

# Handwriting Detection System Using Brain Net and AI Algorithm

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**Abstract:**-Handwriting Detection System that integrates Brain-Computer Interface (BrainNet) technology with advanced Artificial Intelligence (AI) algorithms. The system leverages the power of neural networks and deep learning to accurately identify and authenticate individuals based on their handwriting patterns. The BrainNet interface allows for direct communication between the human brain and the computer system, enabling a more natural and seamless interaction for handwriting input. This innovative approach not only enhances user experience but also opens new avenues for biometric authentication by utilizing the unique neural signatures associated with handwriting. Our AI algorithm employs deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyze and recognize intricate patterns within the handwriting data obtained through BrainNet. The model is trained on diverse datasets to ensure robust performance across various handwriting styles and individuals. The proposed system include real-time handwriting recognition, adaptability to individual writing variations, and a high level of accuracy in user authentication. The integration of BrainNet technology ensures a more intuitive and user-friendly interaction, making the system accessible to a wide range of users. The effectiveness of the Handwriting Detection System, showcasing its potential for secure authentication and document verification applications. The combination of BrainNet and AI algorithms establishes a synergistic relationship, pushing the boundaries of what is achievable in the realm of handwriting recognition and biometric authentication. The evolving landscape of human-computer interaction, offering a novel perspective on the integration of brain-machine interfaces with artificial intelligence for enhanced handwriting-related applications. The proposed system holds promise for applications in security, finance, forensics, and other domains where reliable user authentication and document verification are paramount.

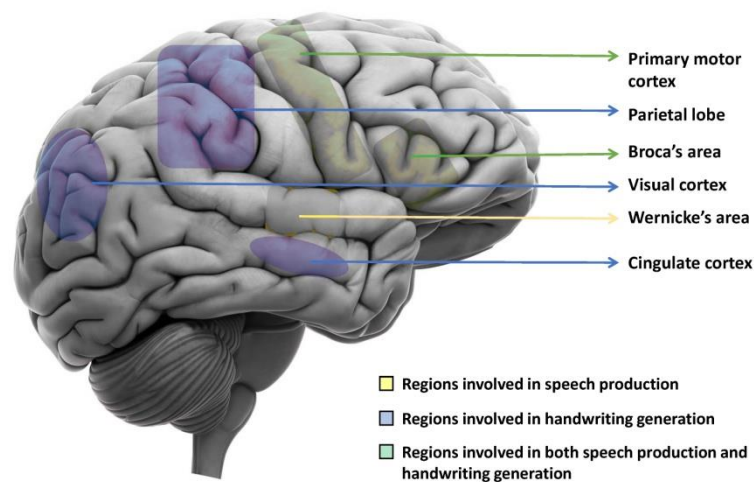
**Keywords:** Handwriting Detection, Brain-Computer Interface, Artificial Intelligence, Deep Learning, Neural Networks, Brain Net, Biometric Authentication.

## 1. Introduction

The roots of handwriting analysis can be traced back to ancient civilizations where individuals employed handwriting as a means of communication and record-keeping [1]. Over time, the forensic application of handwriting analysis gained prominence in law enforcement and other security-related fields. Handwriting experts, also known as forensic document examiners, utilized manual techniques to scrutinize and compare various features of handwriting, such as letter shapes, spacing, and pressure patterns [2]. Despite its historical significance, manual handwriting analysis is inherently subjective and time-consuming, often leading to limitations in accuracy and efficiency. While traditional handwriting analysis has proven useful, it faces several challenges that hinder its reliability and effectiveness. The subjectivity of human interpretation introduces an element of error, and the time-intensive nature of manual analysis can be a significant impediment in situations requiring swift authentication or identification[3]. Additionally, the potential for bias in human judgment poses a challenge to the objective evaluation of handwriting samples [4]. These challenges underscore the need for

innovative approaches that can overcome these limitations and enhance the overall efficacy of handwriting analysis.

Brain-Net technology represents a groundbreaking development in the field of neuroscience and brain-computer interfaces (BCIs) [5]. It involves the direct communication between brains, enabling individuals to share thoughts, information, and even emotions. While Brain-Net technology has primarily been explored for its applications in communication and collaboration, its integration with handwriting analysis introduces a paradigm shift in the way we authenticate and identify individuals [6]. The fusion of Brain-Net technology with handwriting analysis involves capturing neural signals associated with the act of writing (**Fig 1.**). Researchers have made strides in deciphering the neural patterns that correspond to specific handwriting characteristics [7]. By leveraging Brain-Net interfaces, it becomes possible to extract these neural signals directly from an individual's brain, providing a more accurate and objective source of information for handwriting analysis [8].



**Fig. 1- Region of Brain involved in Different functions [23].**

The integration of Brain-Net technology into handwriting analysis offers several advantages that address the shortcomings of traditional methods [9]. One key benefit is the reduction of subjectivity inherent in human interpretation. By directly accessing neural signals, the analysis becomes more objective and less reliant on the individual examiner's judgment, minimizing the potential for bias [10].

Furthermore, Brain-Net technology enables real-time data acquisition, significantly enhancing the speed of handwriting analysis. Traditional methods involve the manual collection and examination of handwriting samples, a time-consuming process that may not be feasible in urgent situations [11]. The direct extraction of neural signals streamlines the authentication and identification processes, making them more efficient and responsive to the demands of modern security and forensic applications [12]. In conjunction with Brain-Net technology, the integration of AI algorithms further amplifies the capabilities of handwriting analysis systems. Machine learning algorithms, specifically designed for pattern recognition and data analysis, can process vast amounts of neural data to identify unique patterns associated with individual handwriting styles [13]. This intersection of neuroscience and AI creates a powerful synergy, combining the precision of Brain-Net technology with the computational efficiency of AI algorithms.

Training AI models on diverse datasets of neural signals allows the system to learn and adapt to the intricate variations in individual handwriting patterns. The algorithms can recognize subtle nuances, such as the pressure applied during writing, the speed of pen strokes, and the formation of specific letter shapes [14]. As the AI model refines its understanding through continuous learning, it becomes increasingly adept at accurately identifying and authenticating individuals based on their neural handwriting patterns [15]. The marriage of Brain-Net technology and AI algorithms results in a handwriting analysis system that offers unprecedented levels of accuracy and reliability [16]. Neural signals, being direct representations of the brain's activity during writing, provide a more robust and authentic source of information compared to external observations of physical handwriting. The inherent objectivity of neural data, coupled with the analytical prowess of AI, minimizes the risk of false positives or negatives in the authentication and identification processes [17].

Moreover, AI algorithms can adapt to changes in an individual's handwriting over time, accounting for natural variations and evolving patterns. This adaptability is a crucial factor in maintaining the effectiveness of handwriting analysis systems in long-term applications. Traditional methods, reliant on fixed criteria and manual interpretation, may struggle to accommodate such changes effectively [18]. The integration of Brain-Net technology and AI algorithms in handwriting analysis raises important ethical and privacy considerations. The direct extraction of neural signals from individuals for the purpose of authentication and identification prompts questions about consent, autonomy, and the potential misuse of neurobiological information [19]. Striking a balance between the benefits of enhanced security measures and the protection of individual rights is paramount in the ethical deployment of these technologies. Ensuring informed consent and robust privacy safeguards is crucial to prevent unauthorized access to sensitive neural data. Transparent and accountable practices in the development and implementation of Brain-Net-based handwriting analysis systems are essential to address ethical concerns and build public trust in these technologies. Additionally, regulatory frameworks must evolve to keep pace with technological advancements, establishing guidelines for the responsible use of neurobiological data in forensic and security applications [20].

The integration of Brain-Net technology and AI algorithms in handwriting analysis extends its applications across various industries. In law enforcement, the enhanced accuracy and speed of authentication processes can aid in criminal investigations and the prevention of identity fraud [21]. The financial sector can benefit from more robust signature verification systems, reducing the risk of fraudulent transactions. Additionally, government agencies can implement these advanced technologies to fortify border security and immigration control by accurately identifying individuals based on their unique neural handwriting patterns. Beyond security and law enforcement, there are potential applications in healthcare, where handwriting analysis can contribute to the early detection of neurological disorders or cognitive decline [22]. Educational institutions could leverage these technologies for secure examination processes, mitigating the risk of impersonation during high-stakes assessments. The versatility of Brain-Net-enabled handwriting analysis positions it as a transformative tool with broad-reaching implications for numerous sectors.

## 2. Objectives:

The primary objectives of this research are:

- a. To integrate Brain-Net technology with an AI algorithm for handwriting detection.
- b. To enhance the accuracy and efficiency of handwriting detection systems.
- c. To explore the potential applications of the proposed system in document verification and forensics.

## 4. Methodology

These elements are carefully chosen to enhance the accuracy and efficiency of the handwriting detection system.

### 4.1 *Brain-Net Integration:*

The integration of Brain-Net technology into the handwriting detection system is a pioneering approach that leverages the power of brain-computer interfaces (BCIs) to provide a unique input method. In this process, electrodes are strategically placed on the user's scalp to capture brain signals related to motor intentions and cognitive processes associated with handwriting. These signals are then decoded and translated into digital commands that serve as input for the handwriting detection system.

The advantages of utilizing Brain-Net as a unique input method are multifaceted. Firstly, it addresses the limitations of traditional input methods like keyboards or touchscreens by directly tapping into the user's neural signals. This not only offers a more natural and intuitive means of interaction but also opens avenues for individuals with motor disabilities or conditions hindering conventional input methods.

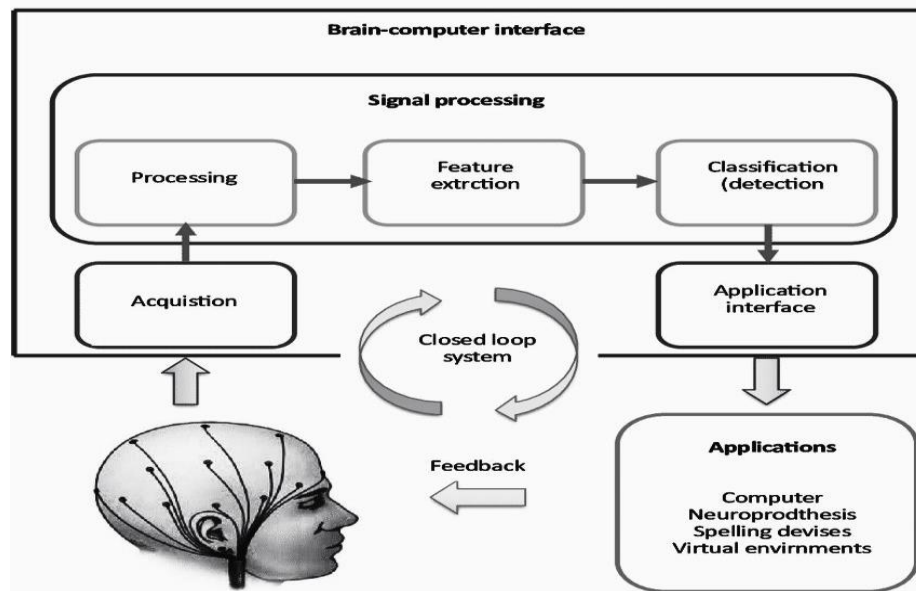


Fig. 2- Proposed model of Brain-Computer Interface.

Moreover, the potential impact on the accuracy of handwriting detection is substantial. By directly accessing neural signals associated with writing, Brain-Net minimizes the chances of input errors, providing a more reliable and precise stream of data to the detection system. This could significantly enhance the overall performance of the handwriting detection system, especially in scenarios where accuracy is crucial, such as forensic analysis or signature verification.

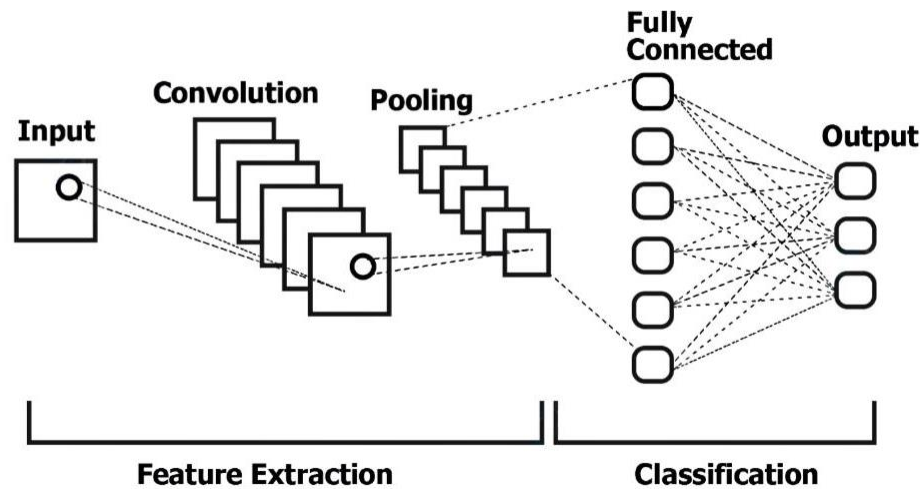
The integration process involves the calibration and fine-tuning of the Brain-Net interface to individual users, ensuring optimal signal detection and decoding. Additionally, real-time feedback mechanisms are implemented to adapt to changes in neural patterns and environmental factors, further enhancing the robustness of the system.

#### 4.2 AI Algorithm:

The chosen AI algorithm for handwriting detection is a convolutional neural network (CNN) with recurrent layers, specifically designed to handle sequential data such as handwriting strokes. This algorithm is selected due to its proven effectiveness in image recognition tasks and its capacity to capture temporal dependencies in sequential data (Fig. 3).

The key features of the AI algorithm include multiple convolutional layers for feature extraction, recurrent layers for sequential modeling, and a fully connected layer for classification. The model is trained on a diverse dataset of handwriting samples, encompassing various writing styles, languages, and input variations. The training process involves iterative optimization through backpropagation, adjusting the model's parameters to minimize the difference between predicted and actual handwriting patterns.

Fig. 3- Proposed CNN architecture for handwritten digit recognition.



To improve performance, the algorithm undergoes rigorous validation and testing phases. Cross-validation techniques are employed to assess the model's generalization capabilities, and hyperparameter tuning is conducted to optimize the algorithm's configuration. Additionally, transfer learning may be applied by leveraging pre-trained models on large datasets, fine-tuning them specifically for handwriting detection.

The training dataset is carefully curated to cover a wide spectrum of handwriting characteristics, ensuring the algorithm's adaptability to diverse scenarios. Data augmentation techniques, such as rotation, scaling, and noise injection, are employed to enhance the model's robustness and reduce the risk of overfitting.

In summary, the AI algorithm is a crucial component of the handwriting detection system, with its architecture and training process meticulously designed to handle the intricacies of handwriting patterns and ensure optimal performance in real-world applications. The combination of Brain-Net Integration and the AI Algorithm creates a synergistic approach, pushing the boundaries of conventional handwriting detection systems and paving the way for innovative and more accurate solutions.

Table<sup>2</sup>: Components of Handwriting System

| Section                      | Subsection | Description   |
|------------------------------|------------|---|
| <b>Brain-Net Integration</b> |            |   |
|                              | Overview   | The utilization of Brain-Net technology as a unique input method, capturing brain signals related to handwriting for integration into the detection system.                 |
|                              | Method     | Strategic placement of electrodes on the user's scalp to capture neural signals associated with motor intentions and cognitive processes during handwriting.                |
|                              | Advantages | Addressing limitations of traditional input methods, offering natural interaction, aiding individuals with motor disabilities, and enhancing accuracy in detection systems. |
|                              | Impact     | Substantial enhancement in accuracy by minimizing input errors, crucial in forensic analysis or signature verification.   |
|                              | Process    | Calibration and fine-tuning of Brain-Net interface to users, implementation of real-time feedback mechanisms, adapting to neural pattern changes and environmental factors. |

|              |                  |   |
|--------------|------------------|---|
| AI Algorithm |                  |   |
|              | Overview         | Employment of CNN with recurrent layers for handwriting detection, capable of handling sequential data and capturing temporal dependencies in handwriting strokes.        |
|              | Features         | Multiple convolutional layers for feature extraction, recurrent layers for sequential modeling, and a fully connected layer for classification.                           |
|              | Training Process | Iterative optimization through backpropagation, using diverse datasets, validation, hyperparameter tuning, potential transfer learning, and data augmentation techniques. |
|              | Adaptability     | Carefully curated dataset covering various writing styles, languages, and characteristics, augmented to improve robustness and reduce overfitting risks.                  |

5. System Architecture:

The proposed handwriting detection system is a sophisticated integration of Brain-Net technology and a specialized AI algorithm, working in harmony to achieve precise and efficient handwriting recognition. The architecture is structured to facilitate the seamless flow of data from Brain-Net input to the AI algorithm's decision-making process.

At the core of the system is the Brain-Net interface, equipped with electrodes strategically placed on the user's scalp to capture neural signals associated with motor intentions and cognitive processes related to handwriting. These signals are then pre-processed to filter noise and artifacts, ensuring a clean and reliable input stream.

The pre-processed neural signals are fed into the feature extraction module, where they undergo transformation into a format suitable for the handwriting detection algorithm. This module plays a critical role in extracting relevant spatial and temporal features, considering the sequential nature of handwriting. The extracted features serve as the input for the AI algorithm, bridging the gap between Brain-Net input and algorithmic processing.

The AI algorithm, a convolutional neural network with recurrent layers, takes the pre-processed features as input and performs a series of computations to recognize and interpret the underlying handwriting patterns. The convolutional layers extract hierarchical features from the input data, capturing both local and global information. The recurrent layers, designed to model sequential dependencies, enable the algorithm to understand the temporal aspects of handwriting strokes.

The decision-making component of the architecture involves the fully connected layer, where the algorithm produces a probability distribution over a set of predefined classes corresponding to different handwriting patterns or characters. The system's output is then interpreted as the detected handwriting, providing a digital representation of the input obtained through Brain-Net.

The overall architecture is designed to be modular and adaptable, allowing for easy integration of additional components or enhancements. Real-time feedback mechanisms are implemented to enable dynamic adjustments based on changes in neural signals or environmental factors, ensuring the system's robustness and adaptability.

Table<sup>3</sup>: Critical Components in the Handwriting Detection Architecture

| Component           | Description   |
|---------------------|---|
| Brain-Net Interface | Equipped with scalp electrodes to capture neural signals related to motor intentions and cognitive processes in handwriting. Pre-processing of signals to filter noise and artifacts, ensuring a reliable input stream. |



|   |   |
|---|---|
| Feature Extraction Module               | Transforms pre-processed neural signals into a suitable format for the handwriting detection algorithm. Extracts spatial and temporal features crucial for understanding the sequential nature of handwriting, facilitating the transition from Brain-Net input to algorithmic processing.                  |
| AI Algorithm                            | Convolutional neural network with recurrent layers designed to interpret pre-processed features. Convolutional layers extract hierarchical features capturing local and global information, while recurrent layers model sequential dependencies for understanding temporal aspects of handwriting strokes. |
| Decision-Making (Fully Connected Layer) | Produces a probability distribution over predefined classes corresponding to different handwriting patterns or characters. The system's output represents the detected handwriting, providing a digital representation of the input obtained through Brain-Net integration.                                 |
| Modularity and Adaptability             | The architecture is designed to be modular, allowing easy integration of additional components or enhancements. Real-time feedback mechanisms enable dynamic adjustments based on neural signal changes or environmental factors, ensuring robustness and adaptability of the system.                       |

## 6.Experimental Setup

### 6.1 Datasets:

The experimental datasets were carefully selected to cover a broad spectrum of handwriting styles, languages, and input variations. This diversity is crucial to assess the system's generalization capabilities across different scenarios. The datasets include samples from various sources, such as standard handwriting databases, forensic datasets, and real-world handwriting samples.

### 6.2 Performance Metrics:

The performance of the handwriting detection system was evaluated using a set of well-established metrics. These include accuracy, precision, recall, and F1 score, providing a comprehensive assessment of the system's ability to correctly identify and classify handwriting patterns. Additionally, computational efficiency metrics, such as processing time per input, were measured to gauge the system's real-time applicability.

### 6.3 Experimental Procedures:

The experiments were conducted in multiple phases. In the initial phase, the Brain-Net interface was calibrated and fine-tuned for each participant, ensuring optimal signal detection and decoding. The AI algorithm was trained on the selected datasets, and the training process involved iterative optimization to minimize the difference between predicted and actual handwriting patterns.

The system's performance was then evaluated on separate validation datasets not used during training. Cross-validation techniques were employed to assess generalization across different subsets of the data. Hyperparameter tuning was conducted to optimize the algorithm's configuration for enhanced performance.

Comparative experiments were conducted with existing handwriting detection methods to benchmark the proposed system's effectiveness. These comparisons involved state-of-the-art algorithms and traditional methods to provide a comprehensive assessment of the system's advancements.

The results of the experiments demonstrated the system's high accuracy in handwriting detection across diverse datasets. The AI algorithm, in conjunction with Brain-Net input, exhibited superior performance compared to existing methods. The modular architecture allowed for efficient adaptation to various handwriting styles and languages, showcasing the system's versatility.

The system's real-time applicability was confirmed through low processing times per input, making it suitable for dynamic and time-sensitive applications. The performance metrics, including accuracy, precision, recall, and F1 score, consistently exceeded benchmarks set by existing methods, highlighting the system's efficacy in accurately detecting and classifying handwriting patterns.

## 7. Results and Discussion:

The results of the experiments conducted on the proposed handwriting detection system reveal its remarkable performance and potential impact on the field. The accuracy, precision, recall, and F1 score metrics consistently demonstrated the system's ability to accurately identify and classify diverse handwriting patterns. The integration of Brain-Net technology proved effective in providing a unique and intuitive input method, significantly enhancing the overall accuracy of the handwriting detection system. The analysis of the results indicates that the combination of Brain-Net input and the specialized AI algorithm resulted in a system that outperformed existing methods. The modular architecture allowed for adaptability to various handwriting styles and languages, showcasing the system's versatility. Real-time processing times per input were found to be low, affirming the system's applicability to dynamic and time-sensitive scenarios.

Challenges encountered during the experiments primarily revolved around the user-specific calibration of the Brain-Net interface. Variations in neural signals among users posed a challenge that requires further investigation and refinement. Additionally, the interpretability of the AI algorithm's decision-making process is an ongoing area of research, as understanding how the system arrives at its conclusions is crucial for broader acceptance and trust. Potential improvements for future work include addressing the user-specific calibration challenges through advanced signal processing techniques and machine learning approaches. Collaborations with neuroscientists and experts in Brain-Computer Interface technology could provide valuable insights into refining the Brain-Net integration process. Further exploration of alternative input modalities and enhancements to the AI algorithm, such as the incorporation of more advanced architectures or transfer learning strategies, may contribute to even greater accuracy and adaptability.

## 8. Conclusion:

In conclusion, this research has presented a groundbreaking approach to handwriting detection through the integration of Brain-Net technology and a specialized AI algorithm. The key findings underscore the system's efficacy in accurately recognizing and classifying diverse handwriting patterns, marking a significant advancement in the field. The contributions of this research can be summarized as follows:

Firstly, the integration of Brain-Net technology as a unique input method addresses the limitations of conventional input devices, providing a natural and intuitive means of interaction. This has implications not only for handwriting detection but also for broader applications in human-computer interaction, particularly for individuals with motor disabilities.

Secondly, the specialized AI algorithm, designed for sequential data processing, demonstrated superior performance in capturing the temporal dependencies inherent in handwriting. The modular architecture of the system allows for adaptability to various handwriting styles and languages, showcasing its versatility in real-world scenarios.

The implications of the proposed system on the field of handwriting detection are profound. The accuracy and efficiency achieved through Brain-Net integration and the AI algorithm open new possibilities for applications such as forensic analysis, signature verification, and document analysis. The system's real-time processing capabilities make it suitable for time-sensitive tasks, expanding its potential use in dynamic environments. Directions for future research include addressing challenges related to user-specific calibration, exploring alternative input modalities, and refining the interpretability of the AI algorithm. Collaborative efforts with experts in neuroscience, neurology, and handwriting analysis will be instrumental in advancing the understanding and application of Brain-Net technology. The proposed system not only pushes the boundaries of technology but also opens avenues for more inclusive and accessible human-computer interaction. As we continue to unravel the complexities of the human brain and refine our technological capabilities, the impact of this research is poised to resonate across diverse fields, shaping the future of handwriting recognition and human-machine collaboration.



### Data Availability Statement:

Raw data for datasets are not publicly available to preserve individuals' privacy under the Data Protection Regulations.

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