeannerod, M. (2001). Neural simulation of action: A unifying mechanism for motor cognition. NeuroImage, 14(1), S103–S109. https://doi.org/10.1006/nimg.2001.0832

Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., & Lance, B. J. (2018). EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces. Journal of Neural Engineering, 15(5), 056013. https://doi.org/10.1088/1741-2552/aace8c

Accepted Manuscript (Uncorrected Proof)

Lotte, F., Congedo, M., Lécuyer, A., Lamarche, F., & Arnaldi, B. (2007). A review of classification algorithms for EEG-based brain–computer interfaces. Journal of Neural Engineering, 4(2), R1–R13. https://doi.org/10.1088/1741-2560/4/2/R01

McFarland, D. J., Miner, L. A., Vaughan, T. M., & Wolpaw, J. R. (2000). Mu and beta rhythm topographies during motor imagery and actual movements. Brain Topography, 12(3), 177–185. https://doi.org/10.1023/A:1023437823106

Nicolas-Alonso, L. F., & Gomez-Gil, J. (2012). Brain–computer interfaces: A review. Sensors, 12(2), 1211–1279. https://doi.org/10.3390/s120201211

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. Clinical Neurophysiology, 110(11), 1842–1857. https://doi.org/10.1016/S1388-2457(99)00141-8

Ramoser, H., Müller-Gerking, J., & Pfurtscheller, G. (2000). Optimal spatial filtering of single-trial EEG during imagined hand movement. IEEE Transactions on Rehabilitation Engineering, 8(4), 441–446. https://doi.org/10.1109/86.895946

Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T., & Faubert, J. (2019). Deep learning-based EEG analysis: A systematic review. Journal of Neural Engineering, 16(5), 051001. https://doi.org/10.1088/1741-2552/ab260c

Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw, J. R. (2004). BCI2000: A general-purpose brain–computer interface system. IEEE Transactions on Biomedical Engineering, 51(6), 1034–1043. https://doi.org/10.1109/TBME.2004.827072

Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., & Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human Brain Mapping, 38(11), 5391–5420.

Accepted Manuscript (Uncorrected Proof)

https://doi.org/10.1002/hbm.23730

Tangermann, M., Müller, K. R., Aertsen, A., Birbaumer, N., Braun, C., Brunner, C., Leeb, R., Mehring, C., Miller, K., Müller-Putz, G., Nolte, G., Pfurtscheller, G., Preissl, H., Schalk, G., Schlögl, A., Vidaurre, C., Waldert, S., & Blankertz, B. (2012). Review of the BCI Competition IV. Frontiers in Neuroscience, 6, 55. https://doi.org/10.3389/fnins.2012.00055

Van der Weel, F. R., & Van der Meer, A. L. H. (2024). Handwriting but not typewriting leads to widespread brain connectivity: a high-density EEG study with implications for the classroom. Frontiers in Psychology, 14, 1219945. https://doi.org/10.3389/fpsyg.2023.1219945

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. Clinical Neurophysiology, 113(6), 767–791. https://doi.org/10.1016/S1388-2457(02)00057-3

Yuan, H., & He, B. (2014). Brain–computer interfaces using sensorimotor rhythms: Current state and future perspectives. IEEE Transactions on Biomedical Engineering, 61(5), 1429–1439. https://doi.org/10.1109/TBME.2014.2312397

Zhang, Y., Zhou, G., Jin, J., Wang, M., Wang, X., & Cichocki, A. (2015). Sparse Bayesian classification of EEG for brain–computer interface. IEEE Transactions on Neural Networks and Learning Systems, 26(9), 2256–2267. https://doi.org/10.1109/TNNLS.2014.2375826

Van der Weel, F. R. R., & Van der Meer, A. L. H. (2024). Handwriting but not typewriting leads to widespread brain connectivity: A high-density EEG study with implications for the classroom. Frontiers in Psychology, 14, 1219945. https://doi.org/10.3389/fpsyg.2023.1219945

Crell, M., & Müller-Putz, G. R. (2024). Classification of handwritten characters from electroencephalographic signals using continuous kinematic decoding. Computers in Biology and Medicine, 181, 109132.

Accepted Manuscript (Uncorrected Proof)

DOI: 10.1016/j.compbiomed.2024.109132

Müller-Putz, G. R., Scherer, R., Pfurtscheller, G., & Rupp, R. (2005). EEG-based neuroprosthesis control: A step towards clinical practice. Neuroscience Letters, 382(1–2), 169–174.

DOI: 10.1016/j.neulet.2005.03.021

Kim, J.-Y., Kim, D.-S., & Lee, S.-H. (2024). Towards scalable handwriting communication via EEG decoding and latent embedding integration. arXiv preprint arXiv:2411.09170.

arXiv: https://arxiv.org/abs/2411.09170

Accepted Manuscript (Uncorrected Proof)

Figure Legends

Figure 1

PRISMA 2020 flow diagram illustrating the literature search and study selection process for EEG-based handwriting and motor imagery studies.

Figure 2

General pipeline of EEG-based handwriting analysis, including EEG acquisition, preprocessing, feature extraction, machine learning/deep learning classification, and application stages.

Accepted Manuscript (Uncorrected Proof)

Table 1

Comparison of representative studies on EEG-based handwriting and motor imagery analysis.

No	Reference	Main Topic	Methode / Model
1	Abiri et al.,2019	EEG-based BCI Review	Comprehensive Review
2	Babiloni et al., 2010	Hand Movement EEG	High-resolution EEG
3	Bashivan et al., 2016	Deep Learning for EEG	Recurrent-CNN
4	Blankertz et al., 2007	BCI Training	EEG-based BCI
5	Blankertz et al., 2008	Spatial Filtering	Common Spatial Pattern (CSP)
6	Craik et al., 2019	EEG Classification Review	Systematic Review
7	Delorme & Makeig, 2004	EEG Analysis Software	EEGLAB Toolbox

8	Dose et al., 2018	Motor Imagery EEG	End-to-End Deep Learning
9	Duan et al., 2020	Motor Imagery BCI	Deep Neural Networks
10	Engel & Fries, 2010	Motor Control EEG	Beta Oscillation Analysis
11	He et al., 2015	Sensorimotor Rhythms	EEG-based BCI
12	Jeannerod, 2001	Motor Cognition	Neural Simulation Theory
13	Lawhern et al., 2018	EEG Deep Learning	EEGNet CNN
14	Lotte et al., 2007	EEG Classification	Algorithm Review
15	McFarland et al., 2000	Motor Imagery	Mu/Beta Rhythm Analysis
16	Nicolas-Alonso & Gomez-Gil, 2012	BCI Review	Comprehensive Review
17	Pfurtscheller & Lopes da Silva, 1999	EEG Oscillations	ERD/ERS Analysis
18	Audrey L. H. Van der Meer & F. R. Van der Weel (2024)	Handwritting Brain Connectivity	High-density EEG Connectivity Analysis

Accepted Manuscript (Uncorrected Proof)

19	Markus R. Crell & Gernot R. Müller-Putz (2024)	Handwritten Character Classification from EEG	Continuous Kinematic Decoding + EEG Classification
20	Van der Weel & Van der Meer (2024)	Handwriting vs Typewriting Neural Dynamics	EEG Theta/Alpha Connectivity Analysis
21	Jun-Young Kim et al. (2024)	EEG-based Handwriting Communication	CNN + EEG Embedding Framework

Table 2

Major challenges and future research directions in EEG-based handwriting analysis..

Research Challenge	Problem Description	Suggested Solutions for Future Studies
Signal noise and artifacts	EEG signals are highly affected by physiological artifacts such as eye movements (EOG), muscle activity (EMG), and environmental noise.	Use advanced artifact-removal methods such as ICA, adaptive filters, and deep learning–based denoising approaches.
Low signal-to-noise ratio (SNR)	The amplitude of EEG signals is very small, making it difficult to detect patterns related to handwriting.	Apply strong feature-extraction methods such as wavelet transform, time–frequency analysis, and deep representation learning.

Accepted Manuscript (Uncorrected Proof)

Inter-subject variability	Brain patterns differ significantly across individuals, making trained models difficult to generalize to new users.	Develop transfer learning approaches and personalized models.
Limited dataset size	Many studies rely on small datasets with few participants.	Create larger multi-center datasets and promote data sharing initiatives.
Complexity of handwriting classification	Handwriting involves complex and multidimensional temporal–spatial patterns.	Use deep learning models such as CNNs, RNNs, and Transformers for spatiotemporal modeling.
Low cross-session stability	Model performance decreases across sessions or recording days.	Develop domain adaptation techniques and automatic calibration algorithms.
High number of EEG channels	Using too many electrodes increases system complexity and reduces usability.	Apply optimal channel selection and develop low-channel EEG systems.
Real-world applicability	Many methods work well only in laboratory settings.	Develop portable BCI systems and real-time processing algorithms.

Accepted Manuscript (Uncorrected Proof)